OBJECT-BASED CLASSIFICATION OF UNMANNED AERIAL VEHICLE (UAV) IMAGERY FOR FOREST FIRES MONITORING

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ABSTRACT: In recent years using of UAV has rapidly increased in assessment and monitoring of forest related studies. Due to higher spatial resolution of UAV images, make them possible to use for the extraction of forest and tree species with higher accuracy. However, the orthophoto map produced from Unmanned Aerial Vehicle (UAV) images must be evaluated and interpreted quickly. Different image classification methods are used for this purpose. Currently, object based image classification method which extracts data with high accuracy from high spatial resolution images has been used as popular classification technique. In this study, Camburnu Natural Park in Surmene District of Trabzon Province located in the Black Sea Region was selected as the study area. This area is unique in the world where yellow pine forests can land at sea level. An unpredicted forest fire realized on January, 8 2017 and around 20 hectares were destroyed. To determine destroyed area, current high resolution UAV images of study area were obtained and image pre-processing steps was employed. Object based classification is applied in two part as segmentation and classification. Firstly, multiresolution segmentation is processed for optimum parameters (scale, shape, color, compactness and smoothness) and segments are assigned proper classes by rule based. In this way images are classified by using object-based classification method. As a result, optimum parameter is determined for segments. The boundaries of forest and burned forest in the study area have been handled with high precision in vector format without salt and pepper effect.

1. INTRODUCTION

Determining the areas that are changing over time due to natural or human-induced causes has great importance for future planning and making rational decisions. For this purpose, there is a need for up-to-date data that will reveal the current situation after fires that have occurred in forest areas. These regions must be monitored at specific time intervals in order for identify these changes. In determining the areas that have been damaged; aerial photos, classical measuring methods (such as electronic distance meter, GNSS), LIDAR (Light Detection and Ranging), Unmanned Aerial Vehicles (UAVs) and satellite images (high or medium resolution) can be used (Nichol et al., 2006). Recently, the evaluation of the images (obtained by UAVs) using the digital photogrammetry techniques has started to be widely used. UAV technology has significant advantages in terms of speed, cost and accuracy.

Since 2009, there has been an increase in the studies on the availability of UAVs in disaster studies. Automatic image extraction with electronic systems has been carried out and these images were used to produce digital terrain models (DTM) and orthophotos. Measurements and interpretation processes were performed on digital images to execute volume calculations and emergency response studies to the affected areas. Some studies have been carried out on obtaining high-resolution landslide images and monitoring landslides (Niethammer et al., 2010), disaster management and monitoring (Chou et al., 2010), management of search and rescue operations (Chiabrando et al., 2011), and mapping of landslides (Ozturk et al., 2016).

Interpretation of the Photogrammetric data produced by visual interpretation or similar methods requires too much time and operator work. It's almost impossible to interpret the damage that occurred in the big diameter areas from this point of view. For this reason, satellite images or orthophotos can be interpreted using classification techniques. In addition, work can be carried out quickly and automatically to determine how much area was damaged after the fire and what operations are to be done. The classification process can be generalized as the process of aggregating objects with similar spectral reflectance values under the same class. In other words, it is the process of comparison the values of all pixels on each band to the pixels of the image and classifying the similar pixels into the classes or class numbers that the user has identified (Campbell, 1996). The purpose of the classification process is to increase the discriminability of data groups with the same spectral characteristics by collecting them under the same group. The desired classes to be extracted from an image can be determined by the user or can be done randomly by selecting only the number of the class (Lillesand et al., 2007). In this context, considering the basic unit and the structure used in classification, it is possible to mention two types of classification as pixel-based classification and object-based classification.

Pixel-based classification is a classification method that classifies all pixels in an image using multispectral classification techniques by comparing their spectral proximity with the class to be assigned. Unlike pixel-based classification, object-based classification does not work on directly on a single pixel. These methods work on objects that are composed of many pixels, grouped in a meaningful way by the segmentation process. Then these objects are used instead of pixels as a classification object (Carleer and Wolff, 2006; Blaschke, 2010).

