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Textural classification of B&W aerial photos for the forest classification

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ABSTRACT: The Ministry of agriculture of the Czech Republic has defined a pilot project to summarize possible information that can be automatically evaluated from black and white aerial photos. This information should serve as input data into the large forest database or as signal data for forest state management organizations. These data were derived in traditional and modern ways. The traditional one used well-known principles of image processing as image distraction and thresholding. Modern tools were applied for other tasks using Fractal Net Evolution Approach commercially introduced by Baatz and Schäpe (1999) incorporated in commercial software eCognition for image segmentation and further classification where not only black and white aerial photos were used but also texture measures of these B&W aerial photos. The textural classification as another way used results of the detailed object oriented classification. The methodology was tested in another project defining the geodynamical model of land. The result of the project is a methodology to delineate forest areas, to distinguish deciduous and coniferous forest, to detect new deforestation and new large illegal dumpings and erosional rills from two different time level aerial photos. These tasks also include uninsured forest area detection. It means to determine six year-old forest (and younger).

1 INTRODUCTION

The Czech Republic owns a large and detailed forest database. The history of the database is quite long, longer than personal computer history. Data collection was performed in several-year-cycles by forest specialists who browsed through forest areas and collected a wide range of forest data (age, height types, forest substand, etc.). Existing aerial orthophotos made in two time levels in 1999 and 2000 for the whole of the country allowed to prepare a pilot project now only for B&W photos, and later for colour aerial photos. The goal of the project is to define which data can be automatically derived from aerial photos and how. This paper comprises methodologies of several types of data extraction. The methodology should be repeatable and will be used for the whole country in a three year cycle using 50 cm pixel size photos.

2 AERIAL ORTHOPHOTOS

Two time levels of scanned aerial photos were processed within the project. The first one from 1999 was delivered with 50 cm pixel size, and the second time level from 2000 with 59 cm pixel size. Mosaicked photos formed both levels with not always good quality colour processing on border between original photos serving for the mosaicking.

3 FOREST AREAS

The studied area is a hilly region with the highest slope of approximately 45°. Forest areas situated in the studied aerial photos are mapped in several hundreds base forest classes of various dimensions – several hectares up to several tens of hectares. One forest class does not represent one tree type. Many of them are mixed and their amount is stored only as percentage information in the database. The forest age varies from 0 to more than 200 years. The crop density ranges from 1 to 10 (the most dense). Definition of one class was adapted and usually grouped tree types and trees of various age categories.

Table 1. The prevailing tree types

Deciduous trees	Coniferous trees
Fagus silvatica	Picea abies
Acer pseudoplatanus	Larix deciduas
Betula pendula	
Sorbus acuparia	
Algus glutinosa	

4 METHODOLOGY

4.1 *Traditional methods used for several tasks*

4.1.1 *New deforestation detection in coniferous forest*

The methodology to find newly deforested areas was based on the traditional method using two steps of image processing. The first step is to find places where an important change can be found in the image distraction of the two time level images. Newly deforested areas have much higher pixel value than forested. The second step was the thresholding for high values in the resulting (calculated) image. The second step cannot be the last one. There are many small areas, which become a member of selected areas. However, they do not belong to this class. They appear there only due to different sun illumination and different orientation of tree crowns in the photos. The automatic elimination of areas smaller than 30 sq. m erases these in fact erroneously classified spots. The areas, which should be detected, are 400 sq. m. This size is sufficiently large to eliminate erroneously found small areas.

Additional errors can be found in results and these are places of shadows with different orientations on both images forming the pair of multitemporal black and white aerial photos. These errors usually cause that found deforested areas are smaller than their actual area.

