Indian Journal of Science and Technology, Vol 8(24), DOI: 10.17485/ijst/2015/v8i24/85355, September 2015
ISSN (Print) : 0974-6846
ISSN (Online) : 0974-5645

Classification of Multispectral Satellite Images using Sparse SVM Classifier

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Abstract

This work proposes an efficient classification scheme for identifying various land classes present in a multispectral satellite image. This spectral image provides extensive knowledge about land cover mapping in multispectral satellite images. This paper proposes an efficient technique in land cover classification which involves fuzzy hybrid with hierarchical clustering applied then to the sparse SVM classifier. Initially preprocessing is done using Gaussian filter and transformed to a suitable form using Wavelet transform. Subsequently, segmentation is performed in the wavelet transformed image using fuzzy hybrid with hierarchical clustering technique. Then the proposed sparse SVM classifier is trained by the features obtained from the clustered output. Thus the multispectral image of various satellite images can be classified into different land classes comparing with the training data given to sparse SVM. The performance is evaluated by comparing with the existing classifiers for different multi-spectral satellite images which provides accurate results. The classification accuracy is measured from the performance analysis graph where the results demonstrate that the proposed sparse SVM classifier can optimally enhance the classification accuracy of any multispectral satellite image.

Keywords: Fuzzy-Hierarchial Clustering, Multispectral Satellite Images, Sparse SVM, Wavelet Transform

1. Introduction

Land cover mapping is nowadays a recent research and challenging task due to the complexity of urban landscapes that impacts changes in environment. Remote sensing applications refer to processing of images obtained from satellites where this paper concentrates mainly on multispectral satellite images having high spatial resolution. There are various conventional techniques available for multispectral land cover classification as said in literature[1]. Thus the ultimate aim of this research is to find an efficient classifier by extracting the best features for land cover images classification. The processing and analysis of multispectral images depends upon the classification parameters such as sensitivity, specificity, accuracy and error rate. The detailed information of the respective classes from the accurately classified multispectral images can be used for further processing applications such as change detection, environmental monitoring etc. Three classifiers have been used for the comparison purpose.

Comparing to Fuzzy C-means classifier and normal RVM classifier, the sparse SVM classifier increases the classification accuracy[2]. Thus the accuracy is better obtained using the proposed classifier. The processing

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time is also comparatively reduced in sparse SVM. The new technique increases the classification efficiency with reduced error rate.

Wang[3] used supervised FCM approach to classify Landsat data. This algorithm identified the mixed pixels and more accurate statistical parameters are generated. However if the knowledge representations are poor, this algorithm produces inferior output. This method does considers the fuzzy beyond the cluster scatter matrices.

The concept of spatial fuzzy membership is incorporated in the fuzzy clustering technique introduced by Lu et al[2]. This work with improved fuzzy clustering algorithm under Markov Random model produces more classification accuracy and reliability but does not consider the fuzzy within and between the clusters of scatter matrices.

This work is implemented with four modules namely pre-processing by Gaussian filter and wavelet transform, segmentation by fuzzy based hierarchical clustering, feature extraction and finally classification using SVM classifier proposed with sparse property.

2. Proposed Work

2.1 Preprocessing

The noise if any present in the input multispectral image is reduced by passing through Gaussian filter. The performance of Gaussian filter provides accurate result as in literature. The Gaussian function is determined and performs convolution with the input data to enhance the image quality in the original input satellite image[5].

The 1D Gaussian filter is given by equation (1),

$$g(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-x^2}{2\sigma^2}} \quad (1)$$

The impulse response of the 1D Gaussian filter is given by equation (2),

$$g(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-\sigma^2 u^2}{2}} \quad (2)$$

From the preprocessed image, the RGB (red, green and blue) planes were extracted and now discrete wavelet transform is applied to all the three planes separately for feature extraction. This step provides detailed information about the multispectral data which increases the classification accuracy.

