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Fusion of High Spatial and Spectral Resolution Images Based on Spatial Domain and Multiresolution Analysis

Kavita Tewari
Heading the Department of Electronics
VESIT,Chembur, Mumbai – 400037
ktewari_vesit@yahoo.co.in

Leena Shah
M.E Student,Department of E & TC
VESIT,Chembur, Mumbai – 400037
leena_wit@yahoo.com

Abstract

Image fusion is one of the important techniques to enhance image information of remote sensing. In order to adequately make use of all kinds of remote sensing images information such as Panchromatic and three-band multi-spectral images, a novel remote sensing image fusion scheme based on wavelet transform is proposed. The fusion of multispectral (MS) and panchromatic (PAN) images, with complementary spectral and spatial characteristics, is becoming a promising technique to obtain images with high spatial and spectral resolution simultaneously. Several commercial earth observation satellites carry dual-resolution sensors, which provide high spatial resolution panchromatic image and low spatial resolution multispectral image. Image fusion techniques are therefore useful for integrating a high spectral resolution image with a high spatial resolution image, to produce a fused image with high spectral and spatial resolutions. The visual and statistical analyses of experimental results show that the proposed fusion method is more effective than the other method mentioned in this paper.

1. Introduction

There are several situations that simultaneously require high spatial and high spectral resolution in a single image. This is particularly important in remote sensing. In other cases, such as astronomy, high spatial resolution and high signal-to-noise ratio (SNR) may be required. However, in most cases, instruments are not capable of providing such data either by design or because of observational constraints. A number of methods have been proposed for merging panchromatic and multispectral data [1], [2]. The most common procedures is the Principal Component Analysis (PCA) based method. However, the PCA methods produce spectral degradation. This is particularly crucial in remote sensing if the images to merge were not taken at the same time [4]. In the last few years, multiresolution analysis has become one of the most promising methods for the analysis of images in remote sensing [3]. Recently, several models are there for image merging that uses a multiresolution analysis procedure based upon the discrete two-dimensional (2-D) wavelet transform. The wavelet approach preserves the spectral characteristics of the multispectral image better than the standard PCA method.

Wavelet-based image merging can be performed in two ways : 1) by replacing some wavelet coefficients of the multispectral images by the corresponding coefficients of the high resolution image and 2) by adding high resolution coefficients to the multispectral data. To decompose the data into wavelet coefficients, we use the discrete wavelet transform. The method is applied to merge satellite panchromatic (PAN) and multispectral (MS) images.

Principal component analysis (PCA) is a mathematical tool which transforms a number of correlated variables into a number of uncorrelated variables. The PCA is used extensively in image compression and image classification. Image fusion algorithm that utilises the PCA is described in this paper. The weights for each source image are obtained from the eigen vector corresponding to the largest eigenvalue of the covariance matrices of each source. Performance metrics are used to evaluate the wavelets and PCA.

One of the important prerequisites to be able to apply fusion techniques to source images is the image registration. In this paper, it is assumed that the satellite images are already registered.

2. Fusion Algorithms

The details of PCA and wavelet algorithm and their use in image fusion are described in this section.

2.1. Principal Component Analysis

The PCA involves a mathematical procedure that transforms a number of correlated variables into a number of uncorrelated variables called principal components. It computes a compact and optimal description of the data set.The first principal component accounts for as much of the variance in data

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and each succeeding component accounts for as much of the remaining variance as possible. First principal component is taken to be along the direction with the maximum variance. The second principal component is constrained to lie in the subspace perpendicular of the first. Within this subspace, this component points the direction of maximum variance. The third principal component is taken in the maximum variance direction in the subspace perpendicular to the first two and so on. The PCA is also called as Karhunen-Loève transform or the Hotelling transform. The PCA does not have a fixed set of basis vectors like FFT, DCT and wavelet etc. and its basis vectors depend on the data set.

Let X be a d-dimensional random vector and assume it to have zero empirical mean. Orthonormal projection matrix V would be such that $Y=V^T X$ with the following constraints. The covariance of Y, i.e., cov(Y) is a diagonal and inverse of V is equivalent to its transpose ($V^{-1} = V^T$). Using matrix algebra:

$$\begin{aligned} cov(Y) &= E\{YY^T\} \\ &= E\{(V^TX)(V^TX)^T\} \\ &= E\{(V^TX)(X^TV)\} \\ &= V^T E\{XX^T\}V \\ &= V^T cov(X)V \end{aligned} \qquad (1)$$

Multiplying both sides of Eqn (1) by V, one gets

$$Vcov(Y) = VV^Tcov(X)Y = cov(X)V \qquad (2)$$

One could write V as $V = [V_1,V_2,......V_d]$

$$Cov(Y) = \begin{vmatrix} \lambda_1 & 0 & 0 & 0 \\ 0 & \lambda_2 & & \\ 0 & & \lambda_{d-1} & \\ 0 & & & \lambda_d \end{vmatrix} \qquad (3)$$

substituting Eqns (1) into the Eqns (2) gives

$$[\lambda_1V_1, \lambda_2V_2, \lambda_dV_d]$$
$$[cov(X)V_1,cov(X)V_2,..........,cov(X)V_d] \qquad (4)$$

This could be rewritten as

$$\lambda_iV_i = cov(X)\ V_i \qquad (5)$$

where i = 1, 2, ..., d and Vi is an eigenvector of cov(X).

