A discriminative manifold learning based dimension reduction method for hyperspectral classification

Article *in* International Journal of Fuzzy Systems · June 2012

Impact Factor: 1.1

4 authors, including:

Tao Chen
China University of Geosciences

Ke Wu
China University of Geosciences

A Discriminative Manifold Learning Based Dimension Reduction Method for Hyperspectral Classification

Bo Du, Liangpei Zhang, Lefei Zhang, Tao Chen, and Ke Wu

Abstract

Manifold learning methods have widely used in ordinary image processing domain. It has many advantages, depending on the different formulation of the manifold. Hyperspectral images are kind of images acquired by air-borne or space-born platforms. This paper introduces a novel manifold learning based dimension reduction (DR) method for hyperspectral classification. The purpose is to fully utilize the spectral and spatial information from hyperspectral images to get confidential landcover and land use class results.

Keywords: Manifold learning, dimension reduction, hyperspectral classification.

1. Introduction

Hyperspectral remote sensing image has been widely used in many fields, due to that it presents a continuous spectrum and the diagnostic spectral features of different land-covers can be revealed [1-2]. Classification by hyperspectral remote sensing images proves promising in fine land cover and land use mapping [3].

Traditional classification methods rely solely on the spectral features of objects. Recently, attention has been drawn to manifold feature learning techniques, such as orthogonal neighborhood preserving (ONP) [4, 5]. These methods focus on constructing a low-dimension space where the different objects are more separable. Some research work has also introduced manifold learning in hyperspectral image (HSI) analysis [6-8], which exploits the local linear relationship between pixels in a global non-linear manifold. In hyperspectral images, most spatial neighborhood pixels consist of different patches that have a local linear embedding structure, but the global data structure is nonlinear. Typical nonlinear dimension reduction algorithms include ISOMAP [9], locally linear embedding (LLE) [10] Laplacian eigenmap (LE) [11] and so on. A unifying framework was proposed and several DR methods can be unified into this framework [12]. Based on this framework, Discriminative Locality Alignment (DLA) [13] and its variants, semi-supervised DLA, are proposed, which are promising for classification application since they aims at enlarging the distance between different classes after DR.

However, current manifold learning methods in hyperspectral images use no constraints to restrict the between-class dissimilarity and the within-class similarity [6-8], and these constraints may be helpful to extrude the anomaly targets [14]. On the other hand, semi-supervised learning (SSL) based methods exploit the manifold of the dataset with the help of similarity and dissimilarity label information [15, 16]. SSL methods have proved to be a good way to solve the small label number problem in hyperspectral image analysis [17]. Metric learning based methods have been developed to project the dataset into more concentrated feature space, mainly in the same form of Mahalanobis distance. Besides, since in practice the Mahalanobis distances are mostly near zero, sparse metric learning may be used to accelerate the optimal separability measurement computation [18]. In other words, a measurement taking the discriminative labeling information into consideration may be able to increase the separability between different objects' pixels.

In this paper, a new discriminative manifold learning based DR method for hyperspectral classification is proposed. The purpose is to construct a more reasonable metric to enlarge the separability of different objects' pixels, learned from a wide scope of the image, not only from discriminative information but also the whole dataset's manifold.

The rest of this paper is organized as follows. Section 2 details our method by rigorous algebraic computations. Experimental results are presented in Section 3 and conclusions are given in Section 4.

Corresponding Author: Bo Du is with the School of Computer Science, Wuhan University, 129 Rd., Wuhan, Hubei, China.
E-mail: gunspace@163.com
Liangpei Zhang is with LIESMARS, Wuhan University, Wuhan, China.
Lefei Zhang is with LIESMARS, Wuhan University, Wuhan, China.
E-mail: zhanglefei@whu.edu.cn
Tao Chen is with Institute of Geophysics and Geomatics, China University of Geosciences, Wuhan, China.
Ke Wu is with Institute of Geophysics and Geomatics, China University of Geosciences, Wuhan, China.
Manuscript received Sep. 2011; revised 1 Dec. 2011; accepted 21 Jan. 2012.

