ANALYSIS OF MULTITEMPORAL AERIAL IMAGES FOR FENYŐFŐ FOREST CHANGE DETECTION

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Abstract
This study evaluated the use of 40 cm spatial resolution aerial images for individual tree crown delineation, forest type classification, health estimation and clear-cut area detection in Fenyőfő forest reserves in 2012 and 2015 years. Region growing algorithm was used for segmentation of individual tree crowns. Forest type (coniferous/deciduous trees) were distinguished based on the orthomosaic images and segments. Research also investigated the height of individual trees, clear-cut areas and cut crowns between 2012 and 2015 years using Canopy Height Models. Results of the research were examined based on the field measurement data. According to our results, we achieved 75.2% accuracy in individual tree crown delineation. Heights of tree crowns have been calculated with 88.5% accuracy. This study had promising result in clear cut area and individual cut crown detection. Overall accuracy of classification was 77.2%, analysis showed that coniferous tree type classification was very accurate, but deciduous tree classification had a lot of omission errors. Based on the results and analysis, general information about forest health conditions has been presented. Finally, strengths and limitations of the research were discussed and recommendations were given for further research.

Keywords: Aerial imagery, Canopy Height Model (CHM), Object Based Image Analysis (OBIA)

1. Introduction

Nowadays, forests are in a high risk of degradation because of natural and anthropogenic factors. These factors include deforestation, forest fires, pests and disease, climate change causing long dry periods resulting loss of forest areas around the globe year by year. Forest degradation can be generally defined as the reduction of the capacity of a forest to provide goods and services (FAO, 2009). Rapidly increasing forest disturbances give rise to a threat for forest health and substantial economic losses (Nabuurs et al. 2013). Therefore, accurate and cost-efficient detection of stand and tree conditions for timely forest management are needed (Näsi et al. 2015).

Remote sensing has been a valuable source of information for mapping and monitoring forests over the course of past few decades. It helps forest managers better understand forest characteristics and also provides opportunities for interpreting forest at an individual tree level. Individual tree delineation techniques enhance the derivation of parameters of interest for forest inventories such as forest stand boundaries, stand density and species composition, tree heights, etc. (Ke – Quackenbush, 2008). Various segmentation methods have been developed to delineate individual tree crowns including local maxima detection (Dralle and Rudemo, 1996), local maxima filtering with fixed or variable window sizes (Wulder et al., 2000), region growing algorithm (Erikson, 2004 a), watershed segmentation (Schardt et al., 2002). These algorithms are mostly based
on the assumption that there are “peaks” of reflectance around the tree tops and “valleys” along the canopy edges (Chen et al. 2006).

The region growing method needs seed points for each region before growing. To find these points, the first band of the image is thresholded with a chosen threshold (20% of max) and a distance transform is performed on the resulting image. The resulting distance image is smoothed with a Gaussian filter and local maxima in the smoothed image are found. These maxima constitute the seeds. Each seed is then grown to become a region. The order each pixel connects to a region is decided by the pixel value if the pixel is a border pixel of a region. If it is not a border pixel it has to wait until that is the case before it is connected to a region. The higher the value of the border pixel the faster it is connected to a region (Erikson 2004b).

This paper aims to develop an effective methodology to identify coniferous and deciduous tree types in individual tree crown level, evaluate their health status and changes in forest parameters between 2012 and 2015 years in Fenyőfő forest reserves by remote sensing.

