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Performance Analysis of Object Oriented Remote Sensing Techniques for Forest Detection in Pakistan

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Abstract-Effective monitoring of forestry in Pakistan is a challenging task for the environmentalists due to lack of automated procedure for land cover classification and forest identification. Currently, manual procedure of utilizing ground surveys and reports is used for forest detection, but such techniques are not reliable because of the possibility of human errors and deliberate alteration. Therefore, it is very important the remote sensing based effective monitoring techniques should be developed for the effective observation of land cover and green forests. Areas which are unapproachable or approachable at the cost of valuable resources can easily be monitor using remote sensing satellite imagery. In our experimental setup we have utilized 4999sqkm with 2.5m resolution multispectral SPOT-5 imagery of Abbottabad district of Pakistan. Classification of the land cover consisting of different regions of interest including the forest is challenging task in pixel based classification approach because of the heterogeneity in local pixel values of neighboring classes and similar spectral properties which restrict the class discrimination and yield undesired results. Visible effect of salt and pepper can also be seen in pixel based analysis. Object oriented classification approach (OOCA) overcomes these constraints and provides higher classification accuracy with more flexibility to extract different types of features. Homogeneous pixels that are consisting of similar spectral, spatial or texture characteristics are segmented to form object slices, which ideally corresponds to real world objects. While employing the OOCA with nearest neighbor classification based on training samples, user and producer accuracies of class forest is 100% with overall accuracy of 96% and kappa coefficient value of 0.96 was achieved. Support Vector Machine is applied on same training samples which were used for nearest neighbor algorithm and achieved improved results from that of NN classification. Overall accuracy of 98.93 % and kappa coefficient of 0.98 is achieved with user and producer accuracies of class forest as 100% each. Visual analysis shows that the classified images using OOCA are smoother due to the process of segmentation prior to classification. Based on these results, we are confident that the object oriented classification approach is favorite for identification of forest in Pakistan.

Keywords: Analysis of Object Oriented Forest Detection, Object Oriented Classification, Remote Sensing

1. INTRODUCTION

Forests maintain the overall ecological condition of atmosphere because they are called the lungs of nature. Northern areas of Pakistan have meaningful green forests which help prevent environmental pollutions, aid into the beauty of the locality and attracts the visitors towards these areas. Herbaceous plants and trees are used to make local medicines as well as provide the source of shelter for wildlife. Country suffers from deforestation which is a serious ecological issue. The environmentalists are facing difficulties to effectively monitor the forestry in Pakistan because ground surveys and reports are not so helpful in this case. Therefore, it is very important that valuable monitoring techniques are to be analyzed and applied for the effective observations. Those areas which are inaccessible or accessible at the huge cost can be monitored by Remote Sensing using multispectral, hyper spectral and panchromatic satellite imagery by applying advanced image processing algorithms. In this research, high resolution SPOT-5 imagery has been utilized for different land cover conditions specifying the forest evaluation and agriculture development in northern areas of the country. Classification of the land cover is based on six different selected regions of interest of each category including forest. Forest identification is possibly becoming more accurate today due to the ability of satellites to capture improved spatial and spectral resolution imagery (Ahmed and Muhammad 2015). For a particular targeted class like forest, a single date imagery after recognizing its proper calendar time can be used to accurately categorize that class by employing more training samples, however for a growing seasonal crops a multi date satellite imagery is beneficial (Yang and Everitt, 2011). The classification of land cover from remotely sensed imagery can be divided into two general image classification approaches, i.e. pixel based classification and object based classification. Pixel-based analysis has long been the core approach for classifying remotely sensed imagery while object-based image analysis has become increasingly commonplace over the last decade (Dennis *et al.,* 2012). In pixel based approach a pixel is considered an individual unit of classification which bears several spectral band values. Pixels having comparable spectral values are assigned to one class (Shridhar *et al.,* 2015.).Classification of the land cover consisting of different regions of interest is challenging task in pixel based classification approach because of the heterogeneity in local pixel values of neighboring classes and similar spectral properties which restrict the class discrimination. Digital number of a pixels if it

