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Remote Sensed Image Classification based on Spatial and Spectral Features using SVM

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Abstract
The main objective of this paper is to use support vector machines (SVMs) classifier for classification. The classification is based on the supervised approach. The problem of unsupervised classification of satellite images into a number of homogeneous regions can be viewed as the task of clustering the pixels in the intensity space. In recent years, 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. 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 remote sensed image is preprocessed and then it is classified. To classify the hyper spectral image some of the features are used. This paper uses following feature extraction techniques. They are Principal Component Analysis, Independent Component Analysis, Morphological profiles, Grey level co-occurrence matrix, urban complexity index and Discrete Wavelet Transform based. Three algorithms are proposed to integrate the multi feature SVM. They are certainty voting, probabilistic fusion, and an object-based semantic approach. To classify the image Support vector machine (SVM) is used. To reduce the noise in the classified image, a Post Regularization (PR) step is employed. Using this SVM classifier the remote sensed images are classified.

Index Terms—Classification, Support vector machine, classifier, feature extraction, Supervised classification

I. INTRODUCTION

Remote Sensing is the science of obtaining information about objects or areas from a distance, typically from aircraft or satellites. Remote sensors collect data by detecting the energy that is reflected from Earth. These sensors can be on satellites or mounted on aircraft. Remote sensors provide high resolution earth observation data in both the spectral and spatial domains. This type of high resolution imagery contains detailed ground information in both the spectral and spatial domains. The classification of high resolution images suffers from uncertainty of the spectral information. Remote Sensing Applications used in the following areas like Forest Monitoring, Environment Management, Precision Agriculture, Security, Defense issues.

Remote sensing has a wide range of applications in many different fields. One important application area is Coastal applications. Monitor shoreline changes, track sediment transport, and map coastal features. Data can be used for coastal mapping and erosion prevention. The next important application area is Ocean applications-Monitor ocean circulation and current systems, measure ocean temperature and wave heights, and track sea ice. Data can be used to better understand the oceans and how to best manage ocean resources. The next important application area is Hazard assessment-Track hurricanes, earthquakes, erosion, and flooding. Data can be used to assess the impacts of a natural disaster and create preparedness strategies to be used before and after a hazardous event. The next important application area is Natural resource management-Monitor land use, map wetlands, and chart wildlife habitats. Data can be used to minimize the damage that urban growth has on the environment and help decide how to best protect natural resources.

By summarizing the existing literature, it can be found that they have used either spectral feature extraction or spatial feature extraction. Different spatial feature extraction and classification methods were implemented, including differential MPs (DMPs)[1],[2], gray level co-occurrence matrix (GLCM)[10], Urban Complexity Index (UCI)[1]. The drawbacks of the existing methods are lower accuracy, Uncertainty of spectral information and Calculation of the spatial features, such as the GLCM, DMP in most cases leads to hyper dimensional feature space since spatial features refer to different parameters such as sizes, scales, and directions.

In this context we propose an SVM-based multi classifier system with both spectral and feature extraction for high resolution image classification. A simple scheme of the processing steps implemented in this approach is as follows.

- A feature extraction procedure is applied to the data to reduce the dimensionality.
- Supervised classifications are performed, comparing results of different spectral and spatial classifiers.
- The best classification images are combined with Certainty voting, Probabilistic fusion, Object Based Semantic Approach.
- A further Post Regularization step is introduced in the classified image.
- The spatial information from the neighborhood of each pixel is taken into account to improve the accuracies.

II. PREPROCESSING

Pre-processing methods use a small neighborhood of a pixel in an input image to get a new brightness value in the output image. Such pre-processing operations are also called filtration. Local pre-processing methods can be divided into the two groups according to the goal of the processing.

- Smoothing
- Gradient operators

III. FEATURE EXTRACTION

Feature extraction can be viewed as finding a set of vectors that represent an observation while reducing the dimensionality. Feature extraction is performed on the preprocessed image using Discrete Wavelet Transform (DWT). DWT allows the analysis of images at various levels of resolution.

