APPLICATIONS OF 2DPCA IN REMOTE SENSING IMAGE FUSION

Xueming Wu [a, b,] *, Cangping Li [a], Wunian Yang [b]

[a] College of Information Engineering, Chengdu University of Technology, Chengdu P.R.C., 610059, nihaowxm@163.com, lcp@cdut.edu.cn
[b] RS and GIS Institute, Chengdu University of Technology, Chengdu P.R.C., 610059, ywn@cdut.edu.cn

KEY WORDS: Image Fusion, Remote Sensing, 2DPCA, L2DPCA, D2DPCA

ABSTRACT:

2DPCA is introduced in remote sensing image fusion, and three forms of 2DPCA-based remote sensing image fusion method are proposed according to the different evaluation methods of the projection vector, including 2DPCA, L2DPCA and D2DPCA algorithms. In the paper, the new image fusion techniques are applied in multi-source remotely sensed image fusion in contrast to PCA, IHS, Brovey and Wavelet algorithms, and then qualitative and quantitative analysis were given on the approaches. Experimental results show that the performance of 2DPCA, L2DPCA and D2DPCA image fusion algorithms outperforms PCA, IHS, Brovey and Wavelet from the point of view of the quality and performance of the fused images. This proves the validity and effectiveness of the new algorithms. The most outstanding advantage of 2DPCA, L2DPCA and D2DPCA fusion algorithms is that they can effectively utilize the two-dimensional structure information of the images, so that they can not only enhance the entropy of the fused images and better improve the spatial resolution of those, but also preserve good spectral information of the lower resolution images.

1. INTRODUCTION

With the rapid development of remote sensing technology and the continunous innovation of new sensor, the ability to access to remote sensing image data is continuously improved. At the same time, remote sensing images acquired by different sensors with different physical properties are growing very fast, and a large number of multi-source image data can acquire in the same area with different scales, different spectrum, different temporals. And， image data obtained by each single remote sensing measure are different in geometric, spectral, temporal and spatial resolutions and have obvious limitations and differences (Li Bicheng, 2004). Such limitations and differences are the major constraints on the ability of their applications. Therefore, it is difficult to meet the actual demand by using only a kind of remote sensing image data in practical applications, and it is usually to integrate different image data to utilize the strengths and complements of those images. This can decrease or restrain the ambiguity, incompleteness, uncertainty and error of the single information in the explaination of the sensed object or environment, and effectively utilize the information provided by a variety of information sources. Accordingly, the validity can be greatly upgraded of the feature extraction, classification, target identification and other aspects, and a more comprehensive, clear, accurate understanding and awareness to the observed objectives can also be achived (Li Bicheng et al, 2004; Wu Kai, et al, 2005).

Image fusion technology has been widely used in image processing, remote sensing, computer vision, as well as the military field (Qin Zheng, 2007). Although the technology of remote sensing image fusion has achieved considerable success, but the fusion technology is still immature and could not meet the needs of the development and applications of technology. At present, image fusion technology, especially the multi-source image fusion is one of the hot spots in the study of image processing technology. Therefore, it is very urgent and necessary to explore new algorithm of remote sensing image fusion.

Principal Component Analysis (PCA) is a classic technology of feature extraction and data presentation. Principal component analysis has been used in remote sensing image processing since 1980's (Chavez, 1982; Chavez, 1984; Chavez, 1986; Chavez, 1991), and that has been used in the field of artificial intelligence and pattern recognition since 1990's (Turk and Pentland, 1991). Since Sirovich and Kirby first used PCA to effectively presented the face images, PCA has been widely used in pattern recognition and computer vision. However, the traditional PCA has significant deficiencies, that is, images need to be converted into one-dimensional long strike vector and the evaluation of the eigenvalues and eigenvectors is very difficult and time-consuming. To overcome these shortcomings, Yang et al (2004) proposed 2DPCA (Two Ddimensional Principal Component analysis), 2004, which was used in face recognition and achieved great success. Important attach have been made by scholars to Two-dimensional principal component analysis after it is first proposed (Ye, et al, 2004; Zhang, et al, 2005; WANG, et al., 2005; KONG, et al, 2005; Liang, et al, 2005 ; Liu, et al, 2006; Nagabhushan, et al, 2006), with in-depth study after several years, different forms of 2DPCA, including 2DPCA, L2DPCA, D2DPCA, 2D-2DPCA, B2DPCA, NIGLRAM have been put forward and successfully applied in face recognition.

On the one hand, one-dimensional principal component analysis (PCA) has been widely used in remote sensing image processing, but has some flaws. On the other hand, compared to PCA, two-dimensional principal component analysis (2DPCA) has some obvious advantages, including not only the simple calculation of covariance, and the easy evaluation of the

* Corresponding author. nihaowxm@163.com

eigenvalues and eigenvectors but also high accuracy and less time-consuming. Therefore, it is worthy of study whether 2DPCA could be applied in remote sensing image processing. Then, the paper introduced 2DPCA into remote sensing image fusion, and three forms of 2DPCA-based remote sensing image fusion method are proposed according to the different evaluation methods of the projection vector, including 2DPCA, L2DPCA and D2DPCA algorithms.

