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Image Classification using Multikernel Learning Algorithm

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ABSTRACT: To enhance adaptability of kernel based machine learning, multiple kernel learning(MKL) strategies have been produced. The kernel learning technique utilize the kernel however it doesn't utilize feature extraction strategy as utilized in other machine learning strategies. The expansion of the separability in the kernel is the optimization in this technique. This method brings about a small within-class scatter and large between class scatter . By uniting the basic kernels, an optimized combined kernel is found. MKL-FC is proposed from Fisher Criterion(FC) for finding the optimal projective direction. Classification of image is done using Support Vector Machine and Relevance Vector Machine. A Matlab based implementation is carried out and the results are tabulated. The parameters like position error, Overall accuracy and run-time are found and tabulated. The implementation using RVM has proved to be better in overall accuracy than SVM for the classification.

KEYWORDS: Classification, Multiple Kernel Learning(MKL),Support Vector Machine(SVM),Relevance Vector Machine(RVM).

I. INTRODUCTION

The important task of remote sensing is to classify landcovers from information contained in hyperspectral images and to develop an accurate landcover maps. Recent advances in hyperspectral remote sensing technology allows the use of hundreds of spectral wavelength for each image pixel. This detailed spectral information increases the possibility of accurately discriminating materials of interest. Many imaging systems are available to provide images for various applications.

- Ecological Science: Hyperspectral images are used to estimate biomass, biodiversity or to study land cover changes.
- Geological Science: It is used to recover mineral properties such as composition and abundance.
- Hydrological Science: It is used to determine water quality, changes in wetland characteristics.
- Military applications: The rich spectral spatial information is used for target detection.

In remote sensing, many supervised methods have been developed to tackle the multispectral and hyperspectral data classification problem. Artificial neural networks and radial basis function neural networks are the successful approach for multispectral image classification. However these approaches are not effective for large number of spectral bands. In recent years, number of machine learning methods are proposed for hyperspectral data processing. Among these methods, Kernel learning become more attractive and attentive with its excellent performance of handling high-dimensional data. The most representative kernel machine is Support Vector Machine(SVM) which provide superior performance on hyperspectral image classification compared to other classifiers such as k-nearest neighbors classifier, decision tree classifier and neural networks. With less sensitivity to dimensionality, SVM can process high-dimensional data with limited training set.

The properties of SVM to tackle the problem of hyperspectral image classification are that they can handle large input spaces efficiently, they can deal with noisy samples and they provide sparse representation of decision boundary.

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Relevance vector machine (RVM) is a recent development in kernel based machine learning approaches and can be used as an alternative to SVM for both regression and classification problems. RVM is based on a Bayesian formulation of a linear model with an appropriate prior that results in a sparse representation than that achieved by SVM. Relevance vector machines (RVM) have recently attracted much interest in various civil engineering applications. RVM can effectively be used for regression and classification problems. Major advantages of RVM over the SVM are: 1. reduced sensitivity to the hyperparameter settings, 2. probabilistic output with fewer relevance vectors for a given dataset.
Instead of single kernel, multiple kernels are used to enhance the interpretability and to improve the performance.

II. RELATED WORK

In [1],authors used remote sensing for identification and accurate characterization of materials on the surface of earth from space and airborne platforms. Both multiple and heterogeneous image sources were obtained for the same geographical area. These sources were combined to enhance classification of materials. Since this type of systems are accurate, it may face some challenges like different spatial, spectral and temporal resolutions. To overcome these challenges, multimodal image fusion comes out. Earth observation from remote sensing images using multimodal classification is summarized. Various techniques to combine both spatial and spectral information were detectedThe main work of this proposed method is considered as the phenomenon of addition of the extracted spatial and spectral information and uniting the information after performing the classification in [2]. In [3], advances in hyperspectral image classifications were proposed. In [4], authors proposed a method for improvisation in classification accuracy. Three steps for minimizing the classification error is used. Initially, elevation in road areas from ground points are extracted to generate terrain model. Later, building database is extracted using output-level fusion of various datasets from satellite image. At the end, Supervised classification is carried out using a support Vector Machine for areas which has no elevated roads and buildings. The proposed method is compared with a pixel based method. The overall accuracy and kappa coefficient of this method is compared with the pixel-based method and it's noted as improved in the proposed method.Authors proposed a method which gives a good performance for high-spatial resolution(HSR) image classification than other classification algorithms in [7]].An integration of object-oriented classification and CRF classification is done to obtain a hybrid object-oriented CRF classification framework suitable for HSR imagery, called CRF+oo. In [8],Support Vector Machine(SVM) is used for hyperspectral remote sensing images classification and the problem associated with this classification techniques are discussed. The performance of SVM's are compared with radial basis function neural networks and the K-nearest neighbour classifier. Finally, the critical issues on binary SVM's to multiclass problems were studied.

