Geoinformation for European-wide Integration, Benes (ed.)
© 2003 Millpress, Rotterdam, ISBN 90-77017-71-2

Digital classification of tree species and spatial structure of forest stands from remotely sensed data

Stanislav Šumbera & Vladimir Židek
Mendel University of Agriculture and Forestry, Faculty of Forestry and Wood Technology, Department of Geoinformation Technologies, Zemedelska 3, Brno, 613 00, Czech Republic
ambrosa@mendelu.cz;zidek@mendelu.cz

Keywords: remote sensing; multispectral aerial photographs; tree top detection; crown delineation; image processing; anisotropy diffusion

ABSTRACT: Scanned multispectral aerial photographs were used to estimate tree and stand variables by means of standard and novel digital image processing methods. Individual tree crown detection and delineation were realized by the brightest pixel technique, template matching, edge detection in gradient direction, pixel tracing and cost surface generation. Several algorithms were tested and implemented into a program "Kernel processor". Automated classification of tree species was carried out in the Idrisi32 environment using traditional and soft classifiers. Bayclass soft classifier provided the most precise results. Described procedures enable to create special forests maps that can be used in alternative or simplified forest management plans at protected territories.

1 INTRODUCTION

Multispectral and colour infrared aerial photographs still remain important sources of information for detailed inventories in forestry, though they are partly edged out by satellite images of high resolution.

Both the visual interpretation of photographs and the computer classification of digitized images allow estimation of tree and stand variables as well as other characteristics of the forest ecosystem. Resulting information in many cases supports, complements of replaces laborious terrain data acquisition. Besides, images of high spatial resolution can provide further detailed information on the texture, shape, area, and mutual influence of particular tree crowns and thus contribute to the high-quality processing and investment valorisation of the image acquirement. A basic unit for this information is just an individual tree whose visual, automatic or semi-automatic identification serves as a key for approximation of the real tree characteristics.

Operators working on remotely sensed data are usually confined to the usage of commercial software packages that in most cases offer only standard algorithms of image data processing. In general there are no special methods for processing forest images, such as tree top or crown detection, special edge detectors etc. Current situation is on the one hand caused by specific algorithms nature, representing either intellectual property or a form of subject expertise, on the other hand by the cost of implementation of these technologies that is too high for common users.

In our research the latter case brought us to implementing some of these algorithms into software product to facilitate tree top detection, crown delineation and other processing steps that are rarely available by common software.

In this paper we present some of these image-processing methods, together with tree species recognition by means of soft and hybrid classification. Multispectral aerial photographs were used as main source data (although colour infrared ones would be equally appropriate), as in Czech Republic practically all large area protected territories were in past covered by MSK4 camera multispectral photographs.

2 MATERIAL AND METHODS

The study area (approximately $1km^{2)}$ covers northern part of Purkyne Reserve and adjacent forest stand in Josef valley (Josefovské údolí). The site is situated 5 km to the north-east of Adamov at protected landscape area Moravian Karst. Prevailing deciduous forest is represented (according to Czech forest typology classification) by forest types 4D3 *Fageta dealpina*, 1CD3 *Corni-acereta campestris* and 3BC3 *Querci-fageta tiliae-aceris*.

Multispectral aerial photographs for Czech Nature Protection Agency were taken 23/7/1990 (12.45-14.30h) in four spectral bands using MSK4 multispectral camera (format 55 x 80 mm, filters 480, 540, 660 and 840 nm). The flight height was 4500 m, overlap 60 % and sidelap 30 %. Our site was covered by 535 28 and 535 29 scenes.

3 PRE-PROCESSING

Each spectral image was scanned with a spatial resolution of 600 dpi and intensity resolution of 256 levels of grey. With mentioned parameters single tree crowns contained approximately 90-120 pixels per crown.

Individual channels were transformed into identical position using polynomial transformation. Colour compositions were made using subtractive colour model CMYK and all 4 spectral bands; they were subsequently transformed into RGB model (Sumbera 2001).

