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Noisy Band Removal Using Band Correlation in Hyperspectral Images

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Abstract : Noise band removal is a crucial step before spectral matching since the noise bands can distort the typical shape of spectral reflectance, leading to degradation on the matching results. This paper proposes a statistical noise band removal method for hyperspectral data using the correlation coefficient between two bands. The correlation coefficient measures the strength and direction of a linear relationship between two random variables. Considering each band of the hyperspectral data as a random variable, the correlation between two signal bands is high; existence of a noisy band will produce a low correlation due to ill-correlativeness and undirectedness. The unsupervised k-nearest neighbor clustering method is implemented in accordance with three well-accepted spectral matching measures, namely ED, SAM and SID in order to evaluate the validation of the proposed method. This paper also proposes a hierarchical scheme of combining those measures. Finally, a separability assessment based on the between-class and the within-class scatter matrices is followed to evaluate the applicability of the proposed noise band removal method. Also, the paper brings out a comparison for spectral matching measures. The experimental results conducted on a 228-band hyperspectral data show that while the SAM measure is rather resistant, the performance of SID measure is more sensitive to noise.

Key Words : Noise band removal, hierarchical classification, spectral matching measure, separability assessment.

1. Introduction

Applications of hyperspectral image mainly derive from the ability of using the spectral reflectance (spectrum) of the earth's surface at different wavelengths to determine the surface's type. By taking advantage of hundreds of narrow and spectrally continuous bands, hyperspectral image provides a tool for detecting materials that can not be solved from multispectral images (Goetz, 1991, van der Meer and de Jong, 2001). Unfortunately, owing to several factors sensing a noise-free image is somewhat impractical. The noise may be the atmospheric noise that is interference effects of the atmosphere on both communication and sensing paths; or the electric noise, that is the random error added to data by the electronic components of a sensing system. Example of noise bands is illustrated

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in Fig.1 below from our experiment data. While, in general, spectral matching methods measure the agreeability between the shapes of an image pixel's spectrum over that from a spectral library to assess the type of surface, noisy bands deform the typical shape of the spectrum, leading to a degraded accuracy.

A few works have been dedicated to solve this problem. The Maximum Noise Fraction (MNF) transformation (Green at al, 1988), which is a modified version of Principal Components (PC) transformation, is widely accepted in practice. The MNF transforms hyperspectral data into components with increasing signal-to-noise. The noise removal is performed on the transformed data before transformation back to the original space. However, the transformation is computationally expensive when applying to hyperspectral data of hundreds of bands, since it needs to compute the left-hand eigenvectors of the $\Sigma_N\Sigma^{-1}$ matrix, where Σ_N is the covariance matrix of noise components and Σ is that of the data cube. Faulconbridge *et. al* (2006) proposed a method of detecting noisy band by first, unsupervisedly classifying the original data into clusters, then looking for spectral locations where all of the clusters are very close to one another. To measure the distance between clusters, a modified Bhattacharyya distance is used. Finally, the bands where the maximum Bhattacharyya distance is less than a given threshold are marked as noise and removed. Letexier and Bourennance (2008) used a generalized multidimensional Weiner filter (MWF) for removing the noise in hyperspectral images by considering a multidimensional data as a third-order tensor, then using multilinear algebra, MWF needs to flatten the tensor.

In general, the noisy bands degrade the performance of ground-type classification. In this paper, a process of removing noisy bands of hyperspectral data under a screening scheme is proposed that uses the correlation coefficient of bands as an indicator. Then, a separability measure is employed in order to demonstrate the effectiveness of the proposed noisy band removal in hyperspectral image classification.

