Machine vision for tea quality monitoring with special emphasis on fermentation and grading

by

Surajit Borah
Registration no. 010 of 2001

A thesis submitted in partial fulfillment of the
requirements for the degree
of
Doctor of Philosophy

July'2005

Department of Electronics
School of Science and Technology
Tezpur University
Tezpur, Assam
India - 784028

DECLRATION

I hereby declare that the thesis entitled "**MACHINE VISION FOR TEA QUALITY MONITORING WITH SPECIAL EMPHASIS ON FERMENTATION AND GRADING**" is an outcome of my research carried out at the Department of Electronics, School of Science and Technology, Tezpur University, India and Electrical and Electronic Division, School of Engineering, University of Warwick, UK. The work is original and has not been submitted in part or full, for any other degree or diploma of any other University or Institute.

Date: 20/07/2005

Borah.

(Surajit Borah)

CERTIFICATE

This is to certify that the thesis entitled "**MACHINE VISION FOR TEA QUALITY MONITORING WITH SPECIAL EMPHASIS ON FERMENTATION AND GRADING**" being submitted by Mr. Surajit Borah to Tezpur University, Tezpur, Assam in fulfillment of the requirement for the award of the degree of Doctor of Philosophy, is a record of bonafide research work carried out by him. He has worked under my guidance and supervision and has fulfilled the requirement for the submission of the thesis. The results contained in the thesis have not been submitted in part or full to any other University or Institute for award of any degree or diploma.

Date: 29/07/05

(**Manabendra Bhuyan**)
Professor
Department of Electronics
Tezpur University
Napam, Tezpur, India-784028.

ABSTRACT

This thesis documents the research into the application of intelligent system engineering (ISE) based machine vision techniques for quality monitoring of black tea manufacturing. Mainly, Computer vision and Artificial Olfaction (Electronic nose) techniques have been explored, as evident from experimental results, as useful techniques for analysing the quality parameters to assist the specified purpose. Presently, organoleptic methods such as visual inspection, sniffing etc. by human sensory panel, and instrument based approach such as Gas Chromatography, colorimetric approach etc. have been reported as the quality monitoring tools in various stages of tea processing. These efforts are based on standard methodologies in the context of the quality perception of tea but such methods are time consuming, laborious, expensive and sometimes inaccurate. Therefore, to overcome the inaccuracy and inefficiency, machine vision techniques can be thought as an efficient alternative technique to support conventional techniques. Main aspects of the research are as follows:

- Colour detection of fermenting tea using computer vision for the judgment of completion of fermentation process;
- Texture analysis of tea grades using computer vision for tea granule size estimation;
- Aroma analysis using electronic nose for quality judgment of tea grades.

The methods for such problems obey certain definite steps namely data acquisition, preprocessing, feature extraction, and classification (decision-making). The third step, feature extraction, is considered as the most significant step as it determines a high degree of the overall performance of the system. A feature extraction method can be termed successful if the resulted features describe uniquely the processed data. Finally the classification step analyses the features and acquired knowledge is store for further classification of data. Different ISE based techniques are used for the data classification.

In the first aspect, colour features are extracted from colour images of fermenting tea captured from the on going fermentation process. Hue and saturation of HSI (hue, saturation and intensity) colour model are used as the colour descriptor. A new colour feature extraction method is proposed on the basis of dissimilarity pixel value (DPV) measurement, which adopts the method of colour histogram comparison. While using the new colour features as colour descriptors of the fermenting tea images, the principal component analysis (PCA) can efficiently categorize images of different groups of different colours. It is also observed that, the unsupervised clustering algorithm, K-mean, can efficiently classify images efficiently into different cluster points. Neural network classifier namely multi layer perceptron (MLP) can classify the test samples with an accuracy of 91.11%.

In the second aspect, a new texture feature extraction method is proposed for the texture analysis, which can discriminate different tea images of different granule size. The approach

employs the knowledge of surface roughness of tea images instead of calculating the actual size of the tea granules in the images. The new feature considers range of different groups of images of the same granule size. These ranges are estimated using the existing texture features in difference form, which adopts the simplified version of Mahalanobis distances. Wavelet transform based sub-band images are used for calculating the existing statistical texture features, namely Variance, Entropy and Energy. Finally, the estimated ranges are taken into account for final feature extraction, measuring the differences of the calculated Mahalanobis distances. The technique adopts the Discrete Wavelet Transform (DWT) based decomposed sub-band images of different scales using Daubechies wavelets. Such DWT technique has been proven as efficient method for texture analysis due to its property of both space and frequency localization in the images. It is observed that, while using new features, unsupervised clustering algorithms K-mean and self organizing map (SOM) can classify the images efficiently into different cluster points. The MLP can classify the test samples with an accuracy of 74.67%. The same samples are tested by Learning Vector Quantization (LVQ) technique, which gives accuracy of 80%.

In the third and final aspect, four tin oxide (SnO_2) EN sensors system is used for the tea aroma acquisition system. The samples are made using the conventional tea making procedure of adding hot water with a specific amount of tea leaves. A difference model is used to compensate the possible drift in the transient response produced by the sensors. The mean and peak of the acquired transient signals are considered as feature vectors for analysis the aroma profiles of different tea samples. It is observed that, while using the selected feature set, PCA can classify different samples into appropriate categories. Moreover, K-mean and SOM are also successful in finding different cluster points among the data set. Finally, the data set are tested by three different neural network techniques, namely MLP, Radial Basis Function (RBF), and Constructive Probabilistic Neural Network (CPNN). The discrimination accuracy found are 90.77%, 92.31%, and 93.85% respectively.

Finally the principal conclusion drawn from this thesis is that the ISE based machine vision techniques for tea quality monitoring can be successfully implemented to assist the traditional methods in the tea industries for quality monitoring.

DEDICATION

*To my parent, **Smt. Renu Dutta Borah** and*

Sri Sobhan Ch Borah

For their love and encouragement

ACKNOWLEDGEMENTS

At the beginning, I would like to express my sincere gratitude to my research supervisor Prof. (Dr.) Manabendra Bhuyan, Department of Electronics, Tezpur University for his enthusiasm and guidance during my research and also for his patience while the thesis was being written. I greatly appreciate his care and dedication in constructively criticizing my works, including my thesis. I have truly enjoyed and benefited from working with him.

I would like to thank Dr E L Hines, Electrical and Electronic Division, School of Engineering, Warwick University, UK, who guided me in the final year of my research, for his constructive support and encouragement. I would also like to thank Prof. J W Gardner, Electrical and Electronic Division, School of Engineering, Warwick University, UK for his time to time suggestions as my research progress panel chair.

I wish to thank all the members of Department of Electronics, Tezpur University for their constant support and encouragement. I am also thankful to the Intelligent System Engineering (ISE) research group of University of Warwick, UK for their encouragement.

I wish to thank the Tocklai Tea Research Association, Assam, India for their supporting attitude towards this research work. Besides, I am thankful to Tata Tea Ltd. of India especially to the Teok R & D section in Assam, India for allowing me to carry out some of my experiments in their research laboratory.

I would like to thank the Council of Scientific and Industrial research (CSIR), New Delhi, India for offering me the full travel grant to attend International conference (QCAV-2003) in USA in 2003, which gave me a new exposure to my research.

I would like to offer my sincere thanks to Commonwealth Scholarship Commission (CSC), London, UK for offering me the Commonwealth Split-site Doctoral Scholarship to continue my final year research at University of Warwick, UK during 2004/2005.

Last but not least, I would like to thank my family including my parent, brother 'Sushanta' and sister in law 'Junmoni', my little nephew 'Dhun' and finally 'Sonali' for their constant support and encouragement and for being so understanding during my entire research.

Surajit Borah

Table of Contents Page

List of Figures

List of Tables

List of Abbreviations

ADC	Analog to digital converter
ANN	Artificial neural network
ASIC	Application specific integrated circuit
BP	Broken Pekoe
BOP	Broken Orange Pekoe
BPS	Broken Pekoe Souchang
CV	Computer vision
CPNN	Constructive probabilistic neural network
CCD	Charge coupled device
CD	Churamoni Dust
CDPV	Cross dissimilarity pixel value
CR	Colorimetric-results
CLB	Configurable logic blocks
CMY	Cyan, Magenta, yellow
CIE	International commission on illumination
CTC	Cutting, Tearing and Curling
CFM	Continuous fermenting machine
DPV	Dissimilarity pixel value
DWT	Discrete wavelet transform
DLL	Delay-locked loops
DSP	Digital signal processing
EPROM	Erasable Programmable Read Only Memory
EN	Electronic nose
ET	Electronic tongue
FWT	Fast wavelet transform
FPGA	Field programmable gate array
FM	Frequency modulation
FL	Fuzzy logic
FD	Fine Dust

GA	Genetic algorithm
GC	Gas chromatography
GLCM	Gray level co-occurrence matrix
GMM	Gaussian mixture model
Hz	Hertz
HSI	Hue, saturation and intensity
HL	High low
HH	High high
IEEE	Institute of electrical and electronic engineers
ICUMSA	International commission for uniform methods of sugar analysis
ISE	Intelligent system engineering
kHz	kilohertz
LUT	Look up table
LVQ	Learning vector quantization
LL	Low low
LH	Low high
MLP	Multi layer perceptron
MOSFET	Metal oxide semiconductor field effect transistor
MRF	Markov random fields
MC	Moisture content
MATLAB	Matrix laboratory
MVC	Micro video camera
Md	Mahalanobis distance
MOS	Metal oxide semiconductor
NIR	Neutral interface reflection
NFS	Neural-Fuzzy System
NTSC	National television system committee
OF	Orange Fannings
PCA	principal component analysis
PDF	Probability density function
PF	Pekoe Fannings

PD	Pekoe Dust
PAL	Phase alternating line
PNN	Probabilistic Neural Network
ppm	Parts per million
RGB	Red, green and blue
Rh	Relative humidity
RB	Radial basis
RH	Reconfigurable hardware
RD	Red Dust
RBF	Radial basis function
SOM	Self organizing map
SECAM	Sequential Couleur Avec Memoire *or* Sequential Colour with Memory
SPD	Spectral power distribution
STFT	Short-term Fourier transforms
SRAM	Static random access memory
TF	Theaflavin
TR	Thearubigin
TRA	Tea research association
VHDL	Very large scale integrated circuit hardware description language
VBI	Vertical blanking interval
VOC	Volatile organic compound
WT	Wavelet transforms
WFT	*Windowed Fourier transforms*
WTA	Wavelet texture analysis
YIQ	Luminance-inphase-quadrature

List of Author's publications

Journals

1. Borah, S., Bhuyan, M., 2003. "*Non-destructive testing of tea fermentation using image processing*", INSIGHT- Non-destructive Testing and Condition Monitoring (The Journal of The British Institute of Non Destructive Testing), Vol. 45, No. 1, pp 55-58.

2. Borah, S., Bhuyan, M., 2005. "*A Computer based colour matching system for use in monitoring tea fermentation*", Int. Journal of Food Science and Technology (UK), Vol. 40, No. 6, pp 675-682.

Conference Proceedings

1. Bhuyan, M., Borah, S., 2001. "*Use of Electronic Nose in Tea Industry* ", Proc. Int. Conf. EAIT, IIT Kharagpur, pp 848-853.

2. Borah, S., Bhuyan, M., 2002. "*Non-destructive testing of tea fermentation using image processing*", Proc. 41st annual British Conference on NDT, pp 199-204, South Port, England, 17-19 Sept' 2002.

3. Borah, S., Bhuyan, M., Saikia, H., 2002. "*ANN based Colour Detection in Tea Fermentation*", Proc. Indian conference of ICVGIP-2002, pp 226-229, SAC, Ahmedabad, India, 16-18 Dec' 2002.

4. Borah, S., Bhuyan, M., 2003. "*Quality Indexing by Machine Vision during Fermentation in Black Tea Manufacturing*", Proc. Int. Conf. on Quality Control by Artificial Vision (QCAV-2003), Gatlinburg, Tennessee, USA, SPIE Vol.5132, pp 468-475.

5. Borah, S., Bhuyan, M., Hines, E, L., 2005. "*A novel feature extraction technique for size estimation applied to the sorting of tea granules*", Accepted for Proc. of third Int. Conf. on Advances in Pattern Recognition, Bath, UK.

CHAPTER I

INTRODUCTION

This thesis presents an investigation into the possibilities of using Computer Vision (CV) and Electronic Nose (EN) olfaction methodology, which are supported by intelligent system engineering (ISE) techniques in order to monitor some tea quality parameters. This chapter introduces the problems considered, and the motivation for the work. The contribution made is stated and the structure of the thesis is outlined.

1.1 Introduction

Colour, size, shape, flavour etc are important 'parameters' that are might consider in different tea processing stages in order to determine the quality of tea. For example the 'colour' and 'aroma' of fermenting tea are two important quality parameters in the tea fermentation process. Similarly, size, shape, colour, and flavour of 'made-tea granules' during the tea grading process are the main attributes to be considered for quality monitoring. Figure 1.1 shows a schematic of the parameters for the tea quality monitoring scheme as considered here to meet the needs of the tea industry during the tea fermentation and grading processes.

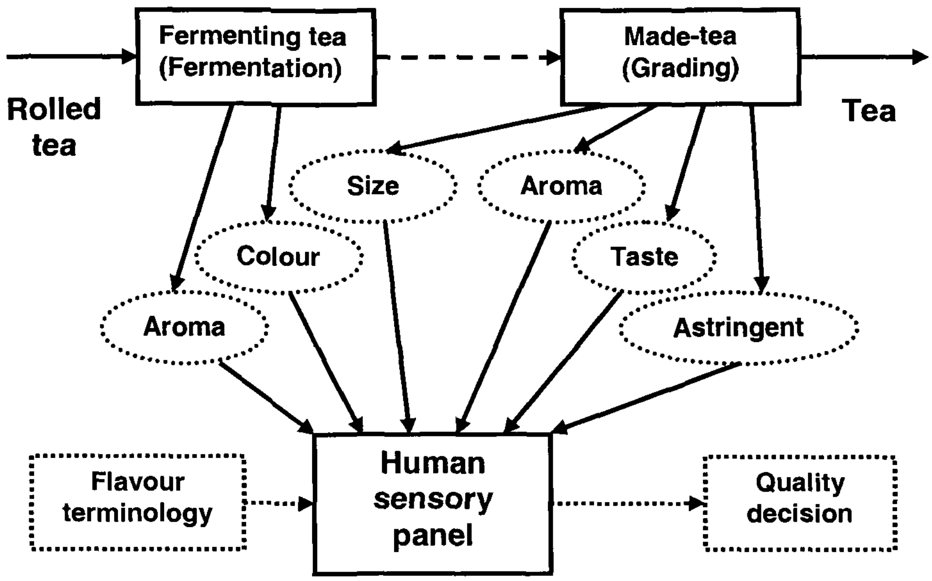


Figure 1.1 Schematic of tea parameters for quality monitoring

The quantitative analysis and standardization of these parameters are treated as the main subjective methods for tasting raw and processed tea. Such methods determine the conformity of tea quality to specifications and for the analysis of quality during processing and final storages. Human sensory panel's judgment by using organoleptic methods (visual inspection, sniffing etc.) is the way in which the evaluation of tea quality is made in tea industries. These tea tasting methods obey certain colour / flavour terminology in making the judgments. The human organoleptic methods are good in justification of colour of objects in particular regions and different flavours in different objects. But such methods are somewhat erroneous in discriminating different objects of nearly the same colour or odour as well as the objects of almost same size and shape. Moreover, such approaches may become inappropriate in some cases creating various errors due to different factors such as human variability, insensitivity due to prolonged exposure, mental state etc. Therefore an alternative way for example machine vision may be more advantageous, which can be used for measuring the parameters during various processing stages in the tea industries. This machine vision might be used as a solution to help the human sensory panel to evaluate their problems effectively.

1.2. **The prospect of machine vision in tea**

Tea is an important high value crop through out the world. Tea leaves are processed through various stages viz., withering, rolling and cutting, fermenting, drying and sorting / grading. Every stage is concerned with some standard methods and failure of one of them may lead to a reduction in the quality of made-tea. Therefore every stage is monitored constantly by evaluating certain parameters (refer to Figure 1.1) to produce quality tea. The basic aspect of this research is to explore the possibilities of application of machine vision techniques for tea quality monitoring during two main processing stages: fermentation and grading. Instead of mimicking the human vision and olfaction this research has attempted to explore a way in which the computer / electronics might be used to support the human sensory panel in making their subjective judgments. This section summarizes the tea quality parameters during fermentation and grading processes and their existing evaluation techniques and then about the application of machine vision in food processing industries and finally its prospects in tea industries.

1.2.1 Quality parameters during fermentation and grading

Tea fermentation is one of the most important processes, which plays a major role in producing good quality of tea. Similarly, the sorting (grading process) of tea according to appearance, size and shape, and quality is a very important process in tea processing industries. The quality parameters during these processes, their importance may be summarized as follows:

(i) **Fermentation**:

The fermentation is an oxidation process and some chemical changes occur during this process. For example proteins get degraded; chlorophyll is transformed into pheophytins; formation of some volatile organic compounds (VOC) from lipids, amino acids, carotenoids and terpenoids etc. These chemical transformations produce the colour and aroma (flavour) (refer to Figure 1.1) in tea, which are considered as the most important quality parameters during the fermentation process (Mahanta, et. al., 1985; Mahanta, 1988). But these tea colour and aroma are complex phenomena since a numbers of different compounds are formed during tea processing. Studies of tea flavour shows that more than ten separately identifiable volatile compounds are formed during processing and different proportion of these compounds corresponds to the flavour sensed. The compounds are t-2-hexenal, cis-3-hexenol, t-2hexenyl formate, linalool oxide (furanoid-cis), linalool oxide (furanoid-trans), linalool, phenylacetaldehyde, cis-3-hexenyl caproate, methylsalcylate, geraniol, benzylalcohol, 2-phenylethanol, cis-jasmone + β-ionone, tobal[b]. The situation is further complicated by the fact that the tea flavour is unstable and its odour will change with time as the chemical composition of the tea changes. On the other hand some non-volatile compounds are also produced, viz., theaflavin (TF), thearubigin (TR), caffeine, pheophytins etc., which imparts to the final tea liquor its characteristic colour and taste. The fermentation process is considered to be completed while optimum amount of these compounds in appropriate ratios are formed in tea (Okinda, et. al., 1998). Though it is possible to directly measure the formations of chemical compounds by chemical methods, but the methods become inefficient as time consuming, laborious and expensive. Therefore it is worthwhile to find some other way to detect the optimum fermentation, for example by some subjective methods. For that it is observed and proved to be efficient to detect the optimum condition of tea fermentation by measuring the fermenting tea colour and aroma. Because the colour and aroma are the true reflections of the chemical compounds produced in tea during fermentation process. Therefore, it is worthwhile and efficient to detect the optimum fermentation by detecting the colour and aroma to be achieved. Therefore, during processing in complex controlled environments of tea fermentation requires supervision (monitoring) and control of the process as early as possible attaining the required colour and aroma.

(ii) **Grading**:

In the sorting process, tea granules are separated from each other in accordance with the variations of their size. The quality factor doesn't come into consideration in the very beginning of separation process of the tea granules. But right after the separation into different categories, they are tasted to assess its quality, its necessary appearance, flavour etc. before final packaging. Generally, from quality point of view, the final product is judged by three main factors, viz., whether hygienically produced, whether free from hazardous chemicals (ex. arsenic, cadmium etc.) and whether required constituents are available for cup characteristics. In these respects, the appearance of tea, basically the blackish brown appearance of black teas is considered as one of the most important attributes to be considered. Moreover, the golden yellow and brownness appearance of tea liquor are also considered as quality parameters. The flavour attributes, for example aroma, taste and astringent are, on the other hand, considered as important parameters for tea quality evaluation. Finally, uniformity of granules size and presence of other unwanted stuffs are also considered at this stage. By measuring these parameters, efficient grading requires high degree of sensing and intelligence for accomplishing these quality evaluation processes.

1.2.2 **Existing techniques for tea process monitoring**

There are two traditional methods of quality monitoring so far in tea industries. The first one is assessment of biochemical parameters and the second one is subjective assessment through tea tasting (measurement of various quality parameters). Of these two methods, the subjective tea tasting method is commonly used in most of the tea industry. Expert human sensory panel are involved for such quality evaluation in tea industries. Visual inspection, sniffing, gas chromatography (GC), and colorimetric approach have so far been reported as the quality monitoring tool in various stages of tea processing. For example, the visual inspection, sniffing and colorimetric approach have been used to detect the optimal fermentation time in the tea industry. Similarly visual inspection, sniffing, tasting by tongue, chemical analysis (TF-TR) etc. are commonly used methods by the sensory panel for the final quality judgment during the grading process.

The human sensory panel (tea tasters) of trained personnel scores the product on the basis of a number of flavour terminologies (flavour descriptors). These human experts, since tea industry was established, have been traditionally determining tea aroma and colour during fermentation process by human olfaction and visual approximation respectively. In the other method (colorimetric approach) a colorimeter is used. This method is achieved by measuring the intensity of colour i.e., optical density of the ethyl acetate extract made from the fermented tea sample. This correlates the measurement of concentration of TF during the fermentation. Therefore optimum fermentation time is found from the maximum concentration of the TF content in tea.

During sorting process the tea granules are separated from each other using some different sized severs. Then they are categorized using the visual approximation. Finally, for quality judgment, the tea tasters adopt their own convention for describing the tea liquor and infused leaf for quality estimation. Some main tea liquor quality describing terms used by the tea tasters are Backey, Body, Bright, Brisk, Burnt, Colour, Cream, Dry, Dull, Full, Pungent, Strength/Strong, Thin, Coppery, Green and Even etc. These descriptors have a positive correlation with the correctness of different processing stages of tea manufacturing. Besides these, the TF-TR analysis, which is a spectro photometric method, is also used to determine the quality of tea.

1.2.3 **Machine vision in food and agriculture**

Colour, texture, flavour etc. are the important process parameters for the subjective determination of the overall product quality of food processing industries and agricultural products (Giese, 2000). In a broader context, colour perception can be used to estimate degree of ripeness (e.g., tomatoes, bananas), extent of cooking (meat, cereal products), and even anticipated flavour strength (tea, fruit juices) etc. (Wright, 1969; Nielsen, 1998; Hutchings, 1999). In the case of processed food like sugar, juice, jam, jelly, chips, chocolates, tea etc. these colour, size and shape are important process parameters determining the overall quality of the products. These facts reveal the importance of analysis and classification of colour and flavour of food products as the major techniques of quality determination. Similarly, texture analysis and classification can be implemented in sorting processed food into different grades in terms of size, shape etc (Brosnan, et. al., 2002; Quevedo, et. al., 2002). Therefore, these process parameters can be implemented as the quality control and automation tool in food processing industries, which can be achieved by continuous process monitoring. It has been elsewhere reported that the quality monitoring has been performed by manual methods or by using different physiochemical methods such as GC (Dewulf, et. al., 2002); colorimeter (Melendez, et. al., 2003) etc. in different food processing industries.

More recently, the developments of machine vision techniques supported by for example the ISE techniques, such as artificial neural networks (ANN), fuzzy logic etc., in food processing industries, have grown extensively. Novel system prototypes, such as computer vision (He, et. al., 1998; Sun, 2000), electronic sensors (For example: EN (Bartlett, et. al., 1997; Huang, et. al., 2001)) for food quality measurement, analysis, and prediction have come into the limelight. The Electronic Tongue (ET) application is also being broadly implemented in flavour profile analysis mainly in milk, fruit juice and wine processing industries (Natale, et. al., 2000; Bleibaum, et. al., 2002; Buratti, et. al., 2004) etc. These advanced process control techniques have proven to be efficient for their various advantages over the conventional quality evaluation methods. Objectives of using of such systems can be summarized as the improvement of food quality, saving energy and increasing productivity etc. Moreover, such advanced techniques explore the possibilities of automation in food quality evaluation, monitoring and process control by analysis, classification of complex parameters. In fact, such advanced techniques and their application to the foods processing industries as a quality-monitoring tool have become a very active field of research. The goal has been, and still is, to have a machine performing the same functions that a human brain does but with higher accuracy; speed for accurate judgment of process parameters; and efficient repeatability.

1.2.4 **Machine vision in Tea**

It has been observed that the various attributes such as colour, aroma, taste, astringent etc., both natural and controlled, are the important quality parameters in production of black tea. The human organoleptic methods, which are used for the measurement these parameters, are not standardized and vary (refer to section 1.1) due to various reasons. Therefore, some possibilities are being proposed to assess some of the attributes like colour and aroma of tea with the aid of instruments (physiochemical methods) (Hazarika, et. al., 1984; Takeo, et. al., 1983; Liang, et. al., 2003). The use of colorimeter in fermenting tea colour is one of such physiochemical method (Ullah, et. al., 1979). Such efforts are comparatively effective and based on standard methodology in the context of the quality perception of tea but they are time consuming, laborious and expensive. Therefore, to overcome such inaccuracy and inefficiency, machine vision techniques can be thought as an efficient alternative technique to support the conventional techniques used by the human sensory panel for tea quality monitoring. The rapid growth of electronic systems, such as the development of charge coupled device (CCD), EN, ET etc. and the possibilities in using them in repeated manner enrich such prospects. Moreover, the implication of ISE based techniques, which can learn from and adapt to the input data, to analyze the data gathered by these system enhances the prospect in more transparent way.

1.3. **Research objective and scope**

The primary objective of this research is to investigate the potential application of ISE techniques based machine vision techniques for tea quality monitoring. Three main key aspects are considered in this research, which are as follows:

- Optimum colour detection in fermenting tea during on-going fermentation process for detection of optimum fermentation time;
- Tea granules size estimation for monitoring the tea sorting process, where size is the only differentiating parameters of the tea granules;
- Aroma analysis of different grades of tea for quality grading as it is one of the main attributes of the flavour analysis.

The whole scheme is summarized in the block diagram as in Figure 1.2.

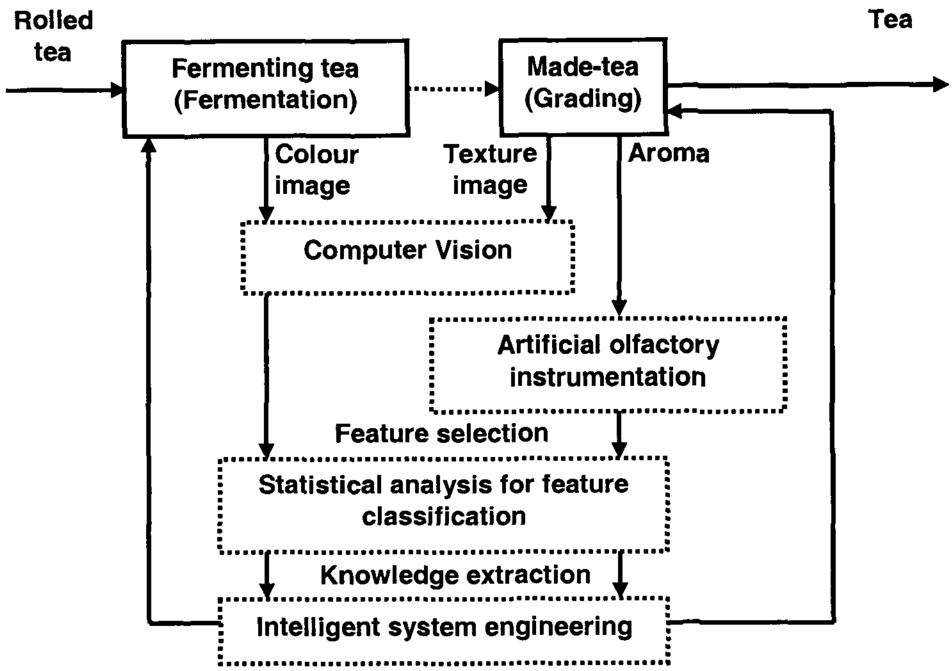


Figure 1.2 Block diagram of the proposed scheme

1.3.1. Computer vision in tea fermentation

This research is with regards mainly to colour matching of fermenting tea images with standard database images. One of the key phenomena of this research is the efficient colour feature extraction from the images. For that the selection of the actual colour model is also important aspect. Colour features are extracted by dissimilarity measurements of the colour histograms generated from the images. The HSI (hue, saturation and intensity) colour model is considered as one of the most useful models for such colour feature extraction. The colour indexing, a technique developed by Swain and Ballard (Swain, et. al., 1991), and then modified for object recognition on the basis of colour content (Funt, et. al., 1995) is considered in this research. The enhanced version of the technique has been faithfully implemented for the colour comparisons and analysis for fermenting tea images. Such approach is needed for optimum fermentation time judgment in tea industries.

1.3.2. **Computer vision in tea granule size estimation**

The tea granule size estimation has been addressed by texture analysis of the images for image surface roughness. As the images consist of stochastic natural textures, efficient texture feature extraction methods also play an important role in this research. Wavelets transform (WT) based sub-band images are considered for the statistical texture feature extraction from the images. The Daubechies' wavelets are implemented using the fast wavelet transform (FWT), which has been shown to be successful technique in the texture analysis of natural images (Wang, et. al., 1997). Such a tea granule size estimation technique would be useful as a monitoring tool for effective tea grading.

1.3.3. **Electronic nose in tea quality grading**

The aroma analysis of 'Made-tea', using EN system, as one of the important quality parameters during tea grading process is the objective of this research. The aim of such an aroma analysis system is that it helps in standardizing the tea aroma. For efficient performance of the system, selection of the sensors for the EN system as applicable to tea aroma analysis is the first key aspect. Then the compensation for possible sensor drifts is considered as another key aspect. Finally the useful feature selection from the transient responses of the EN is also considered as an important aspect of this research.

After extraction of the features from the data in the above three objectives, their overall efficiency is analyzed by the standard statistical analysis methods. The Principal component analysis (PCA) has been implemented. Unsupervised clustering techniques such as K-mean clustering and Kohonen's self organizing map (SOM) are used as the data clustering methods for performance measurement of the extracted features. Then knowledge is extracted from the features in order to model a system for data classification, which has been performed by the different ANN approaches. In this regards, the multi layer perceptron (MLP) technique is used in colour analysis of fermenting tea; MLP and learning vector quantization (LVQ) techniques are used in texture classification of tea images during tea sorting; finally MLP, radial basis function (RBF), and constructive probabilistic neural network (CPNN) are used for EN data classification for aroma of different tea grades.

1.4. Contribution to the knowledge

In the context of the objectives outlined in Section 1.3, this thesis aims to provide a contribution to scientific knowledge via the demonstration of ISE based machine vision quality monitoring scheme in the context of tea production. In particular, it will show the colour analysis and its efficiency in detecting the optimum colour of fermenting tea during the fermentation process. Furthermore it will demonstrate how the image texture analysis and aroma standardization methods during the tea grading process. The novel colour and texture feature extraction methods are explored as the efficient features for their respective purposes. Finally, implementation of ISE based EN system for aroma analysis method is presented. Finally possibility of hardware circuits for computer vision algorithm is discussed as the future prospect.

1.5. Organization of the thesis

Following this introductory chapter, which explains the detail objectives of the research, Chapter II presents the following; the conventional tea tasting, flavour & colour formation biology, the approaches of computer vision, colour model selection, image capturing technique, and database generation etc. The details of need for the preprocessing of the captured images such as removal of noise and blurring are explained. Explanations of various texture measurement methods are presented. The EN system and their corresponding sub systems are introduced. Finally, the ISE techniques are described as the appropriate classification techniques for such problems.

Chapter III focuses more closely on the colour-matching task; describing the algorithms developed and results obtained using these techniques. The technique of colour histogram dissimilarity threshold value measurement for the colour feature extraction methods are described in detail. Statistical methods for feature analysis and implementation of ISE techniques for classifications are presented. The correlation obtained from machine vision results with chemical (TF-TR) analysis is also presented.

Chapter IV describes the imaging methods for tea granule size estimation by image surface roughness analysis are described. The selection of texture feature extraction method out of various texture feature extraction methods is presented. A description of the novel texture feature extraction method is presented. The statistical methods of feature analysis and their efficiency measurement are described. Finally the ISE techniques of feature classification for this purpose are described.

Chapter V deals with the discussion of the prospective use of EN system in tea aroma standardization for quality grading. Selections of the EN sensors are described. The possible drifts in transient responses are discussed along with methods to compensate for them. Feature set calculation methods are presented. Finally the statistical methods of feature analysis and ISE techniques for classification are described.

Chapter VI presents a detailed discussion of this novel method designed for quality monitoring of tea and prospective use of more sophisticated methods as future works. The theoretical possibilities of computer vision tasks by hardware means are described. For that brief justification of using field programmable gate array (FPGA) for computer vision algorithms and their prospective practical implementation are introduced.

References

1. Bartlett, P. N., Elliot, J. M., Gardner, J. W., 1997. Electronic noses and their application in the food industry, Food technology, Vol. 51, pp 44-48.
2. Brosnan, T., and Sun, D., 2002. Inspection and grading of agricultural and food products by computer vision systems - a review Computers and Electronics in Agriculture, Vol. 36, No. 2-3, pp 193-213.
3. Bleibaum, R. N., Stone, H., Tan, T., Labreche, S., Saint-Martin, E., and Isz, S., 2002. Comparison of sensory and consumer results with electronic nose and tongue sensors for apple juices, Food Quality and Preference, Vol. 13, No. 6, pp 409-422.
4. Buratti, S., Benedetti, S., Scampicchio, M., and Pangerod, E.C., 2004. Characterization and classification of Italian Barbera wines by using an electronic nose and an amperometric electronic tongue, Analytica Chimica Acta, Vol. 525, No. 1, pp 133-139.
5. Dewulf, J., Langenhove, H, V., 2002. Analysis of volatile organic compounds using gas chromatography TrAC Trends in Analytical Chemistry, Vol. 21, No. 9-10, pp 637-646.
6. Funt, B. V., Finlayson, G. D., 1995. Color Constant Color Indexing, IEEE Transaction on PAMI, *Vol. 17, No. 5, pp 522-529, May.*

7. Giese, J., 2000. Colour measurement in foods as a quality parameter, Food Technology, Vol. 54, No. 2, pp 62-65.
8. Hazarika, M., Mahanta, P. K., Takeo, T., 1984. Studies on some volatile flavour constituents in orthodox black tea of various clones and flushes in N. E. India, J. Sc. Food Agric, Vol. 35, pp 1201-1207.
9. He, D. J., Yang, Q., Xue, S. P., Geng, N., 1998. Computer vision for colour sorting of fresh fruits, Trans. Scinese society of Agricultural Engineering, Vol. 14, No. 3, pp 202-205.
10. Hutchings, J. B., 1999. Food colour & appearance, second edition, Aspen, Gaithersburg.
11. Huang Y., Whittaker A. D., Lacey R. E., 2001. Automation for food engineering: Food Quality Quantization and Process Control, Culinary and Hospitality Industry Publications Services, Texas.
12. Linag, Y., Lu, J., Zhang, L., Wu, S., Wu, Y., 2003. Estimation of black tea quality by analysis by chemical composition and colour difference of tea infusions, Food chemistry, Vol. 80, No. 2, pp 283-290.
13. Mahanta, P. K., Hazarika, M., 1985. Chlorophyll and degradation products in orthodox and CTC black teas and their influence on shade of colour and sensory quality in relation to thearubigins, J. Sc. Food Agric., Vol. 36, pp 1133-1139.
14. Mahanta, P. K., 1988. Biochemical basis of colour and flavour of black tea, Proc. of 30th Tocklai Conference, Assam, India, pp124-134.
15. Melendez-Martinez, A. J., Vicario, I. M., Heredia, F. J., 2003. Application of tristimulus colorimetry to estimate the carotenoids content in ultrafrozen orange juices. J. Agric. Food Chem. Vol. 51, pp 7266-7270.
16. Nielsen, S. S., 1998. Food Analysis, second edition, Kluwer Academic/ Plenum Publishers, New York.
17. Natale, C. D., Paolesse, R., Macagnano, A., Mantini, A., Arnaldo D'Amico, Legin, A., Lvova, L., Rudnitskaya, A., and Vlasov, Y., 2000. Electronic nose and electronic tongue integration for improved classification of clinical and food samples, Sensors and Actuators B: Chemical, Vol. 64, No. 1-3, pp 15-21.

18. Okinda, P., Obanda, M., 1998. The changes in black tea quality due to variations of plucking standard and fermentation time, Food chemistry, Vol. 61, No. 4, pp 435-441.
19. Quevedo, R., Carlos, L., Aguilera, J., Cadoche, L., 2002. Description of food surfaces and microstructural changes using fractal image texture analysis, J. of Food Engineering, Vol. 53, No. 4, pp 361-371.
20. Swain, M. J., Ballard, D. H. 1991. Color Indexing, Int. J. Computer Vision, Vol. 7(1), pp 11-32.
21. Sun, D. W., 2000. Inspecting pizza topping percentage and distribution by a computer visison method, Journal of Food Engineering, Vol. 44, pp 245-249.
22. Takeo, T., Mahanta, P. K., 1983. Comparison of black tea aromas of orthodox and CTC tea and black teas made from different varieties, J. Sci. Food Agric, Vol. 34, pp 307-310.
23. Ullah, M. R., Bajaj, K. L., Chakraborty, S., 1979. Fermentation test by Dr. M R Ullah, Factory Floor Fermentation Test, pp 3-6, Tocklai Experimental Station, Jorhat, India.
24. Wright, W. D., 1969. The measurement of colour, 4th edition, Hilger & Watts, London.
25. Wang, J. Z., Wiederhold, G., Firschein, O., Wei, S. X. , 1997. Content-based image indexing and searching using Daubechies' wavelets, Int J. Digital Library, Vol. 1, pp 311-328.

CHAPTER II

TEA QUALITY AND PROSPECTIVE APPLICATION OF MACHINE VISION

2.1 Introduction

The term 'tea quality' is concerned with the overall quality (a predefined standard) of made-tea. It depends on various factors, namely tea growing, environment, processing techniques etc. Certain parameters need to be controlled to maintain a preferred quality. With fast-changing tea consuming habits of human being, international competition and need for increasingly stringent standards, improving tea quality is a serious concern for the tea industry. Traditional methods of tea quality monitoring are not standardized and need to apply modern technology to improve the overall tea quality. Machine vision, the computerized analysis of the quality parameters can help in solving some of existing problems of tea quality monitoring methods. The development of sensor devices, for example CCD, EN etc. aid to such prospects and they can be used for a wide range of visual and olfactory inspections such as colour matching during fermentation, packaging into different grades and high-speed accurate sorting, quality grading on the basis of aroma analysis etc. Moreover, they offer certain advantages over common problems encountered with the traditional human sensory panel judgment methods such as human variability, insensitivity due to prolonged exposure, mental state etc. Finally, a model can be made with the help of ISE techniques based classification of the gathered data.

The purpose of the chapter is to furnish the reader with necessary background information of area of interest relevant to this research. For this, it enumerates detailed background on the tea quality perception, prospect of application of machine vision in quality evaluation, and ISE techniques and their prospective applications. It focuses on key requirements for computer vision encountered during the system development for automatic control and inspection systems for the fermentation and grading processes. It introduces EN system and its usefulness for aroma analysis during quality grading.

2.2 Tea quality descriptions

Tea quality is a complex phenomenon and there are no specific terms to explain the overall quality of final tea product. It also varies according to interest of different persons. Still tea tasters obey some sort of tea terms to explain the quality. Again, quality of tea depends upon various agencies those are also not specific. Two methods of quality indexing exist so far in tea industry, mentioned in Chapter I (Section 1.2.2). One is assessment of biochemical parameters and the other one is subjective assessment through tea tasting. In the first process, biochemical parameters are considered for analysing by chemical analysis of the final made tea or tea under processing. On the other hand, physical appearance, olfaction, taste etc are the basis of the second process i.e., subjective assessment. Besides these, the TF-TR (Theaflavin-Thearubigin) analysis, a spectro-photometric method, is also used for the made-tea for quality judgment. The TF and TR are measured in terms of percentage or TF: TR. Here total colour and the percentage of brightness of the made-tea are also measured. However, the subjective assessment is most frequently adopted in tea industries.

2.2.1 **Determinants of Tea Quality**

There are different stages and conditions on which quality of tea depends. Some of those stage and conditions are as follows:

- Tea Bushes (Genetics, Age, Health)
- Environment (Climate, Soil, Pests)
- Seasonality
- Farming Practices (Irrigation, Fertilization)
- Harvesting Practices
- Processing Methods
- Storage & Transport Conditions
- Age of the Tea (After Manufacturing)

Hence the quality of made-tea depends on various parameters related to almost all activities involved in manufacturing of tea. Besides these stages and conditions mentioned above, factors that have major impact on green tea quality include tea variety, harvest, shading, nutrition and pest & disease damage. But if all the other requirements for good quality tea exist, then the most sensible stage for quality is the tea processing.

2.2.2 Tea processing and quality control concepts

Stages involved in black tea manufacturing are as follows: Withering (partial desiccation), Rolling, Cutting, Tearing and Curling (CTC), Fermenting, Drying and Sorting. All processes are explained briefly in the following few paragraphs.

Withering: It is the process of extracting the moisture content of the green tea leaves. The plucked tea leaves contain moisture whish is reduced to at least 70 to 80% in this process. Here the concept of percentage (%) is somewhat different as it means that 100 Kg of green tea leaves reduces to 70 to 80 Kg after loss of moisture content. Different tea industries adopt different withering techniques.

Rolling: Rolling is the next process, where withered tea leaves are rolled by machine so as to destroy the original shape of tea leaves. Maceration of tea leaf cells are performed in this process.

Cutting, Curling, Tearing (CTC): Rolled tealeaves are cut, curled and tear in CTC manufacturing. This stage is not used in orthodox manufacturing.

Fermentation: Fermentation is an important stage during tea processing. This is the process where many enzymes are produced.

Drying: The fermented tea is fed to the dryer after completion of fermentation process. The dryer dries the tea and converts into the final product.

The quality control concept has come here for determining the various parameters involved in different stages and proper control of them to achieve good quality tea. But as it was mentioned earlier that there is no specific measurement to control the parameters and quality depends on the customer's requirements also, it is a difficult task. However, quality control can be achieved with proper controlling in each processing stage during black tea manufacturing. Therefore an efficient quality monitoring system is needed.

2.2.3 Importance of tea fermentation

Processing stages prior to fermentation merely condition the tealeaves for reactions to take place during fermentation. Fermentation is an oxidation process where rolled and cut tea gets oxidised. The traditional method of tea fermentation is spreading the rolled and cut tealeaves in a polished floor or trays at a given thickness in a relatively cool ventilated but moist atmosphere. The duration of black tea fermentation varies from 1 hour (for CTC on a warm day) to 3 hours (for orthodox in a cool day). The Continuous Fermenting Machine (CFM) is also used where the fermentation takes place on a conveyor belt with the same chemical and biological principle. Depending on the extent of oxidation, made-tea can be categorised into three main categories, non-oxidised (Green tea), semi-oxidised (Oolong tea) and fully oxidised (Black tea). Irrespective of the type of tea produced, for proper fermentation, optimum temperature of the fermenting room should be 85^0F to 90^0F with hygrometric difference not exceeding 2^0F so that the relative humidity (Rh) is to be more then 95%. The work that discussed in thesis has considered for manufacturing of black tea.

Fermentation mostly imparts contribution towards the quality of the made-tea because it is the process in which many volatile and non-volatile enzymes are produced. A series of chemical reactions take place during this stage due to the severe damage of the leaf cells followed by intermixing of chemicals during the rolling and CTC stage. Although heat, light and pH affect in degradation of carotenoids, and it is mostly influenced by oxidised flavonols formed during fermentation. Orthodox and CTC are principal categories of black tea. Their production techniques differ considerably and have a pronounced impact on the formation and degrade patterns of various pigments. In the conventional Orthodox method, tea leaves are twisted in a rolling machine to damage the cellular membranes which releases the cell contents without affecting significantly the integrity of tea leaves. But, in CTC machine, the leaf epidermis is stripped off and shredded from the stalk. During the rolling and CTC stages of black tea manufacturing, molecular changes take place in the cellular components exploring pigments to acids and degradative enzymes. On the other hand, oxidative enzymes interact with catechins to form yellowish-red polymerised pigmented products. Thus, the various changes are *manifested in the change of colour from green to coppery red.*

2.2.3.1 **Development of aroma**

Tea aroma is another very important factor to determine the quality of made-tea. From the moment of plucking (Green Tea Leaves) to formation of black tea, many volatile compounds are formed, which are responsible for odour. Several analytical studies on tea aroma have been conducted and more than 200 volatile compounds responsible for aroma are identified (Sanderson, et. al., 1973; Natarajan, et. al., 1975). These volatile organic (VOC) compounds present in made tea in different varieties of tea such as assamica (Sri Lanka and Assam tea) and assamica sinesis species (Darjeeling and Japanese tea) in the ratio of linalool oxides and geranilto the total volatile compounds is shown in Table 2.1 (Takeo, et. al., 1983).

Table 2.1 Ratios of main volatile compounds to total volatiles in black tea.

		Sri Lanka		India				Japan
		Var. assamica		Hybrid of Assamica * sinesis				
				Assam		Darjeeling		
Compound	Rt^b	Uva	Dimbula	(1)	(2)	(1)	(2)	Benihomare
t-2-hexenal	0.4	3.1	2.6	4.9	3.1	0.7	0.3	1.5
cis-3-hexenol	0.53	2.8	4.3	0.2	3.8	1.4	0.1	6.1
t-2hexenyl formate	0.65	9.5	11.8	11.9	5.0	5.7	3.1	5.2
linalool oxide (Furanoid-cis)	0.77	3.4	3.2	3.5	3.6	8.2	4.7	3.8
linalool oxide (Furanoid-trans)	0.83	10.3	8.8	8.0	12.0	16.7	12.0	12.0
linalool	1.00	24.0	15.5	18.3	32.8	15.6	13.7	9.3
phenylacetaldehyde	1.20	0.2	0.5	4.0	5.0	1.1	1.8	1.0
linalool oxide pyranoid -cis	1.40	0.3	0.4	trace	trace	1.0	6.0	0.3
Methylsalcylate	1.50	18.6	18.8	9.0	13.2	9.8	5.3	4.9
geraniol	1.67	1.3	2.2	3.3	1.6	7.3	15.9	21.7
Benzylalcohol	1.71	1.0	1.9	4.3	1.0	1.7	2.0	2.6
2-phenylethanol	1.78	0.2	0.9	4.3	1.0	2.0	6.7	7.5
Cis-jasmone + β-ionone	1.83	0.2	0.1	7.4	1.5	0.5	4.4	0.3

Due to number of organic compounds present in tea, it becomes complex to process tea to any accepted standard as these volatile compounds determine tea quality. As a result the aroma becomes a quality factor of tea which depends upon various VOCs and their ratios present in tea. The results show that the characteristic differences in the flavour property of black tea made from different varieties are related to the effect of genetic properties of the tea plant on the formation of the VOCs in the shoots.

2.2.3.2 **Development of colour**

Nevertheless, fermentation is a process of enzymic oxidation of catechins present in damaged and distorted tea leaves resulting in the formation of two groups of coloury compounds, the Theaflavins (TF) and Therubigins (TR). The TF is golden yellow and TR is reddish-brown in colour. These two compounds together impart to the tea liquor its characteristics colour and taste (Roberts, 1962; Wickremasinghe, 1978; Yamanishi, 1981). In addition to the formation of TF and TR, other chemical changes also take place in the leaf tissues during fermentation process. For instance, proteins get degraded, the chlorophyll is transformed into pheophytins and some volatile compounds are generated due to transformations of certain aroma precursors present in tea leaf. These changes also contribute towards the colour and flavour of made-tea (Mahanta, et. al., 1985; Hazarika, et al., 1983; Takeo, et. al., 1987). These constituents influence the brightness, briskness, strength, body, and colour of the tea liquor to a great extent with respect to which quality is estimated. The colour is a measure of the depth of the tea based on season, growth and grade factors. Out of these quality descriptors, the brightness, briskness and strength are determined by the TF contents while body and colour are associated with TR contents. There is a positive correlation between the TF content and market value of black tea. The concentration of TF increases with the progress of fermentation; it reaches a peak value and then starts declining if the fermentation is prolonged. TF gets degraded to TR in this stage. The concentration of TR, on the other hand, goes on increasing with the increase of fermentation time and the body of the liquor becomes thick. The over fermented tea has 'body' but lacks other desirable characteristics of good cup of tea. As a whole, the highest possible level of TF content is desired in production of tea. The development of colour and quality during fermentation process is shown in Figure 2.1.

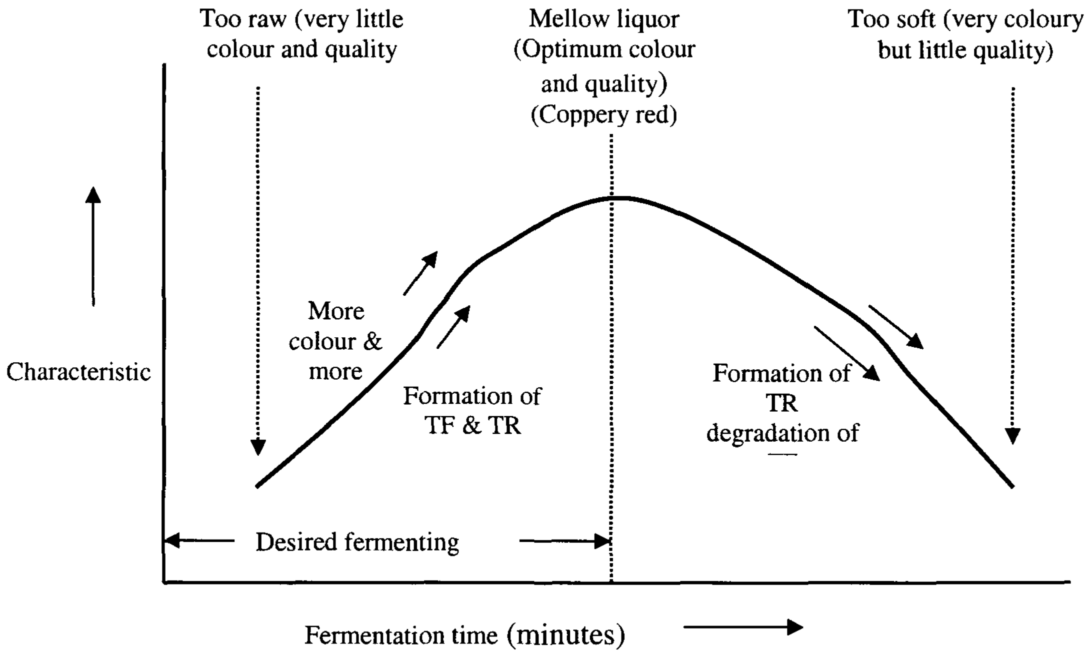


Figure 2.1 Development of colour and quality during tea fermentation.

