ROTATION-BASED OBJECT-ORIENTED ENSEMBLE IN LAND USE LAND COVER CLASSIFICATION OF HYPERSPECTRAL DATA

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***Abstract*— To classify hyperspectral images by using different techniques many classifiers have been produce better performance for object-oriented classification of hyperspectral remote sensing images. To improve the classification accuracy, first time we investigated an ensemble principle named Rotation-Based object-oriented classification of hyperspectral images (RoBOO). It is the combination of segmentation with support vector machine and nearest neighborhood algorithm. It uses random features selection and data transformation (PCA), technique to improve accuracy and diversity. In this paper we explained our new classification strategy which combines the multi-resolution segmentation (MRS) with SVM, NN classifier. MRS is used to obtain the objects by tuning the parameters included compactness, scale and shape. Furthermore, multiple classification results are produced by proposed method and results were integrated by using majority voting rule to release final results. Mostly used data transformation technique PCA was used. An experiential study on one hyperspectral dataset indicates that the suggested RoBOO slightly surpasses the single SVM and NN. The rotation-matrix with the MRS improved the performance. The effect of parameters on accuracy of RoBOO (different training sets, amount of features in each subset, compactness, scale parameters, shape) is examined as well in this document. We deduced that the integrations of SVM and NN with MRS were impressive in the object-oriented hyperspectral classification of land cover land use.**

Index Terms*— *Rotation-base Object-Oriented classification; hyperspectral data; Multi-resolution segmentation; Rotation Matrix; Support vector machine; nearest neighborhood; Principal components analysis; Land use/cover.

I. INTRODUCTION

Recently advances in imaging spectroscopy shows that a great usability for diversity of land use land cover monitoring application [1]. It is now possible to examine and identify sensing on earth surfaces using remotely sensed data and in informed manner using modern tools and examinations. Challenges in hyper spectral images classification techniques are the high dimensionality of data, limited number of training samples, and combination of spatial and spectral information.

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However, High dimensionality of hyper spectral data always produces new challenges to classification process. To obtain accurate classification results it always needs large number of training data to avoid the curse of dimensionality [5]. Pixel-based classification methods always produce mixed pixel problems due to the independency of neighbor pixels. This problem motivates researchers to combine segmentation, color and many other parameters to illuminate the wrongly classified or mixed pixels into their relevant classes. Traditional pixel-based techniques only concentrate on spatial information and often ignore the spatial dependence between neighbor pixels. In recent years, availability of new remotely sensed data with high dimensions, spectral and spatial resolution research attempts have been shifted from conventional pixel-based to object-based hyper spectral image classification is a hot topic to overcome aforementioned challenges[2].

Object-based classification can defeat these problems by segmenting data into groups of comparable neighboring objects. And then classify the groups be agreement to the properties within objects. Up till now number of object-base classification methods have been suggested and applied in the literature review. Some classification methods included support vector machine, decision tree, K-nearest neighborhood, and some ensemble learning algorithms (bagging, Rotation Forest, Boosting, random forest) in object-oriented classification of hyper spectral images has been an exciting topic in remote sensing field [3], [4]. Object-oriented image analysis segments the data and constructs hierarchical network of homogeneous objects. Object-based enable the analysis of aggregated sets of pixels, and exploit shape-related variation, as well as spectral characteristics [8].

Furthermore, Classifier generations target to build interdependent complemented different classifiers. Two very important components, named accuracy and diversity, are frequently considered to build several classifiers [6], [7]. Diversity needs the general errors presented by associated classifiers plan to much unrelated as barely able [7]. Typical methods such as bagging [9] make training samples by altering

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the portioning of original training samples; Random subspace [10] produce training features using randomly choose subsets of real feature set. Booting and Bagging are applicable for insecure base classifier, because of little changes in training features influence big changes in training methods [9]. Such kind of insecure classifiers included Decision Trees (DT) and Neural Networks (NN). Majority voting (MV) is a productive method for results combination. Using MV a pixel is allocated to a class which obtain highest amount of votes from a single classifier [6].

