JOURNAL OF FOREST SCIENCE, *50*, 2004 (4): 161–170

Discrimination of vegetation from the background in high resolution colour remote sensed imagery

P. SUROVÝ[1], N. A. RIBEIRO[2], A. C. OLIVEIRA[3], Ľ. SCHEER[1]

[1]*Faculty of Forestry, Technical University in Zvolen, Zvolen, Slovak Republic*
[2]*Departamento Forestal Universidade de Évora, Portugal*
[3]*Insituto Superior de Agronomia, Lisbon, Portugal*

ABSTRACT: Different transformations of RGB colour space were compared to develop the best method for discrimination of vegetation from the background in open pure cork oak stands in southern Portugal in high-resolution colour imagery. Normalised difference index, i1i2i3 colour space and other indices developed for classic band imagery were recalculated for near infrared imagery and tested. A new method for fully automated thresholding was developed and tested. The newly developed index shows the equal accuracy performance but provides the smallest overestimation error and retains the largest scale of grey levels for a subsequent shape analysis.

Keywords: cork oak; infrared aerial photo; vegetation index; automatic interpretation

In terms of forestry southern Portugal is a specific area where stands with combined agro-silvo-pastoral management dominate. This type of management is essentially important for soil protection on the one hand and for maximum possible land production on the other.

In areas with limited or no possibilities of irrigation the only possibility for people was to graze cattle. But because of the mentioned extreme periods, high temperatures with long periods of drought in summer and heavy rainfalls in winter there is a need of soil protection that is mostly controlled by trees. Trees in pastoral areas are also used as a food component at the end of too long summer when grass is already too dry or gone.

Apart from soil protection and food provision the last but not least function of cork oak trees in these specific areas is cork production. Portugal is the world's biggest producer of cork. Cork is the most widespread material used for wine stoppers, it can also be used as a heat insulator because of its insulating properties.

Actual changes in the management of cork oak stands, mainly due to the reduction of hand labour and increasing mechanisation connected with establishment of new stands, created the need to develop tools to generate scenarios resulting from management options.

The cork oak productive system "*montado*" has some peculiarities due to the fact that it is an agro-silvo-pastoral system that implies the existence of conflicting activities. The system is based on trees and its sustainability can be compromised either by intensification of the understorey activities that leads to a lack of regeneration and consequent disappearance of the crown cover or by extensification that leads to the invasion of shrubs and other oaks increasing the competition and the risk of forest fire.

The system sustainability is also closely linked with soil loss due to erosion because of the activities related to grazing (soil dishing and underground cultivation). The soil exposure plays an important role in the process of erosion; therefore the crown cover is a key factor in controlling the erosive dynamics. The quality of the site for a cork oak area is mainly related with the soil depth, structure and nutrient status, therefore erosion has a hard impact on site quality. The loss of crown cover will result in an increasing soil exposure and loss of site quality, leading to an escalating process of stand degradation.

With better management tools such as individual tree growth simulators – "*corkfits*" the demand for initial (input) data that can influence both quality and costs has also increased (RIBEIRO et al. 2003). Landowner's access to the various types of aerial photo imagery offers a possibility to use it as an easily and fast accessible source of data.

The main goal of this paper was to find a procedure how to fully or partly replace the image interpreter by a computer, capable of making a set of decisions on its

The authors also wish to thank the Scientific Grant Agency, Ministry of Education of the Slovak Republic for the financial support of Project VEGA No. 1/0637/03 where these issues are also investigated.

own, with the interpreter's minimum intervention during image processing and analysis. The term ROI – *Region of Interest* was used. Instead of detection of vegetation some authors use the term *segmentation* (MARR 1978), which should be understood as the process of dividing the aerial image into regions of interest in the (x, y) plane, i.e. visible individual tree crowns that are used as meaningful units in the subsequent process.

REVIEW OF LITERATURE

One of the main approaches in the image analysis is to transform the classical colour space picture to a binary (black and white) one by modulating the most significant colour of vegetation to be the lightest or darkest. For example OHTA et al. (1980) found that the colour features (R + G + B)/3, R – B and (2G – R – B)/2 are effective for colour image segmentation. ANDREASEN et al. (1997) defined the parameter g = 256.(G/(R + G + B)) for separating plants and soil in colour images. WOEBBECKE et al. (1992) established a normalised difference index NDI using the green and red channel to reduce lightning problems; where NDI = (G – R)/(G + R). SCHEER (1993) introduced another R, G, B channel combination for forest damage interpretation. OHTA (1980) and later PHILLIPS and RATH (2002) defined i1i2i3 and $i1i2i3_{new}$ colour spaces to transform the colour image to a binary one. GEORG and BOCKISCH (1992) described different methods using also other colour models like HSI that should be more similar to human colour perception. CHAPRON et al. (1999) tested different colour spaces: XYZ, LUV, LAB, HSI, and LST to optimise the separation. Results were sufficient until the overlapping of the leaves was less than 5%.