As the process time advances, both TF and TR contents increase and colour of the tea also gradually changes. At optimum condition when the ratio between TF and TR becomes almost 1:10 or 1:9, the colour of the processed tea becomes coppery red. If the process still continues, the degradation of TF to TR occurred and colour becomes more deep imparting less quality tea. So it is seen that the compounds imparting colour and taste to the liquor gradually changes and after the optimum condition they get degraded sharply. Due to this continuously changing phenomenon of the lipid formation, the chemical analysis of the tea during fermentation is somewhat difficult to draw any inference to the quality determination during this process. In view of this, in controlled environment, tea fermentation requires precise monitoring in subjective manner and control of the process as soon as possible as the desired quality is achieved. In such situations, the industries usually need to apply tests for optimization of the fermentation process. So, accurate detection of the optimum state of the process is the most important condition of the fermentation process for quality perspective in tea processing industry. Once the optimum fermentation is ensured the tealeaves are sent to the dryer to extract the remaining moisture to stop fermentation.

2.3 Methods for tea quality assessment during fermentation

The detection of colour and flavour of tea during optimum fermentation condition are not directly measurable. In other words, both the parameters represent important meanings and compute a model for quality control of black tea. Therefore, tea fermentation requires supervision (monitoring) and control of the process as early as the required colour and flavour is attained. Practically during the process in the tea fermentation, colour and colour changes should be measured and monitored to correlate essential information about the physical and chemical changes that are taking place. Similarly the odour and odour changes should also be measured and monitored to provide volatile compounds formed due to oxidation of tea and in the other manufacturing processes. Therefore, both the parameters represent meaningful visual and olfaction stimuli and compute a model for quality control of the black tea manufacturing. There are two main ways of quality assessment.

- Subjective assessment by human sensory panel using organoleptic method
- Biochemical parameter measurement by chemical method.

The first method i.e., subjective assessment of completion of tea fermentation is in use since the beginning of tea industry by sensory panel. The second method uses chemical analysis, where instrumental chemical analysis replaces the sensory panel decision.

2.3.1 Human sensory panel judgment

Optimum colour detection is presently assured by the use of sensory panel of trained personnel's with visual inspection. This visual inspection is adopted to detect the achieved deep coppery red colour during fermentation at regular intervals. This method is believed as a reliable and faithful subjective assessment of quality, provided exact colour detection is possible. But it has been reported that the exact matching of the colour of tea at optimum fermenting condition is not always possible due to variability of eye approximation of the sensory panel and other factors. Therefore, machine vision can be better alternative or perhaps replacement for the conventional method (human visual inspection) during fermentation process of tea manufacturing. The flavour is also judged at the same time by olfaction to decide the completion of the process. The trained personnel, who are involved in this task, score the product on the basis of a number of flavour descriptors. It has been reported that different tea tasters judge the same colour and flavour of tea in different levels of quality descriptors. The reasons of such variations may be such as individual variability, adaptation (becoming less sensitive due to prolonged exposure), fatigue, infection, mental state etc.

2.3.2 Use of colorimeter

In some tea factories chemical tests are conducted to find out the correct fermentation of Orthodox and CTC tea. Colorimeter is used in this method. This method is subjective in nature since the completion of measurement is ensured by measuring the intensity of colour i.e., optical density of the ethyl acetate extract prepared from the fermented tea sample. This correlates the measurement of concentration of TF during the fermentation of tea leaves and to find out optimum fermentation time from the maximum concentration of TF. The procedure of this experiment is - ethyl acetate extract of the fermenting tea sample is collected in a test tube and the intensity of colour is matched by viewing through the column of the liquid against a white back ground. After this the intensity of colour i.e., optical density is measured in a colorimeter at 460 nm against water as blank. This test is repeated at every 10 minutes intervals during fermentation and at 5 minutes intervals when the critical period of fermentation is approached. For CTC manufacture, the maximum depth of colour of the ethyl acetate extract at a particular time corresponds to optimum fermentation. On the other hand, in case of Orthodox manufacture, the process is continued for another 10 minutes after obtaining the maximum depth of colour of the ethyl acetate extract (Ullah, et al., 1979). This method is not easy or results are not always faithful due to a considerable period of time required in pursuing the chemical tests. Moreover, for satisfactory result, it requires high patience and concentration of the concerned person.

2.4 Prospect of fermenting tea colour and aroma assessment by electronic means

Different electronic devices have been developed for use in different processes of black tea manufacturing as the quality monitoring or more accurate quality control tool. Some of them are commercially available for use in tea industry. The moisture content (MC) measurement meter during withering, computer based withering percentage measurement, computer based relative humidity (Rh) measurement, automated fan direction reversal during withering for air control, programmable indicator for sequential timing of rolling machines, and finally three level temperature indicator for tea dryer etc. are attempted by many researchers (Kapoor, et. al., 1994, 1999; Bhuyan, 1997). But no report of research on quality control monitoring of tea during fermentation is available so far. Hence there is ample scope for addressing on this topic for determination of degree of fermentation where change in colour and odour of fermented tea is a major factor for quality determination (Roberts, 1962; Mahanta, et. al., 1985; Takeo, 1987; Hazarika, et. al., 1984).

2.4.1 **Computer vision for colour classification**

Computer vision based recognition of colour in image of food products has been reported as an efficient method of quality inspection (Gunasekaran, 1996; Brosnan, et. al., 2002). Colour provides an important feature depending on which an image can be analysed and classified. Since visual colour inspection is affected by wide variety of factors such as lighting condition, angle of observation and individual variability of colour perception etc. machine vision colour analysis method provides a subjective and consistent method of colour analysis. In this research image of tea under fermentation process is analysed in terms of colour variation. In other words, computer vision technique has been carried out to evaluate the optimum fermenting condition by detecting the colour in a non-intrusive way as an alternative subjective method over the human organoleptic methods.

2.4.2 **EN for aroma classification**

Aroma detection by artificial olfaction techniques (EN technology) is a prospective area of research for quality estimation of food products (Mielle, 1996; Schaller, et. al., 1998). The aroma is an important aspect (section 2.2.3.1) of tea fermentation stage along with the colour. EN technology may be an alternative to support the traditional methods of aroma sniffing. The EN technology includes certain advantages over the common disadvantage of human sensory panel.

2.5 **Tea sorting and grading**

The made tea is sorted into different sizes by passing it over a series of vibrating sieves of different mesh sizes. Tea of different grain sizes is collected from the outlet of the sieves results various grades. These grades fall into four main groups, namely, leaf, brokens, fannings and dust in descending order of particle size. They are traded under a wide variety of traditional names as described bellow. The accuracy and consistency of factory tea grading has been checked and recorded using test sieves with meshes of certified quality. Individual tea grade sizing varies between industries but the sieve set used spans most CTC production. Tea Research Association (TRA), Tocklai Experimental Station considers some other CTC tea grades, which are furnished in Table 2.2 along with these grades (http://www.tocklai.org/manufacture/sorting.htm):

Table 2.2 CTC tea grades approved by TRA, Tocklai Experimental Station, India.

Kind of tea	Grades	Nomenclature
Bokens	BOP	Broken Orange Pekoe
	BP	Broken Pekoe
	BPS	Broken Pekoe Souchang
Fannings	OF	Orange Fannings
	PF	Pekoe Fannings
	PF 1	Pekoe Fannings one
Dust	PD	Pekoe Dust
	D	Dust
	CD	Churamoni Dust
	PD 1	Pekoe Dust one
	D 1	Dust one
	RD	Red Dust
	FD	Fine Dust

Among the different grades Pekoe Fannings (PF) is produced about 58-60% and forms the bulk of the production. Broken Pekoe (BP) is produced about 12-14% of the total production. Pekoe Dust (PD) is produced almost 10-12% of the total production. The smallest particle the Dust is produced 4-6 % out of the total production. These data are based on empirical estimation of different tea processing industries in Assam, India.

After separation of the different sized granules of tea using sieves, these are graded for packaging before releasing to the market or for auction. Table 2.3 furnishes eight numbers of different CTC tea grades with their approximate granule sizes. However, there are no internationally recognised standards defining these grades with respect to particle size distribution. Therefore there is every chance of variation in this grading system from factory to factory within a single tea producing country. No scientific method so far has been developed for accurate grading of the tea and everything has so far been done by human visual estimation only. Usually, human expert since the beginning of tea industry has performed this task.

Table 2.3 CTC tea grades along with approximate characterisation size

Grade name	Full name	Characterisation of size (Approx.)
BOP L	Broken Orange Pekoe Large	2.0 mm
BOP	Broken Orange Pekoe	1.7 mm
BOP SM	Broken Orange Pekoe Small	1.3 mm
BP	Broken Pekoe	1.0 mm
PF	Pekoe Fannings	0.5 mm
PD	Pekoe Dust	0.355 mm
OF	Orange Fannings	0.25 mm
Dust	Dust	Not specific

On the other hand, the quality analysis is one another aspect of this grading process. Here three attributes aroma, taste and astringent are analysed by the human sensory panel. They use some standard flavour terminology to score about a particular grade of tea. This is termed as the quality grading of made-tea. Generally, the organoleptic judgment is carried out on the basis of aroma or dry tea; taste and strength of liquor; brightness and briskness of liquor; which are on the other hand the practical measuring parameters. Some most common tea quality tasting terms are summarized along with their definitions:

- Aroma: The smell of tea
- Liquor: The liquid tea; also referred as cup or infusion
- Astringency: The sign of quality, which causes the mouth to pucker
- Body: The strength of the liquor

- Bright: The colour of the tea when brewed
- Character: An attractive taste derived from liquor
- Light: Lack of strength and depth of colour

2.6 **Prospect of tea grading by electronic means**

Human sensory panel based tea sorting and grading of the final tea has been found to involve significant perturbation to the purpose. This is because the whole procedure is not standardized and based only on subjective decision. It is mentionable that different tea grades of tea are found to have profound effect on composition of infusions (Sarma, 1999). For example, TF, TR and caffeine are higher in the dust grades than in the larger size grades. But it does not have any adequate evidences. Similarly, quality grading by analysing the tea flavour profile is based on some flavour terminology, which are also not standardized. Therefore some prospective electronic systems are mentioned here.

2.6.1 **Computer vision for texture classification**

As the size of the tea granules is the important parameter for sorting, it can be addressed by the image texture analysis methods of computer vision. The images of various grades of tea of various granule sizes would be different by texture. So, such texture analysis method would be worthwhile in estimating the tea granule size by classifying the texture into their appropriate categories. This, in turn helps in monitoring the grading process before packaging the final tea in different varieties. Therefore image texture analysis, which is one of the neighbourhood operations of digital images, is explored for tea granule size estimation.

2.6.2 **EN for aroma classification**

The aroma analysis by EN technology for quality grading of tea is one of the important aspects. Such EN system would be worthwhile in standardizing the aroma profiles in tea and would be advantageous over the problems faced due to the traditional method of sniffing. So, it would be considered as one of the prospective field of research for the monitoring of the quality grading of the made-tea. Aroma analysis is carried out for different grades of tea and explored as a useful method for the purpose described.

2.6.3 ET for taste classification

The taste analysis of tea liquor by ET is one another prospect for tasting the tea liquor during quality grading of made-tea. The tasting for the taste of tea liquor one of the most important aspects for this process. Human sensory panel usually use their tongue for this purpose and provide the necessary judgments. But the prospective of ET system is that such system might be advantageous over the many problems encountered by the traditional tea tasting methods. The exploration of ET technology in tea is not addressed in this research and set as a future prospective in this area.

2.7 Computer vision workstation and EN

This section describes the experimental arrangement for the computer vision workstation and the gas sensor for EN system. The extra hardware required for converting personal computers into a computer vision workstation are: a CCD camera with signal conditioning device; and an image capturing add on card (frame grabber). Imaging of fermenting tea and made-tea has been done with the CCD camera, which converts the irradiant at the image plane into an electrical signal. A signal conditioner converts these electrical components of the image to electrical signal of specific frequency level (S-band in this case). Then the computer retrieves this signal from the signal conditioner with the help of the image capturing card and stored in memory spaces (database) of the computer for further processing. The experimental setup of image capturing during fermentation and grading process is shown in Figure 2.2.

During image capturing of the fermenting tea leaves, the CCD camera is mounted over the leaves almost vertically and surface orientations as well as inter reflection phenomenon doesn't occur since tea leaves are spread uniformly with almost equal thickness. The distance between the fermenting tea and the CCD is maintained is approximately fixed (30 cm in this case) throughout the whole experiment. However, the use of high light and illumination colour were avoided during image capturing. The CCD grabs the image frames at specific amount of time interval. Since the colour of tea gradually changes with the progress of the fermentation process, the captured images are of different colours, changing from green to deep coppery red. However the colour turns further deeper as fermentation exceeds a certain point of acceptance.

Similarly, during image capturing of the made-tea for grading control, same setup is used without applying any special light arrangement. The sorted tea from sieves is spread in a white tray and the CCD, mounted over the tray, captures the images for texture analysis purpose. Special care has been taken so that the granules of the tea are arranged in a specified manner (This phenomenon is described in detail in chapter IV; section 4.2).

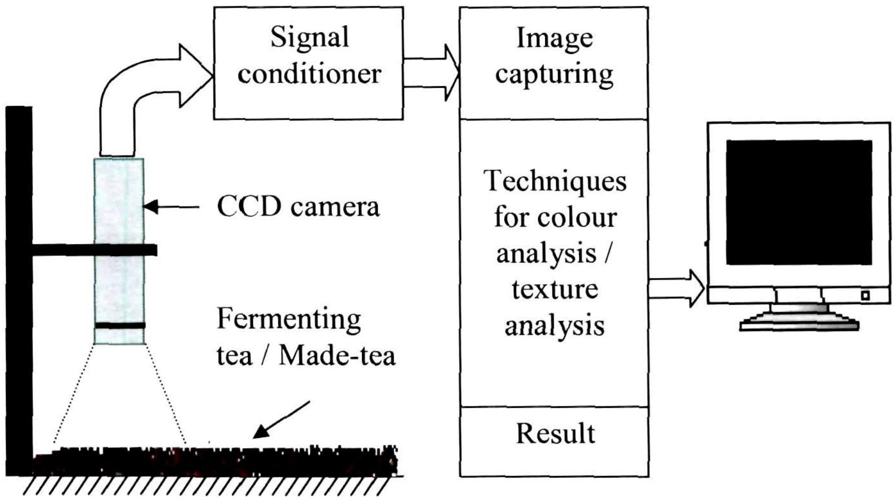


Figure 2.2 Experimental setup's diagram of the camera positioning and image capturing of fermenting tea and made-tea.

On the other hand, the EN system consists of an array of gas sensors. The basic function of the gas sensor is to convert the information of concentration of a specific gas (volatile compound) into usable electrical signal. The sensors used in a particular EN system are of different sensitivities to the different gases. Figure 2.3 shows the schematic of a basic gas sensor. One of the requirements for the sensors to be used in EN system is that they respond in reasonable time. Another requirement is that the sensors respond with a wide sensitivity range from very low concentration of gas to high concentration. Finally the EN system consists of three functional components that operate serially on an aroma sample. They are a sample handler, an array of gas sensors, and a signal processing sub-system (This is described in detail in chapter V; section 5.3).

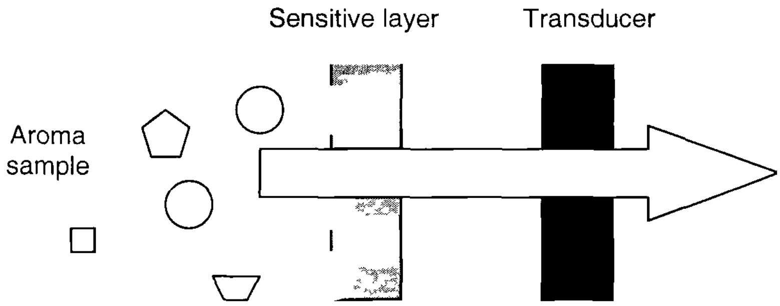


Figure 2.3 Schematic of a gas sensor

2.8 **Image colour processing**

The purpose of the colour image capture of fermenting tea during on going fermentation process is to detect the images with particular colour. This section provides a idea of colour processing in the images, which is the necessary background of computer vision work in the colour analysis purpose. It is elsewhere mentioned that the main uses of colour in image processing and computer vision (Gonzalez, et. al., 1992; Castleman, 1996) are usually for image enhancement and image analysis respectively. Therefore one of the key aspects of computer vision for such colour analysis of the images is to get image data into the right colour model for the specific application. There are different colour models so far developed and used in different applications by different researchers. These colour models have different advantages or disadvantages over one another. Usually, the models that separate intensity from the chromatic properties of light are more useful for analyzing object colour in an image. Basically, one can use any of the methods to process colour images but just have to be careful because colour image concerns with at three pieces of information per pixel, namely red (R), green (G) and blue (B). The accurate separation or combination of these three colour spaces is the real work in processing a colour images. Image compression using colour information. for example, often uses the luminance-inphase-quadrature (YIQ) model because it is more redundant of colour information. When lighting changes across an orange patch, the red, green, and blue parts all change, but in the YIQ model the I and Q parts stay the same while the Y part varies (Funt, 1995; Mark, 1998). Therefore selection of a suitable colour model for the specific purpose of computer vision is important. This section discusses some of the relevant colour models relevant to the research purpose and explores their advantages in such colour based system.

A colour model is a mathematical representation of a set of colour. Several colour models are available in image processing for various purposes. The purpose of a colour model is to facilitate the specification of colour in some standard, generally accepted way. RGB model, CMY model, CIE L*a*b colour space, HSI model are the some common examples of such colour model used in computer vision.

2.8.1 **RGB colour model**

In practical system, visible light is found between 380 and 780nm in the electromagnetic spectrum, bordered by ultraviolet light on the low end and infrared on the upper end. When white light strikes on object, it is reflected back and this reflected light determines the colour of the object. This colour appearance depends on amount of light, the nature of light source, and the observer's angle of view. In computer vision colour image is normally represented using the trio-stimulus model. The image is digitised into pixels where each pixel value represents a particular intensity at that location. For instance, when a black and white image is considered, the image can be quantified into a single space consisting of a number of pixels, and each pixel can be assigned with an integer value. The value of the integers represents the brightness of the image at the corresponding location. When one chooses the eight-bit register to store the values then the maximum possible value of the integer will be 255 and the minimum will be 0, i.e., a total of 256 different values. The value 255 and 0 represent the white and black respectively. This can be easily described by the number line as shown in Figure 2.4.

Black $\longrightarrow$ White

0 ———————————————— 255

Figure 2.4 Number line for monochrome image

For a colour image the image is composed of three primary colours viz. Red (R), Green (G) and Blue (B) with each of values ranging from 0 to 255. Therefore we may conclude that each pixel location is made up of 24 bits of colour for a colour image. Again since each primary colour is represented by 1 part in 256, we may specify an arbitrary colour to a precision of about 1 part in 16 million different colours. This is known as RGB model. In this model, each of these components could be treated as a separate plane and depending upon the application these planes are processed. Practically the quantified image is stored as a matrix of three planes. The first plane stands for R, the second for G and the third for B respectively. The value of the pixel 255 in the first plane and 0 in the rest of the two planes means the pixel is purely red. Similarly the value 255 in the second plane and 0 for the first and the third plane means the pixel is purely green. Similar attribution is also valid to the third plane, which is pure blue. The number line representation of a colour image is shown in Figure 2.5.

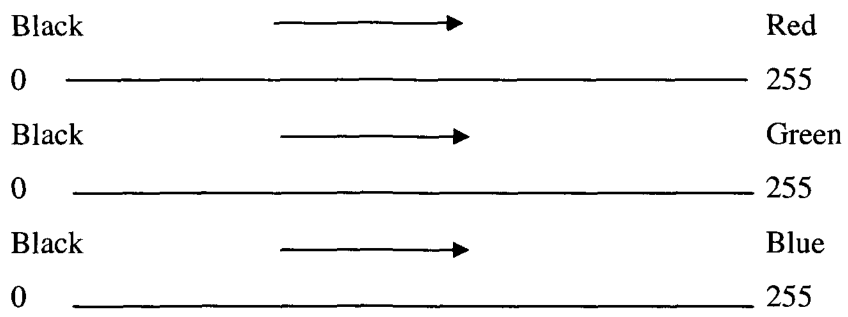


Figure 2.5 Number lines for colour image

As already mentioned, the RGB color space consists of the three additive primaries: red (R), green (G), and blue (B). Spectral components of these colors combine to each other in additive mode to produce a resultant color. A 3-dimensional cube represents the RGB model where the red, green and blue are at the corners on each axis as shown in Figure 2.6. Black is at the origin. White is at the opposite end of the cube. The gray scale follows the line from black to white, which is the diagonal of the cube. In a 24-bit color graphics system with 8 bits per color channel, red is (255, 0, 0). On the colour cube, it is represented as (1, 0, 0), the normalised values of R, G and B to [0,1].

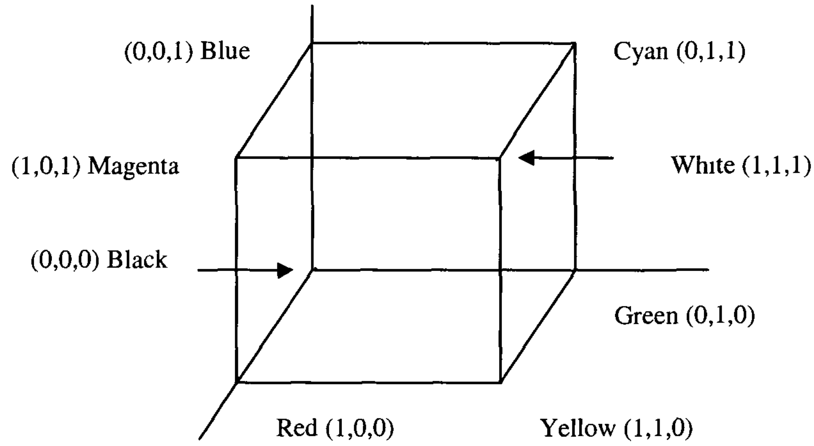


Figure 2.6 The RGB colour model

A variety of colour models or schemes are used to describe colour. For example, CMY (cyan, yellow and magenta), HSI (hue, saturation and intensity) etc. are some colour models generally used for colour image processing. These all colour models are composed from these three planes of colour R, G and B, some of those will be briefly mentioned in latter of this chapter.

2.8.2 **CIE colour model**

The **International Commission on Illumination** (usually known as the **CIE** for its French language names '*Commission Internationale de l'Eclairage*') (CIE publication, 1987) is the international authority on light, illumination, colour and colour spaces. It has defined a system that classifies colour according to human visual system. According to CIE, a colour space is a geometric representation of colours in space, usually of three dimensions. The CIE developed a highly influenced system for description of colour spaces, which is mostly used in food industry for colour measurement. The CIE spaces, which include CIE XYZ, CIE L*a*b*, and CIE L*u*v* are device-independent. A colour is identified by two co-ordinates, x, and y, in this colour space. L* is based on a perceptual measure of brightness, and others two (a*, b* or u*, v*) are chromatic coordinates. The range of colours that can be found in these colour spaces is not limited to the rendering capabilities of a particular device, or the visual skills of a specific observer. Colour can be measured either colorimetrically, or spectrophotometrically.

Also, colour differences in an arbitrary direction are approximately equal in this colour space. Thus, the distance measurement such as Euclidean distance can be used to determine the relative distance between two colours. The CIE L*a*b and CIE L*u*v are nearly linear with visual perception, or at least as close as any colour space is expected to sensibly get. Both the L*a*b* and L*u*v* colour spaces were recommended by the CIE in 1976 as perceptually approximate uniform colour spaces (McLaren, 1976; Agoston, 1979). Three tri-stimulus values X, Y and Z uniquely represent a colour, however since the illuminant and lighting and viewing geometry will affect the measurements these are all carefully defined. For example, the conversion of the RGB to CIEL*a*b is shown here. First the method of calculation of X, Y and Z components from R, G and B components of an image in CIE system is as follows (Equation 2.1):

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} 0.412453 & 0.357580 & 0.189423 \\ 0.212671 & 0.715160 & 0.072169 \\ 0.019334 & 0.119193 & 0.950227 \end{bmatrix} * \begin{bmatrix} R \\ G \\ B \end{bmatrix} \quad (2.1)$$

Then CIE L*a*b is defined, which is a refined CIE model where 'L' stands for Luminance and the 'a' and 'b' are the Chrominance where 'a' ranges from green to red and 'b' ranges from blue to yellow.

$L^* = 116(Y/Y_n)^{1/3} - 16,$ for $Y/Y_n > 0.008856$

$L^* = 903.3 * Y/Yn$ otherwise

$a^* = 500[(X/X_n)^{1/3} - (Y/Y_n)^{1/3}],$ for X/X_n and $Y/Y_n > 0.008856$

$a^* = 500[(7.787 * X/X_n + 16/116) - (7.787 * Y/Y_n + 16/116)]$, otherwise

Similarly,

$b^* = 200[(Y/Y_n)^{1/3} - (Z/Z_n)^{1/3}],$ for Y/Y_n and $Z/Z_n > 0.008856$

$b^* = 500[(7.787 * Y/Y_n + 16/116) - (7.787 * Z/Z_n + 16/116)]$, otherwise

Where, X_n, Y_n, and Z_n are the values of X, Y, and Z for the white reference illuminant.

The schematic diagram of CIE L*a*b colour model is shown in Figure 2.7.

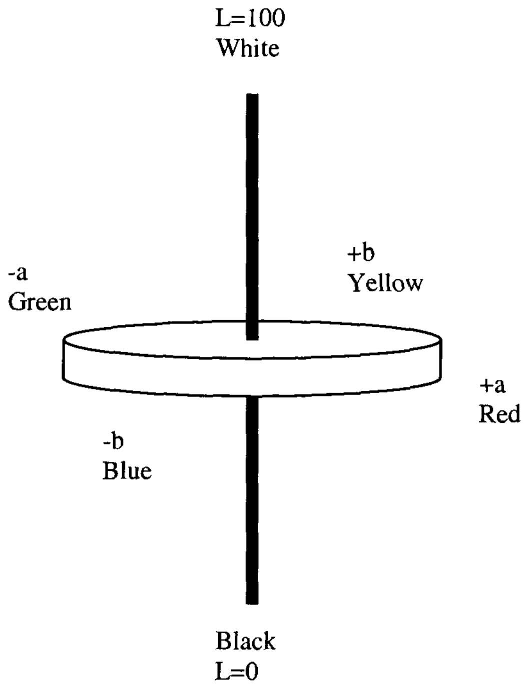


Figure 2.7 The CIE L*a*b colour model.

2.8.3 HSI colour model

The RGB colour model and CIE colour models are not illumination invariant. But they are useful colour model in computer vision with constant illumination conditions. The HSI colour model, on the other hand, is designed to use more intuitively in manipulating colour and to approximate the way humans perceive and detect colour. Three components of colour hue (H), saturation (S) and intensity (I) are defined so that to distinguish the colour components. The components H and S of this colour model are independent to the viewing direction, surface orientation, illumination direction, and illumination intensity. The 'H' represents the actual wavelength of colour (pure colour) by representing the colour's name, for example red, green etc. The 'S' is a measure of the purity of colour. This represents how much the pure colour is diluted to the white light. The 'I' represents for the lightness of the colour. Figure 2.8 shows the HSI colour model, where a projection down the intensity line in the cone and the red axis at 0^0, with green and blue at 120^0 angular intervals.

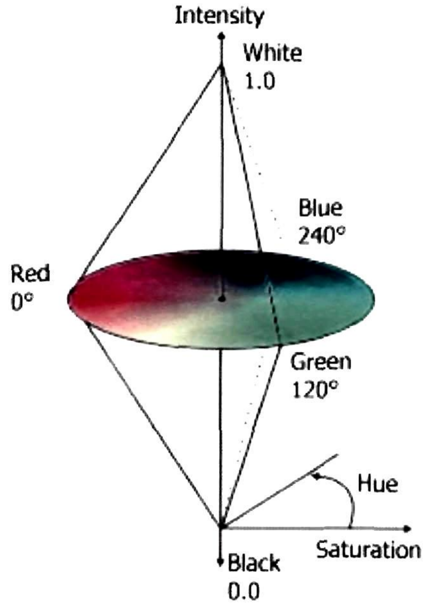


Figure 2.8 The HSI colour model.

The HSI values can be achieved from the RGB colour model. The conversion notations from RGB to HSI are as shown below (Equations 2.2, 2.3 and 2.4):

$$I = \frac{1}{3}(R + G + B) \tag{2.2}$$

$$S = 1 - \frac{3}{R + G + B}[\min(R, G, B)] \tag{2.3}$$

$$H = \cos^{-1}\left[\frac{\frac{1}{2}[(R-G)+(R-B)]}{\sqrt{(R-G)^2+(R-B)(G-B)}}\right] \tag{2.4}$$

The values of 'I' and 'S' range from 0 to 1 while the value of H range from 0^0 to 360^0 however $H = 360^0 - H$, when $B > G$.

2.8.3.1 **Correction of non uniform illumination in HSI**

A simple and effective colour indexing scheme was proposed by Swain and Ballard (Swain, et al., 1991). Colour based processing of image fails, however, when the incident illumination varies either spatially or spectrally. Therefore, uniformity in illumination in object imaging is an important issue during processing of the images. But, it is difficult to assume constant imaging conditions during image acquisition particularly when the database is generated on different days with different weather conditions. There may be two reasons for this non-uniformity in the illumination:

- Non-uniformity of the illuminating source of light
- Intermediate reflections in the object surfaces, when imaging object doesn't have a smooth surface.

Therefore, proper care should be taken for maintaining uniformity in the illumination during imaging. But still some non-uniformity may present, which can be overcome by means of specific method such as using appropriate colour model (Funt, et al., 1995). It is based on indexing on illumination invariant surface descriptors (colour ratios) computed from neighbouring points. Since the ratios of colour RGB triples from neighbouring locations are relatively insensitive to changes in the incident illumination, this circumvents the need for colour constancy preprocessing. From these, it is observed that the choosing a colour model depends on their robustness against varying illumination across the scene (e.g., light with different intensity). The following statements justify the illumination invariance property of HSI colour model that considered in this research.

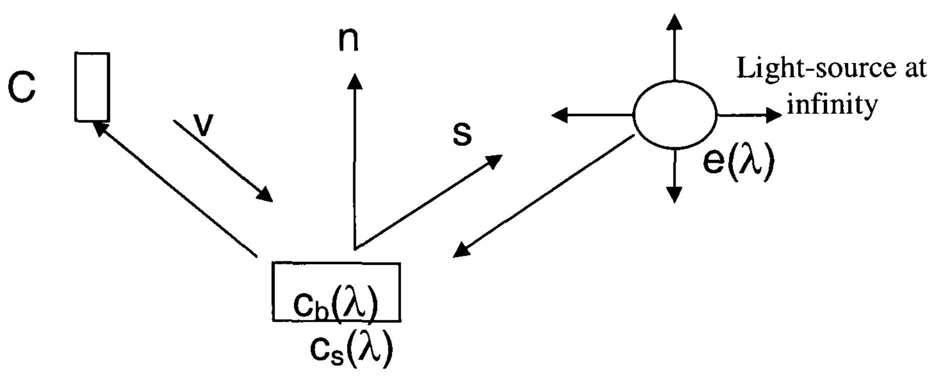


Figure 2.9 The worst case of imaging of object by CCD.

The worst case of imaging condition is shown in the Figure 2.9, where the sunlight is the illuminator of the object to be imaged. Again, the CCD is also mounted inclined to the surface of the object. The terms shown in the figure are described here as:

n:	Surface path normal (unit vector)
s:	Light direction (unit vector)
v:	Direction of the camera (unit vector)
$e(\lambda)$:	SPD of incident light
$c_s(\lambda)$:	Reflectance of the incident surface
$c_b(\lambda)$:	Surface albedo
C:	Sensor (digital camera) response
λ:	Wave length of incident light

The measured sensor response: -

$$C = m_b(\bar{n},\bar{s})\int_\lambda f_c(\lambda)e(\lambda)c_b(\lambda)d\lambda + m_s(\bar{n},\bar{s},\bar{v})\int_\lambda f_c(\lambda)e(\lambda)c_s(\lambda)d\lambda \tag{2.5}$$

Where, m_b & m_s are the geometric dependencies and surface reflection component respectively. Using this formula and illuminating the fermented tea by white light & considering neutral interface reflection (NIR) model, $c_s(\lambda) = c_s$ and $e(\lambda) = e$ (both are constant), the simplified formula becomes:

$$C = em_b(\bar{n},\bar{s})k_c + em_s(\bar{n},\bar{s},\bar{v})c_s\int_\lambda f_c(\lambda)d\lambda \tag{2.6}$$

Where, $k_c = \int_\lambda f_c(\lambda)c_b(\lambda)d\lambda$

That is, k_c is the compact formulation depending on camera parameters and surface albedo (reflected light from object surface) only. When white condition (Sun light) holds,

$$\int_\lambda f_R(\lambda)d\lambda = \int_\lambda f_G(\lambda)d\lambda = \int_\lambda f_B(\lambda)d\lambda = f \tag{2.7}$$

Then,

$$C = em_b(\bar{n},\bar{s})k_c + em_s(\bar{n},\bar{s},\bar{v})c_s f \tag{2.8}$$

$$C = em_b(\bar{n},\bar{s})k_c + const. \tag{2.9}$$

$$C = em_b(\bar{n},\bar{s})k_c \tag{2.10}$$

Therefore, for each R, G, B value becomes:

$$R = em_b(\bar{n},\bar{s})k_R ; G = em_b(\bar{n},\bar{s})k_G ; B = em_b(\bar{n},\bar{s})k_B \tag{2.11}$$

This equation shows that the R, G and B values depend on k_c (i.e., sensors and surface albedo) and the brightness on illumination intensity e and the object geometry $m_b(n, s)$. Therefore, on variation of these parameters the R, G, B values will be different and the as a whole the processing doesn't infer accuracy. Similarly, the CIEL*a*b colour model is also changed with variations of these parameters. But, consideration of the ratios of these colour components, for the case of HSI colour model, reveals that these are relatively insensitive to the variation of incident illumination, sensors and surface albedo etc. The phenomenon can be explained by considering the RGB to HSI conversion equations (Equations 2.2, 2.3 and 2.4) using the R, G, and B definitions (Equation 2.11):

$$I = \frac{em_b(\bar{n},\bar{s})}{3}(k_R + k_G + k_B) \tag{2.12}$$

$$S = 1 - \frac{3}{k_R + k_G + k_B}[\min(k_R, k_G, k_B)] \tag{2.13}$$

$$H = \cos^{-1}\left[\frac{\frac{1}{2}[(k_R - k_G) + (k_R - k_B)]}{\sqrt{(k_R - k_G)^2 + (k_R - k_B)(k_G - k_B)}}\right] \tag{2.14}$$

It is observed from the equations 2.12, 2.13 and 2.14 that the values of 'S' and 'H' are independent of the illumination intensity 'e' and object geometry 'm_b(n,s)'. Rather they are dependent only on the camera parameters and object surface albedo only. But the value of 'I' is not dependent on all the four parameters discussed here. The detail of tea image colour analysis is explained in 'Chapter III'.

2.9 **Image texture analysis**

Texture plays an important role in many computer vision tasks such as surface inspection, scene classification, and surface orientation and shape determination etc. The texture analysis is addressed with the gray scale images. For size estimation of tea granule, during grading, the colour tea images are converted to gray scale images. One main aspect of texture analysis in computer vision applications is the efficient feature extraction technique. The most existing feature extraction methods provide efficient tool for shape and pattern classification in the images (Tianhorng, et.al., 1993; Chen, 1994; Pietikainen, et. al., 2000). But the situation becomes complicated, while the both size and shape of the particles in the images come into the limelight. Such situation is envisioned in discriminating the images of different grades of tea during tea grading process. The detail texture feature extraction, texture classification etc. for tea grading monitoring is discussed in 'Chapter IV'.

2.10 **EN signal analysis**

The overall aim of the EN is to identify an aroma samples and to estimate its concentration. These two steps are further subdivided into four sequential stages: data gathering, feature extraction, classification, and decision-making. The data gathered from the array of gas sensors are stored and processed in order to analyse various tea aroma with different concentrations. It is observed that sometimes unwanted drift occurs during data gathering. Moreover, the transient response of the sensors to the tea flavour is also to be taken into account in order to optimize the performance of the system. The data are preprocessed prior to actual data analysis. This compensates for sensor drift and also compresses the transient response of the sensor array, and reduces sample to sample variations. After preprocessing of the data, the important aspect is the efficient feature extraction from the signals. It has two main purposes: to reduce the dimensionality of the measurement space, and to extract information relevant for the subsequent pattern recognition. Once the sensor responses have been projected in terms of the features vectors in an appropriate low dimensional space, the classification stage is used for decision making about the aroma samples. It helps to identify the patterns that are representative of each different aroma. 'Chapter V' explains these in detail.

2.11 Data processing

This section describes the methods that are adopted for the process of the data in all the three aspects, namely colour of image (fermenting tea image), texture of image (image of tea grades) and EN signals (aroma of tea grades). The data processing is being carried out in three serial steps.

- Data visualisation
- Data clustering
- Data classification

2.11.1 Data visualisation (PCA technique)

The principal component analysis (PCA) is a useful unsupervised pattern analysis technique, which is widely used for such pattern visualization. It is an efficient way of data visualisation. This technique is used to find and reduce the dimensionality of the data. It helps in finding the new meaningful underlying variables. The method involves a mathematical procedure that transforms a number of correlated variables in a smaller number of uncorrelated variables. These uncorrelated variables are termed as principal components of each data vector of the data set. The first principal component accounts for as much of the variability in the data as possible. Then each succeeding component accounts for as much of the remaining variability in the data. Three principal components have been used in the case of data visualisation of the data in this research.

2.11.2 Data clustering

Data clustering is a common technique for data processing and analysis. It consists of partitioning a dataset into subsets (clusters), so that the data in each cluster share some common properties (often similarity). Two different algorithms, namely k-mean and SOM based data clustering are mainly used for data clustering. Both the technique obeys the unsupervised clustering technique algorithm.

2.11.2.1 K-mean clustering

The K-means data clustering (Bezdek, 1981), the 'N' data points into 'k' disjoint subsets, is one of the most widely used methods for EN data analysis. This algorithm affords a method of estimating the numbers of heterogeneous clusters present in a given dataset by iteratively adding and adjusting cluster centres. It takes N observations $\{x_i\}$ in 'd' dimensional spaces as input and partitions the set into the k clusters with centroids $\{y_1 \ldots y_k\}$, where k is defined by the user. It considers a partition that minimises a cost function:

$$J = \sum_{i=1}^{N} \min_{k'} (| x_i - y_k |^2 w_i) = \sum_{j=1}^{k} \sum_{i}^{N_j} | x_i - y_j |^2 w_i \tag{2.15}$$

Where w_i is a scalar weight associated with each observations. In other words, each observation is assigned to the nearest centroid, and the centroid positions are chosen to minimize the weighted within the cluster sum of the squared Euclidean distances. K-means results in a flat or non-hierarchical clustering, in contrast to other clustering algorithms that constructs hierarchical discrimination.

2.11.2.2 **SOM data clustering**

The self organizing map (SOM) (Kohonen, 1982) is an unsupervised neural network (ISE technique) mapping technique of high dimensional input data onto a lower dimensional output space. The SOM has proven to be a valuable tool in data mining. It is also successfully applied to the various engineering applications, namely in pattern recognition, image analysis, process monitoring. The basic idea of a SOM is to map the data patterns onto N dimensional grid of neurons or units. By definition, a SOM is a network formed by N neurons arranged as the nodes of a planner grid; so that each neuron has four immediate neighbors. The grid forms what is known as the output space, as a response to the input space, where the data patterns existed. This mapping tries to preserve topological relations, i.e., patterns that are close in the input space will be mapped to units that are close in the output space, and vice-versa. So as to allow an easy visualization, the output space is usually 2 dimensional (2-D). The SOM adopts the competitive learning method and is based on unsupervised learning. The basic idea of SOM can be summarized as flows:

- Represent high dimensional data in a lower dimensional form without loosing any of the 'essence' of the data

- Organize data on the basis of similarity by putting entities geometrically close to each other.

Following are the six basic steps of SOM learning algorithm:

1. Initialise all the weights to a random value between 0 and 1
2. Randomly select an input vector and evaluate the quadratic distance output dj according to relation

$$d_j = \sum_{i=1}^{n}(w_{ij} - x_i)^2 \tag{2.16}$$

3. Select the neuron with minimum output dj and assign it as the winning neuron
4. Update the weight of the winning neuron (* is to indicate winning neuron)

$$w_{ij*}(k+1) = w_{ij}(k) + \eta(k)[x_i(k) - w_{ij*}(k)] \tag{2.17}$$

5. The weights of the neighbouring neurons are also updated

$$w_{ij}(k+1) = w_{ij}(k) + \eta(k)[x_i(k) - w_{ij}(k)] \tag{2.18}$$

6. Repeat steps 2-5 until all the input vectors have been used at least one time.

The schematic of 2-D SOM is shown in Figure 2.10. The figure shows the steps of calculation of the weight vectors also.

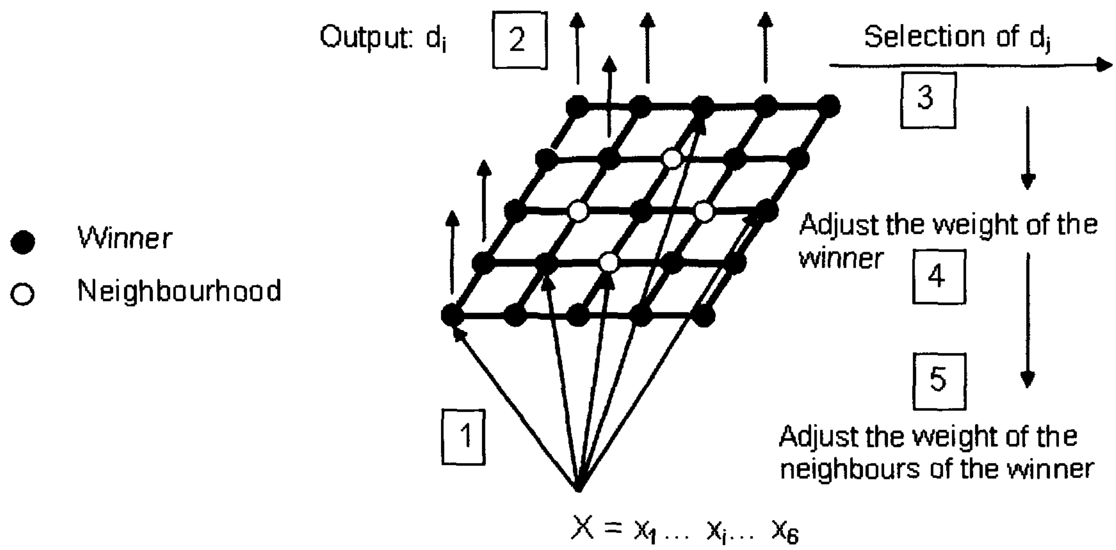


Figure 2.10 Kohonen SOM network (2-D) and the weight calculation method

2.11.3 Data classification

Whilst there is no formal definition for a particular problem to be solved, it can be said that an intelligent system engineering (ISE) is a system that can be considered to learn from and adapt to input stimuli (Bishop, 1995). In particular they can solve the problems by applying knowledge gained from past experiences. ISE are varied and encompass Artificial Neural Networks (ANNs), Fuzzy Logic (FL), Genetic Algorithms (GAs) and hybrid approaches such as Neural-Fuzzy System (NFS) etc. some of which are discussed here. This section presents some of the main principles of ANNs. In particular Multi Layer Perceptron (MLP), Radial Basis Function (RBF) network, Constructive Probabilistic Neural Network (CPNN) architectures are discussed.

An ANN is a collection of inter-connected artificial neurons. Generally, input data is presented to these neurons, which as a collective perform a mathematical transform, generating output data as a result of these calculations. The artificial neuron was first proposed by McCulloch and Pitts in 1943 (McCulloch, et. al., 1943). The Artificial Neural Network model comprises of three main components: the processing elements in which the weighted inputs are summed (Artificial Neuron, shown in Figure 2.11); translated through some activation function f(y); and the output response of the model.

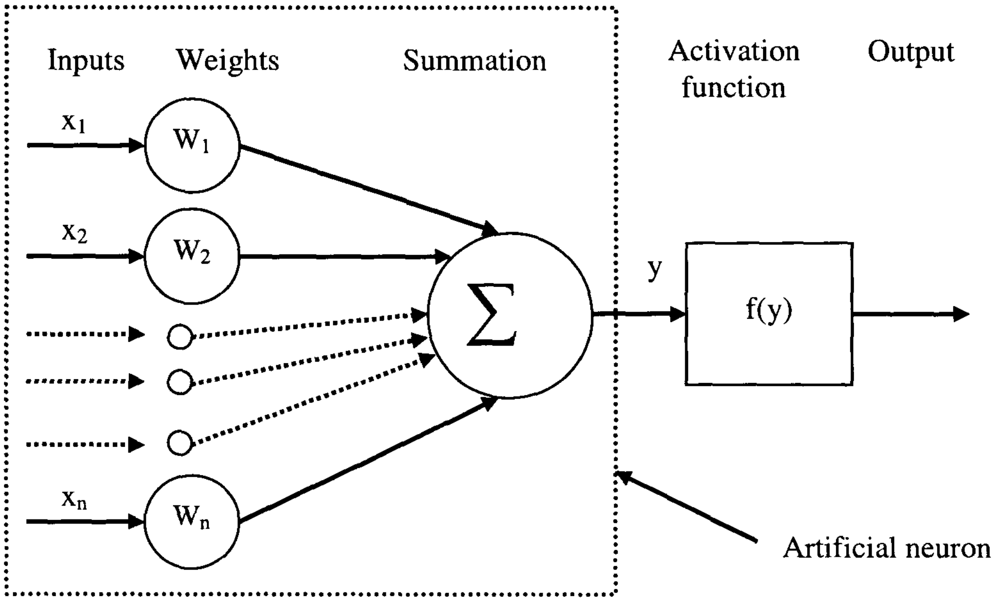


Figure 2.11 Artificial Neuron Network model

2.11.3.1 **Multi-layer perceptron network**

The multi layer perceptron (MLP) network is a widely reported and used neural network in a number of practical problems. It consists of an input layer of neurons, one or more hidden layers of neurons, and an output layers. The layers of neurons are inter-connected in such a way that the outputs of one layer are propagated to the subsequent layer. Figure 2.12 shows the architecture of a common MLP and illustrates the relationships between neurons, layers and inter-connections.

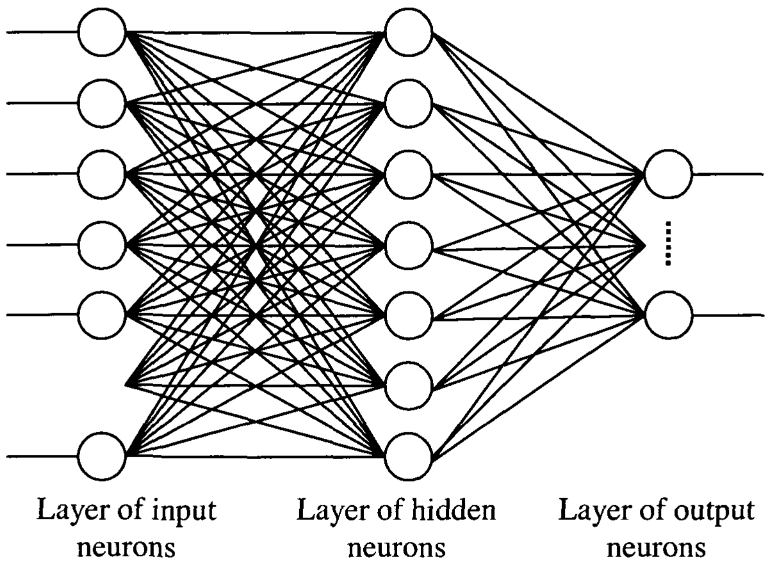


Figure 2.12 Architecture of a MLP

In the MLP, each neuron performs a weighted sum of inputs and transforms it using a non-linear activation function (For example, the most commonly used non-linear function is sigmoid function). The MLP uses the supervised training phase as it is presented with training vectors together with the associated targets.

A MLP network learns from the input data by adjusting the weights in the network using some specific techniques. Many different training algorithms exist that can be applied to the MLP, but the most commonly used algorithm is error back-propagation (Rumelhart, et. al., 1986). The purpose of this algorithm is to minimise the difference between the generated network output and the desired output, termed as error.

2.11.3.2 **Radial basis function network**

Similar to the MLP, the radial basis function (RBF) (Moody, et. al., 1989) network also consists of artificial neurons and number of layers is three. It has a similar architecture as like MLP, exhibiting fully inter-connected layers. It has the only difference with three layers MLP is that the hidden layer employs a different type of neuron, called the Radial Basis (RB) neurons. These neurons are used to cluster the inputs of the network; therefore the neurons in this layer also called the cluster centers.

Like the MLP, RBF also adopts the supervised learning method, being presented with the input patterns and the associated targets. Each hidden neuron in a RBF is turned to respond to a local region of feature space by means of a RB function such as Gaussian. Then the network performs the weight adaptation required by the output layer. The RBF implementation differs mainly in the choice of the heuristic used for selecting the basis function centers and width. Although it doesn't provide the error estimates, it has an intrinsic ability to indicate when it is extrapolating. This is because the activation function of the receptive fields is directly related to the proximity of the last pattern to the training data. One advantage of RBF network over MLP (with error back propagation) is that it can be trained with relatively lower computational overheads than would be required by the later method.