The remainder of this paper is organized as follows. In Section 2, basic thoery of 2DPCA, L2DPCA and D2DPCA are described. The idea of the three proposed 2DPCA-based image fusion methods are shown in Section 3. In Section 4, the experimental results and the performance anlysis are presented for the traditional fusion techniques and the proposed 2DPCA-based algorithms to demonstrate the effectiveness of 2DPCA-based methods. Finally, conclusions are summarized in Section 5.

2. BASIC THOERY OF 2DPCA

2.1 Standard 2DPCA

(1) Idea of Standard 2DPCA

Let X denote an n-dimensional unitary column vector, and image A, an $m \times n$ random matrix, project onto X by the following linear transformation

$$Y = AX \qquad (2\text{-}1)$$

Thus, we obtain an m-dimensional projected vector Y, which is called the projected feature vector of image A. The total scatter of the projected samples can be introduced to measure the discriminatory power of the projection vector X, and can be characterized by the trace of the covariance matrix of the projected feature vectors.

$$J(X) = tr(S_X) \qquad (2\text{-}2)$$

$$\begin{aligned} S_x &= E(Y - EY)(Y - EY)^T \\ &= E[AX - E(AX)][AX - E(AX)]^T \\ &= E[(A - EA)X)][(A - EA)X]^T \end{aligned}$$

$$tr(S_X) = X^T[E(A - EA)^T(A - EA)]X \qquad (2\text{-}3)$$

Let

$$C_t = E[(A - EA)^T(A - EA)] \qquad (2\text{-}4)$$

The matrix C_t, which is an $n \times n$ nonnegative definite matrix, is called the image covariance (scatter) matrix. Suppose that there are M training image samples in total, the j th training image is denoted by an $m \times n$ matrix A_j ($j = 1, 2, \cdots, M$), and the average image of all training samples is denoted by $\bar{A}$. Then, C_t can be evaluated by

$$C_t = \frac{1}{M}\sum_{j=1}^{M}(A_j - \bar{A})^T(A_j - \bar{A}) \qquad (2\text{-}5)$$

Alternatively, the criterion in (3-2) can be expressed by

$$J(X) = X^T C_t X \qquad (2\text{-}6)$$

where X is a unitary column vector. This criterion is called the generalized total scatter criterion. The unitary vector X that maximizes the criterion is called the optimal projection axis. Intuitively, this means that the total scatter of the projected samples is maximized after the projection of an image matrix onto X.

The optimal projection axis X_{opt} is the unitary vector that maximizes the total scatter, i.e., the eigenvector of C_t corresponding to the largest eigenvalue. In general, it is not enough to have only one optimal projection axis, but usually need to select a set of projection axes. Therefore, we select the orthonormal eigenvectors, $X_1, X_2, \cdots, X_d$, of C_t corresponding to the first d largest eigenvalues as the optimal projection axes set.

For a given image sample A, let

$$Y_k = AX_k,\ k = 1, 2, \cdots, d \qquad (2\text{-}7)$$

Then, we obtain a family of projected feature vectors, $Y_1, Y_2, \cdots, Y_d$, which are called the principal component vectors of the sample image A.

The principal component vectors obtained are used to form an $m \times d$ matrix $F = [Y_1, Y_2, \cdots, Y_d]$, which is called the feature matrix or feature image of the image sample A.
After a transformation by 2DPCA, a feature matrix (image) is obtained for each image. Then, M images has M feature matrices (images) $F_i = [Y_1^{(i)}, Y_2^{(i)}, \cdots, Y_d^{(i)}]$, $i = 1, 2, \cdots, M$.

An image can be reconstructed by the principal component vectors and the feature matrices obtained by 2DPCA. This is the procedure of inverse transformation of 2DPCA.
Suppose the orthonormal eigenvectors corresponding to the first d largest eigenvectors of the image covariance matrix C_t are $X_1, X_2, \cdots, X_d$. After the image samples are projected onto these axes, the resulting principal component vectors are $Y_k = AX_k, k = 1, 2, \cdots, d.$

Let $Q = [Y_1, Y_2, \cdots, Y_d]$, $P = [X_1, X_2, \cdots, X_d]$, then

$$Q = AP \qquad (2\text{-}8)$$

Since $X_1, X_2, \cdots, X_d$ are orthonormal, from (3-9), it is easy to obtain the reconstructed image of sample A.

$$\tilde{A} = QP^T = \sum_{k=1}^{d} Y_k X_k^T \qquad (2\text{-}9)$$

(2) The characteristics and essence of 2DPCA

Yang's(2004) work has proved that 2DPCA has better performance than PCA from the experimental aspect in face recognition, but he did not proposed the essence of 2DPCA and discussed the relationship between that and PCA. Kong et al (2005) discussed the essential character and the advantages of 2DPCA as well as the relation to PCA, and drew the essence of 2DPCA is: 2DPCA, performed on the 2D images, is essentially

PCA performed on the rows of the images if each row is viewed as a computational unit.

Therefore, compared with PCA, 2DPCA has some obvious advantages, such as which can avoid dimension disaster, significantly expand feature set, and well preserve the 2D spatial structral information of the images by using the original 2D image matrix rather than reshaping it to a long vector (KONG, 2005).