Among other kinds of aerial photo media (B&W film, colour film, B&W infrared film) the colour infrared films named as CIR or NIR (near infrared) are coming to be frequently used in forestry. The term near infrared is used because a part of the spectrum caught by the film usually extends from about 700 nm to about 1,200 nm (most commercial infrared films are only sensitised to about 900 nm). There are several reasons for using the CIR photos:

– Infrared photography does not provide a way of seeing through fog that consists of water droplets (as thought in the past), but it can improve visibility by means of a certain kind of haze where the light scattering is produced by much smaller particles. According to this, the material from long-distance (aerial) photography can be improved. Infrared photography does not always result in an increase in the range of vision, but it generally increases the contrast of distant subjects and thus the amount of detail that can be seen.
– NIR reflectance decreases as a result of a change in leaf orientation, from predominantly horizontal to predominantly vertical, at a certain stage in the growth cycle (COLWELL 1974; JACKSON, EZRA 1985); NIR reflectance also decreases by the loss of chlorophyll due to different reasons such as diseases. According to this NIR reflectance is undoubtedly species specific due to its dependence on these factors (GITELSON et al. 2001).

MATERIALS AND METHODS

Distinguishing algorithms

All indexes and colour transformations were mostly used for distinguishing inside the normal coloured picture, e.g. green vegetation and non-green background. The most significant colour of vegetation is green, or in other words the vegetation spectrum is mostly spread in the green channel, less in red and blue ones. In NIR imagery the most significant colour is red. Therefore derivatives of all indices were calculated where green channel is substituted with red, red channel with green and finally blue remains the same. The reason for such recalculation is that the blue channel both in normal colour images and in NIR images has the smallest influence in the vegetation spectrum.

So the formulas were as follows:

a) OHTA et al. (1980): (2 . R – G – B)/2
b) ANDREASEN et al. (1997): 256 . (R/(R + G + B))
c) PHILLIPS and RATH (2002): $i1i2i3_{new}$ colour space defined by the following matrix:

$$\begin{bmatrix} i1_{new} \\ i2_{new} \\ i3_{new} \end{bmatrix} = \begin{bmatrix} 0.33 & 0.34 & 0.33 \\ 0.39 & 0.07 & -0.54 \\ -0.51 & 0.35 & -0.14 \end{bmatrix} \cdot \begin{bmatrix} R \\ G \\ B \end{bmatrix}$$

d) WOEBBECKE et al. (1992): Normalised difference index NDI

$$NDI = \frac{red - green}{red + green}$$

Automatic thresholding

The final desired output of this process is binary image consisting only of white and black pixels. Black usually represents the vegetation and white is the background. Because the best system is a fully automatic system, only the automatic threshold was tested.

After applying the index an image histogram is typically bimodal where one peak corresponds to the background and the other to the vegetation. Local minimum between the peaks usually used as a distinguishing edge – threshold is not successful in all cases. Sometimes it is difficult to define the peaks, mostly in images with very high or very low vegetation fraction of the image. But generally the histogram can be split into three parts where two of them are vegetation and background pixels and the third is the distinguishing or edge pixel. This part is always between the other two. The term '*middle valley*' was established for this part of histogram by PEREZ et al. (2000).

So the *middle valley* can be calculated only regarding the scale of histogram bars, in other words, by using the

