Chapter 6

Conclusions and Future Scopes

6.1 Summary

Remote sensing (RS) images generally suffer poor visual quality due to limitations imposed by the sensors used to capture the images, such as limitations in spatial resolution or sensor noise. Image SR can help to improve the quality of RS images by increasing their spatial resolution and enhancing their visual quality. This can make them more meaningful for a wide range of applications, including environmental monitoring, disaster management and land use planning. In recent years, the learning-based SR methods have become immensely popular for improving spatial and spectral resolutions of RS images. However, the existing learning-based SR methods fail to give satisfactory results for RS image SR. Hence, the development of fast and efficient learning-based methods is very crucial in many real-time RS applications.

We first propose a sparse-representation-based algorithms that effectively preserves the edges in HR images. Furthermore, to enhance the efficiency and minimize the computational complexity, we developed highly parallelized algorithms using the CUDA programming model on GPU for real-time applications. However, the limitations of sparse-representation-based methods in extracting features automatically have led to the development of DL-based SISR methods that have shown remarkable performance in recent years. Therefore, to enhance the quality of reconstructed images, we proposed a novel CNN-based deep learning SISR method that achieves the state-of-the-art performance.

In Chapter 2, we first review relevant sparse representations and DL-based SISR algorithms, SR image datasets, and available evaluation metrics that we employed in our work. In Chapter 3, we have developed an effective sparse representations-based SISR approaches for RS images by proposing adaptive dictionary learning with an improved feature extraction strategy. The new feature extraction strategy and the consequent improved dictionary learning technique can enhance the visual quality and restore high-frequency details in the reconstructed image. However, the edge information is not well preserved in the reconstructed RS image as evident from the results presented in Chapter 3. In order to preserve edges, a sparse representation-based SISR problem can be solved jointly using the sparsity prior as well as an edge-preserving prior. Therefore, in Chapter 4, we develop sparse representation strategies that incorporate multiple dictionaries learning, as well as a joint sparse reconstruction. The reconstruction model combines SIFT-driven keypoints and non-local total variation (NLTV) regularization priors, to improve the results and preserve edges. Furthermore, in order to overcome the computational overheads of sparse representations-based methods in Chapter 3 and 4, highly parallelized CUDA-based algorithms have been designed for dictionary learning and sparse reconstructions utilizing GP-GPU for real-time SISR of RS images. In Chapter 5, we have developed a joint dual-branch CNN network for recovering the sharp and clear HR images from LR remote sensing images with Gaussian blur. The proposed network introduces an attention-based gate module for fusing features adaptively from SR and deblurring feature extraction branches, allowing the network to handle deblurring and SR tasks jointly. In particular, we build a RSCSE module to extract SR features efficiently by adopting SCSE and LFF in residual blocks in order to increase the representation ability of the proposed network. Further, the deblurring module uses a simple SCSE-based encoder-decoder CNN module to extract sharp features from blurred LR images.

Extensive simulations are conducted on the proposed methods using the publicly available and real MS remote sensing datasets; results are compared with existing similar works in terms of visual analysis and quantitative metrics for evaluating the quality of super-resolved RS images. Overall, this thesis has contributed to advancing the field of RS by introducing new and effective techniques for high-quality image reconstruction. The proposed algorithms have significant potential in practical applications such as remote sensing, surveillance, and medical imaging. The results obtained from the experimental evaluation demonstrate the efficacy of the proposed methods, thereby validating their potential in real-world applications.

6.2 Future research scopes

In this section, we briefly discuss the following interesting and prospective research directions that are deemed worthy of further investigation based on the findings of this thesis.

A. **Fusion of Sparse and Deep-learning super-resolution framework:**
   In this thesis, we have proposed separate frameworks for Sparse and DL-based SISR. Investigating the fusion of sparse-representation-based and DL-based SISR approaches to benefit from the complimentary strengths of both techniques is one possible direction for future research. Sparse representation methods are good at preserving edge information, while DL-based methods excel at capturing complex image features and textures. One potential approach for fusion is to use sparse representation-based methods as a pre-processing step to enhance the initial input images, while the DL-based SISR methods can be used to further improve the reconstruction quality by learning high-level features from the enhanced images. Furthermore, hybrid approaches can be explored, where both techniques are jointly optimized to learn a more effective and efficient solution for SISR.

B. **Joint spatial and spectral SR for MS images using DL:**
   In this thesis, SISR is employed to enhance MS band images spatially by processing bands separately in order to preserve the spectral properties of the MS images. However, the thesis does not specifically focus on spectral SR of MS images. In the future, DL-based methods may be used to improve the spatial and spectral resolution of MS images jointly. Integrating GANs and SR networks holds promise for improving both spatial details and spectral information.

C. **Unsupervised learning:**

The supervised learning strategy is used in the proposed DL-based SISR network. The main constraints of this kind of network strategy are that it requires a huge quantity of labeled data and is incapable of dealing with unknown image degradation processes. One promising direction for future research is to explore unsupervised DL methods for SISR in RS. This can involve the use of techniques such as self-supervised learning methods, which can learn from unlabeled RS images by utilizing the inherent structure and content of the data. Self-supervised learning methods can involve techniques such as autoencoders, which can learn to reconstruct high-resolution images from LR ones without the need for labeled data.

D. **New evaluation metrics:**
In this thesis, PSNR and SSIM are mostly used for the quantitative evaluation of image quality of RS images. While existing metrics such as ERGAS, SAM, and sCC commonly used in the experiments, were primarily developed for hyperspectral images and may not accurately reflect the performance of multispectral SR techniques. One potential area of future scope is the development of new evaluation metrics specifically designed for MS remote sensing images. To address this issue, new evaluation metrics could be developed that take into account the unique characteristics of MS images, such as the number of spectral bands, the spectral range, and the spatial resolution.

E. **Real-world remote sensing SR:** The LR images in this thesis are generated using Gaussian blurring and bicubic interpolation. The spatial and spectral distributions of real-world LR images are quite different from those of artificially generated LR images. The proposed DL-based SISR network is trained on synthetically generated image degradations, which cannot be generalized to the processes occurring in the real-world LR images. As a result, novel methods for generating degradation models have to be developed in order to provide realistic LR images, which could replicate the real-world deterioration model.

F. **Higher and arbitrary scale factors:**
In this thesis, experiments are conducted on solving the SR problem up to four

($\times 4$) upscaling factor. This choice was made to allow a comparison with state-of-the-art methods, where up to this upscaling factor was commonly used. It is also difficult to perform SR for higher upscaling factors, such as $\times 8$, $\times 16$ and $\times 32$, where objects, structural and textural details recognition becomes even more challenging in RS images. Therefore, new strategies need to be proposed for spares representation and DL-based SISR method to handle the higher upscaling factors in order to recover the fine details in RS image. In addition, a new DL framework that can handle arbitrary upscaling factors can be proposed. This framework may be beneficial for real-time RS applications, when the upscaling factors are arbitrary.