It has a very important guiding significance to the applications of 2DCPA that to study and understand the characteristics 2DPCA in-depth. Through further study on the basic theory of 2DPCA, the following conclusions are drawn about two-dimensional principal component analysis:

Firstly, it is unnecessary to convert the image to one-dimensional vector and the covariance matrix is the mean matrix of the sample images, so that the dimension of the covariance matrix is greatly decreased.
Secondly, it is different from PCA that the sample image collection is regarded as a whole to project on the projection axes, whereas in 2DPCA, every sample image is regarded as a single object to project on the projection axes and to evaluate the principal components of each sample image respectively.

Thirdly, it is different from PCA that the pixel of a image or the whole image is regarded as a feature, but the row or column of the image is regarded as a feature in 2DPCA.
Fourthly, it is the same as PCA, 2DPCA is sensitive to the projection direction.

Last but not the least, 2DPCA can focus the energy and information on a small number of principal components by projection transformation, which can be applied in data compression and dimensionality reduction. This has vital important significance for the application

2.2 L2DPCA

From (4-4) in section 2.1, we can see that the standard 2DPCA is a right multiplication transformation, i.e., the projection matrix is right multicated at the right side of the image matrix, if we use another projection matrix to convert the transformation into a left multiplication transformation then another form of Two-dimensional principal component analysis can be obtained. Zhang et al (2005) proposed this form of two-dimensional principal component analysis, known as alternative 2DPCA. To distinguish with standard 2DPCA discussed in section 2.1, we regarded alternative 2DPCA as Left-sided Two Dimensional Component Principal Analysis (L2DPCA). The idea of L2DPCA is similar to that of 2DPCA.

Let Z denote an n-dimensional unitary column vector, and image A, an $m \times n$ random matrix, project onto Z^T by the following linear transformation

$$B = Z^T A \qquad (2\text{-}10)$$

The covariance matrix of the image

$$C_s = E[(A - EA)(A - EA)^T] \qquad (2\text{-}11)$$

In fact, $C_s = C_t^T$. Suppose that there are M training image samples in total C_s can be evaluated by

$$C_s = \frac{1}{M}\sum_{j=1}^{M}(A_j - \bar{A})(A_j - \bar{A})^T \qquad (2\text{-}12)$$

Evaluate the eigenvectors and the eigenvalues of C_s by using SVD, and select k orthonormal eigenvectors, $Z_1, Z_2, \cdots, Z_k$, corresponding to the first k largest eigenvalues as the optimal projection axes set Z^T.

For a given image sample A, which was projceted onto the Z^T, then

$$B_i = Z_i^T A, i = 1, 2, \cdots, k \qquad (2\text{-}13)$$

Therefore, we obtain an $k \times n$ matrix $F = [Y_1, Y_2, \cdots, Y_d]$, which is called the feature matrix or feature image of the image sample A.

After L2DPCA transformation, M feature matrices $F_j = [B_1^{(j)}, B_2^{(j)}, \cdots, B_k^{(j)}]^T$, was obtianed, $i = 1, 2, \cdots, M$, M is the number of the sample images.

An image can be reconstructed by the principal component vectors and the feature matrices obtained by L2DPCA. This is the procedure of inverse transformation of L2DPCA.

Suppose the orthonormal eigenvectors corresponding to the first k largest eigenvectors of the image covariance matrix C_s are $Z_1, Z_2, \cdots, Z_k$. After the image samples are projected onto these axes, the resulting principal component vectors are $B_i = Z_i A, (i = 1, 2, \cdots, k)$. Let $U = [B_1, B_2, \cdots, B_k]^T$, $V = [Z_1, Z_2, \cdots, Z_k]$, then

$$U = V^T A \qquad (2\text{-}14)$$

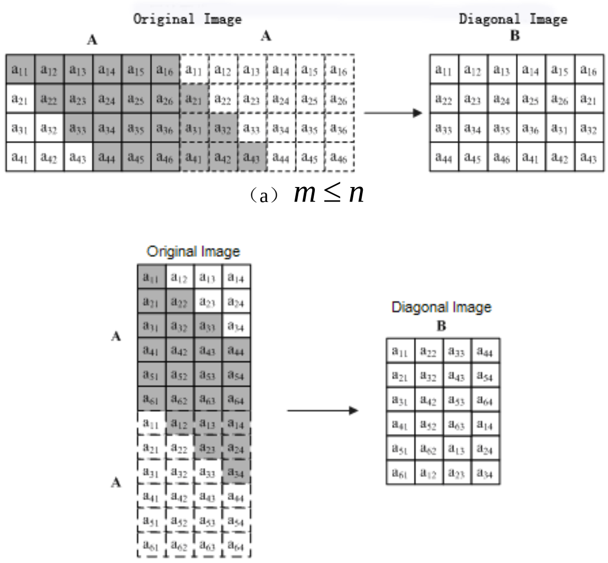
Since $Z_1, Z_2, \cdots, Z_k$ are orthonormal, from (2-15), it is easy to obtain the reconstructed image of sample A.

$$\tilde{A} = VU = \sum_{i=1}^{k} Z_i B_i \qquad (2\text{-}15)$$

2.3 D2DPCA

The main idea of 2DPCA is to find the row directional optimal projection vector from the sample images in condition that the images not to be converted into one -dimensional long vectors, the images in a number of samples. The idea of L2DPCA is similar to that of 2DPCA. However, the projection vectors of 2DPCA only reflect the variation among the rows of the images, but neglect the equally useful that among the columns; whereas, the projection vectors of L2DPCA only reflect the variation among the rows of the images, but neglect the equally useful that among the columns, and loss of some structural information is inevitable. Therefore, Zhang et al (2006) prosoed D2DPCA (It is called Dia2DPCA in Zhang et al 2006) which was successfully used in face recognition. Compared with 2DPCA, D2DPCA evaluate the projection vectors from the diagonal images corresponding to the sample images set, in which the variation among the rows and columns of the sample images are taken into account.

