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Pixel-based Classification of Multispectral Remotely Sensed Data Using Support Vector Machine Classifier

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Abstract: Image Classification is an important task within the field of computer vision. Image classification can be defined as processing techniques that apply quantitative methods to the values in a digital yield or remotely sensed scene to group pixels with identical digital number values into feature classes or categories. The categorized data thus obtained may then be employed to create thematic maps of the land cover present in an image. Classification includes Determining an appropriate classification system, selecting training samples, image pre-processing, extracting features, selecting fitting classification approaches, post-classification processing and accuracy assessment. The objective of this study was to evaluate Support Vector Machine for effectiveness and prospects for pixel-based image classification as a modern computational intelligence method. SVM is a classification technique based on kernel methods that has been proved very effective in solving complex classification problems in many different application domains. In the last few years, SVM gained a significant credit also in remote sensing applications. SVMs revealed to be very effective classifiers and currently they are among the most adequate techniques for the analysis of last generation of RS data.

Keywords: Image classification, Support Vector Machines, Pixel-based, Multispectral, Remote sensing.

I. INTRODUCTION

Remote sensing in earth's perspective is the process of obtaining information about the earth surface features without being in direct contact with it, but using on board camera systems or sensors from the satellite platform. Classification of a remotely sensed data is a complex process that may be affected by many factors. Effective use of multiple features of remotely sensed data and selection of suitable classification method are significant for improving classification accuracy. Non parametric classifiers such as fuzzy classifiers, neural network classifiers, decision tree classifier and knowledge based classifiers have increasingly become important approaches for multisource data classification. In general, image classification can be classified into supervised and unsupervised classification, or parametric and non-parametric classification, or hard and soft (Fuzzy) classification, or pixel, subpixel and perfield classification.

Numerous classification algorithms have been developed since acquisition of the first remote sensed image in early 1970s (Townshend, 1992). Maximum likelihood classifier (MLC), a parametric classifier, is one of the most widely used classifiers (Dixon and Candade, 2007; Hansen et al., 1996). The Support Vector Machine represents a group of theoretically superior non-parametric machine learning algorithms. There is no assumption made on the distribution of underlying data (Boser et al., 1992; Vapnik, 1979; Vapnik, 1998). The SVM employs optimization algorithms to locate the optimal boundaries between classes (Huang et al., 2002) and can be successfully applied to the problems of image classification with large input dimensionality. SVMs are particularly appealing in the remote sensing field due to their ability to generalize well even with limited training samples, a common limitation for remote sensing applications (Mountrakis et al., 2011).

Recently, particular attention has been dedicated to Support Vector Machines as a classification method [1]. SVMs have often been found to provide better classification results that other widely used pattern recognition methods. Thus, SVMs are very attractive for the classification of remotely sensed data.SVM is a general class of learning architecture inspired from statistical learning theory that performs structural risk minimization on a nested set structure of separating hyperplanes. Given a training data, the SVM training algorithm obtains the optimal separating hyperplane in terms of generalization error.

The SVM approach seeks to find the optimal separating hyperplane between classes by focusing on the training cases that are placed at the edge of the class descriptors. These training cases are called support vectors. Training cases other than support vectors are discarded. This way not only an optimal hyperplane is fitted, but also less training samples are effectively used thus high classification accuracy is achieved with small training sets.

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This feature is very advantageous, especially for remote sensing images.

J. A. Gualtieri and S. Chettri[4], has introduced SVM for the classification of RS data. In particular they applied SVM to hyperspectral data acquired by NASA's AVIRIS sensor and the commercially available AISA sensor. The authors discuss the robustness of SVM to the course of dimensionality (Hughes phenomenon). F Melgani and L Bruzzone[5],has addressed the problem of the classification of hyperspectral RS images by SVMs. The authors propose a theoretical discussion and experimental analysis aimed at understanding and assessing the potentialities of SVM classifiers in hyper dimensional feature spaces. Then, they assess the effectiveness of SVMs with respect to conventional feature-reduction-based approaches and their performances in hyper subspaces of various dimensionalities. C.Huang et al.,[6], has explained the theory of SVM and provides an experimental evaluation of its accuracy, stability, and training speed in deriving land cover classifications from satellite images.

In this context, this study attempts to develop robust SVM based techniques for classification of pixel-based data generated from multispectral remotely sensed image LISS-III (Linear Imaging and Self Scanning) of IRS P-6 (Indian Remote Sensing Satellite) with 23.5m spatial resolution. The objective of this study was to evaluate SVMs for their effectiveness and prospects for pixel-based image classification. A secondary objective was to evaluate the accuracy of SVM compared to simpler and widely used classification techniques such as Nearest Neighbor. Also, the computational efficiency and training size requirements of SVMs were set for consideration.

