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Contourlet-Based Multispectral Image Fusion Using Free Search Differential Evolution

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Abstract. In this paper, the multispectral image fusion task is converted into an optimisation problem, to satisfy the objective of maximal injection of spatial information with minimal spectral distortion. Contourlet transform (CT) is employed to extract the spatial high-frequency coefficients from PAN image and they are weighted and injected into each band of the corresponding components of multispectral data. The weighted coefficients are found by using the advanced evolutionary intelligence technique called free search differential evolution (FSDE). The novelty of this paper is to introduce FSDE for improved application of CT for image fusion. The proposed method, CT-FSDE, was tested and compared with principal component analysis (PCA), Laplacian pyramid (LP), wavelet transform (WT), and CT over a WorldView-2 dataset. In order to study the effectiveness of FSDE, I also compared it with two advanced evolutionary algorithms, JADE and PS^2O, which were developed from differential evolution and particle swarm optimisation, respectively. The quantitative results from conducted experiments show that the proposed method provides high-quality spatial details and also preserves spectral information well, which highlights the benefits of the proposed method for multispectral image fusion.

1 Introduction

In order to extend the scope of the emerging remote-sensing technology application, image fusion techniques have now been developed to integrate the information conveyed by data acquired from multiple sensors with different spatial and spectral resolution [1]. A notable development is the fusion of multispectral (MS) and panchromatic (PAN) images. The image fusion techniques take advantage of the complementary spatial/spectral characteristics for producing spatially enhanced MS observations [2]. Because of several bands in MS, pixel-based fusion schemes have been recognised as one of the most efficient tools to implement fusion of images at different resolutions. Generally, there are two major groups of methods: spatial image fusion, such as principal component analysis (PCA) [3], and multi-resolution image fusion, such as multi-resolution analysis (MRA) based on Laplacian pyramid (LP) [4] and wavelet transform (WT) [5]. Previous studies indicate that the MRA-based fusion methods have better performance than the spatial-based fusion methods in many aspects, such as in the presence of noise [6].

Recently, a new MRA scheme, contourlet transform (CT), was proposed by Do and Vetterli [7]. CT is a nonseparable MRA, whose basis functions are directional edges with progressively increasing resolution. The distinguished feature of the contourlet transform is its capability of representing the multiscale and time-frequency-localization properties of wavelets as well as offering a high degree of directionality and anisotropy [8]. To be specific, CT includes basis functions that are oriented at any power of two number of directions with flexible aspect ratios. Compared with wavelets, the rich set of basis functions thus make contourlets represent a smooth contour with fewer coefficients. However, like other MS fusion methods, such as PCA, LP, and WT, CT introduces the spectral distortions to the original MS data. Generally, the MS images fusion can be regarded as an optimisation problem that we want to sharpen the MS images with spatial information extracted from PAN image and preserve the spectral information of original MS images as much as possible. Therefore, we need search for a new robust optimisation tool to solve the problem.

Various new evolutionary algorithms have been proposed by researchers in the last decade, such as genetic algorithms, particle swarm optimisation, and differential evolution. These population-based algorithms are popular search techniques for solving global optimisation problems with unknown structure to the objective function [9]. While these algorithms have been testified for their effectiveness both in theoretical and practical aspects, each evolution algorithm has its own weaknesses. One common drawback is that artifacts in most evolutionary algorithms cannot make free decisions to adjust their behaviours to their environments because these algorithms have previously modelled a system level decision process [10]. With this concern, Omran and Engelbrecht proposed an effective algorithm, called free search differential evolution (FSDE) [11], in which the individuals can make their own decisions based on various senses. An individual level decision process is therefore embedded in the model concept of free search (FS), which provides individuals with an ability of artificial thinking. FSDE addresses the drawbacks of FS [12], and is easy to implement with high computation efficiency and rapid convergence [11, 13].

In this paper, evolutionary intelligence, free search differential evolution (FSDE), is introduced for image fusion using contourlet transform (CT). The proposed scheme is noted as CT-FSDE in short. Specifically, the MS fusion task was converted into an optimisation problem, to satisfy the objective of maximal injection of spatial information with minimal spectral distortion. CT is employed to extract the spatial high-frequency information from PAN image. Then, the high-frequency coefficients of the PAN data are weighted and injected into each band of the corresponding components of MS data. The weighted coefficients are found for each band of the MS image by using FSDE. CT-FSDE was tested and compared with PCA, LP, WT, and CT over the WorldView-2 dataset. In order to study the effectiveness of FSDE, I also compared it with two advanced evolutionary algorithms JADE [14] and PS^2O [15], which were developed from differential evolution and particle swarm optimisation, respectively. The quantitative results highlight the benefits of the proposed method for MS image fusion.