**Study site**

Fenyőfő is a village located at the height of about 270 meters in the northern Bakony mountains of Trans Danubian region (47.35054°N 17.76517°E), Hungary. The number of Fenyőfő’s inhabitants is 155 and the area of the settlement is 863 ha. Research site is a part of forests in a Fenyőfő village with an area of approximately 108 ha (Fig. 1.). Vegetation is mostly scots pine (Pinus sylvestris L.) on sandy soil (Festuco vaginatae - Pinetum sylvestris), other types of scotch pine (Festuco rupicolae – Pinetum sylvestris) and mixed sessile oak (Quercetum petraeae – cerris pannonicum) (Dövényi 2010). According to Gulyás et al. (2014) unfavorable conditions of soil (low water capacity, sandy soils with calcium carbonate content in the topsoil) occurred together with high temperature values in summer periods in the last years leading the trees to die of or diseased. They (Gulyás et al. 2014) investigated that according to the texture of the soil, area contains 56% of sand and 42% of loam. The ground water level is between 4 and 6 meters, which is not available for lower vegetation.
Climate conditions

Climate conditions of the research area are medium wet and medium warm. Annual precipitation is 600-650 mm and annual mean temperature is 10.0 °C. The mean temperature of the warmest month of the year is 19.7 °C and mean temperature of the coldest month of the year is 2.1°C (Gulyás et al. 2014). Yearly sunny days exceed 1980 hours (Dövényi 2010).

Research objectives

Main objective of this research is to develop methodology to classify coniferous and deciduous forest stands, diseased tree extraction and evaluate changes in forest parameters between 2012 and 2015 years in Fenyőfő forest reserves using high resolution aerial images.

2. Materials and methodology

Data

Orthomosaic and point cloud

We were provided with orthophoto-mosaic with RGB and NIR bands and point cloud datasets of the study area from 2012 and 2015 years by the Institute of Geodesy, Cartography and Remote Sensing (FÖMI) in Budapest. Point clouds from 2012 and 2015 datasets cover 280 hectare area including the study area and its surroundings and consist of 16 992 408 and 19 235 821 number of points with RGB color respectively. Density of the point cloud is 6.07 points/m² and 6.87 points/m² for 2012 and 2015 datasets respectively.

Point clouds and orthomosaics had been derived from high spatial resolution aerial images captured by UltraCAM X on the 20th of August, 2012, and on the 12th of May, 2015. Images acquired with 16 bits radiometric and 40 centimeter spatial resolution, visible (RGB) and near-infrared (NIR) bands. Spectral responses of the camera are 410-540 nm for Blue band, 480-630 nm for Green band, 580-700 nm for Red band and 690-1000 nm for Near-Infrared band (USGS 2010).

National Forest Inventory data

National Forest Inventory (NFI) data were obtained from the respective forest management company Bakonyerdő Corporation. Those inventory data had been collected according to forest law (2009/XXXVII. Law) and its 11/2010. agricultural ministerial decree (11/2010. (II. 4.) FVM decree), which includes the characteristics of the forest stands (33. § (2) c). The tree type (coniferous/deciduous), number of trees, crown closure and average tree heights were used from those characteristics collected in the field.

Ground Control Points

20 Ground control points (GCPs) randomly distributed over the study area were measured in a ground survey on 23rd of March, 2016. Three-dimensional positions of these points were measured with a geodetic GPS with differential correction (Leica GPS1200) to get better accuracy, less than 10 centimeters for X, Y and Z coordinates in our case. These points were used to estimate the geometric accuracy of orthophoto-mosaics and digital surface models.

Field check materials

Results were checked on 31 May 2016 in the approximately 2.2 hectare sample plot on the North-Western part of the study area by using Trimble Juno series for tracking and registering individual trees and TruePulse 360B Laser Rangefinder for sample tree height measurement. Finding each tree in the plot has been performed by tracking orthoimage uploaded to Trimble Juno, we tried to find some separable tree crowns or gaps in the field and corresponding places in the image for orientation, and registered along with neighboring trees as a point vector layer and recorded attributes, such as tree types and health status. Height measurement
was quite difficult, because many lower layer
trees and low vegetation such as blackberries
prevented to measure the basement of trees
with rangefinder. We tried to measure some
trees that are close to the gaps and streets,
and which have an accessible top within 45
degrees of vertical angle to get good accuracy.
Field data were used to evaluate the accuracy
of automatic segmentation, classification,
health status and height of individual trees.

