Detecting Forest Damage in Cir Aerial Photographs Using a Neural Network

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Abstract – Nacrtak

Forest dieback is taking on increasing proportions in many parts of Croatia. To improve the situation, it is of primary importance to acquire timely, accurate and inexpensive information on the scale of forest damage. Such information can be collected for large forest areas with remote sensing techniques. This paper explores the possibility of applying segmentations of color infrared aerial photographs (CIR). Self-organizing artificial neural networks are used to detect damage in beech-fir forests and determine its spatial distribution. The results of the research confirm the benefits of applying neural networks to forest damage detection, since there are no statistically significant differences between damage in the field and damage detected with a neural network.

Key words: forest damage, color infrared aerial photographs, segmentation, neural networks, Croatia

1. Introduction – *Uvod*

An increase in the proportion of snag yield in the prescribed annual cut has a negative effect on sustainable forest management. Growing amount of salvage cutting operations requires that the focus be placed on forest health status and the quantity of snag yield. The primary task is to locate stands of poorer health in order to maintain their vitality and naturalness at an optimal level by applying timely measures (Pernar et al. 2007 b). Snag inventories are generally made with an intensive terrestric method, which requires substantial investments. Over large areas, however, it is much more practical, financially more acceptable and more reliable to apply a remote sensing method. Some common uses of CIR aerial photographs in forestry include site planning, description and mapping, temporal studies or disease assessments (Bütler and Schlaepfer 2004). Their features are particularly suited to making inventories of vegetation damage, especially of forests and forest trees (Kalafadžić 1987, Pernar 1994, Haara and Nevalainen 2002, Pernar et al. 2007a, b).

Owing to the six inventories of forest damage undertaken in the Republic of Croatia, this method has reached an operative level. The application of CIR aerial photography in the assessment of the forest condition has proved to be of equal value to terrestrial working methods in terms of accuracy, but much more efficient in terms of speed and objectivity (Pernar and Kušan 2001). According to Mas and Ramirez (1996), the most widely used method is visual interpretation, which achieves the most accurate results, primarily due to human ability to identify features/phenomena of interest. On the other hand, the process itself is relatively time-consuming because each part of the photograph is analyzed separately. Consequently, depending on the size of the area to be classified, this can significantly increase processing time and costs.

An alternative approach to the application of remote sensing in forestry involves the use of artificial neural networks (Ardö et al. 1997, Skidmore et al. 1997, Wang and Dong 1997, Moisen and Frescino 2002, Ingram et al. 2005, Kuplich 2006, Joshi et al. 2006, Verbeke et al. 2006, Klobučar et al. 2008, Klobučar and Pernar 2009). In general, the use of artificial neural networks in remote sensing began in the early 1990s (Benediktsson et al. 1990, Hepner et al. 1990, Civco 1993). Among neural networks with supervised learning, the most commonly used model is the multilayer feed – forward network – MLP (Paola and Schowengerdt 1995, Atkinson and Tatnall 1997, Kanellopoulos and Wilkinson 1997), followed to a much lesser extent by neural networks with radial basic functions (RBF) and a probabilistic neutral network (PNN) (Foody 2001). Neural networks with unsupervised learning, such as, e.g. self-organizing neural networks, are used even less (Beamish 2001).

This research deals with detection of forest damage and determination of its spatial distribution using scene segmentation (CIR) and self-organizing neural networks. The multiple goals are to acquire data with less investments, achieve a high degree of automation which will remove subjectivity contained in classical remote sensing methods, and present some possibilities of applying artificial intelligence to the monitoring of forest ecosystems.

2. Self-Organizing Maps – *Samoorganizirajuća neuronska mreža*

Self-organizing neural networks belong to the category of neural networks with unsupervised learning. Unlike supervised learning, there is no information on the expected response for samples from the training set; consequently, no error of the neural network is known that could be used to manage network training. In unsupervised learning, neural networks are trained by sample detection, by correlation or by input data categories. Each neuron in a self-organizing map has a weight vector whose number of elements corresponds to dimensionality of input data. A self-organizing map first finds the winning neuron. This is followed by the adjustment of a weight factor according to Kohonen's learning rule:

$$iw(q) = iw(q-1) + a(p(q) - iw(q-1)), \text{ or}$$
$$iw(q) = (1-a) \times iw(q-1) + ap(q) \qquad (1)$$

Where:

$iw(q)$ neuron weight in a number of q iterations
$p(q)$ input vector in a given iteration and
a learning constant.

