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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 recover 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 RS 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 representation-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 1.1–3.1 dB and 1.3–4.0 dB for zooming factors 2 and

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