

Plant Species Identification Based on Independent Component Analysis for Hyperspectral Data

Yachao Wang, Gang Wu

Information School, Beijing Forestry University, Beijing 100083, China

Email: wangycyf@163.com, wugang@bjfu.edu.cn

Lixia Ding

School of Environmental & Resource Sciences, Zhejiang Agriculture & Forestry University,

Linan 311300, Zhejiang Province, China

Email: dlxlxy@126.com

Abstract—By investigating the possibility of plant species classification based on independent component analysis (ICA) for hyperspectral data with minor difference, the framework of a general plant species classification model that consists of ICA based data reduction, classifier training and verification is proposed in this paper. Five different types of discriminant analysis classifiers including Linear, Quadratic, DiagLinear, DiagQuatic and Mahalanobis, with data reduction that based on principal components analysis (PCA) and ICA, are implemented and compared. Accuracy assessment of classification for real leaf hyperspectral data is demonstrated, indicating that data reduction based on ICA performs better than that of PCA. Moreover, the proposed classification model with ICA based data reduction and Quadratic Discriminant Analysis works best, and its accuracy is about 98.35% with dimension 25 reduced from 2500.

Index Terms—independent component analysis, data reduction, principal component analysis, supervision classification, hyperspectral data analysis

I. INTRODUCTION

HYPERSPECTRAL sensors collect contiguous data across a large swath of the electromagnetic (EM) spectrum, which enables the identification of objects of interest, since diverse materials reflect individual wavelengths of the spectrum differently. Hyperspectral imagery has become one of the most advanced techniques that used to collect large scale data without any physical or intimate contact with the object. It is very useful for its high spectral resolution provides more diagnostic power in detecting, classifying, and quantifying materials as is applied in resources survey, environment monitor, natural observing, etc [1].

As an important research job in recent decades, plant species classification based on leaf has been carried out by botanists, plant specialist and many scholars [2]. It is shown in many studies that the leaf external shape, color and skeleton can provide rich information for classification, and results in various computer-aided plant classification systems [2], [3].

However, there is little literature touching upon the identification of plant species that based on hyperspectral

data, since hyperspectral data has some special characteristics, such as hundreds of spectral bands, high spectral resolution (nanometer resolution), high redundancy, etc. The development of a quick and efficient plant species classification method for hyperspectral data is a tough challenge.

In this paper, the possibility of classifying plant species with minor difference and high accuracy for hyperspectral data is investigated, and a general classification framework is proposed and verified, which includes a dimensional reduction strategy based on ICA and Quadratic Discriminant Analysis (QDA). For comparing data reduction methods that based on PCA and ICA, the performances of five different types of Discriminant analysis classifiers, including Linear, Quadratic, DiagLinear, DiagQuatic and Mahalanobis are implemented and evaluated. By assessing the classification accuracy for real hyperspectral data of leaf, the proposed classification method based on ICA and QDA shows the best performance.

The rest of the paper is organized as follows. In section II, we describe the related works about classification for hyperspectral data. In section III, we propose our classification framework based on independent component analysis. Experiments and performance are analyzed in section IV. Conclusions and future work are presented in section V.

II. RELATED WORKS

A. Independent component analysis

Independent component analysis is a general-purpose statistical model that has been used in many applications [4]–[7], such as blind source separating, bioinformatics, Machinery Fault Diagnosis [8] and Features Extraction [9], [10]. FastICA [4] and Informax [5] has become the most popular algorithms for calculating the independent components. However, these optimization processes can lead to varying results depending on starting points. In fact, most algorithms obtain different results when running multiple times. One reason lies in that most algorithms only find a local minimum of the objective

function for this optimization problem. ICASSO [6] and RAICAR [7] are frameworks which allow for selecting ICs appearing repeatedly during different runs of the ICA method. ICASSO selects an estimation from a single ICA repetition that corresponds to a cluster center when estimations from all repetitions are pooled and clustered. Alternatively, RAICAR use the average estimations in a cluster.

B. Dimensionality reduction

In hyperspectral image analysis, the principal components analysis (PCA), the maximum noise fraction (MNF) and independent component analysis (ICA) are most commonly used techniques for dimensionality reduction (DR), referred to as PCA-DR, MNF-DR and ICA-DR, respectively [11], [12]. The criteria used by PCA-DR and MNF-DR are data variance and signal-to-noise ratio (SNR) which are designed to measure data second-order statistics, while ICA uses higher order statistics and leads to independent components, with a much stronger statistical assumption. Based on unsupervised analysis of hyperspectral images, ICA can reveal more interesting features than that of PCA and MNF for usually non gaussian hyperspectral data sets [12].