The well-known technique used in research for preprocessing is the wavelet transform as per literature[6]. The wavelet transform is initially applied and tested successfully for signal transformation. The Gaussian filtered image is applied to the wavelet transform through a cascade series of low pass and high pass filters. Now up sampling and down sampling operations were performed to determine the low and high frequency components. The low frequency data of the wavelet transform is the decomposed image consisting of one approximation sub band image and three detailed sub band images. The process of first level decomposition of wavelet transform technique is illustrated in Figure 1. The Figure 2 illustrates that how input image is decomposed to four sub bands as approximation, horizontal, vertical and diagonal positions. The approximation sub image remains similar with the original image, while the detailed sub band image is equivalent to the difference between approximation and original image in vertical, horizontal and diagonal directions. Thus for all three planes, the sub bands were obtained where the approximation sub band image is considered for further processing. Thus the approximation image of all the red, green and blue planes were concatenated to obtain the RGB reconstructed image.

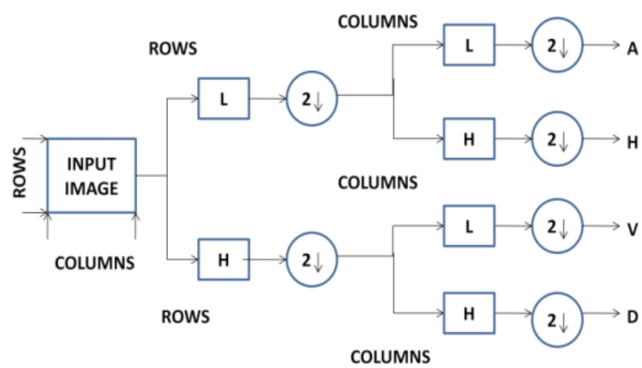

Figure 1. First level decomposition of wavelet transform.

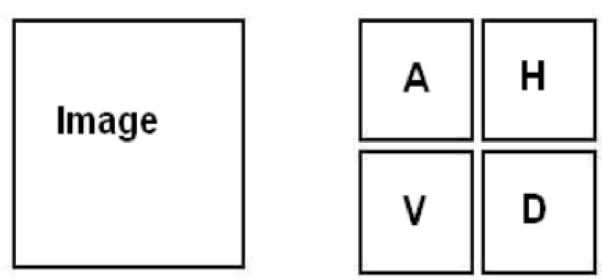

Figure 2. Input image and decomposition into sub bands.

2.2 Segmentation

The reconstructed RGB image is then subjected to Fuzzy based hierarchical clustering for image segmentation. The digitalized RGB image consisting of pixels is grouped by 3x3 matrices. The centroid of each 3x3 matrix is determined repeatedly which can be grouped again to form clusters. Thus the segmented clustered image is obtained. This algorithm yields more accurate results compared to the traditional FCM.

The proposed clustering algorithm overcomes the drawbacks of ordinary Fuzzy clustering[7]. The algorithm of hierarchical clustering combined with Fuzzy C-means is discussed as below:

- Let the preprocessed image is segmented by a group of pixels represented by M number of clusters. The different M clusters of an image is represented as Ci, where $0 < i < M$. Then the pixel difference matrix λ is determined.

$$\lambda = \begin{bmatrix} \partial_{11} & \partial_{12} & \partial_{13} & \partial_{14} & .. & \partial_{1M} \\ \partial_{21} & \partial_{22} & \partial_{23} & \partial_{24} & .. & \partial_{2M} \\ \partial_{31} & \partial_{32} & \partial_{33} & \partial_{34} & .. & \partial_{3M} \\ \partial_{41} & \partial_{42} & \partial_{43} & \partial_{44} & .. & \partial_{4M} \\ .. & .. & .. & .. & .. & .. \\ \partial_{M1} & \partial_{M2} & \partial_{M3} & \partial_{M4} & .. & \partial_{MM} \end{bmatrix}$$

where ∂_{ij} = pixel difference value between i^{th} and j^{th} cluster.

- The clusters with minimum pixel difference are obtained after calculating the pixel difference matrix and then combined together to form a new cluster Cij.
- The centroid Oij is determined from the new cluster by using the formula as in equation (3).

$$O_{ij} = \frac{C_i + C_j}{2} \tag{3}$$

- Repeating the above procedure, the centroid value is calculated for all the clusters. Finally the original centroid value is calculated after obtaining the membership function given by the equation (4).

$$\mu_{ij} = \frac{1}{\sum_{k=1}^{C} \left(\frac{\| P_i - O_{ij} \|}{\| P_i - O_k \|} \right)^{\frac{2}{m-1}}} \tag{4}$$

where, Oij - approximated centroid pixel value

Ok - centroid pixel of other clusters excluding the newly formed cluster.

m - Positive integer.

