MINIMUM COMPONENT EIGEN-VECTOR BASED CLASSIFICATION TECHNIQUE WITH APPLICATION TO TM IMAGES

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ABSTRACT

In this paper, we propose a new classification technique based on the Minimum Component Analysis (MCA) instead of the traditional Principal Components Analysis (PCA). Most existing classification techniques based on PCA represent a class by its principal component. However, the principal component is not always the best choice since there is a high possibility for classes to overlap with each other in the principal component direction. The new minimum component eigen-vector based classification technique overcomes this disadvantage by representing a class with its minimum component. In addition, a minimum likelihood decision rule is employed instead of maximum likelihood decision rule. Good performance of our technique is verified by experimental results on Kennedy Space Center (KSC) TM images.

1. INTRODUCTION

Remotely sensed data of the Earth may be analyzed to extract useful thematic information. Multispetral classification is one of the most often used methods of information extraction[1]. Objects in an image are classified to one of the prespecified classes.

Currently, there are two methods in multispectral classification: Supervised classification and Unsupervised classification[2][3]. In a supervised classification, the identity and location of some of the land cover types, such as urban, agriculture, or wetland, are known a *priori* (before the fact) through a combination of fieldwork, analysis of aerial photography, maps, and personal experience. Specific sites in the remotely sensed data can be located to represent homogeneous examples of these known land-cover types. These areas are commonly referred to as training sites because the spectral characteristics of these known areas are used to train the classification algorithm for eventual land-cover mapping of the remainder of the image. Usually, multivariate statistical parameters (means, standard deviations, covariance matrices, correlation matrices,etc.) are calculated for each training site. Every pixel both within and outside these sites is then evaluated and assigned to the class of which it has the highest likelihood of being a member. Classification methods based on supervised classification include: Minimum Distance, Parallelepiped, Mahalanobis Distance, Binary Encoding, K-nearest Neighbor, and the well known Maximum Likelihood technique(MLC). Among all the supervised classification techniques mentioned above, only the K-nearest neighbor technique doesn't need to calculate the statistics parameters of the class, such as the mean and covariance of each class. Recently, neural network based supervised classification methods have also been developed and used widely[6][7]. In an unsupervised classification, the identities of land-cover types to be specified as classes within a scene are not generally known a priori because ground reference information is lacking or surface features within the scene are not well defined. The computer is required to group pixels with similar spectral characteristics into unique clusters according to some statistically determined criteria. The commonly used unsupervised classification techniques are IsoData and K-means algorithm. Both methods begin with randomly chosen means for classes, then use clustering technique until certain criteria is met. Both supervised classification and unsupervised classification have advantages and disadvantages. The advantage of supervised classification is: it can classify the image according to an existing, possibly standard , classification. The disadvantage is that selection of training sites may be biased, leading to a biased classification. The advantages of unsupervised classification are: the classification is objective classification, it does not depend on the selection of training sites. The disadvantage of it is that sometimes it is hard to reach convergence[1][8][9].

One of the commonly used supervised classification methods for

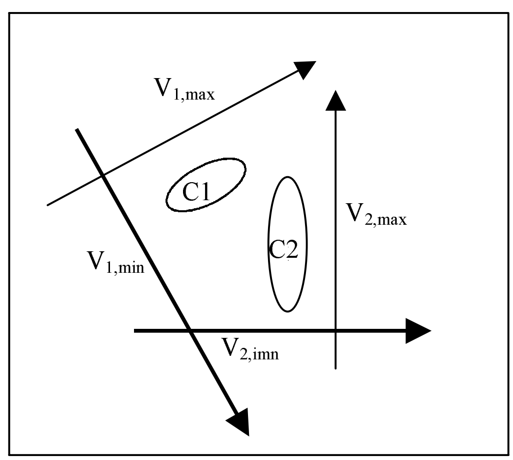

Figure 1. Illustration of the problems in traditional PCA based classification technique.

multi-dimensional pattern classification is to project the multi-dimensional vector, for example, a vector $\boldsymbol{x}$, to a one dimensional space in a certain direction W, i.e., take

$$y = W^T \boldsymbol{x}, \qquad (1)$$

then y is used for the later classification[4]. Traditionally, people like to project the multidimensional data onto the principal component direction and use the projection on this direction to accomplish further tasks. But as seen in Figure 1, a class has the maximum variance in its principal component direction. Therefore, it has high possibility to overlap with other classes in this direction. Using the projections on the principal component directions is not a good way to discriminate the classes. However, a class has the minimum variance in its minimum component direction[5], it will be easy to decide if a pattern vector not belonging in this class in the principal component direction of the class.