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represents the average of several spectral classes in the area on the ground, emitted or reflected by a different type of substance are likely to be misclassified and their existence is highly influenced by the resulting variations caused by the data acquisition process (Blaschke, *et al,* 2014). Object oriented classification approach (OOCA) offers several important benefits to detect target land cover i.e. smoothing of the local noise, incorporating meaningful non-spectral features such as spatial attributes, area and shape properties for class (Dronova and Iryna, 2015). Pixels consisting of similar spectral, spatial or texture characteristics are segmented to form object slices, which ideally corresponds to real world objects. Object based image analysis classifies objects instead of pixels and considers both the spectral and spatial information of remotes sensing imagery to achieve a land cover classification mapping with higher classification accuracy (Gao *et al,* 2006)Mountrakis, Giorgos *et al,* 2011). Visually smooth classification results are achieved using OOCA due to the process of segmentation as now the basic unit of classification is not the individual pixel but the group of similar pixels called object and no two objects are similar in characteristics. Some vegetation classes may be over classified in pixel based classification while the object based approach has the ability to distinguish among separated vegetation classes (Zhang, and Jia, 2014). This research consist of the abject oriented classification of the high resolution satellite imagery to classify the forest in the area.

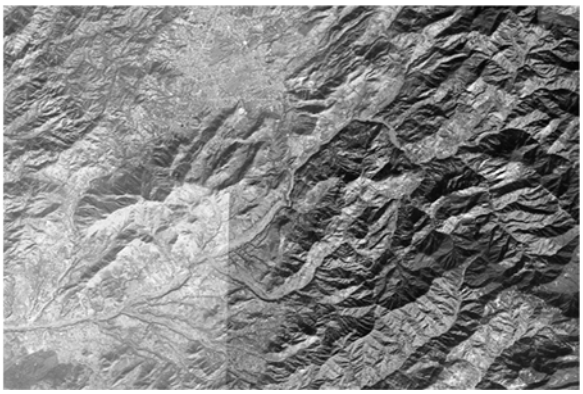


Fig. 1. Original Spot 5 image

2. METHODOLOGY

Object Oriented Classification Approach is often used to recognize the underlying patterns of land cover in remotely sensed data. In this research the analysis started from data preprocessing, Segmentation to form objects, Creating Class hierarchies and assigning training samples to classes inorder to train the supervised classifiers. i.e. Nearest neighbor and Support Vector Machine. Final classification and results are discussed in next section.

Pre-processing

2.5 meter HGR spot5 image has been obtained from Pakistan's Space and Upper Atmosphere Research Commission (SUPARCO). A linear filtering is applied to equalize the image for further processing. image layer mixing is also performed prior to loading it for analysis. This work has been carried out in eCognition Developer.

Segmentation

Main step in the study of OOCA is the creation of objects which further be utilized for the analyses. Image objects are the basic unit of classification in object oriented classification approach. eCognition software provides us choice of several algorithms for image segmentation. Multiresolution segmentation algorithm is applied in this study which forms the objects at pixel level based on the homogeneity in the pixels. Scale, shape and compactness parameters are set. The scale factor is an abstract value to determine the maximum possible change of heterogeneity caused by fusing several objects while Shape is a geometric feature that can be used as indication of smoothness and compactness (Dronova and Iryna, 2015). Smoothness describes the image objects with regard to smoothness of borders while compactness describes the "closeness" of pixels clustered in an object by comparing to circle (Griffith and Jayar 2005).Generally a small scale parameter defines smaller objects (trial and error). In this paper three levels of segmentations have been performed in order to achieve the best possible segments describing the actual scenes in the image. Scale 40, Scale 30, and scale 20. The classification has been applied on the segmented image with scale parameter 30 because it achieved formation of fine objects. **(Fig. 2)** shows the final segmented image with scale value 30 and shape and compactness 0.8 and 0.5 respectively. Multiresolution segmentation provides us the choice of assigning different weights to the spectral bands which allows a balance of multispectral and panchromatic data in the segmentation. In this study a weight of 2 is assigned to NIR band with all other bands having weight equal to 1. eCognition also provide us environment for developing custom algorithms or rule sets for segmentation, classification and other steps of data analysis (Griffith and Jayar 2005).

Creating Class hierarchy

Once the image has been properly segmented up to the desired level, the next step is to create class hierarchy by defining different classes which need to be included for classification along with desired target class. In this study six different classes were created including forest, sparse vegetation, water, bare land, settlements and shrubs & bushes.

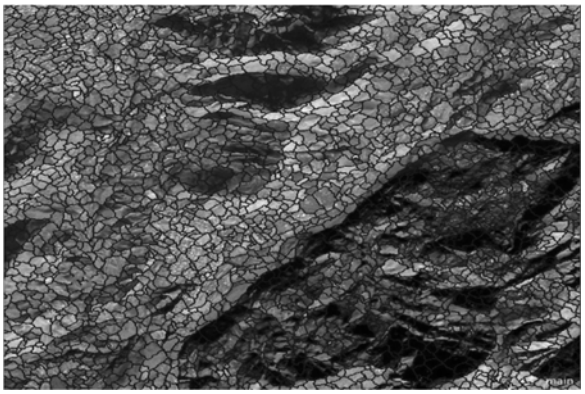


Fig1. Magnified Segmented Image (Scale 30, Shape 0.8, Compactness 0.5)

Assigning training Samples

After creating class hierarchy, each class is selected to assign samples. Samples are selected based on the ground survey by choosing the samples of the region which lies in the specific target class. Accuracy in the classification of the imagery depends upon the precise assignment of samples to the target classes and imperfectly assignment of samples lead to misclassification and hence it affects the precision of the classification. After the best possible assignment of objects/samples to all the classes, the classification algorithms are applied. Standard Nearest Neighbor and Support Vector Machine are applied on the same training samples taken in the high resolution satellite imagery.

Nearest Neighbor Classification

Nearest Neighbor classification uses a set of samples of different classes to assign membership values. The procedure consists of two major steps:

- Training the system by giving it certain image objects as samples
- Classifying image objects in the domain based on their nearest sample neighbors.

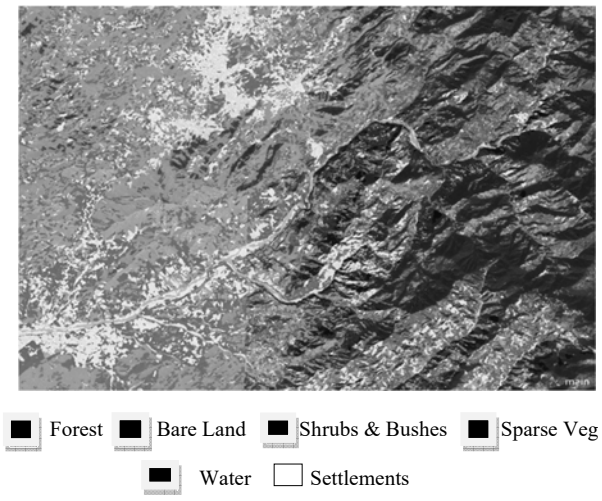


Fig 3. Nearest Neighbor Classified Image

After a representative set of sample objects has been declared the algorithm searches for the closest sample object in the defined feature space for each image object. The user can select the features to be considered for the feature space. If an image object's closest sample object belongs to Class A, the object will be assigned to Class A. In this study the NN classification has been applied on samples taken from the satellite imagery for all the six different classes. The classified image is shown in **(Fig 3).**

Support Vector Machine

SVMs are mainly interesting in the field of remote sensing due to their ability to give meaningful results even with limited training samples. However, they also suffer from parameter assignment issues that can considerably affect attained results (Mountrakis, Giorgos, 2011). SVM is a machine learning algorithm which classify the given data set with the help of hyper planes. In this algorithm, we plot each data item as a point in n-dimensional space (where n is number of features you have) with the value of each feature being the value of a particular coordinate. Then, we perform classification finding the hyper-plane that differentiate the two classes very well. Support Vector Machine is a border line which best segregate the two classes with greater margin. kernel, gamma and C are the important parameters which have higher impact on classification mode lhttp://www.analyticsvidhya.com/blog/2015/10). Kernel is either linear of radial basis function. If the data is distributed linearly in the space , the linear kernel is used and if it is distributed non linearly, the RBF kernel may be used. Support Vector Machines are based on the concept of decision planes defining decision boundaries. A decision plane separates between a set of objects having different class memberships.. In this study, SVM classifier is trained on samples, giving the parameters kernel type linear, penalty factor C=2 as well as for radial basis kernel RBF for non linear hyper-plan and applied for the classification. The SVM classified image is shown in **(Fig 4).**