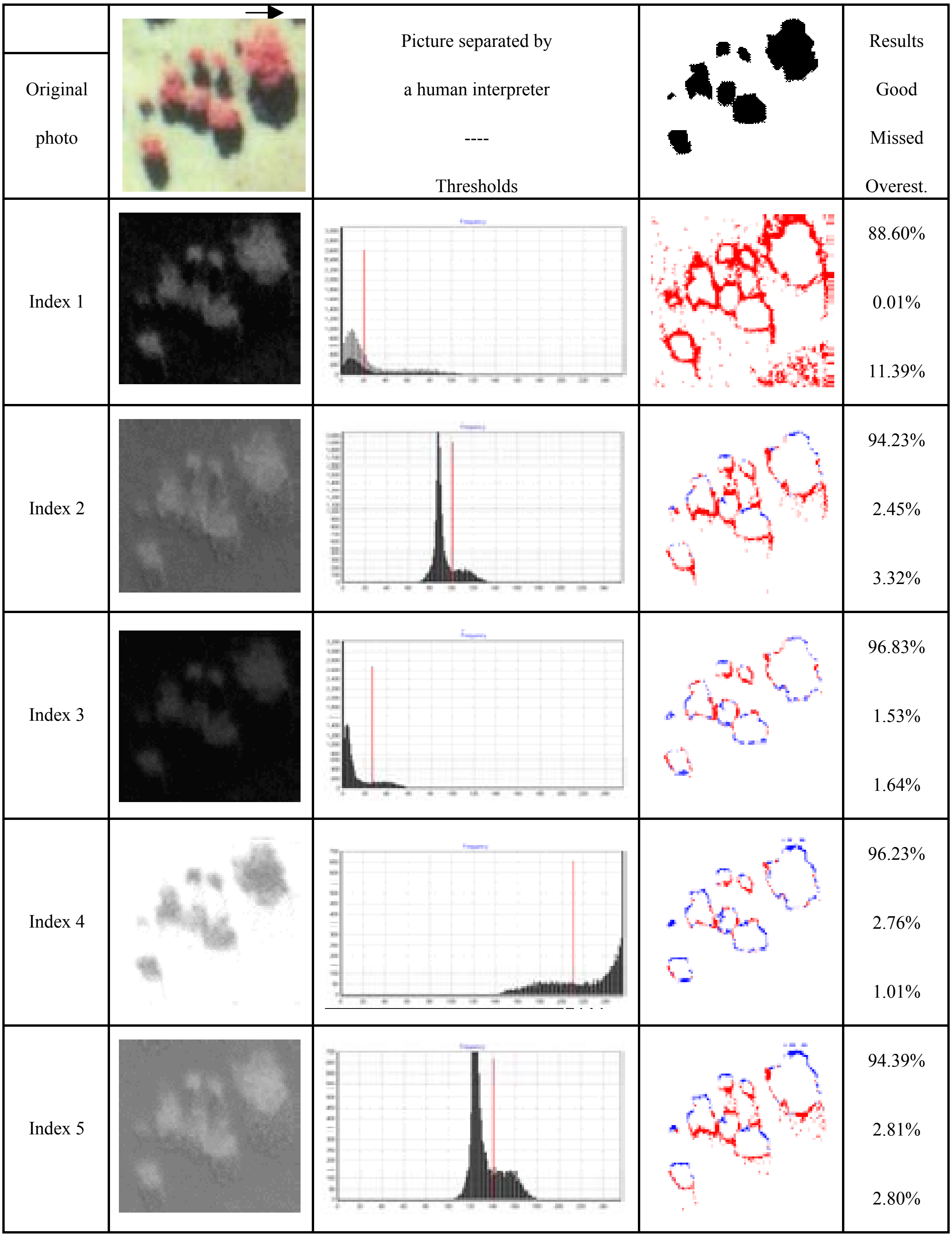

Fig. 1. Application of individual indices in the same photo

x-instead of *y*-values. The exact threshold is then calculated using the *y*-values, where *y* means the amount of pixels in a certain grade of grey. After definition of *middle valley*, five *y*-minimums are searched and their *x*-value weighted by *y*-value is used to define the exact threshold. This process is shown in Fig. 1.

One important step must be mentioned regarding the scale definition. The scale is defined as *x* interval where

y-values are higher than zero. In a fully automatic process the zero value should not be defined strictly because of small photo mistakes or pixels which can appear somewhere far "outside" of the main x scale and influence the final threshold. Therefore instead of "higher than zero" it is better to work with the term "significantly different from zero".

Images

Four different sets of aerial photographs (different year, flight height and scale) were used. 15 scans were taken from different parts of the photo, generally not farther than 60% of the width from the centre. One pixel corresponds to 30, 40 and 20 cm according to the image scale and scanner resolution. Images were stored in *bmp* format with 24-bits per pixel colour depth. An interpreter processed all images; vegetation pixels were marked as black and background as white.

Methods

Every image was displayed, indices were applied and a histogram of grey levels was calculated. Then the automatic threshold was defined. Afterwards, all image pixels under the threshold were marked as black, above the threshold they were marked as white. Binary image from this procedure and binary image defined by an interpreter were displayed and all pixels were compared. Pixels defined as black in the automatic system and as white in the picture obtained by the interpreter were considered as overestimation. The opposite case was considered as missed area. The remaining area was defined as good. The percentage value of vegetation fraction was calculated as amount of black pixels to amount of white pixels in the image defined by the interpreter. And the scale of histogram bars was saved for each filter.

This process was repeated for all filters (indices) and all images without any interpreter's intervention. The system Windows® XP Professional Edition was used and all the procedure was programmed using Borland Delphi 5 Professional environment.

Processing of 45 scans took approximately 10 minutes on Pentium IV 1, 7 GHz, 255 MB RAM memory and 32 MB video card.

Finally statistical calculations were performed. Regression between crown cover and index accuracy was investigated as well as the differences in index performances for different photo qualities were compared. All statistical calculations were processed using software SPSS ver.11. Scheffe test was used for comparison of index performances.

New algorithm description

The problem of colour imagery in automatic processing usually is that full colour systems (24bits per channel) store too many colours that have to be processed. In present computer systems there are usually 32 bits of memory used for storing the colour information. These bits are used in this order from left: 8 bits – alpha channel, 8 – red, 8 – green and lastly 8 – blue channel. 8 bits of memory can store a value between 0 and 255, which means 2^8 = 256 levels of each channel. The alpha channel is not taken into account – it usually serves for special purposes only. Three channels, each in 256 possible levels, equal 256^3 = 16,777,216 different colours.

The interpreter investigating the photo is not usually able to distinguish so many colours but perhaps, in this case it is an advantage. Looking at the estimation of individual tree positions, estimation from black and white imagery, we can see similar problems just from a different point of view.

High resolution imagery in terms of automatic (computer) analysis usually suffers from too detailed crown's "scan" where small holes or a longer branch without leaves can force the automatic system (looking for the local grey maxima) to distinguish more trees than there really are or, on the other hand, at coarser levels of scales, a tree crown may merge together with its neighbours. Therefore there exists a procedure to simplify finer scale images by sophisticated Gaussian smoothing after estimating the Gaussian kernel bandwidth. The idea of this method is to approach in an interpreter's way of vision and to group the details of one crown to one "blob" that represents the crown by its grey level maxima.

Similarly like in colour imagery, the interpreter's vision usually distinguishes between vegetation and ground even in 16 million colours picture by using this "simplifying" of the colour range. The new approach is based on the knowledge that by processing the digital image, by digitalising and even by taking the picture in the plane, there are different light conditions but colour information always remains as the most important fact how the interpreter distinguishes between background and vegetation. In other words: no matter if the picture is too dark or too light or just right, the interpreter is able to distinguish it with respect to the colour information.