Generation of the diagonal image from the original image is shown in Fig. 1.



（a） $m \leq n$

（b） $m > n$

Fig. 1 Generation of the diagonal image（Modified according Zhang, et al., 2006）

After generation of the diagonal images from the original images, the D2DPCA transformation is similar to 2DPCA; therefore, it is unnecessary to discuss the detailed process of D2DPCA.

Let $X = [X_1, X_2, \cdots, X_d]$ as the projection matrix evaluated from the diagnoal images, an $m \times d$ feature matrix can be obtained for every sample image A_k which will be projected onto X

$$C_k = A_k X \qquad (2\text{-}16)$$

If we converted the $m \times d$ matrix C_k to vectors, it will be rewritten in $C_{ki} = A_k X_i$, $i = 1, 2, \cdots, d$. Let $R_k = [C_{k1}, C_{k2}, \cdots, C_{kd}]$,（2-16） will be rewritten in （2-17）

$$C_{ki} = A_k X_i \qquad (2\text{-}17)$$

Since $X_1, X_2, \cdots, X_d$ are orthonormal, from (4-24), it is easy to obtain the reconstructed image of sample A_k .

$$\tilde{A}_k = C_k X^T = \sum_{i=1}^{d} C_{ki} X_i^T \qquad (2\text{-}18)$$

3. 2DPCA-BASED ALGORITHM IN FUSION OF REMOTELY SENSED IMAGE

3.1 2DPCA-based Fusion Algorithm

We know that, in PCA-based method, the histogram of the panchromatic (high spatial resolution) image must be matched with that of the first principal component image, and the first principal component will be replaced with the matched image. Accordingly, the fused image can be obtained by reconstructing the images through inverse PCA transformation. New strategy, however, must be found and applied to 2DPCA-based algorithm, instead of applying the strategy in PCA-based technique. The main reasons lie in: Above all, there some differences between PCA and 2DPCA, and the feature matrices of the multispetral images can not be regarded as real images because of many pixel values of those images are negative. Moreover, there is not an unambiguous the first principal image in 2DPCA-based method, due to the difference between PCA and 2DPCA techniques. In the former, the multispetral images are regarded as a whole in the analysis and reconstruction processes, but it is oppositional in the latter. Therefore, we proposed a new 2DPCA-based algorithm on remotely sensed image fusion, after analyzing the objective of image fusion and the characteristic of PCA and 2DPCA. In a word, 2DPCA-based algorithm is a quite different technique in contrast to PCA-based method. The main steps of this new technique will be listed as follows.

① Image registration will be applied between the panchromatic (high spatial resolution) image and the multispectral (low spatial resolution) images, and the multispectral images will be resampled so that their cell scale equals to that of the panchromatic image.

② The optimal projection axes, $P = [X_1, X_2, \cdots, X_d]$, will be evaluated by eignvalue decomposition the image covariance matrix C_t , where $d = n$, and n is the width of the original images.

③ The histogram of the panchromatic image will be matched with that of the M multispectral images respectively, instead of the first principal component image.

④ It will be obtained that M feature images (matrices) of the M matched panchromatic images after they are projected on the optimal projection axes.

⑤ The r out of n principal components of each feature matrix of the M multispectral images will be replaced with the corresponding principal components of each feature matrix of the matched images corresponding to the multispectral images.

⑥ The fused images will be obtained after the inverse transformation of the 2DPCA.

The flow chart of the 2DPCA-based fuion technique is shown in Fig.2-2.

3.2 L2DPCA-based Fusion Algorithm

The main difference between L2DPCA and 2DPCA is the projcetion direction, so L2DPCA-based image fusion method can be drawn only by brief modification 2DPCA-based one. The main steps of L2DPCA-based image fusion technique will be listed as follows.

① Image registration will be applied between the panchromatic (high spatial resolution) image and the multispectral (low spatial resolution) images, and the multispectral images will be resampled so that their cell scale equals to that of the panchromatic image.