II. METHODS

A. Study Area

The area under investigation was the talluks of Udupi District, Karnataka state, India. The data is spread over an area of approximately 93Km x 72Km between the points 13^{o} 96'N 74^{o} 43'E / 13^{o} 97'N 75^{o}21'E as indicated in Fig. 1. The spatial resolution of the study area considered is 23.5m. The image dimension of the study area is 3980x3201 pixels in multispectral data. It has a good mixture of spectrally overlapping classes comprising of different natural land cover features.

Fig. 1. 23.5m spatial resolution study area considered

B. Support Vector Machine classification

Selection of suitable classification technique is the key success for image classification. Support Vector Machines is a classification technique based on kernel methods that has been proved very effective in solving complex classification problems in many different application domains. In the last few years, SVM gained a significant credit also in RS applications. The pioneering work of Gualtieri in 1998 related to the use of SVM for classification of hyperspectral images has been followed from several different experiences of other researchers that analysed the theoretical properties and the empirical performances of SVM applied to different kinds of classification problems. The investigations include classification of hyperspectral data multispectral images, as well as multisource and multisensor classification scenarios. SVMs revealed to be very effective classifiers and currently they are among the most adequate techniques for the analysis of last generation of RS data.
In all these cases the success of SVMs is due to the important properties of this approach, which integrated with the effectiveness of the classification procedure and the elegance of the theoretical developments, result in a very solid classification methodology in many different RS data classification domains. As it will be explained in the following section, this mainly depends on the fact that SVMs implement a classification strategy that exploits a margin-based "geometrical" criterion rather than a purely "statistical" criterion. In other words, SVMs do not require an estimation of the statistical distributions of classes to carry out the classification task, but they define the classification model by exploiting the concept of margin maximization.

The main properties that make SVM particularly attractive in RS applications can be summarized as follows:

- Their intrinsic effectiveness with respect to traditional classifiers thanks to the structural risk minimization principle, which results in high classification accuracies and very good generalization capabilities (especially in classification problems defined in high dimensional feature spaces and with few training samples, which is a typical situation in the classification of last generation of RS images).
- The possibility to exploit the kernel trick to solve non-linear separable classification problems by projecting the data into a high dimensional feature space and separating the data with a simple linear function;
- The convexity of the objective function used in the learning of the classifier, which results in the possibility to solve the learning process according to linearly constrained quadratic programming (QP) characterized from a unique solution (i.e., the system cannot fall into suboptimal solutions associated with local minima);
- The possibility of representing the convex optimization problem in a dual formulation, where only non-zero Lagrange multipliers are necessary for

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defining the separation hyperplane (which is a very important advantage in the case of large data sets). This is related to the property of sparseness of the solution.

In the two-class scenario, a support vector classifier produces a try to attain a hyperplane that minimizes the distance from the members of each class to the optional hyperplane. A SVM optimally separates the different classes of data by a hyperplane (Karatzoglou and Meyer, 2006; Kavzoglu and Colkesen, 2009; Vapnik, 1998). An optimum separating hyperplane is found out by the SVM algorithm such that:1) Samples with labels ±1 are situated on each side of the hyperplane; 2) The distance of the nearest vectors to the hyperplane in each side of maximum are called support vectors and the distance is the optimal margin.(Meyer, 2001; Mountrakis et al., 2011) (Fig. 2).

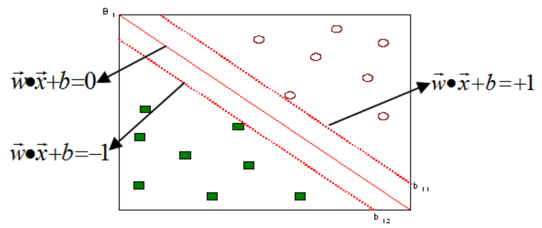

Fig. 2. Maximum-margin hyperplane and margins for an SVM trained with samples from two classes.

A two-class classification problem can be defined in the following way: Suppose there are M training samples that can be given by the set pairs

$$\{(x_i, y_i), \quad i=1,2,\ldots.N\} \tag{1}$$

With x_i being the class label of value ±1 $y_i€^n$ and where feature vector with n components.

The hyperplane is given by the equation by

$$\vec{w}\bullet\vec{x}+b=0 \tag{2}$$

where (w, b) are the parameter factors of the hyperplane.

