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Fusion of Multi-spectral and Panchromatic Satellite Images using Principal Component Analysis and Fuzzy Logic

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***Abstract*—. In this paper, we propose a fuzzy-based multi-spectral (MS) and panchromatic (PAN) image fusion approach which provides a tradeoff solution between spectral and spatial fidelity and is able to preserve more detail in terms of spectral and spatial information. First, we perform principal component analysis on the multi-spectral images and utilise the first principal component to extract matched low and high frequency coefficients. We then apply fuzzy-based image fusion rules to fuse the first principal component with the PAN image, followed by fusing the approximation coefficients. The proposed approach is tested on several satellite images and shown to provide a feasible and effective approach.**

I. Introduction

Remote sensing has many applications including military surveillance, agriculture, hydrology, geology and meteorology among others. Some of these required multi-spectral images and high spatial resolution. Achieving this simultaneously cannot be achieved in practice directly but is possible through remote sensing image fusion [1]. Image fusion combines information from two or more images of a scene into a single image that is more informative or better suited for a certain application. A variety of image fusion techniques have been developed including those based on intensity-hue-saturation (IHS) [2], the Brovey transform [3], the wavelet transform [4], and the principal component analysis (PCA) [5], [6], [7].

Fuzzy logic approaches have also been introduced to find better solutions for the image fusion problem. Image fusion based on fuzzy logic and the discrete wavelet transform to fuse visible and infrared images was used in [8], where fuzzy logic was to estimate important wavelet coefficients to calculate the weighting average coefficients to fuse the images. Fuzzy logic and additive wavelets were employed to fuse multi-spectral (MS) images and panchromatic (PAN) images by injecting high frequency information from the high-resolution PAN image into the low-resolution MS image [9]. A two-stage fuzzy image fusion approach was introduced in [10] to combine multiple radar images of the same scene. A fuzzy logic approach to assess image fusion quality was proposed in [11].

In this paper, we propose a novel approach to satellite image fusion based on principal component analysis and fuzzy logic. The first principal component of multi-spectal images describes information that is common to all bands used as input data to PCA, i.e. most of the spatial information, while the spectral information that is specific to each band is coded in the other principal components. This makes PCA a suitable technique for fusing MS and PAN images [13], [7]. We use PCA to extract features from MS images and a fuzzy logic approach to fuse the first principal component and the PAN image.

II. Preliminaries

A. Principal component analysis

Principal component analysis (PCA) is an essential technique in data compression and feature reduction [12]. It is a statistical technique applied to reduce a set of correlated variables to a set of fewer uncorrelated variables. PCA performs and orthogonal transformation to obtain a set of principal components (PCs). The PCs are typically sorted so that the first principal component PC_1 captures the largest amount of the variance.

Assume that $\{x_t\}$, $t = 1, 2 \dots, N$ represent the n-dimensional input data. The mean μ is obtained by

$$\mu = \frac{1}{N} \sum_{t=1}^{N} x_t, \tag{1}$$

and he covariance matrix of x_t defined as

$$C = \frac{1}{N} \sum_{t=1}^{N} (x_t - \mu)(x_t - \mu)^T. \tag{2}$$

PCA is solved by solving for the eigenvectors of the covariance matrix, i.e. by

$$Cv_i = \lambda_i v_i, \tag{3}$$

where λ_i are the eigenvalues and v_i the corresponding eigenvectors.

To represent the data with lower-dimensional vectors, the m eigenvectors with the largest eigenvalues are computed. If v denotes the approximation precision of the m largest eigenvectors, then the following relation holds:

$$\frac{\Sigma_{i=1}^{m}\lambda_i}{\sum_{i=1}^{n}\lambda_i} \geq v. \tag{4}$$

The low-dimensional feature vector is then determined by

$$x_f = \Phi^T x, \tag{5}$$

where $\phi = [v_1, v_2, \ldots, v_m]$.