4.1.2 *Illegal dumping and erosional rill detection*

Traditional methods were used for large illegal dumping detection or erosional rills too. Both these elements were determined from one level aerial photos as areas with high spectral values for the bare soil. To distinguish them from other areas with similar pixel values – e.g. paths, two tools were offered. The first one based on image processing where two time level images are distracted, newly existing illegal dumpings having bright values on the distraction image the same as newly existing bare erosional rills. The second one using GIS information about existing elements such as paths can eliminate these spectrally similar areas.

4.2 *Texture analysis and object-oriented classification tool*

Texture definition in this project was based on results of the first (detailed) level classification in the first way analysis.

Texture measures implemented in the PCI software were the second way how to use texture in the image analysis.

4.2.1 *Textural classification in object oriented classification tool*

The first level classification tried to find information about tree crowns and shadows. These features seemed to be important to define the image texture.

Automated tree crown detection has been the subject of many research papers. Some of them adopted the method of spectral minima located among tree crowns (Gougeon, 1995). His method called contour-based segmentation defines a valley as a delimiter between two different image objects. Some of them tried to determine tree tops as the local brightest pixel (Culvenor et al., 1996, Dralle et Rudemo, 1996, Šumbera and Žídek, 2002. The systems start with a search for bright blobs in the image usually by low-pass filters. Subsequently, radial brightness distribution is used to determine whether the shape of the object is similar to a tree. Finally, further analysis, e.g. a fusion process, removes double points in a single tree crown.

Both information types – shadows among treetops and bright treetops - were used in this project. The process was oriented only to detect trees and not to delineate exact tree crowns.

The first step of image processing was a multiresolution segmentation done by FNEA. The segmentation creates new object primitives whose classification is a source of meaningful information. The values controlling the segmentation process are colour versus shape and the shape can be sensitive to compactness or smoothness. Working with one black and white aerial photo has proven that the optimal values are colour equal to 0.9 and compactness equal to 1. Scale is the last input value. The scale value must be determined according to the following rules. Object primitives should be so small and so large as to delineate the smallest sought object. It can cause that larger objects are formed by more object primitives.

The following classification is performed by user-defined rules, which can be defined in multilevel definition space according to segmentation levels using fuzzy logic theory. The semantic connection among classes is able to connect classes from different levels. A more detailed description is in Baatz and Schäpe (1999).

The segmentation process was repeated many times and the suitable scale value was chosen for the first segmentation level equal to 6. The resulting average segment size was 17 sq. m after the segmentation process.

The second step of the tree crown detection was the classification. The classification is unlike traditional methods a segment-based classification. That is what can overcome the small information volume about spectral characteristics, which even overlap among different classes.

The classification was based on the fact that we were looking for the brightest and the darkest segments of the image with overlapping average value for coniferous and deciduous trees. Two classes of deciduous, two classes of coniferous trees, and two classes for shadows were defined. FNEA enables users to apply even GIS characteristics of individual segments as classification tools.

To find the brightest or the darkest segment means to find segments whose relative border to darker/brighter neighbours is small or zero. Distinguishing of coniferous and deciduous trees was based on other characteristics and that was the average difference of the segment to its neighbours which was higher at coniferous than deciduous. To find only trees in forest areas, distance to shadows seemed to be the important value.

All these characteristics were implemented as membership functions, which were used in classification. The principle of the membership function resembles thresholding.

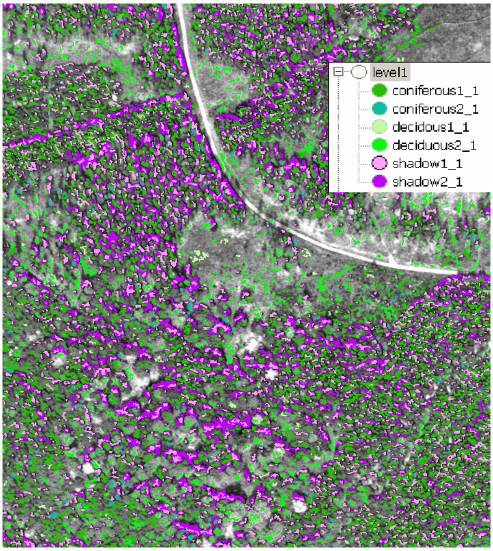

Figure 1. Texture formed by classification of the first level

The classification of the segmented image was not a full image classification. There were only six selected classes bringing information about the number of trees and shadows. The first level classification was used for further classification with a different scale for the new level segmentation and created the texture information. The texture was expressed in the form of ratio of tree crown areas and shadow areas.