4 IMAGE SCALE SPACE

Apparent forest structure depends on spatial resolution that in case of scanned aerial photographs is affected by flight height, camera focal length, image size and resultant pixel resolution. The type of information that can be obtained is largely determined by the relationship between the size of the actual structures in the data and the size (resolution) of the operators (probes) (Lindberg 1996). If we don't know priory the size of structures we need to derive a set of images representing the original signal at different levels of scale. Primary aim of the scale change is to remove fine details like individual branches in tree crown while preserving coarse structures like crown boundaries. We have used two spatial operators for scale change:

1. linear isotropic normalized Gaussian filter (primary used here for tree top detection)
2. nonlinear anisotropic diffusion (used for tree crown delineation).

4.1 *Gaussian filter*

The image representation L at scale level t ($t=\sigma^2$) is given for instance by Hlavac (1998):

$$L(\bar{x},\sigma) = L(\bar{x},0) * G(\bar{x};\sigma)$$

$$G(\bar{x};\sigma) = \frac{1}{(2\pi\sigma)^{d/2}} e\left\{-\frac{\bar{x}\cdot\bar{x}}{2\sigma^2}\right\}$$

where $L(x,0)$ is base image resolution and d is image dimension. Linear Gaussian filter on image can be interpreted also as iteration step in isotropic linear diffusion equation:

$$L_t = \frac{\partial L}{\partial s} = \nabla^2 L = \Delta L = L_{xx} + L_{yy}$$

(for 2D), stating that the derivative to scale equals the divergence of the gradient of the luminance function, which is the Laplacean sum of the second partial derivatives (Romeny 1999). A proper t was taken by the scale where first derivation of generalized entropy over the scale space set of images reaches maximum. This approach was suggested by Jagersand (1995) and used for tree crown detection by Brandtberg (1999). Generalized entropy of order $\alpha \in \mathbf{R}$, where R is real number, was defined in conformity with Sporing et Weickert (1997):

$$S_\alpha[P(t)] = \frac{1}{1-\alpha} \ln \sum_{i \in image} \left(\frac{I(x)}{\sum_{i \in image} I(x)} \right)^\alpha$$

for $\alpha \neq 1$. The equation was used with $\alpha = 5.0$ and normalized with the maximum possible entropy value Ln ($N \times M$) where N resp. M represents the 2D image size.

4.2 *Nonlinear diffusion smoothing*

Alternatively we have used new anisotropy diffusion smoothing presented in the paper of Perona et Malik (1990). They proposed the anisotropy diffusion filter as a diffusion process that encourages intraregion smoothing while preserving interregion smoothing. They suggested the following equation in which the conduction coefficient **c** is not constant in space, but is rather a function of the magnitude of the intensity gradient of the image:

$$\frac{\partial}{\partial t} I(x,t) = \nabla \cdot \Phi(x,t)$$

$$\Phi(x,t) = c(x,t)\nabla I(x,t)$$

$$c(x,t) = f(|\nabla I(x,t)|)$$

where *I(x,t)* is the image, *x* refers to the image axes and *t* refers to the iteration steps. *Φ (x,t)* is the flow function and *c(x,t)* is the diffusion function. By this process the amount of diffusion at each point in the image space is modulated by the function *c (x,t)* and the image gradient at that point. They choose to make *c(·)* a monotonically decreasing continuous function of the image gradient magnitude. Evaluation of this function in a moving window process makes it possible to define smoothing amount for the central pixel according to the diffusion results of the eight closest neighbouring pixels. An exponential function was used in this study as a decreasing function, but an inverse function of image gradient could be used as well.

$$c_1(x,t) = \exp\left(-\left(\frac{|\nabla I(x,t|}{K} \right)^2 \right)$$

K is referred to as the diffusion constant. The function increases with the gradient to the point where $|\nabla I| \cong K$, and afterwards decreases to zero. This function behaviour implies that the diffusion process maintains homogenous areas where $|\nabla I| << K$ since the flow function is small in sections where $|\nabla I| >> K$. The highest flow is reached when the image gradient magnitude approximates to the value of K. Hence by choosing coefficient K to reflect gradient magnitude produced by noise the diffusion process can be utilized to decrease noise in images.

In our study a discrete implementation of the anisotropy diffusion was derived, as used by Gerig et al (1992):

$$I(t+\Delta t) = I(t) + \Delta t \frac{\partial}{\partial t} I =$$

$$= I(t) + \Delta t(\phi_e - \phi_w + \phi_n - \phi_s) \mid \Delta t < \frac{1}{1+n}$$

where $\Phi_e, \Phi_w, \Phi_n, \Phi_s$, denominate a flow function for pixels located in the $n=4$ directions from the central pixel and Δt is the integration constant. To compute diffusion implies the increment of pixel flow located in the neighbourhood of the processed pixel.