B. Fuzzy logic

Zadeh [14] introduced the concept of fuzzy logic to present vagueness in linguistics, and to implement and express human knowledge and inference capability in a natural way. Let X be the input space and x be a generic element of X. A classical set A is defined as a collection of elements or objects $x \in X$, such that each x can either belong or not belong to A, $A \sqsubseteq X$. By defining a membership function on each element x in X, a classical set A can be represented by a set of ordered pairs $(x, 0)$ or $(x, 1)$, where 1 indicates membership and 0 non-membership. Fuzzy sets express the degree to which an element belongs to a set. Hence, the membership function of a fuzzy set can take on any value in the range [0;1], representing the degree of membership of an element in a given set [15]. Membership functions are used in the fuzzification and defuzzification steps, to map non-fuzzy values to fuzzy linguistic terms and vice versa.

III. Proposed approach

In this paper, we present an image fusion technique based on PCA and fuzzy logic. Our approach is divided in to the following major phases:

- Pre-processing.
- Feature extraction based on the principal component analysis.
- Image fusion based on fuzzy set
- Reconstruction of final image.

Fig. 1 gives and overview of our proposed framework.

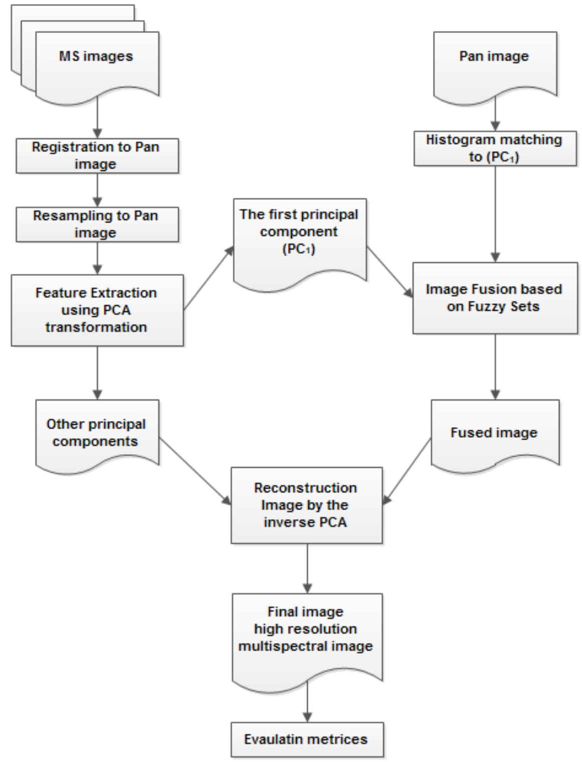


Fig. 1. The proposed image fusion approach.

A. Preprocessing phase

This phase consists of three steps: registration, resampling and histogram matching, which are explained in the the following.

1) Registration: Registration is the alignment and overlaying of two or more images of the same scene taken at different times, by different sensors or from different perspectives. In this paper, we use the ground control point technique to register the MS image to the PAN. The ground control point method uses points on the earth of known locations used as georeference for the scene image. MS images are registered while the PAN images are used as reference images.

2) Resampling: Before any image fusion technique is applied, the MS image is resampled. The resampling operator clearly influences the final result. In our approach, we utilise bilinear resampling which offers a good compromise between computational complexity and accuracy. Bilinear resampling takes a weighted average of the 4 pixels in the original image nearest to the new pixel location.

3) Histogram matching: The histogram of an image illustrates the frequencies of occurrence of all the gray levels in an image. If $n(k)$ is the frequency of the k-th intensity level and n is the total number of pixels in the gray level image then the normalised histogram is given by

$$p(n) = \frac{n(k)}{n}. \tag{6}$$

Conventional histogram matching is based on a cumulative frequency distribution which is described by

$$c(k) = \sum_{j=0}^{k} p(j) \tag{7}$$

to match the histogram of the PAN image with the PC_1 image.