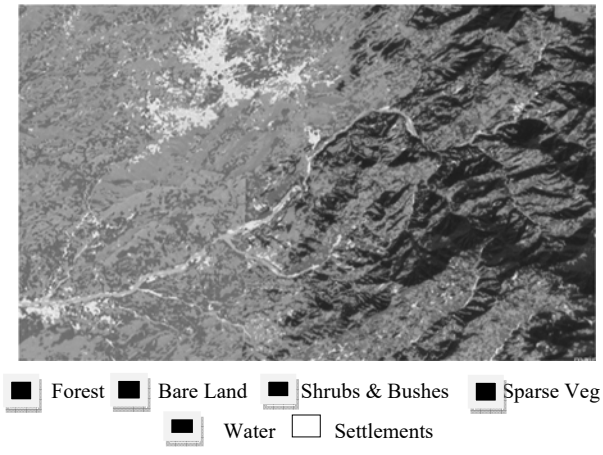


Fig 4. SVM Classified Image with linear kernel

3. ACCURACYASSESSMENT OF RESULTS AND DISCUSSIONS

Accuracy is assessed in final step in sample based Nearest Neighbor classification as well as in Support Vector Machine Classification to find the statistics of the results. An error matrix for Nearest Neighbor classification is generated which is shown in **(Table 1).** Overall accuracy of the classification is 96.9% and the Kappa Coefficient is 0.92. Forest is classified with the user and producer accuracy of 99.38%. Training samples which were used for NN, also used for SVM for the comparison between them. Error matrix for Support Vector Machine is shown in **(Table 2).** Improvement in the results is achieved using SVM, i.e. Overall accuracy of the SVM classification is 98.9% and the Kappa Coefficient value is 0.98 which is greater than that of NN classification. Forest is classified with the user and producer accuracy of 100% (no commission and omission errors) which shows that the Support Vector Machine has classified the class forest more precisely as compared to NN Classifier. Furthermore Settlements and water are more separated and accurately classified using SVM classifier.

4. CONCLUSION

In this study of object oriented classification approach, the image is segmented to form objects and the sample objects for all six classes were selected to train the classifiers. Nearest Neighbor classification is applied on those samples for all the classes and the final classified image (**Fig. 3)** and the error matrix **(Table 1)** is produced for accuracy assessment. It is concluded that the overall accuracy is 96.9% including forest with user and producer accuracy of 99.38% which shows that the class forest is efficiently classified based on the training samples. Support Vector Machine is applied on the same training samples and improvement in the results is achieved. It is apparent from the Confusion matrix which is shown in Table 2 that the Overall Accuracy of 98.9% is achieved and User and Producer Accuracies of our target class forest is 100%. No commission and omission errors are occurred for the target class using Support Vector Machine algorithm in Object Oriented Classification Approach. Producer Accuracy of Water and User Accuracy of Settlements in SVM Classification is higher than those of NN classification as shown in **(Table 3).** Both the classifiers are trained on same samples in order to compare the accuracies and to find out the importance of these methods in Object Oriented Classification Approach (OOCA). Moreover, visual analysis shows that the classified images using OOCA are more smoother, thus avoiding the salt and pepper effect.

These findings reveal the importance of OOCA for land cover classification and forest detection.

In future we will focus on knowledge based threshold classification using rule sets along with the customized object features to classify the HGR satellite imagery.

Table 1. Confusion Matrix of Nearest Neighbor Classification

Confusion Matrix	Forest	Water	Settlements	Sparse Vegetation	Shrubs &bushes	Bare Land	Sum
Forest	9	0	0	0	0	0	9
Water	0	24	0	0	0	0	24
Settlements	0	2	12	0	0	3	14
Sparse Veg	0	0	0	15	1	0	16
Shrubs&Bushes	0	0	0	0	26	5	26
Bare Land	0	0	0	0	0	8	8
Unclassified	0	0	0	0	0	0	0
Sum	9	26	12	15	27	8	
Accuracy							
Producer	1	0.92	1	1	0.96	1	
User	1	1	0.85	0.93	1	1	
KIA per Class	1	0.89	1	1	0.94	1	
Total							
Overall Accuracy	0.969						
KIA	0.961						

Table 2. Confusion Matrix of Support Vector Machine Classification for kernel type linear and RBF, C=100, Gamma = 10

Confusion Matrix	Forest	Water	Settlements	Sparse Vegetation	Shrubs &bushes	Bare Land	Sum
Forest	9	0	0	0	0	0	9
Water	0	24	0	0	0	0	24
Settlements	0	2	12	0	0	3	14
Sparse Veg	0	0	0	15	1	0	16
Shrubs&Bushes	0	0	0	0	26	5	26
Bare Land	0	0	0	0	0	8	8
Unclassified	0	0	0	0	0	0	0
Sum	9	26	12	15	27	8	
Accuracy							
Producer	1	1	1	1	0.96	1	
User	1	1	1	0.93	1	1	
KIA per Class	1	1	1	1	0.94	1	
Total							
Overall Accuracy	0.989						
KIA	0.987						

Table 3. Comparison of Producer and User accuracies of all classes obtained by NN and SVM classification schemes

Class	Nearest Neighbor		Support Vector Machine	
	PA	UA	PA	UA
Forest	1	1	1	1
Water	0.92	1	1	1
Settlements	1	0.85	1	1
Sparse Veg	1	0.93	1	0.93
Shrubs&Bushes	0.96	1	0.96	1
Bare Land	1	1	1	1

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