The correlation coefficient is a statistically mathematic quantity that measures the strength and direction of a linear relationship between two random variables. Normally, two successive signal bands in hyperspectral image are highly correlative thanks to the slight difference of the reflectance when the wavelength interval is small. However, noise can make the bands undirected so that the correlation in the case is relatively low. For the classification after removing noise, the un-supervised *k*-mean clustering algorithm is utilized using the distance measures: Euclidean ED, Spectral Angle Mapper SAM and Spectral Information Divergence SID. In addition, in order to enhance the discrimination ability, a hierarchical combination of above measures is proposed in the intention of taking strong points of each individual measure. The performance of classification is assessed by a separability measure that bases on the post-classified between-class and within-class scatter matrices.

The data used in this work is an EO-1 Hyperion, acquired on June 3, 2001 over an area about 9,200 ha near Han river of the western Seoul, Korea where covers many surface types of urban, road, forest, grass, and water body. The data has 228 bands of size 400 rows $\times$ 256 columns, ranging from 406 to 2,496 nm wavelengths. More specifications can be referred to Kim *et al.*, 2007.

2. Noisy band removal

In this paper, we classify the noise bands into two categories: zero bands and reflectively noisy bands. The zero band term refers to a band where the sensor failed to sense data at that wavelength resulting in a no-data band. The reflectively noise bands may be different at different levels of noise as seen in Fig. 1 below.

Step 1: *Removing zero bands*

The zero bands are simply removed by considering the mean of the bands. If the mean of band is less than a pre-defined threshold $m_j = \frac{1}{N} \sum_{i \in B_j} p_i < \zeta$, the band B_j is marked as noise and removed; otherwise the band is treated as a potential signal band.

Step 2: *Finding true signal bands from potential signal bands*

The correlation coefficients between pairs of most successive potential signal bands are computed as:

$$\rho_{ij} = \frac{E((X-\mu_i)(Y-\mu_j))}{\sigma_i \sigma_j} \qquad (1)$$

where ρ_{ij} is the correlation coefficient between band ith and jth; $\mu_{\bullet}$ and $\sigma_{\bullet}$ indicate the mean and variance of a band, respectively. The correlation coefficients are then normalized to the range [0, 100] and constructed a 100-bin histogram. Since adjacent signal bands normally have a high correlation distributed around the maximum, and the correlation between noisy bands or between a signal and noisy band are small and randomly distributed; the histogram will peaks at a point in the region of high correlation as depicted in Fig. 2. From the histogram, a threshold in the left of the peak is chosen for detecting true signal bands by the following rule:

- If $\rho_{i-1,i} > thres$ AND $\rho_{i,i+1} > thres$

  ith band is a signal band

  Else

  ith band is a potential noisy band

High correlations with the preceding band and the succeeding band indicate that the band under consideration is a signal band.

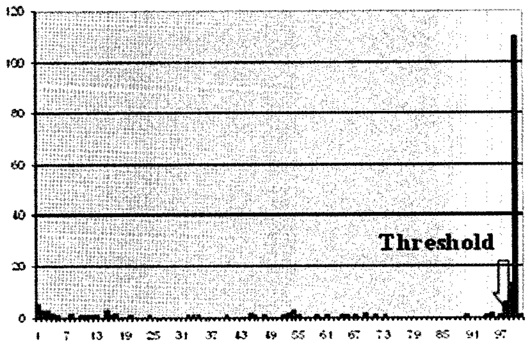
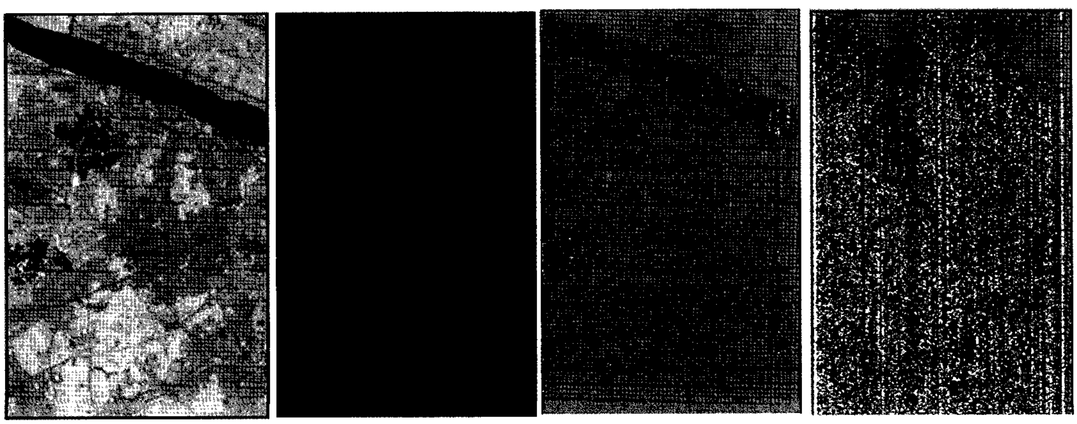


