STATISTICAL NOISE BAND REMOVAL FOR SURFACE CLUSTERING OF HYPERSPECTRAL DATA

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ABSTRACT:

The existence of noise bands may deform the typical shape of the spectrum, making the accuracy of clustering degraded. This paper proposes a statistical approach to remove noise bands in hyperspectral data using the correlation coefficient of bands as an indicator. Considering each band as a random variable, two adjacent signal bands in hyperspectral data are highly correlative. On the contrary, existence of a noise band will produce a low correlation. For clustering, the unsupervised *k*-nearest neighbor clustering method is implemented in accordance with three well-accepted spectral matching measures, namely ED, SAM and SID. Furthermore, this paper 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.

Keywords: Noise band removal, clustering, hierarchical classification, spectral matching measure

I. 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. 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.

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. 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*-nearest neighborhood 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.

II. Noisy band removal

The noisy bands are classified into two categories: zero bands and reflectively noisy bands.

Step 1: Removing zero bands

The zero bands are easily removed by considering the mean of the bands. If the mean of band is near zero, the band 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:

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

where ρ_{ij} is the correlation coefficient between band *i*th and *j*th; $\mu_{\bullet}$ 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 $\rho_{i,i+1} > thres$
  *i*th band is a signal band

  Else

  *i*th band is a potential noisy band

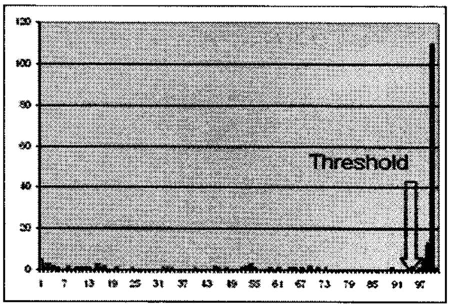


Fig. 2. 100-bin histogram of correlation coefficients

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

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 $\rho_{k,k+n} > thres$

    *k*th band is reset to a signal band

    Else

    *k*th band is a noisy band.

III. 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).

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

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

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

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. 3: firstly using one measure to cluster the original image, and then use the other to further cluster each of the classes.

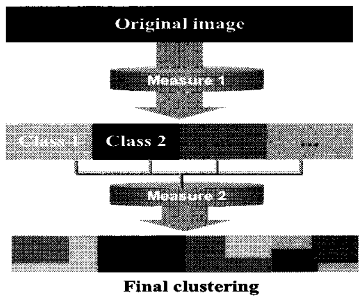


Fig. 3. Diagram of the proposed hierarchical scheme

IV. Assessment of Separability

Results of classification are assessed via the separability criteria (Fukunaga, 1990) based on a family of functions of scatter matrices, namely the within-class and between-class scatter matrices. The within-class scatter matrix indicates the scatter of samples around their respective class expected vector, defined as:

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

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:

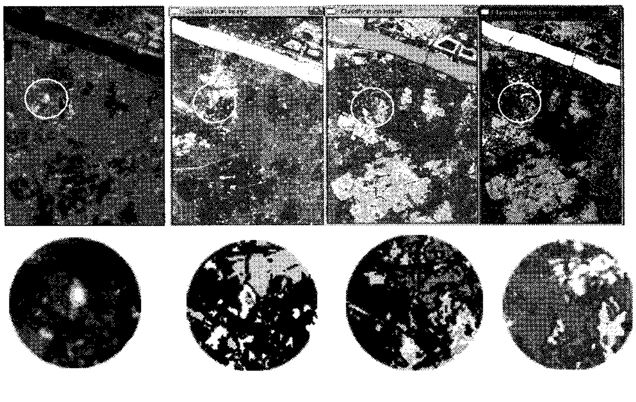
$$s = \frac{trS_b}{trS_w} \qquad trA: \text{ trace of an } n \times n \text{ matrix } A \qquad trA = a_{11} + a_{22} + \ldots + a_{nn} = \sum_i a_{ii} \qquad (7)$$

so that the number would be larger (more separable) when the between-class scatter is larger or the within-class scatter is smaller.

V. Experiments

The unsupervised k-mean clustering is implemented so as to validate the effectiveness of the noisy band removal and the proposed hierarchical classification scheme. By controlling the threshold that is described in Section II, the level of noise to be removed can be controlled also. After clustering, classes that contain less than 20 pixels are discounted from further processes.

As shown in Fig 4 below, 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.



a) b) c) d)

Fig. 4. 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

Separability scores are shown in Fig. 5. 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 simultaneously. For the last case, the order of using measures is reversed: using SAM as the measure 1 in Fig. 3 then ED as the measure 2. Experiments show that the results obtained from the proposed hierarchical scheme give better classification in term of separability.

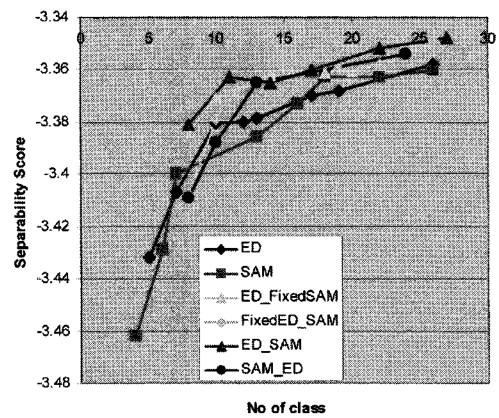


Fig. 5 Plot of separability scores at different settings

Fig. 6 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.

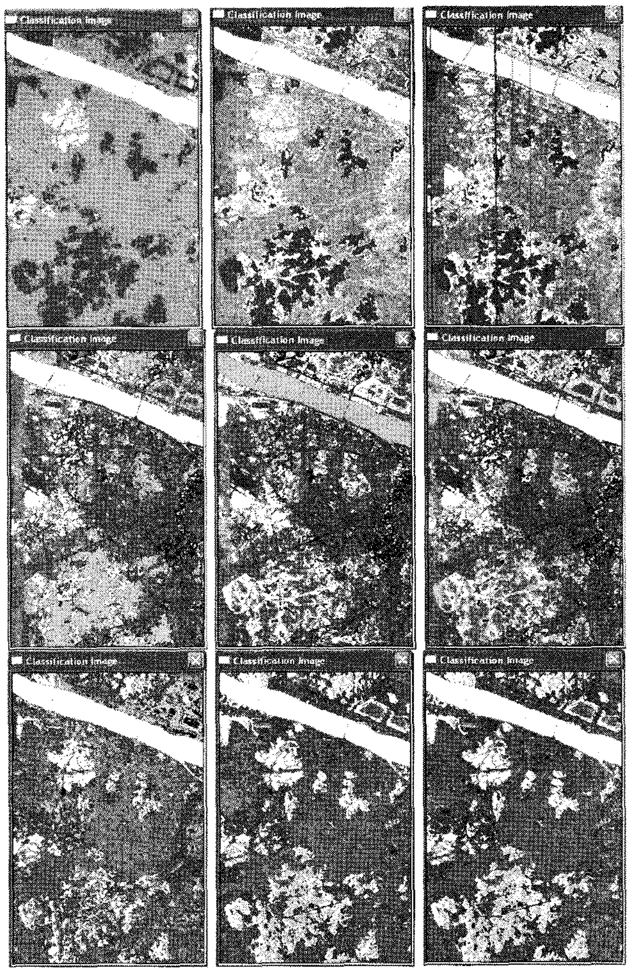


Fig.6 Performance of different measures versus at different level of removed noise bands.

VI. 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 (classes that contain just a few pixels).

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