Therefore a new method of simplifying the huge colour spectrum has been developed. Obviously the image is scanned or is coming to following processes as full colour image in RGB colour system. There are other systems like HSB (Hue, Saturation, and Brightness) that have axis B-brightness concerning directly the brightness (also called luminance, H and S are called chrominance components defining the colour), but transformation of RGB to HSB gets lost and therefore is not suitable for analysis. If we studied the HSB colour model in greater detail, we could see that by increasing or decreasing certain colour along its B-axis in HSB model its equivalent of RGB values would equally increase or decrease. Therefore, instead of transforming the image into HSB colour model this movement can be done in RGB-cube without losing any colour (chrominance) information.

After executing this step the original 16.7 million colours cube is reduced to 3 squares with 256 side lengths,

Table 1. Squares derived from RGB cube, values in gaps correspond to RGB values

A	B	C
[255,255,255] [0,255,255]	[255,255,255] [0,255,255]	[255,255,255] [255,255,0]
[255, 0,255] [0, 0,255]	[255,255, 0] [0,255, 0]	[255, 0,255] [255, 0,0]

e.g. to 196,608 colours, which corresponds approximately to 1.2% of origin with no loss in chrominance components important for further investigation. The reduced squares are in Table 1.

Algorithm of this transformation can be described as follows:

$$\begin{bmatrix} R_{new} \\ G_{new} \\ B_{new} \end{bmatrix} = \begin{bmatrix} R_{old} \\ G_{old} \\ B_{old} \end{bmatrix} + [mov]$$

where: $R_{old}, G_{old}, B_{old}$ – the position of pixel colour in the original RGB system,
$R_{new}, G_{new}, B_{new}$ – the position in a new simplified system,
[*mov*] is the vector of transposing the pixels to a new system:

$$[mov] = RGB_{\max} - \max(R, G, B)$$

where: $RGB_{\max}$ – the maximum frequency value of *R*, *G*, *B* axes,
max*(R,G,B)* – the maximum element value for *R*, *G* or *B* channel.

The biggest advantage of this step is that as far as the other two squares remain untouched, the colour information still remains to be useful and can give successful information about the crown shape. As far as we do not confound the A and C square, it could be used as an indicator of significance of the pixel – defining whether it belongs to the vegetation or not.

The consequent question is how to define which colours from this smaller spectrum belong to trees and which do not. Looking at Table 1, it can be seen that the usual colour spectrum which represents trees and vegetation (from violet through red to pink) is completely missing in square B. Square B then can be used as a filter for further simplifying and producing the final binary image.

It means for computer processing that it will force to display only the new calculated green channel because the B square members have equalled this channel to 255. Therefore the image is transformed to a black and white image where the background becomes white and trees and bigger vegetation become grey. Greyer pixels more significantly belong to the vegetation fraction. The above-mentioned problem of coarser scale level also arises here.

RESULTS

Sixty images of four different photo qualities were processed in this research. Indices were marked by numbers in the following order:

1	2 . (R – G – B)/2	OHTA et al. (1980)
2	256 . (R/(R + G + B))	ANDREASEN et al. (1997*)*
3	$i1i2i3_{new}$	PHILLIPS and RATH (2002*)*
4	B square	
5	NDI – normalised difference index	WOEBBECKE et al. (1992)

General performance of individual indices was compared through the following objectives:

– *Accuracy*: percentage of pixels marked as vegetation and background by a filter and also by an interpreter.
– *Overestimation:* percentage of pixels marked as vegetation by a filter but marked as background by an interpreter. It is a very important value for subsequent tree delineation analysis because overestimation causes defining small spots as trees. Compared to misclassification that causes white blobs in the tree crown it can be easily removed by suitable smoothing.
– *Scale of retained grey levels:* amount of grey levels retained by the index. It is a value that describes the amount of lightness degrees of vegetation (tree crowns) important for subsequent analysis. The higher the retained amount, the better the crown can be seen and analysed.

Overall results and index performance

The accuracy of individual indices is shown in Table 2. The result of Scheffe test of difference significance is included, significant differences are printed in bold. The best overall

Table 2. Accuracy of individual indices

Index difference	1	2	3	4	5	Accuracy (%)	SE
1	–	**4.3619**	–0.6546	–0.7631	0.8893	90.3081	3.60858
2	**–4.3619**	–	**–5.0165**	**–5.1250**	**–3.4726**	85.9462	9.16480
3	0.6546	5.0165	–	–0.1085	1.5439	90.9627	3.52678
4	0.7631	**5.1250**	0.1085	–	1.6524	91.0712	3.56495
5	0.8893	**3.4726**	–1.5439	–1.6524	–	89.4188	4.15417

Table 3. Overestimated pixels by different filters

Index difference	1	2	3	4	5	Overesti-mation (%)	SE
1	–	0.2503	1.2055	**2.5592**	0.2019	5.9368	3.78817
2	–0.2503	–	0.9552	**2.3089**	–0.0484	5.6865	3.51610
3	–1.2055	–0.9552	–	**1.3537**	–1.0036	4.7312	3.31772
4	**–2.5592**	**–2.3089**	**–1.3537**	–	**–2.3574**	3.3775	2.73497
5	–0.2019	0.0484	1.0036	**2.3574**	–	5.7349	4.48441