5 INDIVIDUAL TREE DETECTION

Automated tree crown identification has been subject of many research papers. Here we should quote at least some essential methods. Pollock (1996) proposed synthetic crown template with respect to the crown shape and size, angle of sun illumination, and quantity of received and reflected light. These crown templates were then correlated to the forest image. Larsen (1998) enhanced crown template to the camera scanner angle. Gougeon (1995) adopted the method of tracing spectral minima located between crowns, known as "valley following". Walsworth (1999) proposed to find tree crown top as union of “ridges” lines obtained by the double aspect technique in four directions; tree crowns were estimated by the cost surface generation. Culvenor et al (1996) detected tree tops as the local brightest pixel and the region growing technique delineated tree crown. Dralle et Rudemo (1996) conceived the problem of tree top searching in a similar way. Their activity lied in research of optimal image smoothing for tree counting, providing best correspondence to the ground truth. Brandtberg (1999) studied dependence of two-dimension variograms for texture detection and identified tree crowns by differential geometric operators. Korpela (2000) determined tree tops from image stereopair.

In spite of all above mentioned activities, the tree top detection and crown identification are not very often used in Czech forestry research.

A convenient set of basic methods for tree top identification is presented thereinafter. The problem of single tree identification can be subdivided into two partial tasks:

1. Tree top searching,
2. Tree crowns delineation.

5.1 *Tree top detection*

The tree top identification is based on two principal assumptions, namely that the spectral reflectance (in the study only beech and spruce were considered) is higher than the rest of the crown and that the image was captured during highest solar elevation. Under such conditions reflectance is decreasing downwards the tree top, thus the crown is presented in form of cone or oval shape. In such a way the tree top corresponds to the brightest crown point (Niemann et al 1998), see Fig. 1. Tree crowns on high spatial resolution images usually do not represent ideal geometric shapes (spheres or cones) that could simplify tree tops detecting. This is the reason for the image to undergo scale change by the smoothing process. Gaussian linear isotropic filter (see above) was applied to solve this problem. The actual process of the tree crown searching was modified in this study and called "iterative brightest pixel". Main part of the algorithm is based on a filter in the moving window choosing the pixel with the brightest reflectance located in its centre. In such a way, smaller or larger tree tops can be identified depending on the window size. The supplemental finer conditions were added to define possible crown reflectance disproportion, for instance an incorrect pixel in different places of an illuminated part of the crown. Furthermore, threshold values for the central pixel were determined to eliminate certain amount of defectively demarcated crowns tops. An example of the process is shown at Fig. 1.

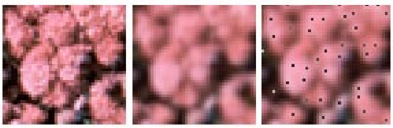

Figure 1. Example of tree top detection using iterative brightest pixel algorithm. From left: original image, scaled image, detected tree tops.

Some tree tops might not be detected by the described steps, as they either lie in shadow, or their colour properties do not match the given condition of the brightest central pixel. However, their number is quite low in comparison with tree tops detected by the above algorithm. An area-based template matching technique can look up such tree tops. This method determines the correspondence between a sample image (*t*) and the original image (*f*) according to the similarity of their grey level values. The sample (template) is derived from the original image where tree tops were not yet identified. Thus this step is semi-automated. The size of sample image is either 3x3 or 5x5 pixels. The template matching between the sample and the compared part of the image is done by a normalized cross correlation formula:

$$\rho = \frac{\sum_{x,y}\left[f(x,y)-\bar{f}_{u,v}\right]\left[t(x-u,y-v)-\bar{t}\right]}{\sqrt{\sum_{x,y}\left[f(x,y)-\bar{f}_{u,v}\right]^2\sum_{x,y}\left[t(x-u),y-v)-\bar{t}\right]^2}}$$

where f is the image, the sum Σ of pixel values is computed according to the size and actual location of the template t positioned in u, v of the image, $\bar{f}_{u,v}$ is arithmetic mean *f(x,y)* at the place of the template actual location and t^{-} is arithmetic mean of the template.

The tree top was chosen from all correlation values using the method of the brightest pixel where $\rho>0.55$. In case of duplicity in tree top identification a new filter was introduced performing duplicity removing. This filter application, realized similarly by the moving window, is based on resulting image adaptation with a special attention to the side effect of complementary conditions that can produce duplex tree top identification.

5.2 *Tree crown delineation*

5.2.1 *Edge based tree crown delineation*

The goal of the edge detection is to determine the pixels in the image with correspondence to the object boundaries seen in the captured scene. It is natural to define edges as those points where the gradient magnitude assumes a maximum in the gradient direction. Thus edges are defined by the differential geometric approach (Lindberg 1993), also known as non-maximum suppression. For the purpose of the method explanation, it is possible to consider, for instance, an ideal tree crown in the sphere or cone shape, supposing the illumination is vertically perpendicular to it. Then the tree crown is build up from isosurfaces (contours) gradually increasing from the tree top center. Next we introduce a new orthonormal coordinate system (u, v) at any image point where v - axis is parallel to the gradient direction of the pixel intensity L at the given point, and u - axis is perpendicular to it. It means u - axis is almost parallel to the tangent of the corresponding isosurface:

$$(\cos\alpha, \sin\alpha) = (L_x, L_y) / (L_x^2 + L_y^2)^{1/2}.$$

The local directional derivative operators in this curvilinear coordinate system follows:

$$\partial_{v'} = \cos\alpha\, \partial_x + \sin\alpha\, \partial_y\,;\;\; \partial_{u'} = \sin\alpha\, \partial_x + \cos\alpha\, \partial_y$$

At an arbitrary image point the gradient magnitude is equal to $\partial_{v'}L$ further marked as L_v. The edge can be identified as a point, the first derivation of which in the gradient direction reaches the maximum (L_v = max), the second one is zero ($L_{vv} = 0$) and the third one is negative ($L_{vvv} << 0$). Here L_{vv} or L_{vvv} is computed as a result of transformation from curvilinear system to the Cartesian system:

$$L_{vv} = \frac{L_x^2 L_{xx} + 2L_x L_y L_{xy} + L_y^2 L_{yy}}{\left(L_x^2 + L_y^2\right)}$$

$$L_{vvv} = \frac{L_x^3 L_{xxx} + 3L_x^2 L_y L_{xxy} + 3L_x L_y^2 L_{xyy} + L_y^3 L_{yyy}}{\left(L_x^2 + L_y^2\right)^{\frac{3}{2}}}$$

where Lx, Ly and their combination are the derivation in the x,y directions. Two passes of the moving window (process?) realize edge detection. In the first pass the derivation values are calculated and in the second one an image gradient value only displayed in areas satisfying criteria mentioned above. Thus output edges from the process are marked by the one of the 256 brightness values corresponding to the gradient magnitude rather then to be displayed only as binary image. In such a way significant edges can be detected easily from those of less importance, for instance by the method of thresholding.

The edge segments obtained by the differential geometric approach are obviously very often discontinued due to the heterogeneous nature of their adjacent regions. Then complete object boundary delineation consists of composition of the different edge gradient values. This is the reason why the threshold method cannot detect the object boundary entirely. Thus morphological and conditional operators were introduced for usage in task of continuous object boundary linking:

1. Joining nearly-linked pixels;
2. Removing small, isolated groups of pixels;
3. Morphological thinning of edges;
4. Removing of unconnected segments.

Joining of nearly linked pixel is based on the filling of the gaps located between single pixels in eight

- directions counting the central pixel in the moving window. A morphological thinning is based on the binary comparison of structure elements sequence $B_{(i)} = \{B_{i1}, B_{i2}\}$ with the image, where i signifies a sequence and B_1 is a subset of X (image objects) and B_2 is a subset of X^c (inversed image, it means the background). In the spot of coincidence of a structural element and the image, reducing by one pixel takes place. For one sequence, it is possible to express the operation in the following way (HLAVAC 1992):

$$X \otimes B = (X \ominus B_1) \cap (X^c \ominus B_2) \quad ; \quad X \circleddash B = X | (X \otimes B)$$

where $\ominus$ is morphological erosion, $\circleddash$ is a morphological thinning and $\otimes$ means a binary comparison (either hit or miss operation). An example of the process is shown at Fig. 2.

Figure 2. Example of crown delineation by edge detection in gradient direction. From left: original, detected edges, adjusted edges by morphological operations.

