OBJECT-BASED CLASSIFICATION USING ULTRACAM-D IMAGES FOR TREE SPECIES DISCRIMINATION (CASE STUDY: HYRCANIAN FOREST-IRAN)

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ABSTRACT:

This research has been conducted to evaluate the proposed object-based method with high spatial resolution airborne remote sensing data in tree species identification and mapping. It has been done in 2 areas of total 10 separate areas; include the disturbed natural broadleaved forest and the broadleaved and coniferous mixed forestation in the Northern forests of Iran. After pre-processing the imagery a trial and error method was employed to reach the ideal segmentation results. Subsequent to class definition, sample objects were selected as representative of defined classes and NN classifier was accomplished using integration of a broad spectrum of different object features. Accuracy assessment of the produced maps, comparing with field reference data shows the overall accuracies and Kappa statistics of 0.79, 0.61 (Area1) and 0.76, 0.69 (Area2) respectively. Relatively low accuracy in both areas demonstrated that the standalone optical remote sensing methods are insufficient for classification of such complex forest structures.

1. INTRODUCTION

Methods of forest state assessment using remotely sensed data have been tested for several decades, with the visual aerial photo interpretation as the main tool widely utilized in practical forestry. Nevertheless, the automated classification of such textured data is still problematic due to enormous class spectral variation (Millette and Hyward, 2004; Naesset and Gobakken, 2005; Baltsavias et al., 2007; Chang et al., 2008; Ozdemir et al., 2008; Bohlin et al., 2007; Wang, 2008; Hirschmugl et al., 2007; Yu et al., 2006).

Object-based classifiers deal with this so-called H-resolution problem by segmenting an image into homogenous segments prior to any classification (Baatz and Schape, 1999). This method especially in forest studies will reduce the local spectral variation caused by crown textures, gaps and shadows. In addition, with spectrally homogeneous segments of images, both spectral values and spatial properties, such as size, shape and texture can be explicitly utilized as features for further classification (Yu et al., 2006). In spite of this, trees vary in crown size/shape and optical properties. This problem depends upon a variety of factors include the age/height/health and freshness of the tree, the dominance of the tree within the stand (e.g. dominant, sub-dominant, suppressed), the sensor-target geometry, topography, illumination and the location in the image (Hirschmugl et al., 2007; Rafieyan et al., 2009). So these parameters should be taken into consideration in the classification framework.

To our best knowledge, few studies have been done in forests of Iran using UltraCamD images (Sohrabi, 2009) and these data have not been evaluated using object-based method in the country. This case study is a part of comprehensive study which has been done as PhD thesis. It has been done in 2 areas of total 10 separate areas; include the damaged natural broadleaved forest and the broadleaved and coniferous mixed forestation (Figure 1b). The investigation presented in this paper has been conducted to assess the potential of the proposed object-based method with high spatial resolution airborne remote sensing data (UltraCamD) in tree species identification and mapping.

2. STUDY AREA

The research was conducted in the plain forests nearby the town Nur in the south of Caspian Sea. The study area is a part of Hyrcanian forests in North of Iran (Figure 1a). It is relatively flat and the height above sea level is approximately 150 m. Because of the degradation in last decade reforestation with broadleaved and coniferous trees have been performed in some parcels. Two separate zones from these forests were selected (Figure 1b).

The first study area (hereafter named Area1) with an area of 3.5 ha, is an open forest that has been occupied dominantly with *Gleditsia caspica* (GL). *Carpinus betulus* (CA), *Pterocarya fraxifolia* (PT) and the shrubs of *Rubus fruticsos* (RU) distributed irregularly and natural regeneration established in some areas (Figure 1c).

The second study area (Area2) covers a forested stand with an area of 2.8 ha and it is more homogeneous in species composition, stocking density and canopy structure (Figure 1d). The dominant planted tree species are *Acer velutinum* (AC) along with *Cryptomeria japonica*. *Gleditsia caspica* (GL) and *Cupressus arizonica* (CU) are placed on the south eastern part of this area

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(Figure 1d). Most of the CU trees had been fallen down because of the heavy snow. The planted stand is relatively young (approximately 20 years old) and mostly of the same age and height.