2.2. PCA Algorithm

Let the source images (images to be fused) be arranged in two-column vectors. The steps followed to project this data into a 2-D subspaces are :

1. Organise the data into column vectors. The resulting matrix Z is of dimension 2 x n.
2. Compute the empirical mean along each column.
3. Subtract the empirical mean vector Me from each column of the data matrix Z. The resulting matrix X is of dimension 2 x n.
4. Find the covariance matrix C of X i.e. $C = XX_T$ mean of expectation = cov(X)
5. Compute the eigenvectors V and eigenvalue D of C and sort them by decreasing eigenvalue.
   Both V and D are of dimension 2 x 2.
6. Consider the first column of V which corresponds to larger eigenvalue to compute P_1 and P_2 as:

$$p_1 = \sum V(1) / \sum V \qquad p_2 = \sum V(2) / \sum V$$

2.2.1. Image Fusion by PCA

The information flow diagram of PCA-based image fusion algorithm is shown in Fig.1. The input images I_1 (x, y) and I_2 (x, y) are arranged in two column vectors and their empirical means are subtracted. The resulting vector has a dimension of n x 2, where n is length of the each image vector. Compute the eigenvector and eigenvalues for this resulting vector are computed and the eigenvectors corresponding to the larger eigenvalue obtained. The normalized components P_1 and P_2 (i.e., $P_1 + P_2 = 1$) using Eqn (4) are computed from the obtained eigenvector. The fused image is:

$$I_f\,(x, y) = P_1I_1(x, y) + P_2I_2(x, y) \qquad (6)$$

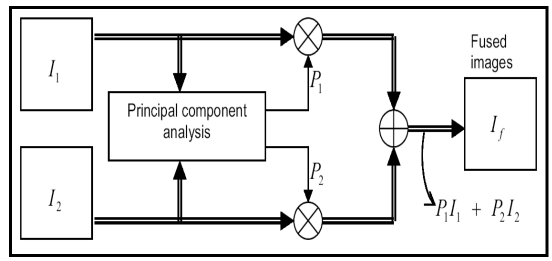

Figure 1. Information flow diagram of PCA method

2.2.2. Wavelet Transform

Wavelet theory is an extension of Fourier theory in many aspects and it is introduced as an alternative to the short-time Fourier transform (STFT). In Fourier theory, the signal is decomposed into sines and cosines but in wavelets the signal is projected on a set of wavelet functions. Fourier transform would provide good resolution in frequency domain and wavelet would provide good resolution in both time and frequency domains. Although the wavelet theory was introduced as a mathematical tool in 1980s, it has been extensively used in image processing that provides a multi-resolution decomposition of an image in a biorthogonal basis and results in a non-redundant image representation. The basis are called wavelets and these are functions generated by translation and dilation of mother wavelet. In Fourier analysis the signal is decomposed into sine waves of different frequencies. In wavelet analysis the signal is decomposed into scaled (dilated or expanded) and shifted (translated) versions of the chosen mother wavelet or function. A wavelet as its name implies is a small wave that grows and decays essentially in a limited time period. A wavelet to be a small wave, it has to satisfy two basic properties:

1) time integral must be zero

$$\int_{-\infty}^{\infty} \psi(t)\,dt = 0 \qquad (7)$$

2) square of wavelet integrated over time is unity

$$\int_{-\infty}^{\infty} \psi^2(t)\,dt = 1 \qquad (8)$$

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2.2.3. Image Fusion by Wavelet Transform

In wavelet image fusion scheme, the input images $I_1(x, y)$ and $I_2(x, y)$ are decomposed into approximation and detailed coefficients at required level using DWT. The approximation and detailed coefficients of both images are combined using fusion rule .The fused image $[I_f(x, y)]$ could be obtained by taking the inverse discrete wavelet transform (IDWT) [5].