The vectors that are not on this hyperplane lead to

$$\vec{w}\bullet\vec{x}+b>0 \tag{3}$$

The support vectors lie on two hyperplanes, which are parallel to the optimal hyperplane, of equation

$$\vec{w}\bullet\vec{x}+b=-1 \tag{4}$$

$$\vec{w}\bullet\vec{x}+b=+1 \tag{5}$$

The maximization of the margin with the equations of the two support vector hyperplanes contributes to the following constrained optimization problem

$$\mathrm{Margin}=\frac{2}{\|\vec{w}\|^2} \tag{6}$$

C. Training data collection

For the successful classification of RS data, a suitable classification system and a sufficient number of training samples are considered as prerequisites. Three major problems are identified when medium spatial resolution data are used for vegetation classifications: defining adequate hierarchical levels for mapping, defining discrete land-cover units discernible by selected remote-sensing data, and selecting representative training sites.

A sufficient number of training samples and their representativeness are critical for image classifications. Training samples are usually collected from fieldwork, or from fine spatial resolution aerial photographs and satellite images. Different collection strategies, such as single pixel, seed, and polygon, may be used, but they would influence classification results, especially for classifications with fine spatial resolution image data.

When the landscape of a study area is complex and heterogeneous, selecting sufficient training samples becomes difficult. This problem would be complicated if medium or coarse spatial resolution data are used for classification, because a large volume of mixed pixels may occur. Therefore, selection of training samples must consider the spatial resolution of the remote-sensing data being used, availability of ground reference data, and the complexity of landscapes in the study area.

D. Data Pre-processing

Image pre-processing may include the detection and restoration of bad lines, geometric rectification or image registration, radiometric calibration and atmospheric correction, and topographic correction. If different ancillary data are used, data conversion among different sources or formats and quality evaluation of these data are also necessary before they can be incorporated into a classification procedure. Accurate geometric rectification or image registration of remotely sensed data is a prerequisite for a combination of different source data in a classification process.

If a single-date image is used in classification, atmospheric correction may not be required. When multitemporal or multisensor data are used, atmospheric calibration is mandatory. This is especially true when multisensor data, such as LANDSAT TM and SPOT or LANDSAT TM and RADAR data, are integrated for an image classification. A variety of methods, ranging from simple relative calibration and dark-object subtraction to calibration approaches based on complex models, have been developed for radiometric and atmospheric normalization and correction.

E. Feature Extraction and Selection

Selecting suitable variables is a critical step for successfully implementing an image classification. Many potential variables may be used in image classification, including spectral signatures, vegetation indices, transformed images, textural or contextual information, multitemporal images, multisensor images, and ancillary data. Due to different capabilities in land-cover separability, the use of too many variables in a

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classification procedure may decrease classification accuracy. It is important to select only the variables that are most useful for separating land-cover or vegetation classes, especially when hyperspectral or multisource data are employed. Many approaches, such as principal component analysis, minimum noise fraction transform, discriminant analysis, decision boundary feature extraction, non-parametric weighted feature extraction, wavelet transform, and spectral mixture analysis may be used for feature extraction, in order to reduce the data redundancy inherent in remotely sensed data or to extract specific landcover information.

Graphic analysis (e.g. bar graph spectral plots, co-spectral mean vector plots, two-dimensional feature space plot, and ellipse plots) and statistical methods (e.g. average divergence, transformed divergence, Bhattacharyya distance, Jeffreys-Matusita distance) have been used to identify an optimal subset of bands. In practice, a comparison of different combinations of selected variables is often implemented, and a good reference dataset is vital for image classification. In particular, a good representative dataset for each class is the key for implementing a supervised classification. The divergence-related algorithms are often used to evaluate the class separability and then to refine the training samples for each class.

F. Post-Classification Processing

Traditional per-pixel classifiers may lead to 'salt and pepper' effects in classification maps. A majority filter is often applied to reduce the noises. Most image classification is based on remotely sensed spectral responses. Due to the complexity of biophysical environments, spectral confusion is common among land-cover classes. Thus, ancillary data are often used to modify the classification image based on established expert rules. For example, forest distribution in mountainous areas is related to elevation, slope, and aspects. Data describing terrain characteristics can therefore be used to modify classification results based on the knowledge of specific vegetation classes and topographic factors.

III. EXPERIMENTAL RESULT

The image data product being used in this study is LISS-III (Linear Imaging and Self Scanning) sensor of IRS P-6 (Indian Remote Sensing Satellite). In Fig.3 shows Selection of training samples from remotely sensed data.