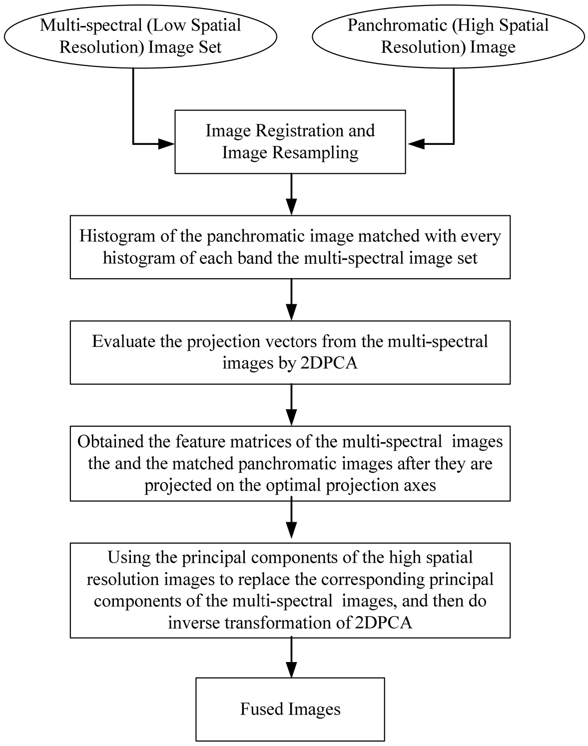


Fig.2 Flow Chart of the 2DPCA-based Fuion Algorithm

① Image registration will be applied between the panchromatic (high spatial resolution) image and the multispectral (low spatial resolution) images, and the multispectral images will be resampled so that their cell scale equals to that of the panchromatic image.

② The optimal projection axes, $V = [Z_1, Z_2, \cdots, Z_k]$, will be evaluated by eignvalue decomposition the image covariance matrix C_s , where $k = m$, and m is the height of the original images.

③ The histogram of the panchromatic image will be matched with that of the M multispectral images respectively, instead of the first principal component image.

④ It will be obtained that M feature images (matrices) of the M matched panchromatic images after they are projected on the optimal projection axes.

⑤ The r out of m principal components of each feature matrix of the M multispectral images will be replaced with the corresponding principal components of each feature matrix of the matched images corresponding to the multispectral images.

⑥ The fused images will be obtained after the inverse transformation of the 2DPCA.

3.3 D2DPCA-based Fusion Algorithm

Because D2DPCA transformation is similar to 2DPCA after the generation of the diagonal images from the original images, the D2DPCA-based image fusion method is similar to 2DPCA-based one. Therefore, it is unnecessary to discussed the detailed process of D2DPCA-based image fusion technique.

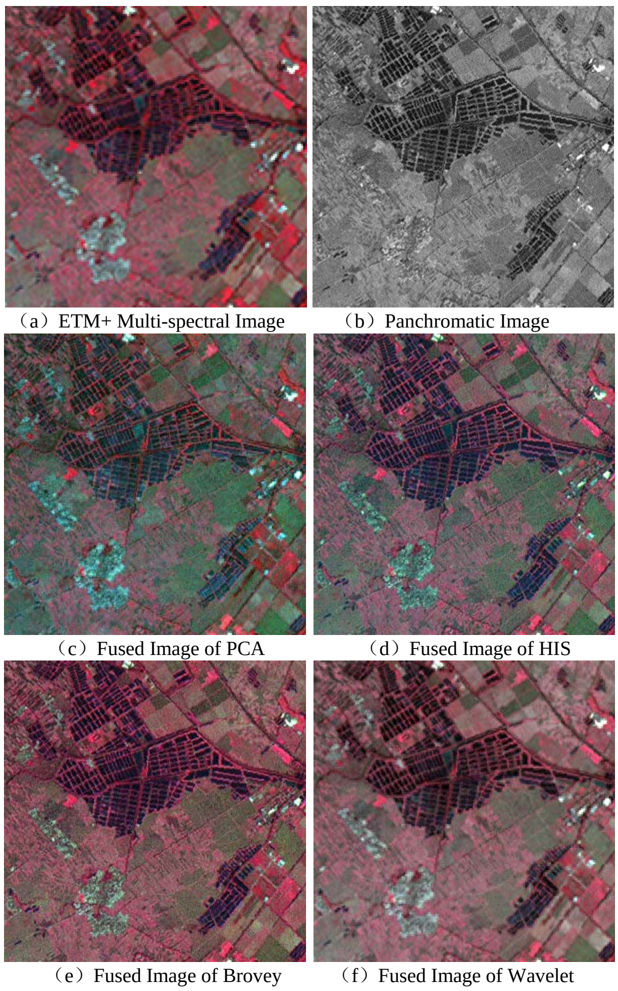
4. EXPERIMENT AND PERFORMANCE ANALYSIS

4.1 Image Fusion Experiment and Result Analysis

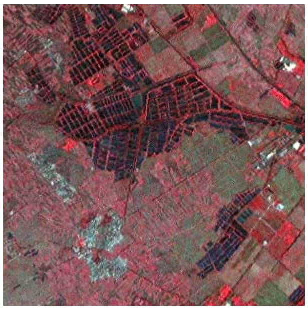
In our work, we have done several fusion experiments, including Landsat ETM+ multi-spectral images with the panchromatic image, multi-spectral images of SPOT 5 with the panchromatic image of that, and ETM+ multi-spectral images of Landsat with the panchromatic image of SPOT 5, to validate the performance of the newly proposed methods. In the experiments, the new proposed image fusion techniques namely 2DPCA, L2DPCA, D2DPCA, will be compared with four classic image fusion algorithms, namely PCA, IHS, Brovey and Wavelet. Due to space limitations, only one experiment is given later. And quantitative and qualitative sdudies are made in the paper. In the quantitative studies, the indice of mean, standard deviation, correlation coefficient, and deviation index and clarity indicator are adopted.