2. Methodology

A. Triple-wise Discriminative Learning

The method focuses on the following points. Firstly, the intra-class distances should be minimized so as to prevent the spectral variation effect. Secondly, the metric used to project the dataset should be robust, so as to separate different kinds of pixels from each other, with enlarged distance between different kinds of objects' pixels. Finally, the metric should reduce the distance between background pixels, so as to suppress the background into a steady range. The first two points are actually referred to as the pair-wise discriminative constraint, like the constraint in linear discriminant analysis and discriminative locality alignment. However, the difference is that only the training dataset is used in these methods, exploiting only the centroid pixels in each class, so that the global manifold structure is not revealed, while our method aims at fully using the whole dataset manifold structure by taking as many of the pixels as possible into consideration. Besides, the discriminative information is utilized by a triple discriminative form, with each element is composed of both intra-class and inter-class labeled samples.

Then, the key becomes the construction of a projection metric from the label information. A Mahalanobis distance metric is employed, since it has proved promising and efficient in analysis for hyperspectral images. Its expression is:

$$\begin{aligned} dis_{\mathbf{M}}(\mathbf{x}_i,\mathbf{x}_j) &= \|\mathbf{x}_i-\mathbf{x}_j\|_{\mathbf{M}} = \sqrt{(\mathbf{x}_i-\mathbf{x}_j)^{\mathrm{T}}\mathbf{M}(\mathbf{x}_i-\mathbf{x}_j)} \\ &= \sqrt{(\mathbf{x}_i-\mathbf{x}_j)^{\mathrm{T}}UU^{\mathrm{T}}(\mathbf{x}_i-\mathbf{x}_j)} \\ &= \|U(\mathbf{x}_i-\mathbf{x}_j)^{\mathrm{T}}\| \end{aligned} \tag{1}$$

where $\mathbf{x}_i,\mathbf{x}_j$ are the samples in the hyperspectral dataset. In order to figure out $\mathbf{M}$, an optimal function should be defined. Some distance constraints are also introduced. In detail, the optimal function comprises two parts: the first part restricts the minimization of distances in the similar dataset S and the second part restricts the maximization of distances in the dissimilar dataset D. This strategy is like the min-max principle [19]. The optimal function is then defined as:

$$d(\mathbf{M}) = \sum_{(i,j)\in S}\|\mathbf{x}_i-\mathbf{x}_j\|_{\mathbf{M}}^2 - \gamma\sum_{(i,k)\in D}\|\mathbf{x}_i-\mathbf{x}_j\|_{\mathbf{M}}^2 \tag{2}$$

where γ is a positive parameter to trade-off the similar and dissimilar constraints. Also, $\mathbf{M}$ is defined as a positive semi-definite matrix in $R^{b\times b}$. b is the dimension of the image dataset. In this way, our method takes into consideration the discriminative information as fully as possible. The basic idea is illustrated in Fig. 1.

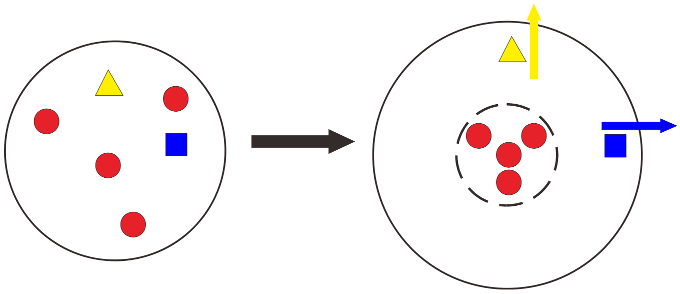


Fig. 1. Illustration of discriminative dimension reduction.

