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Principle component analysis based hyperspectral image fusion in imaging spectropolarimeter

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ABSTRACT

Image fusion is of great importance in object detection. A PCA based image fusion method was proposed. A pixel-level average method and a wavelet-based methods have been implemented for a comparison study. Different performance metrics without reference image are implemented to evaluate the performance of image fusion algorithms. It has been concluded that image fusion using PCA based method showed better performance.

Keywords: Spectropolarimetry, image fusion, performance evaluation

1. INTRODUCTION

Target recognition deals with the detection and identification of a desired pattern or target in an unknown input scene and also with the determination of the spatial location of the target if one is present. The recognition systems should be able to detect, classify, recognize, and identify targets in an environment where the background is cluttered and targets are at long distances and may be partially occluded, degraded by weather, or camouflaged. There is a wealth of information that can be extracted from a scene due to the imaging spectropolarimeter (ISP) which can obtain the spatial, spectral and polarization information simultaneously[1]. Conventionally, the spatial information captured by a traditional camera; the spectral information retrieved by spectrometers; the polarization information retrieved by polarimeters. Each one of these sensors represents a different way of recognizing and identifying a target in a scene.

ISP can be considered as a combination of typical imager, spectrometer and polarimeter. The spatial and spectral information is useful for object and background recognition and detection, because it sources from the information of objects and scenes based on their natural spectral emissions, reflections, and absorption. In addition to factors dominating target spectral information, polarization signatures from a target depend on factors pertaining to surface dynamics (i.e., smoothness, edges, and viewing angle or orientation). Therefore, the data acquired by an ISP can be interpreted as an image of a nine-dimensional volume, since a measure of radiance is obtained for two spatial variables (x, y), wavelength (λ), four polarization elements (S_0, S_1, S_2, S_3), and two additional polarization elements: degree of polarization (P) and the orientation (O) or angle of polarization ellipse[2].

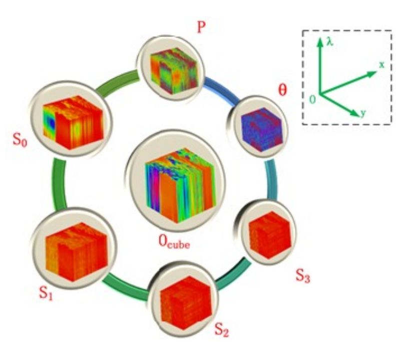

Figure 1. The nine-dimensional volume obtained by ISP.

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Detection accuracy can be improved by introducing to the spatial information additional information such as the reflectance of the target at various wavelengths within the electromagnetic spectrum. Spectral imaging combines the principles of conventional imaging, spectroscopy, and radiometry to produce images for which a spectral signature is associated with each spatially resolved element in the image. The combination of spatial and spectral analyses may be considered as data fusion and can lead to improved image understanding by using the best of both domains. Robust target detection algorithms should utilize spatial, spectral, and polarization information extracted for efficient and accurate target recognition and detection. Further fusion of spatial, spectral and polarization information is expected to enhance target detection[3, 4].

This paper is organized as follows: Section 2 discusses the information fusion method based principal component analyses (PCA), the performance evaluation metrics also are illustrated; Section 3 shows the spatial, spectral and polarization image fusion result using experimental data and discussions. Conclusions is provided in section 4.

2. IMAGE FUSION BASED ON PCA

2.1 Principal components Analysis

PCA is a significant de-correlation technique in statistical signal processing and it is usually used in dimensionality reduction [5], image denoising [6], image compression [7] and image fusion[8] etc. The basic principle of PCA is illustrated as follow. Let $\mathbf{X}=\{x_1,x_1,\cdots,x_m\}^T$ be an m-component vector and given as

$$\mathbf{X}=\begin{bmatrix} x_1^1 & x_1^2 & \cdots & x_1^n \\ x_2^1 & x_2^2 & \cdots & x_2^n \\ \vdots & \vdots & \vdots & \vdots \\ x_m^1 & x_m^2 & \cdots & x_m^n \end{bmatrix}, \tag{1}$$

where x_i^j, $j=1,2,\cdots,\mathrm{n}$ is the discrete samples of x_i, $i=1,2,\cdots,m$. The i$^{\text{th}}$ row of $\mathbf{X}$, X_i, is denoted as

$$X_i=[x_i^1,x_i^2,\cdots,x_i^n]. \tag{2}$$

The mean of X_i is

$$\mu_i=\frac{1}{n}\sum_{j=1}^{n}x_i^j. \tag{3}$$

X_i is centralized as

$$\overline{X}_i=X_i-\mu_i=\left[\overline{x}_i^1,\cdots,\overline{x}_i^n\right]. \tag{4}$$

where $\overline{x}_i^j=x_i^j-\mu_i$. Thereby, $\mathbf{X}$ is centralized as

$$\overline{\mathbf{X}}=\left[X_1^T\ X_2^T\cdots X_m^T\right]^T. \tag{5}$$

The covariance matrix of the centralized dataset is calculated as

$$\Psi=\frac{1}{n}\overline{\mathbf{X}\mathbf{X}}^T. \tag{6}$$

The goal of PCA is to find an orthonormal transformation matrix $\mathbf{P}$ to de-correlate $\overline{\mathbf{X}}$. That is, $\overline{\mathbf{Y}}=\mathbf{P}\overline{\mathbf{X}}$. The symmetrical covariance matrix Ψ can be given by