Over the last decade, spatial resolutions of satellite sensors have undergone tremendous improvements and very high resolution satellite imagery or orthophoto images are started to be used (Duric et al., 2014). In very high resolution satellite images classified by the pixel-based method, the results are inconsistent and cannot meet the desired expectations (Antunes et al., 2003). In particular, the pixel-based classification of objects with sharp or continuous boundaries, such as buildings, roads, agriculture and forests, does not achieve the expected results. As a result of the inability to fully reflect the rich content of these images using the pixel-based classification method, new image processing and classification methods have begun to be investigated and it has been found that object-based classification gives more precise results than pixel-based classification (Wong et al., 2003; De Kok et al., 1999). The idea of classification over objects has arisen from the fact that the characteristic texture property in the image is neglected in other classical methods (Blaschke et al., 2001).

In this study, high resolution orthophoto of the area was produced by using the Photogrammetric evaluation methods using images of forest fire area taken with the UAV. Using this image, the most appropriate segments were determined by the object-based classification method (with E-Cognition software) for the required details to be extracted from the produced orthophoto. For this purpose, the trial and error method and Estimation Scale Parameter Tool (ESP) were used. By using these approaches, the most appropriate segment was determined for the damaged areas after fire. Using the existing bands in the orthophoto, index images in gray color tone were created. Burned areas and normal areas were removed from these index images. Usability of UAV images in forest fires has been examined.

2. METHODOLOGY

In recent years, important developments have been made in remotely sensed images and the classification methods for the need of fast and accurate data production. Unmanned Aerial Vehicle (UAV) images which provide spatial resolution in centimeters and rich content have begun to be used in Remote Sensing. In very high resolution images classified by the pixel-based method, the results are inconsistent (salt and pepper effect) and details cannot meet the desired expectations (Antunes et al., 2003). Since the rich content of these images cannot be fully reflected by the pixel-based classification method, new image processing and classification methods have begun to be investigated and it has been shown that object-based classification gives more precise results than pixel-based classification (Wong et al., 2003; De Kok et al., 1999). The idea of classification over objects has arisen from the fact that the characteristic texture property in the image is neglected in other classical methods (Blaschke et al., 2001).

The object-based classification method consists of two stages as segmentation and classification of segments. In the first stage, neighboring pixels are combined until the desired details are extracted and appropriate segments are created for the classification process in the second step. Segmentation is the process of separating images into objects or areas that reflect the same characteristics. Segmentation is the main element for creating objects from image pixels (Navulur, 2007). Successful object-based classification depends on the quality of the segmentation phase. If a good segmentation stage is achieved, better results are obtained than pixel-based classification (Yan et al, 2006). Misidentification of segments will also affect the classified image in the negative direction. Therefore, it is necessary to create the ideal segments as a result of this process (Bilgilioglu, 2015). The number of image objects and homogeneity are important in the segmentation process. In addition, the scale, color shape and compactness / smoothness parameters are important features used in the segmentation process (Marangoz et al., 2005). Within this process, the accepted ESP and trial-and-error are effective methods for determining the most appropriate segments (Bilgilioglu, 2015). In the second stage, the classification process, objects of gray color tone are created using the objects' band, shape, texture and neighborhood properties or combinations thereof. Subsequently object extraction is performed with the rules specified for the desired classes (road, building, green area, soil, etc.) to be extracted from the objects in this gray color tone (Pankiw, 2013). An object can only belong to one class in the created combination. Separate rule definitions for all classes are made and the classification process is completed (Marangoz, 2009).

3. CASE STUDY

In this study, Camburnu Natural Park in Surmene District of Trabzon Province located in the Black Sea Region was selected as the study area (Figure 1). An unpredicted forest fire realized on January, 8 2017 and around 20 hectares were destroyed. In the area of approximately 8 hectares determined as the test area, 511 high resolution images were obtained by carrying out flights from the flight height of 80 meters with UAV.