The consequence of this learning rule is that the weight of the winning neuron will tend towards the input vector values. The difference between the classical competitive network and the self-organizing network is that in self-organizing maps (according to Kohonen's learning rule) not only the weights of the winning neuron are corrected but also the weights of the neurons adjacent to the winning one. Neighborhood is defined by the distance function, which is closely connected with the selected topology of the self-organizing map. The most common topologies of self-organizing networks are two-dimensional, and less so one-dimensional. Examples of the most common two-dimensional topologies are square, triangular or hexagonal topologies (Kohonen 2001).

If the current value of neuron weights is perceived as coordinates in the space of input features, the neurons of a self-organizing map are trained to shift in this space towards the centers of input vector groups. This allows classification of a particular class of input vectors with each neuron of the self-organizing map. A self-organizing map thus simplifies the problem of classification because dimensionality of the problem is implicitly reduced from an arbitrarily high number of input space dimensions to two topological dimensions of the self-organizing map. Topology is selected experimentally since there is no direct and obvious link between the expected network performance and the selected topology for the selected training set.

If the problem is defined so that sample classification from the training set is known, when training is over we determine which neurons correspond to which class of input samples. This serves as the basis for classification in further network operation.

3. Material and Methods – *Materijal i metode*

A CIR aerial photograph of the area was first visually interpreted in the stereomodel. The image (Fig. 1) was divided into four equal parts, since the process of training the network with all the pixels is very slow or almost impossible.

The matrices (R G B components) of the four scenes for input into the neural network were then prepared. The neural network was created using the *newsom* function, with the number of set classes

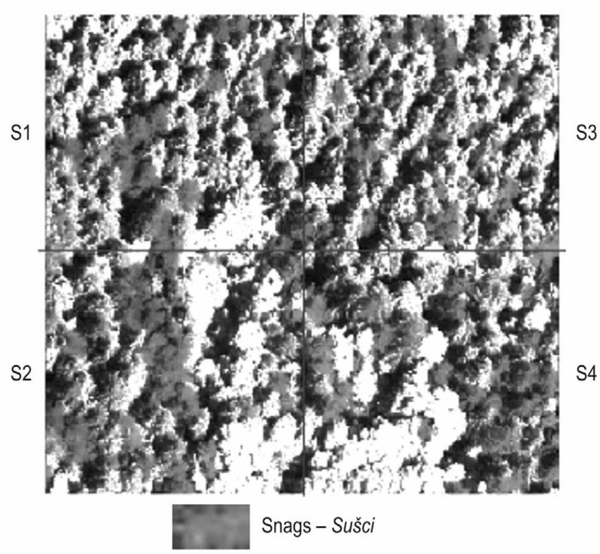

Fig. 1 CIR aerial photograph of the investigation area
Slika 1. *ICK aerosnimak istraživanoga područja*

Table 1 Results of comparison between visual interpretation and segmentation for the scene S2
Tablica 1. *Rezultati usporedbe vizualne interpretacije i segmentacije scene S2*

Cluster – *Klaster*	Visual Interpretation, % – *Vizualna interpretacija, %*		Segmentation, % – *Segmentacija, %*	Ho:p1=p2 p
1	Shadows – *Sjene*	17.29	14.97	0.90
2	Severely diseased trees (considerable loss of color, damage ≥ 60%) *Jako bolesna stabla (značajan gubitak boje, oštećenost ≥ 60 %)*	9.84	12.14	0.83
3	Dead standing trees (snags) – *Mrtva stabla* (*sušci*)	11.92	14.84	0.85
4	Transitional pixels between vegetation and shadows *Prijelazni pikseli između vegetacije i sjene*	19.05	17.24	0.91
5	Diseased trees (damage 25–60%) – *Bolesna stabla* (*oštećenost 25 – 60 %*)	19.61	17.63	0.95
6	Healthy trees – *Zdrava stabla*	22.29	23.18	0.96