**Topographic map**

We also had 1:10 000 scale topographic
map of the study area in EOV (Uniform
National Projection system) projection
created by FÖMI in 2003 based on
photogrammetric methods. Topographic
map was used to create DTM by digitizing
contour lines, creating Triangulated Irregular
Network (TIN) and “TIN to Raster” tool in
ArcGIS 10.2.

**Methodology**

DSMs of study area were generated
by using OPALS software with 0.5 meter,
0.75 meter, 1 meter grid sizes by using
span, moving planes and moving parabola
algorithms to compare and select the optimal
surface model for individual tree detection.
In order to select the optimal DSM, first, CHM
and tree peaks were created by applying the
local maxima algorithm for each created
DSM. Locations of the peaks were visually
estimated based on the corresponding
orthomosaic and DSM. We selected the DSM
created by moving planes algorithm with 0.75
meter grid size, because according to visual
interpretation this model had relatively less
omission and commission errors in tree peak
generation. Moving planes algorithm works
such a way that, for each grid cell n nearest
points (parameter neighbors) are queried
and a best fitting tilted plane (minimizing the
vertical distances) is estimated. The height
of the resulting plane at the grid point (x, y)
position is mapped to the grid cell. The tilted
plane interpolator allows the derivation of
slope measures (nx, ny, slope, exposition)
for each grid point. (http://geo.tuwien.ac.at/
opals/html).

Canopy Height Models (CHM) had been
calculated by subtracting DTM from DSM
for both years using raster calculator tool in
ArcMap 10.2 software. CHMs were the base
for tree peak extraction and delineation of
individual tree crowns.

Geometric accuracy of orthomosaic was
checked by using ground control points
measured in the field with GPS (Leica 1200)
software. We had less than 10 centimeters
RMS error for both images for X, Y directions.
Also, reflectance values of the images were
checked by examining histograms for better
understanding the image.

![Fig. 2. Histograms of 2012 (a) and 2015 (b) images. Both images were stretched with Percent clip stretch type](attachment:image.png)
As we can see from the histogram (Fig. 2a.), radiometry of images not covered full 16 bit range (0 to 65536) in 2012 image, it ranges from 1681 to 22902 only, which caused less detailed image. But, radiometric range of 2015 image (Fig. 2b.) is much better, from 4432 to 56770, which resulted a much better image dynamic.

**Tree peak detection**

Tree peak detection was partly based on the work of Kumar (2012). CHM was masked and extracted the pixels above 2 meters from the ground to exclude ground vegetation, streets, gaps and other non-forest cover areas. Low pass filter was used to smooth the CHMs. After that, focal maximum filter was used to calculate maximum of the cells of 3 * 3 window neighborhood using ArcGIS 10.2 (ESRI). Finally, following algorithm performed on a raster calculator to identify tree peaks:

\[
\text{SetNull (Focal Maxima Raster <2, SetNull (Focal Maxima Raster =! Smoothed Raster, Focal Maxima Raster))}
\]

Visual interpretation had been applied to evaluate the tree peaks by checking the locations of peaks with individual trees on the orthoimage. We found out some noise set of tree peaks, usually 4 or 5 joint pixels on the image. Following method had been used to remove those noise peaks:

Peaks converted to vector points => Integrate (1 meter XY tolerance) and buffer the result (1 meter) => Find count of points in each buffer => Remove points sitting inside buffers with more than 1 point => Merge 2 point layers and convert back to raster.

**Segmentation**

Identified tree peaks and CHMs were used to delineate individual tree crowns using region growing algorithm (Erikson, 2004 a). CHMs were smoothed by Gaussian filter in 3 * 3 square search mode and simple region growing tool in SAGA GIS was used to segment tree crowns by inputting tree peaks raster dataset and smoothed CHMs. Created segments have been vectorized and segments masked by removing non forest cover areas extracted in 2.2.1 in ArcGIS 10.2 (ESRI) software. As a result, we got single segments for each peaks for images 2012 and 2015. Full workflow of delineating individual trees is given in Figure 3.