The aim of preprocessing is an improvement of the image data that suppresses unwanted distortions or enhances some image features important for further processing. It aims to correct some degradation in the image.

TABLE I.

TABLE II. FEATURE EXTRACTION

S. No	Feature Extraction	
	Spatial Features	***Spectral Features***
1.	GLCM	PCA
2.	DMP	
3.	UCI	

There are two types of feature extraction

- Spectral Feature Extraction
- Spatial Feature Extraction

A. *Spectral Feature Extraction*

There are different types of spectral features which are extracted from the images and train those images.

1) *Principal Component analysis (PCA)*

Principal Component Analysis is used for spectral feature extraction from multi spectral images. Principal Component analysis (PCA) is a mathematical procedure that uses orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables. It is simple and fast to implement.

The number of principal components is less than or equal to the number of original variables. This transformation is defined in such a way that the first principal component has the largest possible variance and each succeeding component in turn has the highest variance possible under the constraint that it be orthogonal to the preceding components. Principal components are guaranteed to be independent if the data set is jointly normally distributed. PCA is sensitive to the relative scaling of the original variables.PCA is the simplest of the true eigenvector-based multivariate analyses. Often, its operation can be thought of as revealing the internal structure of the data in a way that best explains the variance in the data.

Suppose the input image is given then the steps to be followed for PCA are

- Normalize the Image
  - Find Mean Image
  - Subtract the mean image from the original image
- Calculate the Covariance Matrix
- Calculate the Eigen vales and Eigen vectors of the covariance matrix.
- The principle components of image are orthogonal.

2. *Independent Component analysis (ICA)*

Independent Component Analysis captures both second and higher order statistics and projects the input data onto the basis vectors that are independent as possible.PCA is used to reduce the dimensionality prior to performing ICA. ICA on image data helps to find an expansion of the form such that for any given window from the image, information about one of the coefficients gives as little information as possible about the others. In other words, *they are independent*. In the standard ICA model **x = As**, the coefficients correspond to realizations of the signals **s** and the basis windows are the column vectors of **A**. The objective gives basis windows which are localized both in space and in frequency, resembling the wavelets.

B. *Spatial Feature Extraction*

There are different methods of spatial feature extraction techniques. They are

- Gray Level Co-occurrence Matrix (GLCM).
- Differential Morphological Profiles(DMPs)
- Urban Complexity Index(UCI)

1) Gray Level Co-occurrence Matrix(GLCM)

It is a standard technique for texture extraction and it is an effective method for enhancing the classification of high resolution images. The texture function of GLCM can be expressed as $\mathbf{f_{GLCM}}$ **(b,m,w,d)**

b- Base image
m- Texture measure
w- Window size
d- Direction

2) Differential Morphological Profiles(DMP)

Differential Morphological Profiles (DMP) [2] has a set of different operations. The fundamental operators in mathematical morphology are erosion and dilation. When mathematical morphology is used in image processing, these operators are applied to an image with a set of a known shape, called structuring element (SE). The application of the erosion operator to an image gives an output image, which shows where the SE fits the objects in the image. The erosion and dilation operators are dual but noninvertible.

The other two operations in the Morphological Profiles are openings and closings [1]. The opening and closing operators are used to remove small bright (opening) or dark (closing) details. These two operations are the combinations of erosion and dilation.

Structuring Elements have a variety of shapes and sizes. Thickening is controlled by a SE shape. In this paper the disk shaped structuring element is used. Structuring elements are typically represented by a matrix of 0's and 1's.Sometimes it is conveniently shows only 1's.

The following figure illustrates the opening and closing operations of the Morphological Profiles. Using these operations the bright and dark pixels are easily identified.