5.3 *Tracing spectral minima*

The original method, known as "valley following" (Gougeone 1995), works as a filter in the moving window. In each processed area a procedure is run, testing if the central pixel (i.e. the starting pixel for tracing) interferes with any neighbouring pairs of minimum pixels. (In total four tests are run for horizontal, vertical, and two diagonal neighbouring pixels). If a condition is accomplished, the program recursively continues tracing in four main directions and tests and marks pixels using the same conditions. As the algorithms are incorporated into the moving window, all image pixels are tested as starting pixels for tracing. The individual steps of entire process are outlined as follows:

1. Visual tresholding of image to separate the forest areas from the non-forested areas;
2. Scanning the image with 3 x 3 moving window to find local spectral minima;
3. Spectral minimum region growing for each found pixel;
4. Edge adjustment (mentioned above).

An example of the process is shown at Fig. 3.

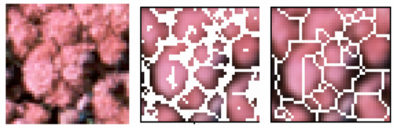

Figure 3. Example of crown boundary detection by tracing spectral minima. From left: original, traced image, final boundaries.

5.4 *Cost surface generation*

The last method for tree crown delineation makes use of cost surface generation and is strongly linked to the precedent tree top detection. Located tree tops are used as starting point for crown filling, thus delineating its borders. For this filling a Cost-Push/CostGrow algorithm from the Idrisi for Windows software package was used. This algorithm uses a crown reflectance surface and calculates cost distance surface. The movement from the tree top is realized in eight directions; it means that around each tree top circular rings of distances are created, depending on the (friction) crown surface (Eastman 1989) The output crown cost surfaces were then processed by the valley-following algorithm mentioned above. An example of the process is shown at Fig. 4.

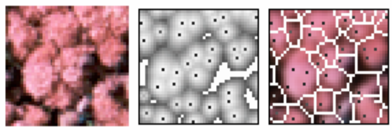

Fig. 4. Example of crown separation by cost surface production. From left: original, inverse cost surface, crown boundaries passed via tracing spectral minima.

6 AUTOMATED CLASSIFICATION

For needs of supervised classification and for classification accuracy assessment training sets were delineated on areas representing individual major object classes: Norway spruce *(Picea abies)*, Scots Pine *(Pinus sylvestris)*, Eastern Larch *(Larix decidua)*, Sessile Oak (*Quercus petraea)*, Crested beech (*Fagus sylvatica).* Spectral signatures were created, based on spectral characteristic of these training sets. Particular procedures in IDRISI facilitate advanced fuzzy signature creation. The whole process allows for data ambiguity and provides better understanding of object nature. A traditional way defines a signature as a spectral representant of the only one and unique object, while concept of fuzzy signatures allows creation of inhomogeneous spectral response patterns with relations to other objects. Following supervised classifications were realized over the area of interest. (The IDRISI module names are given in the parentheses:

1. Maximum basic probability (MAXSET)
2. Supervised hard classification (MAXLIKE)
3. Supervised soft classification (BAYCLASS)

MAXSET hybrid classifier plays an interesting role in the sphere of unsupervised and supervised classifications. This Maximum Basic Probability Classifier belongs to the transition area between supervised and unsupervised classification. Although it is run as if it were a supervised classifier requiring training site data, in the end it behaves as if it were an unsupervised classifier in that it can assign a pixel to a class for which no exclusive training data have been supplied (Eastman 1997).

For example, given training sites for conifers and deciduous forest, MAXSET might determine that a pixel more likely belongs to a class of mixed conifers and deciduous forest than it does to either conifers or deciduous exclusively. The logic that it uses in doing so is derived from Dempster-Shafer theory, a special variant of Bayesian probability theory. It can give raise to the image whose composition is not formed only by the classes defined in an unambiguous way but also of those classes the user did not considerate thus providing information on missing training sites. Once a classification is processed, a very important step is to assess a percentage of occurrences of the mixed classes.

BAYCLASS belongs to a group of soft classifiers. Unlike hard classifiers, soft classifiers defer making a definitive judgement about the class membership of any pixel in favour of producing a group of statements about the degree of membership of that pixel in each of the possible classes. Like traditional supervised classification procedures, each uses training site information for the purpose of classifying each image pixel. However, unlike traditional hard classifiers, the output is not a single classified land cover map, but rather, a set of images (one per class) that expresses for each pixel the probability that it belongs to each class.

BAYCLASS is closely related to the MAXLIKE hard classifier, in that it computes the posterior probability of belonging to each considered class according to Bayes' Theorum:

$$P(h/e) = P(e\mid h) * P(h) \Big/ \sum_i P(e\mid h) * P(h_i)$$

where:

p(h|e) = the probability of the hypothesis being true given the evidence (posterior probability)

p(e|h) = the probability of finding that evidence given the hypothesis being true (derived from training site data)

p(h) = the probability of the hypothesis being true regardless of the evidence (prior probability)

In this context, the variance/covariance matrix derived from training site data is that which allows one to assess the multivariate conditional probability p(e|h). This quantity is then modified by the prior probability of the hypothesis being true and then normalized by the sum of such considerations over all classes. This latter step is important in that it makes the assumption that the classes considered are the only classes that are possible as interpretations for the pixel under consideration. Thus even weak support for a specific interpretation may appear to be strong if it is the strongest of the possible choices given (Eastman 1997).

7 IMAGE PROCESSING SOFTWARE DEVELOPMENT AND IMAGE MANAGEMENT

Current image processing software products seldom come up with the possibility of user-specific operations. If a user needs something of that kind, is up to him to develop necessary routines. Thus in our case the software called "Kernel processor" was developed for Windows NT platform, performing all operations presented above. The software architecture is designed as a complement, enriching existing image processing operations and functions (e.g. Idrisi32 of the Clark Labs, Worcester, Ma). The image processing functions are encapsulated into DLL libraries that comply with a standard of the coding similar to the user code applied in the ER-Mapper program.

The management of raster data can be facilitated by another developed application, “Image Storage” that makes possible to store raster files in Oracle 9 database, allowing long transactions with the help of Workspace Manager and finally localizing raster positions using Oracle Spatial Cartridge. Visualisation of rasters is performed in Bentley MicroStation. Details are given in Sumbera et Zidek (2002).

8 RESULTS AND DISCUSSION

A colour composition technique by means of a subtractive colour model CMYK allowed using simultaneously all four data bands. This untraditional way of processing turned out quite advantageous for creating training sites, permitting to take into consideration all recorded spectral characteristics.

Moreover, CMYK composition enabled visualization of objects in natural colours thus providing a robust support to visual interpretation of imagery. Post-transformation of the CMYK colour composition into RGB colour model did not deteriorated image quality; this transformation permitted to reduce four channels into three.

Hybrid classification by MAXSET module turned out a very good one for the initial search of pertinent classes and for data acquisition on the assessed object signature accuracy. Results of MAXSET classifier proved that the training sites for classes were well chosen, because the representation of derived combinations reached only 6%.
BAYCLASS soft classifier, based on Bayess theorem of probability, appeared the most accurate one. BAYCLASS reached 89% of success in the whole process of classification, compared to 85% of MAXSET and to 87% of MAXLIKE. Due to this module it was possible to discern spruce with the classification accuracy of 98% and pine with 84%. In case of oak and beech results rather worsen, probably by different degree of the crown reflectance, where some parts of the crown closure in the spectral image overlapped. Therefore these two species were integrated into a mixture class oak-beech. Then this mixed class demonstrated 90% of accuracy. Classified map is shown in fig.5.

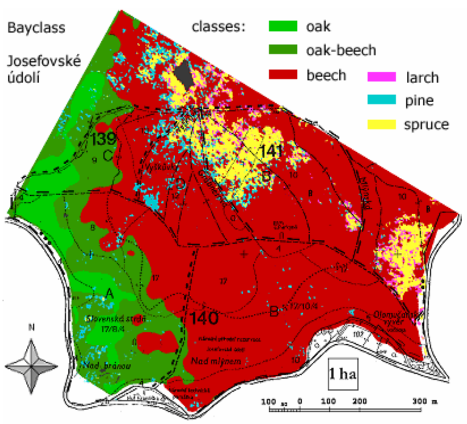

Fig.5. Bayes's classification of Josefovské údolí.

