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HYPERSPECTRAL IMAGE RECOGNITION BASED ON KPCA

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Abstract. *Hyperspectral image recognition is an important problem in practical hyperspectral imagery system. While nonlinear problem leads to identification problems, kernel method has provided a promising way to solve it. The performance of kernel-based algorithm is controlled by the appropriateness of kernel function and parameter greatly. However, simply adjusting the parameter of kernel is not effective enough because the data structures in kernel mapping space differ from each other when the parameters of kernel function differ. We present Kernel Principal Component Analysis (KPCA) applied on hyperspectral image. The learning system is improved by adjusting the parameters and kernel functions to the data structure for better effect on solving complex visual learning tasks. Experimental results proved the feasibility of the proposed methods.*
Keywords: KPCA, Hyperspectral image, Recognition

1. **Introduction.** In recent decades, hyperspectral images have exhibited great potential capability in remote sensing including target detection technology and spectral imaging technology. Among hyperspectral applications, recognitions of all kinds of land coverings have been one of our essential concerns, which benefit from the great amount of spatial and spectral information, compared to other images. However, high spectral dimension coupled with spectral resolution leads to high dimension feature vectors which result in challenges for traditional image classification algorithms [1]. The Hughes phenomenon may come into being during classification procedures if training samples are outnumbered which happens frequently.

The main procedure of the hyperspectral image (HSI) recognition can be divided into two parts: extracting essential features from enormous bands and designing suitable classifiers for significant classification accuracies. Unfortunately, the huge data size of the HSI not only is bad for detecting valuable information but also increases the difficulties of classifiers construction. These problems, coupled with other disadvantages such as the overfitting of classifiers caused by the noise, will seriously influence the classification performance.

Principal Component Analysis is a state-of-the-art method to achieve dimension redution. Each principal component is the projection of data upon a certain orientation, and the value of variance of the projections on different orientations is decided by its eigenvalue. Ordinarily, eigenvectors which contain the largest eigenvalues will be chosen for the great information provided around these orientations which are considered containing messages required. Such choices are made under a few hypotheses: (1) The amount of interested information is in proportion to the value of eigenvalue; (2) The orientations of the eigenvalues are orthogonal to each other; (3) The variances match Gaussian distribution; (4) The affection between variances is linear.

In Kernel Principal Component Analysis, the hypothesis works as well; however, the difference lies in the fact that the original data tends to be presented with more dimensions which allow us to conduct principal component analysis in Hilbert Space. This benefits us by making it possible for us to find a certain linear classification plane around higher dimension for those data which cannot be linearly classified in normal linear space.

In this paper, we provide a solution to object classification on hyperspectral image using Kernel Principal Component Analysis, and the following content is divided into 4 parts: problem statement and preliminaries; main results; control design and conclusions.

2. **Problem Statement and Preliminaries.** The development of sensor technology brought the developing of collecting image data using hyperspectral instruments with hundreds of contiguous spectral channels. As Hyperspectral Imagery Sensing (HIS) is an important technique with the measurement, analysis, and interpretation of spectra acquired with an airborne or satellite sensor, HIS has widely gained popularity in many research areas such as remotely sensed satellite imaging and aerial reconnaissance. With its high dimensions dimensionality reduction based preprocessing of hyperspectral sensing data has become a feasible way through machine learning technology [2]. These papers address the problem of the classification of hyperspectral remote sensing images by Support Vector Machines (SVMs) [3-5], and experimental results indicate that the proposed approaches have a great deal of advantages in classifying hyperspectral images.

Kernel learning provides a promising solution to nonlinear problems. The performance of kernel-based learning system has increased. However, kernel-based system still endures the selection of kernel function and its parameters. Traditional choosing parameters from a discrete value set did not change the structure of data distribution in kernel-based mapping space. Based on this motivation, the authors presented a uniform framework of kernel self-optimization for kernel-based feature extraction and recognition. In this framework, firstly data-dependent kernel is extended and has a higher ability of adjusting the kernel structure; secondly two criterions are proposed to solve the kernel optimization problem [6].

In [7], they present a uniform framework of kernel optimization based on data-dependent kernel from theory to applications to kernel principal analysis and locality preserving projection for feature extraction. Some experiments are implemented to evaluate the performance and feasibility of this framework.

Kernel based nonlinear feature extraction is feasible to extract the feature of image for classification. In order to solve the two problems of large data burden and parameter choosing, [8] presents the method of optimizing matrix mapping with data dependent kernel for feature extraction of the image for classification. The method implements the algorithm without transforming the matrix to vector, and it adaptively optimizes the parameter of kernel for nonlinear mapping. Comprehensive experiments have been implemented to evaluate the performance of the algorithms. The low-dimensional feature representation with high discriminatory power is very important for facial feature extraction, such as Principal Component Analysis (PCA) and linear discriminant analysis [6-8]. Recently, researchers applied kernel machine techniques to solving the nonlinear problem successfully [12-14].