(clusters) for segmentation as follows: 6, 6 (2 x 3), 7, 8, 8 (2 x 4), 9, 9 (3 x 3). After training, the network segmented a given scene into the set number of classes. The segmented scenes were then visually interpreted and compared with the results of photointerpretation of the study area, and the number of classes were defined, which provided the most acceptable segmentation. MATLAB 6.5 software was used to construct the architecture of the artificial neural networks and to conduct digital scene processing.

4. Results and Discussion – *Rezultati i rasprava*

Visual interpretation of the study area delineated the following: four degrees of tree damage, shadows, and transition regions of pixels between vegetation and shadow. The most acceptable results or the best match between visual interpretation and segmentation of individual scenes was achieved for 6 clusters in scene S2 (topology 6, Fig. 2 – 3), which was also determined with visual interpretation of the entire scene.

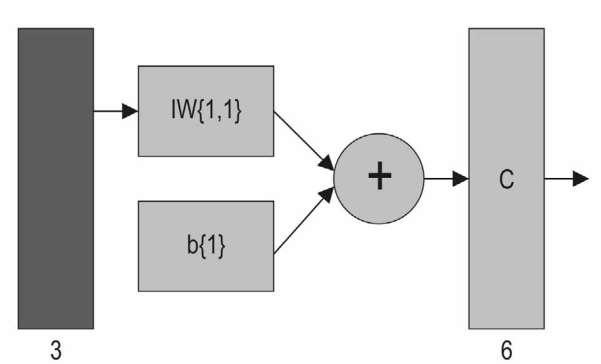

Fig. 2 SOM architecture – with six clusters in the output layer
Slika 2. *Arhitektura SOM-a sa šest klastera u izlaznom sloju*

A proportion test was used to test the percentage equality of visual interpretation and segmentation. The probability that the proportions are equal ranges from 0.83 for cluster 2 (severely diseased trees) to

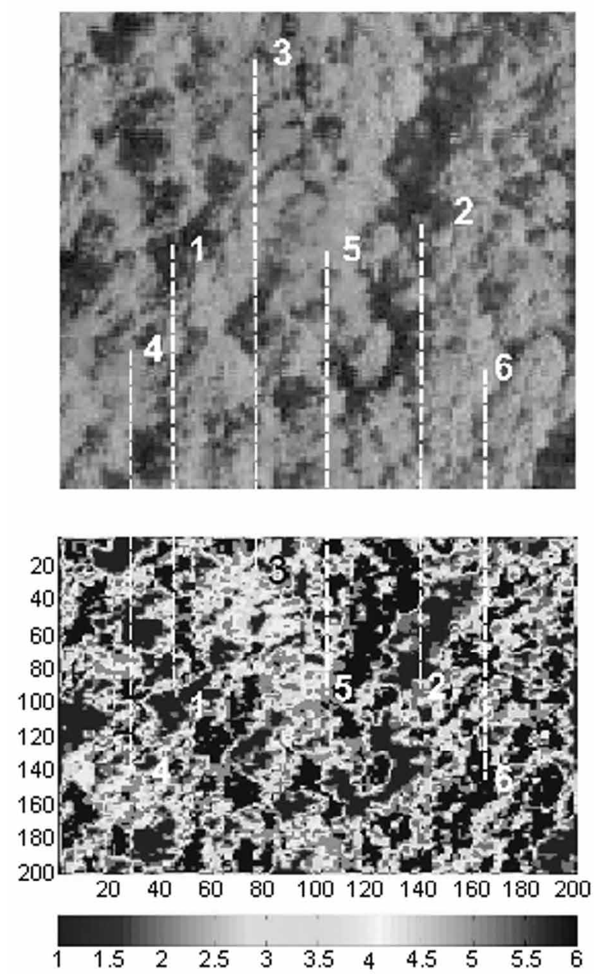

Fig. 3 Scene S2 segmentation in 6 classes
Slika 3. *Segmentacija scene S2 u 6 klasa*