The image scaling by Gaussian smoothing represents a very important feature for number of detected trees by the brightest pixel method and for accuracy measures. Thus a set of image in different scales was produced and for each image normalized generalized entropy together with tree number estimation were computed. A scale was chosen according to the closest number of resulting tree tops from the brightest pixel method related to the number of trees counted on calibration site. Another purpose of the scale change by Gaussian smoothing consists in approximation of the crown surface to cone (in case of spruce) or sphere (in case of beech). Brightest pixel and its iterative alternative method proved very fast, effective and accurate methods to detect majority of trees. Valid kernel size was 3x3 pixels.

The template method of searching for tree tops provided solid foundation for generic tree identification. Disadvantage of the method consists in a manual tree crown samples selection from input image that served as a template. Accuracy assessment of the automated detection of the tree tops depends on canopy thickness, tree species, image quality and smoothing quality. To assess the accuracy of the approach, a sub sample of the processed area corresponding to approximately 10% of the entire area, was randomly selected and divided into 5 areas. The number of tree crowns was counted within this area on site. First area was used for calibration of the proper image scale for used methods. The comparison is illustrated in Table 1.

Number of tree tops can be used in forest inventory for preliminary evaluation of tree density. Moreover, tree tops can serve as starting points for further tree crowns detection.

Table 1. Accuracy of tree top methods. Mean error is computed as an average % error of sites 2-5

Method for	Ctrl	Number of trees on site				Mean
log(t) = -1.83	**1**	2	3	4	5	error
Ground truth	**170**	180	160	165	186	
Visually counted trees	**165**	168	154	151	174	6.3
Template matching ρ=0.55	**165**	182	172	162	162	5.8
Brightest pixel k = 3	**171**	180	161	171	160	4.6
Iterated br. pixel i=6	**168**	181	161	169	165	3.7

Tree crown detection using a tracing spectral minima method turned out to be a logical division of crown canopy. In this manner divided canopy together with tree crown tops provide basis for detailed objective analysis of tree crowns by means of both spectral and spatial characteristic. Results can be used as important layers in GIS.

There is a certain relation between the edge detection, tree top and tree crown. If the tree top is formed by the brightest pixels and crown contour by the darkest ones, detected edges of tree crowns represent the highest changes in crown intensity from its darkest part to the brightest. Delineation of tree crown by means of crown cost surface production starting from the tree top proved to be suitable method for assessment of the minimum surface the particular crown can occupy. The method depends on detection of all tree tops. Fig.6. shows subsets of results produced by these algorithms.

Future development should focus on the accuracy assessment of the image-based crown delineation algorithms. For this purpose special equipments like Field Map (IFER 2001) might be used enabling more precise ground truth estimation of real crown shapes.

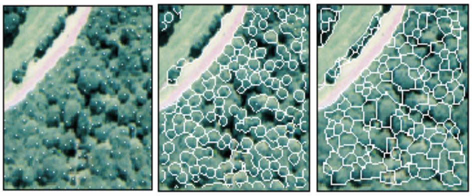

Fig.6. From left. Detected tree tops, tree crown delineation by the cost surface, tree crown delineation by tracing spectral minima.

9 CONCLUSIONS

Based on the presented results it is possible to sum up following conclusions:

- Using available summer imagery, we did not succeed to classify larch. For larch classification, photographs from a spring season would be obviously more appropriate.
- Separation of oak and beech was not successful with regard to their similar course of reflectance in all four channels. Mixture growth characteristics of stand did not allow creating a mask for only one particular species.
- Automated detection of tree crown tops by the brightest pixel method allowed to asses number of trees and their location. The detection can be confirmed by ground-truth measurements.
- Crown delineation tracing the spectral minima facilitates a logical segmentation of images and prepares a basis for a more accurate pixel classification.
- Tree crown edge detection in the directional gradient of pixel intensities showed satisfactory results after further morphological operation.
- Tree delineation assessment methods constitute a basis for further more convenient tree crown contours analysis.
- As user-specific operations are rarely included in current image processing, we have developed into application (Kernel processor) particular routines based on some above mentioned algorithms in C/C++ programming language. Another application (Image Storage) have been developed for storing and management of raster data, allowing long transactions, that are important for preserving intermediate steps of images processing.
- Results of all above-mention methods open new chances of application to forestry planning and management in Czech Republic.