III. PROPOSED ALGORITHM

i. Multiple Kernel Learning(MKL) Algorithm
ii. Initializing the kernel scale values
iii. Compute the basic kernel matrices
iv. Solve the projective direction corresponding to MKL-FC
v. Use projective direction w* to project the basic kernels to a combined kernel k*.
vi. Utilize the combined kernel k* to solve the classification problem based on either SVM or RVM.

The ideal kernel is computed by inner product between data samples and corresponding labels.The values of an ideal kernel are represented by Eq.(1) as follows:

$$k(xi,xj)= \begin{cases} 0, & yi \neq yj \\ 1, & yi = yj \end{cases} \tag{1}$$

Simple MKL is acquired by taking the average of sigma values. Gaussian kernel on 2 samples x and x' are calculated as

$$K(\mathbf{x},\mathbf{x}') = \exp\left(-\frac{\|\mathbf{x}-\mathbf{x}'\|^2}{2\sigma^2}\right) \tag{2}$$

We can observe that the within-class scatter is 0 and the between-class scatter is infinity for the ideal kernel. When using similarity between data points, there is fluctuation within each class and similarity between different classes. As a consequence, the kernel obtained in this way strongly differs from the ideal one. Hence, we want to learn a combination of base kernels that decreases the within-classes scatter and increases the between-classes scatter within the combined

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kernel. DMKL is based on this intuitive idea, which is the foundation of the linear discriminant analysis classifier. we need a series of M basic kernels. M kernel matrices are obtained from candidate basic kernels $K_o=\{K_m, m=1,2,...,M, Km \in R^{N\times N}\}$.A 3-D data cube of size (N ×N ×M) is generated by the series of kernel matrices. In order to facilitate the subsequent operations, the 3-D data cube is converted to a 2-D matrix by using a vectorization operator represented by Eq.(3)

$$km= vec(Km),\ m=1,2,...,M, \tag{3}$$

where vec(·) is the vectorization operator which converts a matrix into a vector. The vectored set of kernels is $P = [vec(k1),vec(k2),...,vec(k_M)]^T = [p_1,p_2,...,p_{N2}] \in R^{M\times N2}$. Once P has been generated, two classes are extracted, denoted as c1 and c2. The elements of c1 were constituted by the diagonal elements of the basic kernels. These elements correspond to those training samples belonging to the same class. The remaining elements of the basic kernels constitute c2, corresponded to the kernel values between points of different classes. Two scalars (nc1 and nc2) are defined as the sum of elements of classes c1 and c2 formulated as $nc_1=\sum_{i=1}^{c} n_i^2$, $nc_2=N^2-\sum_{i=1}^{c} n_i^2$ respectively. Then, we can calculate the mean vectors of each class represented by Eq.(4)

$$m^{c1} = \frac{1}{nc1}\sum_{j=1}^{nc1} k_j^{c1} \in R^{M\times 1}$$
$$m^{c2} = \frac{1}{nc2}\sum_{j=1}^{nc2} k_j^{c2} \in R^{M\times 1} \tag{4}$$

The within-class scatter matrix Si,i=1 ,2 and between-class scatter matrix Sb are defined represented by Eq(5) & (6)

$$S_i=\sum_{j\in ci}\{(k_j^{ci} - m^{ci})(k_j^{ci} - m^{ci})^T\}, i=1,2 \tag{5}$$
$$Sb=(m^{c1}-m^{c2})(m^{c1}-m^{c2})^T \tag{6}$$

where the T superscript denotes the transpose. The total within- class scatter matrix is defined as St = S1 + S2. We have to find an M ×1 projective direction w∗ that decreases the within-class scatter and increases the between-class scatter in mapped 1-D subspace projected by $y = (w*)^T P$. This means finding a projection where samples of the same class are close to each other and far from those of other classes. To find the projective direction, Fisher criterion (FC) is proposed.

