DECLARATION BY THE CANDIDATE

I do hereby declare that the thesis entitled "**Development of Fast Sparse Representation Super-resolution Methods for Multispectral Remote Sensing Applications**", submitted to the Department of Electronics and Communication Engineering, Tezpur University, Tezpur, Assam, is a record of original research work carried out by me. All sources of assistance for my PhD work have been duely acknowledged. I also declare that neither this work as a whole nor a part of it has been submitted to any other University or Institute for the award of any degree or diploma.

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CERTIFICATE OF THE SUPERVISOR

This is to certify that the thesis entitled, "**Development of Fast Sparse Representation Super-resolution Methods for Multispectral Remote Sensing Applications**", submitted to the School of Engineering, Tezpur University in part fulfillment for the award of the degree of Doctor of Philosophy in Electronics and Communication Engineering is a record of research work carried out by **Mr. Helal Uddin Mullah** under my supervision and guidance.

All help received by him from various sources have been duly acknowledged.

No part of this thesis has been submitted elsewhere for the award of any other degree or diploma to the best of my knowledge.

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Dedicated To

Respected Teachers & My Family

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Abbreviations

AID	Aerial image database
ADMM	Alternating direction methods of multipliers
Beby-GAN	Best buddy GANs
BPDN	Basis pursuit denoising
CDLSR	Coupled dictionary learning for super-resolution
CFSRCNN	Coarse-to-fine SR via CNN
CoSaMP	Compressive sensing matching pursuit
CRNS	Collaborative representation and non-local self-similarity
CRR	Collaborative sparse representation
CSAE	Coupled sparse autoencoder
CSC	Convolutional sparse coding
CNN	Convolutional neural network
CUDA	Compute unified device architecture
DCT	Discrete cosine transform
DFT	discrete Fourier transform
DLP	Data level parallelism
DN	Day number
EME	Enhanced measure evaluation
EN	Entropy
ERGAS	Erreur relative globale adimensionnelle de synthese
FISTA	Fast iterative shrinkage thresholding algorithm
GAN	Generative adversarial network
GGD	General Gaussian distribution
GLCF	Global land cover facility
GSR	Group sparse representation
GSRGSiSR	Group Sparse Representation via GAUSSIAN for single image SR
HDTV	High-definition television
HoG	Histogram of oriented gradients
HPC	High performance computing

HR	High-resolution
IBP	Iterative back projection
IHS	Intensity-hue-saturation
ILP	Instruction level parallelism
ISRO	Indian space research organization
ISTA	Iterative shrinkage thresholding algorithm
JSR	Joint sparse representation
K-SVD	K- singular value decomposition
LPF	Low-pass filter
LR	Low-resolution
LRGSC	Low-rank regularized group sparse coding
MAP	Maximum a posteriori
MCA	Morphological component analysis
MHAN	Mixed high-order attention network
ML	Maximum likelihood
MS	Multispectral
MSSIM	Mean structural similarity
NIQE	Natural image quality evaluator
NIR	Near infrared
NLR	Non-local regularization
NLSS	Non-local self-similarity
NP	Non-deterministic polynomial
NSCT	Nonsubsampled contourlet transform
OMP	Orthogonal matching pursuit
OpenMP	Open multi-processing
PAN	Panchromatic
POCS	Projection on convex set
PR	Per-pixel resiltution
PSF	Point spread function
PSNR	Peak signal-to-noise ratio
PSR	Patch sparse representation

QVGA	Quarter video graphics array
RAISR	Rapid and accurate image super-resolution
RCAN	Residual channel attention networks
RCAN-it	RCAN with improved training
RoI	Region of interest
SAM	Spectral angular mapper
SAN	Second-order attention network
sCC	Spatial correlation coefficient
ScSR	Sparse Coding Super-resolution
SD	Spectral distortion
SIMD	Single instruction multiple data
SISR	Single image super-resolution
SparseFI	Sparse Fusion of Images
SR	Super-resolution
SRCNN	SR using convolutional neural network
SRR	Super-resolution reconstrution
SVD	Singular value decomposition
SVM	Support vector machine
TV	Total variation
UCMD	UC merced dataset
UIQI	Universal image quality index
VDSR	SR using very deep CNN

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Symbols

$\boldsymbol{\alpha}$	Sparse coefficient vector
λ	Regularization parameter
S	Downsampling operator
H	Blurring operator
σ	Standard deviation
μ	Mean of Gaussian distribution
$\|.\|_0$	ℓ_0-norm
$\|.\|_1$	ℓ_1-norm
$\|.\|_2$	ℓ_2-norm
$\mathbf{D}_\ell$	LR dictionary
$\mathbf{D}_h$	HR dictionary
$\mathbf{D}_c$	Coupled dictionary
$\mathbf{X}$	HR image
$\mathbf{x}$	HR image patch
$\mathbf{Y}$	LR image
$\mathbf{y}$	LR image patch
$\mathbf{X}_0$	Intermediate HR image obtained from HR patches
c	Regularization constant
σ_{xy}	covariance between $\mathbf{x}$ and $\mathbf{y}$
σ_x	Standard deviation of $\mathbf{x}$
μ_x	Mean value of original image
μ_y	Mean value of reconstructed image
E_p	Patch extraction operator
p	Size of HR patch vector
q	Size of LR feature patch vector
$\mathbf{X}_C$	Combined patch set of LR-HR image
$\mathbf{X}_t$	Texture component of image
$\mathbf{X}_s$	Structure component of image
$\mathbf{d}_i$	Euclidean distance

$\mathbf{X}_g$	Patch-group matrix of similar patches
$\boldsymbol{\beta}_{g_i}$	Group sparse coefficients metrics
Γ	Patch-group extraction operator

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