In addition, another experiment is given whose aim at to prove that 2DPCA-based fusion method can obtain different fusion results with the original image data by using different principal components replacement.

(1) Experiment A
Experimental results of the first experiment are shown in Fig. 3, and the performance indices are shown in Fig. 4.

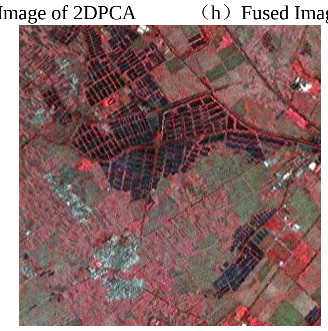


（a）ETM+ Multi-spectral Image （b）Panchromatic Image
（c）Fused Image of PCA （d）Fused Image of HIS
（e）Fused Image of Brovey （f）Fused Image of Wavelet



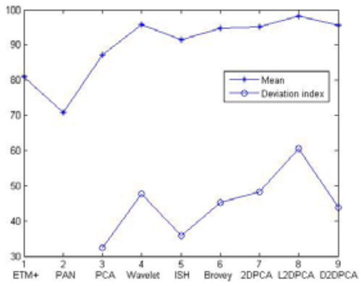
（g）Fused Image of 2DPCA

（h）Fused Image of L2DPCA

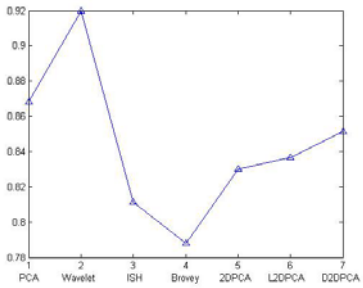


（i）Fused Image of D2DPCA

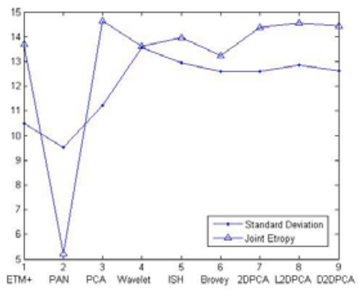
Fig. 3 ETM+ Images Fusion Experiment



(a) DN Mean and Deviation index



(b) Correlation Coefficients



（d）Clearity

Fig. 4 Indice Diagram of ETM+ Image Fusion

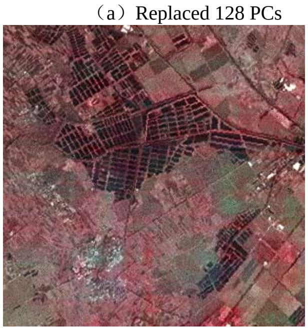
(Notice：The vertical Coordinates are the mean of the indices of the three bands (except Unite Etropy))

In the subjective evaluation from Figure 3: From the point view of the visual effects of the fused images, all the fusion methods showed good performance and the spatial resolutions of the fused images are improved greatly. However, From the point view of spectral information, different fusion methods showed different performance, and 2DPCA, L2DPCA and D2DPCA have better ability to preverve spectral information than other tranditional methods; Ground objects in the fusion images by using these new techniques are more clear and the details of that are easier to distinguish from. A little of variation of the spectral information occurred in the fusion images with the ISH and Brovey, but more serious distortion of the spectral information occerred in those of Wavelet and PCA. From the point view of clear and level of the fused images, ISH, Brovey and PCA are slightly better than other methods.

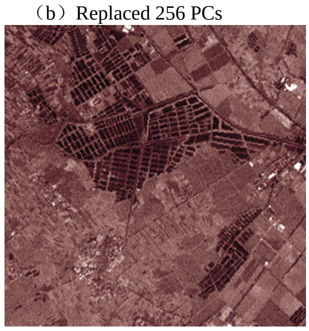
In the objective evaluation of indicators from Figure 4: From the point view of the brightness mean of the fusion images, L2DPCA, Wavelet, D2DPCA, 2DPCA and Brovey are better than ISH and PCA; From the point view of the correlation coefficients, PCA and Wavelet have better performance, the mean value of the correlation coefficients are between the interval of 0.86-0.92, and the rested methods are not very different from each other whose mean values are in the interval of 0.788-0.852; From the point view of the deviation index, there is not big differece among the seven methods, but PCA and ISH have best performance than, and 2DPCA, D2DPCA, Brovey and Wavelet are better, but L2DPCA is worse; From the point view of the joint entropy, PCA, D2DPCA, L2DPCA and 2DPCA have best performance, the joint entropy of those are in the interval of 14.36-14.65, and ISH is better, the joint entropy is 13.9539, but Wavelet and Brovey are the worst, the joint entropy of those are 13.6234 and 13.2441, respectively; From the point view of the standard deviation, Wavelet has the best performance, and ISH, L2DPCA, 2DPCA, D2DPCA and Brovey have better, but PCA has the worst; From the point view of clearity, ISH, Brovey, L2DPCA, D2DPCA, 2DPCA have the best performance, PCA and Wavelet are worse.