The reminder of this paper is organised as follows. In Section 2, the proposed method, CT-FSDE, is described in details. Experiments, results interpretation, and analysis are presented in Section 3. Finally, Section 4 gives a concise summary of this paper.

2 CT-FSDE Algorithm

In this paper, I proposed a new multispectral image fusion algorithm (CT-FSDE) which employs contourlet transform (CT) [7] with an improved optimisation technique by introducing free search differential evolution (FSDE) [11]. To be specific, the CT is employed to extract the spatial high-frequency information from the panchromatic (PAN) data. Then, the high-frequency coefficients of the PAN data are weighted and injected into each narrow band of the multispectral data. The weighted coefficients are calculated adaptively for each band by using FSDE.

2.1 Contourlet-Based MS Fusion

Let $f^{(P)}(x,y)$ be the dataset constituted by a single PAN image having finer spatial resolution with size $X \times Y$. Let $\{f^{(n)}(x,y),\ n = 1,2,\cdots,N\}$ be the dataset made up of N bands of an MS image with size $\hat{X} \times \hat{Y}$. Such bands have finer spectral resolution but coarser spatial resolution. The issue of MS fusion is to obtain a set $\{\tilde{f}^{(n)}(x,y),\ n = 1,2,\cdots,N\}$ of MS bands having the same spatial resolution as PAN data. The enhancement of each band $f^{(n)}$ to yield the spatial resolution of $f^{(P)}$ is synthesised from the CT of the PAN image. The MS bands $\{f^{(n)}(x,y),\ n = 1,2,\cdots,N\}$ are preliminarily interpolated by p (the scale ratio: $p = X \times Y \big/ \hat{X} \times \hat{Y}$) to match the scale of the PAN image. A new dataset, $\{\hat{f}^{(n)}(x,y),\ n = 1,2,\cdots,N\}$, is thus produced. Then, the CT coefficients of each layer, extracted from $f^{(P)}$, are weighted and used to add to the corresponding detail frames of $\hat{f}^{(n)}$. The fused MS dataset, $\{\tilde{f}^{(n)}(x,y),\ n = 1,2,\cdots,N\}$, is obtained by summing the approximations and enhanced detail frames of each band.

2.2 Optimisation Objective Function for MS Fusion

The goal of MS fusion can be achieved by injection of high frequency coefficients (HFCs) of PAN data. These HFCs, however, cannot simply replace the corresponding coefficients extracted from each band MS image because they will bring the spectral distortion to the original MS data. Therefore, the HFCs of PAN data have to be weighted before injecting them into the MS data. In this paper, I employed FSDE to determine the optimal weights automatically. Therefore, we need to build an objective function to measure the quality of optimised weights. To be more specific, the initial weights are randomly generated within $(0,1)$, and then they are optimised by using FSDE.

In consideration of the computational burden, the image gradient is a simple and direct criterion that effectively measures the "details" in an image. The high value of gradient indicates the more "details" information, while the low value means the less "details". Let $I(x,y)$ be the brightness value of the pixel located at (x,y) in an image. The image gradient at (x,y) is defined as

$$\|\nabla I(x,y)\| = \sqrt{\nabla I_x^2(x,y) + \nabla I_y^2(x,y)}, \tag{1}$$

where

$$\nabla I_x(x,y) = \frac{\partial I(x,y)}{\partial x} \doteq \frac{I(x+1,y) - I(x-1,y)}{2}, \tag{2}$$

and

$$\nabla I_y(x,y) = \frac{\partial I(x,y)}{\partial y} \doteq \frac{I(x,y+1) - I(x,y-1)}{2}. \tag{3}$$

For all pixels, the average gradient measures the “details” in an image, which is given as

$$\nabla I = \frac{1}{X \times Y} \sum_x \sum_y \sqrt{\|\nabla I(x,y)\|^2}, \tag{4}$$

where $X \times Y$ represents the size of the image. Because the goal of FSDE is to find the global minimum and large value of average gradient indicates better fusion results, the objective function can be rewritten as

$$f_{opt}(x,y) = \frac{1}{1 + \nabla I}. \tag{5}$$

The f_{opt} can be regarded as the measurement of fusion results. When FSDE minimises f_{opt}, the maximal ∇I can be acquired. This process means the frequency coefficients (FCs) of the PAN are injected into the MS data as much as possible.