$$\Psi=\Phi\Lambda\Phi. \tag{7}$$

where $\Phi=[\phi_1,\phi_2,\cdots,\phi_m]$ is the eigenvector matrix with dimension of $m\times m$ and $\Lambda=\mathrm{diag}\left\{\lambda_1,\lambda_2,\cdots,\lambda_m\right\}$ is the diagonal eigenvalue matrix with $\lambda_1\geq\lambda_2\geq\cdots\geq\lambda_m$. ϕ_i and λ_i is the eigenvector and eigenvalue of Ψ. Let $\mathrm{P}=\Phi^T$, $\overline{\mathbf{X}}$ can be de-correlated as

$$\overline{\mathrm{Y}}=\mathrm{P}\overline{\mathbf{X}}. \tag{8}$$

2.2 PCA based image fusion

As shown in figure 2, for each image $I_i(x,y)$, an image patch with dimension of $L \times L$ and centered on a given (k,l) is denoted as $IP_{i,k,l}$. The image patch can be vectorized as a row vector with dimension of L^2 using lexicographic ordering.

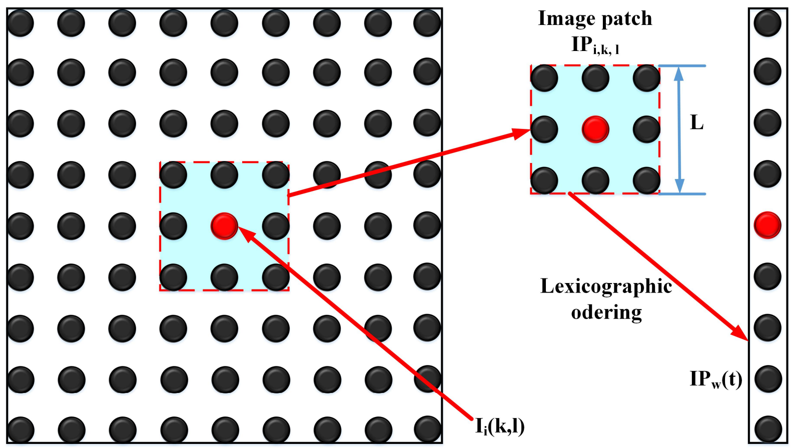

Figure 2. Image patch and vectorization.

Let the p source image patches $IP_{1,k,l}, IP_{2,k,l}, \cdots, IP_{p,k,l}$ be vectorized as p row vectors. The steps followed to fuse them are:

(1) Organize the image patches into row vectors. The resulting matrix M is of dimension $p \times n$.

(2) Compute the empirical mean μ_i along each row. The empirical mean vector $\boldsymbol{\mu}$ has a dimension of $p \times 1$.

(3) Subtract the empirical mean vector $\boldsymbol{\mu}$ from each row of M. The resulting matrix M_s is of dimension $n \times p$.

(4) Calculate the covariance matrix Ψ of M_s.

(5) Compute the eigenvectors ϕ_i and eigenvalue λ_i of Ψ and sort them by decreasing eigenvalue. Both Φ and Λ are of dimension $p \times p$.

(6) Consider the first row of Φ which corresponds to larger eigenvalue to compute the normalized principal component P_i as:

$$P_i = \varphi_1(i) \Big/ \sum_{i=1}^{p} \varphi_1(i). \tag{9}$$

(7) The fused image patch is

$$IPf_{i,k,l} = \sum_{i=1}^{p} P_i IP_{i,k,l}. \tag{10}$$

2.3 Performance evaluation

The fusion algorithms outlined in this paper are directed towards applications in the areas of object detection. In these applications, due to the real-time nature of the scene being imaged, there are no truth data available. Hence, evaluating the performance of such fusion schemes requires the use of non-reference quality metrics. Accordingly, we have used three parameters to measure the efficiency of our namely, the entropy, the mutual information (MI) and the spatial frequency (SF) [9-11].

The entropy is used to measure the information content of an image and has been used by Leung et al. to measure the performance of image fusion. The entropy of an image is given by

$$H_n = \sum_{j=0}^{G} \mathrm{P}(j) \log_2 \mathrm{P}(j) \tag{11}$$

where, G is the number of gray levels in the image and $\mathrm{P}(j)$ is the normalized probability of occurrence of each gray level.

MI is calculated by defining the joint histogram of the source images and the fused image I_f. The i[th] source image is denoted as I_i. The MI between the source images and the fused image is given by

$$\mathrm{MI}=\frac{1}{p}\sum_{i=1}^{p}\mathrm{Mi}_i(I_f,I_i)=\frac{1}{p}\sum_{i=1}^{p}\mathrm{P}(I_f,I_i)\log_2\left(\frac{\mathrm{P}(I_f,I_i)}{\mathrm{P}(I_f)\mathrm{P}(I_i)}\right) \tag{12}$$

where, $\mathrm{P}(I_f,I_i)$ is the joint histograms of the source image I_i and the fused image I_f.