By the use of integral operator kernel functions, one can efficiently compute principal components in high-dimensional feature spaces, related to input space by some nonlinear map; for instance, the space of all possible d-pixel products in images. The issue [15] gives the derivation of the method and presents experimental results on polynomial feature extraction for pattern recognition. In the work of [16], the problem of KPCA which solves nonlinear featrue extraction is detailed. KPCA can be concluded into the following steps: 1) Choose kernel function and its parameters to calculate kernel matrix K; 2) Centralize the kernel matrix obtaining the fixed kernel matrix KL; 3) Calculate the eigenvalues and eigenvectors of KL; 4) Adjust eigenvalues and eigenvectors; 5) Unit orthogonalize eigenvectors; 6) Extract principal component; 7) Calculate projections.

3. **Main Results.** To distinguish the ten objects, we picked ten colors to represent them as shown in Table 1.

The materials on hyperspectral image are marked by different colors in Figure 1. The classification result of the ten materials marked by colors listed in Table 1 is exhibited in Figure 2.

In our experiment, we conducted material classification on ten kinds of materials listed in Table 1 with KPCA method, and the accuracy of classification has reached 100% with time cost of 4.01 seconds. We have also tested the results of other parameters, and the time costs are shown in Table 2.

Table 1. Colors of the ten objects

Object	Color
Corn_No_Till	Blue
Corn_Min_Till	Orange
Pasture	Pink
Grass_Trees	Purple
Hay_Windrowed	Green
Soybeans_No_Till	Dark Blue
Soybean_Min_Till	Light Blue
Soybean_Clean_Till	Qing
Woods	Grey
Nothing	Black
Corn	Light Green

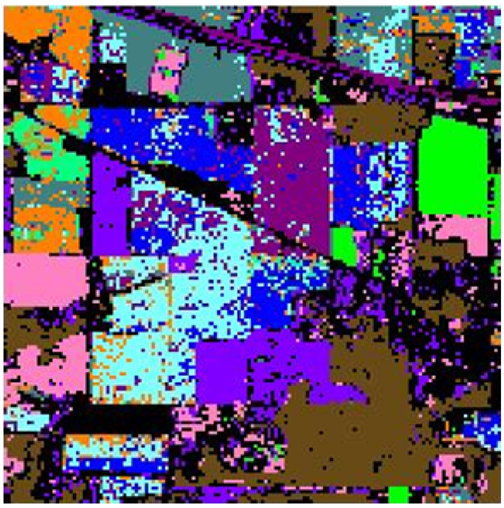

Figure 1. Materials on hyperspectral image

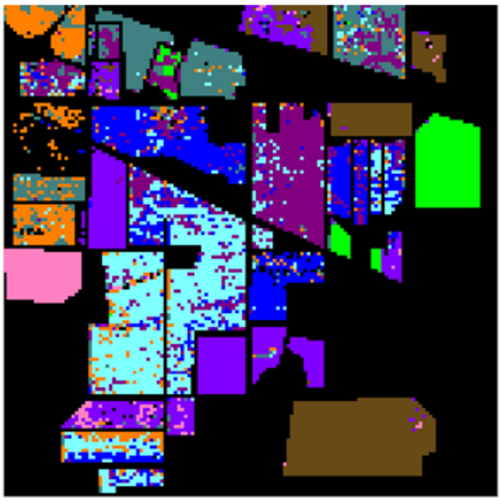

FIGURE 2. Classification result of ten materials on hyperspectral image

TABLE 2. Results of other parameters

	$d = 3$	$d = 4$	$d = 5$	$d = 6$	$d = 7$	$d = 8$	$d = 9$
$\alpha = 1$	4.03s	4.10s	4.18s	4.01s	4.11s	4.05s	4.19s
$\alpha = 2$	4.07s	4.10s	4.12s	4.07s	4.08s	4.11s	4.32s
$\alpha = 3$	4.39s	4.07s	4.07s	4.07s	4.07s	4.07s	4.07s

4. **Control Design.** In this section, we present the procedure of our experiment and the kernel function and parameters chosen. Our experiment is conducted in the steps exhibited in Figure 3.

In our experiment, the ten materials are: corn_no_till; corn_min_till; pasture; grass_trees; hay_windrowed; soybeans_no_till; soybean_min_till; soybean_clean_till; woods; corn.