**Classification of coniferous and deciduous trees**

As we achieved individual tree crown segments in 2.2.2, next task was to classify coniferous and deciduous trees based on the their spectral reflectance in RGB and NIR bands. CHM and orthophoto with all layers, as well as segments created in 2.2.2 had been added as a thematic layers into eCognition Developer software.

In eCognition, segmentation is the starting process of object based image analysis. As we already had segments created, those segments had been accepted for further analysis.

Then, three class types were created, including coniferous and deciduous trees and gaps. After that, the segments that were situated below 2 meters (usually, they consist of lower vegetation, streets, clear-cut areas and other) were classified as gaps with the threshold condition of CHM <2. Spectral reflectance of coniferous and deciduous
trees were analyzed to find the difference for classification. Figure 4 shows that deciduous trees have slightly higher reflectance value in NIR than coniferous.

Next, NDVI (Rouse et al. 1974) and NIR values have been analysed to classify coniferous and deciduous trees.

Finally, the classified thematic map was exported to shapefile for further analysis. The same steps with different threshold values for NDVI and NIR were used to classify image from the year 2012.

**Extraction of cut trees**

We could not find appropriate literature for cut crowns identification which could be directly applied to our research, so the following methodology was developed to extract clearcut areas and cut crowns. We assumed that if there is a hole in the CHM of 2015 and the same hole does not exist in the CHM of 2012, this hole is the subject to clearcut. And those clear-cut areas (holes) can be extracted by subtracting 2015 CHM from 2012 CHM. CHM difference (CHMD) should give us cut canopy area.

\[
\text{CHMD} = \text{CHM}_{2012} - \text{CHM}_{2015};
\]

According to the reference data (NFI), 8 meters was the minimum height of trees in the study area, using that information, CHMD masked with 2 meters to remove noise and growth difference between 2012 and 2015. Also, reference data gave information that minimum crown projection area is 25 square meters for conifers. CHMD was converted to polygon and polygons smaller than 25 m² were removed. Remaining polygons were clipped with 2012 crown segments to get individual trees that were cut between 2012 and 2015 time period.

The perspective centres of the aerial photographs were different in 2012 and 2015, that is why tree crowns in CHMs don’t fit into each other perfectly. One smaller open area seen in one image (2015) may not be seen in another image (2012) because of difference in view geometry, this also affects to image matching process, as a result, there may be false crowns which should be removed from CHMD. To remove them and leave only tree crowns that exist in 2012, we attached tree peaks derived from 2012 image file and queried to select segments that intersect with tree peaks. So that, tree crowns that existed in 2012, but cut in 2015 were extracted. Fig. 5 shows sample area showing orthomosaic of 2012 with almost full forest cover (a), orthomosaic of 2015 of the same place showing clear-cut zones (b) and extracted clear-cut crowns (c).

**Diseased tree detection**

We used eCognition software to extract diseased trees by analyzing orthomosaic and corresponding crown segments that were already created. This methodology was not successful, because in many cases tree segments did not fit to crowns perfectly but, they covered shadow areas that decrease the reflectance of individual segments. As a result, to identify threshold values to differentiate healthy and diseased trees was not possible due to their similar reflectance values.
3. Results

Tree tops

Automatic tree top identification process had found 13 537 and 14 487 tree tops for 2012 and 2015 years, respectively. These tree tops gave information about the location of trees for segmentation, and also height of individual trees.

Boxplots in Fig. 6a and 6b illustrate information about tree heights of the study area in 2012 and 2015 years. From boxplots, we can see that the median value of height of trees slightly less than 20 meters for 2012 where the number was slightly increased in 2015, which can be naturally true. Also, boxplots show that tree heights range from approximately 10 to 30 meters for both years. However, we also can see that there are quite many outliers in the boxplot. Visual interpretation was performed to check those outliers; it was confirmed that there are several trees that are smaller than 10 meters and taller than 30 meters in the study area, but the numbers are relatively low and as a result boxplots showed them as outliers.