2. MIMIMUM COMPONENT EIGEN-VECTOR BASED CLASSIFICATION TECHNIQUE

2.1 New Classification Technique Model

Suppose the vectors to be classified have a dimensionality of N. The total number of classes is S. The minimum component eigen vectors for each training class are: $v_{k,\min} (k = 1,2,\cdots,S)$. Assume for each class k, there are m_k prototypes in the training set. Then the projection of the i-th vector in class k onto the minimum component direction of class l is:

$$y_{ikl} = x_{ik}^T v_{l,\min} \qquad (2)$$

The mean of the projection is:

$$M_{kl} = \mathrm{E}[y_{ikl}] = \frac{1}{m_k} \sum_{i=1}^{m_k} y_{ikl} = \frac{1}{m_k} \sum_{i=1}^{m_k} x_{ik}^T v_{l,\min} \qquad (3)$$

The covariance of the projection is:

$$\sigma_{kl} = \mathrm{E}[(y_{ikl} - M_{kl})^2] = \frac{1}{m_k - 1} \sum_{i=1}^{m_k} y_{ikl}^2 - M_{kl}^2 \qquad (4)$$

In this way, for any class k and l, we can find the mean and the covariance of the projections obtained by projecting every vector in class k onto the minimum component direction of class l. Therefore, both k and l in the above equations can take values from 1 to N.

Minimum likelihood decision rule is used instead of maximum likelihood rule. For a S-class problem, it needs S-1 steps to decide the final class a testing vector belongs to. For each step l, the discriminant function is:

$$P(X \mid S_k)P(S_k) = P(y_{kl} \mid S_k)P(S_k) \quad l = 1,2,\ldots,S \qquad (5)$$

where y_{kl} is a projection of a vector in class k onto the minimum component eigen-vector direction of class l; $P(S_k)$ is a priori probability of class k occuring. The new technique is based on two assumptions: (1). All the classes have the same

$$P(S_k) = P(S_l) \qquad (6)$$

probability of occuring, which is similar to the assumption of maximum likelihood classifier; (2). The projection of the vectors in one class onto any minimum component direction has Gaussian distribution. Expressed in mathmatical form, the two assumptions are:

$$P(y_{kl} \mid S_k) = \frac{1}{\sqrt{2\pi}\sigma_{kl}} \exp\left(\frac{y_{kl} - M_{kl}}{\sigma_{kl}}\right)^2 \qquad (7)$$

Using these two assumptions, the final form of the discriminant functions for step l is:

$$g_l(X) = P(y_{kl} \mid S_l) = \frac{1}{\sqrt{2\pi}\sigma_{kl}} \exp\left(\frac{y_{kl} - M_{kl}}{\sigma_{kl}}\right)^2 \qquad (8)$$

But unlike the decision rule of maximum likelihood which is based on the mostly likelihood, the decision rule of our proposed classification method is based on the mostly unlikelihood. A block diagram of the classifier is in the following:

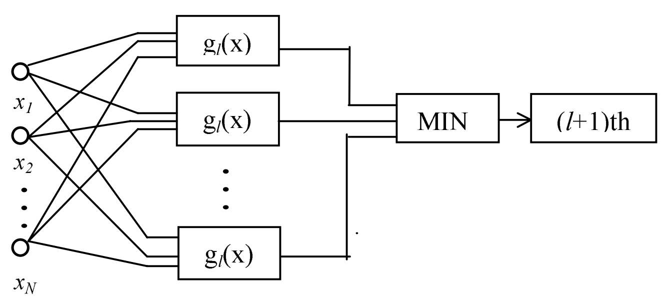

Figure 2. The classifier for l-th step

Let $\boldsymbol{x}$ be a new vector to be classified. First we project $\boldsymbol{x}$ onto the minimum component direction of the first class. Then a projection y_1 is obtained. For each class k, the values $P(y_{k1} \mid S_k)$ are computed at the point $y_{k1} = y_1$. The class which yields the minimum value is disregarded. Then project $\boldsymbol{x}$ onto the minimum component direction of the second class, yielding the projection y_2. This time, the values $P(y_{k2} \mid S_k)$ are computed for every class, except the class which has been disregarded. Using the same rule, the class which yields the minimum value is disregarded. This scheme is repeated until only one class is left. Finally, $\boldsymbol{x}$ is assigned to the only left class.

2.2 The New MCA Based Classification Technique On Multispectral Images

Obviously, the new classification technique is for multidimensional supervised classification. To have a better idea on how the new technique works, a block diagram of the new classification technique on multispetral data—Multispectral images is presented in Figure 3. In which MCV means the minimum component eigen-vectors (MCVs) of the known classes. The left part of the dashed line is the training process while the right is the testing process. The feature vector space means the dimensional space selected for the classification.