2.11.3.3 **Constructive probabilistic neural network**

The constructive probabilistic neural network (CPNN) (Berthold, et. al., 1998) is essentially a PNN (Probabilistic Neural Network) that is grown by sequential addition of the neurons in the hidden and output layers. The neurons are added in response to patterns presented in the training dataset. Prior to adding neurons, an assessment is firstly made as to whether existing neurons can perform the same function. If they can, then they are adjusted to encompass the new training pattern, otherwise a new neuron is added. This method of constructing CPNN often results in a highly compact and efficient architectures requiring low computational overheads. Barthold, et. al., found that CPNN algorithm can offer substantial advantages in terms of network size and generalization capability. So, in comparison, whilst the MLP demands higher computational overhead, the CPNN is inherently computationally lightweight ANN.

2.11.3.4 Learning vector quantization network

The learning vector quantization (LVQ) (Kohonen, 1990) network is also a supervised classification algorithm. As supervised method, LVQ uses known target output classifications for each input pattern of the form. This algorithm does not approximate density functions of class samples like CPNN does, but directly define class boundaries based on prototypes, a nearest-neighbour rule and a winner-takes-it-all paradigm. It consists of two definite steps, the clustering step and the training step. The clustering uses SOM architecture, which classifies the data with competitive learning. Then the network is trained with the winning neurons in supervised manner.

2.12 Summary

The motivation of this chapter was to present the background information of the proposed research objective. For that, the chapter tried to present the following information:

- Description of the research objective, i.e., tea quality perception
- Prospective methods of solving the proposed problems
- Data acquisition techniques for computer vision and EN
- Data processing techniques (visualization, clustering and classification)

At the beginning the chapter has introduced about the tea quality perception in detail. The important quality parameters used for quality monitoring during tea fermentation and grading processes were discussed. Then the prospective electronic and computer based methods were proposed along with the problem associated in the traditional methods of tea quality monitoring. For that three main prospective aspects, namely 'colour' measurement of fermenting tea, 'texture' analysis of tea grade and 'aroma' detection of tea grades were highlighted. The data acquisition techniques of computer vision and EN system were described at this point. The experimental setups were presented. Finally, the chapter has introduced the data processing techniques, namely data visualization, data clustering and data classification. The definition and working principles of the proposed visualization and clustering techniques, namely PCA, K-mean were presented. Finally, the chapter had introduced with the ISE technique of data clustering and classification, namely SOM and ANN and their effectiveness in data processing.

References:

1. Agoston, G. A., 1979. Color Theory and Its Application in Art and Design, Heidelberg.
2. Bezdek. J. C., 1981 Pattern Recognition with Fuzzy Objective Function Algorithms, Plenum Press.
3. Bishop, C. M., 1995. Neural Network for pattern recognition, Oxford University Press, Oxford.
4. Bhuyan, M., 1997. An Integrated PC based Tea Process Monitoring and Control System, Ph.D. Thesis, Gauhati University, October.
5. Berthold, M, J., Diamond, J., 1998. Contructive training of probabilistic neural networks, Neurocomputing, Vol 19, No. 1-3, pp 167-183.
6. Brosnan, T., Sun, D., 2002. Inspection and grading of agricultural and food products by computer vision systems – a review, Computer and electronics in agriculture, vol. 36, pp 193-313.
7. CIE Publication N 17.4, 1987. International Lighting Vocabulary, Definition 845-03-25.
8. Chen, Y. Q., Nixon, M. S., Thomas, D.W., 1994. Neural networks and texture classification, Applications of Neural Networks to Signal Processing (Digest No. 1994/248), IEE
9. Castleman, K. R., 1996. Digital Image Processing, Prentice Hall, Englewood Cliffs, New Jersey.
10. Funt, B. V., Finlayson, G. D., 1995. Colour constant colour indexing, IEEE transactions on PAMI, Vol. 17, pp 522-529.
11. Gonzalez, R. C., Woods, R. E., 1992. Digital Image Processing, Addison-Wesley Publishing Company.
12. Gunasekaran, S., 1996. Computer vision technology for food quality assurance, Trends in food science and technology, Vol. 7, pp 245-256.
13. Hazarika, M., Mahanta, P. K., 1983. Some studies on carotenoids and their degradation in black tea manufacture, J. Sc. Food Agric, Vol. 34, pp1390-1396.

14. Hazarika, M., Mahanta, P. K., Takeo, T., 1984. Studies on some volatile flavour constituents in orthodox black tea of various clones and flushes in N. E. India, J. Sc. Food Agric, Vol. 35, pp 1201-1207.
15. Kohonen, T., 1982. Self-organised formation of topologically correct feature maps, Biological cybernetics, Vol. 43, pp 59-69.
16. Kohonen, T., 1990. The self-organizing map, Proc. IEEE (special issue on neural networks), Vol. 78, No. 9, pp 1464-1480.
17. Kapoor, P., 1994. Intelligent on-line monitoring system for Withering Process in Tea industry, Proc. 32nd Tocklai Conf. Dec 16-17, pp 308-324.
18. Kapoor, P., 1999. Electronic instrumentation and control systems for critical manufacturing stages in tea industry, Global Advances in Tea Science, pp 825-836.
19. Lee, W. E., A suggested instrumental technique for studying dynamic flavour release from food products, J. Food Sc., Vol. 51, pp 249-250.
20. McCulloch, W. S., Pitts, W., 1943. A logical calculus of ideas immanent in nervous activity, Bulletin of Mathematical Biophysics, Vol. 5, pp.115-133.
21. McLaren, K., 1976. The development of the CIE 1976 (L*a*b*) uniform colour-space and colour-difference formula, Journal of the Society of Dyers and Colourists 92, pp. 338-341.
22. Mahanta, P. K., Hazarika, M., 1985. Chlorophyll and Degradation Products in Orthodox and CTC Black Teas and Their Influence on Shade of Colour and Sensory Quality in Relation to Thearubigins, J. Sci. Food Agric., Vol. 36, pp 1133-1139.
23. Moody, J., Darken, C., 1989. Fast learning in networks of locally-tuned processing units, Neural Computing, Vol. 1, No. 2, pp.281-294.
24. Mielle, P., 1996. Electronic noses: towards the objective instrumental characterization of food aroma, Trends in food science and technology, Vol. 7, NO. 12, pp 432-438.
25. Mark, D. F., 1998. Color Appearance Models, Addison-Wesley, Reading, MA.
26. Natarajan, C. P., Anandaraman, S., Shankaranarayana, K. L., 1975. Tea flavour, Journal of Scientific and Industrial research, Vol. 34, pp 282-293.
27. Pietikainen, M., Ojala, T., Xu, Z., 2000. Rotation invariant texture classification using feature distributions, Pattern Recognition, Vol. 33, pp 43-52.

28. Roberts, E. A. H., 1962. Tea fermentation, Economic Importance of Flavonoid Substance, Pergamon Press, New York, pp 468.
29. Rumelhart, D.E., Hinton, G.E. and Williams, R.J., Learning representations by back-propagating errors, Nature, 323, 1986, pp.533-536.
30. Sanderson, G. W., and Graham, H. N., 1973. On the formation of black tea aroma, Journal of Agric. Food Chemistry, Vol. 21, pp 576-585.
31. Swain, M. J., Ballard, D. H. 1991. Color Indexing, Int. J. Computer Vision, Vol. 7(1), pp 11-32.
32. Schaller, E., Bosset, J., Escher, F., 1998. Electronic noses and their application to food, Lebensmittel-wissenschaft und-technologie, Vol. 31, No. 4, pp 305-316.
33. Sarma, S., 1999. Biosynthesis of Precursors for Liquor and Flavour Characteristics in Black Tea. Global Advances in Tea Science, Aravali Books International (P) Ltd., New Delhi, pp 723-732.
34. Takeo, T., Mahanta, P. K., 1983. Comparison of black tea aromas of orthodox and CTC tea and black teas made from different varieties, J. Sci. Food Agric, Vol. 34, pp 307-310.
35. Takeo, T., Mahanta, P. K., 1987. The aroma patterns shown in different kinds of tea, Int. Tea symposium, Rize, Turkey, 26-28th June.
36. Tianhorng, C., Kuo, C. J., 1993. Texture Analysis and Classification with Tree-Structured Wavelet Transform, IEEE Trans. Image Processing, Vol. 2, No. 4, Oct. pp 429-441.
37. Ullah, M. R., Bajaj, K. L., Chakraborty, S., 1979. Fermentation test by Dr. M R Ullah, Factory Floor Fermentation Test, pp 3-6, Tocklai Experimental Station, Jorhat, India.
38. Wickremasinghe, R. L., 1978. Tea, Advances Food Research, Vol. 24, pp 229, Academic Press, New York.
39. Yamanishi, T., 1981. Tea, coffee and cocoa and other beverages, Flavour research, Marcell Dekker, New York, pp 231-304.

CHAPTER III

IMAGE COLOUR MATCHING OF FERMENTING TEA

3.1 Introduction

The dominant parameters that are considered for decision making about completion of fermentation process are 'colour' and 'aroma' of fermenting tea. This chapter discusses about the method of computer vision that adopted to analyze the colour of fermenting tea. The methods recognize the required colour by the using colour constraints of the captured images during on going fermentation process. The detail about the development of colour in fermenting tea and its significance were explained in Chapter II (section 2.2.3.2). It was mentioned that though the colour formation in fermenting tea during fermentation process is not the only quality determining factors, it is one of the most desired phenomenon. Because, this phenomenon (colour of fermenting tea becomes deep coppery red) is useful for judging the completion of fermentation process in tea industries. Such importance of colour attribute can be observed in some other food processing and allied industries such as sugar, paper etc. also, where colour is one of their important parameters for maintaining product quality. Various colour analysis techniques are adopted in such industries as a quality monitoring tool. Some traditional methods include the optical absorption and optical reflection methods. For example, the International Commission for Uniform Methods of Sugar Analysis (ICUMSA) recommended absorption of light at 460nm and 560nm wavelength for computing colour. ICUMSA method specifies the measurement of light intensities transmitted at 720nm in the violet end of the colour spectrum for colour measurement. This technique uses an optical absorption method (Govindaraj, et. al., 1996a). Another technique is to take measurements in the visible spectrum range (400nm – 700nm) by using optical reflectance method and a PC based spectralyser (Govindaraj, et. al., 1996b). This has been used in the paper industry. Variety of colour scale or schemes have been used to describe colour from which the Commission International de I'Eclariage or CIE developed the most influential system for description of colour spaces that is mostly used in the food industry. The CIE spaces, which include CIE XYZ, CIE L*a*b*, and CIE L*u*v* are device-independent. In some food processing industries, colour is measured either colorimetrically, or spectrophotometrically. For example, a colorimeter is used in a study of potato processing to monitor incoming materials, degree of browning during frying and freezing, shelf-life aging and potato respiration during storage (Giese, 2000).

Colorimeter has been widely used in tea processing industries also to analyze the fermenting tea colour (Ullah, et al., 1979). Two types of test are generally available – the first is based on the polyphenol content of the leaf and the second is based on the measurement of the concentration of TF during fermentation mainly to ascertain the optimum fermentation time by using the maximum concentration of TF. In the first method, the maximum depth of colour is calculated by measuring the intensity of colour, i.e., optical density of the solution (made from 5 gm of representative sample of the fermenting leaf with boiled distilled water) in a colorimeter at 700 nm against a blank (made of phenol reagent mixed with sodium carbonate solution diluted in distilled water). In the second method, maximum depth of colour i.e., optical density of the solution (an ethyl acetate extract of 5 gms of fermenting leaf mixed with boiled distilled water) is measured in a colorimeter at 460 nm against water as a blank. These methods need expertise and skill for efficient evaluation of the fermentation process. Similarly, the human sensory panel also needs the same sort of expertise and skill to evaluate the colour information by organoleptic methods and has many disadvantages (Section 2.3.1).

This chapter presents the careful investigations of the fermenting tea in terms of its colour using computer vision techniques. Various colour feature extraction / analysis methods are investigated and applied to the tea images, which mostly considers the average colour content of the images. There have been many colour matching algorithms developed for image retrieval purposes, where colour of the images is treated as one of the main parameters (Funt, et. al., 1995; Pass, et. al., 1996; Jain, et. al., 1996; Huang, et. al., 1997; Colomboa, et. a., 1999; Michael, et. al., 2000; Cinque, et., al., 2001). Some of these techniques have been found effective in the purpose of image colour matching during tea fermentation. However, the basic categories and hierarchy of rules used by human beings in judging similarity and matching of colour patterns are its overall colour, colour purity and colour complexity etc. (Mojsilovic, et. al., 2000a, b; Jianying, et. al., 2000). Therefore, analogous to the human perception, the algorithms that are developed and implemented in this thesis are based on the fact of overall colour in the images.

3.2 **Imaging of fermenting tea**

In tea industries, the eye approximation of the human sensory panel is reasonably accurate in judging the colour. On the other hand the colorimetric approach doesn't need any special environment to carry out the experiments for colour matching. But, in case of imaging by the CCD, a large numbers of parameters such as viewing distance, viewing direction, lighting condition, etc. come into account in such event (section 2.8). These parameters are being adjusted automatically by the unique skill of human being (human eye) in the event of eye approximation. But in computer vision system, utmost cares are to be taken in imaging techniques to enrich the system performance. For example, the same colour might seem to be different in imaging if the direction of illumination, variation of illumination, distance of image capturing etc. are different (Gevers, et. al., 1999). Though these parameters can be adjusted to some extent by preprocessing of the images but maintaining the same conditions throughout the whole imaging processes is advantageous. In this view, the viewing distance, viewing direction and lighting conditions etc. are adjusted to constant at all the time during image capturing of the fermenting tea during fermentation process. Moreover, the tea fermentation process is not a dry process as a certain amount of humidity needed to carry on the process. So there are some possibility of images get degraded by noise due to the reasons such as moisture content of the tea leaves may stick to the CCD producing splitting of light reflected from the leaves. Taking into account of all the conditions, it can be summarized that some special cares have to be taken during imaging for maintaining a constant framework. This section discusses briefly about the care that has been taken during imaging of fermenting tea and image database formation for colour analysis.

3.2.1 **CCD setup**

Some important aspects of CCD imaging are as follows:

- Distance of CCD from object
- Direction of CCD with respect to the object
- Focusing the CCD view point at the object
- CCD exposure time
- CCD calibration

For the sake of experimentation, images of fermenting tea from ten different batches of fermentation processes are considered. The CCD is mounted on the top above the tea samples in perpendicular direction, where tea samples are spread uniformly over a floor or tray. White background is used. The distance from the CCD to the tea samples is being maintained fixed all the time. The CCD view point is focused in the tea samples all the time. One another important aspect of the CCD is its exposure time for a particular sample. Fixed amount of time is maintained as the CCD exposure time for all tea samples. CCD calibration is being done by the subtracting the background frame from each image frame.

3.2.2 Illumination and imaging environment

Some important aspects of illumination conditions during imaging are:

- Constant illumination intensity
- Same illumination direction
- Constant dry environment

The imaging is carried out with constant illumination. White light is being used for this purpose. The experimental setup is made in such a way that the direction of illumination remains same at all the times. On the other hand, the moisture content in air (humid condition of fermentation process) might introduce noise in the images. Therefore the experiment is carried out in dry environment to avoid such conditions.

3.2.3 Image database of fermenting tea

The fermenting tea can be divided into three categories. They are namely 'under' fermented, 'well' fermented and 'over' fermented. The fermenting tea before completion of fermentation process are termed as the 'under' fermenting tea. They are mostly green in colour. Similarly, tea at the time of completion of fermentation is termed as the 'well' fermented tea. The colour of tea at this stage is coppery red. On the other hand, tea after completion of fermentation are called the 'over' fermented tea. At this stage tea attains more colour (becomes redder) than the 'well' fermented tea. Generally 'over' fermentation stage has been achieved in tea processing if the fermentation process is not stopped at proper time. It reveals that the 'over' fermentation stage is not deserved in tea processing industries to maintain a good quality tea. Similarly the 'under' fermented tea are also not considered for the same reason. But both these processes play crucial role in this particular computer vision experiments. This is because, the 'well' fermented tea colour is distinguished from the other undesired colours (colours of 'under' and 'over' fermented tea) only. Therefore the images of both 'under' and 'over' fermented tea are also captured along with the images of 'well' fermented tea. Then three different image databases of these three categories of tea are generated (refer to Figure A.4, A.5, A.6 in Appendix A) to pursue the colour comparison. But before generating the databases, the images are passed with the various preprocessing steps though they were captured with utmost care. Preprocessing is a prerequisite while colour comparison is the aim of the research. These preprocessing tasks such as removals of noise, deblurring etc. can eliminate any chances of disorder present in the images. Finally, these image databases are considered as standard image database for discussing the colour matching techniques throughout the thesis.

3.3 **Colour comparison among the images**

The extraction of the colour contents (colour feature) out from an image is the first step of such comparison techniques. At the simplest level, the colour contents in the images can be represented by the pixel values in the R, G, and B colour plans if the image is represented bye the RGB colour model. By definition, the colour for a pixel is normally written as follows 'Pixel value = (R_level, G_level, B_level)'. On quantization into RGB colour model, each colour pixel of the quantified image is represented with the following notation (Brunelli, et. al., 2001) (Equation 3.1) and shown in Figure 3.1:

$$I = \{(x, y, v(x, y))\}_{(x,y)\in S, v\in V} \tag{3.1}$$

In this notation, S is the set of possible pixel location of an image plane and V is the set of values associated to the pixel location. These are arranged in all the three image planes and contribute towards the overall colour of the image. Each pixel is assigned with an integer value, which varied from 0 to 255 and all total more than 16 million colours are achieved with different combinations of these values.

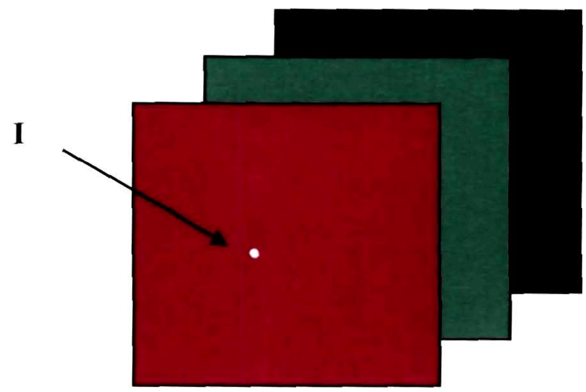
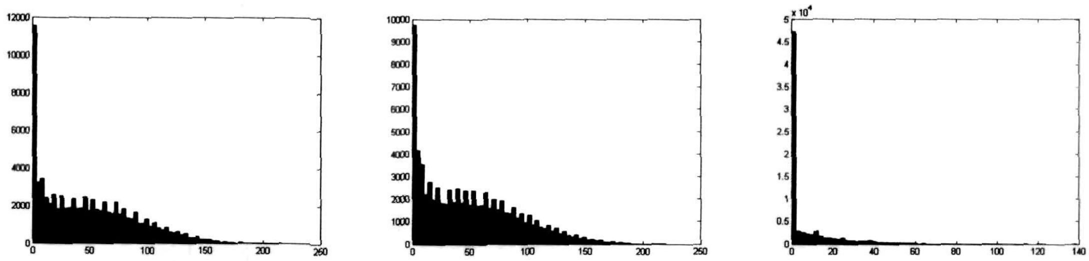


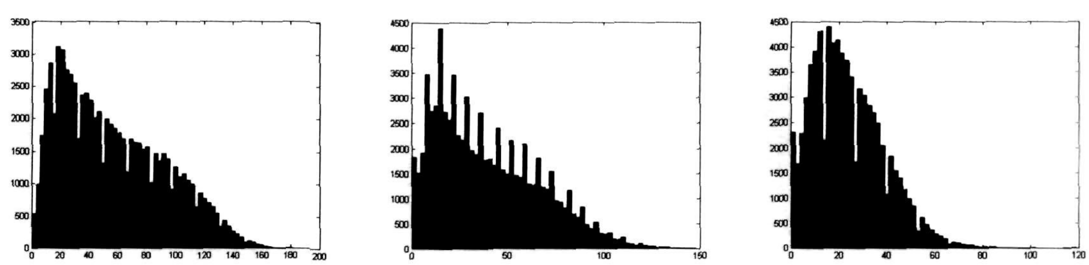
Figure 3.1 Colour pixel of the quantified (R, G, and B) image.

3.3.1 Colour histogram

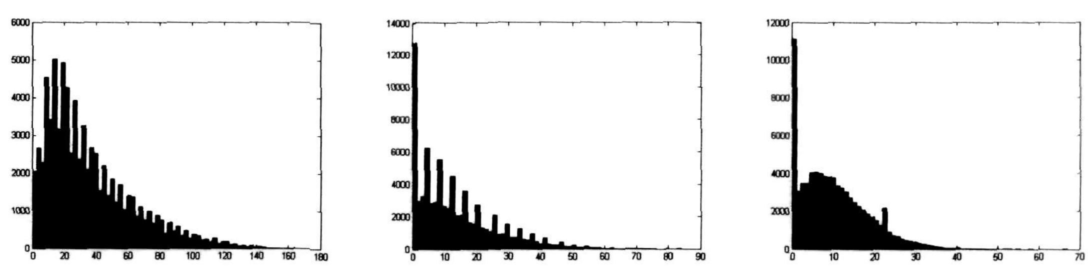
By definition a colour histogram is a vector where each entry stores the number of pixels of a given colour in the image. Computation of histograms has become one of the standard methods to characterize the colour images. A particular colour image produces precisely the same histograms at all the times, although different images may have the identical histograms. Colour histograms are widely used in various methods of image matching as well as retrieval systems because of their high efficiency and robustness. For example, most of the content based image retrieval researches widely use the colour histograms as the colour descriptors (Deng et. al., 2001). This is because the colour histogram records the overall colour composition of the images. However, they contain only the global colour information of the image not the spatial information. While drawing the colour histograms of each colour space (R, G, and B), histogram axes are partitioned uniformly with fixed intervals, called bin. This is an empirical approach to determine the numbers of bins, which is subjective for the problem requirement. The number has to be selected from the values q = {2, 4, 8, 16, 32, 64, 128, and 256}. It is important to choose the small value of 'q' instead of high value to increase computational efficiency of the system. On the other hand, the numbers of bins are kept to be large for increasing recognition accuracy. The statistical study reveals that the numbers of bins was of little influence on the recognition accuracy, when the number of bins ranged from



(a)



(b)



(c)

Figure 3.2 RGB histograms of (a) 'under' fermented tea image; (b) 'well' fermented tea image; and (c) 'over' fermented tea image.

32 to 256 for all the three colour spaces. The number of bins used during histogram formation of tea images was considered to be 64. This is based on trail and error method to maintain both the computational efficiency and recognition accuracy simultaneously. Figure 3.2 (a) (b) and (c) show the colour histograms of 'under', 'well' and 'over' (one from each category) fermented tea images in the three colour spaces.

3.3.2 **Histogram comparison method**

Swain and Ballard (Swain, et. al., 1991) stated, "*Histograms are invariant to translation and rotation about the viewing axis, and change only slowly under change of angle of view, change of the view, change in scale, and occlusion.*" Therefore, it is possible to apply colour histogram to represent "global" similarities of images for image comparison. Therefore, the colour histogram comparison has been adopted for the colour comparison technique in comparing the colour contents in tea images. This technique is reliable for such colour comparison applications, where the prime importance is based on the image colour content only. As the colour histograms drawn in terms of R, G and B colour spaces, histogram comparison has to be carried out for all the three spaces. The histogram based colour comparison approach is described in this section.

As the pixel densities in histogram are spread over in bins, vector distances such as Euclidean and L1 (Manhattan) norms are used to quantify the similarity among the colours in the images. The similarity measure between two images on the basis of histogram intersection is useful for such colour comparison. Swain and Ballard (Swain, et al., 1991) had introduced a histogram intersection method as a measure of histogram similarity. According to this technique, for a given pair of histograms, H(I) and H(Q), of input image I and the standard image Q, each containing 'n' bins, the histogram intersection is defined as follows:

$$S\{H(I),H(Q) = \frac{\sum_{j=1}^{n}\min\{h_j(I),h_j(Q)\}}{N_Q x M_Q} \qquad (3.2)$$

Where $h_j(I)$ is the number of pixels of colour j in image I and N_Q x M_Q is the size of the standard image.

This histogram intersection gives the similarity of two different images in terms of their colour contents, which is effective in colour based recognition systems. For a given distance T (threshold), two histograms are said to be similar if S ≥ T. On the other hand, the intersection measure can be represented by a difference form (Dissimilarity (Rubner, et. al., 1999)) as the Manhattan norm (L1) also, which is represented as:

$$D\{H(I),H(Q) = \sum_{j=1}^{n} \left| \frac{h_j(I)}{N_I x M_I} - \frac{h_j(Q)}{N_Q x M_Q} \right|$$

$$= \frac{1}{(N_I x M_I)} \sum_{j=1}^{n} | h_j(I) - h_j(Q) | \qquad (3.3)$$

Where, N_I x M_I is the image size. Such measurement of dissimilarity is effective in comparing the images in terms of colour contents in the images. For a given distance T, two histograms are said to be similar if D ≤ T and the images can said to be of similar colour. This dissimilarity measurement among the pixel values named as dissimilarity pixel values (DPV), in terms of colour histograms has proven to be efficient on the basis of experiment.

3.3.3 **Histogram comparison experiment**

This section explains about the investigation of the possibility of comparison of images in terms of colour histograms of fermenting tea images with respect to an ideal (optimum colour / coppery red) 'well' fermented tea image. The ideal image is selected on the basis of majority score of human sensory panel's judgments. The colour histograms of the images of the three databases (section 3.2.3) are compared with colour histograms of ideal image using the equation 3.3. The DPVs obtained for twenty eight different images, namely sixteen 'under' fermented, six 'well' fermented and six 'over' fermented tea images are shown furnished in Table 3.1. Figure 3.3 shows the results graphically and it is observed from the figure that the distance value of 'T' may be 0.3 for all the colour spaces for this particular experiment. This value is considered as the threshold level for comparing colours among the other images in the databases in latter experiments. Moreover, a prominent variation of DPV has been observed for the R colour space in most of the experiments in comparison to the poor variation in G and B colour spaces. This reveals the prospect of using the R colour space only for comparing the colour contents in fermenting tea images. Figure 3.4 shows the experimental results obtained for twenty different (five 'under' fermented; ten 'well' fermented; and five 'over' fermented) tea images in terms of histograms. It is observed that while using the value of 'T' as 0.3, sample number 8 and 13 are misclassified.

Table 3.1 Dissimilarity (DPV) measure for R, G, and B colour spaces.

Samples No.	State of fermentation for the sample images	DPV for R Colour Space	DPV for G Colour Space	DPV for B Colour Space
1	NF	0.77	0.56	0.61
2	NF	0.39	0.45	0.41
3	NF	0.38	0.70	0.51
4	NF	0.45	0.41	0.62
5	NF	0.67	0.51	0.48
6	NF	0.54	0.56	0.43
7	NF	0.61	0.62	0.73
8	UF	0.36	0.40	0.39
9	UF	0.42	0.39	0.34
10	UF	0.42	0.46	0.37
11	UF	0.37	0.32	0.55
12	UF	0.35	0.43	0.52
13	UF	0.42	0.53	0.41
14	UF	0.35	0.37	0.36
15	UF	0.41	0.36	0.40
16	UF	0.31	0.35	0.41
17	WF	0.17	0.18	0.24
18	WF	0.22	0.19	0.09
19	WF	0.21	0.21	0.23
20	WF	0.13	0.24	0.25
21	WF	0.13	0.18	0.24
22	WF	0.26	0.15	0.20
23	OF	0.60	0.50	0.54
24	OF	0.38	0.48	0.43
25	OF	0.32	0.44	0.34
26	OF	0.28	0.35	0.42
27	OF	0.59	0.56	0.68
28	OF	0.36	0.39	0.51

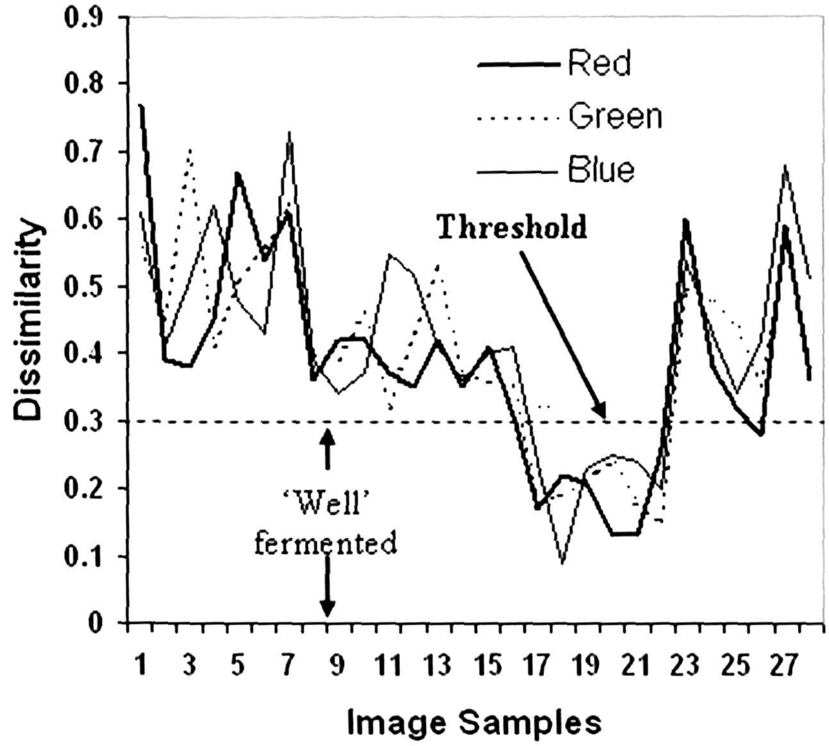


Figure 3.3 DPV measure curves for R, G, and B colour spaces.

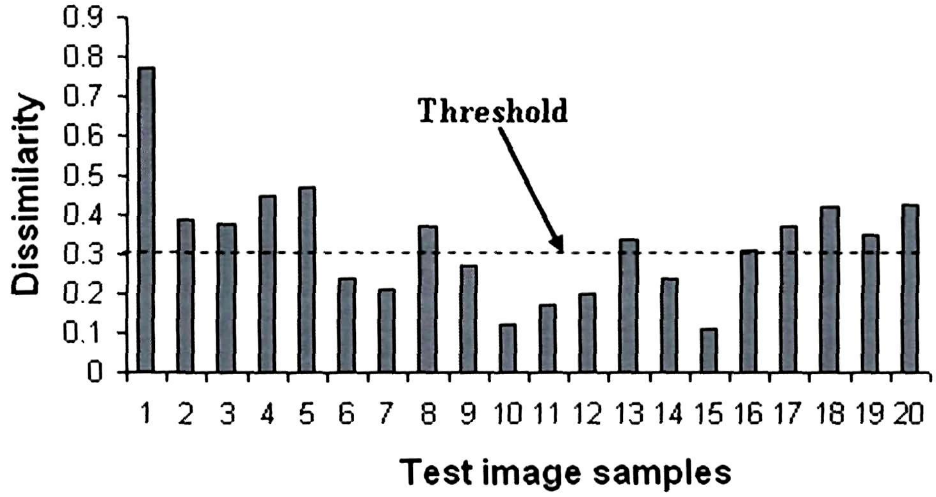
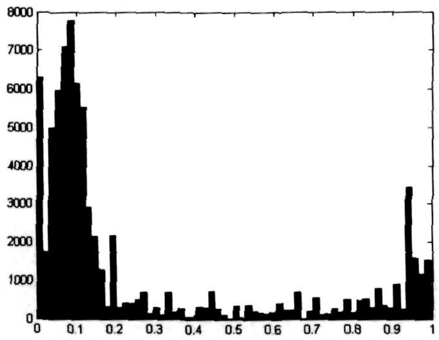


Figure 3.4 Classification of the test images of fermenting tea using T = 0.3.

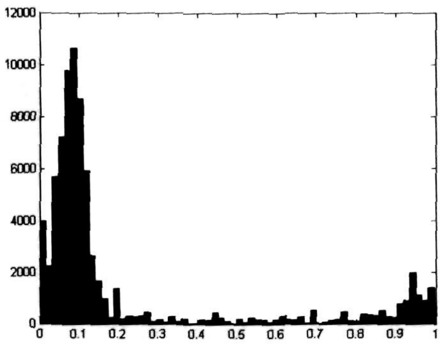
The above investigations, which compare image colour by calculating DPV of colour histograms using RGB colour model, reveals its possibility to apply in such problem of specific colour recognition. But it was observed that the technique has some limitations as some predefined conditions (section 3.2.1 & 3.2.2) are set for the experiments. Among them, the constancy of illumination conditions is not always possible to set into constant predefined conditions. It was discussed in chapter II (section 2.8.1) that the illumination variation can be adjusted by using some other colour models such as HSI, CIEL*a*b etc. These colour models use of colour angular indexing (Gonzalez, et. al., 1992; CIE, 1978) methods instead of direct pixel values to make the colour imaging illuminant invariant. Besides, the computational complexity increases in some cases in using higher numbers of bins in ensuring the recognition accuracy. Therefore, to avoid such disorders, HSI colour model is used to extract colour contents from image in terms of colour features.

3.4 **Colour descriptors of tea images**

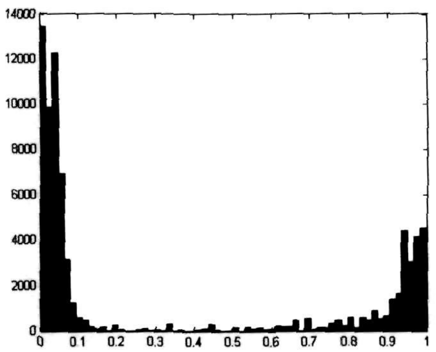
The experimental procedures of the tea image colour features extraction for classification of the images of the three image databases are discussed in this section. The RGB colour spaces are converted to the HSI colour spaces and both the hue (H) and saturation (S) planes have been considered to form the histograms. The intensity (I) component, which is the brightness of each pixel, is not considered in this colour recognition scheme. The three image databases (section 3.2.3) are considered to develop the colour feature extraction technique. The histograms of all the H and S spaces of all the images of the three databases are drawn. Figure 3.5 (a), (b) and (c) shows the H and S histograms plots of three tea images of 'under', 'well' and 'over' fermented tea images respectively using bin size 64. It is observed in the figures that the positions of the histograms mostly in H space are different in all the three images. The majority histograms of the 'under' fermented image are found around 50^0 to 140^0. Similarly the majority histograms are found around the 300^0 to 360^0 and 0^0 to 50^0 in both the side of 0^0 of hue values. On the other hand majority histograms are found almost in the same range in the 'over' fermented tea images also with exception that the number of pixel values near 0^0 or 360^0 are greater in comparison to the 'good' fermented tea images. The same phenomenon is observed in the entire images of different categories.



(a)



(b)



(c)

Figure 3.5 (a) H and S histograms plots of 'under' fermented tea; (b) H and S histograms plots of 'well' fermented tea; (c) H and S histograms plots 'over' fermented tea images.

3.4.1 Threshold DPV (D_{th}) calculation

It is recalled that the DPV of each image for all the three databases were calculated with respect to a standard 'well' fermented tea image in the previous experiment (section 3.3.3). The standard image was selected on the basis of human sensory panel judgment. In this section, one technique is developed, which can select two standard images from the database of 'well' fermented tea images to use them for further calculations of DPVs for other images. The technique is described in this section, which itself based on the same DPV calculation among the images in the database.

The technique development for the standard image selection method includes the calculation of the cross DPV (CDPV) among the images. This CDPV is the calculation of DPV of every image in the database with respect to the rest of the images in the database. For example, if there are five images in the database than for a particular image there will be four possible CDPVs. In that sense the total CDPVs can be calculated for these five images will be ten (${}^{10}C_2 = 10$). Table 3.2 (a) and (b) show the CDPV calculation scheme considering five images in the database.

Table 3.2 (a) and (b) CDPV calculation scheme for a database of five images.

	I_1	I_2	I_3	I_4	I_5
I_1	$CDPV_{11}$	**$CDPV_{12}$**	**$CDPV_{13}$**	**$CDPV_{14}$**	**$CDPV_{15}$**
I_2	$CDPV_{21}$	$CDPV_{22}$	**$CDPV_{23}$**	**$CDPV_{24}$**	**$CDPV_{25}$**
I_3	$CDPV_{31}$	$CDPV_{32}$	$CDPV_{33}$	**$CDPV_{34}$**	**$CDPV_{35}$**
I_4	$CDPV_{41}$	$CDPV_{42}$	$CDPV_{43}$	$CDPV_{44}$	**$CDPV_{45}$**
I_5	$CDPV_{51}$	$CDPV_{52}$	$CDPV_{53}$	$CDPV_{54}$	$CDPV_{55}$

	I_1	I_2	I_3	I_4	I_5
I_1		**$CDPV_{12}$**	**$CDPV_{13}$**	**$CDPV_{14}$**	**$CDPV_{15}$**
I_2			**$CDPV_{23}$**	**$CDPV_{24}$**	**$CDPV_{25}$**
I_3				**$CDPV_{34}$**	**$CDPV_{35}$**
I_4					**$CDPV_{45}$**
I_5					

It is observed that the lower part of the table 3.2 (b) (opposite of the diagonal elements) also calculates the same set of values as the upper part and so ignored. Then the technique tries to find the maximum value among the calculated CDPVs. This maximum value is termed as the threshold CDPV (D_{th}) for the image database, which can be formulated as follows:

$$D_{th} = \max_{I,Q=1\to k}\left\{\frac{1}{(N_I x M_I)}\sum_{j=1}^{n}|h_j(I)-h_j(Q)|\right\} \tag{3.4}$$

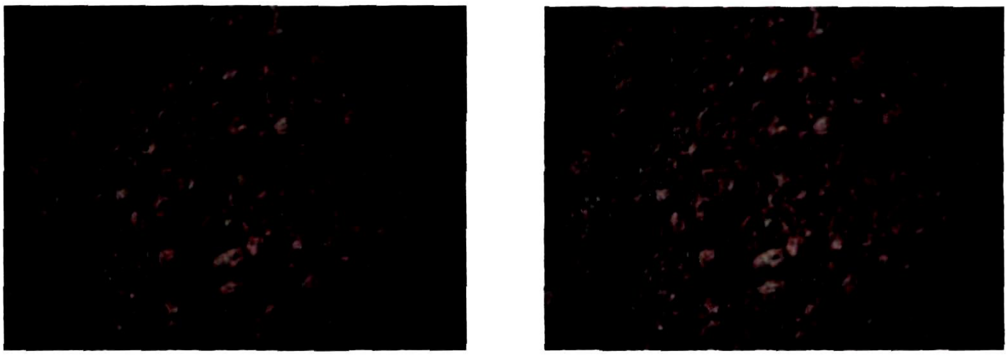
The significance of the D_{th} is that it selects two images (corresponding to the threshold value) out from the database. For example if $CDPV_{24}$ is the D_{th} then the selected images will be I_2 and I_4. The reason behind the selection of the threshold value as the maximum value of CDPVs is that it selects the corresponding images, which are of most dissimilar images in the database. If the images are arranged in some definite order of colour then these images will be placed in the two extreme ends of the database. Therefore these images will be considered as the standard images for the 'well' fermented tea image database for colour comparison to discriminate the other images from other databases. The fact can be explained as; an input test image I_t can be categorized under the particular database (I_2 and I_4 are standard images) provided the following equation (equation 3.5) is satisfied.

$$CDPV\{I_2 : I_t\} and CDPV\{I_4 : I_t\} \leq D_{th} \tag{3.5}$$

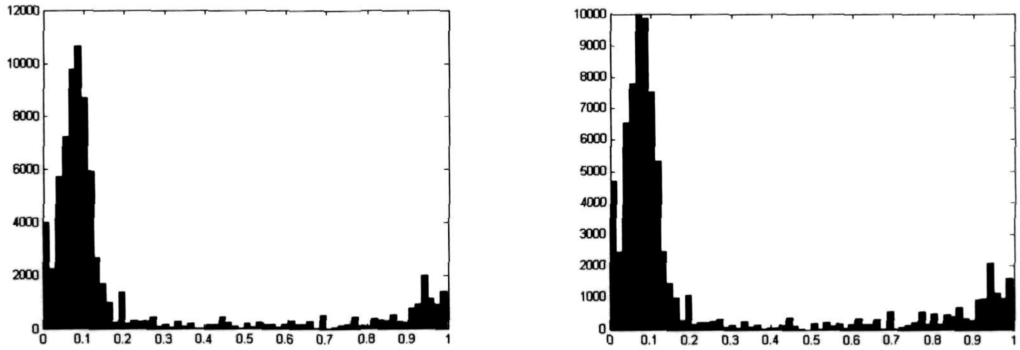
It can be explained from the 'equation 3.5' that both the CDPVs have to be less than the threshold measured if the image is categorized in the 'well' fermented tea image database. Otherwise, if the test image satisfies the other possible conditions (either one or other CDPV is less than D_{th}; both the CDPVs are greater than D_{th}) the image will be categorized out of the database in other categories such as 'under' or 'over' fermented tea image databases. This standard images selection by threshold calculation technique has proven to be effective in discriminating fermenting tea images from one another, which is explained in the next section (section 3.4.2).

3.4.2 *Image discrimination using colour content*

Twenty five 'well' fermented tea images are considered for the threshold calculation and selection of the standard images for discrimination. These images are selected from each of the five batches of tea fermentation in accordance with the decision taken by the human sensory panel. While calculating the CDPVs, these twenty five images produce three hundred (${}^{25}C_2 = 300$) CDPVs. Table 3.3 shows the calculated CDPVs these twenty five standard images. The threshold CDPV (D_{th}) is found in this case is 1.19 corresponding to the images I_{22} and I_{15}. The images and the corresponding hue histograms (numbers of bin as 64) are shown in the Figure 3.6 (a) & (b).



(a)



(b)

Figure 3.6 (a) Standard 'well' fermented tea images and (b) their hue histograms.

Table 3.3 Calculation of CDPVs of twenty five images from 'well' fermented tea image database. D_{th} is found to be **1.19**.

	I_1	I_2	I_3	I_4	I_5	I_6	I_7	I_8	I_9	I_{10}	I_{11}	I_{12}	I_{13}	I_{14}	I_{15}	I_{16}	I_{17}	I_{18}	I_{19}	I_{20}	I_{21}	I_{22}	I_{23}	I_{24}	I_{25}
I_1		.33	.29	.09	.04	.99	.93	.07	1.08	1.04	.99	1.1	.67	1.0	.03	.85	1.03	.89	.19	.67	.12	1.14	.96	.1	.96
I_2			.18	1.11	.12	.58	.62	.34	0.8	.47	.77	.81	.06	.3	.67	.46	.70	.49	.28	.31	.05	1.0	.19	.3	.41
I_3				.52	.11	.57	.47	.18	.79	.58	.79	.79	.43	.56	.6	.67	.52	.70	.05	.54	.03	.89	.40	.5	.51
I_4					.06	.98	.69	.01	.77	.56	.67	.77	.23	.92	.45	.55	.62	.33	.11	.29	.09	.78	.66	.05	.51
I_5						.7	.63	.02	.8	.73	.77	.93	.13	.99	.04	.28	.8	.33	.1	.15	.08	.99	.45	.07	.51
I_6							.19	.9	.22	.30	.41	.33	.87	.32	.9	.52	.21	.37	.72	.87	.65	.27	.21	1.01	.10
I_7								.87	.33	.11	.36	.55	.76	.33	.9	.44	.29	.41	.66	.56	.77	.32	.17	.95	.09
I_8									1.01	.99	1.11	1.17	.44	.78	.41	.66	.99	.76	.06	.51	.05	1.13	.75	.03	.87
I_9										.31	.09	.32	.58	.02	.95	.62	.10	.53	.89	.79	.90	.22	.45	1.15	.32
I_{10}											.22	.18	.55	.11	.92	.41	.11	.76	.87	.89	.84	.32	.42	1.12	.22
I_{11}												.11	.79	.04	.99	.56	.20	.52	.97	1.0	.89	.09	.52	1.16	.53
I_{12}													1.0	.01	1.1	.73	.19	.67	1.01	.73	.95	.02	.60	1.14	.33
I_{13}														.54	.71	.09	.63	.44	.33	.05	.06	.92	.56	.72	.61
I_{14}															1.14	.76	.13	.55	.65	.71	.98	.09	.42	.78	.33
I_{15}																.85	.93	.89	.61	.82	.55	**1.19**	.88	.49	.89
I_{16}																	.42	.11	.39	.08	.41	.53	.33	.87	.34
I_{17}																		.52	.88	.57	.69	.29	.42	1.11	.43
I_{18}																			.47	.11	.55	.63	.31	.9	.32
I_{19}																				.38	.02	1.10	.58	.04	.66
I_{20}																					.16	.89	.17	.77	.55
I_{21}																						1.12	.62	.04	.66
I_{22}																							.22	1.16	.41
I_{23}																								.92	.06
I_{24}																									.95
I_{25}																									

The images from three databases are then used to calculate the DPVs using these two images (I_{15} & I_{22}) as standard 'well' fermented tea images. In this run of experiment the test images are captured from 10 different batches of tea fermentation. In this manner the databases consist of 30 'under' fermented tea images (3 each from 10 batches); 30 'well' fermented tea images (3 each from 10 batches); and 30 'over' fermented tea images (3 each from 10 batches). The decision about the colour similarity has been taken using the threshold value as 1.19 and using the equation 3.5. For these 90 images the total number of DPVs calculated will be 180 for the two standard images. Figure 3.7 shows the plots of these DPVs in terms of line curves. It is observed that the threshold level (1.19) is efficient in discriminating most of the images of 'under' and 'over' fermented tea images from the database of 'well' fermented tea images. Some errors are encountered in this run of experiment, for example the threshold lever had failed to discriminate 11 images from the 'over' fermented database, 2 images from 'well' fermented and another 5 images from 'under' fermented tea image database.

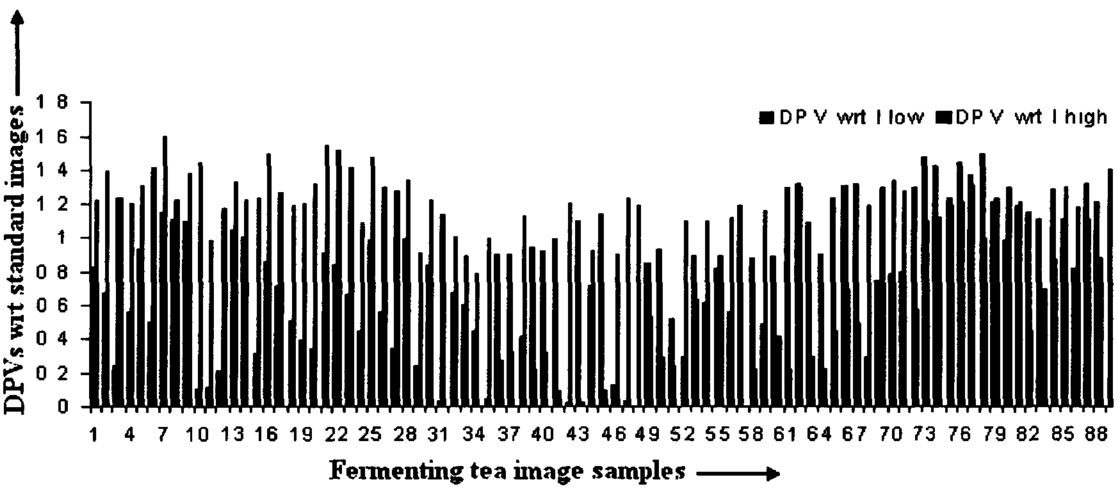


Figure 3.7 The curve of image discrimination in terms of colour contents (Hue)

3.4.3 Colour feature extraction

The colour analysis methods, described above (section 3.4.2), using the HSI colour model has been implemented to extract the colour features from the images. The saturation space is also taken into consideration at this point as it also contributes to the colour information of the images. By definition the 'Hue' of a colour image represents the actual wavelength of colour (pure colour) by representing the colours namely red, green etc. and 'Saturation' is a measure of purity of colour. Therefore these two components of an image represent the overall colour information of the image. Moreover, the HSI colour model is illumination invariant (Intensity, which represents the lightness of the colour image, is not illumination invariant) and so these colour information doesn't vary with various illumination conditions. Therefore the average hue and average saturation values are considered as two principal feature vectors of a tea colour image. On the other hand, the aim of this particular tea image colour analysis scheme is to compare the colours of fermenting tea images with the colours of standard 'well' fermented tea images of the database. Therefore it is advantageous if the information of the standard colours from the standard images is added along with the primary feature vectors. The two standard images (selected by D_{th}; section 3.4.2) of the 'well' fermented tea image database are considered once again as the basis for these extra colour features. It was mentioned that these images are positioned at the two extreme ends (section 3.4.1) of the database, so they can be termed as I_{low} and I_{high} of the database. Then the DPVs are calculated for both hue and saturation spaces of each test image with respect to these two standard images. These values are then used as the colour features along with the primary colour features. Therefore following features are selected for a tea image as the colour descriptors to represent the image in terms of colour content:

- Average Hue
- Hue DPV with I_{low}
- Hue DPV with I_{high}
- Average Saturation
- Saturation DPV with I_{low}
- Saturation DPV with I_{high}

3.4.4 **PCA of colour descriptors**

The principal component analysis (PCA) is selected first for visualization of the selected colour features and analysing them for discriminating properties in them. The length of the feature vector for a particular image is six. The PCA seeks to reduce the vector dimension of the data set and thus considers only the most distinguishing patterns (principal component). The experiment is carried out among 3 different categories of fermenting tea images. The same 90 images (section 3.4.2) are used. Figure 3.8 shows the three dimensional PCA plot in 3 dimensional (3D) spaces.