Figure 1. Study area (Trabzon-Turkey)

Algorithms used in computer vision-based digital photogrammetric software can achieve more accurate image matching with 80% overlap and 60% side lap. For this reason, all flights made in the study area were made considering this coverage ratio. These images were obtained using DJI Phantom 4 type UAV (Figure 2). General features of used UAV;

- Image size 4000*3000 pixels
- 1/2.3"CMOS sensor
- 35 mm focal length
- Pixel size 6 mm x 4 mm



Figure 2. DJI Phantom 4

Agisoft Photoscan software was used for Photogrammetric evaluation of the images. Digital photogrammetric techniques were applied through this computer vision-based software to produce approximately 4 cm resolution orthophotos from the images. A high production type has been chosen for the production of orthophotos in order to be able to perform the classification of the orthophoto which is the main aim of this study more precisely and correctly.

3.1. Determination of Classes

The details to be extracted in this study are determined as damaged forest areas and undamaged forest areas. Sampling areas were selected with the aim of determining the most suitable indices and band combinations. These sampling areas were created with the help of data collected from both the existing maps and study area.

3.2. Segmentation

The quality of objects created by segmentation directly effects the accuracy of classification (Bo and Han, 2010). The selection of these objects is usually determined by trial and error method (Kim et al., 2008). However, there have been recent attempts to automate this process (Witharana and Civco, 2014). Drăgut et al. (2010) have developed a scale parameter estimation (ESP) tool that calculates the scale parameter quickly and easily using the local variances of the image. In this method, a graph that estimates the scale parameter is drawn using the local variance values (Kavzoglu, 2015).

3.2.1. Segmentation by ESP Method

In recent years, scale parameter estimating tools which automatically determine the scale parameter have begun to be developed. The scale parameter estimation (ESP) tool developed by Drăgut et al. on Cognition Network Language (CNL) environment of eCognition Developer in 2010 is the most preferred one (D'oleire-oltmanns ve Tiede, 2014). Drăgut et al. improve this tool in 2014 to develop a ESP2 based tool on statistical analysis of local variance. The ESP2 tool determines the scale parameter by defining eleven parameters. These parameters are; three different scale parameter increment quantities, three different scale parameter start, number of loops, confirmation of use of hierarchy, type of hierarchy usage, shape and compactness parameter (Figure 3).

t Process			?
Name		Algorithm Description	
ESP2 (Estimation of Scale	e Parameter 2)(1,1,1,1,1,1,10,1,100	Algorithm parameters	
Algorithm ESP2 (Estimation of Scale Parameter 2)		Parameter	Value
		Select map	main
		Use of Hierarchy (0=no: 1=ves)	1
Domain		Hierarchy: TopDown=0 or BottomUp=1 ?	1
execute ~		Starting scale_Level 1	1
		Step size_Level 1	1
Parameter	Value	Starting scale_Level 2	1
Threshold condition		Step size_Level 2	10
Map	From Parent	Starting scale_Level 3	1
		Step size_Level 3	100
		Shape (between 0.1 and 0.9)	0.1
		Compactness (between 0.1 and 0.9)	0.5
		Produce LV Graph (0=no; 1=yes)	1
		Number of Loops	100
Loops & Cycles			
Loop while something	changes only		
Number of cycles 1			

Figure 3. ESP2 tool parameter setting display



EPS – LEVEL 1

EPS - LEVEL 2

EPS - LEVEL 3

Figure 4. ESP2 Segmentation levels

3.2.2. Segmentation by Trial and Error Method

There are three parameters in the segmentation process which are: scale parameter, shape parameter and compactness parameter. There is no significant effect of the compactness parameter on the generated segments (Kavzoglu, 2014). For this reason, the compactness parameter was taken 0.5 and the scale and shape parameters were tested. Firstly, we tried to find the most appropriate scale parameter for the orthophoto by giving the values of compactness parameter 0.5, shape parameter 0.1 and scale parameter between 10 and 200.