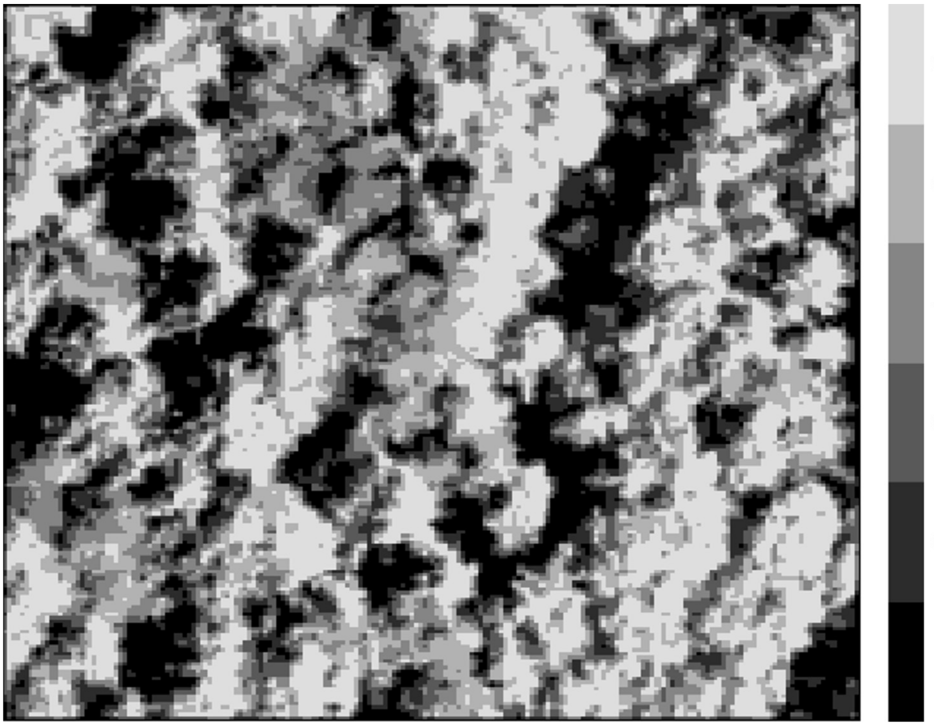

Fig. 4 Delineated clusters of the scene S2
Slika 4. *Delineirani klasteri scene S2*

0.96 for cluster 6 (healthy trees). There is no statistically significant difference between visual interpretation and segmentation of the analyzed scene S2 (Table 1).

Since a digital record of the tree crown contains a larger number of pixels (different digital values), which have been distributed into a certain number of clusters during the segmentation process, it is clear that no conclusions on the damage degree of a particular tree or parts of a standing tree can be made only on the basis of the participation of a particular cluster in relation to the participation of other clusters within the crown. A scene segmented in this manner is a good basis for determining spatial damage distribution by delineating homogeneous clusters (Fig. 4).

Topology 2 x 3 provided poorer results due to the unfavorable neuron distribution in color space. In this case, the results obtained with topology, in which the neurons cover color space in a series, are more acceptable (Fig. 5).

A larger number of clusters obtained by segmentation, i.e. the use of other architectures with a larger number of neurons, did not indicate any new features that could be determined with visual interpretation.

Due to variations of each scene, it is almost impossible to expect that the results of segmentation for each scene will fully correspond to the results of visual interpretation, or that segmentations for all the scenes will be identical.

The structure of the neural network for S2 scene was used in this order. A simulation of this network was made for input matrices of the scenes S, S3 and S4. By simulating the neural network (Scene S2) on

