A Hybrid Approach for Fusion Combining SWT and Sparse Representation in Multispectral Images

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Abstract

Background/Objectives: Image fusion is a remote sensing task for fusing minute differences in multispectral images for further analysis. The objective of this paper is to propose a hybrid approach for image fusion in remotely sensed images. Methods/Statistical Analysis: The objective of this paper is accomplished by a hybrid approach combining Stationary Wavelet Transform (SWT) and sparse representation. SWT is used for pre-processing and sparse is used for fusing the multitemporal LANDSAT image. Results: Various fusion metrics like RMSE, PSNR and FMI are evaluated and the obtained results show that the proposed hybrid approach outperforms well than the existing methods. The proposed approach gives better results in terms of all the features has been fused correctly, less mean square error and high signal to noise ratio compared to the existing methods such as DWT, SWT and Ehlers. Conclusion/Application: The application of this work is mainly on multispectral multitemporal images. It can be used for change detection also can be used to fuse low resolution image with high resolution remote sensing image. Finally this approach provides an efficient fusion result compared to the traditional methods.

Keywords: FMI, Image Fusion, Multispectral, Multitemporal, Sparse Representation, SWT

1. Introduction

Image fusion is the process of combining two or more images to produce single composite image that exhibits more comprehensive information for further analysis. Over the last decade, images fusion has found enormous applications in the area of remote sensing. The ever increasing amount of remote sensing data is continuously producing different types of images including multi-temporal images, multi-spectral images, hyper-spectral images and multi-resolution images. Real world remote sensing applications not only require images with high spatial resolution, but also images with sufficient spectral resolution for accomplishment of change detection, map updating, land-use classification and hazard monitoring. Image fusion provides more feasible solution in remote sensing, since fused images contain improved spatial resolution and adequate spectral resolution which cannot easily be achieved in a single source image. Successful adoption of image fusion in remote sensing has been reported in vast articles include, but not limited to, Brovey Transform (BT), Principle Component Analysis (PCA), Wavelet Transform (WT), Ehlers method, Intensity Hue Saturation (IHS) and Sparse Representation (SP). Generally, methods for remote sensing images fall into three main groups. PCA, HIS, BT, Ehlers methods are based on component substitution, while LP and WT are multi-resolution analysis based, and SP is restoration-based method. In this paper, a hybrid approach has been proposed by combining SWT with sparse coding for fusion. Here initially the source images taken at different timings T1 and T2 are subjected to pre-processing by denoising the image using SWT. The pre-processed images are then analysed using sparse coding for fusion by choose-max fusion rule. The fused image is then compared with the existing algorithms. The proposed approach provides better results compared to the existing ones.

Recently, a large number of research works have been spotlighting on improvement of the quality and

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colour of the fused images. For this very reason sparse representation has received substantial interest of researchers lately.\textsuperscript{8} Utilized sparse regularization constraint in fusion of multispectral and hyper-spectral images. In that article online dictionary learning was used for optimization of the problem.\textsuperscript{9} Employed regularization control based on spatial and spectral characteristics of panchromatic and multispectral images recorded by different sensors deployed at the same area or scene. Another attempt of improving SP proposed by\textsuperscript{7}, where the registered images are decomposed into multiple scales prior to fusion process. Furthermore, decomposition of sparse coefficients from matrix for of input multispectral and panchromatic images has been reported by\textsuperscript{10}. Moreover, in the paper proposed by\textsuperscript{11} improvement of SP though the training dictionary was done by make use of two different types of training dictionaries. One dictionary constitutes of patches from higher spatial resolution image while the other contains patches from lower resolution down sampled image. Likewise,\textsuperscript{12} has also used two separate sparse oriented training dictionaries for fusion of higher resolution image and lower resolution images. Sparse can also be used for watermarking techniques to embed an image\textsuperscript{13}. The studies discussed in this section have shown extensive exploration of sparse based methods. This work serves as an analysis of sparse representation as applied in fusion of multi-temporal remote sensing images.

2. Materials and Methods

The proposed methodology consists of the following steps,

Pre-processing of the multispectral images for removing noise using SWT. The pre-processed remote sensing images are fused using sparse coding. The proposed architecture diagram is given in Figure 1 which shows the approach towards multispectral image fusion.

2.1 Pre-Processing of Input Images

Initially, two multispectral images at two different timings are taken for analysis. The input images are subjected to denoising using SWT.

2.2 Stationary Wavelet Transform

A tool for the analysis of transient, non-stationary or time varying phenomena that has energy concentrated in time is a wavelet. The SWT can be obtained by modifying the basic DWT algorithm. The DWT does not preserve translation invariance due to sub-sampling operations in the pyramid algorithm. The SWT has been introduced because it preserves the property that a translation of the original signal does not necessarily imply a translation of the corresponding wavelet coefficients. To halve the bandwidth from one level to another level, the SWT utilizes recursively dilated filters instead of sampling. The Stationary Wavelet Transform (SWT) was introduced in 1996 to make the wavelet decomposition time invariant. This improves the power of wavelet in signal de-noising.