Unlike LDA, which uses the pair-wise labels from similar and dissimilar pixels, a triple labeling group is utilized to make full use of the dissimilar and similar discriminative information at the same time. As a result, not only within-class distance and between-class distance constrained conditions are constrained, but the margin from between-class pixels to within-class pixels is also enlarged. In detail, the labeling information is composed of both intra-class and inter-class counterparts in our method. Thus, both the large margin between intra-class and small margin between inter-class are taken into consideration. The idea is similar to the large margin nearest neighbor (LMMN) [20]. In detail, the expression is reformed as:

$$\begin{aligned} d(\mathbf{M}) &= \sum_{(i,j)\in D}\|\mathbf{x}_i-\mathbf{x}_j\|_{\mathbf{M}}^2 - \gamma\sum_{(i,k)\in S}\|\mathbf{x}_i-\mathbf{x}_k\|_{\mathbf{M}}^2 \\ &= (\mathbf{x}_i-\mathbf{x}_j)\mathbf{M}(\mathbf{x}_i-\mathbf{x}_j)^{\mathrm{T}} - \gamma(\mathbf{x}_i-\mathbf{x}_k)\mathbf{M}(\mathbf{x}_i-\mathbf{x}_k)^{\mathrm{T}} \end{aligned} \tag{3}$$

For simplicity, γ is taken as 1. The triple discriminative labeling dataset SD is defined as:

$$\begin{aligned} &(\mathbf{x}_i,\mathbf{x}_j,\mathbf{x}_k)\in \\ &SD\{(\mathbf{x}_i,\mathbf{x}_j) = \text{each couple of inter-class samples}, \\ &\quad(\mathbf{x}_i,\mathbf{x}_k) = \text{each couple of inter-class samples}\} \end{aligned}$$

Suppose that the number of triple labeling structures is $|SD|$, the object function is to make sure that the margin of each labeled triple points is enlarged. The equation (3) defines a new margin similar to the large margin method in structural risk minimization statistical methods such as support vector machine. A robust Mahalanobis distance metric usually depends on a positive semi-definite (p.s.d.) matrix to measure the anomalous degree. Our metric measurement uses the same idea. Besides, since different land covers usually come from different landscapes, and due to the complexity of the various sample pixels, a more flexible margin principal is more appreciable. Taking the above points into consideration, the optimal metric matrix is figured out as the following concentrated form (4).

$$\max_{\mathbf{M}} \langle \mathbf{A}_l, \mathbf{M} \rangle =$$

$$\sum_{(i,j,k)\in SD} (\mathbf{x}_i - \mathbf{x}_j)^{\mathrm{T}} \mathbf{M} (\mathbf{x}_i - \mathbf{x}_j) - (\mathbf{x}_i - \mathbf{x}_k)^{\mathrm{T}} \mathbf{M} (\mathbf{x}_i - \mathbf{x}_k)$$

$$= \frac{1}{|SD|} \sum_{(i,j,k)\in SD} \left[(\mathbf{x}_i - \mathbf{x}_j)^{\mathrm{T}} UU^{\mathrm{T}} (\mathbf{x}_i - \mathbf{x}_j) - (\mathbf{x}_i - \mathbf{x}_k)^{\mathrm{T}} UU^{\mathrm{T}} (\mathbf{x}_i - \mathbf{x}_k) \right]$$

$$= \frac{1}{|SD|} \sum_{(i,j,k)\in SD} \mathrm{tr}[U^{\mathrm{T}} (\mathbf{x}_i - \mathbf{x}_j)(\mathbf{x}_i - \mathbf{x}_j)^{\mathrm{T}} U] - \mathrm{tr}[U^{\mathrm{T}} (\mathbf{x}_i - \mathbf{x}_k)(\mathbf{x}_i - \mathbf{x}_k)^{\mathrm{T}} U]$$

$$= \mathrm{tr}_U (U^{\mathrm{T}} \mathbf{A}_l U)$$

$$\mathbf{A}_l = \frac{1}{|SD|} \sum_{(i,j,k)\in SD} (\mathbf{x}_i - \mathbf{x}_j)(\mathbf{x}_i - \mathbf{x}_j)^{\mathrm{T}} - (\mathbf{x}_i - \mathbf{x}_k)(\mathbf{x}_i - \mathbf{x}_k)^{\mathrm{T}}$$

$$\forall (\mathbf{x}_i, \mathbf{x}_j, \mathbf{x}_k)_l \in SD \tag{4}$$

The maximum problem (4) is minimizing the distances among the data points of similar constraints and meanwhile maximizing the distances among the data points of dissimilar constraints. So it is much like min-max problem [19]. Each triple of labeled samples in SD is utilized with the average distance to be maximized. Ours is different and just maximize the gap between two average squared distances on two constraint sets S and D. And the similar and dissimilar information is used simultaneously. So the distance gap or the margin can be maximized.

