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ORIGINAL ARTICLE

An integrated scheme to improve pan-sharpening visual quality of satellite images

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Abstract Pan-sharpening is the process to fuse a low-resolution multispectral (MS) image with a high-resolution panchromatic (Pan) image to construct high spatial and spectral resolution MS image. In this study, a novel pan-sharpening scheme based on integration of Curvelet Transform (CT) and Bi-dimensional Empirical Mode Decomposition (BEMD) is investigated.

First, input MS image decomposes into a sequence of intrinsic mode functions (IMFs) and residues using BEMD to remove large amounts of redundancies and carries their spatial and frequency components of all pixels.

Second, decompose IMFs component and detail coefficient of Pan image using Curvelet Transform (CT), which are directional. Then, we use linear dependency to decide which detail coefficient of Pan should be injected into MS coefficient. Finally, we perform the inverse curvelet and inverse of BEMD to get high-resolution MS image.

In experiments with IKONOS, Quick Bird and GeoEye satellite data, we demonstrated that our scheme has good spectral quality and efficiency. Spectral and spatial quality metrics in terms of SAM, RASE, RMSE, CC, ERGAS and QNR are used in our experiments. We compared our scheme with the state-of-the-art pan-sharpening techniques and found that our new scheme improved quantitative and qualitative results.

1. Introduction

Main objective of pan-sharpening is containing spatial information from a high-resolution image, e.g. Pan or Synthetic Aperture Radar (SAR) image to a low-resolution image, e.g., MS image, while remaining spectral characteristics of MS image. In addition, registration should be done before pan-sharpening to avoid artifacts of the output image and, MS image should be resampled into the similar spatial reference

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and grid like the Pan image, using nearest neighbor or cubic convolution techniques.

Over the last decades, a number of pan-sharpening algorithms have been developed that are either based on Multiresolution Analysis (MRA) or Component Substitution (CS). There are also hybrid methods based on both MRA and CS.

CS-based methods such as intensity hue saturation (IHS) [1,2] have widely used due to the high sharpening capability. Since the intensity component of MS image substituted with the Pan image. In addition, other CS-based methods such as Principle component analysis (PCA) [3], Brovey transform and Gram-Schmidt (GS) [4] provide superior visual high-resolution multispectral images, but have a limitation of high-quality spectral information. Although a variety of modified methods [5,6] have proposed to recompense for such distortion, the limitation of CS-based methods does not fully overcome.

Recently, different methods based on MRA have demonstrated a greater capability of injecting high frequency components from PAN image into MS low-frequency sub-band with low spectral distortion. Between them, the commonly accepted approximation tools are "á trous" wavelet transform [7], generalized Laplacian pyramid [8], in addition to the anisotropic frame-based transforms such as curvelet [9,10], nonsubsampled contourlet [11,12] and shearlet transform [13]. As the MRA-based multiscale transform can efficiently decompose the image into high-pass (HP) and low-pass (LP) sub-bands, not only does it have an improvement on minimizing the spectral distortion, but it also gives a flexibility to describe how the HP coefficients of Pan are injected into the LP sub-band of MS. Initial mechanism recommended directly inserting the HP coefficients into the LP sub-band of MS. However, different techniques using the ARSIS concept [14,15] bend the coefficients based on specified algorithms [16]. Regularly, these algorithms feature in modified injection of information according to the local correlation between Pan and MS images, and do better than the directly injecting method.

Empirical mode decomposition (EMD) is considered as a new signal decomposition technique for analyzing nonlinear and non-stationary signals, which was suggested by Huang et al. [17,18]. EMD is a novel data representation that has better spatial and frequency characteristics than wavelet analysis. Input images are represented by EMD as IMFs taking their spatial and frequency components of each pixel. However, one of the main drawbacks of EMD is the mode-mixing problem, which is defined as either a single IMF contains components of wide disparate scales, or a component of a similar scale residing in different IMFs.

Bi-dimensional EMD [19] is data adaptive decomposition and decomposes 2D signal into near orthogonal (not fully orthogonal) IMFs and taking their spatial and frequency components about each pixel.

Curvelet provides a multiscale and multidirectional decomposition of images. Since, it is sensitive to directional edges and able to represent the high-pass details of contours at dissimilar scales.

Contribution of the paper: proposed scheme is better than some other image pan-sharpening methods in two significant ways. Firstly, it uses the spatial similarity property of IMFs to remove large amounts of redundancies by estimating IMFs at high-resolution levels. Secondly, it uses the curvelet transform, which provides richer information in the spatial, spectral domains simultaneously; enhance spatial resolution and is based on MRA. So, this combination will give superior fusion results.

This paper is structured as follows: In Section 2, we briefly describe BEMD and curvelet transform. Section 3 describes the proposed pan-sharpening scheme in detail. Section 4 gives Quantitative Quality Assessment that used in evaluation. Section 5 presents different results and the comparisons with other methods. Finally, we draw the conclusion in Section 6.

2. Materials and methods

In this section, we describe BEMD and give a brief illustration of curvelet transform.

2.1. BEMD

EMD is a highly efficient approach that offers high frequency information and accurate timing of non-stationary and nonlinear signal. The EMD permits to extract spatial frequency components of different spatial scales from finest to coarsest scales [18]. This signal can be decomposed using EMD into IMFs and a residue as follows:

$$f(x) = \sum_{i=1}^{n} IMF_i(x) + r(x) \tag{1}$$

where $f(x)$ be a signal, $IMF_i(x)$ is described as the ith IMF of the original signal and $r(x)$ is described as the residue.

BEMD is the 2D extension of EMD, which decomposed input image into several IMFs components and a residue component [19–21]. The first IMF includes the highest of local frequencies, the final IMF includes the lowest local frequencies of oscillation and the residue contains the trend of the data. IMF components of BEMD have the following characteristics:

(i) Maximum and minimum points are the same as zero crossing points.
(ii) IMF components represent every frequency of local data; they correspond to high frequency, and low points are the frequency data; the residue component represents development tendency of the original image. BEMD is a kind of completely self-adaptive decomposition. The decomposition process can describe as:

$$I(m,n) = \sum_{j=1}^{J} D_j(m,n) + R_j(m,n), \quad J \in N \tag{2}$$

where D_j is the jth 2D IMFs, R_j is the residue component after J layers decomposition. IMF components are divided into two types, high frequency and low frequency as shown in Fig. 1.

2.2. Curvelet Transform (CT)

Curvelets presented in [22,10,23] as an expansion of wavelets and ridgelet transforms for multidimensional data and detecting curved edges effectively. Main difference between wavelet and curvelet is that curvelets are only directional. The curvelet transform gets good representation in images containing edges; therefore, we can use it to enhance image edges as in Figs. 2 and 3. It is summarized as: