IJCTA, 9(36), 2016, pp. 551-559

A Multi Feature Fusion Based Image Classification Using Multi-Class Support Vector Machine

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Abstract : This paper is an attempt to develop the Multiclass SVM based Image Classification algorithm using the multi feature fusion as the input to the training. Active learning has been realized on the classification algorithms for over a decade. The single feature extraction technique would be of lesser sparseness than that of the MultiFeature based feature extraction technique. This paper implements the remote sensing image classification in MultiFeature fusion perspective. The active learning with MultiFeature fusion, as the feature extraction method, has been implemented and the results are observed. Color histogram and the Histogram of Gradient have been used as the features, which would be fused to get the input to the Multiclass SVM for image classification. The parameters like the kappa coefficient, Overall Accuracy, position error and the False Acceptance Rate (FAR) ,False Rejection Rate (FRR) and True Success Rate (TSR) are found and tabulated. This method is proved to be a better in overall accuracy for the multiclass classification. The analysis of the position error also is taken up in order to develop the amount of mismatch that is available in the classified pixels with the pixels that are not classified.

Keywords : Active Learning, MultiFeature Fusion, Remote Sensing, and Classification.

1. INTRODUCTION

Broadly Classified as supervised, unsupervised and semi-supervised methods, remote sensing image classification methods have been under research and development for the past three decades. From clustering algorithm, which is a unsupervised remote sensing image classification method, classifies the classes by just applying the clustering algorithms on the data instead of learning the data. But the supervised methods are learned methods and they would act in a different situation, which has not occurred before.

The Artificial Neural Network methods are used mostly in the image classification methods and also they are replaced with the Support Vector Machine with the advantage of having a global minima always achieved unlike ANN which finds mostly the local minima. The Neural Network if not chosen with the proper number of hidden layers would over fit .

These disadvantages of the neural network make SVM a better alternate for the ANN.

The advent of these learning methods has introduced the active learning method which involves the oracle presence in the learning process. The oracle is the human who interferes in the learning process whenever there is a need for knowing the label or when the initial dataset for training is chosen.

SVM proposed by Vapnik [1] is a supervised learning algorithm which works on the linear regression concept using many regressive functions like the Radial Basis Function(RBF). SVMs are classification prediction tools that use Machine Learning theory as a principle and very robust method to maximize

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predictive accuracy for detection and classification. SVMs can be considered as techniques which use hypothesis space of linear separators in a high dimensional feature space, trained with a learning algorithm from optimization theory that make a learning bias derived from statistical learning theory [1, 2]. Support vector machine is one of the important methods used in the active learning method. The classification was binary but now the multiclass Support Vector Machine has been introduced for better classification.

This paper is organized as follows, Section 2 will have survey about the Active Learning (AL) Methods, Section 3 deals about AL methods in Remote Sensing Image Classification, Section 4 puts light on the Multifeature based AL methods on remote sensing image classification, Section 5 on Results and Discussion of the proposed method, and the conclusion follows.

2. ACTIVE LEARNING METHODS

Active Learning method is one of supervised learning methods that needs the users intervention for deciding what needs to be learnt from the whole dataset and to which class does it belong. A prior knowledge regarding the dataset that is the learning reference [3] is highly suggested. The supervised learning method reduces the time consumption that would be usually taken for machine learning by making the algorithm to learn by itself.

The Active learning method that uses the intermediate to create a learned black box for the prediction process is one of the major contributors in much remote sensing based image classification process. The knowledge regarding the input data is needed for the active learning method. Thus by knowing the idea about the data to be trained would be a prerequisite for the supervised learning system. These supervised learning algorithms help in a speedy learning process as the oracle helps to decide the labeling of the initial data[4].