ACKNOWLEDGEMENT

The authors acknowledge with thanks the support of the Faculty of Forestry and Wood Technology, Mendel University of Agriculture and Forestry, Brno research program No. 434100005 (grant of the Ministry of Education, Youth and Sports).

REFERENCES

Brandtberg, T.,1999. Automatic Individual Tree-Based Analysis of High Spatial Resolution Remotely Sensed Data. Acta Universitatis Agriculturae Sueciae, Silvestria 118.

Culvenor, D. S.,Coops, N., Preston, R., Tolhurst, K.G.,1998. A Spatial Clustering Approach To Automated Tree Crown Delineation. *In* HILL, D.A.(ed.) Proc. Inter. Forum on High Resolution Remote Sensing in Forestry, Victoria BC, Feb. 10-12, 1998. p. 67-80.

Dralle,K.,Rudemo, M.,1996. Stem number estimation by kernel smoothing of aerial photos. Canadian Journal of Forest Researc*h, 1996, 26*, p. 1228-1236.

Eastman, J.R.,1997. IDRISI, User´s Guide. Clark University, Worcester. 1997.

Eastman, J.R., 1989.Pushbroom Algorithms for Calculating Distances in Raster Grids, proc. Autocarto 9, p. 288-297.

Gerig, G., Kikins, R., Kubler, O., Jolesc, F.A.,1992. Nonlinear Anisotropic Filtering of MRI Data. IEEE Trans. on Medical Imag. 1992, vol. 11, No. 2, June 1992, p 226.

Gougeon, F.A.,1995. A Crown-Following Approach to the Automatic Delineation of Individual Tree Crowns in High Spatial Resolution Arial Images. Canadian Journal of Remote Sensing, 1995, vol 21, No. 3, p. 274-284.

IFER, 2001. Field Map, Corporation documentation.

Hlavac, V.,Sonka, M., 1992. Pocitacove videni. Grada a.s., Praha, p .90. ISBN 80-85424-67-3

Korpela, I.S.,2000. 3-D matching of tree tops using digitized panchromatic aerial photos. Unpublished Licentiate thesis. University of Helsinki, The library of the Department of Forest Resource Management.

Lindberg, T.,1993. Discrete Derivative Approximations with Scale-Space Properties: A Basis for Low-Level Feature Extraction. Journal of Mathematical Imaging and Vision, vol.3, no.4, p. 349-376. ISSN 0924-9907.

Jagersand, M, 1995. Saliency maps and attention selection in scale and spatial coordinates. An informatic theoretic approach. Fifth International conference on computer vision, pages 195-202. IEEE Computer Soc.Press.

Malik, J., Perona, P.,1990. Scale--space and edge detection using anisotropic diffusion. IEEE Trans. on Pattern Anal. and Machine Intelligence 1990, vol 12, p. 629--639. ISSN 0018-9340.

Niemann, K.O., Adams, S., Hay, G.,1998. Automated Tree Crown Identification Using Digital Orthophoto Mosaics *In* Hill, D.A.(ed.) Proceedings International Forum on High Resolution Remote Sensing in Forestry (Canadian Forest Service), Victoria BC, Feb. 10-12, 1998. p. 106.ISBN 0-662-27659-0.

Pollock, R.J.,1996. The Automatic Recognition of Individual Trees in Aerial Images of Forest Based on Synthetic Tree Crown Image Mode, Unpublished PhD thesis, University of British Columbia, Vancouver, Canada. 1996.

Sporring, J.,Weickert, J. 1997.On generalized entropies and scale-space, In Tech. Rep. DIKU-96/37, Univ. of Copenhaguen.

Smidrkal, J., 1989. Zpracování informací DPZ. CVUT, Praha

Sumbera, S., 2001. Digitální klasifikace druhové a prostorové skladby lesních porostů z materiálů DPZ. Unpublished PhD thesis. Mendel University of Agriculture and forestry Brno. czech republic.

Sumbera, S., Zidek, V., 2002. Automated Tree Top Identification Using Colour Infrared Aerial Photographs of High Spatial Resolution. Ekológia 2/2002 (in print).

Walsworth, N.A., King, D.J.,1998. Comparison of two tree apex delineation techniques. *In* HILL, D.A.(ed.) Proceedings International Forum on High Resolution Remote Sensing in Forestry (Canadian Forest Service), Victoria BC, Feb. 10-12, 1998. pp. 93-104. ISBN 0-662-27659-0.