The revised centroid pixel value for the modified cluster is given by Cij as in equation (5)

$$C_{ij} = \frac{\sum_{i=1}^{N} \mu_{ij}^{m} x_i}{\sum_{i=1}^{N} \mu_{ij}^{m}} \tag{5}$$

- The new centroid result obtained above is the combination of two individual clusters having similar features where the number of clusters reduces one by one after each iteration.
- The values of C_i and C_j were replaced by the modified centroid pixel value C_{ij}, which reduces the dimension of the pixel difference matrix. This in turn decreases the dimension of matrix from M x M to (M-K) x (M-K) after completing K loops.
- Finally the step 2 is repeated again until the desired number of clusters is obtained.

2.3 Feature Extraction

After the segmentation process, feature extraction step is performed in the output clustered image. The features such as mean, median and contrast were computed from the Fuzzy c-means clustered image and these features were applied to the sparse based SVM classifier as training data. The formula to determine mean, median and contrast were given below:

$$\text{Mean} \quad \bar{x} = \frac{1}{N^2} \sum_{i=1}^{N} \sum_{j=1}^{N} x_{i,j} \tag{6}$$

$$\text{Contrast} = \sum_{i,j=0}^{N} (i-j)^2 C(i,j) \tag{7}$$

2.4 Classification

At present days, the research has been enormously extended in the field of various land class classification of multispectral remote sensing images. In earlier Maximum likelihood classification technique is implemented[8]. Then artificial intelligence techniques were well suited for the same remotely-sensed land image classification application which requires more training data. The Support Vector Machine (SVM) is a traditional classification technique, which classifies the input image based on the decision boundary[9]. The proposed classifier involves sparse representation technique incorporated in SVM statistical learning algorithm which gives better accuracy compared with existing techniques.

3. Sparse SVM Classifier

3.1 SVM Classifier

The SVM Classifier has a marginal optical hyper plane between two different classes. The SVM classifier utilizes this optical hyper plane for risk minimization. This minimizes the misclassification of data. The SVM classifier works based on the kernel function. This multiclass SVM classifier is made by integrating many binary classifiers[10]. The SVM classifier gives an output which groups similar pixels for each class of data. Initially let's take the set of training data set $f = \{x_k, d_k\}$ where, k = 1, 2 …Q where $x_k \in R^n$, $d_k \in \{-1, 1\}$.

Let the classifier is given as,

$$F(X, W, w_o) = \text{sign}\ (W. X + w_o)$$

where, F = bipolar signum function which allows mapping from input point x_k to respective point dk.

W = set of weights

w_o = bias (which separates positive data and negative data).

As an example the below Figure 3 explains the two class classification scheme with high margin hyper plane. In the figure, class c1 consists of positive data indicated by +1 and class c2 consists of negative data indicated by -1. The hyper plane is defined by $W. X + w_o = 0$. The required set of weights is applied to SVM which classifies the training data based on the value of W[11].

If $W. X + w_o > 0$, then the data belongs to class 1 and

$W. X + w_o < 0$, then the data belongs to class 2. The data lies close to the hyper plane is called as support vector. The support vectors lies on the two parallel planes $W. X + w_o = \pm 1$, which emphasize the SVM classifier margin[12].

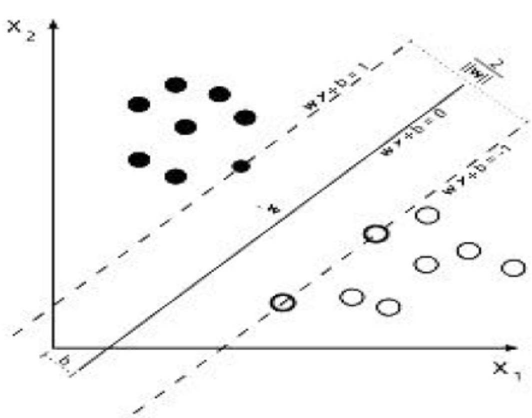

Figure 3. Margins of an SVM trained with samples from two classes.

Initially the input multispectral image is segmented by Fuzzy incorporated Hierarchical clustering. The input multispectral image is divided into clusters having similar number of pixel value and the clusters differ with a small value from the centroid pixel[13]. Hence a cluster is identified with pixels closer to its centroid pixel value. Thus the SVM classifier is trained by the centroid pixels which reduce the complexity and time required for classsification.