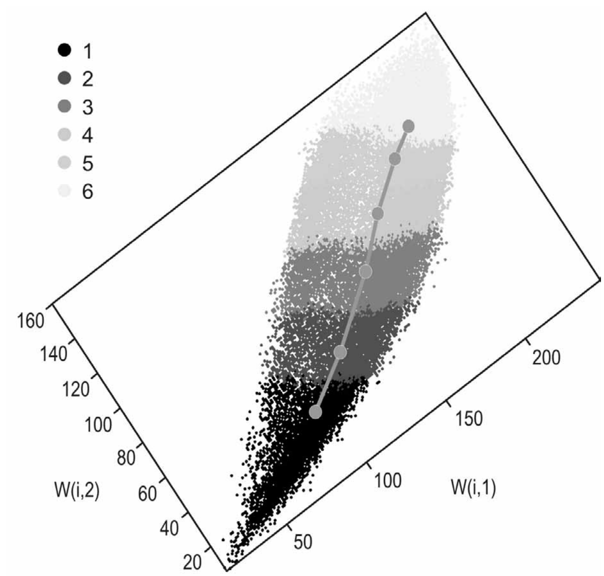

Fig. 5 Neurons in the space of R and G components
Slika 5. *Neuroni u prostoru sastavnica R i G*

the three remaining scenes an improvement was achieved; in other words, the scenes were segmented according to the determined classes in the process of visual interpretation.

The application of simulation is justified by the fact that segmentation results were obtained rapidly; in contrast, neural network training requires a certain period of time, as well as repeated interpretation of the obtained clusters.

Such segmentation makes it possible to monitor (analyze) both the entire area and individual scenes under almost equal conditions. This is enabled by the establishment of a relationship (delineation) between the segmented classes and the corresponding colors in the entire study.

In order to successfully apply remote sensing technologies to forestry, it is necessary to carry out prior terrestrial reconnaissance, as well as check the obtained results afterwards. This relates particularly to the application of unsupervised learning, as is the case in our example.

Accordingly, certain procedures in the use of self-organizing neural network can be outlined for the purpose of detecting forest damage and determining its spatial distribution:

⇒ Form the input matrix of the scene in the size and shape acceptable for neural network training,

⇒ set the number of clusters (classes) according to the results of visual interpretation (one or two classes more can be set with the goal of determining whether segmentation provided an additional feature),

⇒ test the corresponding topology,

⇒ after determining the scene in which suitable segmentation results have been obtained, use the obtained structure of the neural network for simulation on other scenes.

5. Conclusion – *Zaključak*

Some priorities of sustainable forest management refer to detection of forest damage and its spatial distribution and monitoring the forest condition. Remote sensing techniques can be successfully used to install these measures over large forest areas in as short a period as possible. These techniques include an integral approach that consists of utilizing good features of color infrared aerial imagery, methods of digital image analysis, artificial intelligence and visual scene interpretation. This research has proved that self-organizing neural networks can be reliably used to detect stand damage in color infrared (CIR) aerial photographs.

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Sažetak

Otkrivanje oštećenosti šuma na ICK aerosnimcima pomoću neuronske mreže

Povećanje udjela slučajnoga prihoda u propisanim godišnjim etatima negativno utječe na potrajno gospodarenje šumama. Sve veći udio sanitarnih sječa traži da se posebna pažnja posveti zdravstvenomu stanju šuma i količini slučajnoga prihoda od sušaca. Potrebno je u prvom redu otkriti sastojine slabijega zdravstvenoga stanja kako bi se pravodobnim mjerama održala njihova vitalnost i prirodnost na optimalnoj razini (Pernar i dr. 2007b). Sušci se uobičajeno inventariziraju intenzivnim terestičkim načinom, koji zahtijeva značajna materijalna sredstva. Na velikim površinama praktičnija je, materijalno prihvatljivija i pouzdanija metoda daljinskih istraživanja. Infracrveni kolorni (ICK) aerosnimci upotrebljavaju se u šumarstvu u planiranju, opisu i kartiranju staništa, vremenskim studijama ili u procjeni bolesti (Bütler i Schlaepfer 2004). Zbog svojih obilježja vrlo su pogodni za inventarizaciju oštećenosti vegetacije, osobito šuma i šumskoga drveća (Kalafadžić 1987, Pernar i Kušan 1994, Haara i Nevalainen 2002, Pernar i dr. 2007a, b).