Experiments made for the scale parameter in the orthophoto are shown in Figure 5 and the experiments made for the shape parameter are shown in Figure 6.



Figure 5. Scale parameter study for orthophoto



Figure 6. Study of shape parameter for orthophoto

In the first step, 10 scale parameters are used to determine the scale parameter. The scale parameters (20, 30, 40, 50, 60, 70, 80, 90, 100, 120) determined by keeping the compactness and shape parameters constant have been tested one by one. Every detail has its own scale parameter. For this reason, it is important to select segments according to the desired detail. For example; the ideal scale parameter for extraction of forest detail is 70 while the ideal scale parameter for extraction of road detail is 120. If we extract the forest detail with the scale parameter set for the road, the wrong segments will appear as shown in figure xxx, so the classification process will be incorrect. The second step is to determine the target shape parameter. For this purpose, trial and error method was applied to find the ideal shape parameter while keeping the scale and compactness parameter constant. For this purpose, 9 shape parameters (0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9) were applied and tested one by one (Figure 6).



Figure 7. Segments created with inappropriate parameters (missegmentation).

Selecting parameters that are inappropriate for the detail requested to be extracted from the image may cause the segments that will negatively affect our classification result. Selecting the wrong parameter as shown in figure 6 can result in a mixture of forest with the building (Figure 7a), burned forest with healthy forest mixture (Figure 7b-7c), forest and soil mixture (Figure 7d). The classification to be made with these incorrect segments will also be incorrect.

3.3. Determination of Burned Forest Areas

In order to apply object-based classification to the orthophoto, band combinations in the literature have been investigated. Classification has been performed according to these band combinations.

GRVI (Green-Red Vegatation Index)	=	(Green-Red)/(Green+Red)	(1)
RRI (Red Ratio Index)	=	(Red/(Blue+Green+Red))*100	(2)
GRI (Green Ratio Index)	=	(Green/(Blue+Green+Red))*100	(3)

The current maps and the training data obtained by the field studies are processed on the image and the values in the existing indexes are analyzed. According to these analyzes, the best combination to separate burned forest and building details is GRVI (Figure 8a), to separate burned forest and road details is RRI (Figure 8b) and the best combination to separate forest and burnt forest details is GRI (Figure 8c).



Figure 8. The indexed values of the classes specified (burned forest (black), other details (blue))

In this 3 band combination (GRVI, RRI, GRI) the intersection of the values of the burnt forests was taken to eliminate both the confusion between the details and to obtain a better classification result (Figure 9). Thus, burned forest extracted from image without any mixed pixel.

4. RESULTS

In the object-based classification method, the first process is the segmentation process. Segmentation results directly affect the accuracy of the classification result (Bilgilioglu, 2015). In this study, accepted ESP and trial-and-error methods were used and the most appropriate segments were created. As a result of the researches, it is seen that segmentation can be made faster by ESP method, but it is also seen that better segments are created by trial and error method because the creation of segments by trial and error method is directly connected to the user.

The second step in object-based classification is to assign the created segments to classes. For this purpose, the images were converted into gray color images using band combinations. The purpose of this process is to extract the properties of the desired class using the properties in the image. In this study, 3 different band combinations (GRVI, RRI, GRI) were used to separate burned forest areas from other details and burned forest areas were obtained.

As a result of this study, the use of 3-band orthophotos obtained by UAV was investigated and found sufficient for rapid determination of sudden changes in forest areas (due to landslide, fire etc.). It has been observed that the objectbased classification method used for the classification of orthophotos with very high resolution results in a more accurate and faster manner than the other classical methods with the hierarchical and automatic (semi-automatic) classification structure. However, if more detailed information is requested (tree species, healthy plant cover, etc.), the near infrared band defect in the orthophoto is seen as a disadvantage.



Figure 9. Classification result

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