Table 4. Scale of grey levels retained by different indices

Index difference	1	2	3	4	5	Mean (%)	SE
1	–	**10.783**	**24.800**	–0.283	**17.100**	48.583	15.2719
2	**–10.783**	–	**14.017**	**–11.067**	6.317	37.800	18.6164
3	**–24.800**	**–14.017**	–	**–25.083**	–7.700	23.783	7.5444
4	0.283	**11.067**	**25.083**	–	**17.383**	43.867	16.8477
5	**–17.100**	6.317	7.700	**17.383**	–	31.483	14.1870

mean was achieved for index 4 but it is not significantly different from overall means for index 1, 3 and 5. The performance of index 2 was worse than in all other indices.

The smallest overestimation (Table 3) was achieved by index 4. This difference was also significant in all comparisons. Differences between the other indices were not significant.

The best overall mean of the retained scale was also achieved by index 4 and was significantly different from indices 2, 3 and 5 (Table 4). Index 1 does not provide

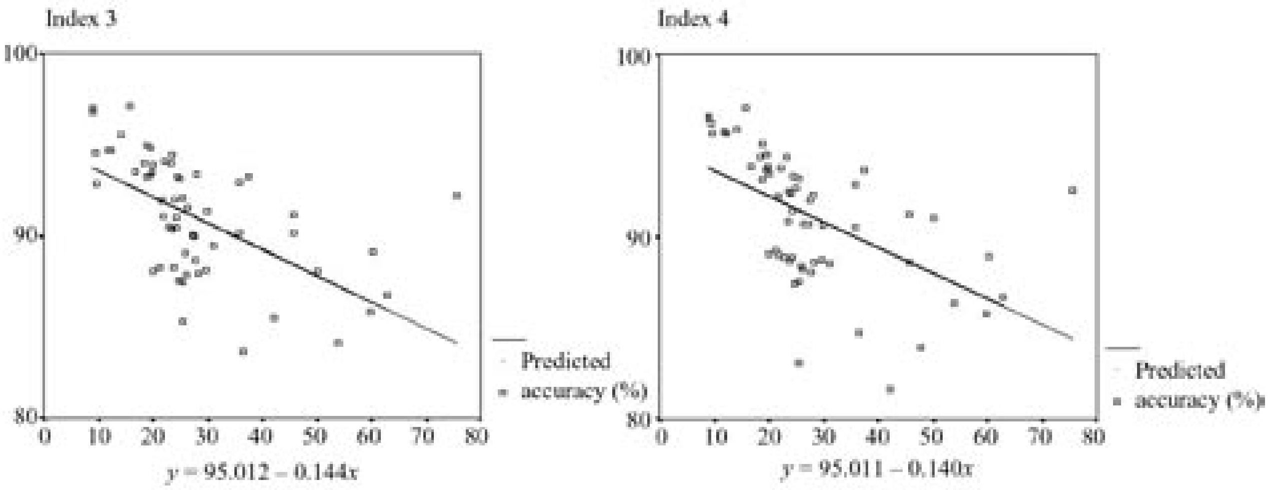

Fig. 2. Regression analyses between filter accuracy and crown cover

Table 5. Accuracy of individual filters in different photo quality

Index	Photo set 1		Photo set 2		Photo set 3		Photo set 4	
	accuracy (%)	SE	accuracy (%)	SE	accuracy (%)	SE	accuracy (%)	SE
1	91.5221	4.8989	92.1408	2.8224	89.5640	2.8440	88.0055	1.8364
2	81.9443	15.2449	89.1260	8.2016	86.2420	4.2160	86.4725	2.8492
3	92.8213	4.6970	92.5113	2.3067	89.9733	2.7351	88.5448	1.9929
4	93.1931	3.6145	93.0489	2.4854	89.4676	3.6298	88.5753	1.6423
5	87.6837	5.8070	89.3747	2.7551	88.1143	1.9573	88.1143	1.9573

Table 6. Multiple comparison of index accuracy by Scheffe significance test

Index 1	Photo set 1	Photo set 2	Photo set 3	Photo set 4
Photo set 1	–	–0.6187	1.9581	**3.5166**
Photo set 2	0.6187	–	2.5768	**4.1353**
Photo set 3	–1.9582	–2.5768	–	1.5585
Photo set 4	**–3.5166**	**–4.1353**	–1.5585	–
Index 2	Photo set 1	Photo set 2	Photo set 3	Photo set 4
Photo set 1	–	–7.1817	–4.2977	–4.5283
Photo set 2	7.1817	–	2.8840	2.6535
Photo set 3	4.2977	–2.8840	–	–0.2305
Photo set 4	4.5283	–2.6535	0.2305	–
Index 3	Photo set 1	Photo set 2	Photo set 3	Photo set 4
Photo set 1	–	0.3101	2.8480	**4.2765**
Photo set 2	–0.3101	–	2.5379	**3.9665**
Photo set 3	–2.8480	–2.5379	–	1.4285
Photo set 4	**–4.2765**	**–3.9665**	–1.4285	–
Index 4	Photo set 1	Photo set 2	Photo set 3	Photo set 4
Photo set 1	–	0.1443	**3.7255**	**4.6178**
Photo set 2	–0.1443	–	**3.5813**	**4.4735**
Photo set 3	**–3.7255**	**–3.5813**	–	0.8923
Photo set 4	**–4.6178**	**–4.4735**	–0.8923	–
Index 5	Photo set 1	Photo set 2	Photo set 3	Photo set 4
Photo set 1	–	**–4.8187**	–1.6910	–0.4305
Photo set 2	**4.8187**	–	3.1277	**4.3882**
Photo set 3	1.6910	–3.1277	–	1.2605
Photo set 4	0.4305	**–4.3882**	–1.2605	–

such a significantly different result as index 4 and is also significantly better than indices 2, 3 and 5.