B. Global manifold preservation

At the same time, one problem with the project matrix constructed is that it may be over-fit for the labeled training samples so that the proper classification pattern cannot be formulated by it. This time, the manifold structure of HSI is taken into consideration by a semi-supervised learning based strategy. In detail, we aim at taking full advantage of unlabeled data that are beneficial to preserve the dataset internal structure.

Suppose we have the collection of n data points X including the labeled training data and the unlabeled data, we can define a neighborhood indicator matrix $W \in R^{N\times N}$ on X:

$$W_{ij} = \begin{cases} 1, & x_j \in N(x_i) \\ 0, & x_j \notin N(x_i) \end{cases} \tag{5}$$

where $N(x_i)$ denotes the set composed of k nearest neighbors of the point xi by the Euclidean metric. A matrix W holds weak similarities between all data pairs. Other strong similarity can also be used. However, for simplicity, the k-nn weak similarities are employed. The constrained condition for avoiding over-fitting problem is defined as:

$$\min f(X,M) = \frac{1}{2}\sum_{i,k=1}^{n} \|\mathbf{x}_i - \mathbf{x}_k\|_M^2 W_{ij} = \frac{1}{2}\sum_{i,k=1}^{n} \|U^T(\mathbf{x}_i - \mathbf{x}_k)\|^2 W_{ij} \tag{6}$$

Then, combining the two parts of constrain function, the finial optimal function for the DR projection metric matrix can be defined.

$$\max \frac{\langle \mathbf{A}_l, \mathbf{M} \rangle_{\mathbf{M}}}{f(X,M)} \tag{7}$$

In order to make the above problem solvable, $f(X,M)$ is re-expressed by Graph Lapacian:

$$f(X,M) = \frac{1}{2}\sum_{i,k=1}^{n} \|U^{\mathrm{T}}(\mathbf{x}_i - \mathbf{x}_k)\|^2 W_{ij} = \sum_{d=1}^{r} u_d^{\mathrm{T}} X(D-W)X^{\mathrm{T}} u_d = \sum_{d=1}^{r} u_d^{\mathrm{T}} XLX^{\mathrm{T}} u_d = \mathrm{tr}(U^{\mathrm{T}} XLX^{\mathrm{T}} U) \tag{8}$$

where D is a diagonalmatrix whose diagonal elements equal the sums of row entries of W, $D_{ii} = \sum_{j=1}^{n} W_{ij}$ and $L = D - W$ is Graph Lapacian.

Then the problem becomes:

$$\max_U \frac{\mathrm{tr}_U(U^{\mathrm{T}} \mathbf{A}_l U)}{\mathrm{tr}(U^{\mathrm{T}} XLX^{\mathrm{T}} U)} \tag{9}$$

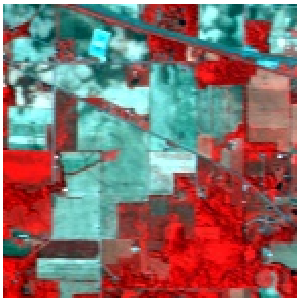
The optimal solution to the above problem is offered by the maximal eigenvalue solution to the generalized eigenvalue problem. Or the optimal subspace $U = [u_1, ..., u_r]$ that maximizes (9) is:

$$A_l u_d = \lambda_d XLXu_d, \; d = 1, 2, ...r \tag{10}$$

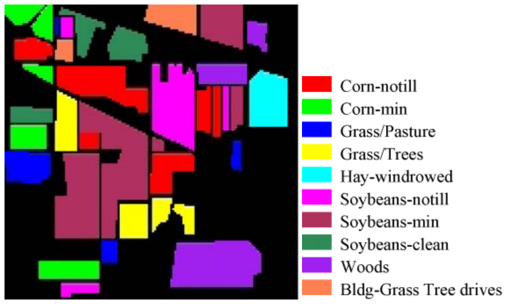
where u_d are r eigenvectors corresponding to r largest positive eigenvalues to ensure that the distance margin in (4) is positive.

