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Hyperspectral Image Classification Using Spatial and Spectral Features

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Abstract— Classification of hyperspectral remote sensing data with support vector machines (SVMs) is investigated. Hyper spectral image classification techniques that use both spectral and spatial information are more suitable, effective, and robust than those that use only spectral information. The Features employed in this include Morphological profiles, Grey level cooccurence matrix, Discrete Wavelet Transform.To classify the image Support vector machine(SVM) is used. To reduce the noise in the classification map, a Post Regularization (PR) step is employed. Experimental results show that it achieves good classification performance on Hyperspectral images.

Index Terms— Support vector machines(SVMs), Image classification, Feature Extraction.

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1 INTRODUCTION

SUPPORT vector machines (SVMs) were originally designed for classification. With the development of remote sensing sensors, hyperspectral remote sensing images are now widely available. They are characterized by hundreds of spectral bands. For a classification task, the increased dimensionality of the data increases the capability to detect various classes with a better accuracy in high dimensional spaces. support vector machines (SVMs) have shown to be well suited for high dimensional classification problems Hyperspectral image data acquired by new generation sensors contain extremely rich spectral and spatial attributes, which offer the potential to discriminate more detailed classes with high classification accuracy using a svm classifier. with the rapid development of space imaging techniques, remote sensors can provide high resolution Earth observation data in both the spectral and spatial domains at the same time. This new type of high-resolution imagery contains detailed ground information in both the spectral and spatial domains; it therefore opens new avenues for remote sensing applications in urban mapping, forest monitoring, environment management, precision agriculture, and security and defense issues, etc. There are 16 different land-cover classes available in the Data set. This study uses 16 categories:Alfalfa (class 1), Corn-no till (class 2), Corn-min till (class 3),Corn (class 4), Hay-windowed (class 5), Grass/trees (class 6), Grass/pasture-mowed (class 7), Grass/pasture (class 8), Oats(class 9), Soybeans-no till (class 10), Soybeans-min till(class 11), Soybeans-clean till (class 12), Wheat (class 13),Woods (class 14), Bldg-Grass-Tree-Drives (class 15), and-steel towers (class 16). There are number of pixels of each class.This experiment randomly chose 10% of the samples for each class from the IPS reference data as training samples. The samples in the whole image were used as the testing set to evaluate the performanceThe classification map of the IPS includes a number of speckle like errors. Considering both spectral and spatial–contextual information in the interpretation of a hyperspectral image is an effective way to decrease specklelike errors. Different spectral spatial feature extraction and classification methods were implemented, including differential MPs (DMPs) [12], gray level co-occurrence matrix (GLCM), Discrete wavelet Transform(DWT), First order, Run length and classification using the Support vector machine (SVM). The experimental results verified the better performance of spatial classification compared to the pure spectral method. Benediktsson et al. proposed extended morphological profiles (EMP) for the classification of hyperspectral data with a high spatial resolution [6]. Gustavo Camps-Valls, proposed Composite kernels for hyperspectral image classification. This presents a framework of composite kernel machines for enhanced classification of hyperspectral images. This exploits the properties of Mercer's kernels to construct a family of composite kernels that easily combine spatial and spectral information. The advantages are enhanced classification accuracy, flexibility to balance between the spatial and spectral information in the classifier, and computational efficiency.