C. Classification of hyperspectral data

In recent years, some important works are devoted to hyperspectral image classification [13]. Combining with machine learning techniques, several feature selection and extraction methods have been successfully used in supervised classification for hyperspectral image data, including support vector machines (SVMs) [14], [15] and multinomial logistic regression (MLR)-based classifiers [16].

Taking advantage of multiple classifiers, the spatial and spectral information simultaneously, multiple-classifier approach is proposed for hyperspectral image classification accurately [17]. Generalized composite kernel is developed for hyperspectral image classification without any weight parameters, which exhibits great flexibility when combining with the spatial and spectral information that contained in the hyperspectral data [13]. With spatialcontextual information, the combination of subspace projection method with multinomial logistic regression algorithm represents an innovative contribution in the literature [16].

Contextual support vector machine (SVM), is developed at jointly exploiting both local spectral and spatial information in a reproducing kernel Hilbert space (RKHS). Within a confined local region, the corresponding local hyperspectral pixels can be uniquely represented by collectively embedding a set of spectral signatures into a single point in RKHS [14]. Considering the influence of distribution bias between source and target domains in hyperspectral classification, pairwise binary classifiers that based on domain transfer multiple-kernel learning are used to minimize the maximum mean discrepancy

criterion and the structural risk functional of SVMs simultaneously [15].

A recent study relevant to the issue of using field reluctance spectra for crop classification is reported in [18], in which the spectral feature fitting and spectral angle mapping methods are examined for a historical airborne hyperspectral images. Different classification methods for detecting infected trees in citrus groves are implemented and compared in [19]. More stable and balanced performance is observed in simpler classification methods, such as minimum distance and Mahalanobis distance. Literature survey reveals that there is a paucity of studies in classifying the plant species for hyperspectral data of leaf.

III. CLASSIFICATION BASED ON INDEPENDENT COMPONENT ANALYSIS

In this section, we first present the main framework of our classification method based on ICA, which consists two strategies: data reduction and classifier training.

A. System framework

The system framework of classification based on ICA is shown in Fig. 1. First, the training data is preprocessed to be with zero mean and whitened, then put into ICA to generate hyperspectral features. Second, the obtained hyperspectral features are used to reduce the dimension of the training data. Third, Supervised classifier is trained by the reduced training data through quadratic discriminant analysis. Finally, testing data is preprocessed to be with zero mean and whitened, then reduced by the hyperspectral features and classified by the newly trained supervised classifier.

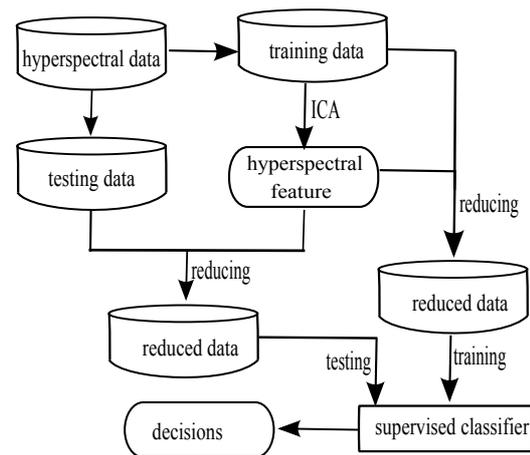


Figure 1. System framework of ICA based classification.

B. Data preprocessing

Given a hyperspectral dataset of leaf that represented by a $N \times L$ data matrix X . It is modelled as a random vector $X = (X_1, X_2, \dots, X_t, \dots, X_N)$, where X_t denotes a random variable, representing one hyperspectral sample

data with L bands at the sample point t , and N is the number of sample points. Centring X by removing the mean of each row, and then whiten the obtained X to yield $\tilde{X} = V \cdot X$. In particular, $V = D^{-1/2}B^T$, where $B = \{b_1, b_2, \dots, b_M\}$, $\{b_i\}_{i=1}^M$ are M eigenvectors of covariance matrix $C_X = E[XX^T]$, and $D = \text{diag}(d_1, d_2, \dots, d_M)$ is a diagonal matrix formed by the M eigenvalues of C_X .