Fig. 2. 100-bin histogram of correlation coefficients.



a) b) c) d)

Fig. 1. Example of signal band and noise band. a) a signal band; b) a zero band (non-sensed); c) and d) noise bands of different levels.

The threshold is determined automatically by the triangle threshold method. Given a Gaussian-like distribution, the triangle threshold method is to find a position on the curve between the peak and the zero-asymptotic point that maximize the distance from the position to the segment line connecting the two points as depicted in Fig. 3 below. In order to control the level of noise removed, the threshold is shifted left (less bands are removed) or right (more bands are removed).

Step 3: *Refining the potential noisy bands*

In the remaining bands, if a signal band is kept between two noisy bands, then the relationships to the preceding and the succeeding are ill-correlative. This step aims at refining such bands as the following:

- For each potential noisy band k
  - Find the preceding nearest signal band (k-m)
  - Find the succeeding nearest signal band (k+n)
  - If $\rho_{k-m,k}$ > *thres* OR $\rho_{k,k+n}$ > *thres*

    kth band is reset to a signal band

    Else

    kth band is a noisy band.

3. Classification

As for the classification, the unsupervised k-nearest neighbor algorithm (Anderberg, 1973) is implemented in accordance with three spectral distance measures: the Euclidean Distance ED (Eq. 2), the Spectral Angle Measure SAM (Yuhas *et. al*, 1992) (Eq. 3) and Spectral Information Divergence SID (Du *et al.*, 2004) (Eq. 4).

$$ED(\mathbf{x,y}) = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2} \qquad (2)$$

$$SAM(\mathbf{x,y}) = \arccos\left[\frac{\langle\mathbf{x,y}\rangle}{\|\mathbf{x}\|_2\|\mathbf{y}\|_2}\right] \qquad (3)$$

$$SID(\mathbf{x,y}) = \left\langle \frac{\mathbf{x}}{\mathbf{x}} - \frac{\mathbf{x}}{\mathbf{y}}, \log\left(\frac{\mathbf{x}}{\mathbf{x}}\right) - \log\left(\frac{\mathbf{y}}{\mathbf{y}}\right)\right\rangle \qquad (4)$$

In an attempt of combining good points of each individual measure, a hierarchical scheme of using the above measures is proposed that operates as the diagram in Fig. 4: firstly using one measure to cluster the original image, and then use the other to further cluster each of the classes.

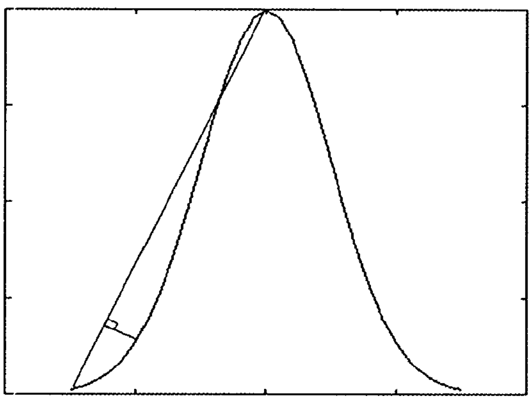


Fig. 3. Illustration of the triangle method to determine the threshold.

