Abstract

The enhancement of spatial resolution in the field of remote sensing is crucial for various applications such as environment monitoring, automatic target recognition and military target identification, etc. However, due to physical sensor limitations, complex atmospheric disturbances, and hardware costs associated with upgrading to high-precision sensors and equipment, remote sensing (RS) earth observation sensors, especially, multispectral (MS) suffer from low-resolution (LR). Therefore, image super-resolution (SR) is a cost effective algorithmic-based post-processing solution that aims to restore high-resolution (HR) images from their LR counterparts. The rapid growth of learning-based approaches, particularly, sparse representation- and deep learning (DL)-based techniques have significantly increased the performance of single image super-resolution (SISR) algorithms designed for RS applications over shallow learning- or dictionary-based techniques.

In this thesis, we first aim to develop a fast sparse representation-based SISR algorithm for RS images that can improve the reconstruction quality of the test LR image. The quality of the LR image reconstruction in the sparse representation-based SISR approach significantly depends on the quality of the trained dictionary and the effectiveness of some hand-crafted feature extraction strategies needed for efficient dictionary construction. To prove the effectiveness of both feature extraction and dictionary learning strategies, we have first developed a novel algorithm for enhancing the resolution of RS images using sparse coding and adaptive dictionary learning. This approach uses the single LR remote sensing image itself to learn patch-based coupled dictionaries based on sparse representations of low- and high-frequency features. The approach includes a novel feature extraction method that makes use of the difference of Gaussians (DoG), Sobel, and fast Fourier transform (FFT) filters to effectively learn coupled dictionaries and reconstruct target HR images. Since it is essential in SR of RS images to preserve both textural and structural features, particularly, the edges, the sparse representations-based SISR using a patch-based coupled dictionary alone fails to produce sufficient results in the recovery of edge information from LR images. To recover edges, we have proposed a SISR framework based on edge preserving dictionary learning and sparse representations. Multiple coupled dictionaries, namely, the scale-invariant feature transform (SIFT) keypoints and non-keypoints patch-based dictionaries are learned. A joint reconstruction model is then developed using both non-local total variation (NLTV)-based gradient and SIFT keypoints-guided patch sparsities. The proposed sparse representation-based methods provide excellent reconstruction quality with average improvements in peak signal-to-noise ratio (PSNR) of 1.4–5.1 dB and 1.3–

4.0 dB for zooming factors 2 and 4, respectively, while edge preserving index (EPI) improvements are 0.051–0.161 and 0.096–0.191 for zooming factors 2 and 4 respectively. However, they are computationally highly demanding due to their ill-posed nature. To address this issue, we propose highly parallelized algorithms based on the compute unified device architecture (CUDA) programming model using general purpose graphics processing unit (GPGPU) for real-time remote sensing applications.

Although in general sparse representation-based methods provide excellent reconstruction quality, they rely on hand-crafted features. On the other hand, automatic feature extraction in DL-based SISR approaches handle complex mappings between LR and HR images and captures image structures without requiring hand-crafted feature selection. Due to these benefits, DL-based SISR techniques are effective for image SR, particularly in RS applications. It is also observed from existing DL-based SISR networks in RS applications that they are not very effective in restoring HR images when their is sufficient degradation due to blurring in LR remote sensing images. Therefore, we have developed a joint dual-branch CNN network for recovering the sharp and clear HR images from LR remote sensing images degraded with Gaussian blur. The feature extraction step is divided into two independent streams, i.e. deblurring and SR, and their individual features are adaptively fused by learning a gate module with attention to generate a clear HR from LR remote sensing images with Gaussian blur. In particular, we have proposed a SR feature extraction module which adopts a residual spatial and channel squeeze-and-excitation (RSCSE) architecture to extract SR features efficiently by integrating concurrent spatial and channel squeeze-and-excitation (SCSE) and local feature fusion (LFF) concepts in the residual module in order to increase its representational ability. Further, the deblurring module uses a simple SCSE-based encoder-decoder CNN module for extracting sharp features from blurry LR. The proposed method outperforms other state-of-the-art DL-based SISR methods in terms of both visual results and quantitative performance metrics, giving an average improvement in terms of PSNR of 1.4–4.2 dB and 0.3–2 dB for zooming factors 2 and 4, respectively.

Extensive qualitative and quantitative experiments are conducted using publicly available RS and self-procured RS datasets to compare the proposed approaches to the state-of-the-art methods. The results obtained using visual analysis and quantitative metrics, including PSNR, structural similarity index (SSIM), erreur relative globale adimensionnelle de synthese (ERGAS), spectral angle mapper (SAM), Universal Image Quality Index (Q-index), and spatial correlation coefficient (sCC), demonstrate that the sparse representation- and DL-based algorithms proposed in the thesis significantly improve the reconstruction quality of LR images and offer a near real-time solution for RS applications.