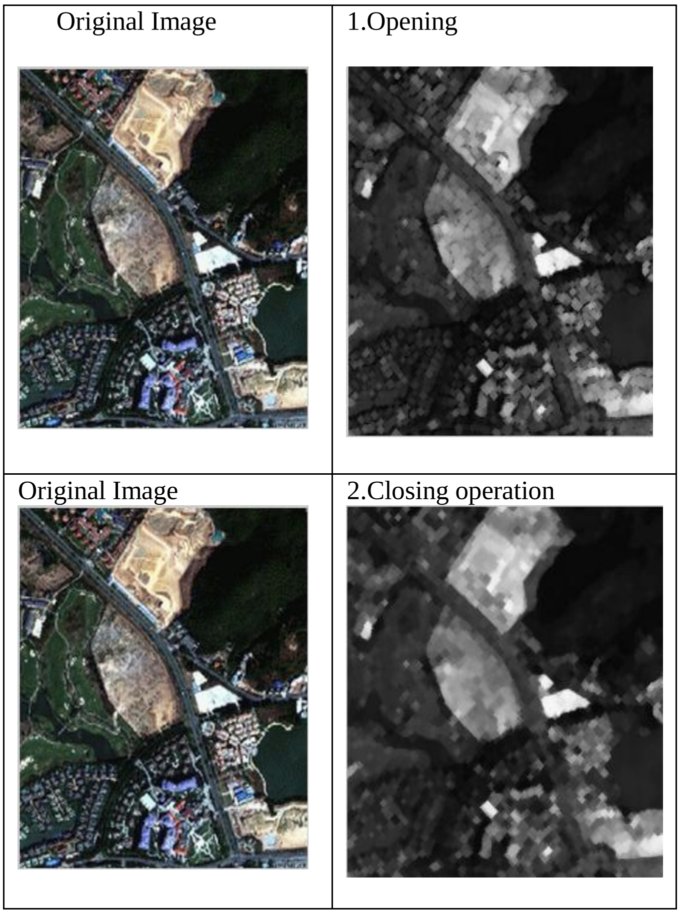

Fig 1: Morphological Operations

3) Urban Complexity Index (UCI)

Most of the existing textural and structural features focus on the spatial domain alone, but few algorithms refer to feature extraction from joint spectral-spatial domains. Some of the natural features are water, forest, grass and soil. The basic idea of UCI is that natural features have more variability in the spatial domain than the spectral domain. UCI is based on 3-D wavelet transform. It processes the multi/hyperspectral image as a cube. It describes the variation information in the joint spectral-spatial feature space.

IV. CLASSIFICATION

The pixels of an image are sorted into classes and each class given a unique color defined by the spectral "signatures".

There are two types of classification like supervised and unsupervised. Classification of remotely sensed data is used to assign corresponding levels with respect to groups with homogeneous characteristics. It is used to discriminate multiple objects from each other within the image. The level is called class. Classification will be executed on the base of spectral or spectrally defined features, such as density, texture. Classification divides the feature space into several classes based on a decision rule.

C. *Supervised Classification*

A supervised classification requires knowledge of the data as the analyst selects pixels that correspond to known features.

In order to determine a decision rule for classification, it is necessary to know the spectral characteristic or features with respect to the population of each class.

The spectral features can be measures using ground based spectrometers. However due to atmospheric effects, direct use of spectral features measured on the ground is not always available. For this reason, sampling of training data from clearly identified training areas and corresponding to defined classes is usually made for estimating the population statistics.

Classification involves the following steps

- Definition of Classification Classes
- Selection of Features
- Sampling of Training Data
- Estimation of Universal Statistics
- Classification
- Analyze the results