（a）Replaced 128 PCs

（b）Replaced 256 PCs



（c）Replaced 500 PCs



（d）Replaced 512 PCs

Fig.5 Fusion Results of Repalced by different numbers of Principal Components with 2DPCA Method

Because the number, *r*, of the feature matice of the matched panchromatic images to substitute the principal components of those of multi-spectral images can be adjusted ($r \in [1, d]$, $d = 1, 2, \cdots, n$, where n is width of the sample images or the number of eigenvalues of the covariance matrix). We can get fused images with different quality and visual effectiveness by adjusting the number of the substituting principal components, so 2DPCA-based methods have good flexibility. With increasing of the number of the substituting principal components, the degree of preserving spectral information integration gradualy decreased, but spatial resolution of the fused images upgraded obviously.

In 2DPCA-based remote sensing image fusion algorithm, through principal component analysis, every sample image can be represented with the feratures, which number is equal to the number of the eigvalues, of the sample image (the maximum number of the eigenvalues is equal to width of the sample images). Since the width of the image size should be much greater than the bands of multi-spectral images, so there is a great flexibility in the remotely sensed image fuion applications using principal-component-replacement in 2DPCA-based methods. Therefore, in 2DPCA fusion algorithm, we can get fused images with different quality and visual effectiveness by adjusting the number of the substituting principal components. From the analysis above we can draw that there are two limit results by 2DPCA fusioin method, namely, $r = 0$ and $r = n$. As $r = 0$, the original multi-spectral images can be accurate reconstructed. Whereas, $r = n$, it is equivalent to using the features of the matched panchromatic images corressonding to the multi-spectral images to reconstruct the original multi-spectral images accurately. Fused images result from such circumstance has the best spatial resolution but the least spectral information.

4.2 Performance analysis

The experimental results in Fig.3 showed that the novel proposed D2DPCA, 2DPCA and L2DPCA based image fusion algorithms can be used not only for the integration of the multi-spectral images and the panchromatic image from the same satellite, but also for that of the multi-spectral and panchromatic image different types of satellites, and can also be used for the integration of optical images and radar ones.

Through a comprehensive comparative analysis to the seven kinds of image fusion algorithms, some coclusions can be drawn from the four experiments discussed in 4.1:

1) In the subjective evaluation from Figure 4-5: From the point view of the visual effects of the fused images, all the fusion methods showed good performance and the spatial resolutions of the fused images are improved greatly, and the ground objects in the fusion images with these new techniques are more clear and the details of that are easier to distinguish from. However, From the point view of spectral information, different fusion methods showed different performance, and 2DPCA, L2DPCA, D2DPCA, Brovey and ISH have better ability to preverve spectral information than other methods, but some regions such as the river have become somewhat vague and spectral information in the fused images with other two methods, Wavelet and PCA, was distorted seriously; From the point view of clear and level of the fused images, Wavelet and Brovey have better performance than 2DPCA, L2DPCA, D2DPCA and ISH, whereas PCA has the worst performance.

1) From a subjective point of view: No matter what type of the newly proposed image fusion techniques, D2DPCA, 2DPCA and L2DPCA, the spectral information were well preserved; Whereas spectral information will be distorted at different degrees int the fused images by the other techniques such as PCA, ISH, Wavelet and Brovey; When the quality of the multi-spectral images is poor, D2DPCA, 2DPCA and L2DPCA algorithms showed worse performance in improvement of the spatial resolution than the others.

2) The objective evaluation indicators showed that: From the point view of the mean of the brightness, 2DPCA, D2DPCA and L2DPCA have better and more relatively stable performance than other tranditional methods mentioned above no matter how the variation of multi-source experimental imagest; From the point view of the correlation coefficients, 2DPCA, L2DPCA and D2DPCA also have better and more relatively stable performance than other tranditional methods; From the point view of the deviation index, 2DPCA and D2DPCA have more relatively stable performance than the remaining methods in the experiments; From the point view of the joint entropy, the performance of 2DPCA, D2DPCA, L2DPCA and PCA are better and more relatively stable than the rest, which can greatly improve the joint entropy so that the amount of information of the fused images is enhanced; From the point view of the standard deviation, the performance of Brovey, Wavelet, ISH, 2DPCA and D2DPCA are better and more relatively stable than the rest.

The theoretical analysis and experimental results showed that the three novel two dimensional principal components analysis based remotely sensed image fusion algorithms proposed in the paper are not only valid and have more flexible and stable performance, but also can remedy some defects of the other fusion algorithms to some extent.

Through theoretical and experimental analysis with the three new remote sensing image fusion algorithms, i.e., 2DPCA, L2DPCA and D2DPCA, which have better and more relatively stable performance than other classic methods. Main reasons for this lie in:

(1) In 2DPCA-based algorithms, the analysis and resconstraction of the sample images is directly applied to the image matrices instead of 1D vector as PCA based algorithm, therefore, the structural information of the images is effectively utilized.

(2) In PCA-based algorithm, the multispetral images are regarded as a whole, i.e., each band of the multispetral images is regarded as a feature, in the analysis and reconstruction processes, but the case in 2DPCA-based algorithms is oppositional, i.e., each band of the multispetral images is regarded as many features whose number is equal to the height or the width of the images. This ensure that 2DPCA-based algorithms have more flexibility.