B. Feature extraction based on the principal component analysis

The PCA is used to calculate the first principal component of the multi-spectral image which contains common spatial information, while most of the spectral information is contained in the the others PCs. The multi-spectral images are used as the input data for PCA to obtain PC_1. The process is outlined in Algorithm 1.

Algorithm 1 Principal components analysis algorithm

Input: MS images (3 bands) in matrix form.

Reshape 3 bands into 1*(m*n)
Subtract the mean
Calculate covariance matrix
Calculate eigenvalues and eigenvectors of covariance matrix
Obtain first principal component PC_1

C. Image fusion based on fuzzy sets

Fuzzy logic can be used to obtain decision rules for image fusion [16]. The two input images are converted into membership values based on a set of pre-defined membership functions, where the degree of membership of each input pixel to a fuzzy set is determined. Then, the fusion operators are applied to the fuzzified images. The fusion results are then converted back into pixel values using defuzzification.

1) Fuzzy sets: Fuzzy sets are used to describe the pixel levels of the input images. The first input is the PAN image and the second input is the first principal component PC_1 of the MS image. The output is the fused image. The 256 graylevels are divided into the five fuzzy sets VL, L, M, H, and VH, and same fuzzy sets are used for inputs and outputs.

2) Membership functions: The membership functions are used to demonstrate the distribution and clustering of the pixel values. The five five membership function are as as follows:

- VL: represents very low graylevels.
- L: represents low graylevels.
- M: represents medium graylevels.
- H: represents high graylevels
- VH: represents very high graylevels.

A triangular function is employed, defined as

$$\mu_{A(x)} = \begin{cases} 0, & x \leq a \\ \frac{x-a}{b-a}, & a \leq x \leq b \\ \frac{c-x}{c-b}, & b \leq x \leq c \\ 1, & c \leq x \end{cases} \tag{8}$$

and illustrated in Fig. 2.

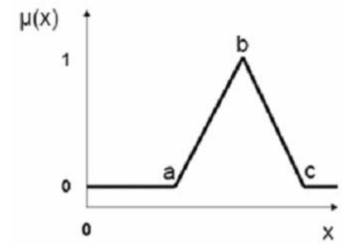


Fig. 2. Triangular membership function.

3) Fuzzy rules: In our proposed image fusion technique, a Mamdani fuzzy inference system is used.Fuzzy IF-THEN rules are employed to convert the fuzzy input into a fuzzy output. These rules are designed in the form of combinations of inputs (PAN and PC_1), for example

$$\beta(z) = \max(x, y) \Longrightarrow \{L, M \rightarrow M\}, \tag{9}$$

where x and y represent the pixel graylevel values of the PAN and PC_1 images respectively.The meaning of the above equation is that if the PAN graylevel is low and the graylevel of PC_1 is medium, then the graylevel of the fused image is medium. In total, we have 25 rules to fuse the PAN and PC_1 images which are summarised in Table I.

TABLE I. THE EMPLOYED FUZZY RULES FOR IMAGE FUSION.