Index performance for a comparison of different photo quality

The performance of individual indices was tested and compared from the aspect of different photo quality. There are four different photo sets:

1 – photos from the year 1990, 1:15,000 scale, pixel resolution 30 cm
2 – photos from the year 1995, 1:40,000 scale, pixel resolution 40 cm
3 – photos from the year 1995, 1:5,000 scale, pixel resolution 20 cm
4 – photos from the year 1995, 1:5,000 scale, pixel resolution 40 cm.

The last two sets are from the same flight but it was scanned twice with different resolution to see the influence of pixel size on index performance.

Scheffe tests (Tables 5 and 6) show that the photo quality has no significant influence on index 2 performance. It can be generally observed in other indices that photo set 4 was significantly worse than photo sets 1 and 2 but there was no significant difference between photo sets 3 and 4. Index 4 performed differently also in photo sets 2 and 3.

The influence of the crown cover on the accuracy of the indexes was tested using linear regression analysis (Fig. 2, Table 7). All indices are in significant negative correlations with the crown cover.

Table 7. Regression analyses between filter accuracy and crown cover

Index	R	*R* square	Adjusted *R* square	SE
1	0.512	0.262	0.250	3.12594
2	0.645	0.415	0.405	7.06682
3	0.572	0.327	0.316	2.91751
4	0.551	0.303	0.291	3.00112
5	0.588	0.345	0.334	3.39012

CONCLUSIONS AND DISCUSSION

The new developed index performed equally to all other filters tested in terms of accuracy except index 2. Index 2 performed significantly worse than all other indices. It is important to note that it does not mean that index 2 does not work properly because the performance can easily be improved by manual thresholding. But on the other hand, all other indices can also provide better results after manual thresholding. The use of any manual input however increases the time and labour consumption of the system and the goal is to find a fully automatic system. Generally it can be concluded that index 2 is not sufficient enough for fully automatic detection of vegetation. All other indices perform equally in terms of the mentioned automatic threshold algorithm and other conditions.

Overestimation was defined as pixels that were defined as background by an interpreter, but as vegetation by a computer. These pixels, especially if standing alone among the trees, cause significant overestimation of tree amount in subsequent tree delineation analysis. The new developed B-square index overestimated significantly less than all other indices. Comparing indices with the same accuracy, if the new index has the same accuracy and smaller overestimation, then it must have higher underestimation. Underestimation can be understood as pixels marked as vegetation by an interpreter but defined as background by an index. It usually occurs as white spots in black vegetation. This problem can be removed very easily by appropriate smoothing. Smoothing the "overestimated" image can cause deletion of small trees.

Retention of the grey level scale is very important for the transformation of image to the black and white one. This image is subsequently processed to delineate individual trees. The retention of a larger scale means smaller losses of information and allows more exact analysis. For example edges between individual trees often appear as dark valleys between lighter blobs or the opposite. Lower amounts of retained grey levels can cause these valleys to disappear or difficult to find automatically. The new B-index retained significantly more grey levels than indices 2, 3 and 5. Index 1 produced an equivalent scale.

Regression analysis between crown cover as an independent variable and index performance (accuracy) was made. This regression is an important sign showing if the index performance has any connection with crown cover and in what sense. If there is a regression, it can be expected that the index will produce worse results in the larger crown cover (density of trees). All indices showed a significant regression with the crown cover percentage. Looking at the regression it can be seen that even in high-density plots the accuracy of the new index performance will not be lower than 80%. It can be concluded not also from the data but also generally that this "disadvantage" appearing in all indices is not a big problem because as it is obvious from the data as well as from the landscape in southern Portugal there are only seldom high crown density sites there.

Acknowledgements

This study was funded by the International Project *Implementing Tree Growth Models as Forest Management Tools*, which is solved by the consortium of seven European universities and research institutes. Especially this part of the project aimed at the automatic vegetation detection from aerial photographs employing different types of spectral indices is solved in cooperation between Portugal and Slovak project partners.

References

ANDREASEN C., RUDEMO M., SEVESTRE S., 1997. Assessment of weed density at an early stage by use of image segmentation. Weed Res., *37*: 5–18.

COLWELL J.E., 1974. Vegetation canopy reflectance. Remote Sensing Envir., *3*: 175–183.

GEORG H., BOCKISCH F.J., 1992. Entwicklung eines Pflanzenunterscheidungssystems auf bildanalytischer Basis zur Bonitierung und zukunftigen direkten Steurung bei der Unkrautbekampfung. Wehenstephan, VDI/IMEG Kolloqium Agrartechnik, Heft 14: 175–183.