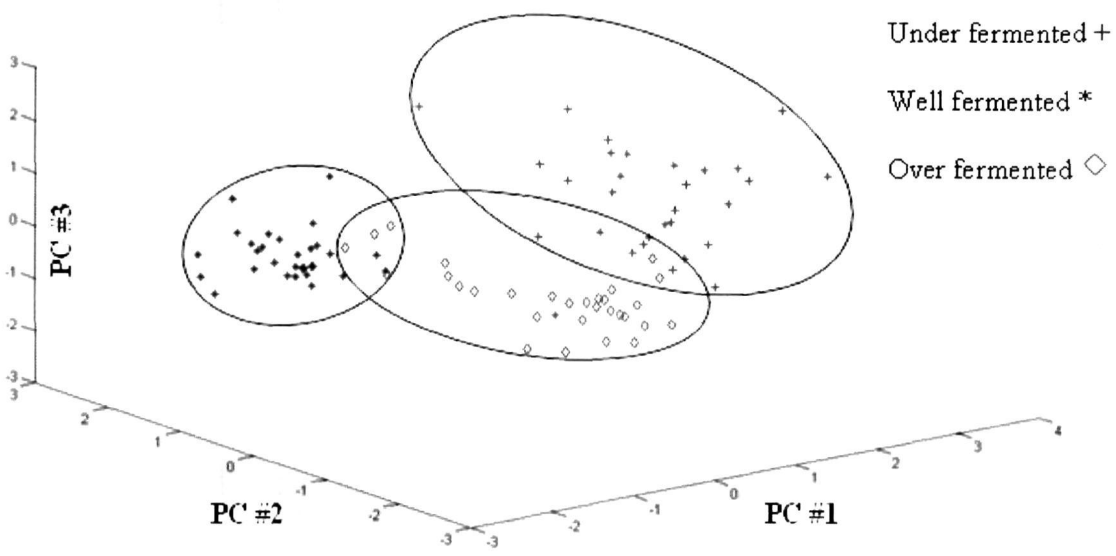


Figure 3.8 PCA plots of the three categories of images using selected feature vectors

The objective of the PCA was to establish the extent to which discrimination for the three different types of tea images using the selected feature vectors. It is clearly observed in the PCA plot that the three categories of images form specific groups in the plot. But some samples are not distinctly separable from some other samples, which mean that the original images are almost similar in colour. But majority of the samples are easily separable using these feature vectors set. These facts explore the possibility of using these selected colour features set as the colour descriptors for the tea images.

3.4.5 K-mean clustering

The features set are being clustered by the K-mean clustering technique (refer to chapter II). The clusters are visualized in Figure 3.9. It shows the K-means clustering of 90 different samples of tea images in terms of a silhouette plot. This plot displays a measure of how close each point in one cluster is to points in the neighboring clusters.

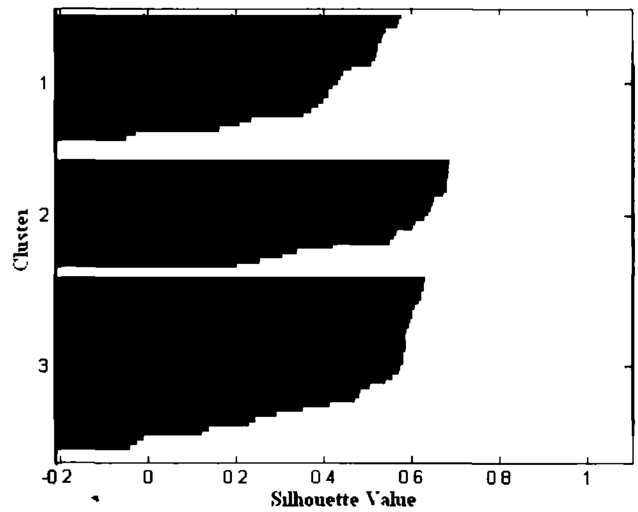


Figure 3.9 Silhouette plot of K-mean clustering showing three different clusters

3.5 Fermenting tea image classification

It is observed in the previous sections that the fermenting tea image data have got discriminating properties in them as then can be categorized in three different groups by the PCA scheme. They can also be successfully clustered by the K-mean data clustering technique. Having this knowledge in mind, the research is carried out to model a system to represent the knowledge directly to it so that it can be useful for further classification process. The ISE system, ANN technique has been implemented for this purpose. The multi layer perceptron (MLP) network is considered to train the all the three databases of images. The extracted features are processed in this method for classification of the images in terms of colour. The ANN are the processing systems analogous to the biological neural networks, presenting neurons, axons, dendrites, neural layers, transfer functions and so on. In biological field, when an image is visualised, the information is collected through eyes and is stored in the brain for processing. In the time of recognition of an object, the human brain put stress on some features, viz., shape of the object, colour of the object etc. In such approach the fact is that the brain always exercise the way of comparing the object with one previously stored (memorized) standard object. This fact is implemented in the ANN based method in any short of application. Therefore, there is one phase of ANN, which is the training phase, where the network has been learnt to a definite shape. As a whole, an ANN based system is an interconnected assembly of simple processing elements, units or nodes, whose functionality is loosely based on the animal neuron (Gurney, 1999). The processing ability of the network is stored in the inter-unit connection strengths, or weights, obtained by a process of adaptation to, or learning from, a set of training patterns. It is described in chapter II (section 2.11.3) that, ANN is an adaptive parallel distributed processor made up of simple processing units, which has a natural propensity for storing experimental knowledge and making it available for use (Haykin, 1999). It resembles the human brains in two ways, viz., knowledge is acquired by the network from its environment through a learning process and inter neuron connection strengths, known as synaptic weights, are used to store the acquired knowledge. Their paradigms fall into three main categories: supervised, reinforced and self-organised (Hudson, et al., 2001). This classification takes into account the amount of data needed for the training phase. Supervised networks use a previous knowledge about the desired outputs, in such a way that the error between the actual input and expected output is a suitable parameter. Self-organizing networks determine by themselves the internal weight representation for the presented input data and don't need supervision. The working principle of the network and their corresponding performances on fermenting tea data are described in this section.

3.5.1 MLP structure

Two different structures of MLP are considered for the image discrimination purpose in terms of colours. The image databases, which are used to train the network, consist of images of three different categories viz., 'well' fermented, 'under' fermented and 'over' fermented tea leaves. These three categories can be though as two discriminating features of the training scheme - 'similar' and 'dissimilar' in colour. The network is standardized to the optimally fermented condition of tea images, which forces the inputs 'under' and 'over' fermented tea images into 'dissimilar' while 'well' fermented tea images into 'similar' colour categories. In this way, the MLP network (The number of layers is set to 2) is tasted so that it transforms the 6 input neurons to 2 output neurons (6::2) using Bayesian Regulation back propagation. The input neurons are calculated from the selected feature vectors (section 3.4.3) as the colour descriptors of the fermenting tea images. The two output neurons are these two categories (similar and dissimilar in colour) of image databases. The network structures are shown in Figure 3.10 (a). The weights are trained with the error feed-forward back propagation algorithm using 6 hidden neurons. The activation function for the neurons in the hidden layers employs the sigmoid function.

The network is designed for 3 output neurons also, which transforms 6 input neurons to 3 output neurons (6::3). The three different categories of outputs are 'under', 'well' and 'over' fermented tea images in this case. Otherwise the rest of the network structure is considered to be same as the first structure so that both the networks can be standardized for the same input image databases. The network structures are shown in Figure 3.10 (b).

3.5.2 MLP implementation

The MLP network is trained with fermenting tea images selected from 10 different batches of tea fermentation. The training of the first network (structure 6::2) is to make the discrimination of two categories of images. Therefore the image databases are categorized into two sets of images so that one set (similar in colour) consist of 'well' fermented tea images and the other (dissimilar in colour) consist of both 'under' and 'over' fermented tea images. The learning method used is of supervised feed forward learning perceptron algorithm, which has been adopted for training. On the other hand the second (structure 6::3) network training is straight forward to the objective of the task. It transforms the input features into the three specified categories of colours. So the information about the colours of images is directly transferred from the databases into the network.

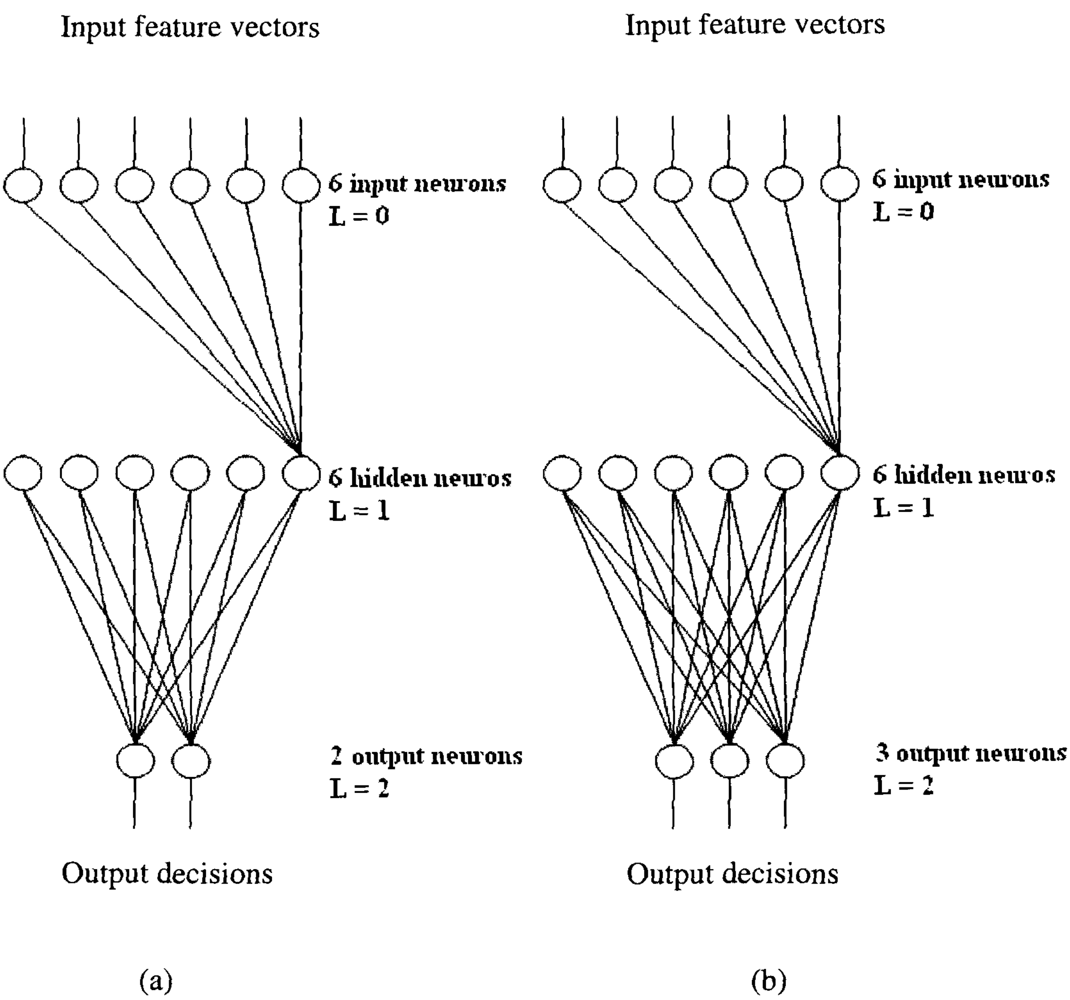


Figure 3.10 MLP network for discriminating three categories of images

Finally, both the networks are trained with 300 different fermenting tea images, out of which 150 'under' fermented; 100 'well' fermented; and other 50 'over' fermented tea images. Another 90 test samples (30 each of all three categories) are considered for simulating the networks. While using the trained network with 90 test samples, the 6::2 network performs 91.11% accurate results. On the other hand the performance of the other network (6::3) is 86.67%, which is lesser than the first.

3.6 **Quality perception of black tea**

In a series of experiment, the computer vision techniques that are developed for colour analysis of fermenting tea are tasted during on going fermentation process in tea industries. It is recalled that the colour analysis methods are developed for detecting the optimum colour achieved by fermenting tea, which finally determine the fermentation time. This section discusses about the efficiency the techniques developed for detecting optimum fermented tea colour in terms of final quality of made-tea. Therefore, these experiments looked for any suitable correlations exist in terms of quality perception of tea for judging the efficiency of the computer techniques. For this purpose, both the dissimilarity measurement (DPV) and ANN techniques have been used for estimating the fermenting tea colours. Some experimental findings about the, which correlates the computer vision decision with the visual and chemical analysis are discussed here. A brief discussion about the quality descriptions made by human sensory panel and the chemical analysis that used in tea industries for quality perception are also given.

3.6.1 **Maximum fermentation time judgment**

Though the human organoleptic decision is a common technique for judgment of optimum fermentation time in tea industries, the colorimeter is also widely used for the same purpose (Chapter II; section 2.3.2). The method continuously reads the depth of colour in the specified solution and takes the decision with the peak achieved. The colorimetric-results (CR) and its correlation with the computer vision results (DPV and d) for a single batch shown in Table 3.4. The development of required colour in the fermented tea of one batch of manufacturing is furnished in the table. In this particular batch of experiment, the colour analysis was conducted using the colorimeter in the tea factory. Usually, the colorimeter tests are carried out in 10 minutes interval of time at the beginning of the fermentation process. But it is being decreased to 5 minutes, when the optimum conditions approaches. Images of the tea samples were captured by CCD camera simultaneously and the analysis of image colour matching was performed. But the Such correlation study of newly developed machine technique (computer vision) with the existing machine technique (colorimeter) gives a clear view between two approaches of colour measurement. Optimum fermentation was achieved at 100 minutes, with a peak CR of 1.2. Lowest hue DPV of 0.99 and 1.19 with the two standard images were obtained for the peak sample (sample no. 8). Similarly, the MLP decision was also achieved for the same sample.

Table 3.4 Optimum fermentation time judgment by colorimeter and computer vision.

Sample	1	2	3	4	5	6	7	8	9	10
Time (min.)	40	50	60	70	80	90	95	100	105	110
CR	0.7	0.8	0.85	0.9	1.1	1.13	1.15	1.2	1.1	0.9
ΔCR	+ve	+ve	+ve	+ve	+ve	+ve	+ve	+ve	-ve	-ve
Remark	Rising	Rising	Rising	Rising	Rising	Rising	Rising	Peak	Falling	Falling
DPV wrt I_{low}	1.95	1.65	0.33	1.51	2.19	1.21	1.41	0.99	0.08	1.20
DPV wrt I_{high}	2.29	1.76	1.07	1.53	1.23	1.83	1.19	1.19	0.87	1.21
MLP	0	0	0	0	0	0	0	1	0	0

In this experiment the decision making techniques are as follows:

Threshold D_{th} = 1.19 for the DPV measurement technique

Colorimeter decision is made by the CR value achieves peak (highest value);

ANN decision is taken by the output 0 or 1.

3.6.2 Correlation of computer vision results with TF-TR analysis

The formation of TF and TR during fermentation process has the major impact towards the quality perception of tea. The development of TF and TR was discussed in chapter II (section 2.2.3.2). These constituents influence the quality in tea liquor to a great extent. It recalled that (chapter II) the tea quality is judged by the human sensory panel in terms of Backey, Body, Bright, Brisk, Burnt, Colour, Cream, Dry, Dull, Full, Pungent, Strength/Strong, Thin, Coppery, Green and Even etc. But in this experiment the organoleptic judgment was carried out on the basis of only strength of liquor, brightness and briskness, which are on the other hand common practical measuring parameters. Out of these main quality descriptors, brightness, briskness and strength are associated with the TF content of tea, while body and colour are associated with TR content. To be more specific with the fermentation process, concentration of TF increases with progress of the fermentation process reaches a peak value and starts degrading if fermentation is prolonged. The concentration of TR, on the other hand, increases with increase in fermentation time and body of the liquor become thick. In the organoleptic test the decisions are spelled in terms of excellent, very good, good, fairly good, fair, only fair and poor. They use the subjective decisions that are made in terms of the strength of liquor, brightness and briskness etc. The cupped liquor and the infused tea are used at this stage for their organoleptic tests. Statistical study reveal that the proportion of the strength and the briskness should be almost same which a sign of good quality tea.

On the other hand, to evaluate the overall quality in tea by chemical method, assessment for the quantity of TF and TR in tea are made in the tea industries, which is called TF:TR analysis. It is a spectrophotometric method, where concentration of the two colour compounds TF and TR are analyzed. It concerns with determination of the percentage of TF content, percentage of TR content, ratio between TF and TR, total colour of the product and the percentage of brightness. The usual variation of TF content is from approximately 0.6% to 1.8% for CTC depending upon quality of tea. Low quantity of TF content makes the liquor dull and is an indication of inferior quality. Similarly the percentage of TR content may vary from 8% to 18% for a good quality tea. This percentage of TR (%TR) value indicates the depth of colour of tea liquor. Higher amount of TR content means very strong and coloured liquor with less briskness as both caffeine and TF contribute towards briskness. This analysis also includes the measurement of total colour, which is the combined contribution of colour from TF and TR present in the tea liquor. Therefore the overall colour (Total colour) of the tea is calculated from the solution of infused tea, where absorbency is measured against distilled water. The brightness of made tea is also measured in this analysis. The brightness is directly proportional to the percentage of TF content present, which is furnished as percentage of brightness (%B). Finally, the TF:TR analysis technique adopts the fact that for good quality tea to be produced the TF:TR ratio should be 1:10 or 1:9 (chapter II; section 2.2.3.2) approximately.

Some experiments were carried out to computer vision results with the TF:TR analysis. These results are supported by the decision of the human sensory panel's organoleptic decision also. Results on twenty batches of tea fermentation by computer vision and their respective TF:TR analysis and organoleptic decision made by human sensory panel are shown in Table 3.5.

Table 3.5 Computer vision results vs. TF:TR analysis

Sample	Time	Computer vision		TF:TR analysis reports					Tea tester's choice
		DPV	MLP	%TF	%TR	TF:TR	Total colour	%B	
1	85	1.02 & 0.20	1	1.42	17.94	1:12.63	7.6	16.28	Good
2	100	0.99 & 0.49	1	1.56	15.67	1:10.04	7.28	19.76	Very good
3	120	1.00 & 0.76	1	1.6	15.53	1:9.7	7.38	20.08	Very good
4	90	0.57 & 1.03	1	0.78	14.76	1.18.92	5.13	13.17	Poor
5	95	0.89 & 0.67	0	1.6	17.52	1:10.95	8.42	16.54	Good
6	115	1.10 & 0.37	1	1.85	17.54	1:9.48	7.95	22.41	Excellent
7	100	0.89 & 0.23	1	1.87	17.27	1:9.24	7.75	24.03	Excellent
8	85	1.27 & 1.29	0	0.71	15.81	1.22.27	5.43	10.6	Poor
9	80	0.56 & 0.49	1	1.57	15.98	1:10.18	7.31	19.88	Very good
10	100	1.08 & 0.49	1	1.32	16.17	1:12.25	7.58	15.96	Good
11	100	2.12 & 1.23	1	0.66	12.99	1:19.68	4.87	12.68	Poor
12	95	1.13 & 0.67	1	1.87	17.34	1:9.27	7.68	23.39	Excellent
13	110	1.04 & 0.76	1	1.33	15.77	1:11.86	6.98	16.12	Fairly good
14	100	1.01 & 1.00	1	1.52	17.11	1:11.26	8.19	16.56	Good
15	95	1.87 & 1.45	1	0.89	17.27	1:19.4	4.98	12.26	Only fair
16	100	2.37 & 1.98	1	0.76	18.31	1:24.09	5.13	10.61	Only fair
17	85	1.04 & 1.15	1	1.39	14.89	1:10.71	7.16	17.87	Very good
18	90	1.08 & 0.95	1	1.58	15.24	1:9.64	7.34	18.27	Very good
19	100	2.01 & 1.93	1	0.98	17.28	1:17.63	3.76	11.20	Poor
20	105	1.01 & 0.98	1	1.95	18.38	1:9.42	8.26	21.67	Very good

3.7 **Summary**

The detection of the specific colour (deep coppery red) in fermenting tea in on going tea fermentation process is one of the most important quality monitoring parameters. This phenomenon along with the aroma produced in fermenting tea play the vital role in judging the completion of fermentation process. The human sensory panel, supported by visual approximation, has traditionally been evaluating the fermenting tea colour and offer important contribution in maintaining tea quality. Colorimeter is also being used for the same purpose, but no machine vision approach has so far been used. This chapter described the research that had been carried out for optimum colour detection in fermenting tea by using computer vision techniques, which in tern determined the optimum fermentation time. The method uses the HSI colour model and H and S spaces for extracting the colour descriptors from the images. Three image databases, namely 'under' fermenting tea images, 'well' fermenting tea images, and 'over' fermenting tea images were generated for carrying out the research. The colour descriptors used a method called DPV measurement for colour feature extraction. It is observed from the PCA that the extracted features had adequate distinguishing properties in them. The SOM technique also efficiently clustered the features into definite cluster points. Finally, the research aimed into an efficient model of feature classification that based on ANN. The MLP network was able to classify the images into three different categories of images with 86.67% accuracy. On the other hand while using the same test sample to classify into two 'similar' and 'dissimilar' colour categories the classification accuracy became 91.11%. Such result revealed efficient performance of the proposed system in detecting the optimum fermenting tea colour from the other categories of colours.

On the other hand, while comparing with the traditional methods, the performance of the proposed system was found satisfactory as good correlation had been obtained between machine vision, chemical analysis (TF:TR) and tasters (human sensory panel) decision (organoleptic) (refer to Table 3.5). But, the performance of the system was judged in a controlled environment for imaging. So, the system needs to be calibrated in the natural environments so as to perform with the same accuracy. For that improvement of feature extraction techniques, and use of other quality parameters for fermentation judgment are the future prospect of research in this area.

References

1. Brunelli, R. and Mich, O., 2001. Histogram analysis for image retrieval, Pattern recognition, Vol. 34, pp 1625-1637
2. Colomboa, C., Bimbo. A, 1999. Color-induced image representation and retrieval, Pattern Recognition, Vol. 32, No. 10, pp 1685-1695.
3. Cinque, L., Ciocca, G., Levialdi, S., Pellicanò A., Schettini. R., 2001. Color-based image retrieval using spatial-chromatic histograms, Image and Vision Computing, Vol. 19, No. 13, pp 979-986.
4. CIE (Commission Internationale de l'Eclairage), 1978. Official recommendation on color spaces, color difference and metric color terms, Supplement No. 2 for CIE-Publication No. 15, Colorimetry (E-1.3.1), 1971
5. Deng, Y., Manjunath, B. S., Kenney, C., Moore, M. S., Shin, H., 2001. An efficient color representation for image retrieval. IEEE Transaction on IP, Vol. 10, No. 1, pp 140- 147.
6. Funt, B. V., Finlayson, G. D., 1995. Color Constant Color Indexing, IEEE Transaction on PAMI, Vol. 17, No. 5, pp 522-529, May.
7. Gonzalez, R. C., Woods, R. E., 1992. Digital Image Processing, Addison Wisley.
8. Govindaraj, R., Sankaranarayanan, P. E., 1996. Estimation of Colour, turbidity and pH values of sugar juice during sugar refining process, Proc. TIMA-96, pp 94-98,.
9. Govindaraj, R., Sankaranarayanan, P. E., 1996. Instrumentation for colour matching in paper and allied process industries - Proceedings of TIMA-96, pp 138-143.
10. Gevers, T., Smeuders, A. W. M., 1999. Color based Object Recognition, Pattern Recognition, Vol. 32, pp 453-464.
11. Gurney, K., 1999. Neural nets by Kevin Gurney, http://www.shef.ac.uk/psychology/gurney/notes/index.html
12. Giese, J., 2000. Colour Measurement in Foods as a Quality Parameter, Food Technology, Vol. 54, No. 2, pp 62-65.
13. Huang, J., Kumar, S. R., Mitra, M., Zhu, W. J., Zabih, R., 1997. Image Indexing using Color Correlograms, Proc. IEEE Conference Computer Vision Pattern, pp 762-768.

14. Haykin, S., 1999. Neural Networks: a comprehensive foundation, second edition, Prentice Hall.

15. Hudson, D. L., Cohen, M. E., 2001. Neural Networks and Artificial Intelligence for Biomedical Engineering, Prentice Hall of India.

16. Jain A, K., Vailaya. A., 1996. Image retrieval using color and shape Pattern Recognition, Vol. 29, No. 8, August 1996, pp 1233-1244

17. Jianying, H., Mojsilovic, A., 2000. Optimal colour composition matching of images, Proc. 15th Int. Conf. Pattern Recognition, Vol. 4, September, pp 47-50.

18. Michael, S. L., Nicu, S., Thomas, S, H., 2000. Improving visual matching, IEEE Conf. computer vision and pattern recognition, South carolina, USA, pp 2058-2065.

19. Mojsilovic, A., Kovacevic, J., Hu, J., Safranek, R. J., Ganapathy, K., 2000. Matching and retrieval based on the vocabulary and grammar of color patterns, IEEE Trans. on Image Processing, Vol. 9, No. 1, pp. 38-54, January.

20. Mojsilovic, A., Hu, J., 2000. A method for color content matching of images, Proc. IEEE International Conference on Multimedia, ICME 2000, New York.

21. Pass, G., Zabih, R., Miller, J., 1996. Comparing images using color coherence Vector. Boston, USA, pp 65-73.

22. Rubner, Y., Puzicha, J., Buhmann, J. M., Tomasi, C., 1999. Empirical Evaluation of Dissimilarity Measures for Color and Texture, IEEE International Conference on Computer Vision, Kerkyra, Greece, pp1165-1173.

23. Swain, M. J., Ballard, D. H. 1991. Color Indexing, Int. J. Computer Vision, Vol. 7, No. 1, pp 11-32.

24. Ullah, M. R., Bajaj, K. L., Chakraborty, S., 1979. Fermentation test by Dr. M R Ullah, Factory Floor Fermentation Test, Tocklai Experimental Station, Jorhat, India, pp 3-6.

CHAPTER IV

IMAGE TEXTURE ANALYSIS IN TEA GRADING

4.1 Introduction

Sorting of tea into different grades in accordance with its appearance, size, and shape is a significant process for its quality evaluation (refer to Chapter II, section 2.5). Efficient grading technique requires high degree of sensing and intelligence for accomplishing the classification of tea into different grades. Human sensory panel, supported by visual approximation have been traditionally monitoring the sorting process in the tea industries. Certain terms are used in describing dry tea leaf and some of the most commonly used terms are as follows:

- **Attractive** or **well-made**: well made, uniform colour and size
- **Even**: comprised of equal size of tea granules
- **Mixed**: presence of different grades in one
- **Bold**: pieces of leaves, which are too big for a grade
- **Stalky**: Undue presence of stalk

However, as analogous to the other food processing industries, tea researchers also seek to modernize their grading monitoring process by applying scientific methods. The reason behind this is to satisfy a market, driven by customer demands, with their products with greater differentiation with enhanced quality. This is not always achievable using by the conventional quality evaluations process, which is based on judgments made by the sensory panel. In this respect, tea industries are interested in the possibilities of on-line monitoring of the sorting / grading process using computer vision, artificial olfaction and artificial tasting methods etc. In view of these circumstances, research is being carried out to determine the most effective means to evaluate appearance and size of the tea granules during grading process using computer vision techniques. Computer vision employs certain advanced techniques for characterizing the complex size, shape, colour, texture, etc, of food products. So for example it is observed that the made-tea images contain some definite patterns (texture) due to different sizes of tea granules and its colour. Such facts that it may be helpful to explore the potentiality of such computer vision based colour and texture analysis methods in this case. The research conducted in this thesis is limited to the consideration of the factors observed in CTC black tea only, not the other varieties such as orthodox, green, oolong tea etc.

The statistical studies reveal the reasons of tea image texture are mainly due to tea granule size, presence of different grades, presence of unexpected sized granule, and presence of stalk etc. For example, the tea term 'even' means the uniform sized tea granules in a particular tea grade, which is desirable in most of the cases. In some cases different grades are intentionally mixed together to make some other variety and it is termed as 'mixed'. But the stalks are unwanted, termed as 'stalky', and these are the result of coarse plucking of tea shoots. Similarly the 'bold' is also unwanted as it is the presence of some big leaf in a particular grade. Such facts demand the careful monitoring of the grading process to ensure the desired quality product. Computer vision based texture analysis is the most prominent aspects in such events and careful investigations are made in this research.

On the other hand, although it is widely pronounced as black tea, but the colour of tea is not black in the true sense, but it is almost blackish brown. A bright colour is always desirable as it represents the good quality tea and on the other hand the unexpected dull colour is the sign of poor quality. The colour and appearance are the consequence of the characteristics of tea shoots and different processing stages. There is a distinct relationship between the amount of TF and TR contents and the colour of tea. The same TF and TR are the key factors of golden yellow and brownness appearance of the liquor respectively. On the other hand, the pheophytin and pheophorbide derived from chlorophylls contribute towards the blackish brown appearance of black teas. This means, all the processing stages, viz., withering, fermentation and drying influence the final tea colour. Such fact reveals the necessity for characterizing the colour attributes of dry tea leaves, which in tern helps in tea quality evaluation. In this regards, the computer vision based technique is proven to be worth full due to its efficiency in colour analysis. The colour analysis methods that discussed in Chapter III are found useful for colour characterization during grading process also.

This chapter presents the careful investigations of the tea images in terms of its uniformity of a particular grade and estimation of its granule size using computer vision techniques, which consider the surface roughness of the images.

4.2 Imaging techniques of tea granules

Imaging of the target object by some specific way is important part in any computer vision based research to enrich the system performance. In tea industries, the visual approximation of the human sensory panel are reasonably accurate in tea granule sizes estimation during sorting of tea into different grades. A large numbers of parameters need to be accounted for in such event. Some important physical parameters include as viewing distance, viewing direction, lighting condition, etc. Besides, some other parameters such as efficient analysing capability, ability in complex decision making such as overlapping of objects etc. are also important for efficient judgment. These parameters are being adjusted automatically by the unique skill of human being during such events. The same parameters are encountered in the event of computer vision based tea granule size estimation problem also. For example, the granule sizes of the same granules may appear to be different in the images if the viewing distance is different, and different granule sizes may appear to be same for the same reason. Moreover, the variation in viewing direction and lighting conditions may make such variations in the images for the same tea granules. Therefore, these parameters are to be adjusted manually to increase the efficiency of the proposed computer vision system. For that, the viewing distance, viewing direction and lighting conditions are made constant at all the time during image capturing. On the other hand, the arrangement of the tea granules in the images is the other important part of the system performance and so, some adjustments are to be made during image capture. Special care is taken during the imaging of tea granules and their impacts in image analysis are discussed in this section.

4.2.1 Arrangement of tea granules in the image

The arrangement of the tea granules during image capturing is discussed here by considering three ideal sized balls. If the balls are spread on the floor or in a tray without any special effort to arrange them, they arrange themselves without having any definite order. There is every possible chance of overlapping of the balls on each other most of the time. Figure 4.1 shows the one possible arrangement of the balls if there are relatively few of them. The balls can be imaged in such arrangements for the computer vision requirements. In this particular case, the sizes of the balls can be estimated by calculating the contour of the balls by considering each individual ball separately. But the problem is in the overlapping of the balls in some cases. Such overlapping phenomenon is also shown in the figure (Figure 4.1). Overlapping makes it very probable the wrong interpretations about the actual sizes of the balls will occur. Because the computer vision system calculates the effective contour of the overlapped balls, which is different from the actual contour. Moreover, it is quiet unpredictable about the extent of the overlapping of the balls or how many balls overlap in a particular position. The entire phenomenon makes the system complicated for estimating the sizes of the balls using computer vision.

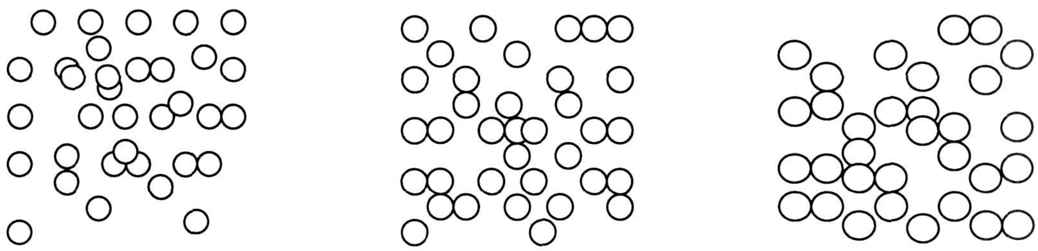
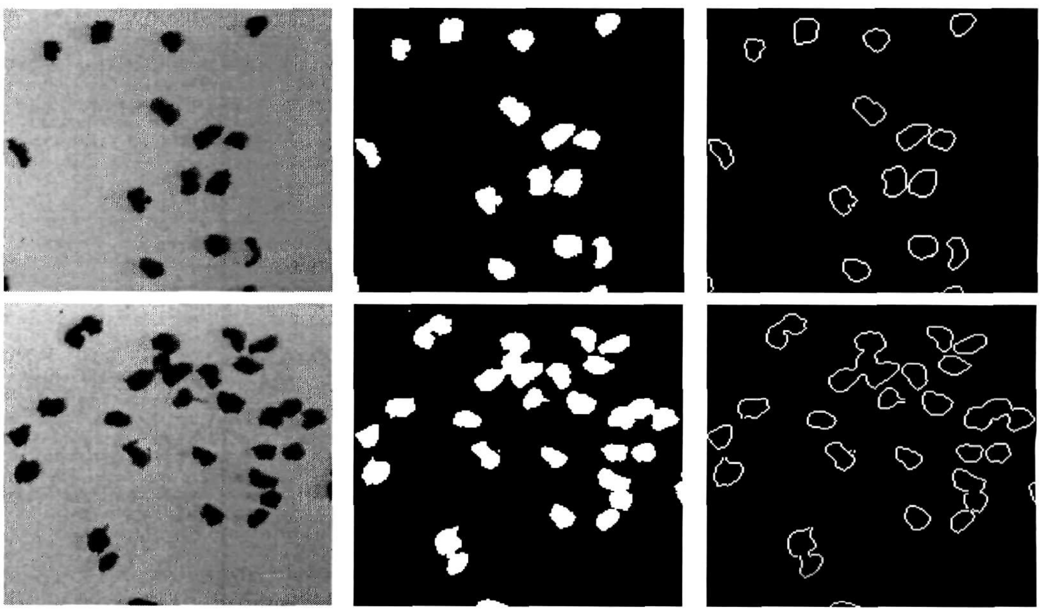


Figure 4.1 Possible arrangements of balls in image



a b c

Figure 4.2 (a) Tea granules; (b) Segmented images; (c) Contours of granules.

Figure 4.2 shows such phenomenon of variations in the case of tea granule images, while tea granules are spread in the specified manner for imaging. It is observed in the figures that the contour lengths are different though the images are of the same sized tea granules. One more disadvantage of this method of imaging (Very less number of tea granules) is the non-uniformity of the tea granules size.

4.2.2 Image surface roughness due to tea granules

Another method of imaging for the tea granule size estimation is of considering large numbers of tea granules and estimating the surface roughness. The method is discussed here by considering the same three types of balls. Figure 4.3 shows the three different possible ideal positions of the balls if they are arranged on a tray or floor. The figure shows in arranging the balls in these manners produce some regular and near-regular texture on its surface. Therefore it is understandable that it is possible to discriminate the images by estimating the texture variations using the concept of surface roughness of the images. This can be done by using the standard texture analysis tools. But the situation is different in case of the natural events.

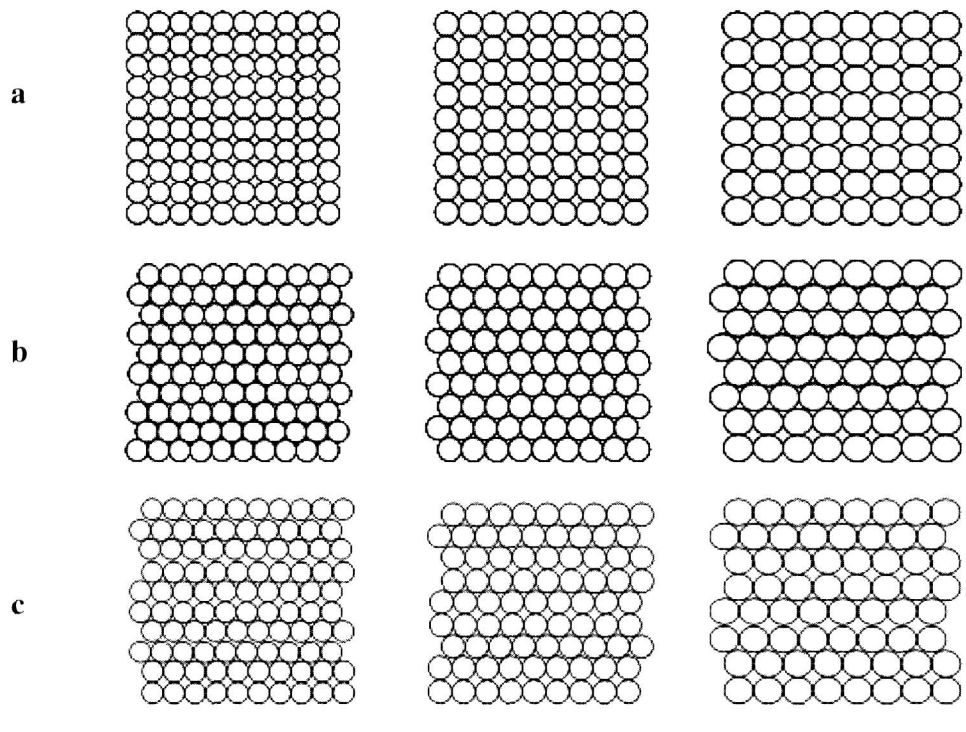


Figure 4.3 (a) & (b) Regular texture; (c) Near regular texture

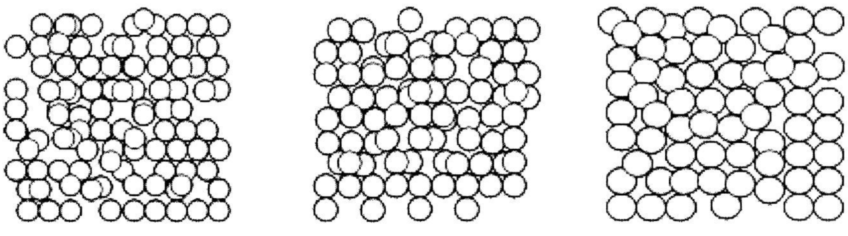


Figure 4.4 Natural stochastic textures

The Figure 4.4 shows some possibilities of arrangements of the balls if they are spread on the tray or floor in reality. It is observed in the Figure 4.4 that the balls are arranged without having any regular or near regular texture. Such phenomena are observed during the tea granule imaging. Figure 4.5 shows images of eight different varieties of tea grades of different sized tea granules. Images of this kind are used for the granule size estimation in this research. The advantage of using such images is to compensate for any variation of the sizes of the tea granules and it minimizes the chances of miss interpretation about sizes. Moreover, such an imaging method is in accordance with the sensory panel's perception of visual approximation for judgment of size of the tea granules.

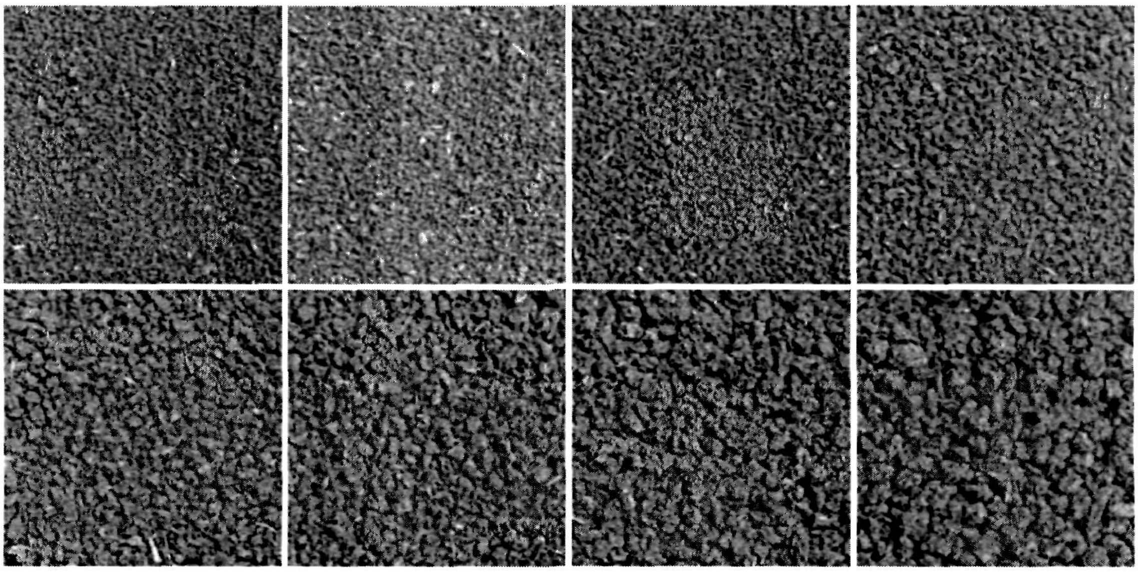


Figure 4.5 Images if eight different tea grades with different granule sizes

The near uniform arrangements of the tea granules play an important role in estimating the surface roughness by texture analysis Therefore, it is important to take the utmost care so that the surfaces of the tea granules become uniform to its maximum extent

4 3 Image texture

The texture is one of the fundamental characteristics of image data and often plays the important role for target discrimination, manual photo interpretation etc It is encountered almost everywhere in natural and real world images Texture, therefore, has long been an important research topic in computer vision and image processing By definition, the texture is one of the visual characteristics of an image that identifies a segment as belonging to a certain class In other words, it is a measure of the variation of the intensity of a surface, quantifying properties such as smoothness, coarseness and regularity It is often regarded as a region descriptor in image analysis and computer vision Some authors give some basic idea of texture on the basis of which the texture discrimination models can be designed According to M Haindl, texture is generally a visual property of a surface, representing the spatial information contained in object surfaces (Haindl, 1991) Bennis and Gagalowicz suggested that texture may represent information that permits the human eye to differentiate between image regions (Bennis, et al , 1989) Another definition was made by Francos and Meiri, which stated that texture is a structure made of a large ensemble of elements that resemble each other with some kind of order in their locations so that there is no single element that attracts the viewer's eye in any special way (Francos, et al , 1988) There are many other definitions of textures defined for different applications and no unified universally acceptable texture discrimination model is available In fact, a complete definition of texture has been elusive as there is no existing encompassing mathematical model of it. However from a human perspective anybody may conjecture that texture is a quality in an image that distinguishes regularity in the visual appearance of local detail in an image (Cross, et al , 1983) According to human perception theory, many parts of an image are recognized by texture rather than by shape, for example grass, hair, water, fur etc The properties, which play important roles in describing texture in human perception, are uniformity, density, coarseness, roughness, regularity, linearity, directionality, direction, frequency, and phase

(Tamura, et al., 1978) etc. Psychophysical research has produced evidence that the human brain does a spatial frequency analysis of the image (Georgeson, 1979). However these properties are very dependent on each other in terms of computer vision research. Figure 4.6 (a), (b) and (c) show some natural, regular and near-regular textual images respectively.

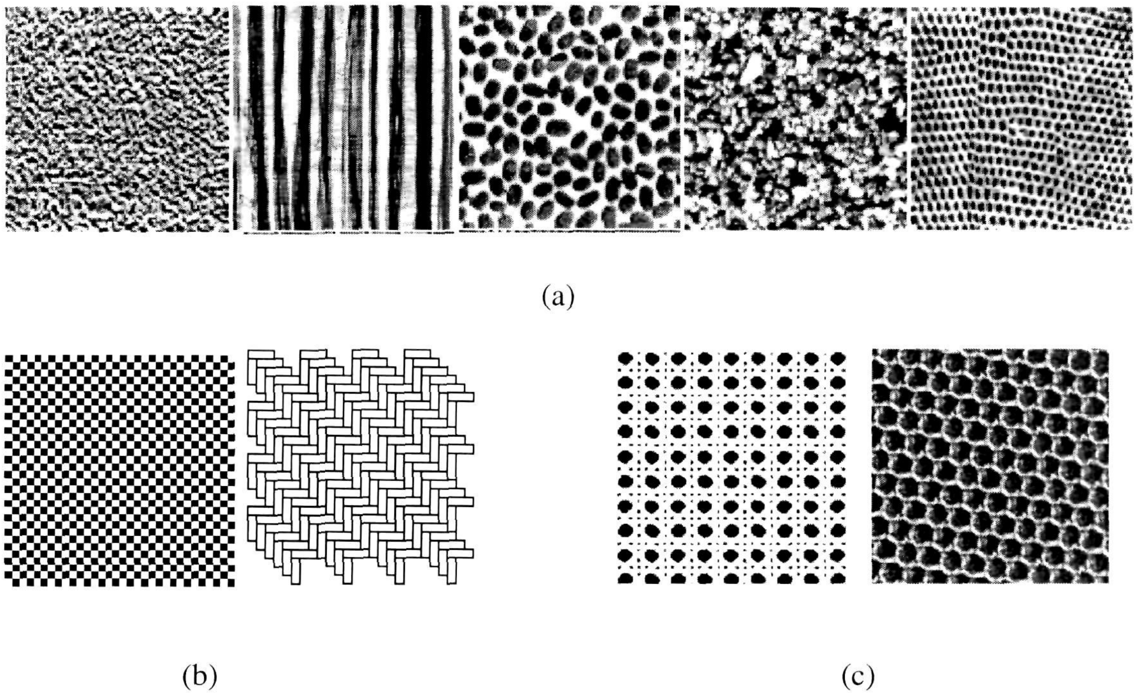


Figure 4.6 (a) Natural textured images, (b) Regular textured images, (c) Near regular textured image

4.3.1 **Application of texture analysis: a brief review**

Texture analysis has found wide application in areas such as remote sensing, medical diagnosis, quality control, food inspection and so forth (Chen, et al., 1994). Successful applications of texture analysis methods have been widely found in industrial, medical and remote sensing areas. In fact, the phenomenal capability of humans to discriminate textures indicates that a large improvement is possible if texture is incorporated into the classification process. It is one of the key parameters in many machine vision tasks and belongs to the important generic research areas. The analysis of texture is a useful aspect in many applications of computer image analysis. For example, texture analysis techniques had been used to evaluate roentgenograms in order to classify normal and abnormal interstitial pulmonary patterns, such as classification, detection, or segmentation of images based on local spatial variations of intensity or colour (Pietikainen, et. al., 2000). These include surface inspection, scene classification, surface orientation, shape determination (Chang, et. al., 1993). In addition, texture analysis techniques had also been applied in the remote sensing area for the identification of crop types by using radar imagery. It has been found useful in analysing the medical images for clinical benefits (Müller, H., 2004). The texture analysis is considered to play a critical role in automatic grading process in some food industries, where the size of the object is the discriminating parameter (Wu, et. al., 1995). Some other important applications include industrial surface inspection; for example for defects, ground classification and segmentation of satellite or aerial imagery, segmentation of textured regions in document analysis, and content-based access to image databases. Finally, the grading of raw food products, in accordance with its quality, size, shape, and cell structure, using the image texture analysis methods are reported useful in terms of efficiency, accuracy, non-laborious etc. (Sinfort, et. al., 1992; Kalab, et. al., 1995; Thomas, et. al., 1996; Quevedo, et. al., 2002). On the other hand, the foreign object detection in some food items is also an important texture analysis application (Patel, et al., 1994). Furthermore, the recent emerging of multimedia and the availability of large image and video archives has made content-based information retrieval become a very popular research topic. The texture is deemed as one of the most important features when performing such content-based information retrieval (Rui, et. al., 1999; Heidemann, G., 2004). As texture is an essential feature when performing image retrieval, food grading, medical imaging, remote sensing and so forth, the study of texture analysis becomes critical and important in its technical point of view in the present decade.

4.3.2 **Image texture analysis methods: a brief introduction**

Computer vision researches have been devoted to solve the texture analysis problems, such as texture segmentation, texture classification and texture primitive detection etc. There are wide varieties of texture analysis methods that have been developed over many years (Reed, et. al., 1993; Tuceryan, et. al., 1998). In general, the subject, texture analysis, lies under the broad field of pattern recognition and it employs four definite stages, viz., image acquisition, image preprocessing, feature extraction and finally classification. Among these four stages, the third stage is to compute a characteristic detail of a digital image that able to numerically describe its textual properties. This is the most significant stage, since it has the major impact on the overall performance of the texture analysis technique. In fact, the various approaches of texture analysis differ from each other mainly in terms of these methods for extracting textual features from the images. It is found that the approaches of texture analysis are very diverse and in this respect, four categories can be defined (Tuceryan, et. al., 1998), which are as follows:

(1) Statistical methods
(2) Geometrical methods
(3) Model based methods
(4) Signal processing methods.

Statistical methods: The use of statistical features is one of the early methods proposed in the machine vision. A large number of features have been proposed in the various literatures under this heading. The texture is defined for this category as a spatial distribution of gray values. Two main methods fall into this category are the use of co-occurrence matrices and autocorrelation features. Of these the gray level co-occurrence matrix (GLCM) was being widely used in many applications (Gibson, 1950; Haralick, 1979). It estimates the second order joint probability and texture is described in terms of descriptors such as contrast, entropy, energy, correlation etc. On the hand, the autocorrelation function of an image can be defined for an image as an assessment of the amount of regularity as well as the fineness / coarseness of the texture in the image. This function is related to the size of the texture primitive (Rosenfeld, et. al., 1970; Davis, et. al., 1981), i.e., the fineness of the texture. If the texture is coarse, then the function drops off slowly; otherwise, it drops very rapidly. In the case of regular texture the autocorrelation function exhibits peaks and valleys.

Geometrical methods: Geometrical methods characterize the texture in image as being composed of 'texture element' or primitives (texels). The method of analysis usually depends on the geometric properties of these primitives. Once the primitives are identified in the image, this method follows two major approaches to analyze the texture. One computes the statistical properties of the texture and the other tries to analyze the texture geometrically. Two main methods can be mentioned under this category of texture analysis, namely the Voronoi tessellation features (Tuceryan, et. al., 1990) and structural methods (Vorhees, et. al., 1987; Blostein, et. al., 1989). Laplacian-of-Gaussian (LoG or $\nabla^2 G$) filtering is extensively used in both the methods for extracting tokens from the texture images.