2.3 Implementation of the Proposed Methodology

Let $C_{i,j}(f^{(P)}(x,y))$ be the frequency coefficients (FCs) of the PAN data decomposed by using CT at the i^{th} level and the j^{th} component, and let $C_{i,j}(\hat{f}^{(n)}(x,y))$ be the corresponding FCs of the n^{th} band of MS image. The injection FCs, $C_{i,j}(\tilde{f}^{(n)}(x,y))$, can be acquired by using the rule given as

$$C_{i,j}\left(\tilde{f}^{(n)}(x,y)\right) = w_{i,j} \times C_{i,j}\left(f^{(P)}(x,y)\right) + v_{i,j} \times C_{i,j}\left(\hat{f}^{(n)}(x,y)\right), \tag{6}$$

where $\{w_{i,j}\}$ and $\{v_{i,j}\}$ are the weight coefficients, which are subject to

$$w_{i,j} + v_{i,j} = 1, \tag{7}$$

where $w_{i,j}, v_{i,j} \in (0,1)$. All the weight coefficients are the optima calculated by using FSDE.

The implement details of CT-FSDE are described below.

Step 1: Each band of MS image, $\hat{f}^{(n)}(x,y)$, is decomposed by using the CT. Find the FCs of each band, $C_{i,j}(\hat{f}^{(n)}(x,y))$, at each level.

Step 2: PAN image, $f^{(P)}(x,y)$, preliminarily performs histogram matching with each band of MS image, $\hat{f}^{(n)}(x,y)$. Then, the PAN images, $\{f_n^{(P)}(x,y),\ n = 1,2,\cdots,N\}$, are produced. The FCs of each $f_n^{(P)}(x,y)$, $C_{i,j}({f_n}^{(P)}(x,y))$, are similarly calculated, which are used for further injecting into $\hat{f}^{(n)}(x,y)$.

Step 3: For each band of MS image, $C_{i,j}(\hat{f}^{(n)}(x,y))$ and $C_{i,j}({f_n}^{(P)}(x,y))$ are weighted. The weighted coefficients are calculated by using FSDE with the goal of minimizing the objective function in Eq. (5). Then, the fusion coefficients, $C_{i,j}(\tilde{f}^{(n)}(x,y))$, are obtained by using Eq. (6).

Step 4: The fused MS dataset, $\{\tilde{f}^{(n)}(x,y),\ n = 1,2,\cdots,N\}$, is obtained by using inverse CT, reconstructed by the approximations of each band $\hat{f}^{(n)}(x,y)$ and the enhanced $C_{i,j}(\tilde{f}^{(n)}(x,y))$.

3 Experiments & Results

3.1 Fusion Result Evaluation Criteria

To be able to quantify the quality of the fusion results, I use a broad variety of seven different quality metrics which are common in literature for fusion evaluation purposes. To be specific, the following evaluation criteria were used: the signal to noise ratio (SNR) [16], discrepancy index (DI) [17], relative dimensionless global error in synthesis (ERGAS) [18], universal image quality index (UIQI) [19], correlation coefficient CC [20].

3.2 Dataset Depiction

The proposed CT-FSDE based fusion procedure has been assessed on the very high-resolution image dataset collected by WorldView-2. This dataset displays the urban of Rome, in Italy, and was acquired in Dec. 2009. The WorldView-2 provides a high resolution PAN band and 8 MS bands spanning 4 standard colours (red, green, blue, and near-infrared 1) and 4 new bands (coastal, yellow, red edge, and near-infrared 2). The wavelengths of 8 bands are spectrally disjoint: coastal blue ($400-450$nm), blue ($450-510$nm), green ($510-580$nm), yellow ($585-625$nm), red ($630-690$nm), red edge ($705-745$ nm), near-infrared 1 ($770-895$nm), and near-infrared 2 ($860-1040$nm).