(3) In the 2DPCA-based algorithms, at first the panchromatic (high resolution) image must be matched with each band of the multispectral image, and then obtain the feature matrice of the corressponding matched panchromatic images after which were procjected onto the optimal projection matrix evaluated from the multispectral images; Furthermore, the principal components of the multispectral feature matrice were substituted by the corressponding principal components which refelect the detail information of the panchromatic image in the

matched panchromatic feature matrice. As a result, there is not only good spectral information in the multispectral image but also the high spatial resolution and the details reflected in the panchromatic image.

5. CONCLUSIONS

In the paper, 2DPCA is introduced in remote sensing image fusion, and three forms of 2DPCA-based remote sensing image fusion method are proposed according to the different evaluation methods of the projection vector, including 2DPCA, L2DPCA and D2DPCA algorithms. Theoretically, 2DPCA, L2DPCA and D2DPCA have several advantages lie in not only the calculation of the covariance matrix and its eigenvalues and eigenvectors is easy, efficient, and high precision, but also the effective utilization of the two-dimensional structure information of the image. The new image fusion techniques are applied in multi-source remotely sensed image fusion in contrast to PCA, IHS, Brovey and Wavelet algorithms, and then qualitative and quantitative research and analysis have been done on the approaches. Every band image of the fused images by using the new techniques has not only the good spectral information of the lower resolution image but also the detail information of the higher resolution image. Therefore, the most outstanding advantage of 2DPCA, L2DPCA and D2DPCA fusion algorithms is that they can effectively utilize the two-dimensional structure information of the images, so that they can not only enhance the entropy of the fused images and better improve the spatial resolution of those, but also preserve good spectral information of the lower resolution images. Experimental results show that not only the new fusion algorithms outperforms PCA, IHS, Brovey and Wavelet ones, but also the new techniques are more flexible, stable and robust.

REFERENCE

Chavez, P.S., Jr., G.L. Berlin, and L.B. Sowers, 1982. Statistical Method for Selecting Landsat MSS Ratios. Applied Photographic Engineering, 8(1), pp. 23-30.

Chavez, P.S., Guptill, S.C., and Bowell, J. H., 1984. Image Processing Techniques for TM Data. Technical papers. Proceedings 50th Annual Meeting of ASPRS, WaIHSngton DC, U.S.A., 2, pp. 728-742.

Chavez, P.S., 1986. Digital Merging of Landsat TM and Digitized NHAP Data for 1: 24 000 Scale Image Mapping. Photogrammetric Engineering and Remote Sensing, 52(3), pp. 1637-1646.

Chavez, P.S., S.C. Sides, and J.A. Anderson, 1991. Comparison of Three Different Methods of Merge Multiresolution and Multispectral Data: Landsat TM and SPOT Panchromatic. Photogrammetric Engineering & Remote Sensing, 57(3), pp. 295-303.

Daoqiang Zhang, Zhi-Hua Zhou, Songcan Chen, 2006. Diagonal principal component analysis for face recognition, Pattern Recognition, 39, pp. 140-142.

Daoqiang Zhang, Zhihua Zhou, 2005. Two-directional two-dimensional PCA for efficient face representation and recognition. Neurocomputing, 69, pp. 224-231.

Jian YANG, David ZHANG, Alejandro F. Frangi, et al, 2004. Two-Dimensional PCA: A New Approach to Appearance-Based Face Representation and Recognition. IEEE Transactions on Pattern Analysis and Machine Intelligence, 26(1), pp.131-137.

Jieping Ye, 2004. Generalized Low Rank Approximations of Matrices.In: Carla E. Brodley (Ed.), Proceedings of the Twenty-First International Conference on Machine Learning (Outstanding Student Paper), Banff, Alberta, Canada, pp. 887-894.

Jun Liu, Songcan Chen, 2006. Non-iterative genera-lized low rank approximation of matrices. Pattern Recognition Letters, 27, pp. 1002–1008.

KONG Hui, WANG Lei, Eam Khwang Teoh, et al., 2005. Generalized 2D Principal Component Analysis for Face Image Representation and Recognition. Neural Networks, 18, pp. 585–594.

Liwei Wang, Xiao Wang, Xuerong Zhang, et al., 2005. The equivalence of two-dimensional PCA to line-based PCA. Pattern Recognition Letters, 26, pp. 57–60.

P. Nagabhushan, D.S. Guru and B.H. Shekar, 2006. Visual learning and recognition of 3D objects using two-dimensional principal component analysis: Arobust and an efficient approach. Pattern Recognition, 39, pp. 721-725.

WU Xue-ming, YANG Wu-nian, 2007. A novel image fusion method based on 2DPCA in remote sensing[C]. International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences. Vol. XXXVI，Part 7/C54, Comm. VII, ISPRS, Chengdu, China, pp. 215-218.

Zhizheng Liang, Pengfei Shi, 2005. An analytical algorithm for generalized low-rank approximations of matrices. Pattern Recognition, 38, pp. 2213 – 2216.

Li Bicheng, Peng Tian, and Peng Bo, et al, 2004. Intelligent Image Processing Technology (In Chinese). Beijing: Publishing House of Electronics Industry.

Qin Zheng, Bao Fu-Min, Li Aiguo, et al, 2007. Digital Image Fusion (In Chinese). Xi'an: Xi'an Jiaotong University Press.

Wu Kai, Zhou Jianjun, 2005. Military Applications of Multi-sensor Image Fusion Technology (In Chinese). Video Engineering, 9, pp. 94-96.