Rotation Forest (RoF), an ensemble learning algorithm lately introduced and has been applied in prosperous manners in number of machine learning studies in the past years. Its induction performance was found vigorous and effective for different datasets [11]. Also in recent years, has been utilized for classification of remotely sensed images. For an instance, [12] analyzed classification perfection of RoF with three common ensemble learning algorithms includes (Rotation Forest, bagging, Boosting) using Terra ASTER data. [13] Investigated the utility of RoF for classification of hyper spectral data.

In the aforementioned studies were applied for pixel-based classification on low or middle resolution images. Nevertheless in the literature the RoF has not been utilizing for Object-oriented hyper spectral images. In this paper, encourages by the concept of Rotation Forest [16], [15], [24], [17] we introduced Rotation-Based Object-Oriented NN and MRS is introduced. It produced image objects and exploit autonomous variant results. Besides traditional pixel-based classifications we exploit MRS with NN and multiple classification outcomes are combined together by utilizing majority voting rule. Besides traditional pixel-based classification, this strategy expected to produce better performance. The aim of this meditation was to examine the performances of Rotation-Based NN in the circumstance of object-oriented classification using hyper spectral imagery. In state to assess the method performance, greatly used Nearest Neighborhood (NN) and Support Vector Machine (SVM) algorithms were put into practice. Moreover, we estimate the performances of suggested method based on few experiments carried out on one hyper spectral dataset, farming culture area of Indian pines, USA.

This paper is ordered into the following segments.

SVM and NN are briefly expressed in Section II. We bring to the notice of RoBOO ensemble in Section III. Experimental setup, results and discussions are demonstrated in Section IV.

Conclusions and perspectives are presented after all other segments.

II. RELATED WORKS

A. SVM

Support Vector Machine is a theory-base supercilious machine learning algorithm with best performances in the field of pattern recognition. It has been tending to compete against other machine learning classification methods included supervised maximum likelihood [22] and Spectral angle mapper [19]. Therefore, SVM is a highly suggested algorithm for classification.

Main purpose of SVM is to provide the optimum distinct hyper plane between with highest margin which can directly divide the classes. These training data are noun as support vectors and other data discarded. Optimum hyper plane can be settled out by using training data and generalization is proving using a validation dataset. SVM produce linear distinct hyper plane with maximum margin in the dimensional space. The description of SVM has been presented in [23] [14].

Recently, SVM has been applied successful in the remote sensing area for hyper spectral classification. With their great benefits to solve problems such as limited samples, small size of samples, poor principles.

At first, SVM aimed to implement binary classification. SVM is a supervised learning method. Number of work has been done on it and it has proved impressive work in the classification of land use/cover classification.

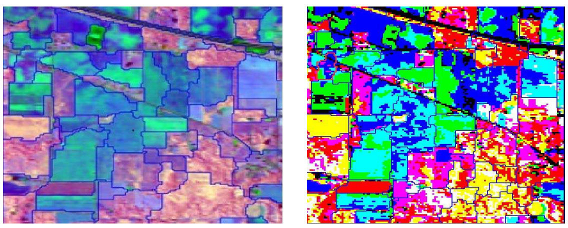
In this paper, we utilized the Radial base function (RBF) as a kernel function. SVM performance depends upon the kernel function. Soft margin C and kernel parameters are two important part of kernel function. In [18], SVM shown better accuracy with RBF as against linear kernel SVM. Because of the reason, Gaussian RBF with ð parameter is selected and the good combination of both parameters C and ð were determined by grid search method.

B. NN

NN is a non-parametric and simplest algorithm, which has been used for the image classification. [32] Used it for object-based classification of very high resolution images of worlview-2 and produced excellent accuracy. It is uses the mode for categorical or mean for continuous variable of interest for the already define neighborhood as an estimator [29]. By neglecting its simplicity it is still providing good results. An introduction and its general method can be found in a book [32].

C. Segmentation

Segmentation is the very important step in object-oriented data analysis techniques. The MRS was implemented to hyperspectral image, to create image objects using eCognition developer 8. MRS is a bottom-up segmentation algorithm; it is based on region merging procedure was first proposed by [33]. Segmentation method starts with single objects of one pixel and merges them in large objects as long as upper limit of the homogeneity is not satisfied. Homogeneity can be defined as shape and spectral homogeneity. Scale and shape and compactness parameters are the main parameters for user to control the algorithm influence. Large or small objects are dependent on scale parameters [35]. Color and shape (Smoothness and compactness parameters) exploit spectral properties and shape of the objects [36].



(a) 220 bands (b) 200 bands

Fig. 1: Segmentation of Indian pines

III. ROTATION-BASEDD OBJECT-ORIENTED (ROBOO)

SVM and NN algorithm has been performed great performances for hyperspectral classification. Because it's higher stability and little changes in training data does not give very hug difference in results. In [28], analysis of bagging-boosting-based SVM on recently produced Advanced very high resolution radiometer (AVHRR) data and shown its results which did not enhanced the SVM results. Nevertheless, [30] implement bagging-boosting-based SVM on land sat ETM+ data and shown the bagging-based SVM increased the accuracy but booting-based SVM reduce the performance. [2] Investigated the high resolution worldview-2 images with combination of three PCA's and produced the comfortable overall accuracy but unsuccessful to provide maximal performance.

By the full motivation of random subspace submitted by [26] organized an ensemble methodology, which was based on SVM and randomly selected features for hyperspectral data classification. Furthermore, to increase diversity within RoBOO ensemble we used the concept of randomly selection of features and data transformation techniques. It is the best way to design the diverse classifiers. As stated in fig. 1 the main flow of RoBOO can be described as following:

Let {X, Y} $=\{x_i, y_i\}_{i=1}^{n}$ is training data, $\mathbb{F}$ exhibit the features of dimension $\boldsymbol{D}$ and $\boldsymbol{L}$ depict the classifiers. $\boldsymbol{K}$ represents the subsets count and $\boldsymbol{M}$ exhibit the features count in each subset.

Here we follow the step by step process, first step: $\mathbb{F}$ split in $\boldsymbol{K}$ subsets and each subset consist of $\boldsymbol{M}$ features.

Second step: we select new training data $\widetilde{\boldsymbol{X}}_{i,j}$ from the training data $\boldsymbol{X}_{i,j}$ by simply 75% in size. Here we should note that $\boldsymbol{X}_{i,j}$ exhibits j^{th} $(\mathrm{j}=1, \ldots .\mathrm{K})$ number of subsets of i^{th} (i=1…L) number of classifier to the number of

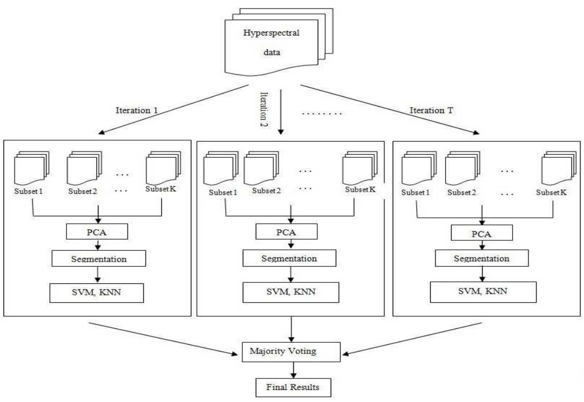


Fig. 2: Flow chart of Rotation-Based Object-Oriented

features $\mathbb{F}_{\mathbf{i},\mathbf{j}}$.

Third step: $\widetilde{\boldsymbol{X}}_{i,j}$ to be transformed using PCA algorithm to obtain coefficients $v_{i,j}^{(1)}, \ldots, v_{i,j}^{(M_j)}$ of size $v_{i,j}^{(.)}$ by $\boldsymbol{M}$x1.

Fourth step: Multi-resolution segmentation was carried out by using eCognition developer 8.0 to construct hyperspectral image into objects by depending on different parameters included (scale, shape, compactness). Image segmentation is an important step in object-oriented classification. It is implemented by region merging method called MRS suggested by [33].

Fifth step: $\boldsymbol{R_i}$ Rotation matrix acquire by using above coefficients:

$$\boldsymbol{R_i} = \begin{bmatrix} v_{i,j}^{(1)}, \ldots, v_{i,j}^{(M_j)} & 0 & \cdots & \mathbf{0} \\ \vdots & & \ddots & \vdots \\ \mathbf{0} & & \cdots & v_{i,K}^{(1)}, \ldots, v_{i,K}^{(M_K)} \end{bmatrix}$$

Sixth step: training features data $\boldsymbol{XR}_i$ for i^{th} SVM and NN, and each SVM and NN is trained by using parallel topology.