3. Experiments and analysis

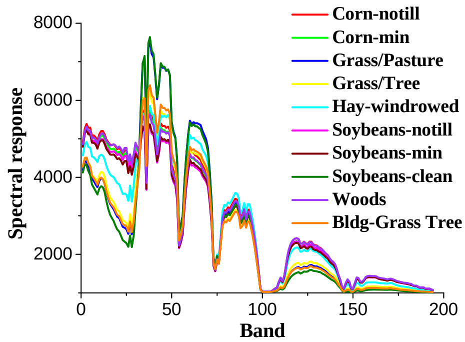
In this section, we present experimental results of our method for object classification on a hyperspectral image. The Indian Pine hyperspectral data set is from a mixed forest/agricultural site at the Indian Pine test site in north-west Indiana, taken on June 12, 1992, which was gathered by the airborne visible/infrared imaging spectrometer (AVIRIS) sensor. It covers a significant number of ground cover classes, includes many regions containing a large number of contiguous pixels from a certain class, which makes it relatively easier to classify the data with automated algorithms and the ground truth is available. This dataset was obtained from an aircraft flown at 19 812 m altitude and operated by the National Aeronautics and Space Administration (NASA) Jet Propulsion Laboratory. The dataset has a size of 145 × 145 pixels and 220 spectral bands which cover the 0.40-1.00 μm region of the spectrum. In the experiment, a total of 7000 pixels from 10 classes are used, with half chosen as training samples and half chosen as testing samples. Figure 2 show different class of materials' spectrum. Ground truth maps are also shown in Figure 2.



(a) Pseudo-color image.



(b) Ground truth.



(c) Corresponding spectral curve.

Fig. 2. Detail of Experimental AVIRIS Dataset.

TABLE I. Detailed Experimental Results.

DR methods	Class										OA	KAPPA
	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10		
Original	68.50	67.23	82.77	88.05	95.39	77.23	80.68	75.44	91.12	64.18	78.12	0.7554
PCA	73.22	69.68	94.34	97.39	100	68.63	78.34	49.88	99.42	61.13	81.61	0.7775
LPP	82.68	76.45	96.87	97.57	100	71.13	82.98	62.41	97.23	62.64	83.88	0.8185
LDA	82.91	73.76	97.91	99.30	100	67.45	84.51	74.65	98.55	65.63	85.12	0.8411
DLA	86.72	79.94	100	98.31	100	79.09	85.16	91.15	99.52	64.53	71.37	0.8757
Proposed	89.63	81.25	100	100	100	80.25	91.82	93.88	99.1	100	100	0.9313

Several state-of-art DR methods are employed and combined with the 1-NN classifycation method, including principal component analysis (PCA), locality preserving projections (LPP), discriminative locality alignment (DLA), linear discriminative analysis (LDA). Besides, original dataset without feature extraction is also used and input into 1-NN classifier. The classification results of those methods are analyzed. All the ten classes of testing samples in the classification results are calculated by the ground information truth. Each class samples' classification accuracy and the overall accuracy (OA) and KAPPA coefficient of all the classes are calculated, listed in Table I.. From the experimental results in Table I., several points are revealed: 1) linear DR method performs the worst. The reason may be that the spectral difference is so minor and the separability cannot be expressed in any linearly projected feature space; 2) nonlinear DR method presents better than linear ones, which combines the local linear relationship and global non-linear manifold feature; 3) discriminative information based methods improve the classification ability by imposing the labeled training samples on the projection manner; 4) our proposed method achieves best classification results. The reason is that ours fully uses the discriminative information by a triple-wise structure of training datasets. Besides, the preservation of the whole manifold structure proves effective in avoiding over-fitting problem in the projection on the whole dataset.