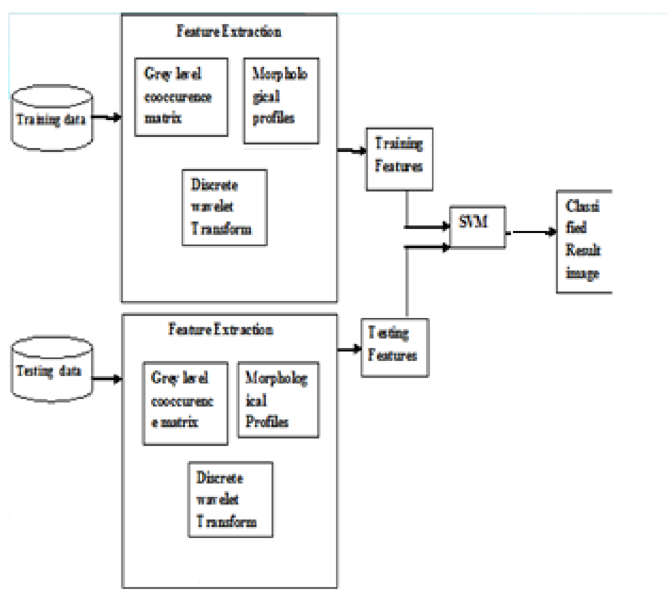

Figure 1. Block Diagram for the system

Lorenzo Bruzzone and Lorenzo Carlin proposed A Multilevel Context-Based System for Classification of Very High Spatial Resolution Images.The technique used in this system is that a novel pixel-based system for the supervised classification of very high geometrical (spatial) resolution images. The system is made up of a feature-extraction module that adaptively models the spatial context of each pixel according to a complete hierarchical multilevel representation of the scene under investigation and a proper classifier based on SVMs. A hierarchical segmentation is applied to the images to obtain segmentation results at different levels of resolution according to tree-based hierarchical constraints. The results confirm that the proposed feature-extraction module outperforms the reference method. Liangpei Zhang, Xin Huang, Bo Huang, and Ping xiang Li proposed A Pixel Shape Index Coupled With Spectral Information for Classification of High Spatial Resolution Remotely Sensed Imagery. The technique used in this system is that spatial feature index, pixel shape index (PSI), to describe the shape feature in a local area surrounding a pixel. PSI is a pixel-based feature which measures the gray similarity distance in every direction. A fast fusion algorithm that integrates both shape and spectral features using the support vector machine has been developed to interpret the complex input vectors. PSI is capable of describing shape features effectively and result in more accurate classifications. spectral and shape features can complement each other and their integration can improve classification accuracy, the transformed spectral components are also found to be more suitable for classification. Jon Atli Benediktsson,, Martino Pesaresi, and Kolbeinn Arnason proposed Classification and Feature Extraction for Remote Sensing Images From Urban Areas Based on Morphological Transformations.The Technique used in this system is that Classification of panchromatic high-resolution data from urban areas using morphological approaches. It has three steps. First, the opening and closing operations of different sizes is used in order to build a differential morphological profile that records image structural information. Although, the original panchromatic image only has one data channel, the use of the composition operations will give many additional channels, which may contain redundancies. Therefore, feature extraction is applied in the second step. Third, a Support vector machine is used to classify the features from the second step.It performs well in terms of classification accuracies. Qiong Jackson proposed Adaptive Bayesian Contextual Classification Based on Markov Random Fields. The Technique is an Adaptive Bayesian Contextual classification procedure that utilizes both spectral and spatial inter pixel dependency contexts in statistics estimation and classification is proposed. In this classifier, the joint prior probabilities of the classes of each pixel and its spatial neighbors are modeled by the Markov Random Field . The Advantages of both classifiers are incorporated. Starting with a limited training sample set, this method is able to steadily raise classification accuracy and eventually drive it close to the optimal value. The total improvement in the classification accuracy is significant and the convergence rate is fast even though a simple sub-optimal contextual classifier is used.. Gabriele Moser Sebastiano proposed Contextual Classification of hyperspectral images by support vector machines and markov random fields . The Technique Used in this is in the context of hyperspectral-image classification, a key problem is represented by the Hughes' phenomenon,which makes many supervised classifiers ineffective when applied to high-dimensional feature spaces. Furthermore , most traditional hyperspectral-image classifiers are non contextual, i.e., they label each pixel based on its spectral signature but while neglecting all inter pixel correlations. The Methods are novel supervised classification method for hyperspectral images, that is based on the integration of the support vector machine (SVM) and Markov random field (MRF) approaches. The method represents a rigorous contextual generalization of SVMs and is based on a reformulation of the Markovian minimum-energy rule in terms of the application of an SVM in a suitably transformed space. The Advantages are Spectral signatures are a very important source of information that may allow land-cover classes and ground materials to be accurately separated by pattern-classification methods .The SVM is a pattern classification technique proposed by Boser et al.. Unlike traditional methods, which minimize empirical training errors, SVM attempts to minimize the upper bound of the generalization error by maximizing the margin between the separating hyperplane and the training data. Hence, SVM is a distribution-free algorithm that can overcome the problem of poor statistical estimation. SVM also achieves greater empirical accuracy and better generalization capabilities than other standard supervised classifiers . In particular, SVM has shown a good performance for high-dimensional data classification with a small size of training samples .The information contained in hyperspectral data allows the characterization, identification, and classification of land covers with improved accuracy and robustness. Using the kernel method, SVMs map the data into higher dimensional space to increase the separability and then fit hyperplane to separate the data significantly. Tarabalka et al. presented a spectral–spatial classification scheme based on partitional clustering techniques(SVM+EM). This approach segments an image into more homogeneous regions and combines the results of these regions using pixelwise SVM classification. A spatial postregularization(PR) of the classification map was performed to reduce the noise. This approach is particularly suitable for classifying images with large spatial structures, when spectral responses of different classes are dissimilar, and the classes contain a comparable number of pixels. If the spectral responses are not significantly different, this approach may result in misclassification.