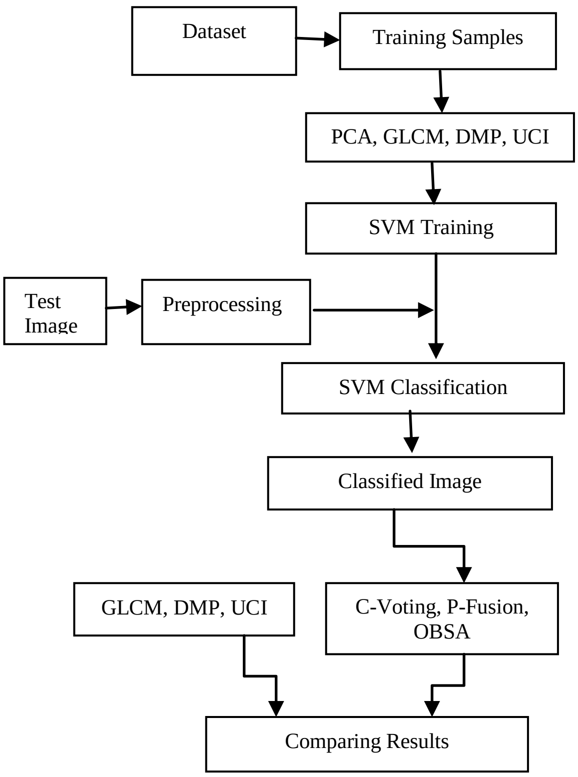

Fig: 2: Remote sensed Image classification

D. *Unsupervised Classification*

- Unsupervised classifications are more computers automated and cluster pixels which have similar spectral characteristics.

V. SUPPORT VECTOR MACHINE (SVM)

SVM classifies binary data by determining the separating hyper plane which maximizes the margin between the two classes in the training data. Support vector machines (SVMs) [4], which are a classification paradigm developed over the last decade in machine learning theory, have been successfully applied within the remote sensing community to hyperspectral image analysis. Recent studies comparing SVMs with other classification schemes have concluded that they provide significant advantages in accuracy, simplicity, and robustness.

Kernel functions provide SVM with the powerful additional ability of efficiently determining the nonlinear decision surfaces. The SVM structure maximizes performance attainable by training.

VI. MULTIFEATURE SVM

Multiple features are integrated for the proposed system. Three algorithms are proposed to integrate the multifeature SVM.

- Certainty voting(C-Voting)
- Probabilistic fusion(P-Fusion)
- Object based semantic approach(OBSA)

Algorithm 1: C-Voting
Step 1: Single feature SVM classification.
Step 2: Pixel based C-voting. Results of the multiple SVMs are utilized to determine the reliable and unreliable objects.

Step 3: Object based C-voting

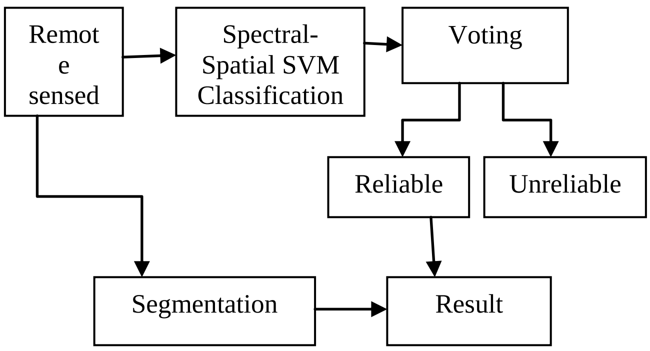

Fig 3: C-Voting

Algorithm 2: P-Fusion
Step 1: Single feature SVM classification.
Step 2: Pixel based P-fusion. The soft outputs of the multiple spectral spatial SVMs are integrated, and

final result is determined by the maximum posterior probability.
Step 3: Object based P-fusion.

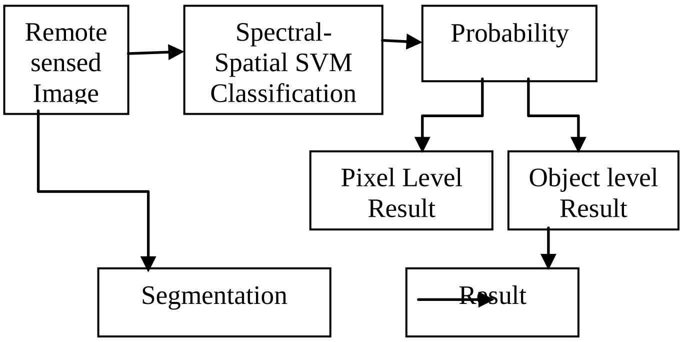

Fig 4: P-Fusion

Algorithm 3: OBSA
Step 1: Single feature SVM classification.
Step 2: Adaptive mean-shift segmentation
Step 3: Find Object based probabilistic outputs.
Step 4: Divide the objects as reliable and unreliable.
Step 5: Classification of reliable and unreliable objects.