The initial literature regarding the active learning method was based on the query learning algorithm which would be using the set of queries that would be used to select the label for the initial training set [5]. The number of queries that is included and the number that has to be excluded are demarcated in the literature [6]. The application in Robotics for the coordinate prediction of the robotic arm by querying the angles of the joint as the input [7]. The human annotator would have the query prediction done on the intuition which would vary with every annotator. This occurred in [8] in which the ANN was used as human intermediate to choose the training samples of the handwriting character recognition.

The above disadvantages of the query based active learning method made the introduction of the stream based, popularly known as pool based active learning method. Before these methods replaced the query based active learning method a selective sampling method was noticed in [9].The selection of the samples that has to be taken for the learning process removing the redundant sample from learning is carried out.

This method is extended to be the stream based active learning. Application of these stream based active learning method was introduced in [10]. Many applications in pool based active learning methods are introduced in [11-14].The applications like the text classification [14-17] , information extraction [20,21] video classification and retrieval [22,23],speech recognition and cancer diagnosis[24] are covered through the pool based active learning method. The ranking of the selection of the input sample while training is carried out in order to have a higher speed in the training with lesser cost ,occurs in the pool based active learning.

Advancement in active learning methods were followed after the implementation of these kinds of the active learning methods.

3. ACTIVE LEARNING METHODS ON REMOTE SENSING CLASSIFICATION

Remote sensing classification methods have the accountability of automatically generating the land cover maps, which are largely accomplished by the supervised learning based classification techniques.

The land cover map is the output of the remote sensing image classification technique, whose prediction is dependent on the number of samples that are needed to be chosen when the labeling is carried out in the learning process[25]. Many classification algorithm on the active learning algorithms which would reduce the computational cost and the execution time reduction are carried out in [25-33]. The advanced methods like the cost effective learning method [34] are carried out where this classification algorithm is a cost minimization algorithm involved in the image classification in remote sensing images. Choosing an effective and the cost efficient sample for training is carried out by using the Genetic algorithm. Thus making the remote sensing based image classification a very computationally efficient algorithm on the image classification is found.

4. PROPOSED MULTIFEATURE FUSION BASED ACTIVE LEARNING METHOD ON REMOTE SENSING CLASSIFICATION

The Multifeature fusion method is the implementation where both the spectral and the spatial features of the pixels are taken into consideration for the classification on the pixel based image classification. The current implementation takes up the multifeature fusion for training the Multiclass Support Vector Machine (MFFMSVM).MFFMSVM uses the fusion of the colour histogram and the Histogram of gradient as the features that are fused with each other to produce a multifeature fusion that is trained on the MFFMSVM in order to classify the pixels in the test image. The robustness being the major criteria as many methods has emerged in the classification platform the multifeature fusion is a solution which would integrate many aspects of the features like the color and the edge effects as depicted in the Figure1.