Tree heights were grouped as smaller than 5 (< 5), 5 and 10 (5-10), 15 (10-15), 20 (15-20), 25 (20-25), 30 (25-30), 35 (30-35), 40 (35-40) for better data interpretation. Figure 7a and 7b show that height of the majority number of trees is between 15 and 25. We can see that many trees in the height group 15 - 20 grew up and moved to the group 20-25 between 2012 and 2015 years.

Accuracy of height of the trees from 2015 was checked by field measurement...
methodology described in 2.1.4 of randomly selected 16 trees. Boxplots in Figure 8a and 8b show that median values of measured heights are higher than automatically generated heights. This can be explained as tree height automatically generated cannot be equal to natural height of trees because automatically generated tops are derived from interpolated DSM and smoothed CHM (Kumar 2012). Creation of DSM and CHM are based on the neighboring pixels in a filtering window selected by the user. As a result, heights of generated tree peaks are decreased depending on the value of neighboring pixels. However, we achieved 88.5% of accurate tree heights.

Crown segmentation

Region growing segmentation gave very good results, it created individual tree crowns based on the tree tops and Canopy Height Model. We had 13 537 and 14 591 segments delineated, each representing individual tree crowns for 2012 (Fig. 9a. and 9b.) and 2015 (Fig. 10a and 10b.).
Segmentation accuracy assessment

Results were checked in a 2.2 hectare sample plot to examine the accuracy of segmentation and classification. We had 303 segments of coniferous trees were delineated in the sample plot, but 381 trees were found in the field. There was many under-segmentation errors occurred in our result. By under-segmentation, we mean one segment delineated more than one tree. Overall accuracy for coniferous trees was 75.2%. We did not succeed with individual deciduous tree delineation, because the automatic segmentation algorithm created 30 segments in the sample plot, but there were 137 deciduous trees found during the field check. A number of reasons can be the source of this under-segmentation. First of all, study site consists of mainly oak deciduous tree species and the majority of them are young trees and located close to each other, therefore they have very mixed branches which make automatic segmentation process difficult. Secondly, according to NFI, height of trees differ depending on the upper layer ranging between approximately 16 and 24 meters and lower layer ranging between approximately 8 and 20 meters. Field check also confirmed that, the height of deciduous trees is much lower than conifers and are growing under the coniferous trees, so that some of them may not be visible from aerial image. However, at least we have deciduous trees delineated as a group of trees which can also be useful for some forest management purposes.

Tree types classification

Numbers of coniferous and deciduous trees detected in 2012 are 11 355 and 2 182 respectively, and number of coniferous trees...
slightly less with 11,023 and deciduous trees was more about 60% with 3,568 in 2015 (Fig. 11).

**Classification accuracy assessment**

We had less than 5% and slightly more than 20% commission and omission errors respectively for coniferous trees, but deciduous tree classification accuracy gave 27% commission and almost 70% omission errors. Although, overall accuracy was 77.6% which is also fine. There are certain reasons of lower accuracy of deciduous tree classification.

**Extraction of cut trees**

According to our analysis, 754 trees were cut out with median height of 18 meter including 711 coniferous and 43 deciduous tree individuals between 2012 and 2015 years. Total area of clear-cut was 4.3 hectares. Despite visual interpretation and DSM were reliable enough in assessment of clear-cut detection accuracy, field checking of clear-cut areas in the sample plot also gave very good accuracy. Unfortunately, we did not have a reference data about the number of cut crowns to check our results.

**Diseased tree detection**

During the field check, we found 12 diseased trees in 2.2 sample plot, but our automatic detection methodology could not find any of them. Field investigation confirmed that many diseased trees are already leaves-off and have only stand with couple of branches left which may not be detectable in the image with 40 centimeter resolution that we had, or there are some trees which’s top is diseased only, but lower part is still healthy and can reflect big amount of infrared light, which may also be difficult to detect by remote sensing technologies.