C. Data Reduction Based on ICA

The classical noise-free ICA approach models the pre-processed hyperspectral data as

$$X = A * S \quad (1)$$

where A is an unknown mixing coefficient matrix of size $(M \times R)$, and $S = (S_1, S_2, \dots, S_R)^T$ denotes N independent components with each IC, S_i , $(i = 1, \dots, R)$, corresponding to a hyperspectral feature. Typically, R is smaller than M . These ICs can be estimated by optimizing their independence, such as minimizing their mutual information or maximizing their non-Gaussianity measured by negentropy or kurtosis.

Particularly, the Infomax algorithm is a common method for estimating independent components. Infomax is based on a neural network with three columns of neurons, each representing: (1) the original data (X); (2) the registered data (r); (3) the approximated independent data (Y). Each column of neurons combines linearly by matrices A and W . The principle of this algorithm is maximizing the mutual information, which outputs Y of a neural network processor that containing its input X . It is defined as

$$I(Y, X) = H(Y) - H(Y|X), \quad (2)$$

where $H(Y)$ is the entropy of output Y . $H(Y|X)$ is the entropy of the output that does not come from the input. In fact, $H(Y)$ is the differential entropy of Y with respect to some references, such as noise level or accuracy for the discretization of variables in X and Y . Thus, only the gradient of information-theoretic quantities with respect to certain parameter w is considered [5]. Eq.(3) can be differentiated with respect to w as:

$$\frac{\partial}{\partial w} I(Y, X) = \frac{\partial}{\partial w} H(Y), \quad (3)$$

because $H(X|Y)$ does not depend on w .

Using the natural (or relative) gradient method, the following iteration of the gradient method is developed to estimate the W matrix:

$$W(t+1) = W(t) + \eta(t)(I - f(Y)Y^T)W(t) \quad (4)$$

where t represents a given approximation step, $\eta(t)$ a general function that specifies the size of steps for unmixing matrix updates (usually an exponential function or a constant), $f(Y)$ a nonlinear function that usually chosen according to the type of distribution (super or sub-Gaussian), I the identity matrix of dimensions $M \times M$. In the case of super-Gaussian distributions, it is usually set to:

$$f(Y) = \tanh(Y) \quad (5)$$

and for sub-Gaussian distributions:

$$f(Y) = Y - \tanh(Y) \quad (6)$$

The infomax algorithm for this ICA is summarized as algorithm 1.

Algorithm 1 Infomax algorithm for ICA

- 1: Initialize $W(0)$ (e.g. random)
 - 2: $W(t+1) = W(t) + \eta(t)(I - f(Y)Y^T)W(t)$
 - 3: $t_e = \|W(t+1) - W(t)\|$
 - 4: **if** ($t_e > 1.0e \times 10^{-5}$) **then**
 - 5: go to step 2
 - 6: **else**
 - 7: Stop and output.
 - 8: **end if**
-

When hyperspectral features $S = (S_1, S_2, \dots, S_R)^T$ are obtained, the dimension of hyperspectral data can be reduced to

$$A_r = X * [S_1, S_2, \dots, S_m]^T \quad (7)$$

where m , ($m < R$) is the target dimension.

D. Quadratic Discriminant Analysis Classifier Training

There are many methods that can be used to train a classifier, such as linear discriminant analysis (LDA), quadratic discriminant analysis (QDA), diagonal linear discriminant analysis (DiagLDA), diagonal quadratic discriminant analysis (DiagQDA) and Mahalanobis distance based analysis. We have compared these methods, as shown in experiments 1 and 2 in section V, and found that QDA classifier shows the best performance. So, we focus on the details of QDA classifier.

QDA classifier is a kind of Bayes classifier, whose principle is to calculate the posterior probability for a given object from its prior probability via Bayes formula, and then place the object in the class with the largest posterior probability.