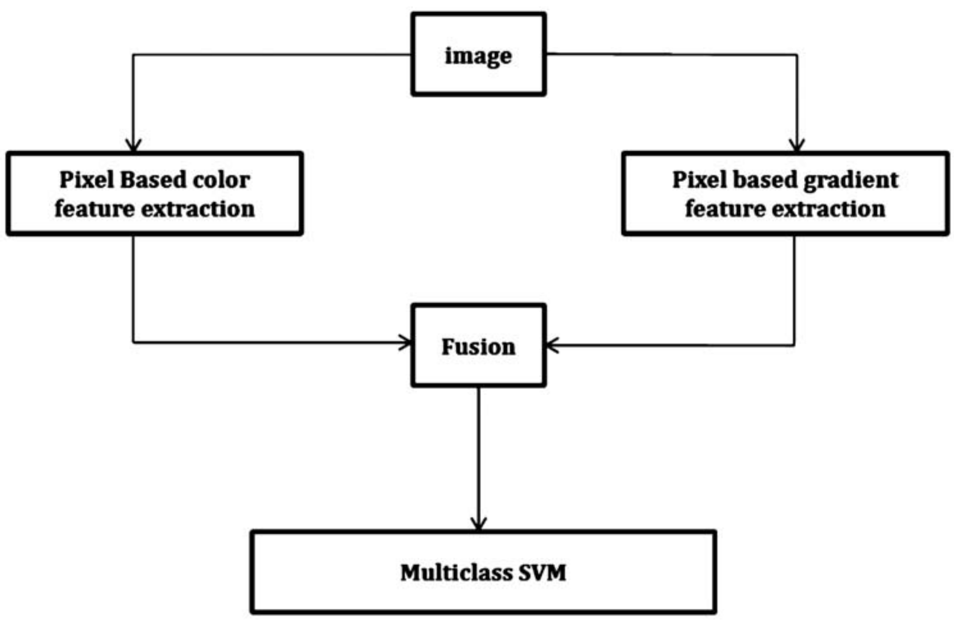

Figure 1: Proposed Multifeature Fusion Method (MFFMSVM)

Indian Pines datasets are taken from the NASA AVIRIS setup which is used in this implementation and the multifeature fusion based implementation is carried out.

In order to compute multifeature fusion, we need to specify those, which correspond to the selected features. In this paper, spatial color gradient and spatial gradient histogram are adopted to represent the object. The color feature has gained more attention, as it is a powerful alternative to characterize the appearance of object, especially if it can achieve robustness against deformation and partial occlusion.

The features are fused together to get a single feature that would be used as the input to the MFFMSVM and the fusion is carried out by the use of the following formula.

$$K = \sum_{i=0}^{n} K_i * \omega_i$$

Where Ki is i_{th} feature and ω_i is the weight factor for the fusion. This fused feature is taken for the pixels in the image to be trained for the Multiclass SVM algorithm and the multiple classes were classified. K is the fused feature taken as the input to the SVM algorithm and n is the number of features which is equal to two in this case.

Figure 2: The ground truth image with one object

The ground truth image that provides the preliminary idea about the different classes on the original Indian Pines image id depicted in Figure2.

5. RESULTS AND DISCUSSION

Matlab based simulation of the proposed algorithm is carried out on the set of images collected with water bodies and green cover from the public available hyperspectral scenes database. One of the images from the database is given as in the Figure 1.The classification was done for the different classes in the Indian pine images. Around 40 images were taken for classification from the database and the classification was applied on the images for both 10 and 5 objects. False Rejection Rate (FRR), False Acceptance Rate (FAR) and Total Success Rate (TSR) were tabulated for the different threshold values of the number of weight values.

The threshold provided in the Table 1&2 is the number of weight values used by the SVM to classify the objects during the testing phase. The SVM is used to decide whether how many images to add while the testing phase to have the resample done on the new set of data created.

The selection of the pixel to be classified is taken from the ground truth image and the Multifeature extraction is applied on the image and the detection and classification of the pixel is carried out. Then the algorithm for SVM is applied in order to detect and classify the pixel of the selected object in the original image.

Table 1

Performance analysis of proposed MFFMSVM for 10 object classification

Threshold	*FAR*	*FRR*	*TSR*
0	1	0	0
1	1	0	9.0713
2	1	0	25.8093
3	1	0	58.5764
4	1	0	84.5
7	0.5844	0.007	95.28
20	0	1	95.28

Table 2

Performance analysis of proposed MFFMSVM for 5 object classification

Threshold	*FAR*	*FRR*	*TSR*
0	1	0	0
1	1	0	9.8813
2	1	0	26.9067
3	1	0	60.645
4	1	0	87.453
7	0.5844	0.007	97.66
20	0	1	97.67

It can be inferred that the number of weight values if it is chosen to be 7, would be optimal for the maximum performance of the SVM to provide the best results. The analysis of the position error also is taken up in order to develop the amount of mismatch that is available in the classified pixels with the pixels that are not classified.