4. **Discussion**

Aerial image taken in 2012 was not so high quality, so the segmentation and classification accuracy of that was also relatively lower. Image captured in 2015 has very good radiometric and spatial resolution, but it was not enough to detect diseased trees, higher spatial resolution would be more helpful to make segmentation more accurate and detect diseased trees.

There have been many researches on tree top detection and each of them had different data source or forest type which makes difficult to compare their results with our findings.

Since segmentation accuracy for coniferous trees was 75.2%, it means we got the same accuracy for tree top detection, because each tree segment was generated based on corresponding tree top. However, there are a couple of issues which should be considered, since tree tops gave not only three locations, but also the height of the trees as well. If we compare boxplots about tree heights (Figure 7) we can see that the height of trees is increasing between 2012 and 2015. Comparison of heights of 40 randomly selected tree segments from both years also ensured that tree heights increased with approximately 2.1 meters during this period.

However, since 2015 data are sharper, number of peaks for deciduous trees was more than 2012 data. This also confirms that
the quality of aerial imagery also influences the accuracy of the automatic tree detection.

We assume and list the possibilities to improve tree peak detection as following:

- Detection of tree tops might be improved by applying different interpolation methods for point cloud or DSM generation, but that requires raw aerial images which we did not have;
- DSM was generated from point cloud with 0.75 meter grid size; this might lead to many omission errors. Because, too fine a cell size results in many “no data” cells, whereas too coarse a cell size results in loss of detail (Kukunnda, 2013). We might need to create a surface model with higher resolution and try to detect more peaks and apply some methodology to remove noise peaks.

Simple region growing segmentation in SAGA delineated individual tree crowns very well based on the generated CHM and tree peaks, however it has some limitations. First, the algorithm creates segments on the pixels with NoData value and they require post-processing to remove. Secondly, simple region growing does not stop on the edge of the crown, but continues until reaching the next segment which makes segmentation and classification inaccurate. Another algorithm should also be tried which preserves tree crowns to get more accurate crown delineation as proposed by Erikson (2004 a).

Forest condition

From the analysis above, we can evaluate the general forest condition. We detected cut crowns between 2012 and 2015, and there were 754 trees cut out and they covered 4.3 hectare area. Automatic diseased tree detection methodology did not really work as explained in 3.5, however field check found 12 diseased trees in the 2.2 hectare sample plot. These statistics prove that the number of trees in the study area is decreasing. However, according to height analysis (3.1) trees are slightly growing. Statistics also show that older trees are vulnerable to disease, because we had found an average height of 18 meters of diseased trees. We can also note that mainly coniferous trees are subject to disease.

5. Conclusion and recommendation

Conclusion

According to our methodology, tree peaks had been defined with 75.2% accuracy. However, it can be improved with applying different algorithms of smoothing. We also had almost 90% accurate tree heights generated using this methodology. Simple region growing algorithm is highly depends on the generated tree peaks and CHM, more accurate peaks and more detailed CHM can generate more accurate segments. We achieved 75.2% accurate individual tree crown delineation and detected clear-cut areas using CHMs of 2012 and 2015 years. This methodology did not only identify the clear-cut areas, but parameters of individual tree crowns that have been cut out between 2012 and 2015 as well. Overall classification accuracy was 77.2%; we had very good accuracy in coniferous tree classification, but deciduous tree classification had quite big omission errors of 60.8%, which decreased the overall classification accuracy. However, our methodology was not successful with identification of diseased trees.

Clear-cut areas, number of cut tree crowns and field check statistics and thematic maps clearly show that forest canopy have been significantly decreased between 2012 and 2015. It also shows that mainly coniferous tree species were diseased and cut out during this period, there are significant number of diseased trees still exist. However, there was slight growth of trees in the study area in this period of time.
Recommendation

Analysis proved that the number of trees in the investigated area of Fenyőfő forest reserves is declining, diseased and very vulnerable to disease. Since our methodology was not successful with individual diseased tree detection, future work should deal with it by acquiring higher spatial resolution images in proper time and developing appropriate methodology.

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6. References


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