Seventh step: hyperspectral image classification final results can be produced by integration of each classification result using majority voting rule for final output.

Here we noticed that selecting 75% size of training data would enhances the diversity in ensemble [34]. Size of training data between 50% and 75% always produced excellent performances.

Moreover, it is also worth of noticing that the prosperity of proposed method RoBOO relies on PCA. First time the PCA was applied to construct rotation based ensemble named rotation forest (RoF).

IV. EXPERIMENTAL SETUP AND DATA

In this section, SVM and NN classifiers are implemented using one hyperspectral dataset. The only datasets is AVIRIS data, was obtained for a vegetation of Indian Pines, Indiana, and USA. This data is 145 x 145 pixels with spatial resolution of 20 mega/pixel. Original data consist of 220 spectral bands and after removing 20 water absorption bands (104-108, 150-163 and 220, remaining 200 spectral bands. this dataset contains total 16 class but we ignored 3 classes with lowest labeled pixels so 10090 labeled pixel for SVM classification. Moreover, total 16 classes were used for NN classification with 10249 labeled pixels.

For the only dataset total labeled samples were divided into training and testing data.

In state of implementation classification performance of SVM and NN, PCA data transformation was used and first 12 highest valued components were selected for MRS. PCA and Segmentation was implemented using eCognition developer 8 [35] for SVM and NN classification. Scale, compactness and shape are the fundamental parameters in object-based classification. Shape parameter was tuned between values 20 and 55. Compactness and scale parameters were checked between 0.4 and 0.9until required segmented image is not acquired. Selects random samples as a training data (75%) for

Indian Pines dataset were selected. And the remaining samples were selected as a testing data. Ensemble sizes (L) and the number of features in each subset (M) were use as fundamental parameters in RoBOO. Therefore we choose different combinations of L and M, L were selected between 200 and 220. And M was selected between 3 and 9.

SVM classification was implemented using ENVI 4.5 software. Gaussian RBF kernel is used and combination of C and ð were analyzed for best results. In literature review we found that the bagging-and-boosting-based SVM did not produced good results as compare to traditional SVM and NN. Thus we are not including comparison of bagging-boosting-based in this study. Random Subspace support vector machine and traditional support vector machine comparison is included in this study [37]. Percentage of overall accuracy (OA) of well classified samples is used to measure the accuracies.

Table I
Details for Indian pines dataset experimental settings

Number of samples	Randomly selected
Ensemble size	200 to 220
Number of features in each subset	3 to 9
Base classifier	SVM, NN
Data transformation	PCA
Objects creation	Multi-resolution segmentation

V. Results and Discussion

We investigated the classification performances for suggested RoBOO ensemble method using Indian Pines AVIRIS image Fig. 3(a) and with ground truth in Fig. 3(b). Table. II showed the training data and Table III showed the overall accuracy with randomly selected samples for training and remaining for testing. The best accuracy depends on the different values of M between 200 and 220. As you see in the Table III and IV, the performances of RoBOO are better than as compare to RSSVM and regular SVM.

Here we noticed that, the regular SVM [37] achieved the overall accuracy between 57.18% and maximum 74.22%. But RoBOO achieved highest overall accuracy between 90.99% and 93.13% using PCA and MRS.

The output of our proposed methodology in comparison of others traditional classifiers SVM etc was analyzed for RoBOO. Rotation-based Object-Oriented method using SVM and NN classification model was constructed with optimal parameters and were applied to the MRS segmented image of objects. Number of iterations took place between 1 and 10. It is noticed that the results slightly varied. And no parameter took desire advantage.

Table: II
Training and Testing data

Class Name	Training	Test
Corn-no till	196	1428
Corn-min till	236	830
Corn	63	237
Soybean-no till	93	972
Soybean-min till	223	2455
Soybean-clean till	94	593
Grass-pasture	162	483
Grass-trees	171	730
Hay-windrowed	98	428
Wheat	59	295
Woods	164	1265
Buildings-Grass-Trees-Drives	136	386
Stone-Steel-Towers	44	93

Here we found that there are no dependency between accuracy and iterations [38]. Optimum number of features in each subset was 9 and varied between 3 and 9. For SVM the optimum parameters setting for kernel width and cost parameters were selected different for all subsets.