VL	L	M	H	VH
L	L	M	H	VH
M	M	M	H	VH
H	H	H	H	VH
VH	VH	VH	VH	VH

D. Reconstruction of final image

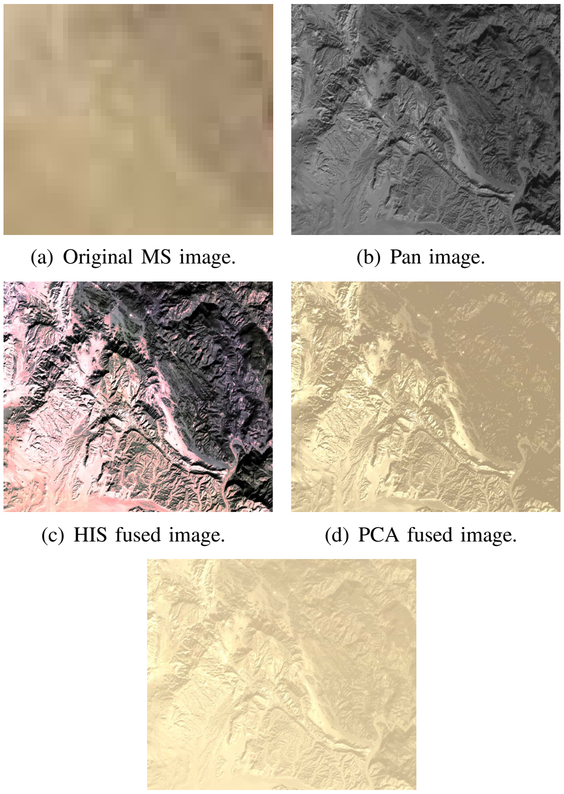
Obtaining the final fused image is performed by

$$\begin{bmatrix} x1_j \\ x2_j \\ x3_j \end{bmatrix} = A^{-1} \begin{bmatrix} Fnew_j \\ y2_j \\ y3_j \end{bmatrix} + \begin{bmatrix} m1 \\ m2 \\ m3 \end{bmatrix}, \tag{10}$$

where A^{-1} is the inverse matrix of the PCA transform, m_k ($k = 1, 2, 3$ are means of the three images of the original MS images, yr_j ($r = 2, 3$, $j = 1...N_p$ with N_p the size of the PAN image) are the values of the other principal component images, and $Fnew_j$ ($j = 1...N_p$) is value of the fused image.

IV. RESULTS AND DISCUSSION

We used two different datasets to evaluate our proposed new image fusion technique. The first data set comprises multi-spectral bands of the Modis satellite (bands 1, 3 and 4) as the MS image, which has a low resolution 250m and a Spot panchromatic satellite image. The second dataset uses multi-spectral bands of the ETM+ landsat satellite (bands 2, 4 and 7) as the MS image which are again fused with Spot panchromatic satellite images.

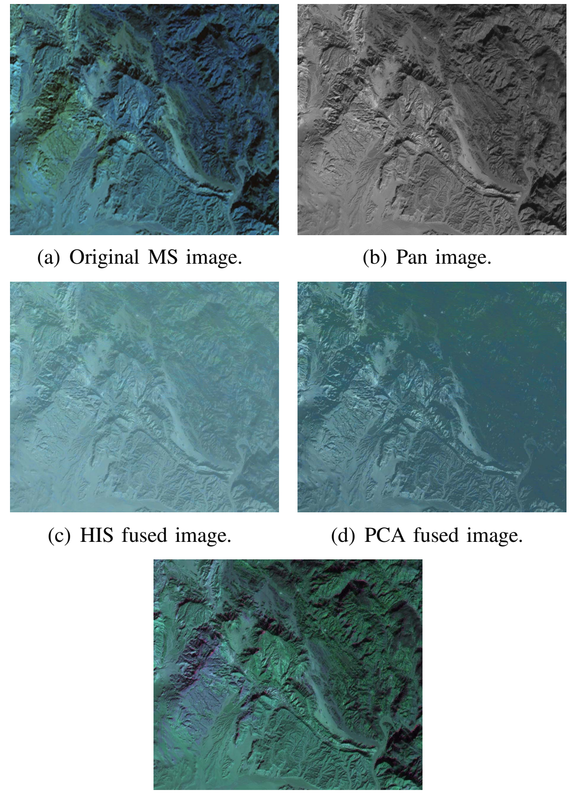


(a) Original MS image. (b) Pan image.

(c) HIS fused image. (d) PCA fused image.

(e) Our fused image.

Fig. 3. Image fusion results for fusing a Modis satellite image with a Spot panchromatic image.



(a) Original MS image. (b) Pan image.

(c) HIS fused image. (d) PCA fused image.