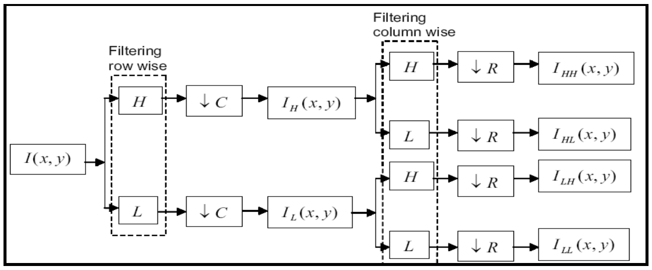

Figure 2. One level of 2-D image decomposition

Notations :
↓C Keep 1 column out of 2 (down sampling in column)
↓R Keep 1 row out of 2 (down sampling in row)
X convolve with X, where X indicates block name.

Wavelet separately filters and down samples the 2-D image in the vertical and horizontal directions. The input (MS) image is $I(x, y)$ filtered by low pass filter L and high pass filter H in horizontal direction and then down sampled by a factor of two (keeping the alternative sample) to create the coefficient matrices $I_L(x, y)$ and $I_H(x, y)$. The coefficient matrices $I_L(x, y)$ and $I_H(x, y)$ are both low pass and high pass filtered in vertical direction and down sampled by a factor of two to create sub bands $I_{LL}(x, y)$, $I_{LH}(x, y)$, $I_{HL}(x, y)$ and $I_{HH}(x, y)$. The $I_{LL}(x,y)$, contains the average image information corresponding to low frequency band of multi scale decomposition. It could be considered as smoothed and sub sampled version of the input image $I(x, y)$. It represents the approximation of input image $I(x, y)$, $I_{LH}(x, y)$, $I_{HL}(x, y)$ and $I_{HH}(x, y)$ are detailed sub images which contain directional (horizontal, vertical and diagonal) information of the input image $I(x, y)$, due to spatial orientation.

Inverse 2-D wavelet transform is used to reconstruct the image $I(x, y)$ from sub images $I_{LL}(x, y)$, $I_{LH}(x, y)$, $I_{HL}(x, y)$ and $I_{HH}(x, y)$ as shown in Fig.3 This involves column up sampling and filtering using low pass $\tilde{L}$ and high pass filter $\hat{H}$ for each sub images. Row up sampling and filtering with low pass filter and high pass filter of the resulting image and summation of all matrices would construct the image $I(x, y)$.

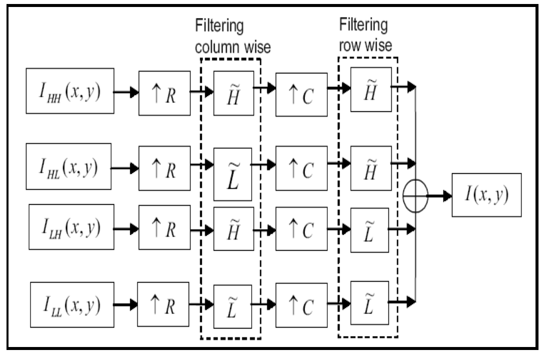

Figure 3. One level of 2-D image reconstruction.

Notations :
↑C insert column of zeros in between columns
(up sampling in columns)
↑R insert row of zeros in between rows
(up sampling in rows)

3. Experimental Results

The satellite panchromatic and mutlispectral images of circular quay, Sydney is shown in figure (a) and figure (b) to evaluate the performance of fusion algorithm. The low resolution 2 m MSI and high resolution 0.5 m PAN image of size 140 × 299 are fused using standard PCA method and DWT method.

Table 1 : The quality indices for Fusion Algorithms

Fusion Models	Entropy	Mean	Correlation Coefficient (CC)
PCA	6.612	161.058	0.919605
DWT	7.69732	110.096	0.968023

The fusion result of standard PCA and standard DWT with fusion rule used in this paper is simply averages the approximation coefficients and pick the detailed coefficient in each sub band with the largest magnitude. To quantify the statistical behaviour of both methods we compute three indices to analyze fusion results that is the mean, the entropy and the correlation coefficient (CC).The calculated parameter for both methods are shown in table 1.

Figure a
Pancromatic Image

Figure b
Multispectral Image

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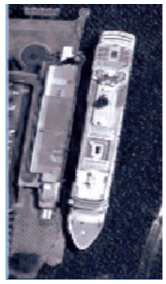
 Fused Image by using PCA	 Fused Image by using DWT

From visual effect, the PCA method gives a slightly worse effect with color distortion; this is expected as it has no scale and direction selectivity. The mean value indicate the intensity of image, the PCA shows higher mean which implies better visual effect, concerning the correlation coefficient, DWT method has higher value indicating the best spectral information preservation and spatial details enhancement. The entropy index of DWT is moderate which measure the richness of information in an image.

4. Conclusion

In this paper we have presented a pixel-level image fusion based on PCA and DWT fusion techniques. Experiments carried out on MS image and PAN image and comparative analysis with PCA and DWT by visual inspection and quality indices calculation demonstrate the superior spectral preservation ability and spatial details enhancement ability of the DWT method to the PCA methods.

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