SVM/RVM operates in two modes for proposed DMKL: Training mode(Fig.1) and testing mode(Fig.2)
Training mode: During this mode, we are going to train the SVM/RVM by assigning the classes for various features of the image. This is done by naming different classes.

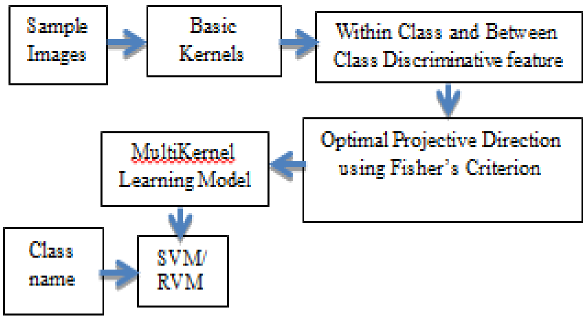

Fig 1:Training mode of proposed MKL

Testing mode: During this mode, new images are taken to classify their features. They are going to classify as the SVM/RVM are trained i.e., if the feature in the new image are trained initially, then it will classify that feature of the image by using training data.

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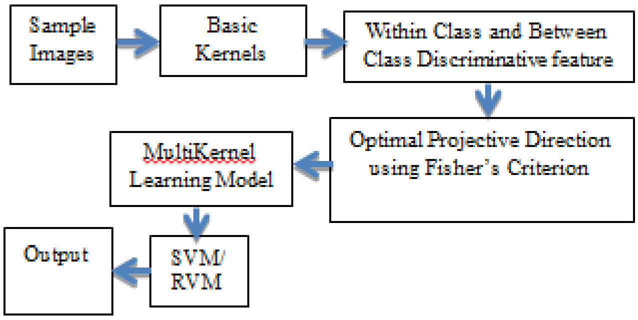
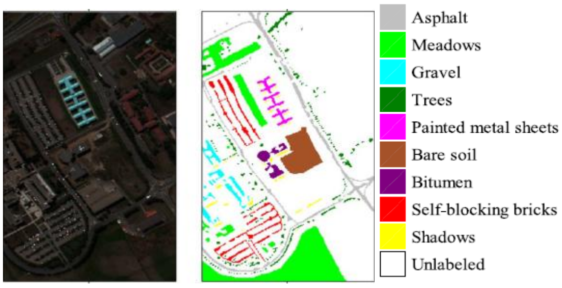


Fig 2:Testing mode of proposed MKL

IV. DATA DESCRIPTION

The data sets considered are real multispectral and hyperspectral remote sensing images. They are detailed as follows.

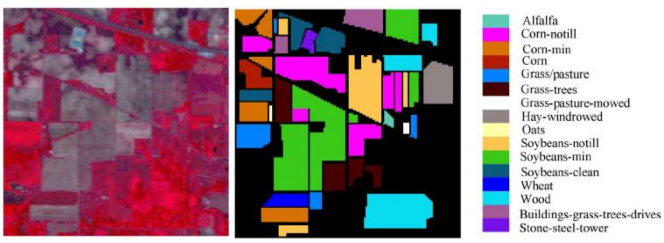
1. ROSIS Pavia U Data Set: The second data set was acquired by the Reflective Optics System Imaging Spectrometer (ROSIS-03) optical sensor over an urban area surrounding the University of Pavia, Pavia, Italy, on July 8, 2002. There are 42776 labeled samples in total and 9 classes of interest. The false-color composite image and class information are shown in Fig.3.



(a) (b)

Fig.3.Pavia University data set.(a) RGB composite image of three bands.(b)Ground truth map.

2. Indian Pines Sample Data Set: The second data set was acquired by the Indian Pines test site in North Western India. The scene consists of two-thirds agriculture,one-third forest and other oerennial vegetation. The available ground truth consists of 16 classes and are not mutually exclusively. The false-color composite image and class information are shown in Fig.4.