(e) Our fused image.

Fig. 4. Image fusion results for fusing a ETM+ satellite image with a Spot panchromatic image.

Visual examples are given in Fig. 3 and Fig. 4 which show the output of our fusion algorithm as well as those of two other techniques. It is apparent that our method provides improved image quality compared to HIS and PCA fusion.

In addition, we perform objective evaluation using the following measures:

- **Standard deviation (SD):** For the spatial quality, the standard deviation (SD) is used. SD is an important parameter to measure the information of image.
- **Entropy information (EI):** of an image is a measure of the information contained in the image. It is defined as

$$H = -\sum_{m=0}^{j-1} p(m) log_2 p(m), \tag{11}$$

  where $p(m)$ is the probability of graylevel m, and the range of g is $[0; L-1]$.
- **Correlation coefficient (CC):** is used to measure how the convergence between the input and output images co-vary. CC is widely used for comparing image [17] and expresses the spectral information contained in the fused image depending on the original MS image; the ideal value is 1. CC is calculated by

$$CC = \frac{\sum_{i=1}^{n}(X_i - X)}{\sqrt{\sum_{i=1}^{n}(X_i - \bar{X})^2}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}}, \tag{12}$$

  where X_i is the intensity of the i-th pixel in the first image, Y_i is the intensity of the i-th pixel in the second image, and X and Y are the mean intensities of the two images respectively.
- **Root mean square error (RMSE):** is used to determine the amount of change per pixel due to the processing. The RMSE between a reference image R and the fused image F is given by

$$RMSE = \sqrt{\frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n}(R(i,j) - F(i,j)} \tag{13}$$

- **Peak Signal to Noise Ratio (PSNR):** The PSNR is commonly used as measure of image quality. In this case, the signal is the original image and the noise is the error introduced. PSNR is calculated as

$$PSNR = 10\log_{10}\frac{L^2}{RMSE}. \tag{14}$$

  where RMSE is as defined above and L is the number of graylevels in the image.
- **Structural Similarity Index (SSIM):** is a method for measuring the similarity between two images. The SSIM index is a quality measure of one of the images being compared, provided the other image is regarded as of perfect quality. It is an improved version of the universal image quality index [18].

As shown in Table II and Table III, the numerical results also show that our proposed image fusion technique based on the PCA and fuzzy logic shows better performance compared to HIS and PCA fusion.

TABLE II. COMPARATIVE ANALYSIS RESULTS OF MODIS/SPOT IMAGE FUSION.

Image	SD	EI	CC	RMSE	PSNR	SSIM
IHS	81.7014	5.5744	0.3709	78.7215	29.1699	0.1377
PCA	36.8083	6.3922	0.7856	36.0846	32.5576	0.4977
proposed	30.1154	6.5776	0.9031	39.2340	32.1942	0.6314

TABLE III. COMPARATIVE ANALYSIS RESULTS OF EMT+/SPOT IMAGE FUSION.

Image	SD	EI	CC	RMSE	PSNR	SSIM
IHS	34.6	6.7791	0.7199	61.2810	30.2575	0.3322
PCA	29.2863	6.4793	0.7130	29.4169	33.4448	0.3624
proposed	28.5334	7.0785	0.7964	22.8563	34.5407	0.3816

V. CONCLUSIONS AND FUTURE WORKS

Image fusion of multi-spectral and panchromatic satellite images is a useful technique for enhancing the spatial quality of low resolution multi-spectral images. In this paper, we have proposed an image fusion approach for MS and PAN satellite images using principal component analysis in conjunction with a fuzzy logic decision process. For this, we first perform PCA on the MS image to obtain the first principal component which is the fused with the PAN image using a fuzzy rule base. The proposed approach is tested on a variety of satellite images. The experimental evaluation shows that good fusion results are obtained, and that the fused images appear superior to those obtained using other fusion strategies, both visually and based on objective measures.

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