Wavelet transform is first performed on each source images to generate a decomposed image and then soft threshold is applied to denoise the image. After applying SWT to the noisy image, soft thresholding method is applied to the details subbands; then a transformed image is generated from approximation subband only while the other subbands are made equal to zero. After that the approximation band is returned by applying SWT to the denoised signal, the resulted approximation subband is grouped with the thresholded subbands, applying inverse SWT to obtain the denoised image.

2.3 Algorithm

Step 1: Load the multi-spectral images at time T1 and T2.
Step 2: Perform multi-level stationary wavelet decomposition of the image using db2 wavelet.
Step 3: Generation of coefficient matrices at level 2 approximation.
Step 4: Display the coefficients of approximation and details.
Step 5: Reconstruct the coefficient of approximation at level 2.
Step 6: Remove noise by soft thresholding, for level 2 threshold is set as 4.
Step 7: Apply Inverse SWT to get the denoised image at time T1 and T2.
2.4 Image Fusion using Sparse Representation

In sparse representation image is approximated as a linear combination of few atoms from dictionary. The training dictionary contains definite number of overlapped patches mined from observed images. Learned dictionary from training patches produce better results to pre-constructed one\textsuperscript{11,13}. Image signals $x \in \mathbb{R}^n$ can be estimated as,

$$ x = D \alpha \quad (1) $$

where $D \in \mathbb{R}^n$ is the dictionary and $\alpha$ is the sparse vector. To obtain sparse vector which contain smallest number of non zero elements the following optimization problem is to be solved,

$$ \min \| \alpha \|_0 \quad \text{such that} \quad \| x - Da \|_2^2 \leq q \quad (2) $$

where $\| \alpha \|_0$ denotes the number of nonzero components in $\alpha$. The above optimization is an NP-hard problem and can be solved only by combination of columns. The simplest algorithm to solve this problem is Orthogonal Matching Pursuit (OMP)\textsuperscript{14}.

2.5 OMP Algorithm

The OMP method to compute sparse coefficients for each image,

$$ S = \min_{\alpha \in \mathbb{R}^n} \frac{1}{2} \| x - D \alpha \|_2^2 \quad \text{such that} \quad \| \alpha \|_0 \leq L $$

Step 1: Initialization: $\alpha = 0$, residual $r = x$, active set $\Omega = \phi$

Step 2: While $\| \alpha \|_0 < L$

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Select the element with maximum correlation with the residual

$$ \tilde{i} = \arg \max_{i=1,2,...,m} \| d_i^T r \| $$

Update the active set, coefficients and residual

$$ \Omega = \Omega \cup \tilde{i} $$

$$ \alpha_{\Omega} = (d_{\Omega}^T d_{\Omega})^{-1} d_{\Omega}^T r $$

$$ r = x - d_{\Omega} \alpha_{\Omega} $$

$\} $

Step 3: End

Since the sparse representation globally handles an image, it cannot directly be used with image fusion, which dependson the local information of source images. In our method, we divide the source images into small patches and use the fixed dictionary $D$ with small size to solve this problem. In addition, a sliding window technique is adopted to make the sparse representation shift invariant, which is of great importance to image fusion.

2.6 Sparse Fusion Algorithm

Input: Denoised images $D_{I_i}$ and $D_{I_k}$

Output: Fused image $D_{I_f}$

Initialize: $q = 0.1$, block size = 8x8

Step 1: Load input images $D_{I_i}$ and $D_{I_k}$

Step 2: Sparse representation using OMP and dictionary,

$$ \min \| \alpha \|_0 \quad \text{such that} \quad \| x - Da \|_2^2 \leq q $$

Step 3: Fuse sparse coefficients

Step 4: Restore fused image vectors as,

$$ \hat{V}_{I_f} = D \hat{\alpha} $$

Step 5: Reconstruct fused image vector and used fused vectors to reconstruct the image,

$$ \hat{V}_{I_f} = D \hat{\alpha} $$

Step 6: End

Finally the fused image is reconstructed from $\hat{V}_{I_f}$

3. Simulation and Outcome

The proposed method is compared with existing general multi-focus image fusion methods DWT, the Stationary Wavelet Transform (SWT), and the Ehlers on several pairs of multi-focus images. In order to carry out an experimental analysis aimed at assessing the effectiveness of the proposed approach, we considered two multi-temporal data sets corresponding to geographical areas of Istanbul in Turkey and Huelva province in Southern Spain. A detailed description of each data set is given below.

3.1 Data Set 1 Related to Huelva Province in Southern Spain

The first data set used in the experiment is made up of two multispectral images acquired by the Landsat Thematic Mapper sensor of the Landsat-5 satellite and Landsat-8 OLI in an area of Huelva province, Southern Spain on October 12, 1984 and August 24, 2014. From the entire available Landsat scene, a section of 512_512 pixels has been selected as test site.

Experiment has been conducted using data acquired by Landsat 5 and Landsat 8 with resolution of 30 meters. Two multi-temporal images are fused by using proposed fusion, SWT, DWT and Ehlers fusion methods. Original
images and fused images are as shown in Figure 2 and Figure 3.