This method was usefully applicable in coniferous forests older than 45 years. Younger coniferous forest crowns are too small compared to pixel size of the photo to create individual segments for individual tree crowns in one level segmentation. Crowns in younger deciduous forest are hardly distinguishable due to small radiometric differences on top of their crowns and their crown borders.

4.2.2 *Texture measures for image data classification*

Texture measures developed by TNO in the Netherlands and later enhanced and implemented in PCI commercial software were used to enlarge data colour information volume.

Texture as one of the important characteristics describes the average tonal variation in various bands of an image, textural features contain information about the spatial distribution of tonal variations within a band. The texture measures produce output images in which the grey levels represent textural measures of the input image. They are derived from a grey level co-occurrence matrix (GLCM) or grey level difference vector (GLDV) computed for each rectangular window of user specified dimensions and spatial relationships of the input image. The texture measure is put at the centre of the window at the appropriate position in the output image.

The texture measures used in this methodology were

$$\text{Dissimilarity} = \sum_{i,j=0}^{N-1} P(i,j) \cdot |i-j| \quad (1)$$

$$\text{Mean\_i} = \sum_{i,j=0}^{N-1} i \cdot P(i,j), \text{ and} \quad (2)$$

$$\text{Variance\_i} = \sum_{i,j=0}^{N-1} P(i,j) \cdot (i - Mean\_i)^2 \quad (3)$$

where *P(i,j)* is the normalized grey level co-occurrence matrix (GLCM) of dimension N x N such that

$$\sum_{i,j=0}^{N-1} P(i,j) = 1 . \quad (4)$$

Figure 2. Extracted area of the aerial photo

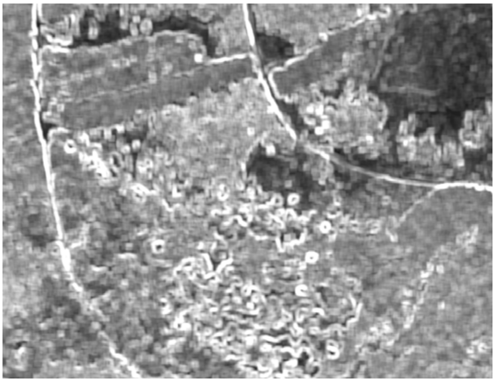

Figure 3. Variance_i of the extraction

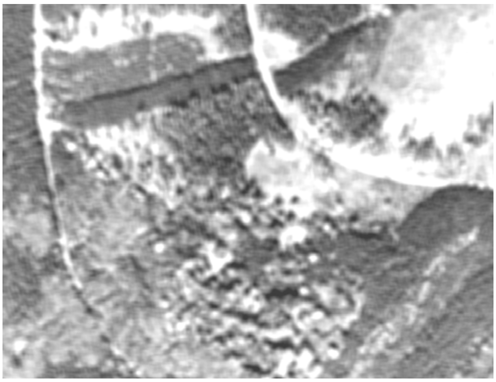

Figure 4. Mean_i of the extraction

Figure 5. Dissimilarity of the extraction

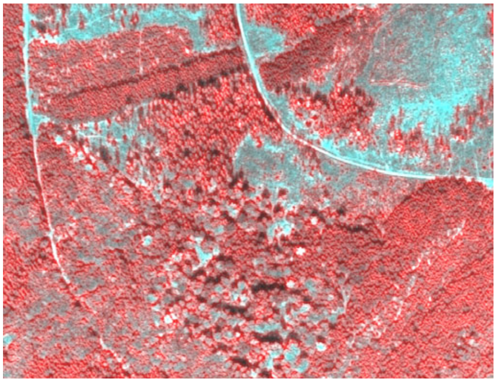

Figure 6. The useful visualization of the B&W photo using the original photo in RGB combined with the dissimilarity in R band