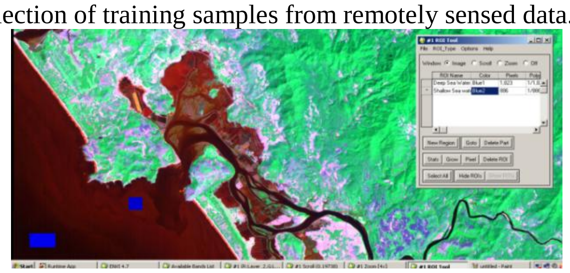

Fig. 3. Define training regions for each class

TABLE 1. COLOUR ASSIGNED FOR EACH CLASS

Class	**Colour**
Deep Sea Water	Blue1
Shallow Sea Water	Blue2
River Water	Black
Dense Forest	Green3
Vegetation	Green2
Green Cultivated Fields	Green1
Dry Cultivated Fields	Red1
Fields	Red3

Here we have been considered eight classes in the selected Area of Interest using SVM classification and they are, Deep Sea Water, Shallow Sea Water, River Water, Dens Forest, Vegetation, Green Cultivated Fields, Dry Cultivated Fields, and Fields. Colours assigned for each class are given in TABLE 1.

The Fig. 4 shows the classified image for 8 classes per pixel. Colour Blue1 shows area of deep sea water, Blue2 shows area of shallow sea water, Black shows area of river water, Green3 shows area of dense forest, Green2 shows area of vegetation, Green1 shows area of green cultivated land, Red1 shows area of dry cultivated land and Red3 shows area of field.

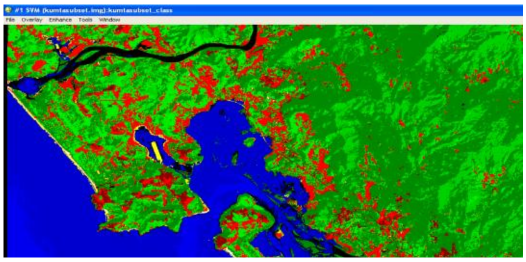

Fig. 4.Classified image for 8 classes per pixel.

The figures from Fig. 5 to Fig. 8 are the Gray scale images that show area of each class.

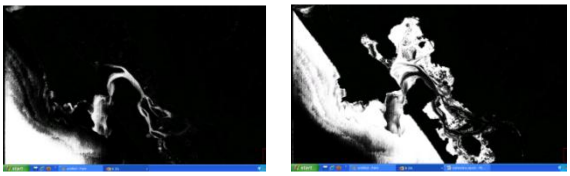

Fig. 5. Area of Deep Sea Water and Shallow Sea Water

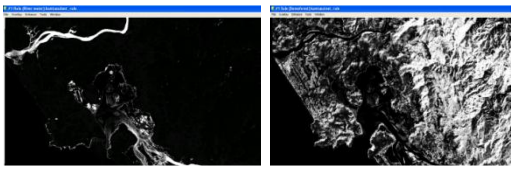

Fig. 6. Area of River Water and Dense Forest

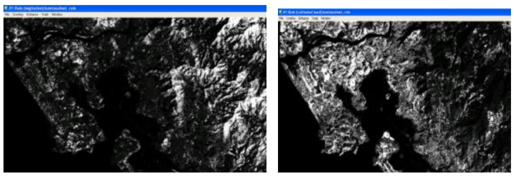

Fig. 7. Area of Vegetation and Green cultivated Land

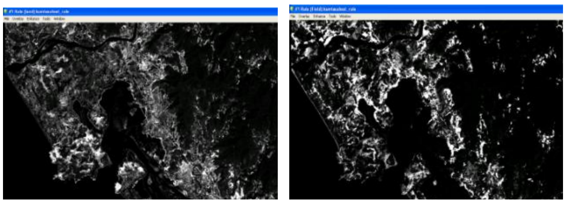

Fig. 8. Area of Green cultivated Land and Field

IV. CONCLUSION

In this paper, Udupi, Brahmavar and Kundapur surroundings in Udupi and Uttar Kannada district, Karnataka State, India were considered for the purpose of the study. The area considered for analysis purpose is a rectangular area between the points 13^o 96'N 74^o 43'E / 13^o 97'N 75^{o}21'E. The region of interest (ROI) contains both land and water bodies abundantly. The land region is thickly vegetated and cultivated: Mangrove Vegetation, Tree cover, Crop. The water bodies contain both shallow rivers and Arabian Sea. The objective of this study is to evaluate the new technique i.e. Support Vector Machines and its importance in image classification.

The work carried out indicates the SVM effectiveness in image classification. It is apparent from the study that SVM classification is reasonably good choice for classifying satellite data where within class variability is high.

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