3.2 Data Set 2 Related to Istanbul in Turkey

The second data set used in the experiment is made up of two multispectral images acquired by the Landsat Thematic Mapper sensor of the Landsat-5 satellite and Landsat-8 OLI in an area of Istanbul, Turkey on June 12, 1984 and October 21, 2014. From the entire available Landsat scene, a section of 512_512 pixels has been selected as test site.

Experiment has been conducted using data acquired by Landsat 5 and Landsat 8 with resolution of 30 meters.

Two multi-temporal images are fused by using SP, SWT, DWT and Ehlers fusion methods. Original images and fused images are as shown in Figure 4 and Figure 5.

4. Performance Evaluation

In this section performance evaluation of SWT, SP and DWT is demonstrated through the results obtained from qualitative assessments as shown in Table 1 and Table 2.

To evaluate the quality of fused image, comparing the results will adopt both objective and subjective assessment criterions. Objectively, PSNR, RMSE and FMI are good criterion to evaluate difference between the

![Figure 2](image1)

**Figure 2.** (a) Original Landsat 5 image recorded on 12 October 1984 from Huelva, Spain. (b) Original Landsat 8 image recorded on 12 August 2014 from Huelva, Spain.

![Figure 3](image2)

**Figure 3.** Fused images. (a) DWT fused image. (b) SWT fused image. (c) Ehlers fused image. (d) proposed fused image.

![Figure 4](image3)

**Figure 4.** (a) Original Landsat 5 image recorded on 12 June 1984 from Istanbul, Turkey. (b) Original Landsat 8 image recorded on 21 October 2014 from Istanbul, Turkey.

![Figure 5](image4)

**Figure 5.** Fused images. (a) DWT fused image. (b) SWT fused image. (c) Ehlers fused image. (d) Proposed fused image.
original images and the fused results. Table 1 and Table 2 demonstrate the PSNR, RMSE and FMI of four different algorithms for two test images. In terms of PSNR, RMSE and FMI the combined approach of SWT-SR outperforms well compared to other existing methods. Subjectively, according to the results of each Figure, it is shown that the proposed method is able to obtain better visual quality than existing methods.

The metrics used here to measure the quality of the fused image is Root Mean Square Error (RMSE) which represents the sample standard deviation of the differences between the fused and the original images. Peak Signal to Noise Ratio (PSNR) represents approximation of human perception on the fused quantity of the image. Feature Mutual Information (FMI) is a non-reference image fusion metric based on mutual information of image features depending on original images and fused image.

Results from Table 1 and Figure 6 and 7, show that sparse representation has lowest RMSE value and highest FMI value compared to DWT and SWT but DWT has lowest PNSR value. These findings indicate that, SWT-SR out performs DWT and SWT in fusion of multi-temporal remote sensing images.

Results from Table 2 and Figure 8 and 9 illustrate that DWT, Ehlers and SWT have higher RMSE and lower PNSR and FMI compared to SWT-SR.

Table 1. Quantitative evaluation results for Dataset 1

| Method  | RMSE  | PSNR  | FMI    |
|---------|-------|-------|--------|
| DWT     | 29.1144 | 18.2295 | 0.4074 |
| SWT     | 29.0112 | 29.0112 | 0.4212 |
| Ehlers  | 32.7972 | 17.8141 | 0.3388 |
| SWT-SR  | 24.7183 | 20.2704 | 0.4519 |

Table 2. Quantitative evaluation results for Dataset 2

| Method  | RMSE  | PSNR  | FMI    |
|---------|-------|-------|--------|
| DWT     | 33.1203 | 17.7289 | 0.3441 |
| SWT     | 22.4543 | 21.1048 | 0.3482 |
| Ehlers  | 39.3298 | 16.2364 | 0.1267 |
| SWT-SR  | 20.5390 | 21.8792 | 0.3490 |

Figure 6. Performance evaluation w.r.t. RMSE and PSNR for dataset 1.

Figure 8. Performance evaluation w.r.t. RMSE and PSNR for dataset 2.

Figure 7. Performance evaluation w.r.t. FMI for dataset 1.

Figure 9. Performance evaluation w.r.t. FMI for dataset 2.
5. Conclusion and Future Work

In this paper, a hybrid methodology has been adopted for image fusion combining SWT and sparse coding. The qualitative experimental results obtained using SWT-SR is comparatively good than the existing methods. The feature mutual information FMI obtained by the proposed method is 0.4519 for dataset 1 and 0.3490 for dataset 2 which is higher compared to the existing methods. The root mean square error RMSE obtained by the proposed method is lesser i.e. 24.7183 for dataset 1 and 20.5390 for dataset 2. Hence the proposed SWT-SR outperforms well compared to the traditional existing methods. Further sparse can be improved and can be adopted for change detection also. In future works, we concentrate on approximation of sparse regularization parameter and dictionary updating for better results of multi-temporary image fusion.

6. References

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