2. PROBLEM STATEMENT

2.1 System Model

The framework can be divided into the training phase and the testing phase. In the training phase, features are extracted using Morphological profiles,Grey level cooccurence,Discrete wavelet transform,First order ,Run length.In the testing phase same features are extracted and then apply SVM to classify an image. ,if any error arises apply spatial post regularization (PR)and finally get classified result image.

3. CLASSIFYING SATELLITE IMAGES USING SVM

In machine learning, support vector machines (SVMs) are supervised learning models with associated learning algorithms that analyze data used for classification . The SVM is a pattern classification technique which minimize empirical training errors, SVM attempts to minimize the upper bound of the generalization error by maximizing the margin between the separating hyperplane and the training data. Hence, SVM is a distribution-free algorithm that can overcome the problem of poor statistical estimation. SVM also achieves greater empirical accuracy and better generalization capabilities than other standard supervised classifiers. In particular, SVM has shown a good performance for high-dimensional data classification with a small size of training samples SVMs with both spectral and spatial information achieve effective and stable hyperspectral image classification.

4. TRAINING PHASE

4.1 Morphological Profiles:

Two morphological operators are opening and closing. The opening and closing transforms is to isolate bright (opening) and dark (closing) structures in images, where bright/dark means brighter/darker than the surrounding features in the images.

4.2 Grey level co occurence matrix

It is a standard technique for feature extraction.

The co occurence matrices define spatial organization of image features. A GLCM matrix p[i , j] is formed by calculating how often a pixel with intensity I occurs in a specific spatial relationship to a pixel with the intensity j, arranged according to their intensities.

4.3 Discrete Wavelet Transform

The DWT of a signal is calculated by passing it through a series of filters.To get low pass filter and high pass filter from an image DWT is used. DWT is applied on image it is split into four levels and get low and high pass filter at horizontal and vertical level.ie LL,LH,HL,HH.

5. TESTING PHASE

5.1Morphological Profiles:

Two morphological operators are opening and closing. The opening and closing transforms to isolate bright (opening) and dark (closing) structures in images, where bright/dark means brighter/darker than the surrounding features in the images.

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5.4 First order

Features are derived from the gray level. Mean, Standard deviation, Skewness, and Kurtosis are calculated in first order features.
The equations for first order features are as follows.

Mean

$$F01 = \mu = \frac{1}{N}\sum_{i=1}^{m}\sum_{j=1}^{n} p[i,j]$$

Where,

N is the number of pixel in the image,

i and j are the initial value of the row and column of image, m and n are the final value of the row and column of image, p[i,j] is a matrix value of the image.

Standard Deviation

$$F02 = \sigma = \sqrt{\frac{1}{N-1}\sum_{i=1}^{m}\sum_{j=1}^{n} (p[i,j]-\mu)^2}$$

Skewness

$$F03 = \frac{1}{(N-1)\sigma^3}\sum_{i=1}^{m}\sum_{j=1}^{n} (p[i,j]-\mu)^3$$

Kurtosis

$$F04 = \frac{1}{(N-1)\sigma^4}\sum_{i=1}^{m}\sum_{j=1}^{n} (p[i,j]-\mu)^4$$

5.5 Run-Length Matrices

The basic idea of run-length is to extract information of an image.The number of runs of different lengths and gray levels ,arranged according to the lengths and gray levels , form a two dimensional matrix called run length matrix. Consecutive pixels of the same gray value or level, in a given direction, constitute a run. The number of runs of different lengths and gray levels, arranged according to the lengths and gray values, form a two-dimensional matrix called run-length matrix. Elements of the run-length, p(i,j), represents the number of runs of length j and gray value i .