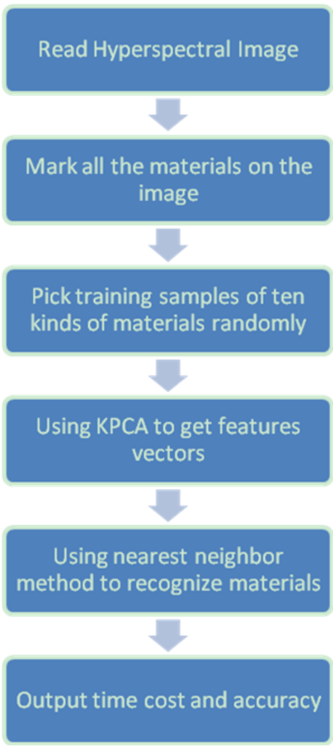

FIGURE 3. Work flow of KPCA on hyperspectral image

The kernel function we choose for the experiment is polynomial, and the kernel function is designed as Formula (1) while $\alpha = 1$ and $d = 6$:

$$K(x, y) = \left(\alpha x^T y + 4\right)^d \tag{1}$$

The space complexity of KPCA is $O\left(n^2\right)$, and n represents the amount of samples. The time complexity is $O\left(n^3\right)$. With the function and parameter in Formula (1), we have successfully conducted our experiment on hyperspectral image.

5. **Conclusions.** We have executed experiments on hyperspectral image using KPCA for material classification, and the results proved the significance of applying KPCA on hyperspectral image problems. However, the insufficient database and trial of kernel functions are reducing the credibility of the experiment. In the future, we tend to take advantage of different kernel functions such as Gaussian kernel function or multiple-kernel function in KPCA and apply it to other areas.

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REFERENCES

[1] Y. Cui, J. Q. Wang, S. B. Liu and L. G. Wang, Hyperspectral image feature reduction based on Tabu serach algorithm, *Journal of Information Hiding and Multimedia Signal Processing*, vol.6, no.1, pp.154-162, 2015.
[2] X. D. Xie and B. H. Li, Kernel-based nonparametric fisher classifier for hyperspectral remote sensing imagery, *Journal of Information Hiding and Multimedia Signal Processing*, vol.6, no.3, pp.591-599, 2015.
[3] F. Melgani and L. Bruzzone, Classification of hyperspectral remote sensing images with support vector machines, *IEEE Trans. Geoscience and Remote Sensing*, vol.42, no.8, pp.1778-1790, 2004.
[4] P. Du, J. Xia, J. Chanussot and X. He, Hyperspectral remote sensing image classification based on the integration of support vector machine and random forest, *IEEE International Geoscience and Remote Sensing Symposium*, pp.174-177, 2012.
[5] F. Melgani and L. Bruzzone, Support vector machines for classification of hyperspectral remote-sensing images, *IEEE International Geoscience and Remote Sensing Symposium*, vol.1, pp.506-508, 2002.
[6] X. F. Liu and X. X. Zhu, Kernel-optimized based fisher classification of hyperspectral imagery, *Journal of Information Hiding and Multimedia Signal Processing*, vol.5, no.3, pp.431-438, 2014.
[7] J. Q. Qiao and H. T. Yin, Optimizing kernel function with applications to kernel principal analysis and locality preserving projection for feature extraction, *Journal of Information Hiding and Multimedia Signal Processing*, vol.4, no.4, pp.280-290, 2013.
[8] D. L. Zhang, J. Q. Qiao, J. B. Li and L. Y. Qiao, Optimizing matrix mapping with data dependent kernel for image classification, *Journal of Information Hiding and Multimedia Signal Processing*, vol.5, no.1, pp.72-79, 2014.
[9] P. N. Belhumeur, J. P. Hespanha and D. J. Kriegman, Eigenfaces vs. fisherfaces: Recognition using class specific linear projection, *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol.19, no.7, pp.711-720, 1997.
[10] A. U. Batur and M. H. Hayes, Linear subspace for illumination robust face recognition, *Proc. of IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, pp.296-301, 2001.
[11] A. M. Martinez and A. C. Kak, PCA versus LDA, *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol.23, no.2, pp.228-233, 2001.
[12] B. Schölkopf, C. J. C. Burges and A. J. Smola, *Advances in Kernel Methods: Support Vector Learning*, MIT Press, MA, US, 1999.
[13] A. Ruiz and P. E. López-de-Teruel, Nonlinear kernel-based statistical pattern analysis, *IEEE Trans. Neural Networks*, vol.12, no.1, pp.16-32, 2001.
[14] K. R. Müller, S. Mika, G. Rätsch, K. Tsuda and B. Schölkopf, An introduction to kernel-based learning algorithms, *IEEE Trans. Neural Networks*, vol.12, no.2, pp.181-201, 2001.

[15] B. Schölkopf, A. Smola and K. R. Müller, Kernel principal component analysis, *Lecture Notes in Computer Science*, vol.1327, no.1997, pp.583-588, 2005.
[16] M. Welling, Kernel Principal Components Analysis, *Advances in Neural Information Processing Systems*, vol.15, pp.70-72, 2003.