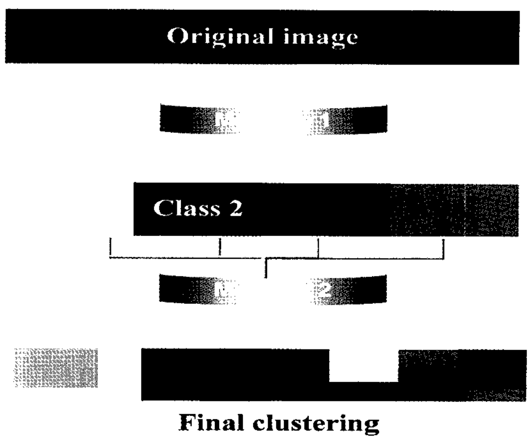


Fig. 4. Diagram of the proposed hierarchical scheme.

4. Assessment of Separability

The data used in this paper do not include a truth map; therefore a measure for assessing the separability of clustering results is required. The separability criteria (Fukunaga, 1990) based on a family of functions of scatter matrices, namely the within-class and between-class scatter matrices is utilized in our experiments. The within-class scatter matrix indicates the scatter of samples around their respective class expected vector, defined as:

$$S_w = \sum_{i=1}^{L} P_i E\{(\mathbf{X} - M_i)(\mathbf{X} - M_i)^T \mid \omega_i\} \qquad (5)$$

$$= \sum_{i=1}^{L} P_i \Sigma_i$$

Σ_i : Covariance matrix of class i

P_i : A priori probability of ω_i

whereas the between-class scatter matrix indicates the scatter of the expected vectors of classes around the mixture mean:

$$S_b = \sum_{i=1}^{L} P_i (M_i - M_0)(M_i - M_0)^T \qquad (6)$$

$$M_0 = E\{\mathbf{X}\} = \sum_{i=1}^{L} P_i M_i$$

In order to give out a number for assessing the separability, the above matrices are associated as:

$$s = \frac{trS_b}{trS_w} \quad \begin{array}{l} trA : \text{trace of an } n \times n \text{ matrix } A \\ trA : a_{11} + a_{12} + \ldots + a_{nm} = \sum_i a_{ii} \end{array} \qquad (7)$$

A good classification results in a larger between-class scatter and a small within-class scatter. Thus, a bigger s indicates a more separable result.

5. Experiments

The experiments are set up to evaluate the validation of the noise removal approach as well as the performance of the proposed hierarchical clustering scheme. The unsupervised k-mean clustering is implemented. By controlling the