QDA assumes that every density within each class is a Gaussian distribution, and the covariance matrix Σ_k can be estimated separately for each class C_k , ($k = 1, 2, \dots, K$). QDA uses the following quadratic discriminant function forms

$$\delta_k(x) = -\frac{1}{2} \log |\Sigma_k| - \frac{1}{2} (x - \mu_k)^T \Sigma_k^{-1} (x - \mu_k) + \log \pi_k \quad (8)$$

where

$$\mu_k = \frac{1}{|C_k|} \sum_{i=1}^{|C_k|} x_i, \quad x_i \in C_k$$

$$\Sigma_k = \frac{1}{|C_k|} \sum_{i=1}^{|C_k|} (x_i - \mu_k)(x_i - \mu_k)^T, \quad x_i \in C_k$$

$$\pi_k = \frac{|C_k|}{\sum_{i=1}^K |C_k|}$$

The classification rule of QDA is

$$\hat{G}(x) = \arg \max_k \delta_k(x) \quad (9)$$

E. Testing and Application of QDA classifier

First, the testing or application dataset of leaf will be preprocessed to be with zero mean and whitened, as mentioned in the Data preprocessing subsection. Then dimension of the preprocessed data will be reduced using Eq.(7). Finally, the reduced data will be classified by the newly trained supervised classifier according to Eq.(9).

IV. EXPERIMENTS AND ANALYSIS

A. Leaf collection and spectral measurements

The City of Linan is selected as the sample. It is a typical city in the south of Zhejiang Province in China. In this analysis, a total of 66 broadleaf species are selected to test the capability of discriminating different plant species based on hyperspectral data. Leaves at different ages in the same tree may exhibit distinctive spectral characteristics. Considering spectral variation, five mature leaf samples are collected from each of the ten randomly selected plants for every broadleaf species.

All leaves were collected in June 2012. They were immediately sealed in plastic bags, kept in an ice chest, and then transported to the laboratory for spectral measurements. Leaf reflectance was measured with a Field Spec Pro FR (Analytical Spectral Devices Inc., Boulder, USA). The ASD instrument consists of three separate spectrometers and covers a spectral range from 350 nm to 2500 nm. The light source was a 100W halogen reflectorized lamp. All spectra were measured at the nadir direction of the radiometer with a 25 FOV. A standard whiteboard was employed as the white reference and measured per five minutes to convert leaf radiance to spectral reflectance. Reflectance spectra of leaves, picked randomly from the upper hemisphere of the leaf, were collected by measuring spots of 10 mm diameter using a plant probe. Spectral reflectance was originally measured over the ranges from 350 to 1000 nm at 1.4 nm intervals and 1000 to 2500 nm at 2.2 nm intervals. The entire spectral range (350 to 2500 nm) was automatically resampled to 1 nm resolution. A hyperspectral data of pillow leaf is shown in Figure 2. The total 3300 hyperspectral data samples of 66 plant leaves are shown in Figure 3.

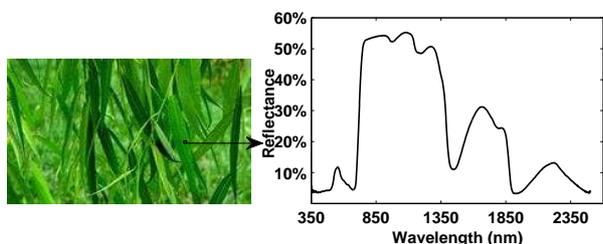


Figure 2. Hyperspectral data of pillow leaf.

B. Implementation of the proposed method

The ICA program

$[weights, sphere, activations, bias, signs, lrates]$

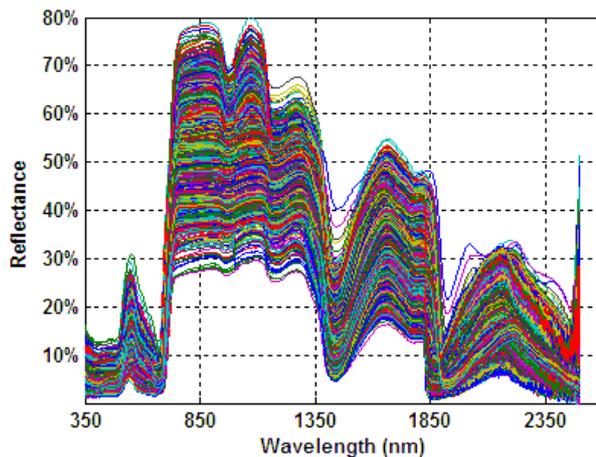


Figure 3. The total 3300 hyperspectral data samples of 66 plant leaves.