For the ith cluster having n number of pixels with each pixel having a value of Pk, the centroid value is calculated by the equation,

$$O_i = \frac{\sum_{k=1}^{n} P_k}{n} \tag{8}$$

For n number of clusters, the centroid set O.O = (O1, O2… O_n) is then applied directly to the input of the SVM classifier. The test multispectral image is classified accordingly based on the features extracted from the clustered image[16].

3.2 Sparse SVM Technique

In this module, the state-of-the-art classification technique is proposed which uses the Sparse Representation (SR) technique hybrid with the SVM classifier. The sparse representation classifier has achieved better results in multispectral land cover classification, introducing spatial nature of the image. In literature, it is known that the SR technique has achieved great success in face recognition domain[17]. The input image is factorized into patches with respective to the number of clusters. Each patch consists of a collection of patchlets containing group of pixels of same patch. These patchlets were organized in a spatial-spectral dictionary, which uses sparse coding for the reconstruction of the image patches. Each patch is represented by sparse weights in its dictionary and then used for classification of the patch. The sparse SVM can be identified by a vertical hyperplane. This is because the x-component is zero and only the y-component is nonzero so that it is "sparse"[18].

The overall procedure of the proposed sparse classification technique is illustrated as below:

Algorithm:

- Given an input multispectral image *I* that contains *J* overlapping patches of size Z x Z.
- Each patch X_j where $j \in \{1, \ldots, J\}$ is classified and the final classified image is obtained by combining the classified patch results.

- A test sample image x can be represented by a linear combination of few training image patches from dictionary D, so that $x=D^1\alpha^1+\ldots+D^K\alpha^K = D\alpha$, where α consists of the class-wise sparse parameter vectors α^K with $k \in \{1, \ldots, k, \ldots, K\}$, multiplied with the sub-dictionary D^k.
- The objective function is given by the equation (9).

$$\hat{\alpha} = \arg\min \left\| D_\alpha - x \right\|_b \tag{9}$$

$$\text{Subject to } \left\| \hat{\alpha} \right\|_0 \prec W$$

which results a sparse weighting vector $\hat{\alpha}$, whereas W is the number of nonzero elements and b specifies the used norm.

- The reconstruction of the patch X_j using sparse representation can be obtained by using the equation given by,

$$\hat{\alpha}_j = \arg\min \left\| D_j \alpha_j - x_j \right\|_b \tag{10}$$

$$\text{Subject to } \left\| \hat{\alpha}_j \right\|_0 \prec W$$

where x_j= vec(X_j) is the vectorized image patch.

- As the sparse representation of the patch x_j are determined, then the residual for each pixel in the patch can be obtained.
- Since the image patches are overlapped with same pixels, the residual for a single pixel in a patch is used for the final classification of the whole image.
- The residual for class k of the t_{th} pixel $x_{j,t}$ with $t \in \{1, \ldots, (Z.Z)\}$ in the j_{th} patch can be obtained as

$$r_i = \left\| A.x_i^q - I_i^q \right\| \tag{11}$$

4. Results and Discussion

The proposed work is validated by collecting a set of multispectral satellite images from Google Earth and www.usgs.com and implemented by MATLAB software. For each class, the color, texture and shape features are used to characterize the properties of the segmented regions.

4.1 Experimental Results

This section explains about the results obtained by the proposed sparse SVM classification algorithm. The input multispectral satellite images were subjected to preprocessing using Gaussian filter for noise reduction and given to wavelet transform which transforms the preprocessed image to a suitable form easier for segmentation[14]. The wavelet coefficients are obtained which produces four sub band images where the approximation sub band images were concatenated to produce RGB plane. This preprocessed RGB image is then applied to segmentation process using hybrid Fuzzy hierarchical clustering[15]. From the clustered segmented image, color features are taken and training data were chosen for the Sparse SVM classifier. Now the test multispectral satellite image is given to the classifier and based on the training data, the proposed Sparse SVM classifier classifies the test image as different land cover classes. The Figure 4 represents the input image; Figure 5 represents segmented output of hybrid Fuzzy hierarchical clustering. The Figure 6 shows the training and testing performance of Sparse SVM classifier whereas Figure 7 represents the classified output image of Sparse SVM Classifier.