GITELSON A.A., KAUFMAN Y.J., STARK R., RUNDQUIST D., 2001. Novel algorithm for remote estimation of vegetation fraction. Remote Sensing Envir., *80*: 76–87.

CHAPRON M., REQUENA-ESTESO M., BOISSARD P., ASSEMAT L., 1999. A method for recognizing vegetal species from multispectral images. In: STAFFORD J.V. (ed.), Precision Agriculture '99. Proc. 2nd European Conference on Precision Agriculture. Sheffield, Academic Press Publishers: 239–247.

JACKSON R.D., EZRA C.E., 1985. Spectral response of cotton to suddenly induced water stress. Int. J. Remote Sensing, *6*: 177–185.

MARR D., 1978. Representing visual information In: HANSON A., RISEMAN E. (eds.), Computer visions systems. New York, Academic Press: 61–80.

OHTA Y., KANADE T., SAKAI T., 1980. Colour information for region segmentation. Comput. Graphics and Image Processing, *13*: 222–241.

PEREZ A.J., LOPEZ F., BENLLOCH J.V., CHRISTENSEN S., 2000. Colour and shape analysis techniques for weed detection in cereal fields. Comput. and Electronics. Agric., *23*: 197–212.

PHILLIPS I., RATH T., 2002. Improving plant discrimination in image processing by use of different colour space transformations. Comput. and Electronics Agric., *35*: 1–15.

RIBEIRO N.A., OLIVEIRA A.C., PRETSCH H., SUROVÝ P., 2003. Growth simulation and sustainability of cork oak stands. Modelling Forest Systems. CABI Publishing, Wallingford: 259–267.

SCHEER Ľ., 1993. An Application of Remote Sensing for Spruce Damage Estimation in Slovakia. The Netherlands, Geodetical Info Magazine, *7* (4): 63–65.

WOEBBECKE D.M., MEYER G.E., VON BARGEN K., MORTENSEN D., 1992. Plant species identification, size, and enumeration using machine vision techniques on near – binary images. SPIE Optics Agric. Forestry 1836: 208–219.

Received for publication July 7, 2003
Accepted after corrections January 9, 2004

Rozlíšenie vegetácie od pozadia na infračervených leteckých snímkach s vysokým rozlíšením

P. Surový[1], N. A. Ribeiro[2], A. C. Oliveira[3], Ľ. Scheer[1]

[1]*Lesnícka fakulta, Technická univerzita vo Zvolene, Zvolen, Slovenská republika*

[2]*Departamento Forestal Universidade de Évora, Portugal*

[3]*Insituto Superior de Agronomia, Lisbon, Portugal*

ABSTRAKT: Práca je zameraná na porovnanie rôznych transformácií vo farebnom priestore RGB a odvodenie optimálneho postupu k rozlíšeniu vegetácie od pozadia na infračervených leteckých snímkach s vysokou rozlišovacou schopnosťou v rovnorodých, otvorených porastoch duba korkového v južnom Portugalsku. Boli skúmané a testované rôzne druhy indexov, bola navrhnutá nová, plne automatizovaná metóda interpretácie rozlíšenia vegetácie od pozadia. Novo odvodený vegetačný index je výhodný v tom, že pri rovnakej správnosti výsledku poskytuje menšiu chybu nadhodnotenia a zachováva najväčšiu škálu odtieňov šede pre následnú analýzu tvaru korún.

Kľúčové slová: dub korkový; infračervená letecká snímka; vegetačný index; automatizovaná interpretácia

Cieľom práce je prezentovať novovytvorený index na úpravu a následnú automatickú interpretáciu vegetácie od pozadia pomocou farebných infračervených snímok a zároveň porovnať jeho úspešnosť s výsledkami doteraz používaných spektrálnych indexov.

Lesy sú na území južného Portugalska značne odlišné od lesov v oblasti strednej a východnej Európy – nielen čo sa týka drevinového zloženia reprezentovaného prevažne teplomilnými druhmi, ale aj jeho štruktúry a funkcií. Lesníctvo sa tu vo svojej klasickej forme prakticky nevyskytuje, prevažuje štýl hospodárenia známy v mediteránnom pásme ako agro-silvo-pastorálny hospodársky systém. Tento je charakteristický už podľa svojho názvu kombináciou hospodárskych opatrení, ktorých zmyslom je zabezpečiť maximálny kombinovaný výnos z pôdy, t.j. poľnohospodársky výnos (dobytok, obilie) kombinovaný v primeranej miere s úžitkami produkovanými lesom, t.j. hlavne ochrana pôdy, produkcia dreva, doplnkový zdroj potravy pre pasúci sa dobytok a v neposlednej miere na veľkej časti územia aj produkcia korku.

Štruktúra lesa je preto viac menej korešpondujúca jeho funkcii. V malej miere sa vyskytuje zapojený les, prevažuje les otvorený (kryt pôdy do asi 50 %) so stromami rastúcimi ako solitéry s minimálnym výskytom prirodzeného zmladenia.

Kvôli moderným manažérskym nástrojom (CORKFITS – simulátor rastu a produkcie jednotlivých stromov), ktorých používanie sa čím ďalej tým viac rozmáha, je dôležité vedieť zabezpečiť kvalitné vstupné údaje, najmä čo sa týka pozícií a rozmerov jednotlivých stromov.