$= runica(data, 'Key1', Value1', ...)$

written in MATLAB is used for ICA calculation (<http://sccn.ucsd.edu/eeglab/allfunctions/runica.html>) in the proposed classification method based on ICA (CBICA). The classifier training part in CBICA is implemented by calling the function

$[outclass, err, posterior, logp, coeffs]$

$= classify(sample, training, group, type, prior)$

with the type parameter 'quadratic' in the classification toolbox of software MATLAB.

The accuracy of CBICA is evaluated in the similar way as that used in ICASSO [6] and RAICAR [7]. That is, the data reduction based on ICA will be repeated twenty times with randomized initial values and results in twenty ICA features. For each ICA feature, the QDA classifier will be trained and evaluated. The classifier with the best accuracy is recorded and compared with classifiers that generated by other methods.

C. Comparison

The performances of the following five different types of Discriminant analysis classifiers have been investigated for the identification of plant leaves. 1) Linear: using linear discriminant function to fit a multivariate normal density to each group, with a pooled estimation of the covariance matrix. 2) Quadratic: using quadratic discriminant function to fit multivariate normal densities with covariance estimates stratified by group. 3) DiagLinear: using diagonal linear discriminant function is similar to linear discriminant function but with but with a diagonal covariance matrix estimate. This diagonal covariance matrix is estimated by taking only the diagonal of the estimated sample (pooled) covariance matrix, and ignoring the rests. 4) DiagQuadratic: similar to quadratic discriminant function, excepting that the estimation of covariance matrix is diagonal. 5) Mahalanobis: using Mahalanobis distances with stratified covariance estimations. For all of these classifiers, the underlying analysis is carried out

based on the evaluation of discriminant functions. All these classifiers are implemented by calling the function *classify()* that mentioned above with the type parameter 'linear', 'quadratic', 'diagLinear', 'diagQuadratic', or 'mahalanobis' respectively. We have made two experiments to test our method. In these two experiments, the total hyperspectral broadleaf data is used as the testing data set.

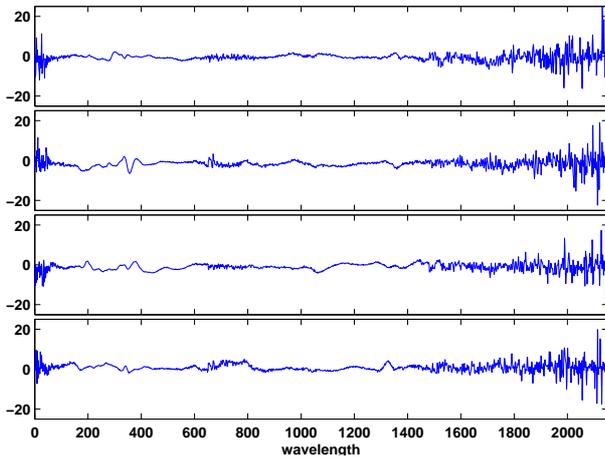


Figure 4. Examples of hyperspectral features.

D. Experiment 1

In this experiment, 70% of the total hyperspectral broadleaf data is used as the training data set. Four hyperspectral features are shown in Fig. 4. The performance of the CBPCA is shown in figure 5. The Quadratic discriminant function shows the best performance among these five discriminant functions. The classification accuracy increases with the dimension of the reduced data dramatically, before reaching the best value 87.245% with the reduced data dimension 18. After that, the growth of the dimension of the reduced data will not lead to the increase of the classification accuracy.

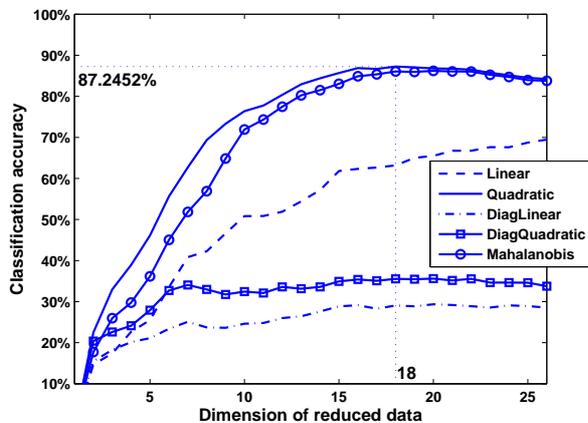


Figure 5. Performance of classification based on PCA.