Figure 2 shows a part of the processed photo, Figures 3, 4, 5 show results of its texture measures. Figure 6 is a useful enhancement of the photo combined with the texture dissimilarity when the photo is in RGB channels and the dissimilarity in R channel.

The texture measures were calculated for filter size equal to 13 x 13 pixels. This size was the most suitable to distinguish tree crown size of coniferous and deciduous trees.

4.2.3 *Object-oriented classification*

Two main methods are used for the forest mapping and monitoring: segmentation and photointerpretation. Segmentation has been used by several specialists who applied various interpretation keys (Borisov et al., 1987, Jagtap et al., 1994, Naesset, 1996, Žihlavník, Palaga, 1995). The segmentation is based on visual interpretation.

The segmentation was again the Fractal Net Evolution Approach (FNEA).

4.2.4 *Segmentation and classification*

Two ways of processing were applied. The first one processed the aerial photo without any texture measures. The second one used three texture measures: contrast, dissimilarity and mean mean_i. The workflow for both methods was the same. The classification was based on the standard nearest neighbour classifier.

The segmentation using the original photo and mean_i bands was performed for two levels. It means for two different scale values – for small (rough) with 250 scale value and for a detailed one. The detailed one was done for scale equal to 35 and for the scale equal to 60. All segmentations were performed for colour = 0.9 and compactness = 1. These values were chosen after many segmentation testings and proved to be the most suitable for distinguishing these two forest types. The first level (scale = 35) meant that no deciduous trees were in coniferous segments and no coniferous in deciduous. The problem was in steep slope areas where high difference between tree crowns and shadows split these two parts into different segments. The higher scale caused that this problem was not so often, but brought another problem: segments with deciduous trees in mixed forest contained often a small part of coniferous trees and *vice versa.*

The higher-level segmentation was classified into four classes by the standard nearest neighbour classifier – old forest, young forest, meadow, and urban areas.

The lower level segmentation was classified into classes in Table 2.

Table 2. Class overview in two level classification and their final regrouping for forest areas delineation

Higher level classification	Lower level classification	Semantic grouping
Forest old	F_ forest old2 decid1	Forest
Forest old	F_ forest old2 conif1	Forest
Forest young	F_ forest young2 7year1	Forest
Forest young	(F_ forest young2 decid1)*	Forest
Forest young	F_ forest young2 conif1	Forest
Meadow	F meadow2 tree1	Forest
Urban	F urban2 tree1	Forest
Forest old	M_ forest old2 6year1	Meadow
Forest young	M_ forest young2 6year1	Meadow
Meadow	M meadow2 meadow1	Meadow
Urban	M urban2 meadow1	Meadow
Forest old	U forest old2 urban1	Urban
Meadow	U meadow2 urban1	Urban
Urban	U urban2 urban1	Urban

*This class was not used by automatic classification due to misclassification with F_ forest young2 7year1

The table shows that classes belonging originally to certain classes can be by useful regrouping correctly classified to finally different classes. The class definition is as follows (number 2 reflects belonging to the higher level classification):

The forest old2 class is a class where the ground surface is not visible.

The forest young2 is a class where the tree distance and tree size allows to "see" the ground surface.

The meadow2 is a class of fields, meadows or water.

The urban2 is a class comprising urban areas with a large range of surface classes.

Classes having in their names 7year and 6year distinguish areas with recognizable and non-recognizable young trees.