(a) (b)

Fig 4.Indian Pines data set.(a) False-color composite image.(b)Ground truth image

3. Salinas Data Set: The third data set was collected by AVIRIS over Salinas Valley, California, and is characterized by high spatial resolution.The area covered comprises 512 lines by 217 samples. This image was available only as

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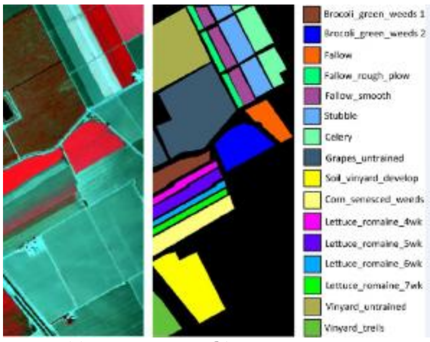
at-sensor radiance data. It includes vegetables, bare soils, and vineyard fields. Salinas groundtruth contains 16 classes.



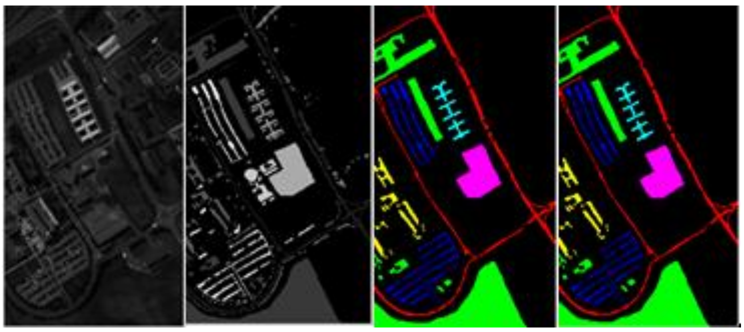
(a) (b)

Fig 5.Salinas dataset.(a)Sample set (b) Ground-truth set

V. SIMULATION RESULTS

Matlab based simulation of the proposed algorithm is carried out on three sets of data. One of the image from the database is taken and Multiple Kernel Learning algorithm is implemented. After applying MKL, the effective classification is done using both SVM and RVM.. The overall accuracy, position error and run time were tabulated for both SVM and RVM.

Initially,Pavia University dataset is taken . Downloading of image with different variations is done using MATLAB coding. The corresponding Simulation result is as shown in Fig.6(a). The groundtruth image for the corresponding downloaded image is as shown in Fig.6(b). 6 classes with 50 training samples for each classes were defined. Thus 6 different features/objects were detected and classified.Thus objects in an image are detected using the proposed MKL algorithm and classification of the detected object in an image is done using Support Vector Machine and Relevance Vector Machine. SVM classification is as shown in Fig.6(C) and RVM classification is as shown in Fig.6(d)



(a) (b) (c) (d)

Fig 6.Pavia university dataset results

Likewise, identification and classification of objects in an image is carried out for the remaining two datasets i.e.,Indian pines and Salinas data set. Accuracy, position error and run time were tabulated for all the datasets using SVM classifier in table I and RVM classifier in table II. By analysing these tables, RVM is considered as best classifier.

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Table I: Accuracy, position error and run time for SVM classifier

	Pavia	Indian pines	Salinas
Accuracy(%)	96.43	96.28	97.14
Position Error(%)	3.57	3.72	2.86
Run time(Sec)	364.2	48.19	198.5

Table II: Accuracy, position error and run time for RVM classifier

	Pavia	Indian pines	Salinas
Accuracy(%)	97.21	97.64	98.08
Position Error(%)	2.79	2 .36	1.92
Run time(Sec)	497.6	69.75	287.6

VI. CONCLUSION AND FUTURE WORK

The discriminative multiple kernel learning(MKL) algorithm has been proposed. we found a discriminative projective direction and have built the multiple kernel by projecting the base kernels. DMKL-FC is proposed and applied to very high spatial resolution spectral image classification. Three experiments were carried out using three datasets. Two classification techniques, SVM and RVM are used . The Matlab based implementation were carried out and the results were satisfactory. The position error, accuracy and run time are tabulated using both SVM and RVM classifier. The results thus obtained is an indicative that using RVM rather than SVM for image classification gives less position error and more accuracy. Future work is to reduce the number of basic kernels, to increase the classification accuracy and applying the proposed methods in several application, such as target detection.

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