Model based methods: In the model based methods, an image model is considered that describes and synthesizes the texture. It constructs a parametric generative model, which could have created the observed intensity distribution in the textured image. The intensity function is considered to be a combination of a function representing the known structural information on the image surface and an additive random noise sequence. Markov random fields (MRFs) have been popular for modeling the textured images under this category (Cross, et. al., 1983; Chellappa, et al., 1985; Cohen, et. al., 1987). Another method, the fractal calculation is also popular in modeling the texture in images (Mandelbrot, 1983).

Signal processing methods: Finally, the signal processing methods convert the image into the frequency domain using the spatial frequency properties of the intensity variations in the image surface. It is well known that, in a gray scale image, time domain is the spatial locations of the gray values; and the frequency domain is their spatial intensity variation. This method further looks for a basis function for texture classification, which can effectively represent the intensity variations in each local spatial region of the images of different texture details. Certain filters are designed for the transformation of the images and the success of the technique lies in the type of transform, which is used to extract the textural characteristic of the images. Of all of them, the spatial domain filters are the most direct way to capture the images textual properties. This method tries to find the texture edge density per unit area. The edges are usually computed by simple edge masks such as the Laplacian operator (Voorhees, et. al., 1987). One other popular technique for doing this is the frequency analysis in Fourier domain (Montes, et. al., 1988). It adopts the concept of global frequency content in the image. But experimental evidence based on human vision agrees with the fact that simultaneous analysis of both spatial and frequency domains (multi-scale) information improves the localization of texture information more precisely. This finding has motivated the researchers to look for some other techniques for analysing the frequency contents in the localized spatial domain. The Gabor filter and Wavelet based extraction of texture features are the outcome of such studies. The Gabor filters have been widely used in texture analysis for image segmentation (Bovik, et. al., 1990; Wang, et. al., 2000). Similarly, the Wavelet transform (WT) methods of feature extraction have been used to characterize texture in images and that has proven to be useful for segmentation and classification (Laine, et. al., 1993; Unser, 1995; Wang, et. al., 1997; Van de Wouwer, et. al., 1999; Kociolek, et. al., 2001; Arivazhagan, et. al., 2002).

4.4 **Tea images and texture analysis**

It was described earlier (Section 4.2.2; Figure 4.5) that, while imaging different tea granules in the specified manner, the image are consisted of natural stochastic textures. As evidence of statistical study carried out among the tea industries, tea sorting / grading process is almost a confusing and misunderstood phenomenon as the tea granules are not uniform in their size. Moreover, the different grades of tea are not standardized worldwide and may vary according to their origin. Besides, it was mentioned earlier (section 2.5) that tea grade does not necessarily indicate flavour or quality but are sorted according to granule size. Therefore, it is worthwhile to standardize the tea sorting process, which indeed shows a very alternative area for research in which to conduct further work. Therefore, discriminating the tea grades in terms of granules sizes is considered to be the preliminary stage of such research. In this context, images of sorted tea of different grades are captured in order to analyze them according to texture variation using computer vision techniques. This section discusses about some of the experimental aspects of developing the texture analysis method for the purpose.

4.4.1 **Image database**

In order to develop a computer vision based tea granule size estimation technique, eight image databases of eight different sized tea granules are considered in this experiment. The samples are eight different grades of tea are collected from the tea processing industries during the sorting process. Images were captured using the specified arrangement of the camera as discussed earlier (section 4.2) to minimize the computational complexity in the technique. It is observed in the images that some of the grades are of almost the same size tea granules but some of them are very distinctive in their sizes (refer to Figure 4.5). Appendix A shows some forty images five each from each category of tea grades for reference.

4.4.2 **Selecting the method for tea image texture analysis**

To select a suitable method of texture discrimination among the images the human perspective of differentiating between the tea granule sizes can be conjugated. The local details of intensity variation in the images are considered in differentiating the texture in such case. The first three texture analysis methods, described in section 4.3.2, are found suitable for the regular and near regular texture analysis. For example, geometrical techniques characterize texture as being composed of 'texels', which are regularly arranged on a surface according to some rules. These rules are formally defined by grammars of various types. But such regularity is not available in the natural texture such as in the case of tea image textures.

In comparison to the above methods, the signal processing methods are comparatively well suited to stochastic textures. Among them, Fourier transform based texture analysis considers only the global frequency content in the images. This spectral technique is based on properties of the Fourier Spectrum and it describes only the global periodicity of the gray levels of the image surface by identifying high-energy peaks in the spectrum. It doesn't infer any spatial information about the image surface. But it is important to obtain the information about the structure of the frequency content along with the spatial information in the image for texture classification. One way to obtain both spatial information and frequency localization by Fourier transform is to use the Windowed *Fourier Transform (WFT) or Short-term Fourier Transform (STFT). As the name* suggests, the image signal is multiplied by a window function in this technique. The function of the window is to cut the signal into some non-overlapping slices of specific length to generate the spatial information out of the image. While the window function is Gaussian the transform becomes Gabor transform. But the disadvantage of this technique is that it is not very flexible as the window size is fixed (fixed length). Once the window size is chosen for the WFT, the space-frequency resolution is fixed over the entire space-frequency plane. Therefore the spatial resolution at small scale and scale resolution at large scales are limited. Moreover, such technique is computationally complex for applications such as the natural texture application as discussed here.

Whilst the Fourier transform based texture analysis method performs only a frequency decomposition of an image; and the WFT based method estimates both frequency and spatial information using the window function; the wavelet transform based technique performs the space-frequency decomposition with low computational complexity. This technique maintains a flexible window width while frequency changes in the neighborhood locations. The wavelet transform based texture analysis method has proven to be an efficient method for texture analysis due to its property of both space and frequency localization (Mallat, 1989) in this specified manner. The technique deals with the analysis of image data on different resolution. Subsequently, a wavelet-based method, which is often called wavelet texture analysis (WTA), is considered to be the state of the art texture analysis technique. It shows better performance than other methods in many cases when applied to natural texture classifications (refer to section 4.3.2) in various different types of applications. This technique is considered for the purpose of the tea image texture classification in this research. The classification process is being carried out in two folds:

- Firstly wavelet transform based sub-band images are derived.
- Secondly, the statistical features such as energy, entropy and variance are extracted out of all sub-band images for classification.

Then ANN based methods applied for classifying the textures. The performance of various combinations of features is tested. The analysis and classification performance achieved from wavelet transform based techniques are discussed in the later sections.

4.5 WTA based texture analysis

For a gray scale texture image the time domain is the spatial location of a gray value and the frequency domain is the intensity variation around the pixels (spatial intensity variation). Therefore in order to analyze the texture variation in the images, an appropriate basis function is needed that can effectively represent the intensity variation in each local spatial region of the image. The wavelets are considered as the basis function in this case as discussed below.

Wavelets, originally developed in mathematics, are functions that decompose a given signal into different frequency components and analyze each component with a resolution matching its scale. WT decomposes a given function 'f' into its components on difference scales or frequency bands. By definition, convoluting 'f' with the translated and dilated wavelet 'ψ' does this operation.

$$L_{\Psi} f(a,b) = \frac{1}{\sqrt{a}} \int f(t) \Psi\left(\frac{t-b}{a}\right) dt \tag{4.1}$$

The parameter 'b' allows in investigating different parts of the signal 'f' separately. The dilation parameter 'a' determines the width of the window function ψ(-b/a), for small 'a' the wavelet transform zooms into the small details of the signal 'f'. The size of a detail is related to a specific range of frequencies, i.e., by varying 'a' the function 'f' is examined in different frequency bands. For this reason 'a' is sometimes called the frequency or scale parameter. The value of 'a' increases from a minimal value to the maximum (to minimize the window size) as per resolution selected. For images, the discrete wavelet transform (DWT) is used. The DWT is carried out on a multi-scale level, which produces different sub-band images of different resolutions.

4.5.1 WT based sub-band image

The fundamental tools, used for DWT based processing of an image, are the conjugate of a filter bank and the concept of a wavelet frame. Two channel filters, namely a low pass filter 'L' and its conjugate quadrature high pass 'H' form a pair of prototype filters for generating the filter bank. The filter bank is obtained for the images recursively, indexed by the different scale factor and combination. Consequently, four sub-band images are formed, which are assigned for the filters LL, LH, HL and HH. These filters are described as follows:

- LL: Both horizontal and vertical directions have low-frequencies
- LH: The horizontal direction has low-frequencies and the vertical direction has high-frequencies
- HL: The horizontal direction has high-frequencies and the vertical direction has low-frequencies
- HH: Both horizontal and vertical directions have high-frequencies

The filter bank decomposes the image into orthogonal components and specifies the localization of the region boundaries in the image. Moreover, these filters generate the different order filters by up-sampling or down-sampling with a factor of 2, so that the whole ranges of bands are covered. Of these, the sub-band assigned with 'LL' filter bank is used to decompose the image in the next higher order scale. Figure 4.7 shows the wavelet decomposition for a digital image. It represents the scheme of how the filter bank decomposes an image a_j to produce its sub-bands images a^{LL}_{j+1}, d^{LH}_{j+1}, d^{HL}_{j+1}, and d^{HH}_{j+1} in its next scale. Then, the basic idea of the wavelet transform based image analysis is to represent an arbitrary function as a superposition of wavelets. Such superposition decomposes the image into different scale levels, where each level is further decomposed with a resolution adapted to that level.

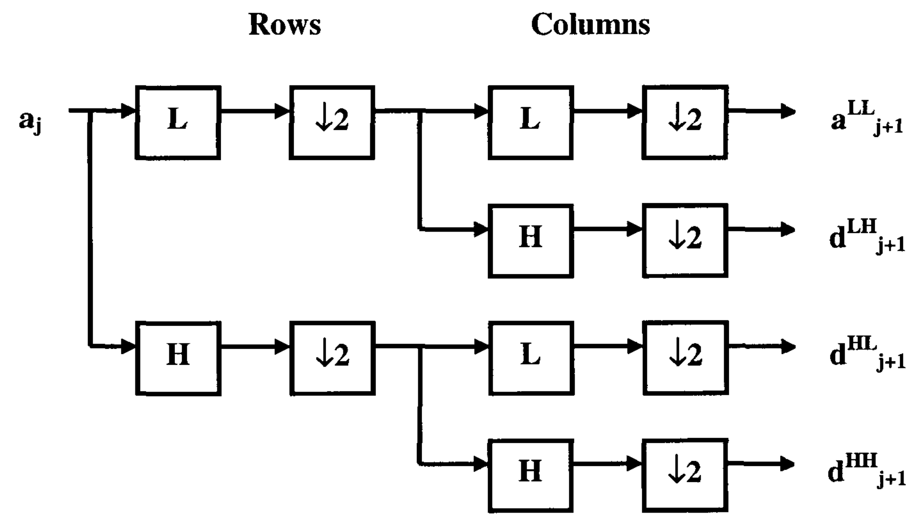


Figure 4.7 Wavelet decomposition for a digital image.

By applying DWT, for one state of wavelet transform, the transformed images will be a combination of one lower frequency sub-band image and three higher frequency sub-band images. At first, the DWT is performed for all image rows and then for all columns. It generates a pyramidal structure of image decomposition. Figure 4.8 shows a four level pyramidal or tree structured decomposition of an image into its sub-band images in different resolutions. At the first level the image is decomposed into four different sub-bands, viz., $d^{LL}1$, $d^{LH}1$, $d^{HH}1$, and $d^{HL}1$. In texture classification paradigm, particularly in the case of natural texture analysis, it is worthwhile to consider all the sub-bands for feature vector calculations. But while calculating the energy value of the sub-bands like d^{LH} and d^{HL} always show significantly smaller values, so only the d^{HH} is considered for the feature calculations. On the other hand, the a^{LL} has always been used for further decomposition into sub-images in the next level. But other sub-bands may also be used for further decomposition if it has a significantly higher energy value. In this manner $a^{LL}2$, $d^{LH}2$, $d^{HH}2$, and $d^{HL}2$ have become the second level sub-band images of the original image. The third and fourth level sub-band images are also calculated in the same manner. These sub-bands, namely $d^{HH}1$, $d^{HH}2$, $d^{HH}3$, and $d^{HH}4$, are stored for second fold of the texture classification (section 4.4.2) techniques.

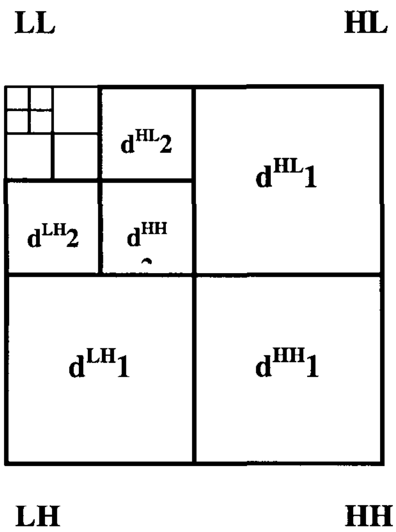


Figure 4.8 Pyramidal decomposition of image into sub-band images

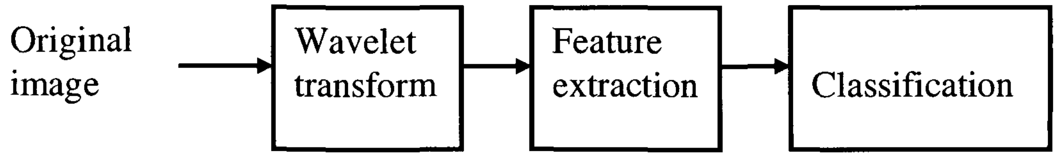


Figure 4.9 Schematic of wavelet transform based texture classification

Finally, the basic idea of WTA is to generate a textural feature from these wavelet coefficients at each resolution. Therefore each sub-band image is treated as matrix and different statistical features (energy, entropy, variance etc.) are calculated out of them. If the frequency spectrum is decomposed appropriately, different texture will have different features. Figure 4.9 shows the schematic of the WTA based texture classification.

4.5.2 **Wavelet bases for texture analysis**

Various wavelet bases can be found in literature in different texture analysis applications. These include Haar, Daubechies, Gabor, etc. The Daubechies' wavelet (Daubechies, 1988) is selected as bases due to its orthonormal characteristics. In comparison to Haar wavelet, the Daubechies' wavelet has continuous derivatives that respond well to discontinuities of the textures, while Haar wavelet doesn't allow the sharp transitions and fast attenuation. Moreover, Haar can't efficiently separate the image signals into low and high frequency sub-bands. On the other hand Gabor filter uses the Gaussian window function, which is of fixed width for all the frequencies. One more disadvantage of Gabor filter is its high computational cost. But, in comparison to these, Daubechies constructed smooth scaling functions of compact support having orthonormal shifts and then applied the DWT method to obtain smooth orthogonal wavelets. Therefore these advantageous characteristic of Daubechies' wavelet allow a compact coding of the image. Textured image analysis, comparison and segmentation have already been shown using Daubechies' wavelets as a successful technique (Salari, et. al., 1995; Wang, et al., 1997; Manian, et. al., 1998). Salari, et. al., in 1995 shows better performance in texture segmentation by using Daubechies' WT based technique. Wang, et. al., in 1997 uses it for image indexing on the basis of texture variability and got better performance. Similarly, Manian, et. al., in 1998 shows that the Daubechies WT based texture analysis produces the best result in invariant texture classification. The fast wavelet transform (FWT) with a set of Daubechies' wavelets are carried out to decompose the gray valued tea images into different sub-band images. This is described in the later section.

4.6 Tea image texture classification

The two main stages of texture analysis namely feature extraction and classifications are discussed in this section (refer section 4.3.2). The algorithm described in this thesis is developed in MATLAB using a combination of the Image Processing Toolbox, Wavelet toolbox (The Math works) for MATLAB; and Uvi_Wave version 3.0 for MATLAB. In the context of different texture analysis approaches, the technique employed in this research adopts the features extraction from different sub-bands of the pyramidal decomposed images. That is, a four level pyramidal decomposition of a tea image into its sub-band images is adopted. This technique reveals that the lower sub images of the size 16x16 and 32x32 also contain useful information about tea images texture variability. Variance, Entropy, Energy are calculated for all the sub-band images of the different tea grades and used as feature vectors, containing the information about the texture variations in the images. Thence having the information regarding textures, in terms of feature vectors, intelligent system techniques are applied to model the classification system for discriminating between them.

4.6.1 Feature extraction

The experimental procedure for tea image texture feature extraction method is as follows:

- Tea images are preprocessed and the sizes of the images are made fixed to all the images to make the system computationally less complex.
- The Daubechies wavelet based low pass and high pass filters are designed.
- A two dimensional FWT is applied to decompose the image into its sub-band images. Four-level pyramidal decomposition is used in this work.
- All the sub-band images are stored for calculating the statistical features from the sub-bands.

Figure 4.10 (a) and (b) show 2 and 4 sub-bands that are created from one 128x128 tea image (gray scale) respectively. The sizes of the lower sub-bands have become 64x64, 32x32, 16x16 and 8x8 respectively down the order. It is observed during the decomposition that the sub-bands such as d^{LH} and d^{HL} contain significantly much less energy, so they are ignored. Therefore d^{HH} is the only sub-band used for the feature calculation. Therefore, there will be four sub-band images from four level in different resolution will be available for feature vector calculation. During statistical feature calculation, if the decomposed sub-band image is f(x,y) with dimension (X,Y), then the various statistical features like mean, variance, entropy and energy feature vectors of the particular sub-band are calculated using the standard notations (Laine, et. al., 1993; Wang, et. al., 1998), which are as follows:

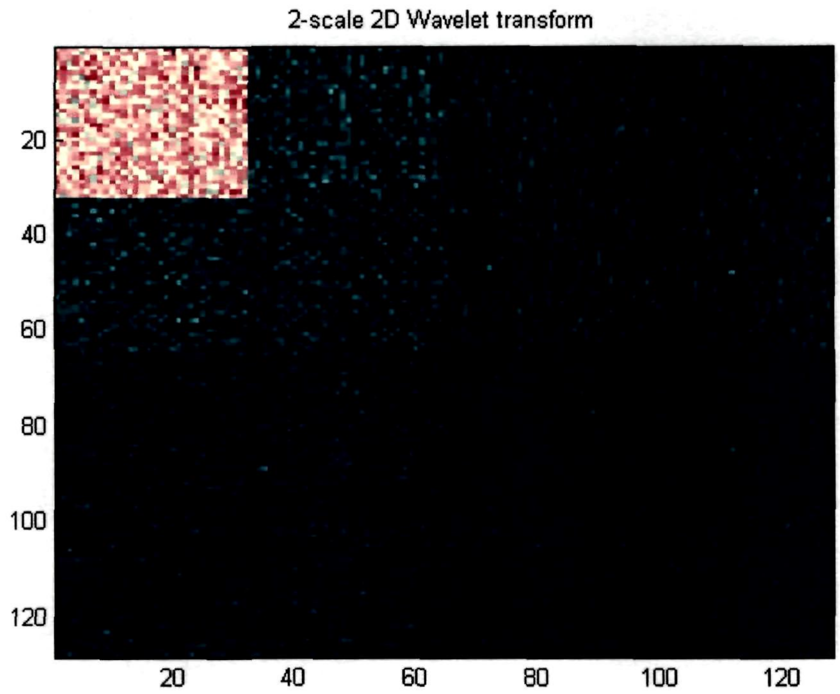
$$Mean = \frac{1}{XY}\sum_{x=1}^{X}\sum_{y=1}^{Y} f(x,y) \tag{4.2}$$

$$Variance = \frac{1}{(XY)^2}\sum_{x=1}^{X}\sum_{y=1}^{Y} | f(x,y) - Mean |^2 \tag{4.3}$$

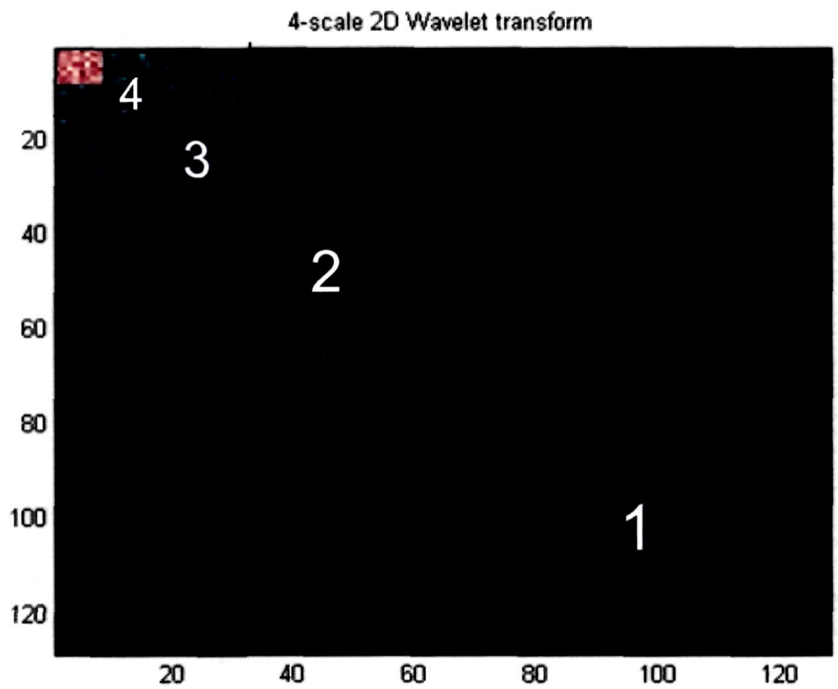
$$Energy = \frac{1}{(XY)^2}\sum_{x=1}^{X}\sum_{y=1}^{Y} | f(x,y) |^2 \tag{4.4}$$

$$Entropy = -\frac{1}{(XY)^2}\sum_{x=1}^{X}\sum_{y=1}^{Y} | f(x,y) |^2 \log\{f(x,y)\} |^2 \tag{4.5}$$

Of these features, mean doesn't tell much about the variations of the elements in the matrices as different matrices might produce same mean. But, on the other hand, the other statistical features, namely variance, energy and entropy are distinctive in nature for different matrices of different variations in elements. Therefore, these later three features are considered to be used as the texture feature and calculated from all the four selected sub-bands of the tea images. The following sections produce the results that are analyzed by the PCA and SOM techniques.



a



b

Figure 4.10 (a) 2 sub-bands are created from the 128x128 gray scale images; (b) 4 sub-bands are created from the 128x128 gray scale images.

4.6.2 PCA of the data

The principal component analysis (PCA) is selected for the visualization of the selected features and analysing the discriminating properties in them. There are four sub-band images of four different resolutions to be considered for feature vector calculation. Two different features energy and entropy are considered as the feature set in the first instance. Therefore the length of the feature vector for a particular image has become eight. The PCA seeks to reduce the vector dimension of the data set and thus considers only the most distinguishing patterns (principal component) The experiment is carried out among the eight different grades (refer figure 4.5) of tea and 160 different images are considered 20 each of each grade. Figure 4.11 shows the three dimensional PCA plot of 160 different samples of 8 different categories of tea grades in 3 dimensional (3D) spaces.

It is observed from the figure that the PCA can not find any sharp distinction between the feature vectors though they are calculated from 8 different sized tea granules.

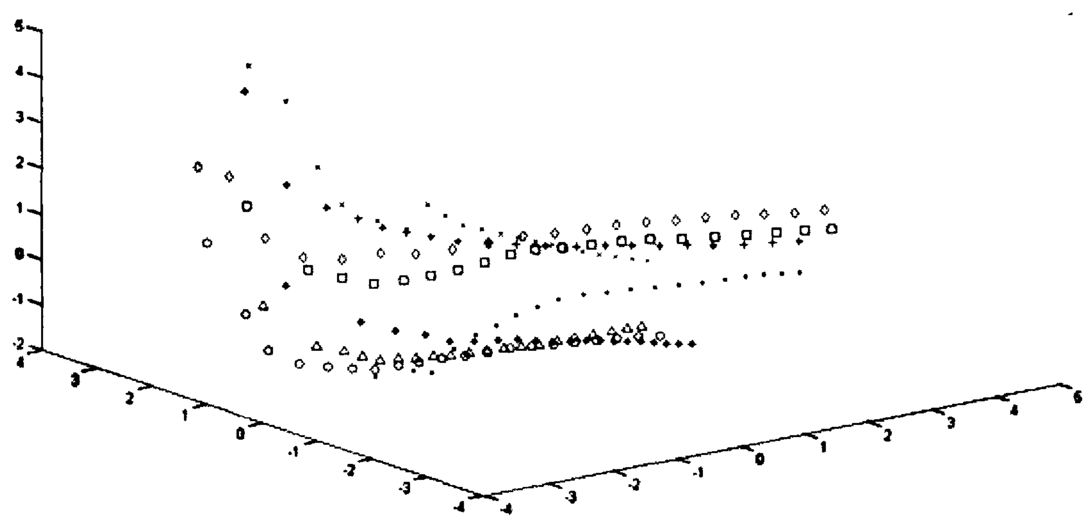


Figure 4.11 PCA plots of 8 tea grades in 3 dimensional (3D) spaces.

4.6.3 SOM of the data

The feature set is then used to try to find any possible clusters. Self organizing map (SOM) based data clustering techniques is used here as this method adopts the competitive learning method and is based on unsupervised learning (Refer to chapter II). Figure 4.12 represents the surf of the codebook generated by the SOM training using the input data. It is observed that the SOM based technique has also failed to find any sharp distinction among the data set. The SOM clusters the dataset into more than 11 clusters though the features were extracted for only 8 different categories images.

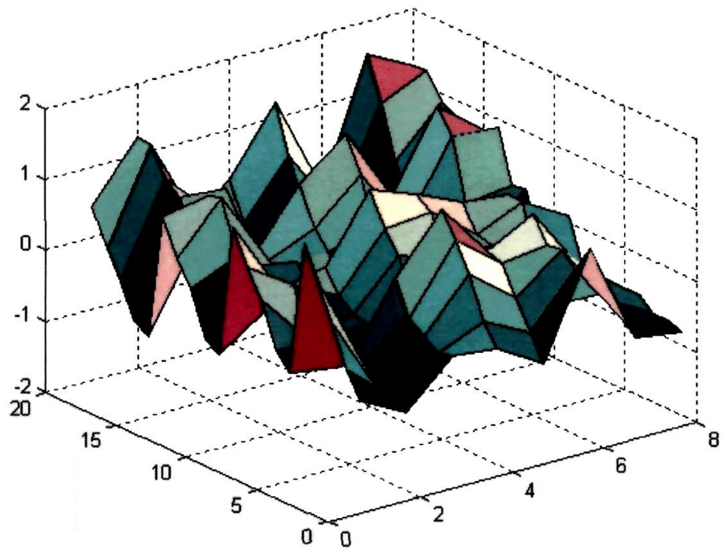


Figure 4.12 SOM clustering results using the data.

It is observed (Section 4.6.2 and section 4.6.3) that the feature set that calculated in the specified manner is not distinctly separable either by PCA or clustering techniques like SOM. It is then worthwhile to try some other method for feature extraction technique for efficient performance of the classification techniques. Therefore a novel texture feature extraction technique has been proposed here, which is described in the later section.

4.7 New feature calculation method

The new feature extraction method consists of two distinct steps prior to the final feature extraction step. The first step is the existing feature extraction from the wavelet transform based sub-band images (Same as section 4.6.1) and the second is the estimate of the range of different groups of images. Three types of feature vectors - variance, entropy and energy are calculated for all the gray scale tea images in the database. The technique is developed using the same eight most significant tea grades of completely distinctive in granule size. Therefore there are eight different tea image databases created. The Mahalanobis distances among the features of each images of each group are calculated for threshold measurement to estimate the range of the groups.

4.7.1 Mahalanobis distance measurement

The Mahalanobis distance is a distance measure, which was invented by P C Mahalanobis in 1936. It can be defined as the dissimilarity of two random vectors $\vec{x}$ and $\vec{y}$ of same distribution and if C is their covariance matrix between them (Equation 4.6).

$$d(\vec{x}, \vec{y}) = \sqrt{(\vec{x} - \vec{y})' C^{-1} (\vec{x}, - \vec{y})} \quad (4.6)$$

Recently, Mahalanobis distance has become a common use in computer vision systems is for comparing feature vectors, whose elements are quantities having different ranges and amounts of variation. It has been shown as a useful measure of similarity if some statistical properties of the texture features are known (Chang, et. al., 1993). This is found one of the most effective methods for determining the dissimilarity of the set of features from an unknown image to the set of features measured from the collection of known images. This distance classifier does not infer which feature is the most important for discrimination of the textured images, but measures the dissimilarity between two different images. Since the Mahalanobis distance is measured in terms of standard deviation from the mean of the samples, the matching values provides a statistical measure how the features of the test image match. If e_l denotes L feature out of the three adopted, m_i is the mean of the decomposed sub-band of the image of class 'i' and $c_{i,l}$ is the covariance of feature 'l' of class 'i' then the Mahalanobis distance (Md) is defined as:

$$Md = \sum_{l=1}^{L} \frac{(e_l - m_i)^2}{c_{i,l}} \tag{4.7}$$

The equation 4.7 is used to measure the dissimilarity between two images in terms of extracted features. This provides the difference between two images in terms of texture variations. This dissimilarity measurement is carried out among the images of same group of the eight databases.

4.7.2 **Threshold calculation for a group of images**

As the Mahalanobis distance measures similarity among the feature vectors, it has become useful for measuring the differences among the images. That is to measure the amount of dissimilarities. The technique that is proposed here considers a range of different groups of images of the same granule size and finds the dissimilarities. Having the dissimilarity values (Mahalanobis distances) of a particular group of images, a threshold value is selected (either minimum or maximum). This threshold value is efficiently used to select the ranges of the groups and select the most significant images from the group. While choosing the minimum as the threshold, then it gives the significant image that lies in the middle of the group. On the other hand choosing the maximum, gives the two images those lie in the two extreme ends of the group. The minimum is considered as threshold here to avoid computational complexity, which gives only one image to be considered from each group of images. The technique can be described as follows:

The first step is to calculate the 'Md' of every image with respect to the rest of the images of the same group. In doing so, a set of distance values is formed. The number of elements in this set to be calculated can easily be defined by using the combination formula, which calculates the number of ways of picking 'k' unordered outcomes from 'n' possibilities. In this case k = 2 and n = 'number of images considered in a specific groups'. Then the method tries to determine the two most significant images having minimum 'Md' value, i.e., threshold. The significance of finding these images is that these images will be treated as the standard images of a particular database. Moreover, they are having the minimum dissimilarity, which means they are the most similar images in the database. So either one image will be used to calculate the final feature set. The other standard images from other databases are also identified in the similar manner and finally used to calculate the final feature set for each images. Figure 4.13 (a) and (b) show sample threshold calculation schematic considering five images in a particular group. Here images are considered as I_1, I_2, I_3, I_4 and I_5. The 'Md' is calculated for all the five images with respect to the rest of the images.

	I_1	I_2	I_3	I_4	I_5
I_1	Md_{11}	**Md_{12}**	**Md_{13}**	**Md_{14}**	**Md_{15}**
I_2	Md_{21}	Md_{22}	**Md_{23}**	**Md_{24}**	**Md_{25}**
I_3	Md_{31}	Md_{32}	Md_{33}	**Md_{34}**	**Md_{35}**
I_4	Md_{41}	Md_{42}	Md_{43}	Md_{44}	**Md_{45}**
I_5	Md_{51}	Md_{52}	Md_{53}	Md_{54}	Md_{55}

a

	I_1	I_2	I_3	I_4	I_5
I_1		**Md_{12}**	**Md_{13}**	**Md_{14}**	**Md_{15}**
I_2			**Md_{23}**	**Md_{24}**	**Md_{25}**
I_3				**Md_{34}**	**Md_{35}**
I_4					**Md_{45}**
I_5					

b

Figure 4.13 (a) and (b) Sample threshold calculation schematic in a group of images

The first step of this method is to calculate the 'Md' among the images using the existing texture features. 'Md_{xy}', in Figure 4.13 (a) and (b), indicates this calculation between images x and y, where x, y =1, 2 ...5 in this case. The number of elements in the set is ${}^5C_2 = 10$ and outcomes are shown as 'bold' in the table (refer to section 3.4.1). The lower part of the table (opposite to the diagonal elements) also indicates the same set of values and so ignored (Figure 4.13 (b),). The next step is to find the lowest valued element. This value is treated as the threshold and takes the corresponding two images are selected. For example if 'Md_{23}' is the lowest value in the set then images I_2 and I_3 will be the two images to be considered as the most significant images in the group. Either I_2 or I_3 can be considered for the subsequent steps in the algorithm. So, if 'm' different groups of images are considered then 'm' numbers of images are to be considered for the final feature calculation. But in some cases some different groups merge together and in that sense the number of final images become less than 'm'.

4.7.3 **Final feature set calculation**

The last step of the method is the final feature calculation. The same 'Md' calculation is also carried out for this step but in this case with respect to the selected images only. Therefore, having a particular image to be categorized into a definite group of 'm' different groups, one needs to calculate the 'Md' with respect to the 'm' selected images. These resulting values themselves are considered as the final feature vectors of the particular image. Figure 4.14 shows this feature estimation technique schematically.

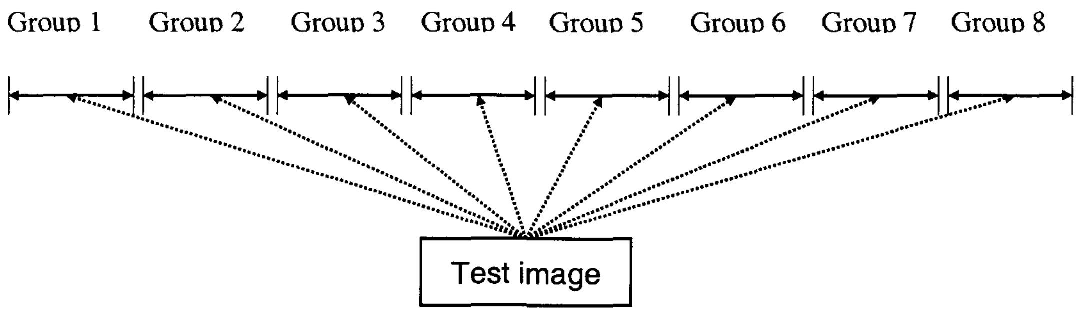


Figure 4.14 Scheme of this new feature estimation technique.

The significance of this feature set is that it consists of the information of the entire databases of all different groups but contains fewer dimensions. The advantage of such an approach of feature extraction is that it reduces the feature vector lengths without loosing any significant information about the texture and finally minimizes any chance of misclassification.

4.7.4 **PCA of the new feature set**

Figure 4.15 shows the PCA plot of 160 different samples of 8 different categories of tea grades in 3 dimensional (3D) spaces using the new feature set calculated in the previous section. It is found that some of the categories of images form specific groups in the plot. But some of the groups are not distinctly separable from each other, which mean that the original images are almost identical in nature. This phenomenon indicates the better performance of the new feature set in comparison to the previous feature set.

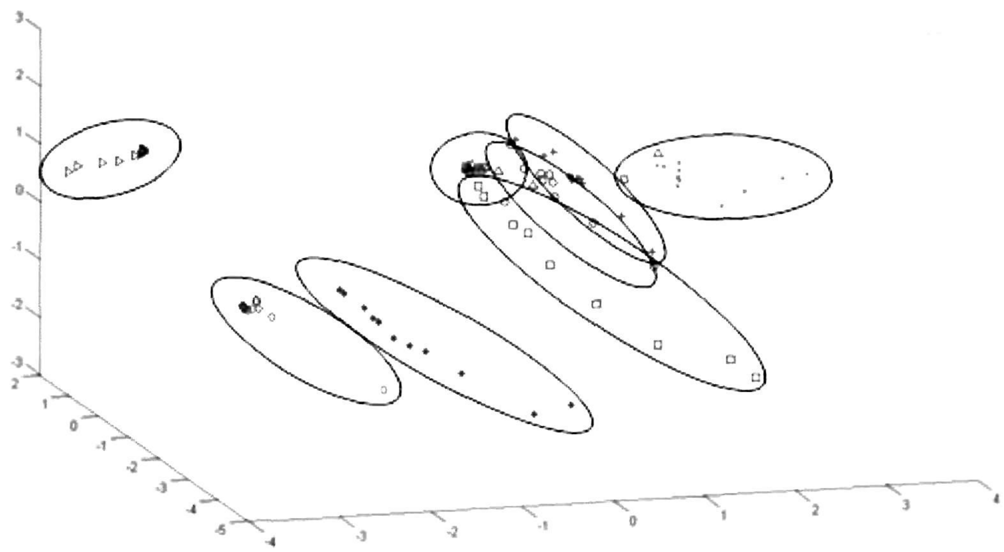


Figure 4.15 PCA plots of 8 tea grades in 3D spaces using the new feature set.

4.7.5 **K-mean clustering of new feature set**

The new feature set is here clustered using the K-mean clustering technique (refer to chapter II). The clusters formed are visualized in Figure 4.16 as the Silhouette plot. It shows the K-means clustering of 160 different samples of 'k' (eight) different grades of tea data. The figure shows some miss clustering of the feature set, which indicates the similarity of data points by nature in those categories.

4.7.6 **SOM clustering of new feature set**

The SOM technique is also applied in the new feature set to explore the clustering in them. Figure 4.17 represents the surf of the codebook generated by the SOM. It is observed that the performance of the SOM based technique is enriched in using the new dataset. That is the SOM can find eight distinct clusters in the dataset. This reveals the better efficiency of the new feature set in comparison to the original features set as described in section 4.6.

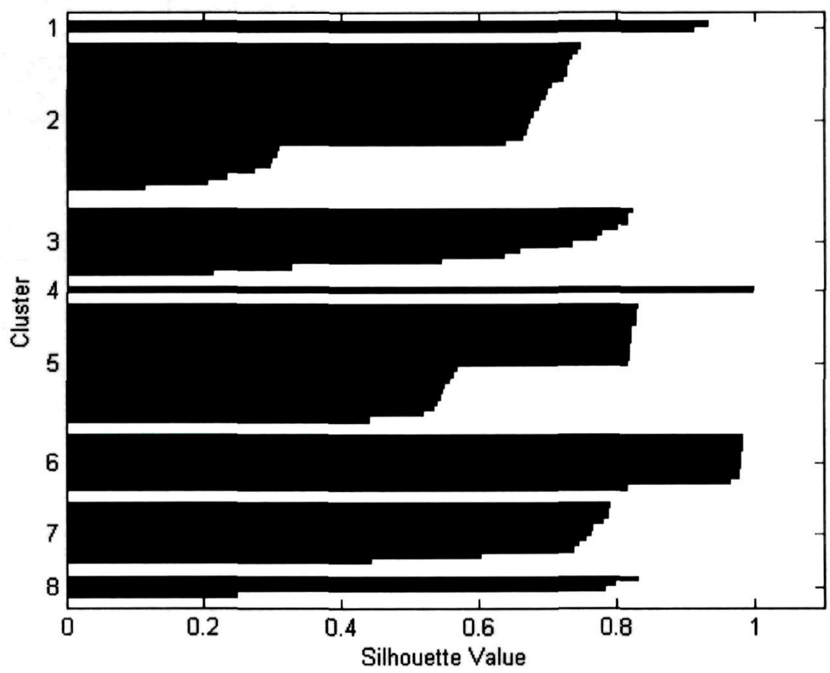


Figure 4.16 Silhouette plot of K-mean clustering showing eight different clusters

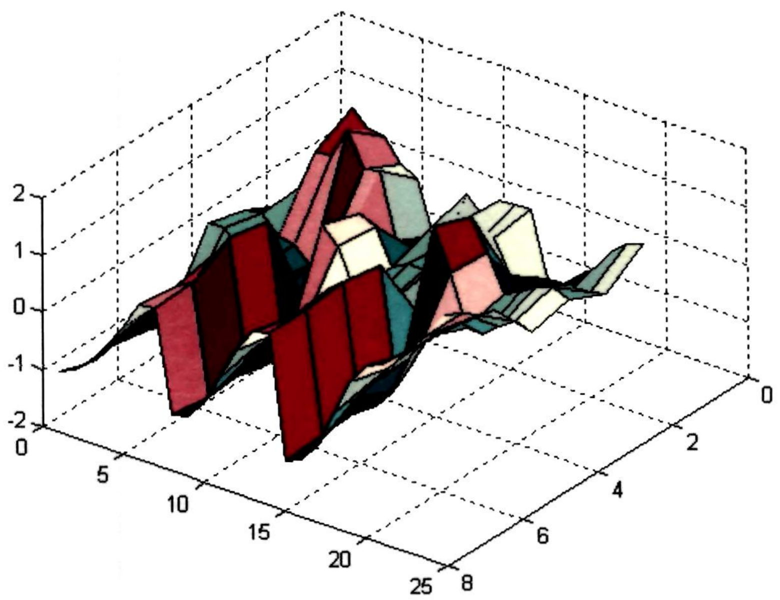


Figure 4.17 SOM clustering of the new feature set

4.8 **Data classification**

It was observed in the previous sections that the new feature set can be successfully clustered by the K-mean as well as more accurately by the SOM (section 4.7.5 and 4.7.6). It was also observed that though the data set were constructed for eight different categories of samples, some of them are nearly identical in nature. Keeping these knowledge in mind, the feature set classification by the ISE technique is carried out to model a system to represent the knowledge directly to the system. Two different algorithms, namely MLP and LVQ are selected from the literatures and implemented with the new feature set. The working principle the algorithms and their corresponding performances are described in this section.

4.8.1 **MLP**

The length of the feature set is 8 and the there are 8 different varieties of categories of textures to be classified. Therefore, the MLP network is tested so that it transforms the 8 input neurons to 8 output neurons. The network structure is shown in Figure 4.18, where the number of layers is set to 2.

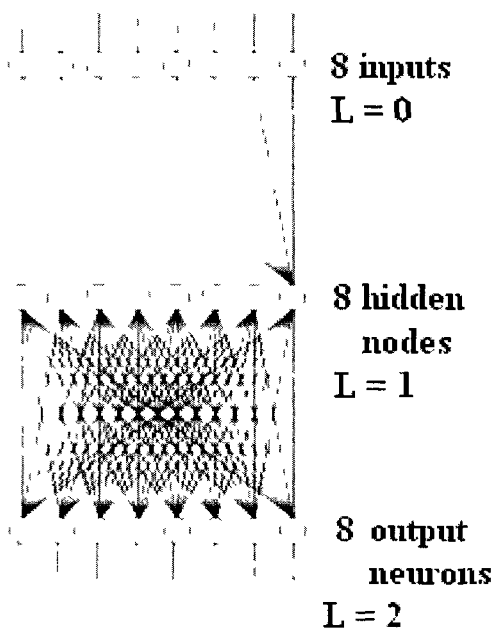


Figure 4.18 Architecture of MLP networks (8:8 networks).

The weights are trained with the error feed-forward back propagation algorithm. The activation functions for the neurons in the hidden layers (8 neurons in this case) employ the sigmoid function. It is observed that the network has very low computational complexity as training using 700 samples took <15 minutes on a PC with a 3GHz CPU. While using 150 testing samples, the network results in 74.67% correct classification. On the other hand, while testing with the original feature set the accuracy achieved was just 46% with the same training and test samples.

4.8.2 LVQ

Kohonen's LVQ (refer to chapter II) is also tested using the same sample of images using the new feature set. Figure 4.19 shows the LVQ network, which uses R: Number of elements for the input vector (8); S1: Number of competitive neurons (21); S2: Number of linear neurons (8).

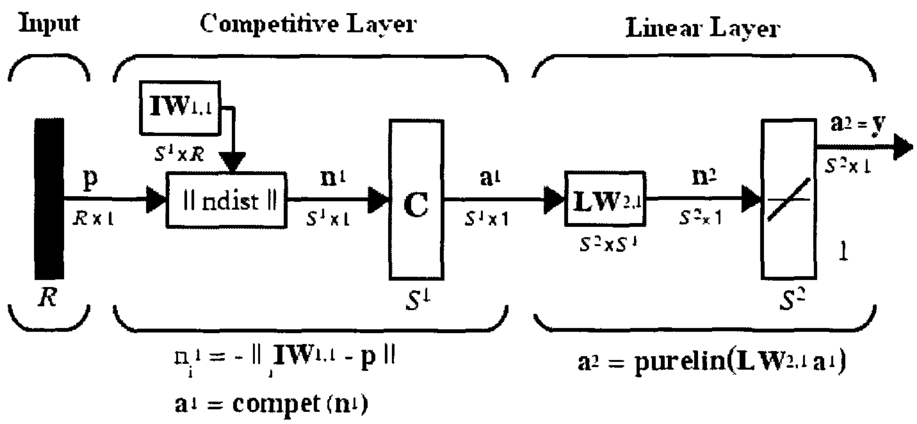


Figure 4.19 Architecture of the LVQ network

While using 700 training samples and 150 testing samples, the network results in 80% correct classification. This result outperforms the result obtained by the MLP network in the previous section.

4.9 Summery

The grading of tea products according to the quality, size and shape is a very important process in the tea processing industry. Efficient grading requires high degree of sensing and intelligence for accomplishing the classification. The human sensory panel, supported by visual approximation, has traditionally been maintaining the grading standard, but no machine vision approach has so far been used. Tea research associations seek to modernize their quality monitoring process in scientific way to satisfy a market driven by customer demands with products with greater differentiation. As a consequence, research interests grow in the possibilities of on-line monitoring of the sorting / grading process using scientific methods (computer vision and artificial olfaction etc.). In view of the disadvantages of manual methods, a novel approach by using computer vision for tea granule size estimation is carried out in this research. The research is mainly dedicated towards finding an efficient texture feature as the existing features are not very efficient in estimating the size of the objects in images. This size classifier method is based on surface roughness of the images. The method uses the Daubechies' wavelet based decomposed sub-band images and existing useful feature vectors for calculating the new set of features. Eight different databases of images of eight different grades of tea are used to develop this system. The performance of the system is satisfactory as evident by the results obtained; although it appears to compromise computational complexity with higher number of distinctive groups. But such feature doesn't make much complexity with the lesser number of groups as the case of tea grades. This is because; there is not very high number of grades to be classified in tea industry. The method is found to be advantageous in terms of both accuracy and complexity in the problem specified.

The observations drawn from the texture discrimination methods adopted in this research, as applied to tea image classifier scheme, are satisfactory. It is observed from the clustering techniques that some of the groups can not be clustered as definite cluster points, i.e., these groups merge with each other. This phenomenon was observed during the feature extraction step also. Some images really fall into some other categories of images though they are grouped as different from each other. This is due to the phenomenon of almost the same texture pattern though the size of the tea granules is slightly different from each other. The experiment is carried out only for eight specifically different types of texture (size of tea granules). Moreover, sub-bands with the first and second scale are more sensitive to the nature of texture as evident from the energy contents. All the features have produced distinctive numerical values, which are effective in the discrimination. Finally, the intension of this research is to extract the efficient texture features that increase the accuracy of performance of the intelligent system in using a large number of input vectors without compromising its computational complexity.

This research is mainly aimed towards exploring an efficient model for the determination of the sizes of tea granules, which uses well-made, uniform sized (even) tea granules of different categories. The system performance for the feature selection is satisfactory for such samples. For example up to 80% (highest) accuracy is obtained using the Kohonen's LVQ network. Extraction of much more efficient texture feature for more accurate discrimination in terms of size of tea granules may be one of the prospective future works to further improve the performance. Moreover, from the prospect of tea grading automation some other attributes such as the presence of stalk, the presence of other grades, the presence of bold etc may be considered as part of any future research work in this area.

References:

1. Arivazhagan, S., Ganesan, L., 2003. Texture classification using wavelet transform, Pattern recognition letters, Vol. 24, No. 16, pp 3197-3203.
2. Bennis, C., and Gagalowicz, A., 1989. 2-D macroscopic texture synthesis, Computer Graphics Forum, vol. 8, pp. 291-300.
3. Blostein, D., Ahuja, N., 1989. Shape from texture: Integrating texture element extraction and surface estimation, IEEE trans. Pattern analysis and machine intelligence, Vol. 11, pp 1233-1251.
4. Bovik, A. C., Clark, W., Geisler, W. S., 1990. Multichannel texture analysis using localized spatial filters, IEEE trans. Pattern analysis and machine intelligence, Vol. 12, No.1, pp 55-73.

5. Cross, G. C., Jain, A. K., 1983. Markov random field texture models, IEEE trans. Pattern analysis and machine intelligence, Vol. 5, pp 25-39.
6. Chellappa, R., Chatterjee, S., 1985. Classification of textures using Gaussian markov random fields, IEEE trans. Acoustic, speech and signal processing, Vol. 33, pp 959-963.
7. Cohen, F. S., Cooper, D. B., 1987. Simple parallel hierarchical and relaxation algorithms for segmenting noncausal markovian random fields, IEEE trans. Pattern analysis and machine intelligence, Vol. 9, pp 195-219.
8. Chang, T., Kuo, C. C. J., 1993. Texture Analysis and Classification with Tree-Structured Wavelet Transform, IEEE Trans. Image Processing, Vol. 2, No. 4, Oct. pp 429-441.
9. Chen, Y. Q., Nixon, M. S., Thomas, D.W., 1994. Neural networks and texture classification, Applications of Neural Networks to Signal Processing (Digest No. 1994/248), IEE Colloquium on , 15 Dec., pp 6/1 -6/4.
10. Daubechies, I., 1988. Orthonormal bases of compactly supported wavelets, Communications on pure and applied mathematics, Vol. 41, pp 909-996.
11. Davis, L. S., Clearman, M., Aggarwal, J, K., 1981. An empirical evaluation of generalized concurrence matrices, IEEE Trans. Pattern analysis and machine intelligence, Vol. 3, pp 214-221.
12. Francos, J. M., Meiri, A. Z. 1988. A unified structural-stochastic model for texture analysis and synthesis, Proc. 5th Int. Conf on Pattern Recognition, (Washington), pp. 41-46.
13. Georgeson, M. A., 1979. Spatial Fourier analysis and human vision, Tutorial Essays, A Guide to Recent Advances (N. S. Sutherland, ed.), vol. 2, ch. 2, Hillsdale, NJ: Lawrence Erlbaum Associates.
14. Gibson, J. J., 1950. The perception of the visual world, Boston, Greenwood Press.
15. Haralick, R. M., 1979. Statistical and structural approaches to texture, Proc. IEEE, Vol. 67, pp 786-804.
16. Heidemann, G., 2004. Combining spatial and colour information for content based image retrieval Computer Vision and Image Understanding, Vol. 94, No. 1-3, , pp 234-270

17. Haindl, M., 1991. Texture synthesis, CWI Quarterly, vol. 4, pp. 305-331.

18. Kaláb, M., Allan-Wojtas, P., and Miller, S. S., 1995. Microscopy and other imaging techniques in food structure analysis, Trends in Food Science & Technology, Vol. 6, Issue 6, pp 177-186.