The used dataset is geometrically and radiometrically calibrated. It is available as geocoded product, re-sampled to uniform ground resolutions of 2m (MS) $-$ 0.5m (PAN). All pixel values are packed in 16-bit words. The original PAN image is of size 4600×4604, while the original MS images of size 1150×1151 with each band. Sub regions in MS data of size 200×200 and PAN data of size 800×800 around the Colosseum were analysed.

To allow quantitative distortion measures to be achieved, the PAN image and MS images are preliminarily decimated by 4, to yield 2m PAN $-$ 8m MS. Such spatially degraded data are used to re-synthesize the 8 spectral bands at 2m. Thus, the true 2m 200×200 MS data are available for objective distortion measurements.

3.3 Results & Analysis

The experiments are conducted on the degraded MS data with pixel resolution of 8 m and degraded PAN data with pixel resolution of 2 m for the WorldView-2 dataset. Principal component analysis (PCA), Laplacian pyramid (LP), wavelet transform (WT), and contourlet transform (CT) are employed to decompose every image in three levels, considering that the used image size is of 200×200. I also use two advanced evolutionary algorithms JADE and PS^2O proposed in [14] and [15], respectively, to compare against the effectiveness of using FSDE in the proposed algorithm. For fair comparison, I set the all the parameters and used filters in all comparison algorithms to be fixed for the two investigated datasets. For LP, the “PKVA” filter is used; for WT, the DB4 filter is used; for CT and comparison algorithm based on CT, the “9/7” filter and the “PKVA” filter are used. For CT-based MS image fusion using JADE (CT-JADE), I set the constants $p = 0.2$ and $c = 0.1$. For CT-based MS image fusion using PS^2O (CT-PS^2O), I set the number of swarms $n = 5$, $C1$ and $C2$ both 2.05, $C3 = 2.0$, the constriction factor $\chi = 0.729$, and the maximum velocity was set to be 50% of the search space. For CT-FSDE, there is no extra parameter to be set. The values of common parameters for CT-JADE, CT-PS^{2}O, and CT-FSDE were set as follows: the population $NP = 30$ and the maximum iteration times $G = 500$. It should be noted that I just present the comparison on the quantitative results because fused images are similar which might not be distinguished by visual comparison, and it is more objective.

In the conducted experiments for the WorldView-2 dataset, the reported quantitative results are SNRs, DIs, UIUQs, ERGASs, and CCs in Tables 1 and 2, in which the best results for each quality measure are labeled in bold. The SNR is a direct index to compare the fused image with the reference MS image. Table 1 shows that the proposed method provides the highest SNR values for all the eight bands. The DI yields a global measurement of spectral distortion of the fused images. The results shows that the CT-FSDE method gives the lowest DI in B1, B2, B7, and B8, while CT-PS^{2}O just has a weak advantage on the rest four bands compared with the results achieved by CT-FSDE. From Table 1, we can see that the proposed method gives the best results for ERGAS. Since ERGAS only consider root mean square error, and DI only considers spectral distortion, a more comprehensive measure of quality UIQI has been developed to test both spectral and spatial qualities of the fused images. From Table 2, we can see that the proposed method only loses the B3, B4, and B5 for the UIQI, but it is almost the same between the best results acquired by using CT-PS^{2}O. We can also see that the proposed method gives the lowest CC values for all the eight bands. This is mainly due to the advantage of the proposed scheme over other comparable methods that uses FSDE to calculate the weighted coefficients adaptively when the information extracted from the PAN data is injected into the MS data. Thus, the reconstructed fused MS images can preserve well both spatial and spectral information of the source images.