Vlastníkom pozemkov zo zákona vyplýva povinnosť financovať (kupovať snímky) letecké snímkovanie vykonávané pravidelne v niekoľkoročných intervaloch. Existuje viacero metód na získavanie pozícií a vylišovanie jednotlivých stromov na snímkach, v otvorených lesoch je však v prvom rade dôležité odlíšiť vegetáciu (stromy) a pozadie.

V práci boli použité rôzne spektrálne indexy: (2 . R – G – B)/2 (Ohta et al. 1980); 256 . (R/(R + G + B)) (Andreasen et al. 1997); i1i2i3$_{new}$ – farebný systém (Phillips, Rath 2002) a NDI = (r – g)/(r + g) (Woebbecke et al. 1992). Všetky indexy sú pôvodne odvodené pre klasické farebné letecké snímky zachytávajúce plné spektrum, kde je vegetácia charakterizovaná hlavne zelenou zložkou. Pri farebných infračervených snímkach dochádza k posunu kanálov, pričom zelená sa zobrazuje ako červená; preto boli indexy definované v zmysle tohoto posunu.

Novo odvodený spektrálny index je definovaný ako priemet plnej farebnej škály na steny RGB kocky – ekvivalentný algoritmus transformácií RGB na HSB-farebný model – a následne je použitý jeden zo štvorcov (tab. 2) ako filter, pomocou ktorého sa obraz prefiltruje len na odtiene šedej farby. Algoritmus sa dá pomerne jednoducho vyjadriť nasledovne:

$$\begin{bmatrix} R_{new} \\ G_{new} \\ B_{new} \end{bmatrix} = \begin{bmatrix} R_{old} \\ G_{old} \\ B_{old} \end{bmatrix} + [mov]$$

kde: $R_{old}, G_{old}, B_{old}$ – pozície bodu (farby) v pôvodnom plnom systéme,
R_{new}, G_{new}, B_{ew} – pozície bodu (farby) v novom systéme, resp. v niektorom zo štvorcov,
$[mov]$ – vektor posunu do nového systému

$$[mov] = RGB_{\max} - \max(R,G,B)$$

kde: $RGB_{\max}$ – maximum osí R,G,B,
max (R,G,B) – maximálna hodnota spomedzi hodnôt R, G, B daného bodu (farby).

Boli použité štyri rôzne druhy fotografií:

1 – z roku 1990, mierka snímok 1 : 15 000, veľkosť pixelu 30 cm

2 – z roku 1995, mierka snímok 1 : 40 000, veľkosť pixelu 40 cm
3 – z roku 1995, mierka snímok 1 : 5 000, veľkosť pixelu 20 cm
4 – z roku 1995, mierka snímok 1: 5 000, veľkosť pixelu 40 cm.

Vyhodnocované boli nasledovné veličiny: správnosť interpretácie, nadhodnocovanie, škála zachovaných odtieňov šede a regresná závislosť medzi pôdnym krytom a správnosťou. Nadhodnocovanie je percento pixelov, ktoré index vyhodnotil ako vegetáciu a interpretátor ako pozadie. Tieto obrazové prvky sú v nasledovných automatických analýzach zdrojom mnohých problémov a nepresností, pretože sú často považované za stromy. Opačný problém – podhodnocovanie – je možné pomerne ľahko odstrániť pomocou vyhladenia obrazu, avšak pri väčšine metód vylišovania jednotlivých stromov sú tieto „biele diery“ v korunách stromov eliminované použitým algoritmom.

Regresná závislosť bola použitá ako ukazovateľ spoľahlivosti indexu v rôznych podmienkach pôdneho krytu.

Ďalší dôležitý krok pri automatickom vyhodnocovaní leteckej snímky je tzv. „thresholding“. Jedná sa o určenie prahovej hodnoty stupňa šede, ktorá je následne považovaná za hranicu medzi vegetáciou a pozadím, inými slovami hodnoty, ktoré sú nad touto hranicou (v závislosti od typu indexu), sú vegetácia, hodnoty pod hranicou sú pozadie. V ideálnom prípade je histogram obrazu po úprave indexom typicky dvojvrcholový, pričom vrcholy oddeľuje jasne vylíšiteľný priesek. Takýto prípad však nastáva málokedy. Preto bola navrhnutá a použitá metóda, kde sa v strednej tretine oblasti šede, ktorá sa na osi y významne odlišuje od nuly, definuje 5 miním a ich vážený aritmetický priemer je použitý ako hľadaná deliaca hodnota.

Výsledky sú zrejmé z uvádzaných štatistických charakteristík. Novodefinovaný index vykazoval rovnakú úspešnosť ako indexy 1, 3 a 5. Štatisticky významne najmenej vykazoval nadhodnocovanie zo všetkých indexov a spolu s indexom 1 zachovával najväčšiu škálu odtieňov šede. Bola preukázaná záporná regresná závislosť medzi veľkosťou pôdneho krytu a spoľahlivosťou indexu; táto je však platná pre všetky použité indexy.

Corresponding author:

Prof. Ing. ĽUBOMÍR SCHEER, CSc., Technická univerzita vo Zvolene, Lesnícka fakulta, T. G. Masaryka 24, 960 53 Zvolen, Slovenská republika
tel.: + 421 45 520 63 04, fax: + 421 45 533 26 54, e-mail: scheer@vsld.tuzvo.sk