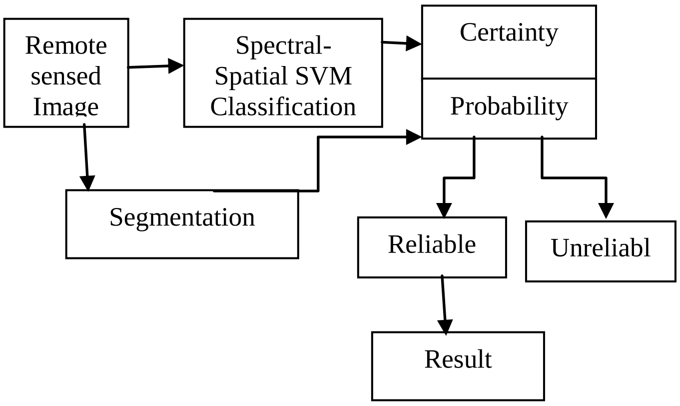

Fig 4: OBSA method

VII. RESULTS

Original Image Labeled Image

Fig 5: classified image

The above figure gave the result of the classified image. The classification is purely based on supervised approach. The original image is mapped with the trained image and classifies the remote sensed image based on the training. If the images are well trained then it provides accurate classification.

A. Fig 6: Original Image

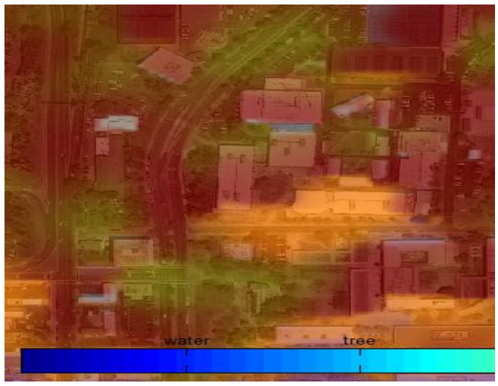

Fig 7: Classified Image

VIII. PERFORMANCE ANALYSIS

The performance analysis is used to prove the efficiency and accuracy of the proposed system. In the existing system they have used either spectral features or spatial features. But both the spectral and spatial features are used in the proposed system. It improves the efficiency of the existing system. The remote sensed image is classified as different classes. The following table illustrates the overall accuracy of the features used in this project. It can be seen that SVM gave higher accuracies than the other classifiers. The overall accuracies for different classification algorithms are examined and compared with the features used in this paper.

CLASS-SPECIFIC ACCURACIES AND OVERALL ACCURACIES (OA) (%) FOR DIFFERENT CLASSIFICATION ALGORITHMS

Classes	Spectral(OA)	Spatial(OA)
Roads	92	95
Grass	96	96
Water	85	99
Trails	49	77
Trees	97	97
Shadow	73	86
Roofs	75	89

Table 1: Comparison of Features with OA

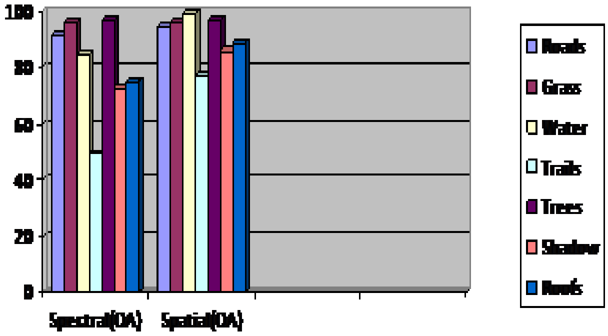

Fig 8: Comparison of Features with OA

IX. CONCLUSION

The proposed algorithms are effective for SVM-based multi feature SVM. The proposed methods improve the overall performance. The important conclusions are summarized as follows.
1) It has the potential to enhance the discrimination between spectrally similar classes by forming a hyper dimensional feature space.
2) It provides the most accurate results for both quantitative evaluation and visual inspection.
3) High accuracy.

X. FUTURE ENHANCEMENTS

This paper is applicable in different areas like Forest Monitoring, Coastal applications. It can be used to locate Incipient Volcanic Vents.

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