5.6 Standard SVM

Support vector machines are supervised learning

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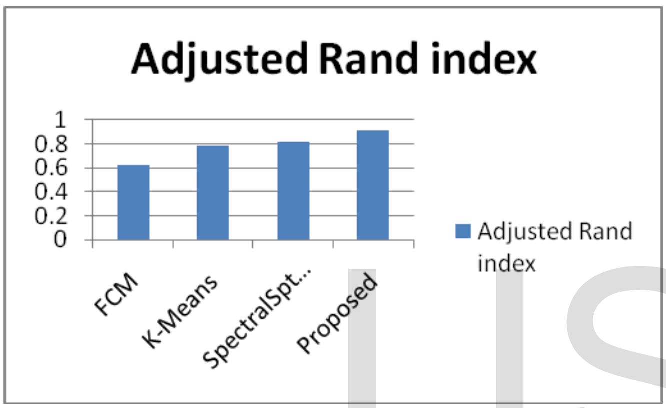
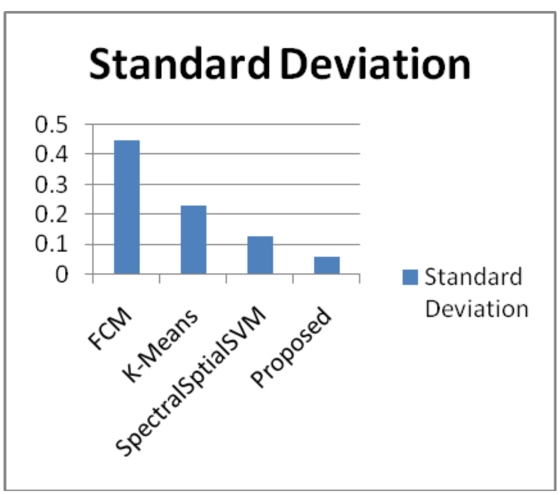
models with associated learning algorithms that analyze data and used for classification.Given some training data D, a set of n points is of the form where yi is either 1 or −1, indicating the class .SVM tries to find a separating hyperplane in the feature space. SVM algorithm has constrained minimization optimal problem. Trying to solve this optimal problem directly with inequality constraints is generally difficult. The inner product of samples in the feature space can be computed directly from the original data items using a kernel function.

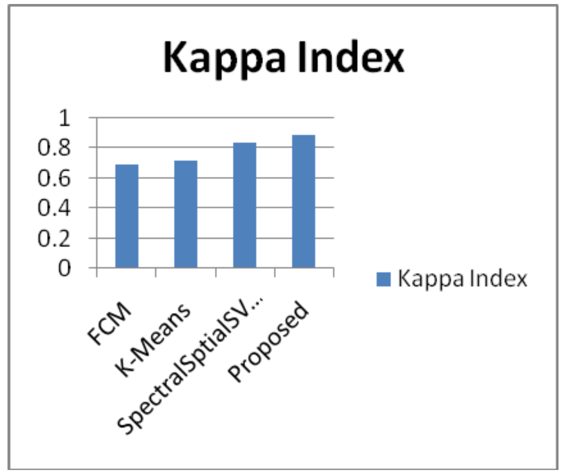
Algorithms	Adjusted Rand index
FCM	0.62
K-Means	0.78
SpectralSptialSVM	0.82
Proposed	0.91



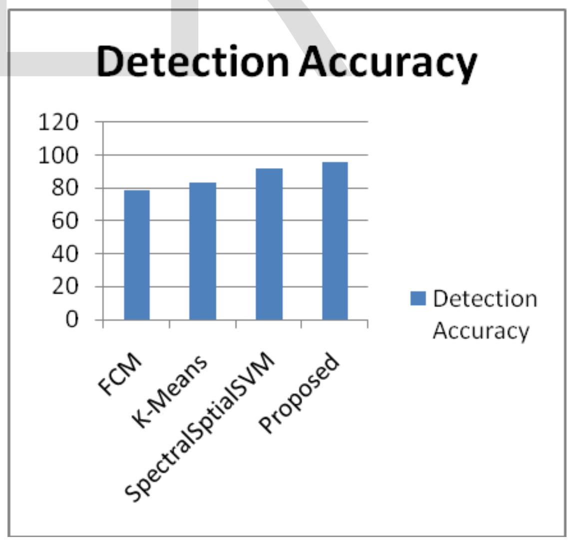
Algorithms	Standard Deviation
FCM	0.45
K-Means	0.23
SpectralSptialSVM	0.13
Proposed	0.06



Algorithms	Kappa Index
FCM	0.69
K-Means	0.72
SpectralSptialSVM	0.84
Proposed	0.89



Algorithms	Detection Accuracy
FCM	79
K-Means	83
SpectralSptialSVM	92
Proposed	96



6. PERFORMANCE EVALUATION

In SVM classification approach image classify is consider as true positive and not classify is consider as true negative. By apply svm get 90.1 accuracies. To improve accuracies scsvm is applied and get 92.9 accuracies.svm is a classification technique separating hyperplane and training data. scsvm have generalization of pixels with similar spectral attributes but located in different regions.It decrease errors. Then apply postregularization to reduce noise in an image and get 95.4 accuracies. It improves classification performance.

7. CONCLUSION

Feature is extracted using Grey level co occurence matrix, morphological profiles, Discrete wavelet transform. Support vector Machine is used to classify an image. To reduce noise in classification, Post Regularization(PR) step is employed. Using this it improves the classification accuracies .

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