The performance of CBICA is shown in figure 6. The Quadratic discriminant function also shows the best

performance among the five discriminant functions. The best classification accuracy is 92.6036% with the reduced data dimension 20. Only 11 dimensions are needed for CBICA to reach the best accuracy (87.245%) of CBPCA.

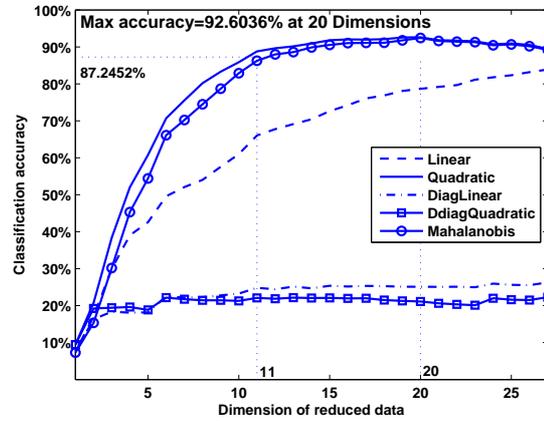


Figure 6. Performance of classification based on ICA.

E. Experiment 2

In this experiment, training data with different percent of the total hyperspectral data are used to generate the classifier with the range from 10% to 90%. The performances of CBPCA and CBICA are compared in Tab. I. The first column is the percent of the training data to the total data. The second column is the best accuracy for CBPCA and the third column is the corresponding dimension of the reduced data. The fourth column is the best accuracy for CBICA and the fifth column is the corresponding dimension of the reduced data. The sixth column is the dimension of the reduced data with which CBICA can reach the best accuracy of CBPCA. From Tab. I, it is obvious that the performance of CBICA is better than that of CBPCA with higher accuracy and less dimension of reduced data. Large size of training dataset is needed to generate accurate classifiers.

TABLE I. PERFORMANCE COMPARISON OF CBICA AND CBPCA

PTD	CBPCA	n1	CBICA	n2	n3
10%	63.31%	50	64.53%	22	21
20%	70.55%	52	72.06%	30	28
30%	78.47%	53	79.91%	35	31
40%	81.33%	53	83.07%	40	38
50%	83.89%	53	87.18%	45	42
60%	84.55%	54	89.48%	50	35
70%	87.25%	18	92.60%	20	11
80%	92.08%	23	94.84%	22	14
90%	96.94%	25	98.65%	25	15

V. CONCLUSIONS

Classification models of hyperspectral broadleaf data are investigated in this paper. We propose data reduction method based on ICA and generate a classification method which integrating quadratic discriminant analysis.

By two experiments on real data, the proposed method (CBICA) is fully compared with the corresponding one which based on principal component analysis (CBPCA). Results show that CBICA outperforms the others in terms of accuracy and reduced data dimension. Moreover, we find that large training dataset is needed to obtain high accuracy of classification.

Future work includes considering more efficient classification method in the generation of classifier. For instance, the performance of SVM and neural networks will be investigated to generate more efficient classifiers with less training data.