The Possible cause for the great performance of RoBOO is that on randomly selected data and its providing reliable rotation-matrix, which increase the base classifier accuracy.

Table: III
Performance of the SVM, NN with first 12 PCA with highest value setting in term overall accuracy

Methods	Ensemble size	OA (%)
SVM	200-220	93.17
RSSVM [37]	100	78.28
NN	200-220	90.99
RoSVM [37]	50	89.14

Ground truth image was used to analyze the accuracy. Overall accuracy estimated by using confusion matrix and majority voting. The classification results are shown in table II. It is noticed that the highest classification results were estimated by SVM by using first 12 PCA components with highest values is 93.17%. It is also noticed that the accuracy between SVM and NN is slightly different the overall accuracy of NN is lower than NN range from 1% to 3%.

As compared the accuracy to [37] the classification accuracy of our proposed method accuracy is better slightly 0.85% in terms of number of samples and ensemble size. Here we confirmed that the machine learning methods outperform for Rotation-Matrix Object-Oriented classification. Here in addition, when we took images objects support (segmentation, 12 PCA) the accuracy is slightly increased. We also noticed that when we used total bands included water bands, it decrease the accuracy slightly 2% using SVM and NN 1%.

Table: IV
Performance of the SVM, NN with 200 bands with optimal parameter settings in term overall accuracy

Methods	Ensemble size	OA (%) with 200 bands
SVM	200-220	**91.28**
NN	200-220	**90.00**

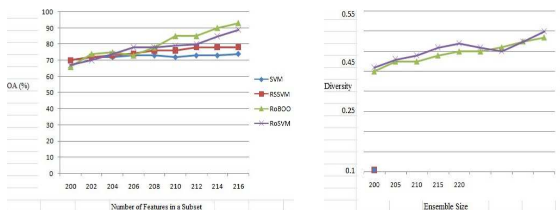


Fig: 4 Indian pines AVIRIS

a) OA accuracy with respect to number of features in a subset
b) Diversity in terms of Ensemble size

Table: V
User's and producer's accuracies for RoBOO SVM

Class	Prod. Acc. (Percent)	User Acc. (Percent)	Prod. Acc. (Pixels)	User Acc. (Pixels)
Corn-no till	83.16	100.00	163/196	163/163
Corn-min till	100.00	76.87	236/236	236/307
Corn	100.00	100.00	63/63	63/63
Soybeans-no till	49.46	100.00	46/93	46/46
Soybeans-min till	38.12	100.00	85/223	85/85
Soybeans-clean till	52.13	100.00	49/94	49/49
Grass/Pasture	87.04	100.00	141/162	141/141
Grass/Tress	77.78	75.14	133/171	133/177
Hay-Windrowed	100.00	100.00	98/98	98/98
Wheat	100.00	100.00	59/59	59/59
Woods	100.00	89.62	164/164	164/183
Bldg-Grass-Trees	100.00	100.00	136/136	136/136
Stone-Steel Tower	100.00	100.00	94/94	94/94
Others	100.00	93.97	2931/2931	2931/3119

Overall Accuracy = 93.1780%
Kappa Coefficient = 0.8820

VI. CONCLUSION

In this study the use of SVM and NN algorithms are analyzed for rotation-base object-oriented hyperspectral classification (RoBOO). And their performances were comparing with previously well-known investigated algorithms for classification named RSSVM. For this objective, combining different sources including 12 PC and segmentation were for investigation and classification accuracy was produced thoroughly.

Results of the study lead us to some conclusions. For K subsets combinations the RoBOO strategy produced great performance as compare to RSSVM ensemble and traditional SVM. RoBOO increased the diversity by combining the randomly feature selection and PCA. We also analyzed the affect of parameters on over all accuracy. Final results with spatial-spectral resolution on one hyperspectral dataset showed that the RoBOO produced comfortable performances with comparison of RSSVM and regular SVM. PCA and MRS methods have produced performances on randomly selected training data and parameters settings. Despite the benefits of RoBOO, it major drawback is computational cost which is greater than traditional SVM and RSSVM. Future investigation will pay attention of fast learners for object-base hyperspectral classification.

VII. ACKNOWLEDGMENTS

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