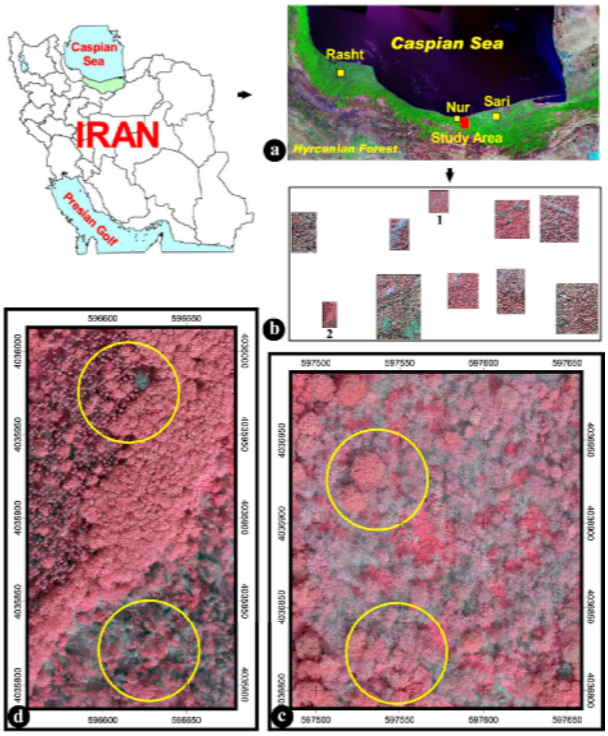


Figure 1. Location of the study area: Location in Hyrcanian forests (a), 10 separate regions studied as a comprehensive research (b), Overall view of Area1 and Area2 and ground truth plot site (yellow circles) in each of them (c and d). Images are displayed in 432 (RGB) false colour composite.

3. METHODS

3.1 Imagery Pre-processing

For the present study, two pan-sharpened colour images were obtained. The images contain the full resolution 16-bit (i.e. 12 bit stored as 16 bit). There were collected in 17th October 2008 from an aircraft at 800 m above ground level with a spatial resolution of 7 x 7 cm.

Exterior orientation parameters provided by an onboard GPS/IMU navigation platform (Neumann 2005). Using these parameters (X, Y, Z, ω, φ, κ) and ground control points, the geometric correction of the multispectral imagery was accomplished. An optimal number of ground control points were derived using differential GPS to increase the geometric corrections of the imagery.

In segmentation and classification processes, transformed images like NDVI, HIS and PCA have also been produced and used beside origin spectral bands.

3.2 Segmentation

The segmentation approach is a bottom-up merging process based on heterogeneity of image objects and controlled by three parameters: *color/shape*, *compactness/smoothness* and *scale parameter* (Benz et al., 2004).

There is not any tools to determine the ideal parameters, so a trial and error method was employed. The initial *scale parameter* setting was determined by visual inspection. It is obvious that the segments should not be so large as to encompass multiple trees from different species. Final selected parameters to achieve the ideal segmentation results were showed in table 1.

Table 1. considered parameters in the segmentation process.

Study Area	Color	Shape		Scale Parameter
		Compactness	Smoothness	
1	0.5	0.1	0.9	1000
2	0.5	0.1	0.9	800

For heterogeneous data the resulting objects for a given *scale parameter* will be smaller than in more homogeneous data. It is important to produce image objects of the biggest possible scale which still distinguishes different image regions (as large as possible and as fine as necessary) (Definiense Reference Book, 2006). In addition to original spectral bands, NDVI was considered as input data in segmentation process. The result of the final segmentation in the part of Area2 has been illustrated in Figure 2.

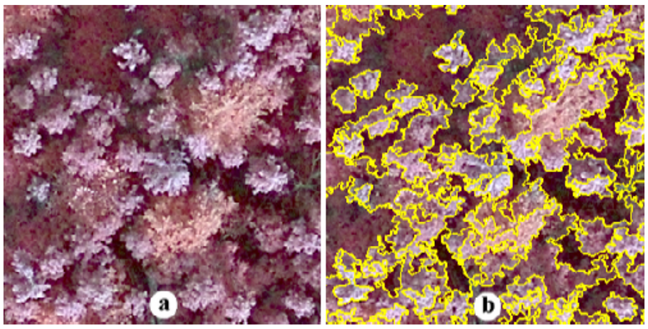


Figure 2. The results of segmentation in the part of Area2: the original image (a), the result of segmentation (b).

3.3 Classification

Considered classes in both study areas have been represented in Figures 3e and 4c. The exposure to the direct sunlight may cause tree crowns partially lighter (i. e. *AC in full sun*) and being under higher canopy shadow would cause them darker in some parts (i. e. *AC in shadow*). So each of these child classes would be defined in a distinct class. These two classes on the whole headed genus of that tree i. e. *AC* in group hierarchy.

Sample objects were selected as representative of defined classes. Samples for each class were selected from the image objects to act as training areas for the classification according to the field measurement results.

Nearest Neighbour classifier was utilized to classification. Consequently, after testing features and different bands, also correction of training areas, optimum classification framework was selected and finalized. In order to find the best classification result, *Class separability*, *Best classification results*, *Class stability* and *Accuracy assessment*, was considered based on training area and ground truth. Utilized features for both study areas mostly included spectral features such as "mean", "standard deviation", "ratio", "brightness" and "Max diff". Saturation, NDVI and PCA processed bands were utilized in addition to 4 main original bands (R,G,B,IR) in both study areas. The resulted maps were showed in Figures 4a and 5c.

3.4 Field Data Collection

In each of the areas, couples of circular plots were acquired in the field to generate the ground truth maps. These plots with an area of 0.28 ha, cover about 16 and 20 % of Area1 and Area2 respectively. Existing images were used to design the sample plots and tree information was collected by the field survey.

Field measurement was done in October 2009. After finding plot center using differential GPS receiver, diameter at breast height (DBS) was measured and tree species was recorded for all trees thicker than 15 cm, in a radius of 30 meters from plot center. To geo-locate the trees, distance and azimuth for each tree was measured using laser distance meter and precise compass. According these gathered data tree's location point map in the plot was prepared. In the next stage, a large scale photomap of plots was produced and printed. Attending in the field for the second time, each tree crown area was determined and after correction of errors on photomap, a tree species polygon map was resulted. (Figures 4b and 5b).

Accuracy assessments of both classifications were undertaken using confusion matrices. Producer's and User's accuracies for each class were calculated along with the overall accuracies and Kappa statistics (Congalton, 1991; Lillesand and Kiefer, 2000).

Coincident with gathering field data for preparing ground truth map, adequate number of individual tree species with proper distribution was selected in the area. The trees species were written down on a related tree crown on the printed image map to be used as training areas (Figure3). These trees were all selected outside of the plots area in order to not interfering in final accuracy assessment.

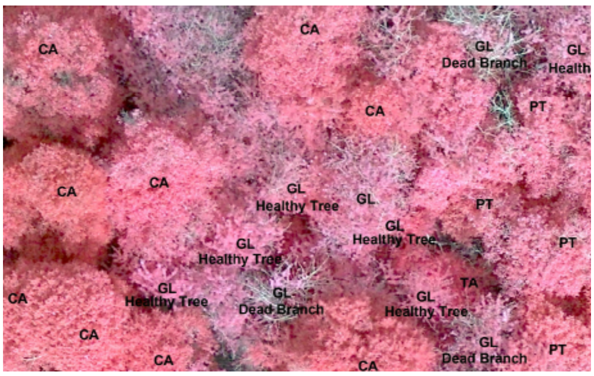
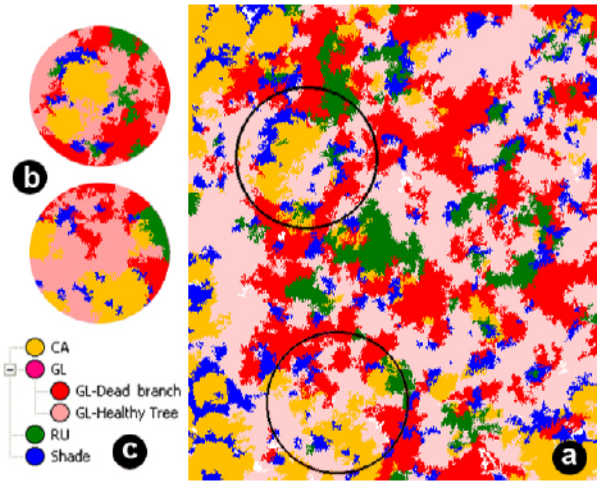


Figure 3. The appearance of some main species on the image in the small part of Area1.

4. RESULTS

4.1 Area1

Classification output is illustrated in Figure 4. According to the map presence of *GL* trees is noticeable and there are plenty of these species with dead branches in this area.



Feature 4. Classification results and the boundary of ground truth plots on it (a), the ground truth plots (b) and class hierarchy (c) in Area1.

Overall accuracy and Kappa index for detailed classification was 0.73 and 0.63 respectively (Table 2). On the basis of KIA, lowest accuracy was achieved by *GL-Healthy* Tree which was caused by confusion with class *CA*.

Table 2. Error matrix of classification accuracy assessment based on detailed classes in Area1.

User \ Reference Cl	RU	CA	GL-Dead branch	GL-Healthy Tree	Shade	Sum
Confusion Matrix						
RU	51127	1114	1822	14334	0	68397
CA	7713	172946	10433	67091	102	258285
GL-Dead branch	2521	849	232577	36356	2780	275083
GL-Healthy Tree	9472	73951	31398	331055	0	445876
Shade	13385	2069	13581	17041	59914	105990
unclassified	0	124	0	1296	3376	4796
Sum	84218	251053	289811	467173	66172	
Accuracy						
Producer	0.607	0.6889	0.8025	0.7086	0.9054	
User	0.7475	0.6696	0.8455	0.7425	0.5653	
Hellden	0.67	0.6791	0.8234	0.7252	0.696	
Short	0.5038	0.5141	0.6999	0.5688	0.5338	
KIA Per Class	0.5824	0.5996	0.741	0.5263	0.8959	
Totals						
Overall Accuracy	**0.7317**					
KIA	**0.6312**					

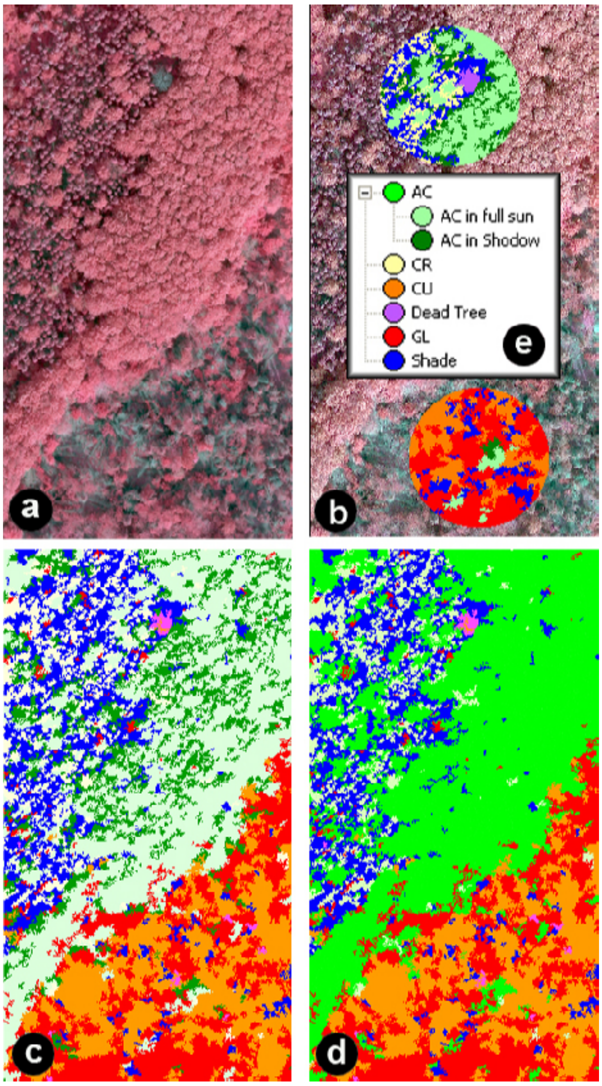
As indicated in the mentioned table, *in shadow* and *in full sun* classes' interference for *GL* was considerable and these two classes were mostly classified as each other and they reduced the accuracy. Thus these classes merged together in the next stage and create a general class named *GL*. The results of the accuracy assessment of final main classes are represented in Table 3. Accordingly, overall accuracy and Kappa index were determined 0.79 and 0.61 respectively.