The frequency in spatial domain indicates the overall activity level in the fused image. The SF is expressed as

$$\begin{aligned} SF &= \sqrt{RF^2+CF^2}, \\ RF &= \sqrt{\frac{1}{MN}\sum_{x=1}^{M}\sum_{y=2}^{N}\left[I_f(\mathrm{x},\mathrm{y})-I_f(\mathrm{x},\mathrm{y}-1)\right]^2}, \\ CF &= \sqrt{\frac{1}{MN}\sum_{x=2}^{M}\sum_{y=1}^{N}\left[I_f(\mathrm{x},\mathrm{y})-I_f(\mathrm{x}-1,\mathrm{y})\right]^2}. \end{aligned} \tag{13}$$

3. EXPERIMENT RESULTS

As shown in Figure 3, 16 images (including 8 spectral and 8 polarization images) obtained by PIS are used to verify the feasibility of the proposed method. The 8 images in the first 2 rows are the spectral images corresponding to the stokes parameter S0. The 8 images in the last 2 rows are the images representing the degree of polarization.

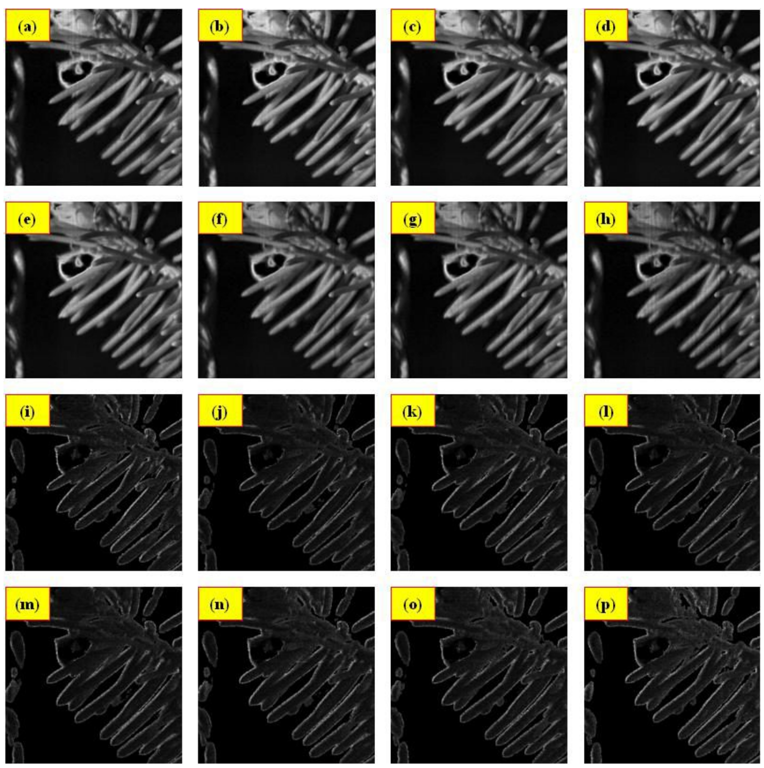

Figure 3. 16 images obtained by ISP, figures (a)-(h) are the spectral images, figures (i)-(p) are the polarization images.

To compare with the proposed method, a pixel-level average method and wavelet based method [4] was also used to fuse the above 16 images. The resulted images, respectively, are shown in figures 4(a) and (b).Using the proposed method, the fused image is shown in figure 4(c).

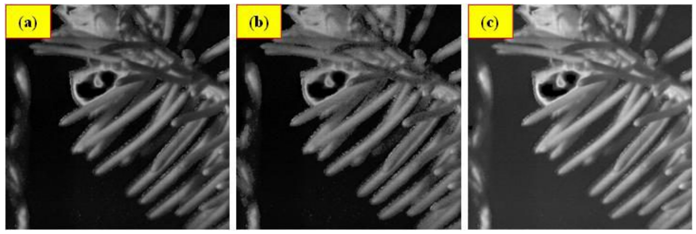

Figure 4. Fused images obtained by different methods: (a) Pixel-level Average method; (b) Wavelet-based method;(c) The method proposed in the paper.

Table 1. Performance evaluation of different methods.

Method	H	MI	SF
Proposed method	6.87	5.24	361
Pixel-level averge	6.55	4.54	237
Wavelet-based	6.65	4.65	60

The fused images shown in figure 4 are evaluated by entropy, mutual information and spatial frequency. The 3 performance metrics of the fused images were obtained and listed in table 1. It can be found that the proposed method generated a better fused image.

4. CONCLUSION

A PCA based method was proposed in this paper to implement the multi-bands spectral and polarization images fusion. By contrast, the pixel-level average, wavelet-based and the proposed fusion methods are implemented. Different image fusion performance metrics without reference image have been evaluated. The PCA based method shows better performance.

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