The two level performed classification can be used either for forest delineation or for non-forested areas in forests. F character in front of the first level classification semantically determines the forest delineation. Non-forested areas in forests are equal to class M_forest young2 6year1 and define real uninsured forest areas.

5 RESULTS OF THE CLASSIFICATON

5.1 *Textural classification*

The textural classification using only information about texture expressed by the ratio of relative areas of forest and areas of shadows should distinguish coniferous and deciduous forests. However, the classification was successful only in 71 % forest areas. The classification accuracy increased if additional information was used (mean values and standard deviation of segments for the nearest neighbour classifier). This method was applicable only in areas with forest age higher than 45 years.

5.2 *Classification with and without texture measures*

Results of the classification of the whole set of photos were different for different classes. Classification on the first level segmentation (scale = 60) was successful for distinguishing coniferous and deciduous forest in case of texture measures in 91 % of the image area and in case when only the aerial photo was classified in 89 % of the image area.

Trees of 6-year-age and younger were not even visually interpretable on aerial photos and were classified as non-forested areas. This class represents the uninsured forest thematic class. The classification using texture measures was correct in 95 %; the classification without texture measures was corrected in 91 % areas.

F_ forest young2 7year1 class comprised also classification of deciduous forest and their distinguishing was performed manually in both classifications.

The classification using texture measures was with two exceptions better than without texture measures.

Classification of the imagery with texture measures caused in certain areas even worse delineation due to co-occurrence matrix, which shifts borders between neighbourhood classes.

Table 3. Results of both classifications – with and without texture measures

Higher level classification	Lower level classification	Classification successfulness (%*)	
		Without texture	With texture
Forest old	F_ forest old2 decid1	86	89
Forest old	F_ forest old2 conif1	91	93
Forest young	F_ forest young2 7year1	87	92
Forest young	F_ forest young2 conif1	83	85
Meadow	F meadow2 tree1	96	93
Urban	F urban2 tree1	88	91
Forest old	M_ forest old2 6year1	92	95
Forest young	M_ forest young2 6year1	91	95
Meadow	M meadow2 meadow1	96	97
Urban	M urban2 meadow1	94	94
Forest old	U forest old2 urban1	85	87
Meadow	U meadow2 urban1	74	78
Urban	U urban2 urban1	88	85

* % of the class area

6 CONCLUSION

The automatic classification of the B&W aerial photos with pixel sizes 60 cm is possible by the object-oriented classification in case if two level segmentation is performed.

The textural classification where the texture is defined by a detailed classification of lower segmentation level used for distinguishing coniferous and deciduous performed without additional information by object-oriented classification brings only limited results (71 %). It can be performed in areas with forest age higher than 45 years.

Two level segmentation in the reverse order of segmentation (from higher to lower) is suitable for the above-mentioned results. The first one ensures dividing of the image data with overlapping pixel values for different classes into thematically closer and smaller image parts whose further segmentation and classification offers results with accuracy 80 –95 %. The lower level classification offers demanded results, which for certain tasks (forest delineation) are merged into final areas.

Visual control is necessary after the higher-level classification and certain parts need to be corrected manually.

Classification using texture measures is better for all forest areas compared to classification without texture measures. Texture measures deteriorate segmentation in urban areas.

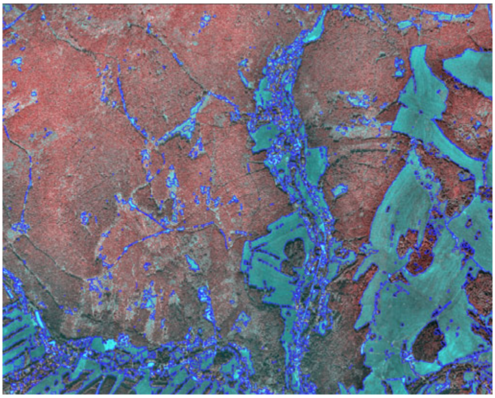

Figure 7. Forest delineation after classification and merge process

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