Table 3. Error matrix of classification accuracy assessment based on main classes (integrated child classes) in Area1.

User \ Reference C	GL	RU	CA	Shade	Sum
Confusion Matrix					
GL	631386	11993	74800	2780	720959
RU	16156	51127	1114	0	68397
CA	77524	7713	172946	102	258285
Shade	30622	13385	2069	59914	105990
unclassified	1296	0	124	3376	4796
Sum	756984	84218	251053	66172	
Accuracy					
Producer	0.834	0.607	0.6889	0.9054	
User	0.8758	0.7475	0.6696	0.5653	
Hellden	0.8544	0.67	0.6791	0.696	
Short	0.7458	0.5038	0.5141	0.5338	
KIA Per Class	0.5606	0.5824	0.5996	0.8959	
Totals					
Overall Accuracy	**0.7902**				
KIA	**0.6082**				

4.2 Area2

Figure 3 gives an overview of classification stages and results in Area2. The classification could be compared with the original image visually.



Feature 5: Classification stages and class hierarchy in Area2: Original image (a), ground truth plots on the image (b), resulted classified map according to detailed classes (c), final tree species map after detailed class's semantic grouping (d) and class hierarchy (e).

Accuracy assessment results in Area2 are represented in Table 4. As it could be considered, overall accuracy and Kappa index of 0.72 and 0.66 were achieved respectively. *AC in Shadow* and *GL* classes have the most notable classification error in this area. The first one was wrongly classified as class *Shade* most of the time and *GL* was often confused with *CA*.

Final merged child class's accuracy assessment was showed in Table 5. In this case overall accuracy and Kappa index increase to 0.76 and 0.69 respectively.

Table 4. Error matrix of classification accuracy assessment based on detailed classes in Area2.

User \ Reference Cl	CR	Shade	Dead Tree	AC in Shadow	AC in full sun	CU	GL	Sum
Confusion Matrix								
CR	61530	2546	0	3391	22158	1	1711	91337
Shade	3439	138651	0	33725	152	1630	1162	178759
Dead Tree	837	753	11220	0	0	2583	0	15393
AC in Shadow	8293	7042	0	69999	29363	317	5099	120113
AC in full sun	6292	293	0	15763	207443	45	4537	234373
CU	0	46389	1843	245	0	149467	81115	279059
GL	3118	4158	0	6039	6629	17199	203208	240351
unclassified	0	0	0	0	0	0	135	135
Sum	83509	199832	13063	129162	265745	171242	296967	
Accuracy								
Producer	0.7368	0.6938	0.8589	0.5419	0.7806	0.8728	0.6843	
User	0.6737	0.7756	0.7289	0.5828	0.885	0.5356	0.8455	
Hellden	0.7038	0.7325	0.7886	0.5616	0.8296	0.6639	0.7564	
Short	0.5430	0.5779	0.6510	0.3905	0.7088	0.4968	0.6082	
KIA Per Class	0.7143	0.638	0.857	0.489	0.725	0.8325	0.6017	
Totals								
Overall Accuracy	**0.7257**							
KIA	**0.6660**							

Table 5. Error matrix of classification accuracy assessment based on main classes (integrated child classes) in Area2.