Figure 4. Input multispectral satellite image.

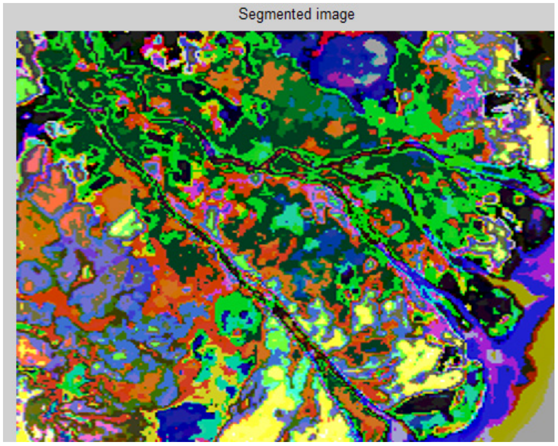

Figure 5. Segmented image.

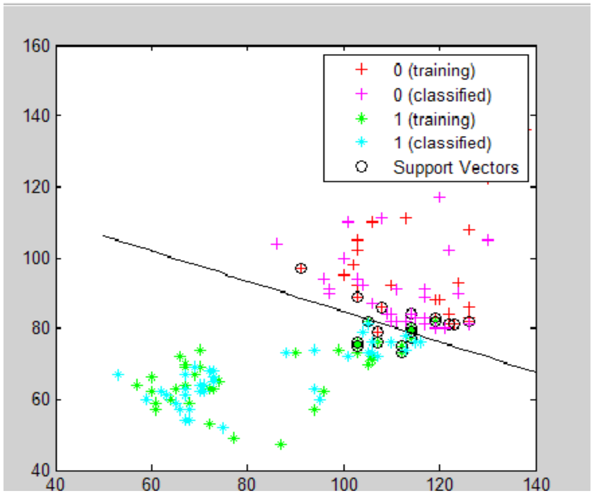

Figure 6. Train and test output of Sparse SVM Classifier.

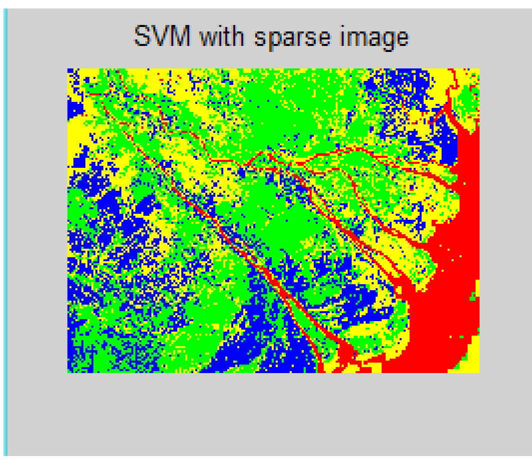

Figure 7. Classified output image using Sparse SVM Classifier.

4.2 Performance Evaluation

This section compares the land cover classification algorithm based on sparse SVM with the other existing techniques whose performance evaluation is analyzed. The various existing state-of-the-art methods like Fuzzy C-Means Clustering (FCM) technique Support Vector machine (SVM) and Reluctance Vector Machine (RVM) were compared with the proposed Sparse combined SVM classification technique. The results are summarized in Table 1 analyzed for an average of 100 test images. The input multispectral images have an average spatial resolution of 1.6 m per pixel of 610 x 340 pixels image size.

Table 1. Performance comparison

Classifiers	Accuracy	Error Rate	Sensitivity	Specificity
sparse SVM	0.8919	0.1081	0.8649	0.9189
RVM	0.8120	0.1935	0.8221	0.8732
SVM	0.7027	0.2973	0.7297	0.6757
FCM	0.6081	0.3919	0.7297	0.4865

5. Conclusion

An accurate new classification technique is proposed in this work. Unlike most existing algorithms via sparse representation, we proposed a new algorithm Sparse SVM classifier. The segmented image is divided into small image patches. Then features are extracted from the image patches and sparse representation is applied. Then the sparse representation is solved again for the test image pixels and optimized to improve the classification accuracy. The experimental outputs demonstrate that the proposed scheme produces improved performance. The performance analysis by various parameters ensures accurate classification by the proposed algorithm. The work can be extended for other applications such as change detection and environmental monitoring in future.

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