High-dimensional image data has opened new vistas for the monitoring of the earth’s surface by using remote sensing images. However, the huge amount of hyperspectral data presents challenging problems for information processing, such as heavy computational burden and Hughes phenomenon\cite{1}. As a result, dimensionality reduction of hyperspectral image without a significant loss of information is important. Principal Component Analysis (PCA) is one of the most widely used dimension reduction techniques in remote sensing. But, Luis O. Jimenez et, al\cite{2} had shown that high-dimensional data spaces are mostly empty, and the data structure involved exists primarily in a subspace, so using PCA to the full spectral space may lose the detail information. In this paper, an approach of data dimensionality reduction and classification is proposed.

The proposed method consists of three parts. Firstly, every band $x_j (j=1,2,\cdots,N)$ in the hyperspectral image is looked on as ants with different features, every ant is 2-D vector with the feature of mean and variance. In terms of the correlation between band $x_i$ and band $x_j$, the hyperspectral data is adaptively decomposed into subgroups with different dimensionalities by ant colony algorithm (ACA) (see Fig.1); Secondly, the PCA is applied to the subspaces to extract features and reduce dimensionalities; Finally, the classification of the hyperspectral image is carried out by the maximum likelihood classifier.

1. Calculate the correlation $R_{ij}$ between ants $X_i$ and the centers $X_j$ of clusters
2. Repeat
   For each ant Do
   2.1 If $R_{ij} = 0$, then the membership $p_{ij}$ that one band belongs to some class is 1
   2.2 If $R_{ij} < r$, the heuristic desirability is $\eta_{ij}(t) = 1/R_{ij}$, and the pheromone intensity $\phi_{ij} = 1$
   then
   $$p_{ij} = \frac{\sum_{x \in S} \phi_x^{\alpha}(t) \eta_x^{\beta}(t)}{\sum_{x \in S} \phi_x^{\alpha}(t) \eta_x^{\beta}(t)}$$
   if $j \in S$, where $S = \{X_S | R_{ij} \leq r, S = 1,2,\cdots,N\}$ is the aggregate of routes which have been traveled
   otherwise 0
   2.3 If $p_{ij} > \lambda$, then update the pheromone intensity according to $\phi_{ij}(t') = (1 - \rho) \phi_{ij}(t) + \Delta \phi_{ij}$, where $\rho$ is the coefficient of evaporation of pheromone; $1 - \rho$ is the residues factor of pheromone; $\Delta \phi_{ij}$ is the increment of pheromone on the route $(i,j)$ in this cycle, and Update the center of cluster $C_j$
   else register the ant to the aggregate $S$ which isn’t classified
3. If the distance between two classes is smaller than preset threshold, the two classes are incorporated.
4. Partition the full band into N subgroups according to the attained centers of clusters.

Fig1. Algorithm for partitioning hyperspectral data based on ACA
In the ant colony algorithm, the moving of ant is random and blind. A band in the hyperspectral image is considered as an ant. When say the number of bands is \( N \), every pixel needs to calculate correlation and probability of choosing route with other \( N-1 \) bands in the process of searching. Only the system is repeated many times, cluster is finished, leading to the long searching time and complicated computation. So we select \( n \) bands as the centers of cluster, \( C_j (j = 1, 2, \cdots, n, n \ll N) \), i.e. the source of food. Initially, the amount of the source of food is two times of the result of the final cluster. Accordingly, the blindness of ant moving is reduced, the complication of computation is decreased and the time of cluster is saved.

To testify the effectiveness of the proposed method for dimensional reduction and classification, experiments are conducted on an AVIRIS image of mixed agriculture and forestry in Northwestern Indian, USA recorded in June 1992. Water absorption bands were removed, leaving 200 of original 220 bands. A scene \( 145 \times 145 \) pixels in size was selected for our experiments (Fig. 2 shows channel 29 of the sensor). The available ground truth is shown in Fig. 3. In the experiments, we considered the eight most representative land-cover classes. Using ant colony algorithm, the hyperspectral data is partitioned into 6 subgroups and the subgroups’ dimensionalities are 40, 13, 15, 23, 38, and 71 respectively. Then the PCA is applied to these six subgroups to extract features. After the selected samples are trained, the classification is realized by maximum likelihood method. The proposed method and standard PCA method which extracts features from all bands are compared to show their performance in hyperspectral data classification. The classified results are shown in Fig. 4 and Fig. 5, and the classification accuracies are shown in Table 1. From the results, we consider that compared with the conventional PCA method, at the condition of same numbers of feature, the classification accuracy of the proposed method is capable of providing very acceptable results. Especially in the classes with low classification accuracy, such as C1, C2, C7, C8, the classification accuracy of our method are obviously higher than the standard PCA.

Table 1 The classification accuracy compared the standard PCA with the proposed method

<table>
<thead>
<tr>
<th>Class Number</th>
<th>C1</th>
<th>C2</th>
<th>C3</th>
<th>C4</th>
<th>C5</th>
<th>C6</th>
<th>C7</th>
<th>C8</th>
<th>overall</th>
</tr>
</thead>
<tbody>
<tr>
<td>Standard PCA</td>
<td>77.68%</td>
<td>66.50%</td>
<td>98.53%</td>
<td>99.23%</td>
<td>99.59%</td>
<td>100%</td>
<td>78.78%</td>
<td>87.79%</td>
<td>87.47%</td>
</tr>
<tr>
<td>Proposed method</td>
<td>82.91%</td>
<td>86.67%</td>
<td>98.13%</td>
<td>98.61%</td>
<td>99.39%</td>
<td>99.53%</td>
<td>85.73%</td>
<td>93%</td>
<td>91.32%</td>
</tr>
</tbody>
</table>

Fig.2  29-th band of AVIRIS data

Fig.3  Ground truth of AVIRIS data

Fig.4  Classified result of standard PCA

Fig.5  Classified result of the proposed method

REFERENCES