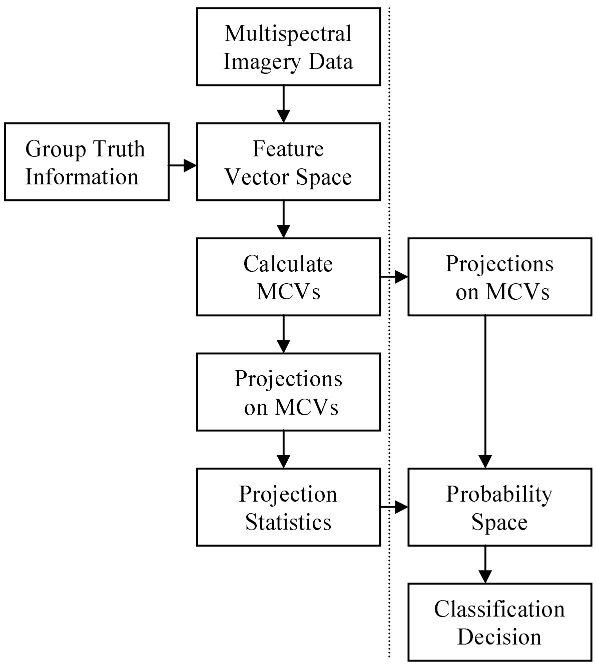

Figure 3. Block Diagram Of The New Technique

3. EXPERIMENTAL RESULTS AND COMPARISON

The new minimum component eigen-vector based classification technique is tested on several NASA Kennedy Space Center TM images. Three (band 3, 4, and 5) of the 7 bands of an original TM images are shown in Figure 4. Ground truth image of the same region is shown in Figure 5. For this test, half of the regions of the classes in the ground truth are used as training sites. Band 1, 2, 5 and 7 are used as the multidimensional input data. To evaluate the performance of the new technique, we use the tradition maximum likelihood classification technique on the same data sets. Figure 6 and Figure 7 are the corresponding classification maps. Pixel-by-pixel classification accuracy are given in table I. We got higher classification accuracy for most vegetation classes by using the new technique that those by MLC.

4. SUMMARY

In this paper, we proposed a new classification technique which is based on minimum component analysis and minimum likelihood principle. Both theoretical and remote sensing application experiments proved that this technique is better than some traditional methods. However, more future work is needed to improve the speed and explore further applications.

5. ACKNOWLEDGEMENT

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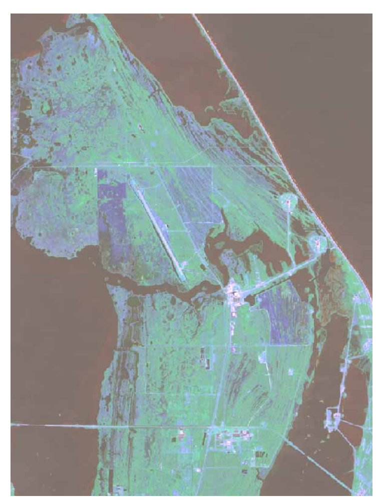

Figure 4. Testing TM image, combination of band(3,4,5)out of 7 bands ate shown

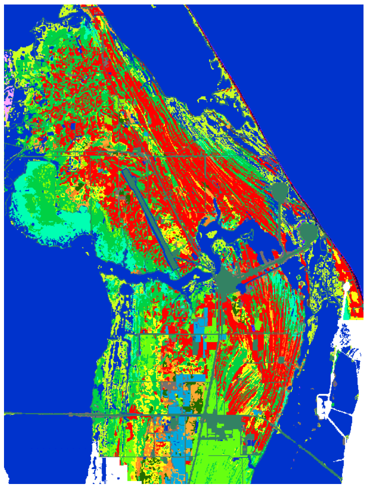

Figure 5. Ground truth image

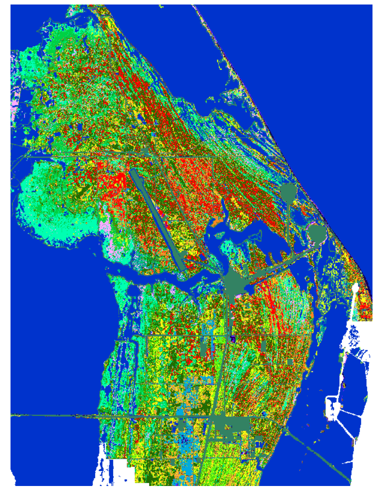

Figure 7. Maximum likelihood classificaition result

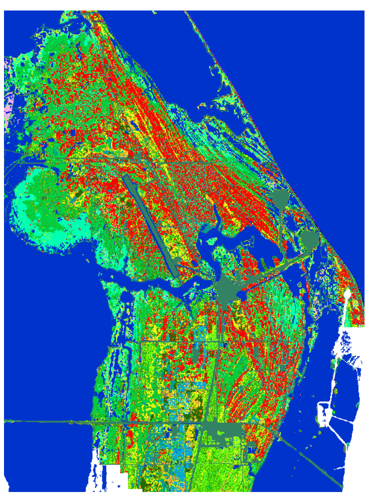

Figure 6. New technique classification result

Table I. Classification Accuracy Comparison

Class Name	New Technique Approach(%)	Maximum Likelihood (%)
Salt Marsh	75	53
Cabbage Palm Hammock	94	90
Graminoid Marsh	82	48
Oak/Cabbage Palm Hammock	89	88
Mixed Oak/saw palmetto	85	69
Oak Hammock	81	83
Dune	54	89
Beach/bare Ground	50	79
Cattail Marsh	86	24
Mixed Others	54	56
Pine Flatwoods	97	94
Willow Swamp	80	84
Mud Flats	78	56
Hardwood Swamp	86	91
Citrus	62	70
Spartina Marsh	73	36
Oak/cedar Hammock	75	76