User \ Reference Cl	CR	Shade	Dead Tree	AC	CU	GL	Sum
Confusion Matrix							
CR	61530	2546	0	25549	1	1711	91337
Shade	3439	138651	0	33877	1630	1162	178759
Dead Tree	837	753	11220	0	2583	0	15393
AC	14585	7335	0	322568	362	9636	354486
CU	0	46389	1843	245	149467	81115	279059
GL	3118	4158	0	12668	17199	203208	240351
unclassified	0	0	0	0	0	135	135
Sum	83509	199832	13063	394907	171242	296967	
Accuracy							
Producer	0.7368	0.6938	0.8589	0.8168	0.8728	0.6843	
User	0.6737	0.7756	0.7289	0.9100	0.5356	0.8455	
Hellden	0.7038	0.7325	0.7886	0.8609	0.6639	0.7564	
Short	0.5430	0.5779	0.6510	0.7557	0.4968	0.6082	
KIA Per Class	0.7143	0.638	0.857	0.7362	0.8325	0.6017	
Totals							
Overall Accuracy	**0.7647**						
KIA	**0.6963**						

5. DISCUSSION

Segmentation-based classification can only be as good as the underlying segmentation. Inaccuracies encountered here cannot be corrected at a later stage. No segmentation result -even if it is quantitatively evaluated- will be fully convincing, if it does not satisfy the human eye (Baatz and Schape, 1999). In this case the separation of different regions is more important than the scale of image objects. (Definiense User Guide, 2006).

The crown of mature deciduous trees is often interlocked and not always possible to delineate with geometrical information. Therefore, the shape of the objects has no obvious pattern and texture that could be used as evidence for classification (Yu et al., 2006).

Obviously if the field surveying date for preparation of the ground truth map close to the imagery date as much as possible and minor changes occurred in this duration of time, the result of accuracy assessment would be more reliable. In this case study, field measurement has been done just one year after imagery date in the same season and some probable annual changes in trees crown such as colour alteration of the leaves in fall would be considered in their appearance in the images.

6. CONCLUSIONS AND OUTLOOK

There are variety and helpful facilities in object-based classification method such as easily utilizing ancillary data and using Fuzzy classification method. But in order to finding out which features composition, in which classification method, by which imagery or thematic data and at which weighting rate the best classification result is accessible, it would be needed to have better knowledge and proficiency about utilized data, used methods and considered features.

As showed in several previous studies, the standalone optical remote sensing methods are insufficient for classification of complex forest structures. This is particularly true for initial stages and heterogeneous mature stands. Classification of tree species composition with such high level of detail and accuracy would be suitable to combine with DSM, DTM or LiDAR data for advanced 3D stand modelling (Naesset and Gobakken, 2005; Baltsavias et al., 2007; Chang et al., 2008; Matthew and Ramanathan, 2008; Hirschmugl et al., 2007). But these kind of data have not been yet produced particularly in the forests of Iran.

The accuracy of detailed vegetation classification with very high-resolution imagery is highly dependent on the segmentation quality, sample size, sampling method, classification framework, and ground vegetation distribution and mixture (Yu et al., 2006; Rafieyan et al., 2009). A satisfactory level of accuracy can be very difficult to achieve in deciduous mixed forests, where several species of one family or genus coexist in a stand with interlaced crowns.

To evaluate the data and applied method in this study and to improve the accuracy of the classification, similar studies are necessary in different forest structures like degraded stands, undisturbed and old-growth forests and forest parks established in natural forests.

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