4 Conclusions

A new approach of MS fusion method based on discrete contourlet transform using free search differential evolution are presented and assessed. Compared with traditional methods (PCA, LP, WT, and CT) which often introduce the spectral distortions to the original MS images, the proposed method performs better by converting MS fusion issue into an optimisation problem to meet the goal of maximising spatial information abstracted from PAN data while minimising spectral distortion. Specifically, the low-resolution MS bands are resampled to the scale of the PAN image and sharpened by injecting highpass directional details extracted from the high-resolution PAN image. Here, the highpass directional details are weighted before injecting into each band of the MS image. The image gradient is employed as the rule for calculating the weighted coefficients because it is a simple and direct criterion that measures the “details” in an image, and its computational burden is low. Then the objective function can be built based on the image gradient, which is further optimised by using evolutionary intelligence, FSDE. FSDE is an effective population-based continues global optimisation technique, which is easy to implement. Because of its high computation efficiency and rapid convergence, FSDE can be expected to present good performance on optimising the objective function in MS fusion. The proposed method, CT-FSDE, was tested and compared with PCA, LP, WT, and CT over the WorldView-2 dataset. I also used two advanced evolutionary algorithms JADE and PS^{2}O to compare against the effectiveness of using FSDE in the proposed algorithm. The results show that CT-FSDE achieves the best results in terms of overall performance. The proposed algorithm not only provides high-quality spatial details but also preserves spectral information well. However, it should be noted that the performance will be better by using PAN data that covers the wavelengths of most MS bands. Using PAN data that only covers the wavelengths of a few MS bands might bring spectral distortion to the fused MS images.

Table 1. Results Comparison on SNR, DI and UIUQ

		B1	B2	B3	B4	B5	B6	B7	B8	Mean
PCA	SNR	8.1678	8.0287	7.8444	7.5859	7.1431	8.3757	8.1930	8.3727	7.9639
	DI	17.7855	17.0747	16.5178	17.5091	17.4937	20.9749	24.3356	24.4559	19.5184
	UIUQ	0.7146	0.7283	0.7539	0.7411	0.7508	0.7836	0.8004	0.8024	0.7594
LP	SNR	8.7427	8.6306	9.1818	8.5886	8.2141	9.3428	8.2301	8.4547	8.6732
	DI	17.8031	17.3248	15.8293	17.2264	17.3174	21.3262	26.6042	26.5925	20.0030
	UIUQ	0.7929	0.8082	0.8554	0.8350	0.8436	0.8645	0.8433	0.8455	0.8361
WT	SNR	8.7816	8.6417	9.1445	8.5706	8.1854	9.3673	8.2724	8.5019	8.6832
	DI	17.5546	17.0373	15.5597	16.9205	16.9642	21.0060	26.1354	26.1254	19.6629
	UIUQ	0.7958	0.8093	0.8544	0.8349	0.8431	0.8653	0.8449	0.8471	0.8369
CT	SNR	8.7666	8.6861	9.2783	8.6570	8.2834	9.4529	8.2710	8.4968	8.7365
	DI	17.5833	16.9926	15.3710	16.8131	16.8858	20.8640	26.1815	26.1734	19.6081
	UIUQ	0.7927	0.8094	0.8577	0.8367	0.8453	0.8672	0.8437	0.8459	0.8373
CT-JADE	SNR	7.4449	7.3938	7.5518	7.2879	6.6043	7.8677	6.6475	7.0689	7.2333
	DI	20.8662	20.4282	18.7338	19.6190	20.4036	24.9724	31.4635	30.6726	23.3949
	UIUQ	0.7335	0.7593	0.7996	0.7876	0.7834	0.8186	0.7871	0.7954	0.7831
CT-PS^{2}O	SNR	8.5134	8.4965	9.8781	9.0661	8.5328	9.7454	7.7895	7.5540	8.6970
	DI	18.0222	17.6529	**13.7962**	**15.4138**	**15.5783**	**19.7136**	26.8069	27.7294	19.3392
	UIUQ	0.7733	0.7978	**0.8729**	**0.8476**	**0.8501**	0.8720	0.8186	0.8017	0.8293
CT-FSDE	SNR	**9.8729**	**9.5760**	**9.9448**	**9.3089**	**8.6311**	**9.9873**	**9.0086**	**9.2648**	**9.4493**
	DI	**15.3130**	**15.2818**	14.3599	15.6363	16.3806	19.8513	**24.1886**	**24.0716**	**18.1354**
	UIUQ	**0.8221**	**0.8314**	0.8705	0.8471	0.8450	**0.8762**	**0.8581**	**0.8608**	**0.8514**

Table 2. Results Comparison on ERGAS and CC

	PCA	**LP**	**WT**	**CT**	**CT-JADE**	**CT-PS^{2}O**	**CT-FSDE**
ERGAS	241.2568	192.0876	192.1080	190.8240	227.0342	192.7621	**176.1888**
CC	0.1409	0.0989	0.0967	0.1031	0.0584	0.1855	**0.0384**

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