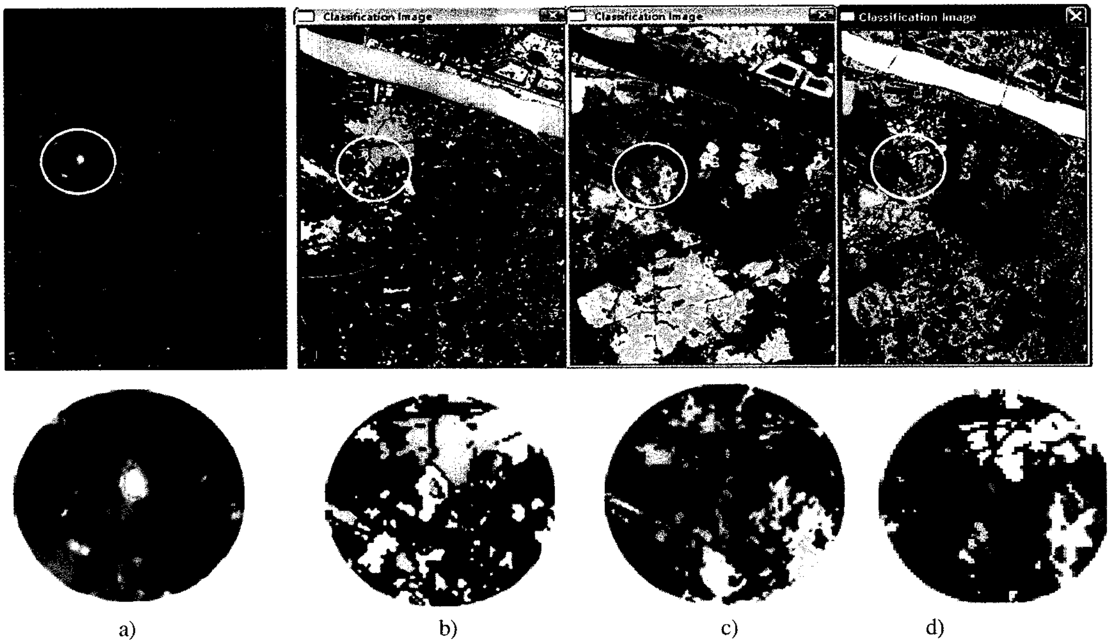


Fig. 5. Results of classification using different measures. a) a signal band and results of classification b) using ED measure; c) using SAM measure; and d) using the hierarchical scheme.

threshold that is described in Section 2, the level of noise to be removed can be controlled also. After clustering, classes that contain less than 20 pixels are discounted.

As shown in Fig. 5 above, if the result of using ED measure can distinguish the bright spot caused by a light source, it is not able to distinguish the bridges over the river or the road maze in the scene. This happens because the ED measure takes into account the brightness; therefore it is sensitive to the change of illumination. An opposite result can be found for the SAM measure which is invariant to the illumination. The proposed scheme can give a better result of successfully combining the strength of measures.

Separability scores are shown in Fig. 6. The experiment settings accord to the measures used and the order of using measures in the hierarchical scheme. In the first run, the ED measure is utilized; for the second, only use of SAM. The next three ones are performed in the order of using ED as the measure 1 in Fig. 3 then SAM as the measure 2. We in turn fixed the threshold of SAM and controlled the number of clusters by changing the threshold of ED; or fixed the ED or in the third case, controlled the number of clusters by changing both measures

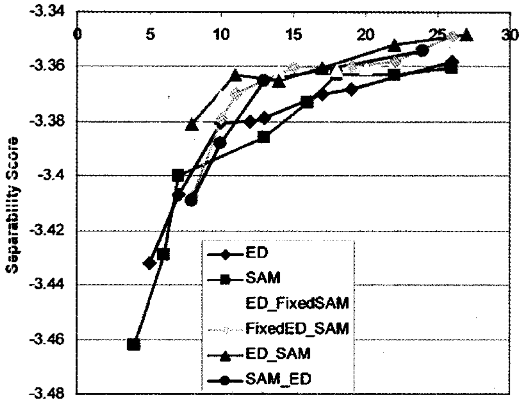


Fig. 6. Plot of separability scores at different settings

simultaneously. For the last case, the order of using measures is reversed: using SAM as the measure 1 in Fig. 4 then ED as the measure 2. Experiments show that the results obtained from the proposed hierarchical scheme give better classification in term of separability.

Fig. 7 shows the clustering results of individual measure at different level of noise. In the figure, the first row shows the results of clustering using the SID measure; the second row is for SAM and the last row is for ED. The first column shows the results of clustering using 86 out of 196 non-zero bands as signal bands. For the second column and third column, the numbers are 136 and 141 respectively. The experiments show that, the SID measure is sensitive to the noise bands, while SAM is rather resistant. However, best visual clustering can be obtained using SID with an appropriate level of noise band removed.

6. Conclusions

Noise in hyperspectral image is sometimes unavoidable that can divert the result of surface classification. The method proposed makes use of the correlation coefficients in a screening scheme to determine noisy bands. Unlike other methods that are based on the SNR as a lodestar, the proposed method is invariant to the contrast of bands. Due to the lack of a ground truth map, the separability criterion is used to assess the performance of the unsupervised clustering. The experiments show that the ED measure gave the worst classification and created the most virtual classes.