The position error calculation of the classification has been taken care as in the following manner. There will be a little change in the position while finding the classified object on the image under query. The position error is calculated by finding the distance between the center's actual ground truth object and the object classified.

$$Poserr \;=\; \sqrt{(C_c^x - C_g^x) + (C_c^y - C_g^y)^2}$$

where C^x, C_c are the *x* and *y* coordinates of the classified portion and C_g, C_g are the ground truth of the object detected

The overall accuracy in this implementation can be done by the use of position error of the matched template as this is a template matching method. The kappa coefficient is calculated from this error value in terms of percentage for each class. The position error for each classes is calculated and the results obtained are given below. The overall accuracy of the classification is calculated by knowing the number of pixels in the object which is classified correctly and that which is classified wrongly. The overall accuracy for each of the classes is calculated and the results are tabulated. By the use of overall accuracy the Kappa coefficients are calculated and the execution time for the current system requirement and the Matlab version are also tabulated.

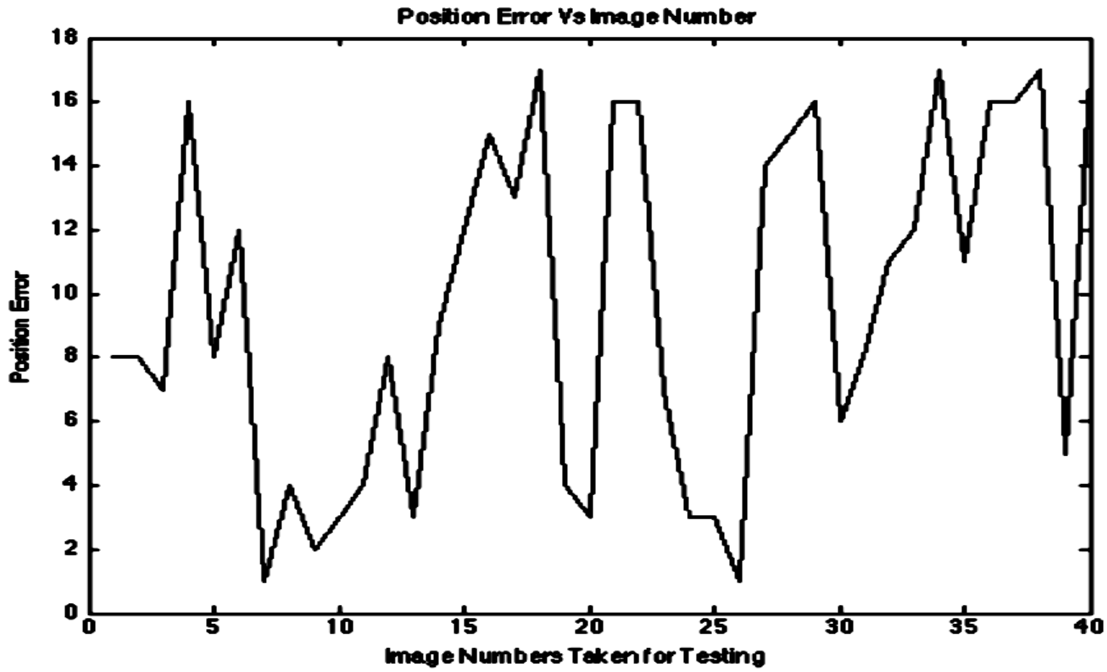

Figure 3: Position error Vs Image number for testing with 5 objects Considered

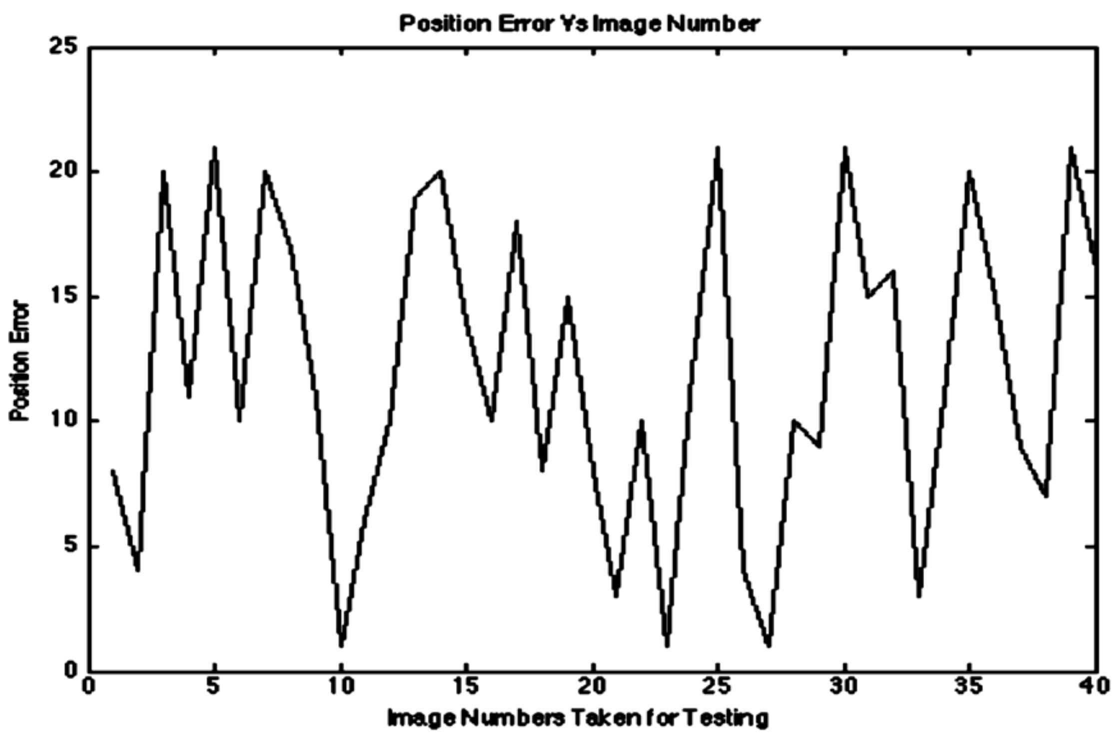

Figure 4: Position error Vs Image number for testing with 10 objects Considered

The overall accuracy of classification from the implementation is calculated from the following formula,

$$\mathrm{OA} = \frac{\sum_{i=1}^{k} n_{ii}}{|\mathrm{T}|}$$