19. Kociolek, M., Materka, A., Strzelecki, M., Szczypinski, P., 2001. Discrete wavelet transform – derived features for digital image texture analysis, Proc. Int. Conf. Signals and Electronic systems, Lodz, Poland, pp 163-168.

20. Laine, A., Fan, J., 1993. Texture classification by wavelet packet signatures, IEEE trans. Pattern recognition and machine intelligence, Vol. 15, No. 11, pp 1186-1191.

21. Mandelbrot, B. B., 1983. The fractal geometry of nature, Freeman, New York.

22. Montes, J., Cristobal, G., Bescos, J., 1988. Texture isolation by adaptive digital filtering, Image and Vision Computing, Vol. 6, No. 3, pp 189-192.

23. Müller, H., Michoux, N., Bandon, D., and Geissbuhler, A., 2004. A review of content-based image retrieval systems in medical applications - clinical benefits and future directions International Journal of Medical Informatics, Volume 73, Issue 1, pp 1-23

24. Mallat, S. G., 1989. A theory for multi resolution signal decomposition: the wavelet representation, IEEE trans. Pattern analysis and machine intelligence, Vol. 11, No. 7, pp 674-693.

25. Manian, V., Vásquez, R., 1998. Scaled and rotated texture classification using a class of basis functions, Pattern Recognition, Vol. 31, No. 12, pp 1937-1948

26. Pietikainen, M., Ojala, T., Xu, Z., 2000. Rotation invariant texture classification using feature distributions, Pattern Recognition, Vol. 33, pp 43-52.

27. Patel, D., Hannah, I., Davies, E. R., 1994. Texture analysis for foreign object detection using a single layer neural network, Neural Networks, IEEE World Congress on Computational Intelligence, Vol. 7, 27 June-2 July, pp 4265 -4268.

28. Rui, Y., Huang, T. S., Chang, S. F., 1999. Image retrieval: current techniques, promising directions, and open issues, J. Visual Commun. Image Representation, Vol. 10 (1), pp 39–62.

29. Reed, T. R., du Buf, J. M. H., 1993. Image understanding, CVGIP, Vol. 57, pp 359-372.

30. Rosenfeld, A., Troy, E. B., 1970. Visual texture analysis, Conf. Record for SymposiNm on Feature Extraction and Selection in Pattern Recognition, IEEE Press, pp. 115-124

31. Salari, E., Ling, Z., 1995. Texture segmentation using hierarchical wavelet decomposition Pattern Recognition, Volume 28, Issue 12, pp 1819-1824.

32. Sinfort, N., Bellon V., and Sevila, F., 1992. Image analysis for in-flow measurement of particle size, Food Control, Vol 3, No. 2, pp 84-90

33. Thomas, C. R., and Paul. G. C., 1996. Applications of image analysis in cell technology, Current Opinion in Biotechnology, Vol. 7, Issue 1, pp 35-45.

34. Tuceryan, M. and Jain, A. K., 1990. Texture Segmentation Using Voronoi Polygons, IEEE Trans. on Pattern Analysis and Machine Intelligence, Vol. 12, pp. 211-216.

35. Tuceryan, M., and Jain, A. K., 1998. Texture Analysis, The Handbook of Pattern Recognition and Computer Vision (second edition), C. H. Chen, L. F. Pau, and P. S. P. S. P. Wang, Editors, World Scientific Publishing Co. pp. 207-248.

36. Tamura, H., Mori, S. and Yamawaki, T., 1978. Textural features corresponding to visual perception, IEEE Transactions on Systems, Man and Cybernetics, vol. 8, pp. 460-473, June.

37. Unser, M., 1995. Texture classification and segmentation using wavelet frames, IEEE trans. Image processing, Vol. 4, No. 11, 1549-1560.

38. Quevedo, R., Carlos, L. G., Aguilera, J. M., and Cadoche, L., 2002. Description of food surfaces and microstructural changes using fractal image texture analysis, Journal of Food Engineering, Volume 53, Issue 4, Pages 361-371.

39. Van de Wouwer, G., Schenders, P., Van Dyek, D., 1999. Statistical texture characterization from discrete wavelet representation, IEEE trans. Image processing, Vol. 8 , No. 4, pp 592-598.

40. Vorhees, H., Poggio, T., 1987. Detecting textons and texture boundaries in natural images, Proc first Int. conference on computer vision, London, pp 250-258.

41. Wu, Q. M., de Silva, C. W., Beatty, A., Cao, L. X., Gamage, L., Gosine, R., Kurnianto, I., 1995. Knowledge-based system for on-line grading of herring roe, IEEE Int. Conf. on Intelligent Systems for the 21st Century, Volume: 4, 22-25 Oct., vol.4, pp 3742 -3747.

42. Wang, J. Ze., Wiederhold, G., Firschein, O., 1997. Wavelet based image indexing techniques with partial sketch retrieval capability, In Proc. 4th Forum on Research and Technology Advances in Digital Libraries, pp 13-24.
43. Wang, J., Asundi, A K., 2000. A computer vision system for wineglass defect inspection via Gabor-filter based texture features, Information Sciences, Vol. 127, pp 157-171.

CHAPTER V

IMPLEMENTATION OF ELECTRONIC NOSE TECHNOLOGY IN TEA

5.1 Introduction

The characteristic fragrance of tea is the 'aroma', i.e., the odour of either infused leaf or the tea liquor itself, is one of the most significant factors of its quality determination (Mahanta, et al., 1993; Horie, et. al. 1993; Togari, et. al., 1995). This is also known as the 'nose' or 'fragrance' in 'tea taster's language'. The development of 'aroma' in tea was introduced in Chapter II (section 2.2.3.1). This aroma is one of the three attributes of flavour, i.e., sense of smell, used for quality tasting. The other two flavour attributes are senses of taste, and astringent and these are perceived within the human mouth. The aroma represents the tea is having at least one of a certain number of odours, which are desirable and are highly valued for good quality tea. It is formed in tea as different volatile organic compounds (VOC) that are formed during processing stages and are derived from carotenes, amino acids, unsaturated fatty acids and terpene glycosides (Yamanishi, 1981; Takeo, et. al., 1981). The difference in aroma in different teas is caused by the amount of the VOCs and variations of their ratios. There are many causes of such variations in aroma profile. For example, one of the main reasons is due to tea being made from different varieties of tea clones (Takeo, et. al., 1983). Moreover, the processing techniques, the pruning and time of pruning also have the major impact on the variations in VOCs affecting the aroma profiles (Owuor, et. al., 1992; Ravichandran, et. al., 1998; Ravichandran, et. al., 2004). But in evaluating the quality of the tea, the tea tasters and tea brokers use certain standard terminology for describing the flavour without considering the chemical composition of it. In fact, there is nowhere a mention of the numerical descriptor or score for these flavour terms.

There are almost forty different flavours terms generally used in tea industries, which are approved by Tocklai Tea Research Association (TRA), Assam, India (Tocklai TRA bulletin, 1992). There are some overlapping terminology are also found among these terms. Finally, twenty four non-overlapping flavour terms have been identified (Bhuyan, M., et al., 2001). It is observed that the flavour terms are not descriptive of the organic compounds but are rather characterized in a subjective manner. For example, an undesirable odour 'smokey' is due to the fault in a drier, where tea is fired. 'Papery' is due to the smell of paper that is used for wrapping the tea and similarly baggy is also an undesirable taint as a consequence of being stored in a bag used for storing. In a similar manner 'flat' and 'plain' describe the poor quality of tea, where flat is caused either by damp storage conditions or age. 'Plain' is due to manufacturing tea in odd the season of the year, for example monsoon period. Experienced tea tasters make an important contribution to the evaluation of tea quality. They evaluate the aroma in three different ways. These are smell of dry leaf, smell of infused leaf and smell of wet leaf after infusion. The results of statistical studies reveal that the traditional tea tasting method is based on decision only of these human sensory panels involved for flavour profiling. But additionally such traditional organoleptic techniques is not only time consuming but also inexact due to reasons such as individual variability, adaptation (becoming less sensitive due to prolonged exposure), fatigue, infection, mental state etc (Bhuyan, M., et al., 2001). Moreover, though it is observable that the varying amount or ratios of VOCs of tea is responsible for the final tea aroma, the tasting of the final product is purely subjective; like sniffing by human beings. This fundamental fact therefore makes it worthwhile to explore the potential application of electronic nose (EN) in 'aroma' profiling.

EN typically comprises of an integrated chemical sensor array, together with interfacing electronic circuitry and a pattern recognition unit. It is the system that detects and identifies odours and vapours, typically by linking the chemical sensing devices with the signal processing and pattern recognition subsystems (Gardner, et. al., 1990; 1994). The most appropriate tool for representing odour quality would be the application of 'mono-osmotic' or primary odours, which is based on a unified theory of olfaction but unlike unified theory of colour description, there is no unified and universal representation of odour. Hence the only way of odour description would be via comparison with other prototypical and ambiguous odours. This chapter deals with the prospects for 'aroma' analysis of black tea using the metal oxide sensors based EN and pattern recognition sub-systems using statistical methods and intelligent system engineering (ISE) techniques. The chapter starts with a description of the application of EN in some other food processing industries, which gives a clear indication of the potential of EN in such uses. Then its application to the tea industry is explored.

5.2 EN and its application: A brief survey

Electronic nose (EN) is an instrument, which comprises an array of electronic chemical sensors with partial specificity and an appropriate pattern recognition system capable of recognizing simple or complex odours (Gardner, J. W et. al., 1994). This technique of artificial olfaction has emerged into the limelight in the recent years due to its outstanding performance in classifying flavours in many industries such as food, drinks, cosmetic etc. The researchers have been trying to implement this EN system along with the pattern recognition sub-systems for food quality monitoring classifying food samples into different categories (Bartlett, P. N., et. al., 1997). The majority of the current research concentrates on quality control in the foods and drinks industry, such as detection of microbial contamination (bacteria, fungi and yeast) and authenticity (beverages, coffee and meat) (Gibson, et. al., 1997; Anklam et al., 1998; Eklov et al., 1998). For example, six MOS sensors array EN system with pattern recognition was used for discriminating different coffee samples and liquors (Aishima, T., 1991, 1, 2). Then a set of twelve MOS were used for discriminating between Brazilian and Colombian Coffee (Gardner, J. W., et. al., 1992). A set of six MOS sensor array was used for identifying three different Cola, and six different brands of sausage (Tan, T., et al., 1995). A study of response of five alpha MOS sensors was carried out to try to detect two compounds responsible for foul odor produced in meat cooking (Borrounet, et. al., 1995). The EN system was also used in discriminating different vintage of wines (Di Natale, C., et. al., 1995). Investigation into the quality meat freshness was also conducted using single semiconductor gas sensor (Funazaki, et. al., 1995). EN was employs an array of inexpensive commercial tin-oxide odours sensors to analyze the state of ripeness of bananas (Llobet, et. al., 1999). Studies to discriminate the alcohol and tobacco odours were tried using tin oxide (SnO_2) sensors (Shurmer, et. al., 1989). The TiO_2/rutherium sensor was used to detect tri-methylamine, a compound responsible for fish freshness (Egashira, et. al., 1990). The EN system was also applied in classification and characterization of olive oils and vegetable oils (Guadarrama, et. al., 2000; Martin, et. al., 2001). Besides, the application of artificial olfaction EN covers not only the food processing industries but also in the biomedical fields (Gardner, J. W et. al., 2000), where EN was proposed for diagnose of illness. EN *system was also used to detect cyanobacteria in water (Gardner, J. W., et. al, 2000). The* potentiality of such work is due to the fact that human tasting may be inaccurate, laborious and unhygienic. Therefore an EN can be thought as a better alternative than conventional methods for tea olfaction and quality monitoring as it is a fast, reliable, and robust technology. It has the potential for the real time monitoring of aroma at specific sites in the field over hours, days, weeks, or even months. It can also circumvent many other problems associated with the uses of human panels. For example, the most important advantage of EN is in analysing capability of the odours that are too complex for conventional techniques. Human being can't smell until the odour concentration reaches 50 parts per million (ppm) but EN sensor can be designed to sense even 1 ppm. It can be designed to sense a particular odour, which is not in the case of human beings. Another advantage of EN is it doesn't get tired or sick. Moreover, unlike the human beings, the EN is not affected by the factors such as fatigue, working condition, emotional state, compensation etc.

5.3 **EN technology: an overview**

The EN is a system consisting of three functional components that operate serially on an odorant sample, a sample handler, an array of gas sensors, and a signal processing sub-system. Figure 5.1 shows the conventional schematic of the EN system used for the aroma profiling. The function of the EN is to identify an odorant and to discriminate it from other different samples. Therefore the output of the EN can be the identity of the odorant, or characteristic properties of the sample, an estimate of the concentration of the odorant, or the characteristic properties human might perceive the odour to be.

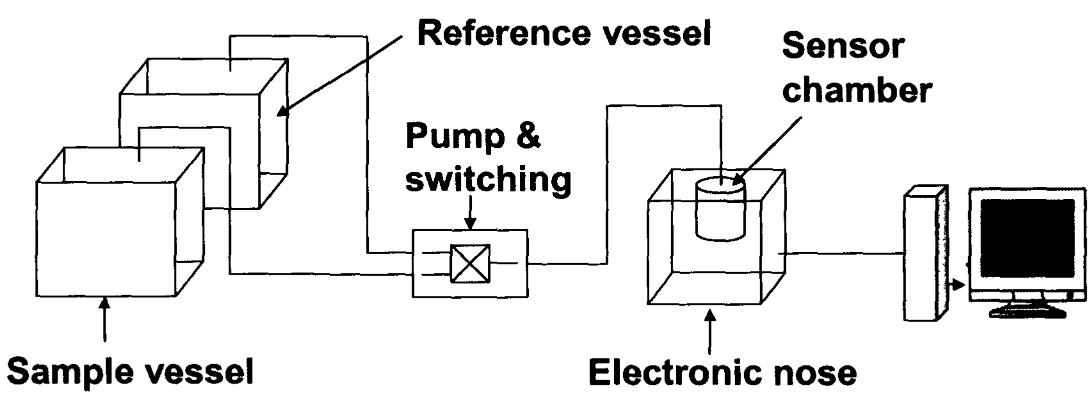


Figure 5.1 Schematic of EN system

5.3.1 **Sample handler**

The sample handler of EN is the necessary arrangement to transport the odourant molecules of a sample from the sample collection device to the contact of the sensor headspace. It consists of an interface unit, the data acquisition card installed in the computer, and the necessary software for recording the signals generated by the sensors and transfers them to the computer. The interface unit needs to control a valve also, which allows the odour molecules to pass in accordance with the user's requirement. Usually, two vessels are used (Figure 5.1) as sample and reference vessels respectively. The sample, whose aroma is to be detected, is put in the sample vessel and distilled water is introduced in the reference vessel. In using the reference vessel, it generates a stable baseline signal and reduces the chances of interference from unwanted aroma (Gardner, et. al., 1994). Moreover the room temperature and humidity may affect the sensor voltages and so may be useful parameters.

5.3.2 **Sensor array**

Fundamental to the artificial nose is the idea that depends on the odour problem. Electronic nose sensors fall into five categories: conductivity sensor, piezoelectric sensors, MOSFETs, optical sensors, and spectrometry-based sensing methods. There are two types of conductivity sensors: metal oxide sensors and conducting polymer sensor, both of which exhibit a change in resistance when exposed to volatile organic compounds. Of the two types, metal oxide semiconductors have been used more extensively in electronic nose instruments and are widely available commercially. Typical offerings include oxide of tin, zinc, titanium, tungsten, and iridium, doped with a Nobel metal catalyst such as platinum or palladium. These categories of metal oxide semiconductor based EN is mostly available commercially also and most of the researches mentioned in section 5.2 are done using such sensors. This is because of its high performance in terms of chemical sensitivity and ease of to fabricate as an array of sensors. Each sensor of the EN has different sensitivity and therefore it is able to discriminate between different compositions. Although many metal oxides show gas sensitivity under suitable conditions the most widely used material is tin-oxide, SnO_2, doped with small amount of catalytic metal additives such as palladium or platinum (Gardner, et. al., 1999). The sensitivity has been changed by changing the choice of the catalyst and operating conditions so that they become sensitive to a range of specific odours.

On the other hand, the conducting polymer sensors, a second type of conductivity sensor, are also commonly used in electronic nose systems. Here, the active material is a conducting polymer from such families as the polypyrroles, thiophenes, indoles, or furans. It is the semi-conducting polymer film coated to adsorb specific species of molecules. Changes in the conductivity of these materials occur as they are exposed to various types of chemicals, which bond with the polymer backbone. The bonding may be ionic or, in some cases, covalent. Since conducting polymer sensors operate at ambient temperature, they do not need heaters and thus easier to make. The electronic interface is straightforward, and they are suitable for portable instruments. The sensors can detect odors at sensitivities of 0.1 ppm, but 10 to 100 ppm is more usual. But, it is found to be disadvantageous in some cases of aroma profiling as conducting polymer sensor based EN is highly sensible to humidity.

5.3.3 **Pattern recognition**

The task pattern recognition stage of EN is to identify an odorant sample and to estimate the concentration of the aroma. These two steps are further subdivided into four sequential stages: Preprocessing, feature extraction, classification, and decision-making. Preprocessing compensates for sensor drift, compresses the transient response of the sensor array, and reduces sample to sample variations. Feature extraction has two purposes: to reduce the dimensionality of the measurement space, and to extract information relevant for pattern recognition. This dimensionality reduction stage projects the initial feature vector onto a lower dimensional space in order to avoid problems associated with high-dimensional, sparse data sets etc. The resulting low-dimensional feature vector is then used to solve a given prediction problem, typically classification, regression, or clustering. Moreover, optimum feature extraction removes a major portion of redundant data, which behave as noise in the signal. Once the aroma samples have been projected on an appropriate low dimensional space, the classification stage can be 'trained' to identify the patterns that are representative of each odour. When presented with an unidentified aroma, the classification stage is able to assign to it a class label (identify the odorant) by comparing its pattern with those compiled during training. A final decision-making stage is used if any application specific knowledge is available, such as confidence thresholds or risk associated with different classification errors. So, the pattern recognition stage is the most important parts of EN, which handles the data gathered by the sensors array.

5.4 The EN experiment on tea

The EN used in this research is comprised of four different SnO_2 sensors, commercially available manufactured by Figaro Engineering Inc. (Japan). These are chosen on the basis of their probability of response to the basic aroma of the samples. Among them, the sensor TGS 822 has high sensitivity to the vapors of organic solvents as well as other volatile vapors. It also has sensitivity to a variety of combustible gases such as carbon monoxide, making it a good general-purpose sensor as applicable to the purpose of food vapour recognition. The sensor TGS 880 is sensitive to cooking vapours. The tea samples are prepared by adding boiled water so as to produce as much vapour as possible from them. On the other hand the other two sensors, viz., TGS 825 and TGS 826 are sensitive to the toxic gases hydrogen sulphide (H_2S) and ammonia (NH_3) respectively. These sensors are used so that they can detect any unwanted aroma present in the tea samples. But though the sensors are most sensitive to a particular odour or a set of particular odours, it is sensitive to some other odours also. Moreover, the sensors are different in the range of typical detection capability (concentration of odour) specified as ppm. Table 5.1 lists the sensors along with their main characteristics.

Table 5.1 The list of SnO_2 sensors along with their manufacturer and sensitivity.

Sensors		TGS 880	TGS 826	TGS 825	TGS 822
Main characteristics	**Sensitive to**	Cooking vapours	Toxic gases NH_3	Toxic gases H_2S	Organic solvents. Alcohol, toluene, xylene, etc
	Range (ppm)	10 to 1000	30 to 300	5 to 100	50 to 5000

5.4.1 Tea samples for EN sniffing

Most of the current EN systems use 1 of k odour representation schemes. In this scheme a specific class of odour is to be determined to the seclusion of all other classes specifies a certain odour. Though the scheme provides only comparative descriptions and does not use any absolute standard, it is the initial process to generate an aroma profile of a certain product. This is the situation that faced while the researchers start to analyze the tea aroma. It was mentioned in section 5.1 that tea odour description would be via comparison with other prototypical and ambiguous odours due to lack of any absolute aroma standard. Therefore the organoleptic decision of tea aroma is most useful in developing an EN based aroma declaration or decision. Such observations are paid much attention in the data processing stage and try to correlate the knowledge of existing aroma profiling methods with the EN based methods. Figure 5.2 shows the schematic of the basic idea of correlating the EN data and the organoleptic decision on tea grades. It is observed that though the organoleptic decision is based on the existing flavour terminology, the experiment described here is accounting only EN aroma profiling, not the other taste and astringent attributes. The taste and astringent may be analyzed using Electronic Tongue (ET) as analogous to EN, which is to be addressed in future study.

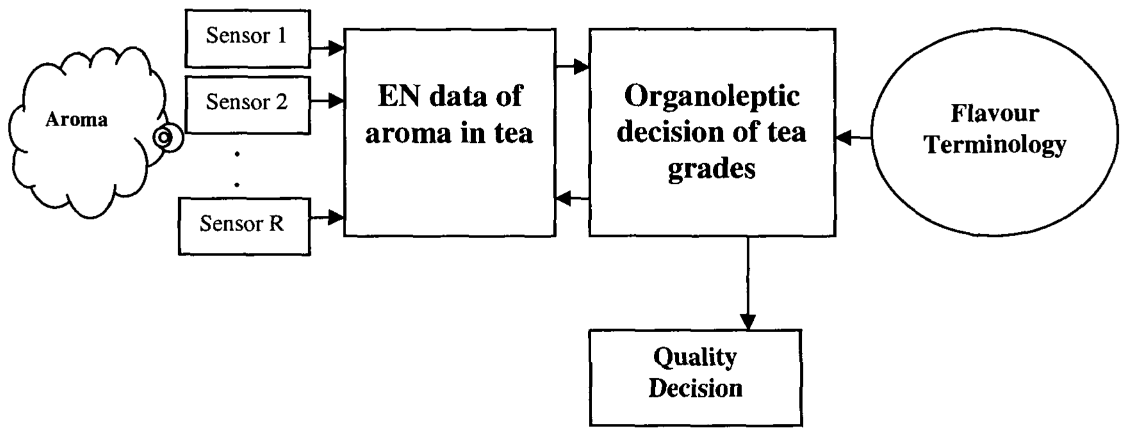


Figure 5.2 Multi sensor tea aroma data correlating the organoleptic decision

Thirteen different grades of tea of different qualities (randomly selected) of three different tea gardens (Comaibund, Tamulbari and Geleky) of Assam, India are used for the experiment. The grades are namely BOP, BOPS, BOPL, BOPSM, BP, PD, PF, and Dust. Some common grades of different tea gardens are considered for system justification and comparison. The raw samples used for this run of the experiment are listed as follows:

- BOP : Comaibund, Tamulbari
- BP : Comaibund, Geleky
- BPS : Comaibund, Tamulbari
- BOPSM : Tamulbari
- PD : Comaibund, Tamulbari
- PF : Comaibund, Tamulbari
- BP(F) : Geleky
- Dust : Comaibund

The sensory panel judgments of aroma shows some of the samples are assigned with the same score though they are of different grades from different tea gardens and vice versa. There are two steps of aroma profiling adopted by the tea tasters. One is scoring out of 10 ranges, which provides the strength of the aroma. The statistical study shows that the tea tasters usually score in the range of 4 to 10 in accordance with its aroma if the sample is tea. That means, the scores 1 to 3 are not accounted by the tea tasters for ea tasting. But it comes into scenario if the sample is something other than tea, for example aroma of distilled water. The next step is categorizing the teas in terms of the variability of the aromas. Some commonly used terms are: fresh floral, sweet floral, citrus, sweet fruity, fresh green, sweet, resinous, roasted, dimethyl sulfide-like, green, burned, acidic, fermented, oily, earthy and moldy. The valuation and pricing of the final product is determined by accounting the other flavour attributes along with these two steps of aroma profiling. The collected samples that are divided into seven different categories by the sensory panel are shown in Figure 5.3. The quality of the tea grades are categorized from highest quality towards lowest quality from top to bottom as in the figure. The information of sensory panel judgments may be useful in terms of correlating them with the EN based data analysis. It was mentioned earlier that the aim of this research is to explore the possibility of use of EN system in discriminating the aroma profile of tea. But the comparative study of sensory panel analysis and the EN based aroma profiling is also worthwhile in terms of standardization of the tea aroma. The aroma standardization process by EN system will be addressed in some future work.

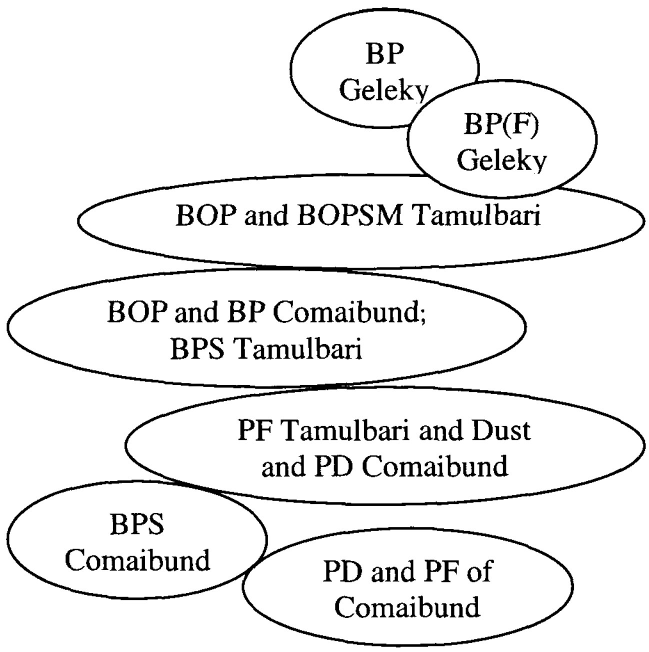


Figure 5.3 Organoleptic categories of the selected tea grades for the EN experiment.

5.4.2 EN sniffing of tea samples

Statistical study, among the tea tasters and tea brokers, reveals that the best way of sniffing tea aroma is from the tea liquor. This is actually the conventional tea making process in most of the time. Hot water is added with a specific amount of tea in making tea liquor. This is the main procedure used by the tea tasters for sniffing the tea aroma, i.e., having 'nose' to provide quality judgments. In analogous to this method of sniffing, the samples are prepared picking 1.5Gms each from each of the selected tea grades for the EN sniffing also. The tea liquor is produced from each by adding 200ml of boiled distilled water to each of the samples. Hot distilled water is also used as the reference vapour in the separate reference vessel.

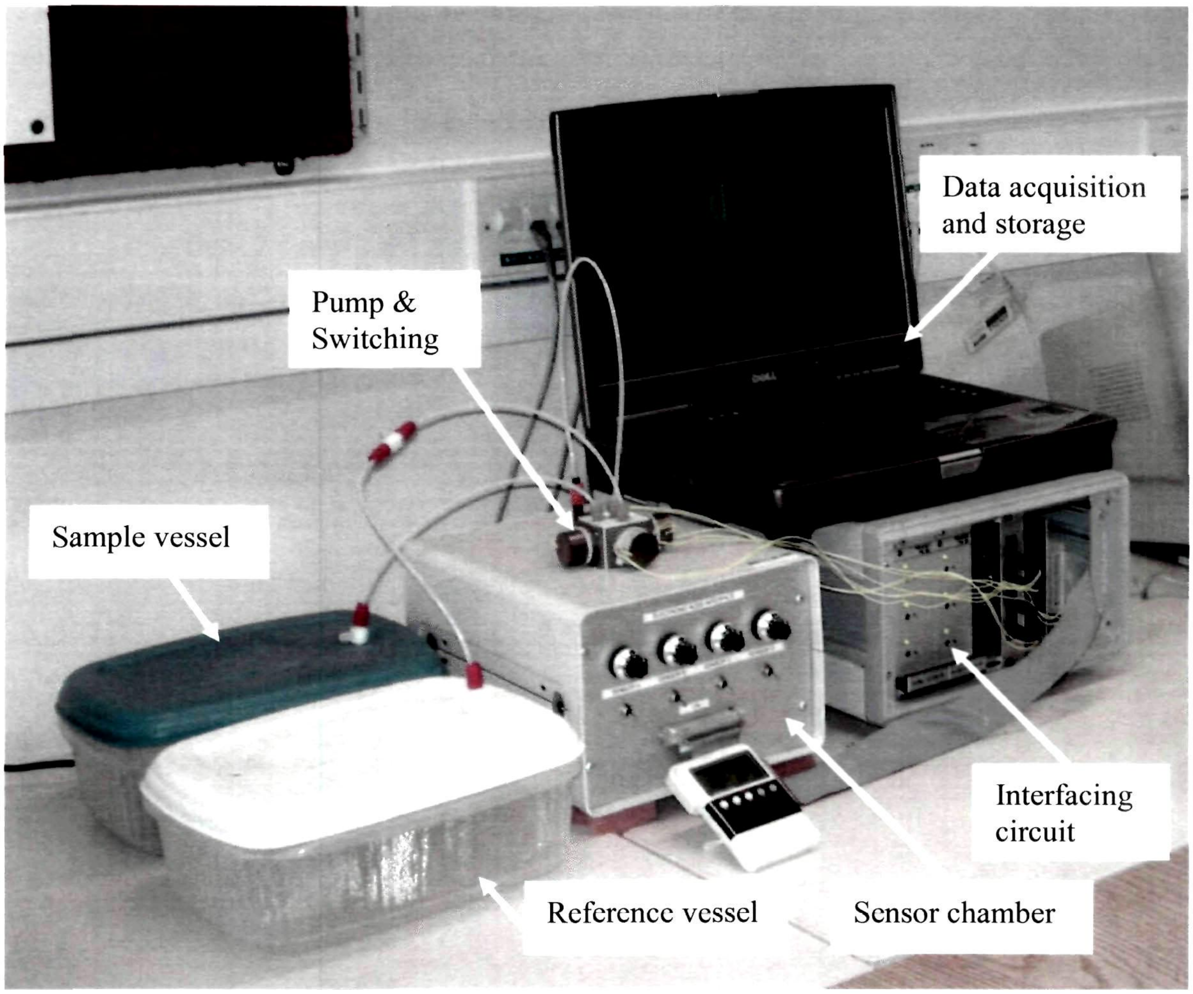


Figure 5.4 The EN setup used for tea aroma sniffing

Figure 5.4 shows the photograph of the experimental setup at Intelligent System Engineering (ISE) laboratory, School of Engineering, the University of Warwick. Thin plastic tubes are connected from input to the sensor chamber for transporting the aroma. A diaphragm pump is used to facilitate the sampling of the headspace of the vessels. The data acquisition and storage systems are controlled by using the LabVIEW© software (National Instruments Inc).

Throughout the EN tea aroma sniffing, tea aroma of each tea sample is injected into the EN sensors headspace for 20 complete cycles. The duration of each cycle is set to be 600 seconds. There are 20 other cycles also in which the vapour of distilled water from the reference vessel are injected into the sensor headspace. These cycles are also of 600 seconds duration. The pumping frequency is set with sampling time of 1 second for the whole experiment. The sniffing process follows the following sequences:

(i) Injection of vapour into the sensor headspace from the reference vessel.

(ii) Injection of tea aroma into sensor headspace from the sample vessel.

(iii) Repeat the processes (i) and (ii) for twenty cycles each.

This means the sniffing process continues sequentially and the pump injects the vapour from either sample vessel or reference vessel alternately one at a time. The pumping from reference vessel vapour of 600 seconds duration are found sufficient to bring the sensors back into their baseline between two consecutive cycle of tea aroma sniffing. It makes sure that the EN system responds to the tea aroma only rather than any residual smell of the surroundings. Figure 5.5 shows a response curve obtained during EN sniffing of tea samples.

It is observed in the curve that it increases exponentially in sniffing the tea samples and decreases for reference odour (distilled water). The sensor responses are continuously monitored and stored in data files for the purpose of subsequent data processing off line. The response curves of thirteen samples one each from thirteen different tea grades are produced in Appendix B.

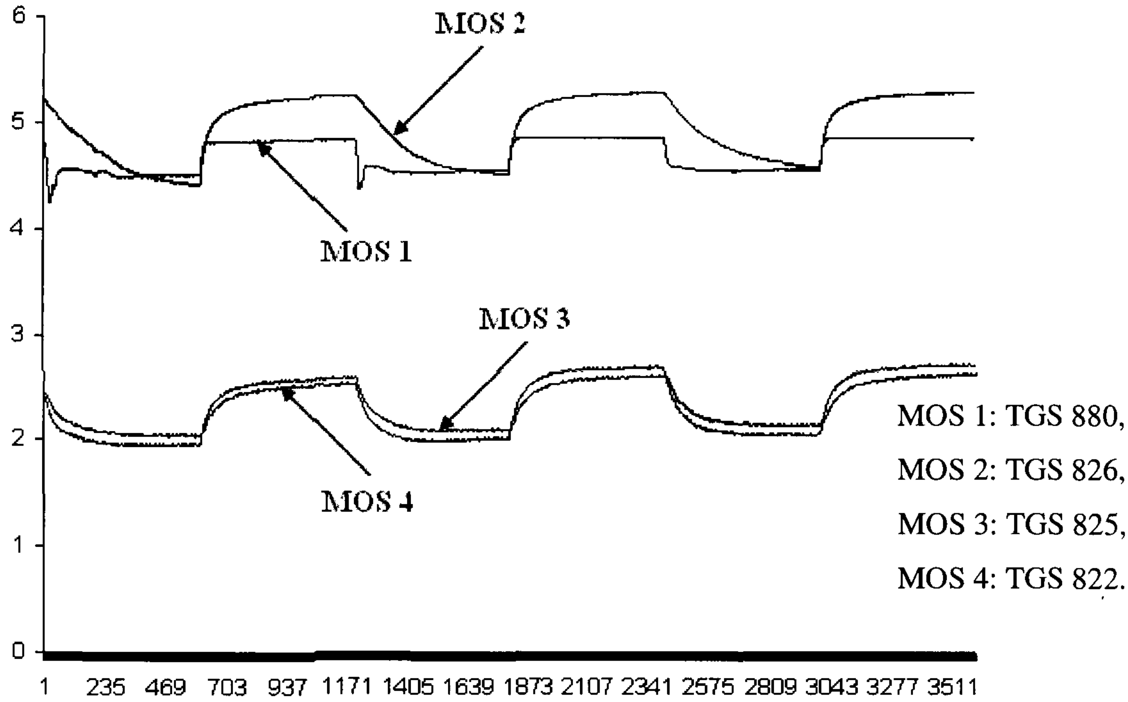


Figure 5.5 EN sensors response curve.

5.4.3 Data processing

In the conventional EN setting, researchers typically gather data and extract the useful features and then adopt statistical methods to analyse them. Recently, novel techniques such as neural network, fuzzy logic and genetic algorithms have been applied to help in the improvement and effectiveness of the data classification techniques (Hines et al., 1999) by, for example, extracting key features and relevant information in order to draw the best conclusions. The aim of the data processing is the direct representation of the knowledge and information contained in the data set in a systematic way. Finally such approach contributes to the EN sniffing of tea samples in order to help the researchers to find more universally acceptable aroma terminology for quality monitoring.

Data processing is a general concept with a lot of implications; however techniques can be divided into two broad approaches. Firstly, algorithmic or parametric methods are function based conventional methods based on mathematical analysis requiring a complete knowledge of the system to be modeled [for example PCA]. These techniques require the intervention of the expert's skill. Such data visualization techniques are most useful to analyze the nature of the data set. On the other hand the intelligent system approaches model a system knowing the input parameters, and sometimes the desired corresponding output parameters. The PCA analysis is adopted at the first instance and described in next section. The next useful approach is data clustering and it is concerned with separating the data set into a number of desired groups, called clusters. But data clustering is an unsupervised learning technique that process data in terms of structural and spatial relationships and similarity among them. The K-Mean (Bezdek, et. al., 1981), and SOM (Kohonen, 1990) based data clustering are mostly used clustering techniques in EN based research as is evident in the scientific literature. Finally, the aim of this research goes mainly in implementation of intelligent system techniques. Such systems extract the knowledge from the data set in supervised manner in order to model a system so that the model can be used latter on for decision making purpose (tea quality monitoring, in this research). In this context, Back propagation MLP (Rumelhart, et al., 1986), RBFN (Haykin, 1999), CPNN (Berthold et al., 1998) and LVQ (Kohonen, 1990) learning algorithms offer attractive framework for the incremental construction of near-minimal neural network architecture for such research. These algorithms are implemented, in this research, with the EN tea data set and explore the usefulness of such intelligent system engineering techniques and the possibility of implementing them in quality monitoring in terms of the aroma profile of tea.

5.4.3.1 **Signal preprocessing**

As mentioned earlier, a major drawback with the sensors employed in the EN is drift in the signals. Some possible reasons are sensor headspace, difference of temperature, change of humidity etc. The analysis of tea aroma by EN can be problematic as the composition of the headspace is monitored rather than the sample itself. The concentration of the headspace of a particular substance is related to the vapour pressure and to the liquid-phase concentration of the substance. This means that the more volatile compounds are present in greater quantities in the headspace and may not be a true reflection of the composition of the sample itself. Although most of the drift effect is overcome by using the reference material (distilled water in this case), variation of the sensor output remains in different cycles of the sniffing. The second possible reason for drift in this experiment is the water is boiled for preparing the samples and it gets cold as time passes. Finally, the variation of temperature and humidity of the room environment may be another reason for sensor drift. Figure 5.6 shows one cycle of EN sniffing (a particular senor response) of tea aroma along with some possible variations of the signal due to drift. The thick solid line shows the acquired signal and the thin solid lines represent the possible variation of the signal due to drift. It is observed in the Figure 5.6 that the signal may vary in different ways for the same sample and same concentration of aroma.

Therefore, the first computational stage on EN data set, called signal preprocessing, is performed to affect the performance of the pattern recognition stage. A difference model is used to compensate the possible drift in the signal. The complete tea EN data are normalized by subtracting the base line of the transient signal. That means, if R is the signal response then the difference model reveals that the actual signal as: $\Delta R = R_{DE} - R_{BF}$.

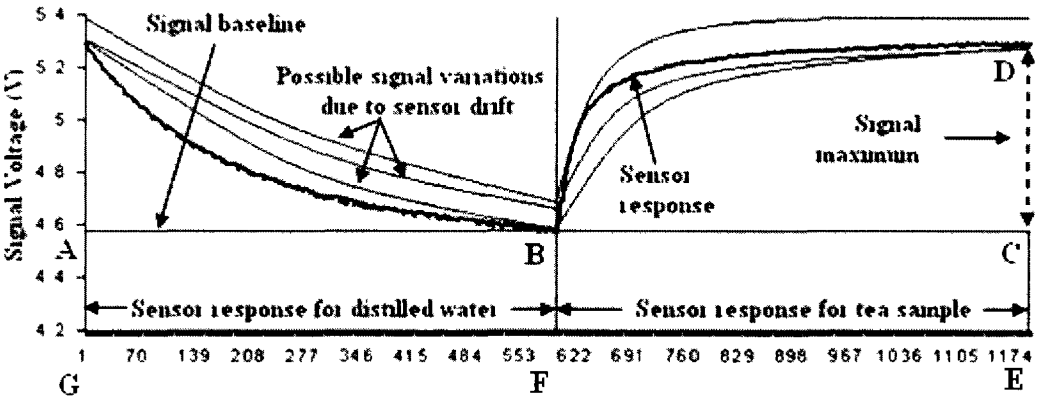


Figure 5.6. Sensor response and variations due to sensor drift

5.4.3.2 **Feature extraction**

This is the process of data analysis that carried out with the preprocessed EN sensor signals and is the most significant step, since it determines to a high degree the overall performance of the EN system. The common practice in this step is to extract the descriptive parameters from the sensor array response, i.e., feature extraction and preparing a set of feature vector for further processing. In common practice, the standard feature extraction methods obey some simple purely geometric definition. The same methods are considered in the EN tea data set feature extraction also. Two different characteristics of the response curves are selected for this purpose. These are the 'peak' and 'mean' of the transient signal acquired for the tea aroma. Here, the peak is the difference between the signal's peak and its base line (Figure 5.6); the mean is the difference between the mean transient response and the signal's base line. The area of the curves is also selected as the third feature but it produces some unwanted variations of the same samples in different times. The peak and mean, on the other hand, proves to be reliable features for the EN signal. But, it is necessary to analyze these features to determine their usefulness in discriminating the tea samples from each other. So, some data visualization and clustering techniques are carried out in the following sections.

5.4.3.3 **PCA of the data**

The principal component analysis (PCA) is selected first for visualization of the selected patterns and analysing the discriminating properties of them. PCA is one of the useful unsupervised pattern analysis techniques, widely used for such pattern visualization. It seeks to reduce the vector dimension of the data set and thus considers only the most distinguishing patterns (principal component) (Chapter II, section 2.11.1). It was mentioned in the last section that the selected features are only the mean and peak of the EN response curve for the sample. That means the length of the feature vector is eight dimensional for four different sensors used in the EN system. PCA results in three principal components from each of the vectors. Figure 5.7 shows the PCA plot of 195 different samples of 13 different categories of tea samples in 3 dimensional (3D) spaces.

The objective of the PCA was to establish the extent to which discrimination for the thirteen different types of tea samples exist. It is clearly observed in the PCA plot that some samples can be easily separated and others are less easy to separate into clusters.

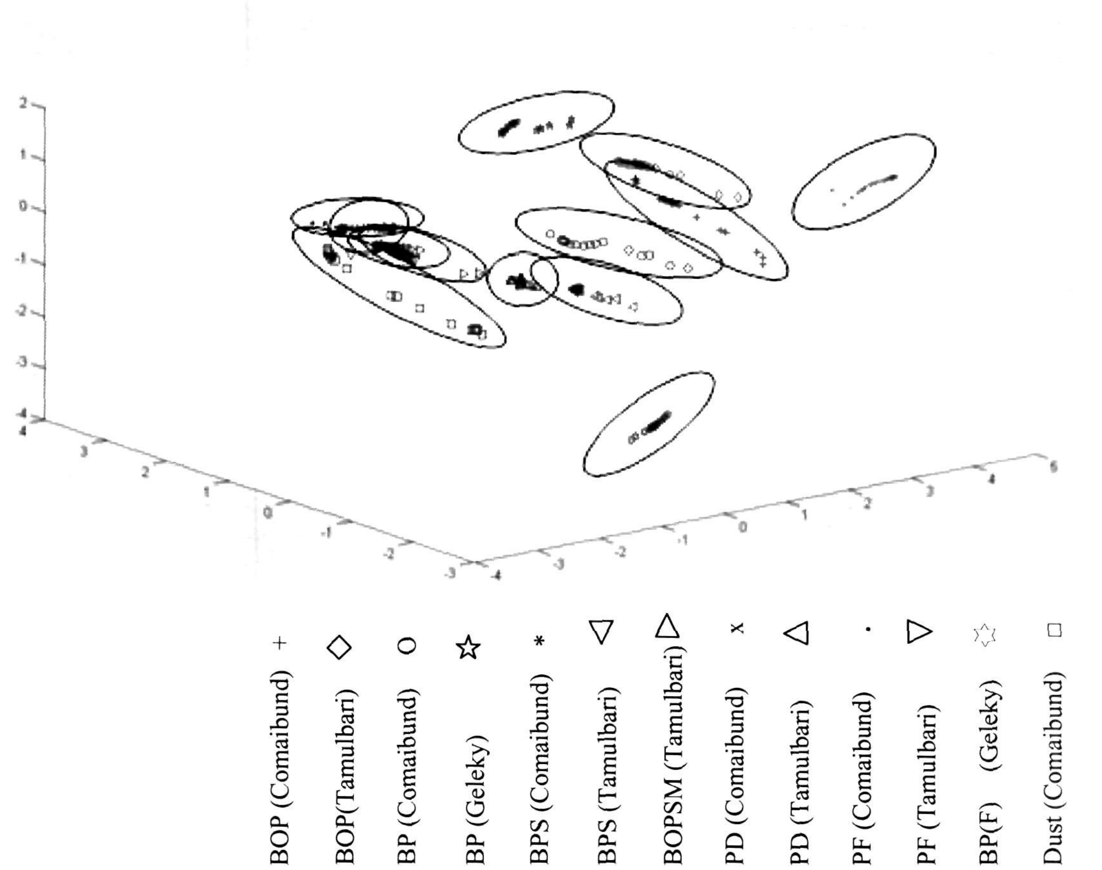


Figure 5.7 PCA plots of the EN data for thirteen tea samples and corresponding symbols.

5.4.3.4 **K-mean data clustering**

The clusters are visualized in Figure 5.8. It shows the K-means clustering of 195 different samples of EN tea data in terms of a silhouette plot. This plot displays a measure of how close each point in one cluster is to points in the neighboring clusters. It is observed that some vectors are miss-classified in these thirteen clusters using the K-means clustering algorithms.

As described, the K-mean algorithm calculates the sum-squared distances of each data point to its cluster centre and therefore provides an error associated with each cluster configuration. This method is particularly efficient at estimating the number of basis function neurons required in an RBFN (Section 5.5.2) hidden layer. Figure 5.9 gives the error associated with a number of cluster configurations for this data set. As is evident from Figure 5.9, the optimal number of clusters appears to be in between 10-20.

5.4.3.5 **SOM data clustering**

The basic idea of a SOM is to map the data patterns onto N dimensional grid of neurons or units. By definition, a SOM is a network formed by N neurons arranged as the nodes of a planner grid; so that each neuron has four immediate neighbors (Chapter II, section 2.11.2.2). The grid forms what is known as the output space, as a response to the input space, where the data patterns existed. This mapping tries to preserve topological relations, i.e., patterns that are close in the input space will be mapped to units that are close in the output space, and vice-versa. So as to allow an easy visualization, the output space is usually 1 or 2 dimensional. The SOM adopts the competitive learning method and is based on unsupervised learning. This algorithm is useful in clustering EN data as it doesn't consider the previous knowledge about the class membership of the data. Figure 5.10 (A) shows the SOM based data clustering (U-matrix) of the EN data set of 195 different samples. Similarly Figure 5.10 (B) represents the surf of the codebook generated by the SOM training of the input data.

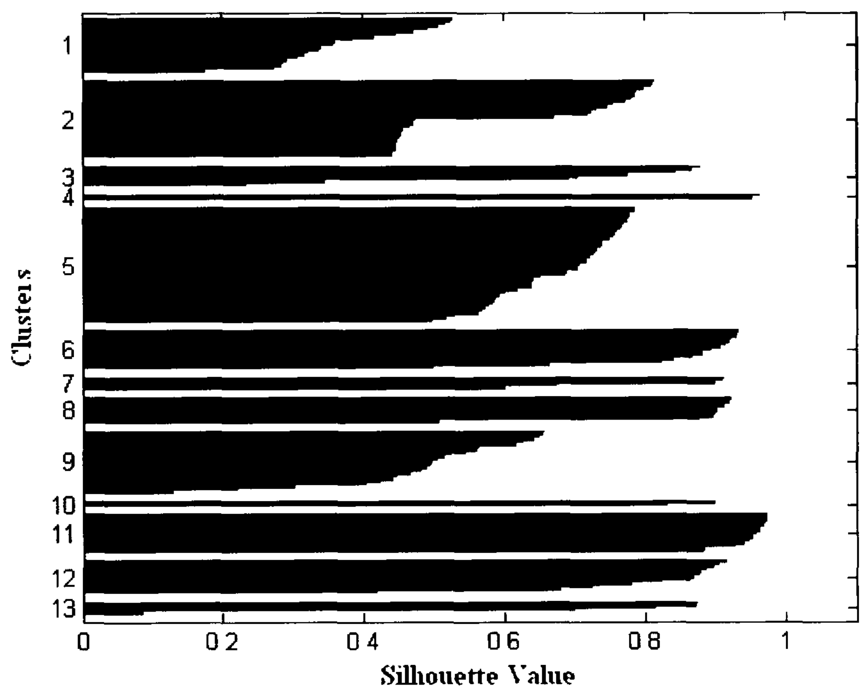


Figure 5.8 K-means clustering Silhouette plot

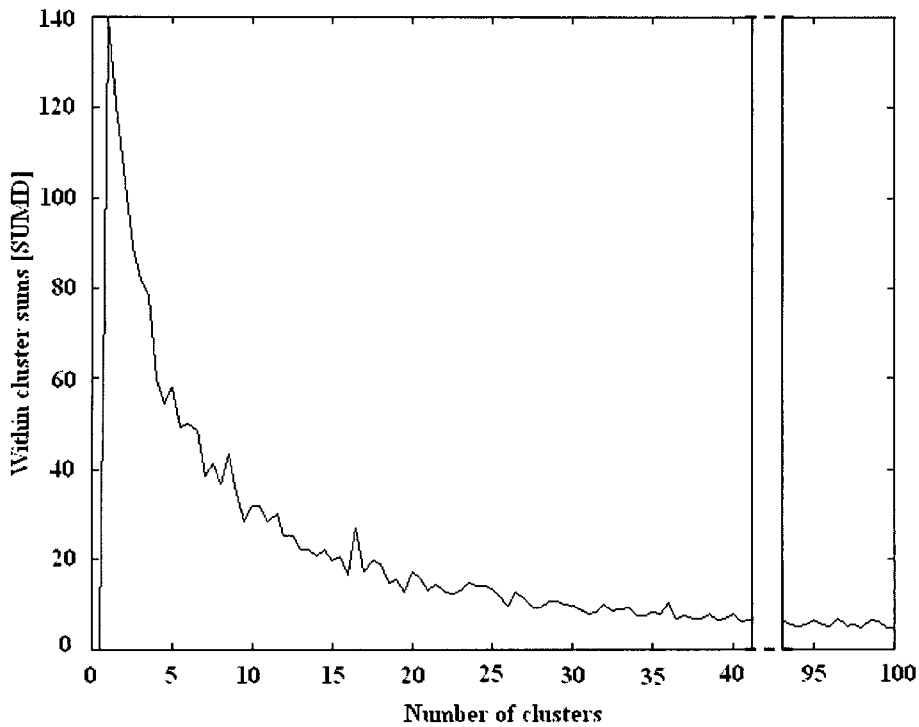


Figure 5.9 Error associated with number of clusters configurations by K-Means

It is observed that the SOM network can cluster the data set into 8 (eight) distinct clusters instead of thirteen different categories. This result is in support of the PCA plot shown in section 5.4.3.2 (Figure 5.7), where the principal components are placed in eight different places in the 3D plot. The same conclusion is observed in the organoleptic results also (Section 5.4.2, Figure 5.5). It is concluded that clustering performance is enriched in this method of clustering in comparison to the previous K-means clustering technique. Moreover, it brings the actual numbers of clusters present in a data set, as evident from the results.