4. Conclusions

This manuscript proposes a novel discriminative manifold learning based dimension reduction method for hyperspectral remote sensing images. By constructing triple-wise discriminative information, enhanced discriminative constraint can be imposed on the projected low dimension feature space; the local and global manifold of HIS is taken into consideration by a semi-supervised learning based strategy to avoid the over-fitting problem. Experiments prove our method outperforms other state-of-art hyperspectral dimension reduction methods.

Acknowledgment

The authors would like to thank the editor and reviewers for their insightful and constructive comments. This work was supported by the National Natural Science Foundation of China under Grants 61102128, the National Basic Research Program of China (973 Program) under Grant 2012CB719905 and 2011CB707105, HuBei Province Natural Science Foundation under Grant No. 2011CDB455, China's Post-doctoral Science Fundation under 211-180788, the National Natural Science Foundation (40901206) and Open Research Fund Program of Key Laboratory of Digital Mapping and Land Information Application Engineering, State Bureau of Surveying and Mapping, and the Fundamental Research Funds for the Central Universities under 211-274633.

References

[1] L. Zhang, B. Du, Y. Zhong, "Hybrid Detectors Based on Selective Endmembers," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 48, no. 6, pp.2633-2646, June, 2010.

[2] B. Du and L. Z hang, "Random Selection Based Anomaly Detector for Hyperspectral Imagery," *IEEE Trans. on Geoscience and Remote Sensing*, vol. 49, no. 5, pp. 1578-1589, May, 2011.

[3] L. Zhang, L. Zhang, D. Tao, and X. Huang, "On Combining Multiple Features for Hyperspectral Remote Sensing Image Classification," *IEEE Trans. Geosci. Remote Sens.*, 10.1109 / TGRS.2011. 2162339, 2011.

[4] Y. Bengio, J. F. Paiement, and P. Vincent, "Out-of-sample extensions for LLE, Isomap, MDS, eigenmaps, and spectral clustering," *Advances in Neural Information Processing Systems* 16, Cambridge, MIT Press, pp. 177-184, 2003.

[5] E. Kokiopoulou and Y. Saad, "Orthogonal Neighborhood Preserving Projections: A Projection-Based Dimensionality Reduction Technique," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 29, no. 12, pp. 2143-2156, 2007.

[6] L. Ma and M. M. Crawford, "Anomaly Detection for Hyperspectral Images Based on Robust Locally Linear Embedding," *J. Infrared, Millim*. Te., vol. 31, no. 6, pp. 753-762, 2010.

[7] D. H. Kim and L. H. Finkel, "Hyperspectral image processing using locally linear embedding," *First Int. IEEE EMBS Conf. Neural Engineering*, pp. 316-319, 2003.

[8] L. Ma and M. M. Crawford, "Anomaly detection for hyperspectral images using local tangent space alignment," *IEEE Geoscience and Remote Sensing Symposium (IGARSS)*, pp. 824-827, 2010.

[9] J. B. Tenenbaum, V. Silva, and J. C. Langford. "A global geometric framework for nonlinear dimensionality reduction," *Science*, vol. 290, no. 2319, 2000.

[10] S. T. Roweis and L. K. Saul, "Nonlinear dimensionality reduction by locally linear embedding," *Science*, vol. 290, no. 2323, 2000.

[11] M. Belkin and P. Niyogi, "Laplacian eigenmaps and spectral techniques for embedding and clustering," *In Advances in neural information processing systems*, vol. 1, pp. 585-592, 2002.

[12] T. Zhang, D. Tao, X. Li, and J. Yang, "Patch alignment for dimensionality reduction," *IEEE Transactions on Knowledge and Data Engineering*, vol. 7, pp. 1299-1313, 2008.

[13] T. Zhang, D. Tao, and J. Yang. "Discriminative locality alignment," In *European Conference on Computer Vision*, vol. 2, pp. 725-738, 2008.