Kao alternativni pristup u primjeni daljinskih istraživanja u šumarstvu se koriste umjetne neuronske mreže. Stoga se u ovom istraživanju opisuje otkrivanje oštećenosti šuma i utvrđivanje njezina prostornoga rasporeda primjenom segmentacije scene i samoorganizirajuće neuronske mreže radi pridobivanja podataka, što traži manja materijalna ulaganja. Time se postiže visok stupanj automatizma, kojim se uklanja subjektivnost klasičnih metoda daljinskih istraživanja te prikazuju neke mogućnosti primjene umjetne inteligencije u praćenju šumskih ekosustava.

Prvotno je provedena vizualna interpretacija ICK aerosnimaka istraživanoga područja u stereomodelu. Zatim je snimak (slika 1) podijeljen na četiri jednaka dijela (S, S2, S3, S4) jer je jako sporo ili gotovo nemoguće trenirati mrežu pomoću svih piksela. Nakon provedenoga treniranja mreža je segmentirala određenu scenu u zadani broj razreda (6 – 9). Zatim su vizualno interpretirane segmentirane scene i uspoređene s rezultatima fotointerpretacije istraživanoga područja te definiran broj razreda s kojima je dobivena najprihvatljivija segmentacija.

Provedenom vizualnom interpretacijom područja izdvojena su četiri stupnja oštećenosti stabala, sjene, te regije prijelaznih piksela između vegetacije i sjene. Najprihvatljiviji rezultat, odnosno najbolja podudarnost vizualne interpretacije i segmentacije pojedinih scena postignuta je kod scene S2 za 6 klastera (topologija 6, slike 2, 3), koliko je i bilo utvrđeno vizualnom interpretacijom cijele scene. Naime, veći broj klastera, koji je dobiven segmentiranjem, tj. korištenjem ostalih arhitektura s većim brojem neurona, nije upućivao na nova obilježja koja bi se utvrdila *vizualnom interpretacijom. Testom proporcija testirane su postotne jednakosti vizualne interpretacije i segmentacije. Vjerojatnost da su proporcije jednake jest u rasponu od 0,83 za klaster 2 (jako bolesna stabla) do 0,96 za klaster 6 (zdrava stabla). Nema statistički značajne razlike između vizualne interpretacije i segmentacije analizirane scene S2 (tablica 1).*

Zbog varijacija svake scene gotovo je nemoguće očekivati da rezultati segmentacije za svaku scenu u potpunosti odgovaraju rezultatima vizualne interpretacije, odnosno da su segmentacije za sve scene identične. Tim je slijedom iskorištena struktura neuronske mreže za scenu S2. Naime, provedena je simulacija ove mreže nad ulaznim matricama scena: S, S3 i S4. Simulacijom neuronske mreže (scena S2) na trima ostalim scenama postignuto je poboljšanje, odnosno segmentiranje scena prema utvrđenim razredima u postupku vizualne interpretacije. Postupak (primjena) simulacije ima i opravdanost u brzom dobivanju rezultata segmentacije, dok treniranje neuronske mreže zahtijeva određeno razdoblje te ponovnu interpretaciju dobivenih klastera. Ovako provedena segmentacija omogućuje promatranje cijeloga područja i pojedinih scena pod gotovo jednakim uvjetima. Naime, uspostavljen je odnos segmentiranih razreda i korespodentnih boja na cijelom promatranom području.

Utvrđivanje oštećenosti šumâ, njezina prostornoga rasporeda te praćenje njezina stanja važna je sastavnica potrajnoga gospodarenja šumama. U provođenju tih mjera u što kraćem roku na velikim šumskim površinama uspješno se mogu primijeniti tehnike daljinskih istraživanja integralnim pristupom, korištenjem dobrih svojstava infracrvenih kolornih aerosnimaka, metoda digitalne analize slike, umjetne inteligencije i vizualne interpretacije scene. Ovim je istraživanjem potvrđeno da se samoorganizirajuća neuronska mreža može pouzdano primijeniti u otkrivanju oštećenosti sastojina na infracrvenim kolornim (ICK) aerosnimcima.

Ključne riječi: oštećenost šuma, infracrveni kolorni aerosnimak, segmentacija, neuronske mreže, Hrvatska

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