Where, n_{ii} is the number of pixels that the current class is correctly traced by the current class is correctly traced by the template matching and T is the total number of pixels that the current class is using in the database image. And *k* is the number of isolated places where the current class is available on the database image. The kappa coefficient is the measure of the classifier performance from the position error.

Figure 5: Indian Pines Original Image

Table 3
Tabulation of Result

	Indian Pines Image		
Class Number	*Overall Accuracy in %*	*Kappa Coefficient in %*	*Execution time in secs*
Class1	81.114765	83.869533	3.019756
Class2	91.397043	91.736826	4.349269
Class3	91.134831	91.621535	4.240104
Class4	86.514188	87.632689	7.144424
Class5	95.815603	95.726131	5.577614
Class6	73.047619	78.284329	4.778422
Class7	77.977273	81.612784	2.698653
Class8	78.816514	82.181882	3.773842
Class9	85.363636	86.993659	3.015000
Class10000	87.607595	88.770792	1.717707

6. CONCLUSION

Multifeature fusion based active learning method was used to develop a classification technique on the remote sensing images. The advantage of the multifeature fusion from the different literature was realized. The Matlab based implementations were carried out and the results were satisfactory. The position error and the FAR , FRR and TSR values were calculated and tabulated .The results thus obtained are at par to the current implementations carried out in the recent past in the image classification techniques used in some of the literature. The Kappa coefficient has been proved better than some recent SVM based algorithms for remote image classification.The position error details also has been taken and analyzed in this implementation in order to analyse the mismatch of pixels that are taken in to account while classification and those that are ignored.

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