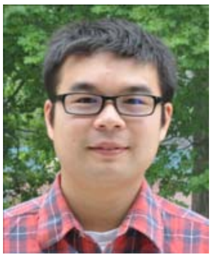
[14] F. Zhouyu and A. Robles-Kelly, "Learning Object Material Categories via Pairwise Discriminant Analysis," *IEEE Conf. Computer Vision and Pattern Recognition*, pp. 1-7, Jun. 2007.

[15] X. J. Zhu, "Semi-supervised learning with graphs," *PhD dissertation*, Carnegie Mellon University, 2005.

[16] T. Zhang, D. Tao, X. Li, and J. Yang, "Patch alignment for dimensionality reduction," *IEEE Trans. Knowl. Data Eng.*, vol. 21, no. 9, pp. 1299-1313, 2009.

[17] Jun Li, J. M. Bioucas-Dias, and A. Plaza, "Exploiting spatial information in semi-supervised hyperspectral image segmentation," *Hyperspectral Image and Signal Processing: Evolution in Remote Sensing (WHISPERS), 2nd Workshop on*, pp. 1-4, 2010.
[18] W. Liu, S. Ma, D. Tao, J. Liu, and P. Liu, "Semi-supervised sparse metric learning using alternating linearization optimization," *KDD' 10 Proc. 16th ACM SIGKDD Int. Conf. Knowledge Discovery and Data Mining*, New York, 2010.
[19] K. Q. Weinberger and L. K. Saul, "Distance metric learning for large margin nearest neighbor classification," *J. Mach. Learn. Res.*, vol. 10, pp. 207-244, 2009.
[20] K. Q. Weinberger, J. Blitzer, and L. K. Saul, "Distance metric learning for large margin nearest neighbor classification," in *Proc. Adv. Neural Inf. Process. Syst.*, Vancouver, Canada, Dec., pp. 1475-1482, 2006.

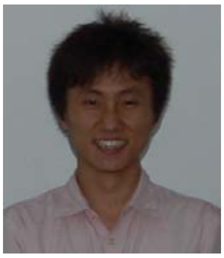
Bo Du received the Ph.D. degree in Photogrammetry and Remote Sensing from State Key Lab of Information Engineering in Surveying, Mapping and Remote sensing, Wuhan University, Wuhan, China, in 2010.
He is currently a lecture and postdoctoral associate with the School of Computer, Wuhan University, Wuhan, China. His major research interests include pattern recognition, hyperspectral image processing, and signal processing.



Lefei Zhang received the B.S. degree in sciences and techniques of remote sensing from Wuhan University, Wuhan, China, in 2008, where he is currently pursuing the Ph.D. degree at the State Key Laboratory of Information Engineering in Surveying, Mapping and Remote Sensing (LIESMARS). His research interests include remote sensing image processing and pattern recognition.

Liangpei Zhang received the B.S. degree in physics from Hunan Normal University, ChangSha, China, in 1982, the M.S. degree in optics from the Xi'an Institute of Optics and Precision Mechanics of Chinese Academy of Sciences, Xi'an, China, in 1988, and the Ph.D. degree in Photogrammetry and Remote Sensing from Wuhan University, China, in 1998.

He is currently with the State Key Laboratory of Information Engineering in Surveying, Mapping and Remote Sensing, Wuhan University, as the head of the Remote Sensing Division. He is also a "Chang-Jiang Scholar" Chair Professor appointed by the Ministry of Education, China. He has more than 200 research papers and 5 patents. His research interests include hyperspectral remote sensing, high resolution remote sensing, image processing and artificial intelligence.



Tao Chen received the B.S. and Ph.D.degrees in photogrammetry and remote sensing from Wuhan University, Wuhan, China, in 2003 and 2008, respectively. He is with the Institute of Geophysics and Geomatics, China University of Geosciences, Wuhan. His current research interestsfocus on multi- and hyper-spectral image processing, remote sensing of vegetation, and remote sensing application.

Ke Wu received the B.S. and Ph.D.degrees in photogrammetry and remote sensing from Wuhan University, Wuhan, China, in 2003 and 2008, respectively. He is with the Institute of Geophysics and Geomatics, China University of Geosciences, Wuhan. His current research interestsfocus on multi- and hyper-spectral image processing, pattern recognition.