5.5 Data classification

It is observed in the previous sections that the EN data can be successfully clustered by the K-mean as well as more accurately by the SOM training. It is also observed that though the data set were constructed for thirteen different samples, there are eight different verities of aroma present in the data. This fact is depicted for the classification section, which is based on the organoleptic panel decision, PCA plot and the SOM based data clustering. This is considered to be a useful finding for application in the supervised classification techniques. Having this knowledge in mind, the research is carried out to model a system to represent the knowledge directly to it so that it can be useful for further data classification process. Three different algorithms, namely MLP, RBFN and CPNN are selected from the literatures and implemented with the EN data set. The working principle the algorithms and their corresponding performances on tea EN data are described in this section.

5.5.1 MLP

Two MLP networks (The number of layers is set to 2) are tasted so that one transforms the 8 input neurons (features) to 13 output neurons using Bayesian Regulation back propagation. Whereas, the second one transforms same 8 input neurons to 8 output neurons (as is evident from the organoleptic, PCA and SOM results). The network structures are shown in Figure 5.11. The weights are trained with the error feed-forward back propagation algorithm. The activation functions for the neurons in the hidden layers (8 neurons, in both the cases) employ the sigmoid function.

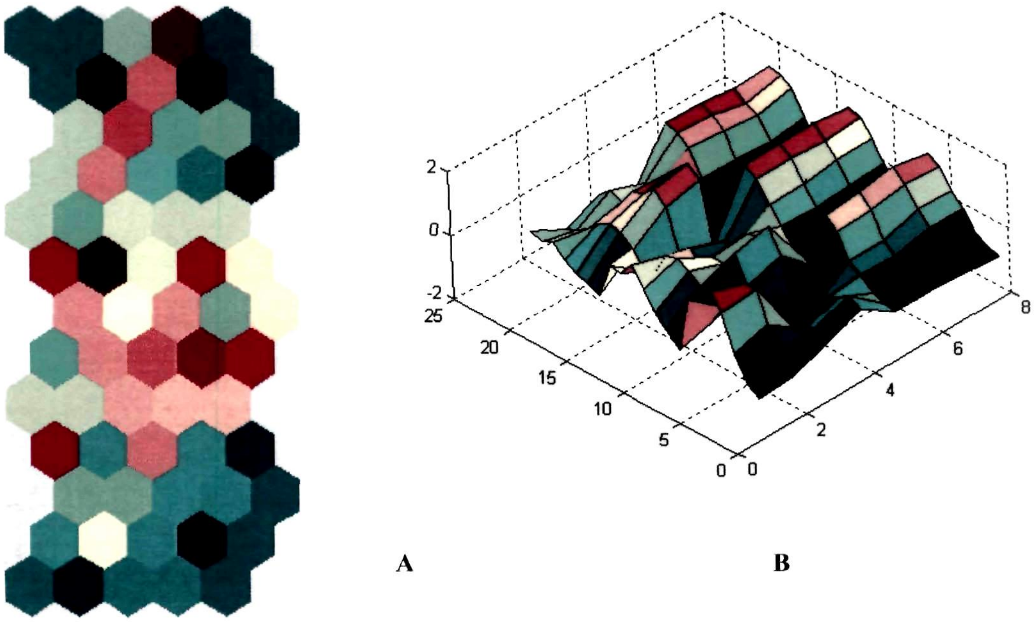


Figure 5.10 (A) SOM U-matrix, and (B) Surf representation of SOM codebook.

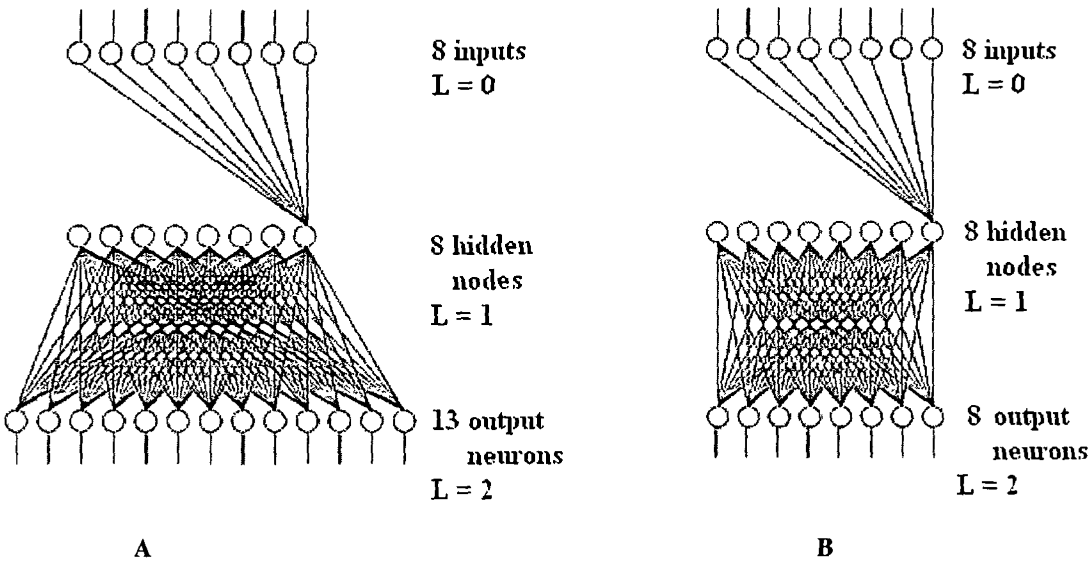


Figure 5.11 Architecture of MLP networks; (A) 8:13 network, (B) 8:8 networks.

It is observed that the network has very low computational complexity as training took <5 minutes in 3GHz CPU. While using with 195 training samples and 65 testing samples, the 8:13 network results in 61.54% accurate classification. On the other hand, the 8:8 network outperforms the with 90.77% accurate classification on the same data set.

5.5.2 **RBF**

The RBF network has been proven as a good approach for interpolating scattered data and has been applied in various fields. The approach is the feed forward connectionist architectures consisting of 10 hidden neurons of radial kernels and an output layer of linear neurons. Each hidden neuron in an RBF is tuned to respond to a local region of feature space by means of a radially symmetric Gaussian function. It can be seen that the radial basis functions form Gaussian component densities that are used in conjunction with a Gaussian mixture model (GMM). The result of this GMM is a system that similarly attempts to estimate the probability density functions. Figure 5.12 shows the structure of the network.

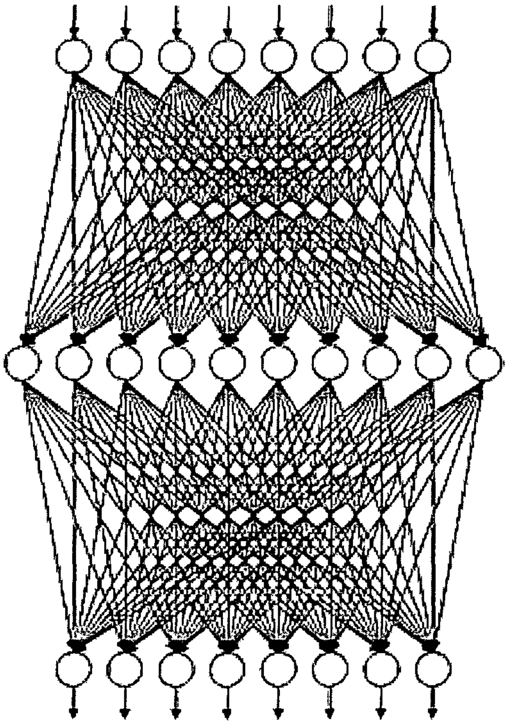


Figure 5.12 RBF network for EN tea data classification

The RBF is trained using a hybrid algorithm that employs unsupervised learning for the hidden layer followed by supervised learning of the output layer. The RBF is trained and tested for the data set used for previous techniques. It is observed that the RBF classify the test sample with 92.31% accuracy.

5.5.3 CPNN

The CPNN takes the given number of input in its input layer, whereas the output classes are represented by Gaussian components with predefined probability density function (PDF). By definition, the basic PNN consists of four layers, namely input layer, pattern layer, summation layer and output layer. Figure 5.13 shows the structure of the CPNN for the 8 input and 8 output neurons for the EN tea data set. Here, the second layer forms the product of the input vector (supplied from the first layer) and its weight vector, whereas the third layer calculates the PDFs for each pattern. The fourth layer classifies an input pattern into one of the possible classes based on the third layer output. But this model is not well suited for the large dataset as it saves each training vector as one pattern unit. Therefore, this shortcoming is accounted for by using the CPNN; by considering each Gaussian component in the pattern layer to be a cluster centre of a group of similar input vectors; which reduces the number of Gaussian components.

The training and testing of the CPNN was performed depicting the knowledge of 8 data clusters in the EN tea data. It is observed that the network created 29 hidden neurons (out of 195 maximum) during training, which suggests that, the dataset exhibited heterogeneous clusters. While tasted with 195 training samples and 65 testing samples, it results in 93.85% accurate classification.

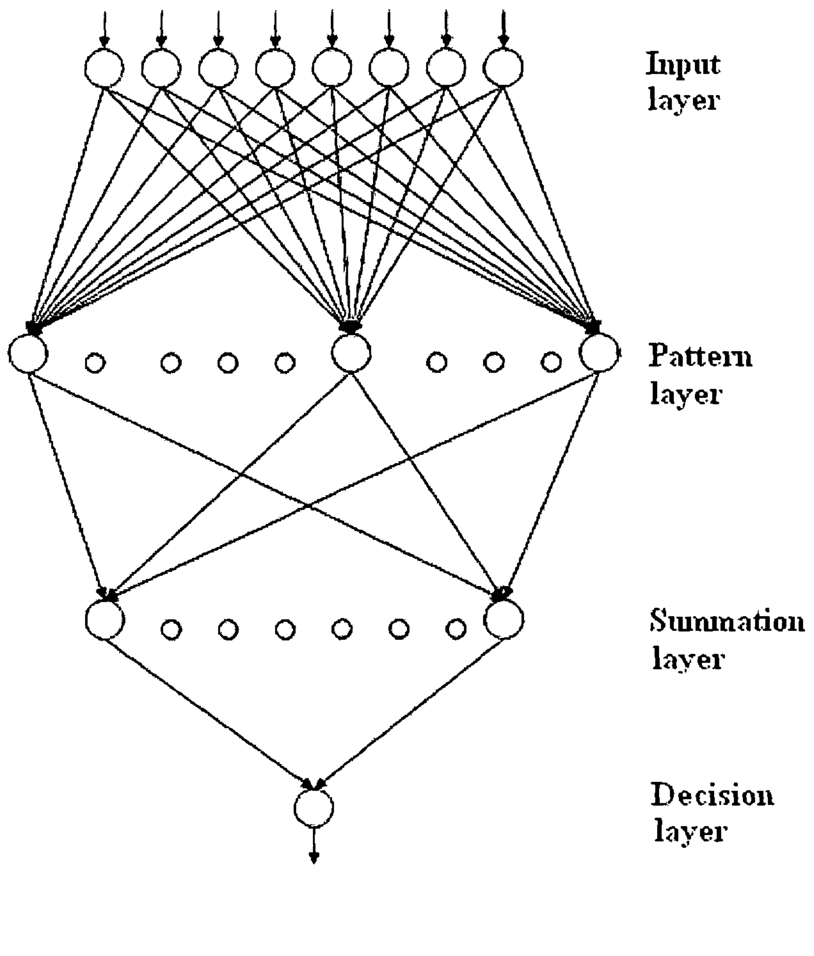


Figure 5.13 CPNN structure for 8 input and 8 output neurons.

5.6 Summery

It is understandable that although tea quality is evaluated on a number of parameters, an attractive aroma is essential for good quality tea. Indeed, the composition and concentration of aroma compounds has been shown to play an important role in the valuation and pricing of tea. Efficient grading requires high degree of sensing and proper intelligence for accomplishing the classification. Black tea is a high value crop with a world market. Experienced tea tasters have been traditionally ensuring the grading judgment of different qualities of tea. However, as in the other food industry generally, tea research associations seek to modernize their quality monitoring process in scientific way to satisfy a market driven by customer demands with products with greater differentiation. In consequence, they are interested in the possibilities of on-line monitoring of the sorting / grading process using computer vision, artificial olfaction and artificial tasting. In view of the disadvantages of manual methods a novel approach by using EN system is applied in this research for aroma profiling.

This research is mainly aimed towards exploring an efficient model for quality monitoring in terms of aroma. In this view, some tea samples are selected that are based on the organoleptic judgments. Sensors are selected in terms of the VOCs present in tea, though it has been a trial and error process. EN sensed data sets are tested for differentiability in terms of statistical analysis methods, for example PCA. Furthermore, it is a common interest of the pattern recognition technique in merging the common patterns altogether for the sake of high degree of accuracy in recognition. For this purpose data set are allowed to cluster in unsupervised manner. K-mean and SOM based data cluster techniques are adopted. It is observed that the K-mean technique clusters the data into the appropriate numbers of groups but some misclassifications are observed in this case. On the other hand SOM clustered the data set into 8 different clusters though it was originally taken as 13 different samples. But the SOM clustering supports the organoleptic judgments and the PCA analysis of the same samples. In that sense, SOM is found useful in terms of its judgment of data differentiability of the tea EN data. Moreover, the classification techniques also support this fact of fewer clusters. For example, classification accuracy of the MLP is 61.54% only while considering the number of clusters as 13.

Though the intelligent system techniques are proven to be useful in applying the EN in tea aroma classification, this is not enough for the aroma profiling of tea. This is because the EN research is carried out with the samples that are based on the subjective decision of the organoleptic panel of tea industry. The EN data is not correlated with the chemical composition, which is based on chemical analysis. Therefore it is difficult to draw a specific conclusion of such research that is not based on chemical analysis of the VOCs. Though it is found that a good correlation exists between the organoleptic judgments and the EN based systems, one can't predict about the efficiency of EN benchmarking against the subjective methods. Therefore, the correlation of the EN system based aroma analysis with chemical analysis of the VOCs may be more appropriate method for evaluating the performance accuracy of the EN system. But as an initial step in applying EN to tea samples, the work carried out in this research explores its potentiality in sniffing for tea quality judgments. So, for further judgments of the EN systems in terms of the VOCs present in the samples would be the chemical analysis and that may be one of the future prospects of justifying the EN system in more accurate way. Moreover, the application of the EN during the processing stage, for example the fermentation process, is also has high potentiality of such EN based research. On the other hand, the sensors used in this research for tea aroma sniffing are not specifically made for tea aroma. Rather, the sensor selection process is based on the trial and error method. So, devising the sensor type, which shows high sensitivity to the tea aroma, may also offer future prospects. Lastly, the on-line sniffing and recognizing capability of EN system may be the final goal in terms of cost effectiveness real-time application. Therefore, devising real time circuitry for sample handler and pattern recognition may be one of further work in this area of research.

References

1. Aishima, T., 1991. Aroma discrimination by pattern recognition analysis of responses from semiconductor gas sensor array. Journal of Agricultural Food Chemistry, Vol. 39, pp 752-756.
2. Bezdek, J. C., 1981. Pattern Recognition with Fuzzy Objective Function Algorithms, Plenum Press.

3. Anklam, E., Lipp, M., Radovic, B., Chiavaro, E., Palla, G., 1998. Characterisation of Italian vinegar by pyrolysis-mass spectrometry and a sensor device (Electronic nose). Food Chem, Vol. 61, pp 243–248.
4. Bulletin on Tea Tasting Terms of Tocklai Tea Research Station, Jorhat, Assam, India –Serial No. 69/2 copyright- Nov'1992.
5. Bartlett, P. N., Elliot, J. M., Gardner, J. W., 1997. Electronic noses and their application in the food Industry, Food technology, Vol. 51, pp 44-48.
6. Bhuyan, M., Borah, S., 2001. Use of Electronic Nose in tea Industry, Proceeding of International Conference Energy, Automation and Information Technology (EAIT01), IIT Kharagpur, India, pp 848-853.
7. Borrounet, B., Talou, T., and Gaset, A., 1995. Application of a multi-gas sensor device in the meat industry for boar taints detection. Sensors Actuators B, Chemical, Vol. 26-27, pp 250-254.
8. Natalie C, D, Davide FAM, D'Amico A, Sberveglieri G, Nelli P, Faglia G, and Perego C 1995. Complex chemical pattern recognition with sensor array: The discrimination of vintage years of wine. Sensors Actuators B. Vol. 24-25, pp 801-804.
9. Egashira M, Shirnizu Y, and Takao Y 1990. Trimethylamine sensor based on semiconductive metal oxides for detection of fish freshness." Sensors Actuators. B, Vol. 1, pp108-112.
10. Eklov, T., Johnsson, G., Winquist, F., Lundstrom, I., 1998. Monitoring sausage fermentation using an electronic nose. J. Sci. Food. Agric. Vol. 76, 525–532.
11. Funazaki, N., Hemmi, A., Satoshi, I., Yasukazu, A., Yano, Y., Miura, N., and Yamazoe, N., 1995. Application of semiconductor gas sensor to quality control of meat freshness in food industry." Sensors Actuators B, Chemical, Vol. 24-25, pp 797-800.
12. Guadarrama, A., Rodriguez-Mendez, M. L., Saja, J. A., Rios, J. L., Olias, J. M., 2000. Array of sensors based on conducting polymers for the quality control of the aroma of the virgin olive oil, Sensors and Actuators, B: Vol. 69, pp 267-282.
13. Gardner, J. W., Bartlett, P. N., 1999. Electronic noses principles and applications, Oxford University press, UK.

14. Gardner, J. W., Bartlett, P. N., 1994. A brief history of electronic noses, Sensors and Actuators B, Chemical, Vol. 18, No.1-3, March, pp 210-220.
15. Gibson, T., Prosser, O., Hulbert, J., Marshall, R., Corcoran, P., Lowery, P., Ruck-Keene, E., Heron, S., 1997. Detection and simultaneous identification of microorganisms from headspace samples using an electronic nose. Sensors Actuators B. Vol. 44, pp 413–422.
16. Gardner, J. W., Shurmer, H. V., and Tan, T. T. 1992. Application of an electronic nose to the discrimination of coffees, Sensors and Actuators B: Chemical, Vol. 6, No. 1-3, pp 71-75.
17. Gardner, J. W., Shin, H. W., Hines, E. L., and Dow, C. S., 2000. An electronic nose system for monitoring the quality of potable water, Sensors and Actuators B: Chemical, Vol. 69, Issue 3, 25 October 2000, pp 336-341
18. Gardner, J. W., Shin H. W., and Hines, E. L., 2000. An electronic nose system to diagnose illness, Sensors and Actuators B: Chemical, Vol. 70, No. 1-3, 1 pp 19-24.
19. Horie, H., Fukatsu, S., Mukai, T., and Kawanaka, T. G. M., and Shimohara, T., 1993. Quality evaluation on green tea, Sensors and Actuators B: Chemical, Vol. 13, No. 1-3, pp 451-454.
20. Hines, E. L., Llobet, E., and Gardner, J. W., 1999. Electronic noses: a Review of Signal Processing Techniques, IEE Proceedings Circuit Devices Systems, 146 (6).
21. Kohonen, T., 1990. The self organizing map, Proceeding of IEEE (special issue on Neural Network), Vol. 78, No. 9, pp 1464-1480.
22. Llobet, E., Hines, E. L., Gardner, J. W., Franco, S., 1999. Non-destructive banana ripeness determination using a neural network-based electronic nose, Meas. Sci. Technology, Vol. 10, pp 538-548.
23. Mahanta, P. K., Tamuli, P., and Bhuyan, L. P., 1993. Changes of fatty acid content, lipoxygenase activities and volatiles during black tea manufacture. Journal of Agricultural Food Chemistry, Vol. 41, pp 1677-1683.
24. Martin, Y. G., Oliveros, M., Pavon, J., Pinto, C. G., Cordero, B. M., 2001. Electronic nose based on metal oxide semiconductor sensors and pattern recognition techniques: characterization of vegetable oils, Analytica Chimica Acta, Vol. 449, pp 69-80.

25. Natale, C. D., Paolesse, R., Macagnano, A., Mantini, A., Arnaldo D'Amico, Legin, A., Lvova, L., Rudnitskaya, A., and Vlasov, Y., 2000. Electronic nose and electronic tongue integration for improved classification of clinical and food samples, Sensors and Actuators B: Chemical, Vol. 64, No. 1-3, pp 15-21.
26. Owuor, P. O., 1992. Changes in quality parameter of commercial black seedling tea due to the time of the year in the eastern highlands of Kenya, Food Chemistry, Vol. 45, pp 119-124.
27. Togari, N., Kobayashi, A., and Aishim, T., 1995. Pattern recognition applied to gas chromatographic profiles of volatile components in three tea categories. Food Research International, Vol. 28, No. 5, pp 495-502.
28. Yamanishi, T., 1981. Tea, coffee and cocoa and other beverages, Flavour research, Marcell Dekker, New York, pp 231-304.
29. Takeo, 1981. Production of linalool and geraniol by hydrolytic breakdown of bound forms in disrupted tea shoots, Phytochemistry, Vol. 20, pp 2145-2147.
30. Takeo, T., and Mahanta, P. K., 1983. Comparison of black tea Aromas of orthodox and CTC Tea and black Teas Made from Different Varieties, Journal. Sci. Food Agric. Vol. 34, pp 307-310.
31. Ravichandran, R., and Parthiban, R., 1998. The impact of processing techniques on tea volatiles, Food Chemistry, Vol. 62, No. 3, pp 347-353.
32. Ravichandran, R., 2004. The impact of pruning and time from pruning on quality and aroma constituents of black tea, Food Chemistry, Vol. 84, No. 1, pp 7-11.
33. Shurmer, H. V., Gardner, J. W., and Chan, H. T., 1989. The application of discrimination techniques to alcohol's and tobaccos using tin oxide sensors. Sensor Actuators B, Chemical, Vol. 18, pp 359-369.
34. Tan, T., Lucas, Q., Moy, L., Gardner J. W., and Bartlett, P. N., 1995. "The electronic nose- A new instrument for sensing vapors." LC GC INT, Vol. 8 No. 4, pp 218-225.

CHAPTER VI

CONCLUSIONS AND FUTURE WORK

This chapter summarizes the main results of the proposed research and presents the principal conclusion drawn from the research. The areas of significant contributions to knowledge together with possible areas for future investigations and research are discussed. The section 6.1 summarizes the main findings of the research. The section 6.2 presents the main conclusions reviewed in terms of experimental results, feature extraction and performance of the ANN for classifications. Possible areas of future work are presented in section 6.3 that includes taking the research further, finding robust techniques for the purpose described and prospect of real time system implementation.

6.1 **Results overview**

The research described in this thesis is about the exploration of possibilities of machine vision techniques for quality monitoring of tea. In this regard, the important parameters in different tea processing stages are identified along with the traditional techniques of process evaluations. Among them, in this research, three important parameters are tested by using the machine vision techniques. They are colour attribute of fermenting tea, granule size of tea grades, and aroma of tea grades. The first two objectives are addressed using the computer vision technology, whereas the aroma is sniffed by the electronic nose (EN) technology. The data, gathered by the charge coupled device (CCD) camera and electronic nose, are processed using the intelligent system engineering technique, namely artificial neural network, for classification of data. The main results of this research are presented as follows:

- In chapter III, the colour analysis techniques of colour tea images are discussed. The colour content (colour feature) of images is represented as colour histograms. Hue saturation intensity (HSI) colour model is mainly used for its illumination invariance property. The procedure of the work is to discriminate some images, belongs to 'under' fermenting and 'over' fermenting tea images, from the database of images consisting of 'well' fermenting tea images. For this purpose the two specific images are identified from the 'well' fermenting tea image database by calculating a threshold value of histogram dissimilarity and used for the feature calculation for the other images (refer to chapter III, section 3.4.3). The technique developed is tested by the data visualization technique such as principal component analysis. The three dimensional plot of the three principal components of the feature set shows that the colour features have got adequate discriminating properties. While analysing three different databases of images ('under', 'well' and 'over' fermenting tea images) the principal components are placed in three respective positions in the plot. Similarly, the self organizing map (SOM) based unsupervised clustering is able to cluster the data set in three different clusters efficiently. This phenomenon is distinctly visualized in the plot of the data codebook generated during the SOM training. Finally, artificial neural network (ANN), namely multi layer perceptron (MLP) network is able to classify the images into three different categories of colours with 86.67% accuracy. On the other hand, while using the same test samples to classify into two 'similar' and 'dissimilar' colour ('well' fermenting tea as having similar colour; 'under' and 'over' fermenting tea as having dissimilar colour) categories the classification accuracy becomes 91.11%. Results show good correlation of this proposed technique of colour analysis with the tasters' choice and colorimeter results also that used for evaluating the tea fermentation.

- In chapter IV, tea granule size estimation techniques are discussed in terms of surface roughness of the tea images. This is carried out by analysing the texture variations in the images due to the variation of tea granules size. Discrete wavelet transform (DWT) is carried out in a multi-scale level, which produces different sub-band images of different resolutions from the gray scale tea images. The statistical features, namely variance, entropy and energy are calculated from these sub-band images. Finally, a new feature extraction method is proposed, where the information of the different textures, produced from different images, is conjugated (refer to chapter IV, section 4.7). The feature extraction technique developed here is tested by the data visualization technique, namely PCA. The three dimensional plot of the three principal components of the feature set shows that the colour features have got adequate discriminating properties, though some of them are not distinctly separable. While analysing eight different databases of images of different textures, the K-mean clustering technique can cluster the feature vectors into eight different clusters. Some misclustering of the feature set indicates the similarity of data points by nature in those categories. In a similar manner, the performance of SOM based unsupervised clustering is efficient, where it can clusters the features set into eight different clusters with less numbers of misclustering than K-mean. This phenomenon is distinctly visualized in the Silhouette plot of K-mean and plot of the data codebook generated during the SOM training. Finally, the artificial neural network (ANN), namely MLP and learning vector quantization (LVQ) networks are able to classify the images into eight different categories of textures with 74.67% and 80% accuracy respectively.

- In chapter V, tea aroma analysis of different grades of tea is discussed. This research is mainly aimed towards exploring an efficient model for quality monitoring of tea in terms of aroma. The aroma is one of the three flavour attributes along with the taste and astringent of tea, usually considered by the human sensory panel in tea industries for final quality judgment. The electronic nose that is designed with four different metal oxide semiconductor sensors is used for sniffing the aroma of thirteen different tea grades. The transient responses produced by the sensors are stored to analyse their patterns. While mean and peak of the transient responses of four sensors are taken as the feature vectors for each of the samples, the PCA data visualization method shows discrimination of the dataset into eight distinctly separable points. The K-mean clustering technique is able to cluster into thirteen different clusters with some miss clustering. Finally, the clustering technique SOM also shows the dataset into eight different clusters. The dataset is further classified with the ANN based techniques. The MLP shows 61.54% accuracy while tried to classify the dataset into thirteen different categories. But it enriches in performance while trying to classify the dataset into eight different categories with 90.77% accuracy. The other ANN techniques such as radial basis function (RBF) network and constructive probabilistic neural network (CPNN) architectures can also classify the dataset into eight categories with reasonable accuracy. The RBF and CPNN show 92.31% and 93.85% accuracy respectively.

6.2 **Conclusions**

This research proposes a novel approach for feature extraction, which conjugates the features information of one class of data along with the others. This technique is successfully implemented both in colour analysis of fermenting tea and texture analysis of made-tea experiments. In analysing the colour in images, the objective is to separate the other colours from a database of images of almost similar colours. The database, in this research, consists of 'well' fermented tea images. The conjugation of colour information of this database with the other images is carried out by calculating a threshold value of histogram dissimilarity inside the database (chapter III, section 3.4). Similarly, during texture feature extraction the conjugation is made in terms of calculating the Mahalanobis distances among the images of same categories (chapter IV, section 4.7). This new technique of feature extraction is found to be successful in discriminating the images from the one category to other. For example, the accuracy of classification technique, the MLP, for colour feature is found to be 91.11%. On the other hand, in the experiments of tea granule size estimation, the new texture feature extracted using this method found to be successful in comparison to the conventional method. For example, the maximum accuracy found, using Kohonen LVQ network, is 80%. The level of accuracy of the conventional features shows 46% using the MLP, while using the same network with the new feature set shows 74.67% accuracy. Such efficiency in classification reveals the usefulness of the conjugation technique of feature information with each other for such computer vision work as stated in this research.

Finally, in context of the overall objective of the research, computer vision technique is explored as a successful technique in detecting the optimum colour of fermenting tea. This is described in chapter III. The computer based analysis of the image colour is efficient in comparing the minute changes of the colours in the images. Therefore, such sophisticated system can be worthwhile in analysing the image colour in changing environment to assist the sensory panel involved with the purpose as the accurate colour detection is important for fermentation process evaluation in the tea industry. Similarly, the tea image texture analysis, described in chapter IV, for estimating the tea granule size while sorting tea into different grades may also be useful to assist the human sensory panel. As tea granules are separated, using different sized sieves, from one another in accordance with the granules size only, such computer vision technique is worthwhile in assisting for the final judgment of its various aspects such as uniformity, presence of stalks etc. On the other hand, chapter V describes the usefulness of the EN system in analysing the tea aroma for quality judgment at the final stage. It is shown that the EN technique is effective in discriminating the tea samples from one another in accordance with the variation of aroma in them. Such technique will be worthwhile in standardizing the tea aroma in assisting the tea tasters (human sensory panel) for their quality evaluation.

6.3 **Future work**

This thesis has been culminated in delivering a toolset that combines computer vision, artificial olfaction, and intelligent system engineering techniques to assist tea quality monitoring process. In this context, different tea quality parameters were efficiently addressed in terms of features by extracting them for the required classification. Nevertheless, this research can be further extended in the following manner:

- As stated in the Chapter I and Chapter II, tea quality monitoring during processing stages is a complex phenomenon as many parameters come into focus at the same time. To date, many different advanced techniques are being implemented for the sake of overall good quality tea. This thesis has documented the machine vision as a useful technique for such purposes for evaluating the process parameters. Therefore, consideration of the other parameters also, which are not considered in this research, using some efficient techniques for evaluating them is a future prospect of research in this area. For example, optimum aroma detection at the fermentation stage by electronic nose technique would assist the fermentation time judgment as aroma is the other fermenting tea parameter along with its colour.

- The feature extraction techniques, developed in this research, have been proved to be efficient by intelligent system engineering techniques based classification technique in the controlled environment of imaging and aroma sniffing. For example, the imaging of fermenting tea was carried out in almost uniform day light during on going fermentation process in tea industry. On the other hand, for texture images, the imaging was carried out with constant illumination inside the laboratory. Besides, tea granules are arranged in accordance with the specified manner as discussed in chapter IV (section 4.2.2). The feature extraction techniques need to be developed so that they might be useful in discriminating the colour and texture in natural environment. Moreover, more efficient feature vector is needed for more accurate classification so as to further improvement in system performance. Therefore, improvement of feature extraction technique for robust and efficient performance of the proposed system in natural environment and to increase the classification accuracy may be one future prospect for research in this area of computer vision. On the other hand, the tea aroma is also sniffed in controlled environment so that only tea aroma comes into contact with the sensor headspace. The sensors used in this research for tea aroma sniffing are not specifically made for tea aroma. Rather, the sensor selection process is based on the trial and error method as the selected sensors show high sensitivity to tea aroma. Therefore, devising the sensor type, which shows high sensitivity only to the tea aroma, may also offer future direction of research in this area.

- The usefulness of a proposed software system depends on parameters such as its efficiency, cost effectiveness, fast processing capability etc. The realization of an efficient software system into hardware circuit may be an alternative solution for achieving the cost effectiveness and fast processing. Therefore development of hardware circuit, based on the proposed software methodology, is the logical next step of this research in order to make any significant impact in industrial setting. This real time system can be achieved by using the reconfigurable hardware (RH) such as field programmable gate arrays (FPGA) that can be proposed for such purposes. A preliminary discussion of FPGA implementation of the computer vision algorithm (colour matching) is furnished in the Appendix C.

APPENDIX A

CV WORKSTATION AND IMAGE DATABASES

A.1 **Introduction**

The purpose of this appendix is to furnish the information about the computer vision workstation that has been used for imaging during the computer vision experiments. Detail specifications of the individual components, namely CCD, image capturing add on card are furnished. Lastly, some of the images used in the research are also furnished.

A.2 **Charge coupled device (CCD)**

The charge coupled device (CCD), which is used for the experiment, is the CCD COLOR CAMERA SYSTEM (TOSHIBA), Model No. 1K-M48PK. This belongs to the category of the Micro Video Camera (MVC) of high resolution. This ultra-small camera is equipped with the digital signal processing (DSP) technology. The camera uses a high resolution sensor capable of scanning an image more than 460 lines (horizontal) with a signal to noise ratio greater than 46dB. The camera model is measured approximately 17 mm in diameter and 54 mm in length with the standard 7.5mm lens. The camera head is small enough to be enclosed in the fist. A 30m long cable is used to link the camera head to the camera control sub unit. Figure A.1 (a) and (b) show the CCD and signal conditioner used for the experiment carried out in the tea industry. The detail of specifications of CCD is as follows:

- Power Supply: 12V ± 0.5V. 0.48A
- Power Consumption: 360 mA
- Image Sensor: ½" IT CCD
- Effective Pixels: 752H x 582V
- Effective Image Area: 6.47 mm (Horizontal) x 4.83mm (Vertical)
- Scanning System: 2:1 interlace
- Scan Frequency: 15.625 kHz (Horizontal), 50 Hz (Vertical)
- Synchronization: Internal / External (Automatic switching)

- Resolution: More than 470 TV lines (Horizontal).
  More than 420 TV lines (Vertical)
- Standard Intensity of Illumination for Objects: 60 lux (f1.6, 3000°K)
- Minimum Subject Illumination: 5 lux (F1.6, 3000°K)
- Signal to Noise Ratio: 46dB or more
- White Balance: Automatic / set / Manual

(a)

(b)

Figure A.1 (a) TOSHIBA (Model: 1K-M48PK) mini CCD colour camera, (b) TOSHIBA (Model: 1K-M48PK) mini CCD colour camera along with the signal conditioner.

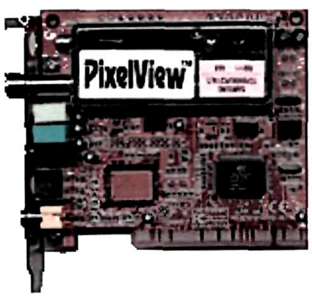


Figure A.2 Pixel View Play TV Pro (Model: PV-BT878PT)

- Operating Temperature / Humidity: -10°C to + 40°C / Less than 90%
- Anti-vibration / shock characteristics: $70m/s^2$ (10 to 200Hz) / $700m/s^2$
- Weight: Camera Head: 26g (Approximately) with 7.5mm lens
  Control Unit: 390g (Approximately)
- Dimensions: Camera Head: 54 x 17mm (Approximately) with 7.5mm lens
  Control Unit: 85mm (width) x 40mm (height) x 156mm (length)

A.3 Image capturing (Pixel view TV Pro (Bt878P))

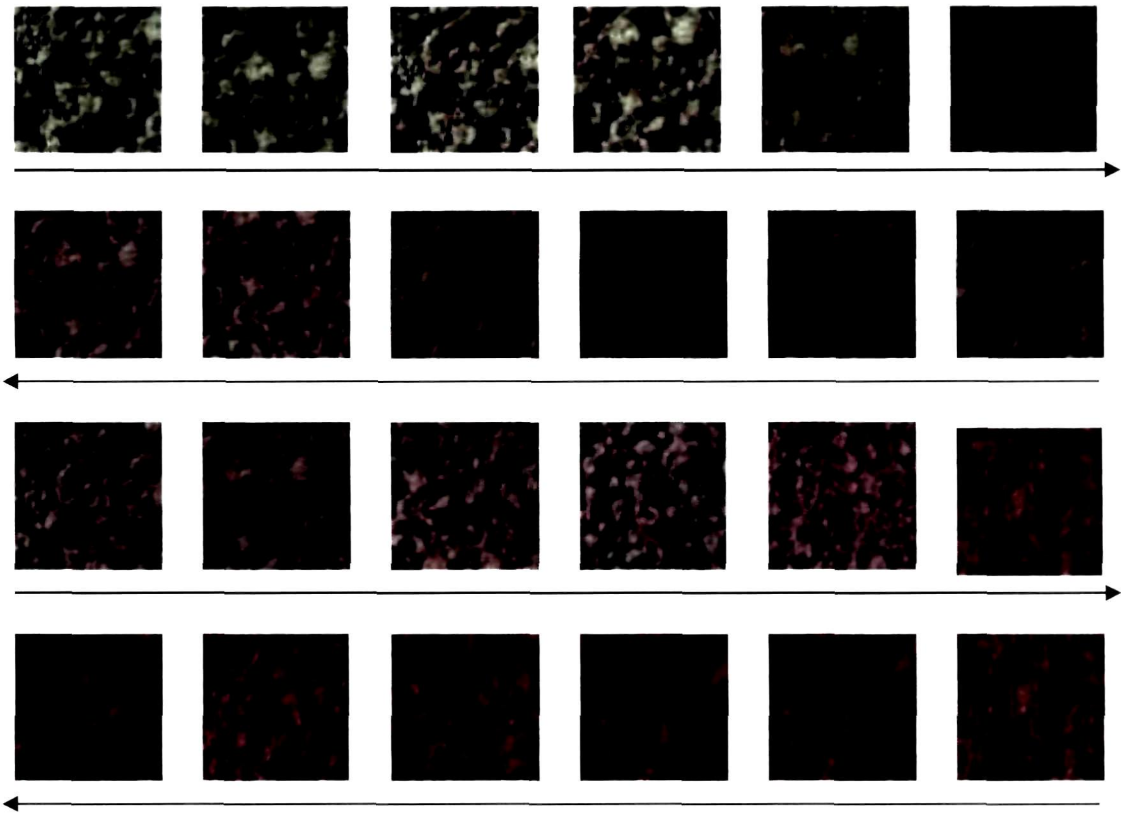
The image capturing has been performed by using a commercially available frame grabber card. Figure A.2 shows the Pixel View Play TV Pro (Model: PV-Bt878PT) add on card used in this experiment. The card (CyberLink Corp. Copyright © 1997, All Right Reserved) has other functions also such as TV and FM tuning. The signal produced by the signal conditioner of the CCD camera is in S-band of frequency. The VideoLive Plus 3.071 facility of TV Pro is utilized in generating the images from the S-band frequency. Some important specifications of the card are as follows:

- Single-Chip video capture/TV tuner/FM radio multimedia adapter.
- PCI bus master interface.
- Supports NTSC/PAL/SECAM video input.
- Composite / S-Video input and audio input.
- Supports Windows 95/98/98SE/ME/XP.
- Multiple composite, S-Video and 8 pin mini-Din connector for video camera.
- Multiple YcrCb and RGB pixel formats supported on output.
- Video capture rates maximum 30 frames/ second.
- Vertical Blanking Interval (VBI) data capture for closed caption, Teletext and inter cast data decoding.

A.4 Fermenting tea image

Figure A.3 shows some fermenting tea images captured from a particular batch of tea fermentation. The images were captured with five minutes interval. The variation of colour in the images can be visualized from the images.

Start of the fermentation



Completion of the fermentation

Figure A.3 Images of fermenting tea of a particular batch of fermentation

Figure A.4, Figure A.5 and Figure A.6 furnishes some sample images of 'under' fermenting tea, 'over' fermenting tea, and 'well' fermenting tea respectively. On the other hand Figure A.7 furnishes five images each of eight databases of images of eight different grades of tea.

Batch 1 Batch 2 Batch 3 Batch 4 Batch5

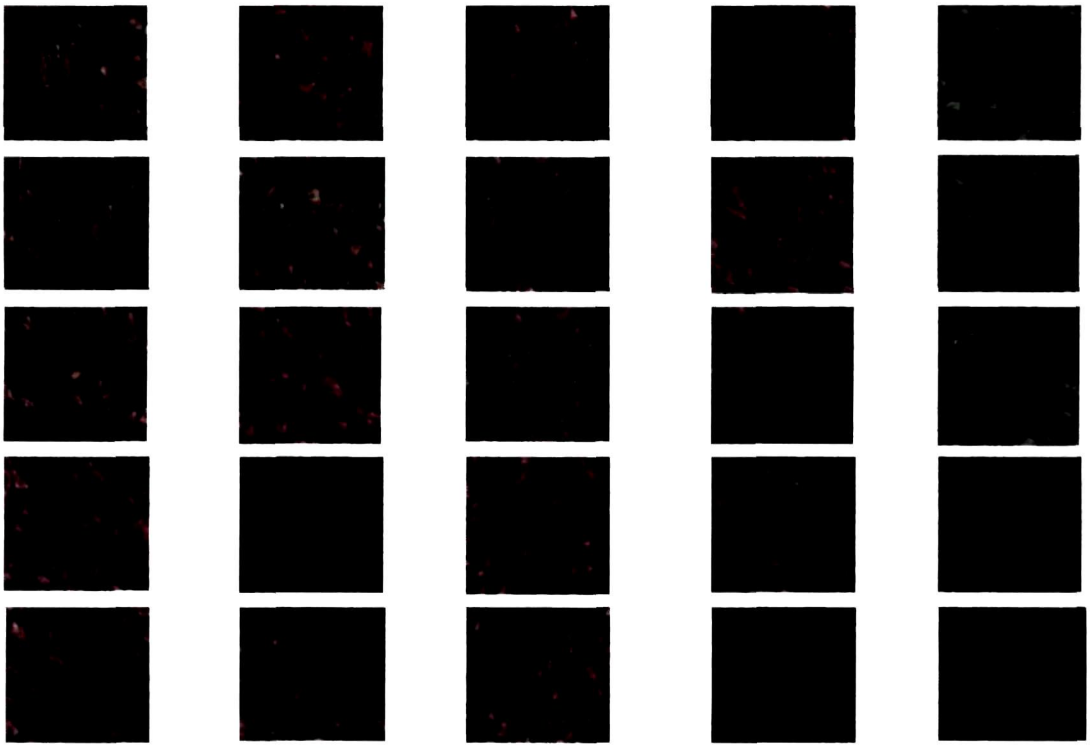


Figure A.4 Images of the 'under' fermenting tea of five batches of fermentation

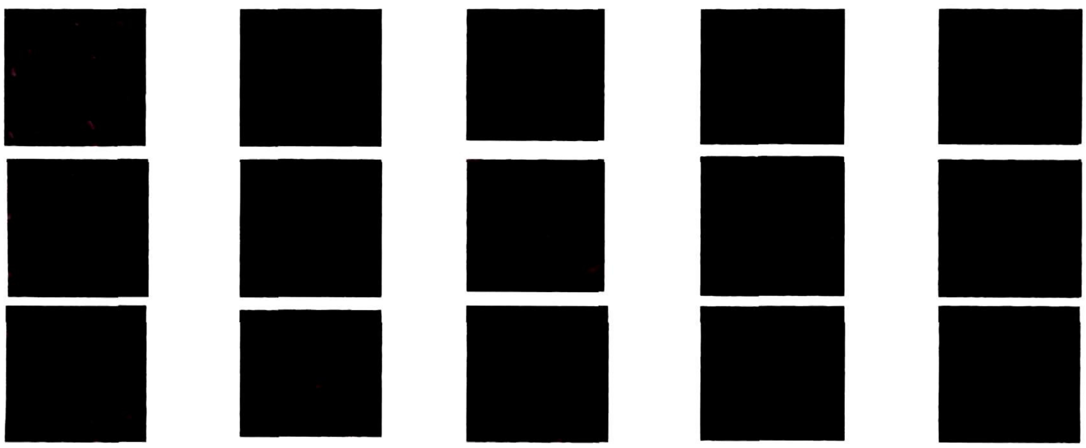


Figure A.5 Images of the 'over' fermenting tea of five batches of fermentation

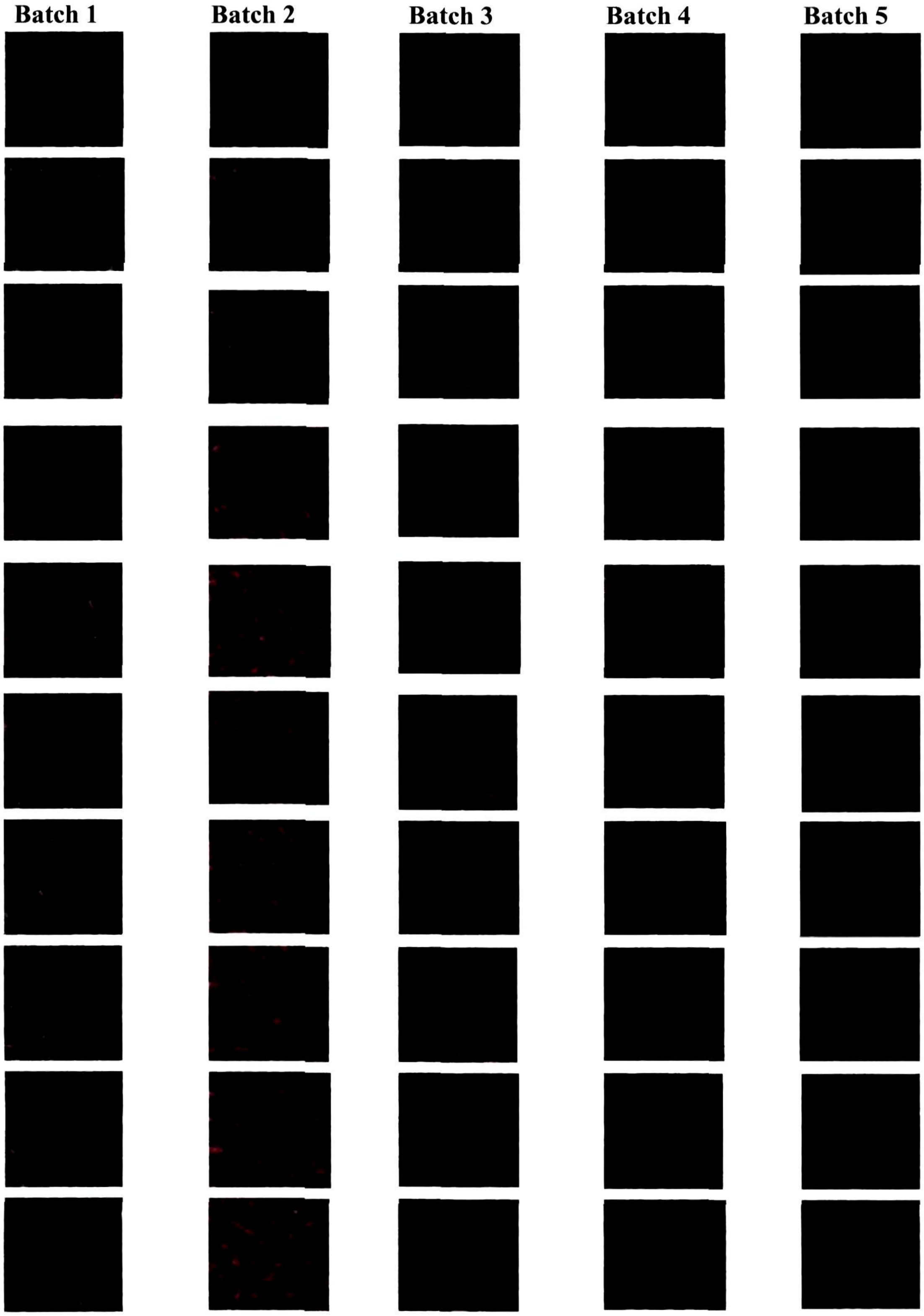


Figure A.6 Images of the 'well' fermenting tea of five batches of fermentation

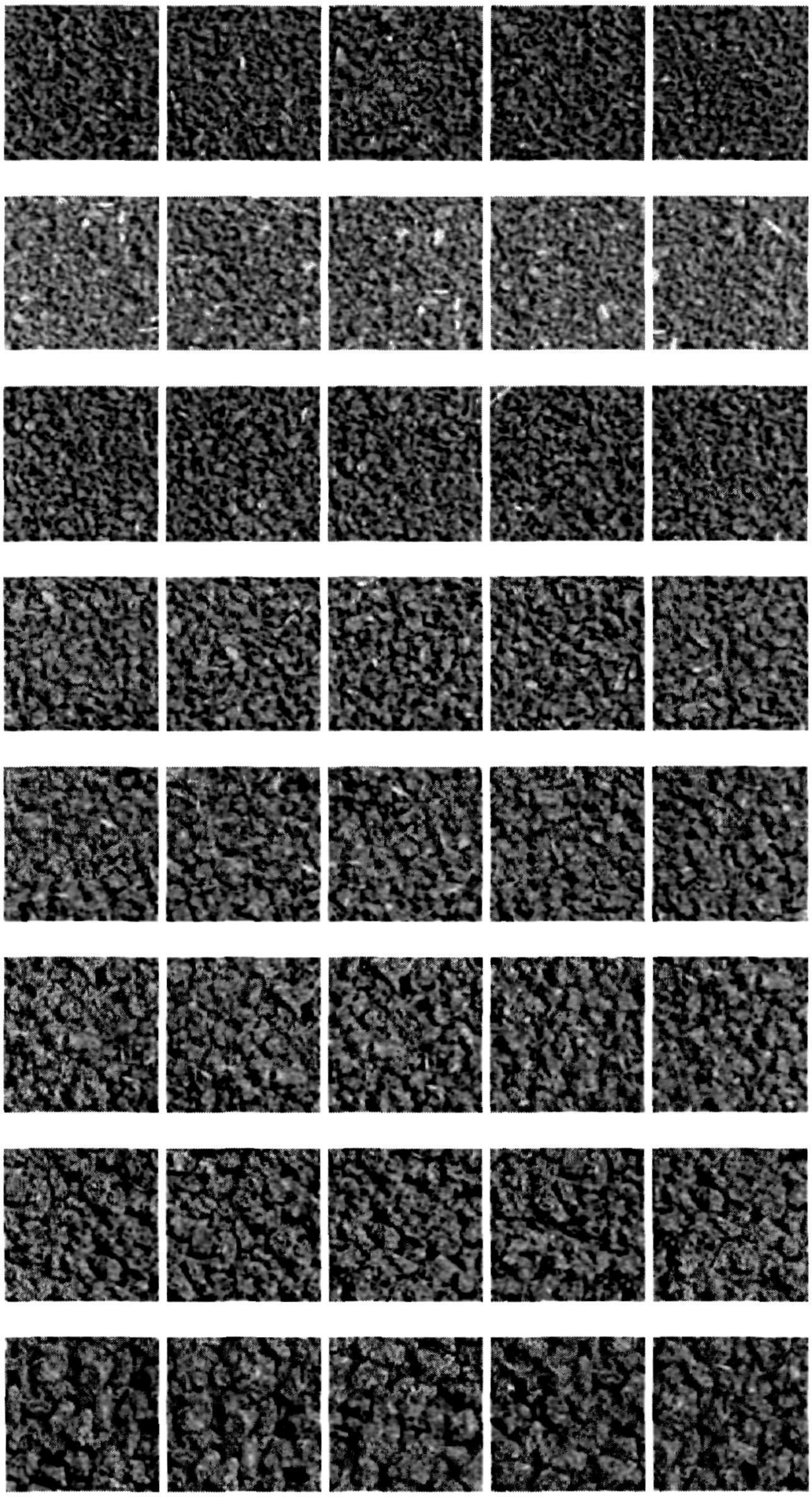


Figure A.7 Image of eight different tea grades of different granule sizes.