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REFERENCES

- [1] A. Erener, "Classification method, spectral diversity, band combination and accuracy assessment evaluation for urban feature detection," *International Journal of Applied Earth Observation and Geoinformation*, vol. 21, pp. 397–408, 2013.
 - [2] S. Zhang, Y. Lei, T. Dong, and X.-P. Zhang, "Label propagation based supervised locality projection analysis for plant leaf classification," *Pattern Recognition*, vol. 46, no. 7, pp. 1891–1897, 2013.
 - [3] J. C. Neto, G. E. Meyer, D. D. Jones, and A. K. Samal, "Plant species identification using elliptic fourier leaf shape analysis," *Computers and Electronics in Agriculture*, vol. 50, no. 2, pp. 121–134, 2006.
 - [4] A. Hyvarinen, "Fast and robust fixed-point algorithms for independent component analysis," *Neural Networks, IEEE Transactions on*, vol. 10, no. 3, pp. 626–634, 1999.
 - [5] A. J. Bell and T. J. Sejnowski, "An information-maximization approach to blind separation and blind deconvolution," *Neural Computation*, vol. 7, no. 6, pp. 1129–1159, 1995.
 - [6] J. Himberg and A. Hyvarinen, "Icasso: software for investigating the reliability of ica estimates by clustering and visualization," in *Neural Networks for Signal Processing, 2003. NNSP'03. 2003 IEEE 13th Workshop on*, 2003, pp. 259–268.
 - [7] Z. Yang, S. LaConte, X. Weng, and X. Hu, "Ranking and averaging independent component analysis by reproducibility (raicar)," *Human Brain Mapping*, vol. 29, no. 6, pp. 711–725, 2008.
 - [8] F. Wang and D. Zhao, "Emd based on independent component analysis and its application in machinery fault diagnosis," *Journal of Computers*, vol. 6, no. 7, 2011.
 - [9] H. Zhao, L. Hu, X. Peng, G. Wang, F. Yu, and C. Xu, "An improving mfcc features extraction based on fastica algorithm plus rasta filtering," *Journal of Computers*, vol. 6, no. 7, 2011.
 - [10] Z. Zhou and K. Yang, "Fetal electrocardiogram extraction and performance analysis," *Journal of Computers*, vol. 7, no. 11, 2012.
 - [11] Y. C. Du, W. Hu, and L. Shyu, "The effect of data reduction by independent component analysis and principal component analysis in hand motion identification," in *Engineering in Medicine and Biology Society, 2004. IEMBS '04. 26th Annual International Conference of the IEEE*, vol. 1, 2004, pp. 84–86.
 - [12] J. Wang and C.-I. Chang, "Independent component analysis-based dimensionality reduction with applications in hyperspectral image analysis," *Geoscience and Remote Sensing, IEEE Transactions on*, vol. 44, no. 6, pp. 1586–1600, 2006.
 - [13] J. Li, P. R. Marpu, A. Plaza, J. M. Bioucas-Dias, and J. A. Benediktsson, "Generalized composite kernel framework for hyperspectral image classification," *Geoscience and Remote Sensing, IEEE Transactions on*, vol. PP, no. 99, pp. 1–14, 2013.
 - [14] G. P. and H. Kwon, "Contextual svm using hilbert space embedding for hyperspectral classification," *Geoscience and Remote Sensing Letters, IEEE*, vol. 10, no. 5, pp. 1031–1035, 2013.
 - [15] Z. Sun, C. Wang, H. Wang, and J. Li, "Learn multiple-kernel svms for domain adaptation in hyperspectral data," *Geoscience and Remote Sensing Letters, IEEE*, vol. 10, no. 5, pp. 1224–1228, 2013.
 - [16] J. Li, B.-D. J.M., and A. Plaza, "Spectral-spatial hyperspectral image segmentation using subspace multinomial logistic regression and markov random fields," *Geoscience and Remote Sensing, IEEE Transactions on*, vol. 50, no. 3, pp. 809–823, 2012.
 - [17] Y. Tarabalka, J. Benediktsson, J. Chanussot, and J. Tilton, "A multiple classifier approach for spectral-spatial classification of hyperspectral data," in *Geoscience and Remote Sensing Symposium (IGARSS), 2010 IEEE International*, 2010, pp. 1410–1413.
 - [18] R. R. Nidamanuri and B. Zbell, "Classification method, spectral diversity, band combination and accuracy assessment evaluation for urban feature detection," *Journal of Photogrammetry and Remote Sensing*, vol. 66, no. 5, pp. 683–691, 2011.
 - [19] X. Li, W. S. Lee, M. Li, R. Ehsani, A. R. Mishra, C. Yang, and R. L. Mangan, "Spectral difference analysis and airborne imaging classification for citrus greening infected trees," *Computers and Electronics in Agriculture*, vol. 83, no. 2, pp. 32–46, 2012.
- Yachao Wang** received his B.S. degree in computer science from Shanxi University, China in June 2001 and his M.S. degree in information science from Beijing Forestry University, China in June 2007. He is currently working towards his Ph.D. degree in forest management at Beijing Forestry University, China. His current research interest includes forestry Informatization and forestry information management.
- Gang Wu** received M.S. degree in applied mathematics from Tianjin University, Tianjin, China, in 1983. He is an professor and the vice President of information school at the Beijing forestry university, Beijing, China. His research interests include forestry information management, decision system, system integration and electric business.
- Lixia Ding** received the Ph.D degree in environmental & resources from Zhejiang University, Zhejiang, China, in 2005. He is an associate professor at the School of Environmental & Resource Sciences, Zhejiang Agriculture & Forestry University, China. Her research interests include remote sense and GIS application in environmental supervision and management.