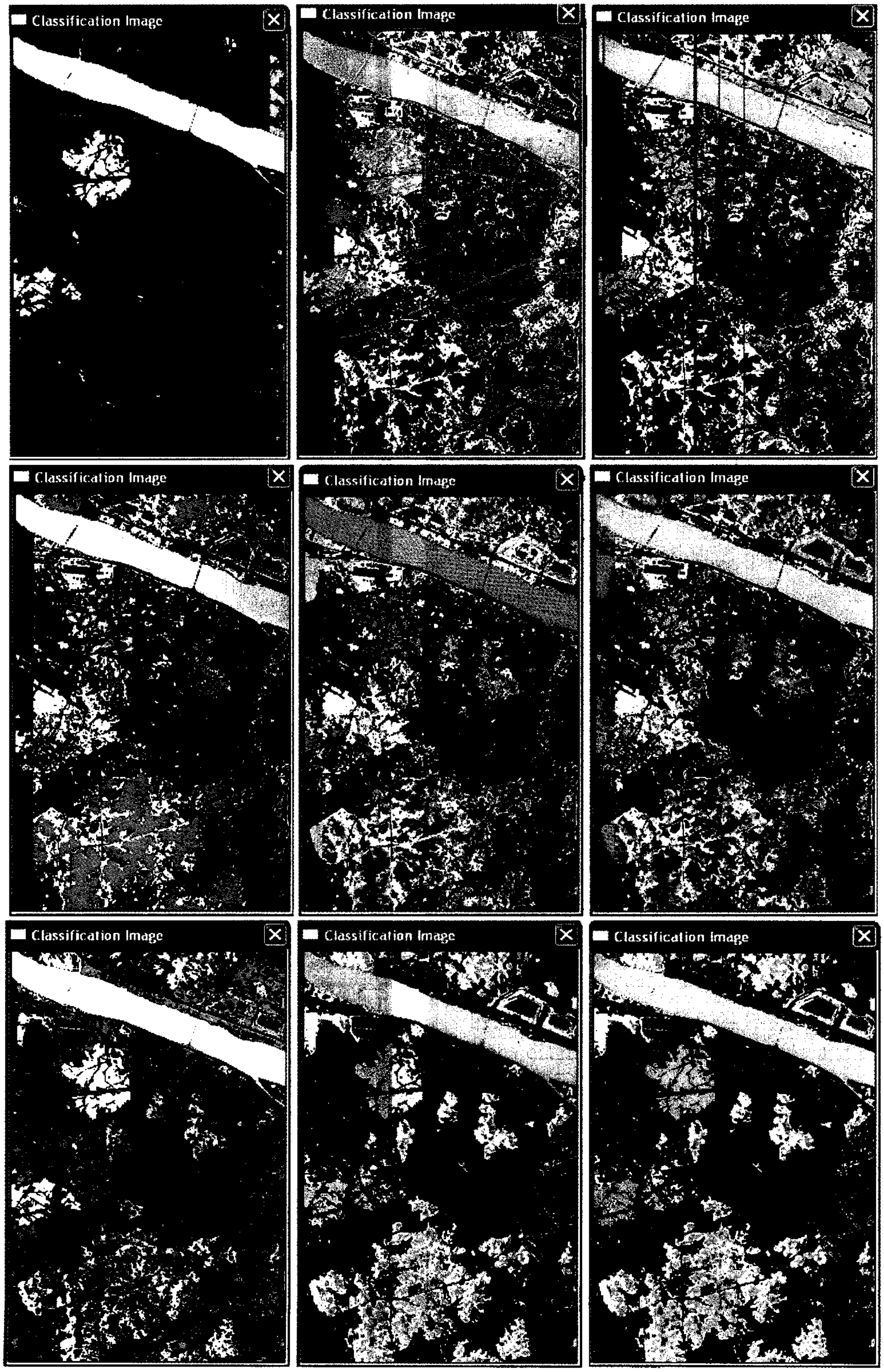


Fig. 7. Performance of different measures versus at different levels of removed noise bands.

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