APPENDIX B

TRANSIENT RESPONSES OF EN

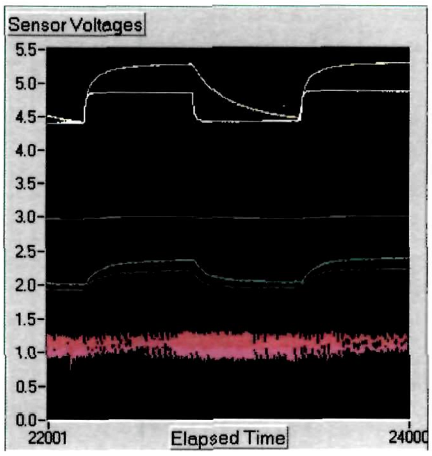
B.1 **Introduction**

This appendix provides some transient responses of the EN system during the aroma sniffing of tea grades. Thirteen different tea grades were collected for aroma analysis that was furnished in the chapter V (section 5.4.1). The experimental setup of EN system that was used for the sniffing was also shown in chapter V (Figure 5.4). Four different SnO_2 gas sensors, namely TGS880, TGS825, TGS826 and TGS882 of Figaro Engineering Inc. of Japan, were used in the experiment. Figure B.1 shows the pictures of these sensors copied from the manufacturer's website (www.figarosensor.com). Then Figure B.2 shows the responses produced by these sensors while sniffing tea aroma (refer to Figure 5.5 of chapter V).

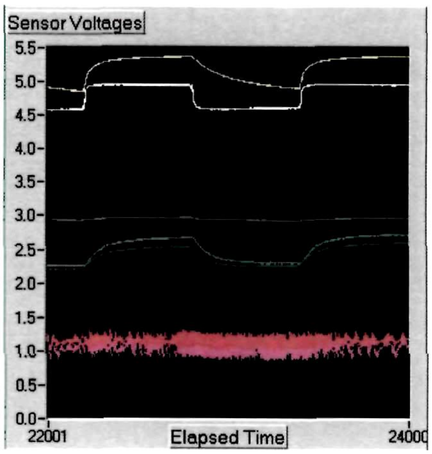
(a) (b)

(c) (d)

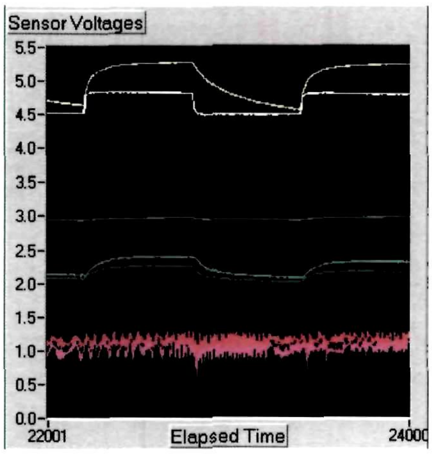
Figure B.1 (a) TGS 880, (b) TGS 882, (c) TGS 825, and (d) TGS 826



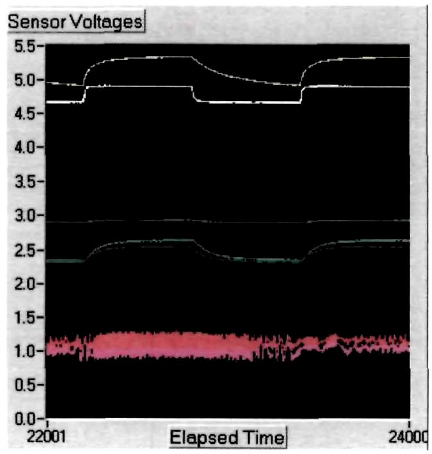
(a)



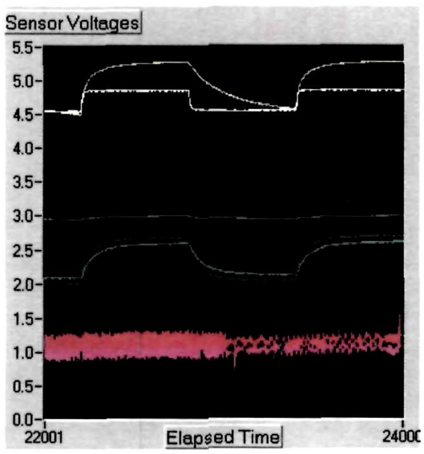
(b)



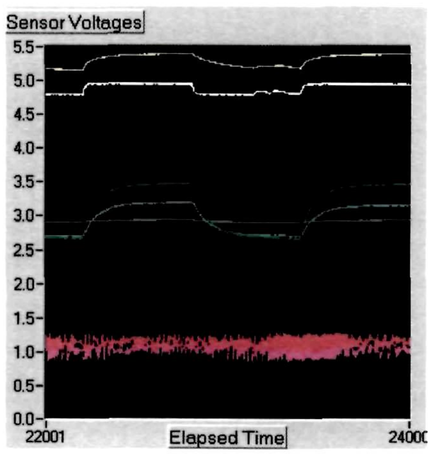
(c)



(d)



(e)



(f)

Figure B.2 (a) BP of Geleky; (b) BP(F) of Geleky; (c) BOP of tamulbari; (d) BOPSM of Tamulbari; (e) BOP of Comaibund; (f) BP of Comaibund

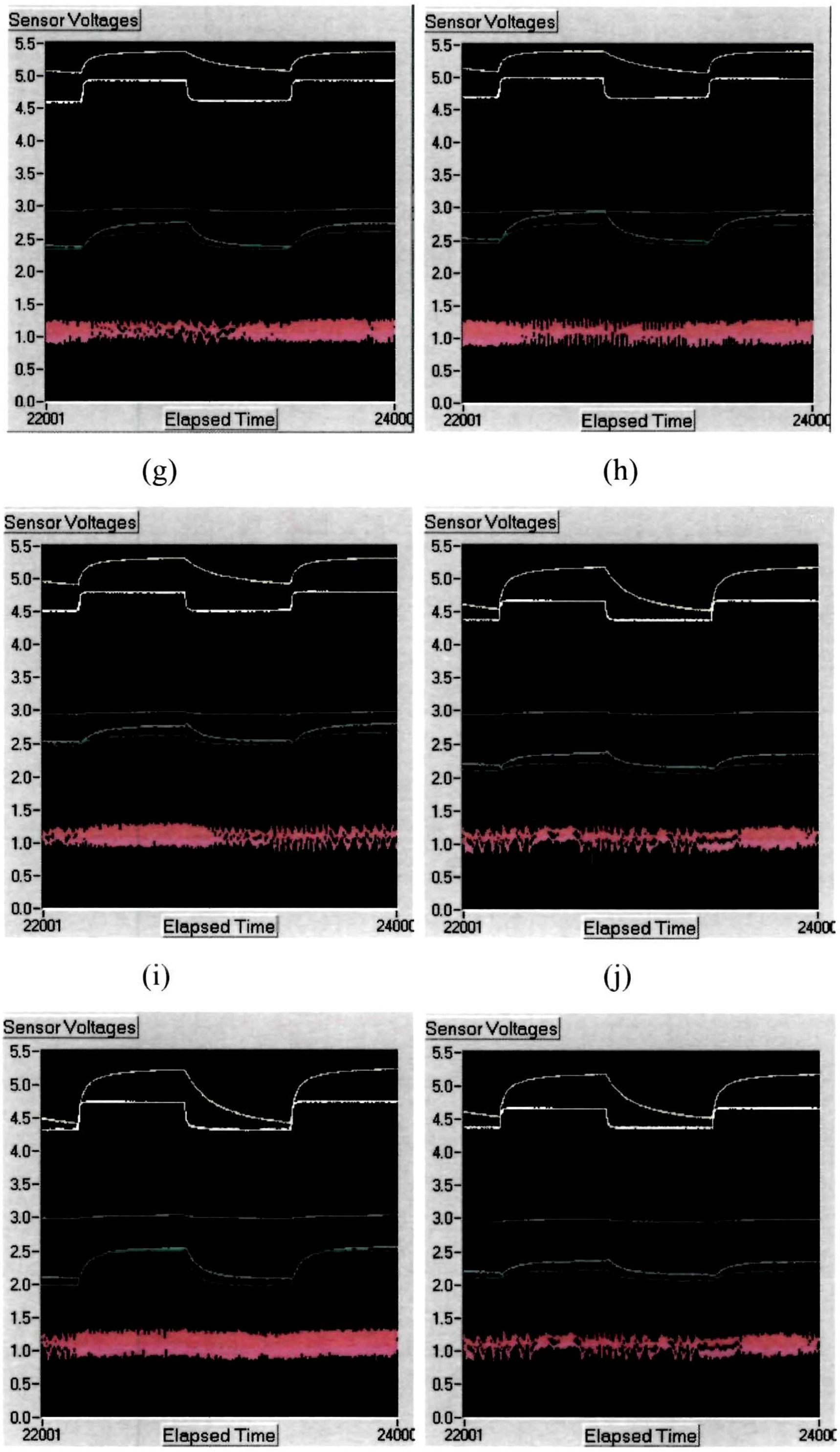
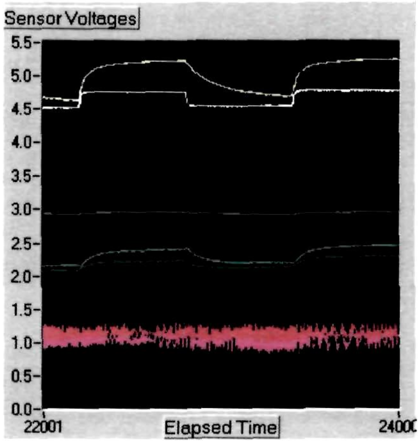


Figure B.2 (g) BPS of Tamulbari; (h) PF of Tamulbari; (i) Dust of Comaibund; (j) PD of Comaibund; (k) BPS of Comaibund; (l) PD of Comaibund



(m)

Figure B.2 (m) PF of Comaibnd

APPENDIX C

REAL TIME IMPLEMENTATION OF CV ALGORITHM

C.1 Introduction

This appendix describes the idea of prospects of hardware implementation of the proposed computer vision (CV) algorithms. Though the algorithms are developed mainly in software, it is advantageous in many ways in implementing the same algorithms in hardware circuit. The reasons behind the effort are cost affective and fast processing using programmable hardware. In addition, developing a CV application in hardware circuit tends to be experimental and interactive to the end users in industrial applications. Recently, it is observed through the literatures that some of the researchers are carrying out various researches in the field of image processing and computer vision, whose objectives are the development of specific circuits to handle the image data (Chan, et al., 1993; Benkrid, et al., 1999; Dawood, et al., 2002). These developments that are related in devices such as field programmable gate arrays (FPGA) or application specific integrated circuit (ASIC). Such device developments are usually carried out by means of standard hardware description language such as very large scale integrated circuit hardware description language (VHDL). The main disadvantage of using ASIC is that the circuit is usually limited to work for one application. On the other hand FPGA is competitive compared to ASIC in terms of capacity (number of equivalent gates contained in one chip) and performances. This allows to quickly having a prototype of the circuit that has to be designed, and able to operate in real conditions. Over the last several years, FPGA have evolved from simple "glue logic" circuits into the central components of the reconfigurable computing systems (DeHon, 2000). Reconfigurable hardware (RH) in the form of Field Programmable Gate Arrays (FPGA) has been proposed as a way of obtaining high performance for the computationally intensive digital signal processing (DSP) applications such us image processing (IP) and CV under real time requirements (Crookes, et al., 2000).

The following sections of this appendix describes the preliminary experiments that were carried out for hardware implementation of the DPV based colour analysis algorithm (Chapter III, section 3.3.2 and section 3.4) that used for colour matching. The proposed RH, specifically FPGA, Vertex II, which is used for implementing the circuits, uses VHDL. The M27256 EPROM is used as the storage device to store the image data for implementing the algorithms by FPGA. Programming language 'C' is used for transferring the data, which are calculated in the PC, to the microcomputer.

C.2 **Hardware setup**

The simplest block diagram of the hardware setup, which is simulated for the experiment is shown in Figure C.1. The necessary devices used for the system setup are as follows:

- CCD COLOR CAMERA SYSTEM (TOSHIBA), Model No. 1K-M48PK)
- Video ADCs to sample the image frame into digital form (ADC1175-50CIJM)
- EPROM to store the image data (M27256, NMOS 256K (32K x 8) UV EPROM)
- Microcomputer for programming the EPROM (MICROFRIEND 86/88)
- FPGA for the hardware circuit (Vertex II)
- XILINX ModelSim simulator for hardware programming VHDL

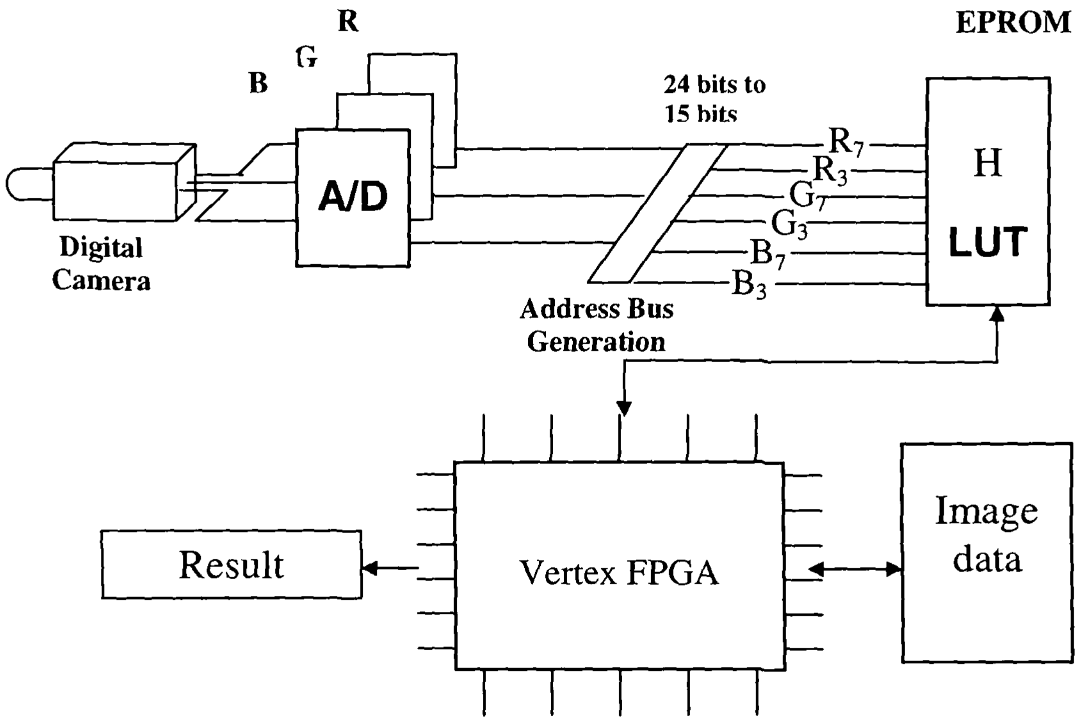


Figure C.1 Block diagram of the hardware setup for image colour matching.

The following sections enumerate the functions of the hardware devices that used for the setup. The possible interconnections of the hardware and their utilities for the purpose are furnished.

C.2.1 **Image signal of CCD**

Three different analog signals, each of R, G and B primary colour components, are taken directly from the signal conditioner. The digital camera (CCD) captures the image frame and fed to the signal conditioner with scan frequency 15.625KHz (Horizontal), 50Hz (Vertical), where effective pixel size is 752 (Horizontal), 582 (vertical). Therefore, the signal conditioner produces signal of a single frame of image for the duration of 20 ms in three different channels. A low sync signal is formed for every 20 ms intervals in the all three channels, which differentiates two image frames from each other. These signals are available in the 15-pin RGB signal port of it. The Figure C.2 shows the signal conditioner with the concerned port. The schematic diagram along with the different pin voltages of the port is shown in Figure C.3. The pin nos. 7 and 8 produce 0.5V DC each. The pin no. 1 produces the R signal, where for a pure red the measured voltage is around 0.12V analog signal. Similarly, the pin nos. 3 and 5 produce the G and B signal respectively. These two signal pins should produce 0V for ideal condition when the target object is pure red. But, in practical condition around 10 to 20 mV is always produced by these pins. On the other hand, these pins produce around 0.12V voltage for corresponding pure colours (G and B), having 10 to 20 mV in rest of the pins. The other pins are internally connected to the grounds. Figure C.4 shows a signal of 20 ms time period from pin no. 1, where the target object for the CCD is a pure red colour patch. Table C.1 summarizes the voltage produced in pin nos. 1, 3 and 5 for the three primary colours R, G, and B.

Table C.1 Voltages produced by the pin nos. 1, 3 and 5 for R, G and B respectively.

Target Colour	Pin 1	Pin 3	Pin 5
Red	0.12V	14mV	13mV
Green	14mV	0.12V	13mV
Blue	14mV	15mV	0.12V

C.2.2 **Analog to digital conversion**

The analog-signals are digitized with the help of three video-ADCs. The analog signal available in the pin nos. 1, 3 and 5 for the three primary colours R, G and B respectively, are used as the input of the video ADCs. The signal remains high for a particular frame of image only for 20ms, which is distinctly visible in Figure C.4. After that, there is a low sync signal, which separates the frames of images from each other. Again, the concerned CCD scans the image with 752 (Horizontal), 582 (vertical) pixel size. Therefore, the time period to scan one horizontal line is 0.02659574468085ms and for a particular pixel it is 4.569715580902 X 10^{-5}ms. Therefore, the video ADC, chosen for the conversion of analog signal to digital form should have the higher scanning frequency (typically more than 50MSPS). All sort of video ADCs produce the digital signal into 8-bits. Therefore, the total length of the whole signal in term of R, G and B is 24-bit long.

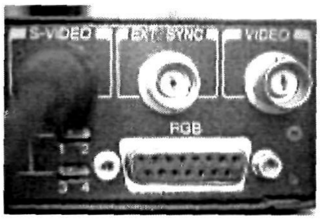
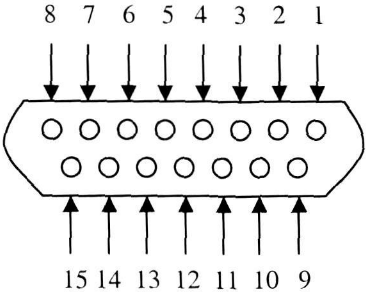


Figure C.2 Part of the signal conditioner with the 15-pin RGB port.



1. Signal (R), 0.12V
2. Ground
3. Signal (G), 0.12V
4. Ground
5. Signal (B), 0.12V
6. Ground
7. 0.5V (DC)
8. 0.5V (DC)
9. Ground
10. Ground
11. Ground
12. Ground
13. Ground
14. Ground
15. Ground

Figure C.3 Schematic diagram of the port with the different pin voltages

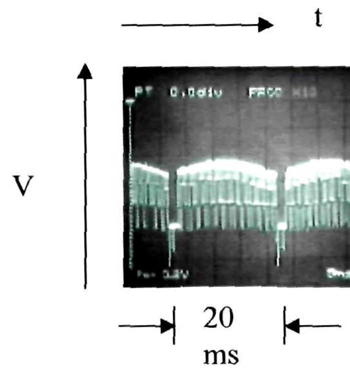
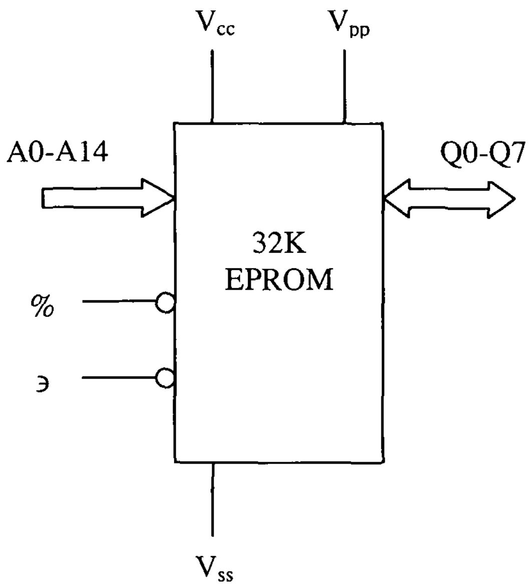


Figure C.4 Signal of 20 ms time period from pin no. 2, where the target object for the CCD is a pure red colour patch.

C.2.3 **Look up table for H**

Two NMOS 256K (32K x 8) UV EPROMs are used as the Look up table (LUT) to store the hue (H) values of some specific combinations of R, G, and B of the RGB colour model. This part of the system is designated as the colour conversion module as the RGB colour is transformed into HSI colour model. The length of the address bus is 15-bit long. The logic diagram of a standard 32K EPROM is shown in Figure C.5, where A0-A14 and Q0-Q7 are the address bus and data outputs respectively. The aim of the system is to address the particular memory location where the desired H value is stored previously. Therefore, the five most significant bits (MSB) of the R, G and B digital values are considered for generation of these address buses. Some of the entry of the address bus is omitted by doing so. For example five MSB of binary of 0 and 7 is same in values. Therefore, it is convenient to consider only one entry out of this range. The entry '4' is chosen in this range and considered as one value for LUT generation. The other values chosen in the range of 0 - 255 are 12, 20, 28, 36... 252 in their respective ranges. By doing this, instead of 256 data only 32 nos. are used and a less memory spaces are sufficient for storing the values. Therefore, total 32^3 nos. possible combinations are achieved by using these selected values of R, G and B. The H values of all combinations are calculated by using the standard equation (Equation 2.4, chapter II, section 2.8.3) and stored in definite order in the memory spaces of the EPROM.

The H values range from 0^0 to 360^0 and when B > G however, H = 360^0 - H. Therefore, two bytes are required for storing those H values in the memory locations, whose values are greater than 255. For generalization, two bytes are allotted for all the values of H. Then, if the two bytes are considered as the 16-bit long data, then the value 8 MSB of the range 0-255 will be 0 and 256-360 will be 1. Again, the values of 8 LSB of the range 0-255 will be the value itself, but for the range 256-360 will be starting from 0 to 104. The total bytes required for storing all the possible H values 64K and two 32K EPROMs are used for this purpose. The EPROMs are used in parallel and the corresponding memory locations of both the EPROMs are utilized for storing the data of a single 16-bit long H values.



A0-A14	Address Inputs
Q0-Q7	Data Outputs
%	Chip Enable
϶	Output Enable
V_{pp}	Program Supply
V_{cc}	Supply Voltage
V_{ss}	Ground

Figure C.5 Logic diagram of the 32K EPROM.

C.2.4 **Hue calculation and formation of LUT**

The H values of all combinations of the selected R, G and B values are carried out in software based program in PC. A view of the way of ordering the combinations of the R, G and B is shown in the Table C.2. The H values are calculated in ASCII format, which is then send to the parallel port allowing the microcomputer to read the data sequentially from it. The microcomputer reads the data and stores in its memory locations and finally writes in the memory locations of the targeted EPROMs.

Table C.2 Order of the combinations of R, G and B for H calculations.

R	G	B	H
4	4	4	H_1
4	4	12	H_2
4	4	20	H_3
•	•	•	
•	•	•	
4	12	4	H_{33}
4	12	12	H_{34}
4	12	20	H_{35}
•	•	•	
•	•	•	
4	20	4	H_{65}
4	20	12	H_{66}
4	20	20	H_{67}
•	•	•	
•	•	•	
12	4	4	H_{1025}
12	4	12	H_{1026}
12	4	20	H_{1027}
•	•	•	
•	•	•	
252	252	236	H_{32766}
252	252	244	H_{32767}
252	252	252	H_{32768}

In the experiment, EPROM-1 is assigned for the 8 MSB of the 16-bit data. Similarly, EPROM-2 is assigned for the 8 LSB. It has found that the possible values of the EPROM-1 are 0 and 1 only as the maximum H value is 360. Again, the maximum value of the memory locations of EPROM-2 is 255, i.e., 11111111. Once the memory locations of the EPROMs are stored with the different H values, they are ready to use as LUT in the colour conversion module of the colour matching real time system. Figure C.6 shows both the EPROMs along with the memory address and data values.

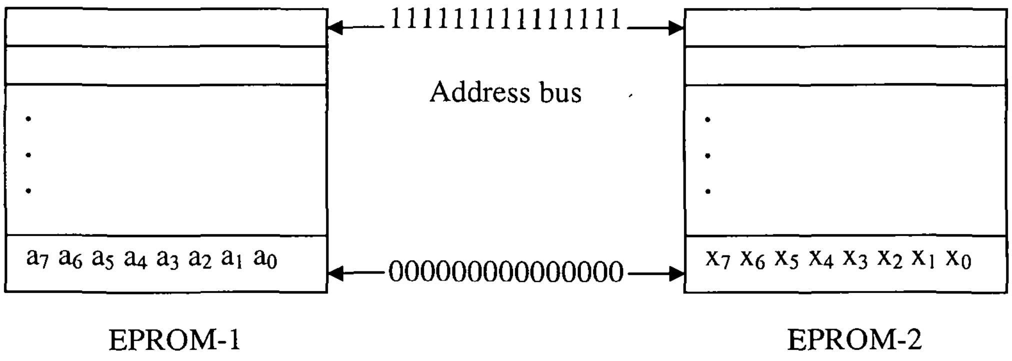


Figure C.6 EPROM-1 and EPROM-2 along with the data and address buses.

C.2.5 **Addressing the LUT**

Once the LUT is created, it is utilized for the values of H using the different combinations of the R, G and B generated by the output of the ADCs. For this purpose, these digital data are used as the address of the different locations of the EPROMs. The colour camera takes an image, and its digitized RGB signal feeds into the colour conversion module. For this particular system the Colour Conversion module performs the RGB to H real time conversion as stated in equation by means of the proposed LUT. It was mentioned that the digital signal of RGB consists of 24-bits, but the five most significant bits of the each output of the ADCs are only considered as the address of the EPROM. Therefore, the address bus of the EPROMs becomes 15-bit long (Campos, et al., 1996). Figure C.7 shows the 15-bit long address bus generation by omitting three LSB from all the three 8-bit R, G and B digital data from the ADC. This is analogous to the calculation of the H values to the specific entries of the R, G and B as illustrated in last paragraph (5.2.3). Then, this bus addresses the 32Kb EPROM used as LUT. Here the addressing of the LUT by one generated address has to be done into two memory locations, as the H values are stored in two corresponding locations of both the EPROMs used for LUT. Therefore, the generated address bus is applied for addressing both the memory locations of both the EPROMs sequentially. Figure C.8 illustrates the phenomenon of addressing. As the addresses of the corresponding memory locations of both the EPROMs are same, the phenomenon seems to be addressing the 16-bit data from a single memory location.

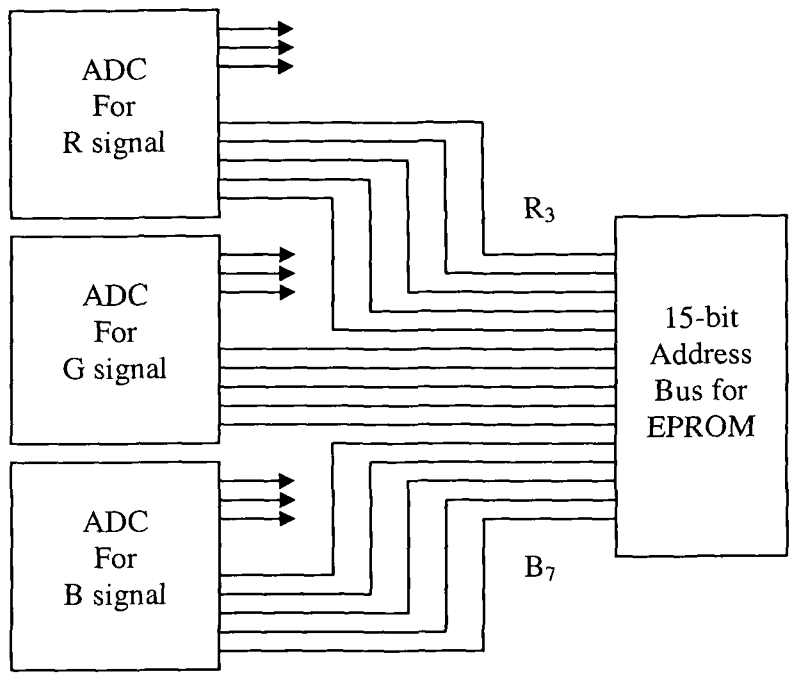


Figure C.7 Generation of 15-bit address bus for the EPROM.

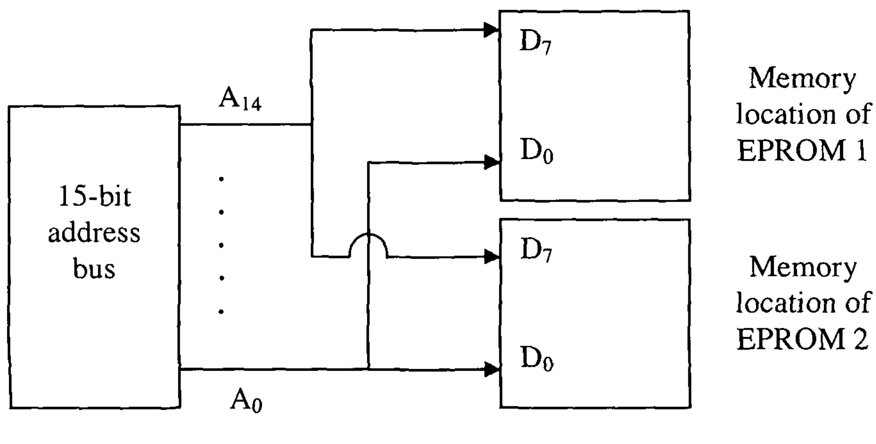


Figure C.8 Addressing two memory locations of two LUT at a time.

Once the address bus addresses the two memory locations of the both the EPROMs at a time for a particular combination of input address, the corresponding H values are fetched by the system instantly. These 16-bit values are then directly used by the rest of the system for processing for colour matching purpose. Practically the output data bus of the EPROMs is available to the rest of the system FPGA and the desired data are used by the FPGA for colour processing.

The FPGA is selected as like fast (200MHz system performance; 66MHz PCI compliant), high-density (from 50K to 1M system gates), Multi-standard SelectIO™ interfaces, hierarchical memory system (LUTs configurable as 16-bit RAM, 32-bit RAM, 16 bit shift register) and unlimited re-programmability etc.

C.2.6 **FPGA for circuit implementation**

The main disadvantage of using the hardware such as Microcomputer for real time image processing is its operating speed and memory spaces available. Therefore the hardware architecture such as application specific integrated circuit (ASIC) can be used for this purpose. Selecting the field programmable gate arrays (FPGA) for real time image processing is due to its speed of operation and numbers of gates available for implementing the desired circuit in it. In this specific application of colour matching, the overall algorithms are simulated in the ModelSim simulator of XILINX and the circuit is tested in the Virtex trainer MXVFK-240-001. The trainer is consisted of any one of the Virtex FPGAs such as XCV400, XCV600, XCV800 and XCV1000. Xilinx Virtex Device family is shown in Table C.3.

Table C.3 Vertex FPGA lists

Virtex FPGA	CLB Array	System Gates	Logic Cells	Maximum available I/O	Block RAM bits	Maximum Select RAM+™ Bits
XCV400	40 x 60	468,252	10,800	404	81,920	153,600
XCV600	48 x 72	661,111	15,552	512	98,304	221,184
XCV800	56 x 84	888,439	21,168	512	114,688	301,056
XCV1000	64 x 96	1,124,022	27,648	512	131,072	393,216

The FPGAs are SRAM-based, and is customized by loading configuration data into internal memory cells. The Virtex XCV400 is used for this specific application and it features a flexible architecture comprised of an array of configurable logic blocks (CLBs) and input/output blocks (IOBs). The Virtex XCV 400 FPGA comprises of two major configurable elements, viz., the CLBs and IOBs, all interconnected by a rich hierarchy of fast, versatile routing resources (www.xilinx.com). The CLBs provide the functional elements for construction logic and the IOBs provide the interface between the package pins and the CLBs. Four dedicated delay-locked loops (DLL) are there in the FPGA itself for advanced clock control for high performance logic solution, as the FPGA reads the image data from the external EPROM in master serial mode. However, the configuration data is written into the FPGA in Select MAP^{TM} mode.

C.3 **Real time image colour matching**

Histogram generation in terms of counters for the colour histogram comparison method is carried out for the first algorithm (DPV measurement) at this point. Sixty counters are considered by empirical basis for this comparison. Therefore, six different H values of certain ranges are counted in a particular counter as the possible values of the H ranges from 0^0 to 360^0. These counters are formed in the FPGA itself and the rest of the circuitry for colour matching purpose uses the output values of these counters. Two another 8-bit EPROMs are used for storing the output values of these counters of the two standard images (standard images are same as considered in the software part) for dissimilarity test. For the ANN based methods the two weight vector matrices, calculated by the training of the network by MLP are stored in these EPROMs. The image H data is considered of the size 128 x 128. Therefore, total amount of 16384 H data are considered for a particular image. Same size of weight vector matrix is needed for the activation function calculation purpose. Again, some of the weights are negative valued floating-point number. Therefore, two EPROMs are considered to store the final weight vector matrix. IEEE-754 - compliant variable word length floating point arithmetic cores for Xilinx Virtex, Virtex E and Virtex-II FPGA families (IEEE Computer Society, 1985). Before a floating-point binary number be stored correctly, its mantissa must be normalized. For example, decimal 1234.567 is normalized as 1.234567 x 10^3 by moving the decimal point so that only one digit appears before the decimal. Likewise, the floating-point binary value 1101.101 is normalized as 1.101101 x 2^3 by moving the decimal point 3 positions to the left, and multiplying by 2^3. The exponent expresses the number of positions the decimal point is moved left (positive exponent) or moved right (negative exponent). Again, in most of the cases the floating-point number is exactly the same as what the normalization needs, i.e., one digit before the decimal. The FPGA takes the H values from both the EPROMs (LUT) for calculating the activation function. The FPGA chip is programmed so as to handle the all data available to it and make the necessary decision for the colour matching algorithms.

C.3.1 **DPV measurement**

Sixty-four bin sizes were taken for composing the histograms for this histogram comparison method. The technique now simulated in hardware of real time operation of the same algorithm. Bin size that is considered here is sixty and they are realized in terms of counter circuit in the FPGA. The FPGA is programmed like those sixty counters are made each to count the different digital values taken from the LUT. As there are 360 possible values and these are divided into sixty counters, the range for one particular counter is eight. This means that the first counter will be incremented if the addressed hue value of LUT is in the range of 0 to 8 (decimal). Likewise the other counters also obey the same principle in incrementing themselves.

On completion of one frame of image, the dissimilarity evaluation is carried out with the corresponding counter output values of two extreme images already stored in the two other EPROMs. Analogous to the software technique of the same algorithm, the dissimilarity test is calculated using the following mathematical equation.

$$D\{C(I),C(Q)\} = \frac{1}{N_I x M_I} \sum_{j=1}^{n} | c_j(I) - c_j(Q) | \tag{C.1}$$

Where, C(I) and C(Q) are the output values of the counters of two images.

'n' is the numbers of counters (sixty)

N x M is the size of the image considered.

C.3.1.1 Counter selection colour histogram

For a particular entry of the H value from the LUT a particular counter is to be incremented. This is achieved by using a Comparator circuit, which provide the output high (logic 1) when the two input binary numbers are equal. The X-NOR gate is the basic Comparator, because its output is a 1 only if its two input bits are coincide. Figure C.9 shows the simplest X-NOR gates as the Comparator of the input logic 1 and 0. The Comparator circuit selects the actual counter to be incremented according to the values fetched from the LUT for a particular pixel location of the image. For this purpose the five MSB of the H values of the EPROM-2 is considered, as the range of the H values for a particular counter is eight. This means that the values 0-7 will be count by the first counter-1 and 8-15 will count by counter-2 and so on. Finally the values ranging from 353-360 will be count by the counter-60. Figure C.10 shows six X-NOR gates for Comparator, where outputs are taken as the input of six input AND gate. The inputs of the X-NOR gates are shown in the Figure 5.11 as (a_0, b_0), (x_7, y_7)...(x_3, y_3) (Refer to Figure C.6). As the variation of the data in the EPROM-1 is only 0 and 1 taking the LSB is sufficient for the input of the Comparator. Again, the input combinations b_0, y_7, y_6, y_5, y_4, y_3 are applied in accordance with the desired input combinations to the Comparator. These values of y_7, y_6, y_5, y_4, y_3 are the binary forms of the decimal nos. such as 4, 12, 20, 28... 252. Table C.4 shows some of the significant logic of these combinations.

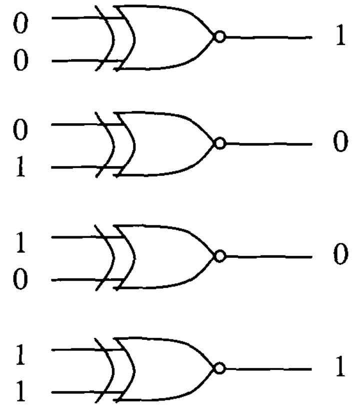


Figure C.9 Simple X-NOR for the basic Logic Comparator circuit

Table C.4 Some significant desired inputs to the Comparator.

b_0	y_7	y_6	y_5	y_4	y_3
0	0	0	0	0	0
0	0	0	0	0	1
0	.	.	.	.	.
0	1	1	1	1	0
0	1	1	1	1	1
1	0	0	0	0	0
1	0	0	0	0	1
1	.	.	.	.	.
1	1	1	0	1	0

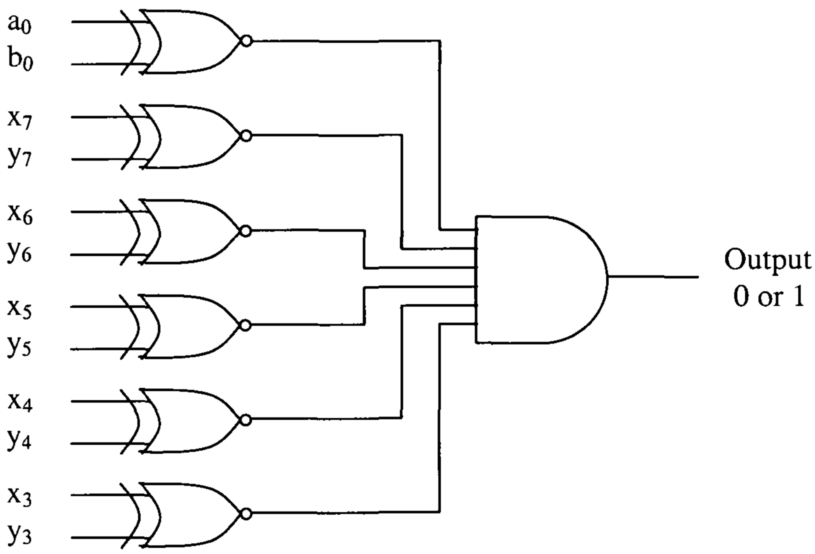


Figure C.10 Counter selection by the H values from the LUT.

The output of the AND gate (Figure C.11), which is EQUALITY is shown as the following notation:

EQUALITY = $(a_0 \odot b_0)(x_7 \odot y_7)(x_6 \odot y_6)(x_5 \odot y_5)(x_4 \odot y_4)(x_3 \odot y_3)$

The notation indicates that the two six bit numbers, '$a_0x_7x_6x_5x_4x_3$' and '$b_0y_7y_6y_5y_4y_3$' are equal if and only if, '$a_0 = b_0$', '$x_7 = y_7$', '$x_6 = y_6$', '$x_5 = y_5$', '$x_4 = y_4$', and '$x_3 = y_3$'. The output from the LUT is any one of the combinations mentioned in the Table 5.3. Therefore, for a particular pixel location of the image only one Comparator output will be logic 1 and all others will be logic 0. Once the actual counter has been selected the by using this Comparator circuit according to the H values of the LUT the number of logic 1 is counted by the counter and the final result is used for the rest of the process. Therefore, the respective counter values will be incremented and likewise the colour histograms are formed in terms of hardware circuit. This function continues during one operation till the end of the image frame. The maximum possible output value of a counter is 437664 as all the pixels of the image having the same values. Nineteen bits is sufficient to represent this number and therefore the counter outputs are represented in 19-bit format. Therefore, 1140 numbers of flip-flops are needed for this purpose.

C.3.1.2 **DPV calculation**

After composing histograms, the subtraction operation can be done in terms of Adder circuit for the dissimilarity measurement. A schematic is shown in Figure C.11.

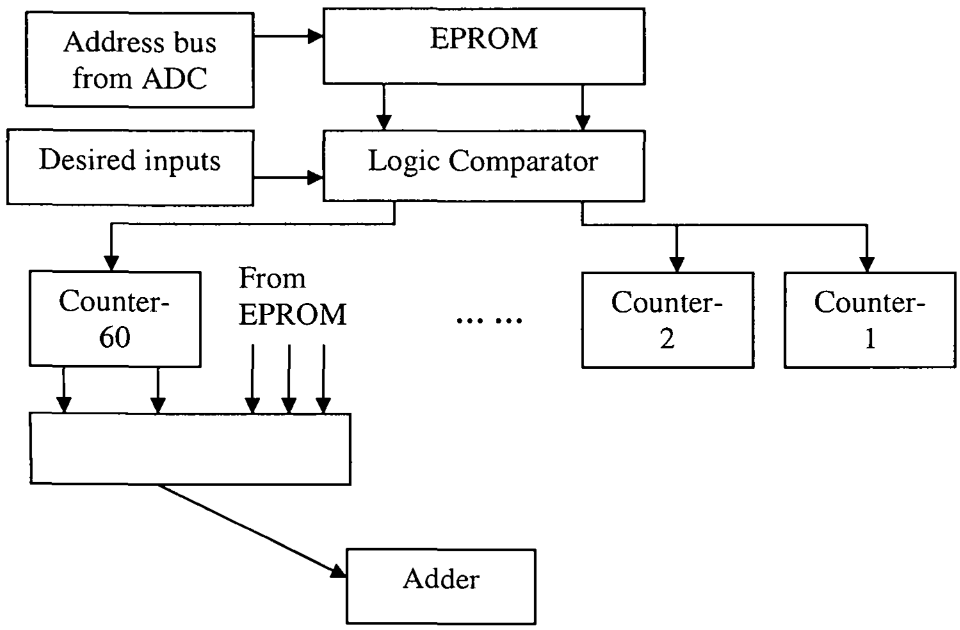


Figure C.11 Schematic for DPV calculation

C.4 Conclusions

The objective of this appendix was to present an overview of the prospects of hardware circuits for implementing the CV algorithms developed for the tea quality monitoring. For this purpose, a preliminary discussion (logic gate level architecture) is presented in terms of the DPV algorithm using the HSI colour model. The basic hardware devices that would be required are introduced. The proposed architecture uses only the hue (H) values to be processed for the colour matching purpose as the entire colour information is contained in this colour space. The prospective use the FPGA and its usefulness for real time system design for the purpose described here is being tried to present through this discussion. Such design of on-line system is one of the future aspects of the research that presented in this thesis.

References

1. Chan, S. C., Ngai, H. O., Ho, K. L., 1993. A programmable image processing system using FPGAs, Int. Journal of Electronics, Vol 75, No 4, pp 725-730.
2. Benkrid, K., Crookes, D., Bouridane, A., Corr, P., Alotaibi, K., 1999. A high level software environment for FPGA based image processing; Image Processing and Its Applications, 7th Int. Conf., Vol. 1, pp 112-116.
3. Dawood, A. S., Visser, S. J., Williams, J. A., 2002. Reconfigurable FPGAs for real time image processing in space, Digital Signal Processing, 14th Int. Conf. Vol. 2, 1-3 July, pp 845-848.
4. DeHon, A., 2000. The density advantage of configurable computing, IEEE Computer, Vol. 33, No. 4, pp 41-49.
5. Crookes, D., Benkrid, K., Bouridane, A., Alotaibi, K., Benkrid, A., 2000. Design and implementation of a high level programming environment for FPGA-based image processing, Vision, Image and Signal Processing, IEE Proceedings, Vol. 147, Issue 4, pp 377 -384.
6. Campos, R. G., Battle, J., Bischoff, R., 1996. Architecture of an Object-based Tracking System Using Colour Segmentation, 3rd International Workshop on Image and Signal Processing, Manchester, UK, November, Proc. IWISP'96, pp. 299-302.

The notation indicates that the two six bit numbers, '$a_0x_7x_6x_5x_4x_3$' and '$b_0y_7y_6y_5y_4y_3$' are equal if and only if, '$a_0 = b_0$', '$x_7 = y_7$', '$x_6 = y_6$', '$x_5 = y_5$', '$x_4 = y_4$', and '$x_3 = y_3$'. The output from the LUT is any one of the combinations mentioned in the Table 5.3. Therefore, for a particular pixel location of the image only one Comparator output will be logic 1 and all others will be logic 0. Once the actual counter has been selected the by using this Comparator circuit according to the H values of the LUT the number of logic 1 is counted by the counter and the final result is used for the rest of the process. Therefore, the respective counter values will be incremented and likewise the colour histograms are formed in terms of hardware circuit. This function continues during one operation till the end of the image frame. The maximum possible output value of a counter is 437664 as all the pixels of the image having the same values. Nineteen bits is sufficient to represent this number and therefore the counter outputs are represented in 19-bit format. Therefore, 1140 numbers of flip-flops are needed for this purpose.

C.3.1.2 **DPV calculation**

After composing histograms, the subtraction operation can be done in terms of Adder circuit for the dissimilarity measurement. A schematic is shown in Figure C.11.

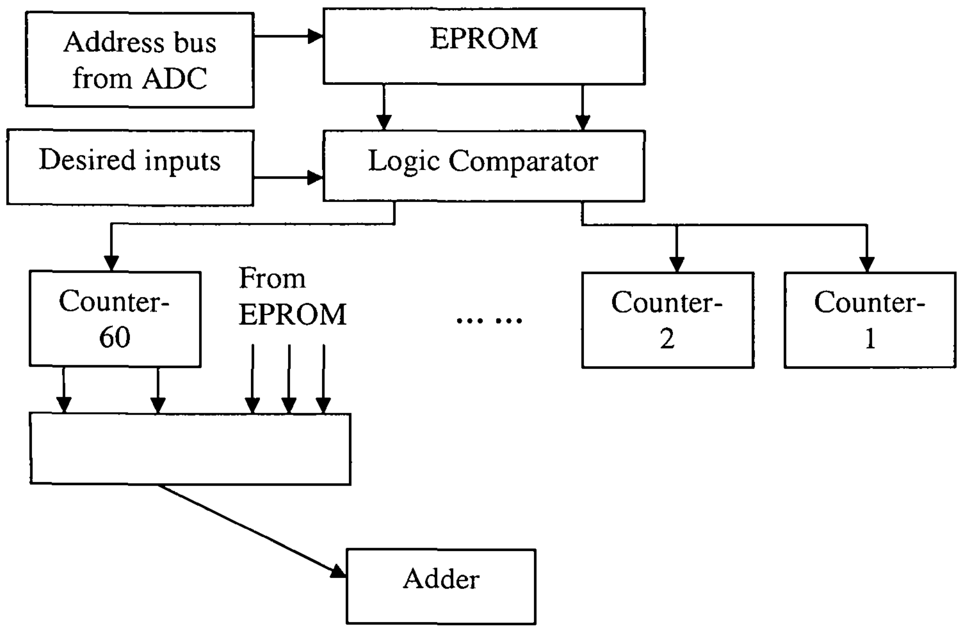


Figure C.11 Schematic for DPV calculation