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CROP CLASSIFICATION WITH NEURAL NETWORKS USING AIRBORNE HYPERSPECTRAL IMAGERY

KLASYFIKACJA UPRAW ZA POMOCĄ SIECI NEURONOWYCH Z WYKORZYSTANIEM LOTNICZYCH OBRAZÓW HIPERSPEKTRALNYCH

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Introduction

Mainly due to size of input data, the artificial neural networks (ANNs) methods for remote sensing image classification can be expensive to use, in terms of computer resources and expert analyst time (Mahesh, Mather, 2006). In the case of hyperspectral data, neural networks training process may take weeks of time, in order to determine the number of input nodes in network structure needed by hundreds of image bands. In addition, not every neural networks package, such as the Stuttgart Neural Network Simulator (SNNS) used in this study, works with binary data, which makes dimensionality data reduction methods necessary to develop an effective classification scheme based on an ASCII text file. Despite these reservations, ANNs offer a wide field of research and investigation in crop and land cover classification, because they are a non-parametric method in the sense that they make no assumptions about the statistical distribution of the classes to be identified. As additional benefit, they can accept non-numeric inputs as well as ratio- and interval-scale data. Moreover, the SNNS software provides the user a unique opportunity to design the input layers in a network structure, such as sub pattern window, which makes it possible to include texture information as additional data in the classification process (Zell et al., 1995). This method is especially useful in discrimination of non-homogeneous classes (Zagajewski, Olesiuk, 2008), and has been applied in this study.

The objective of this work was to compare the results of crop classifications based on two data sets derived from hyperspectral HyMap imagery: (1) after MNF transformation, (2) vegetation and soil indices.

The minimum noise fraction (MNF) transformation is used to segregate noise in the data, to determine the inherent dimensionality of the image data, and to reduce the computational requirements for subsequent processing (Boardman, Kruse, 1994). Essentially, it is two cascaded transformations. The first transformation, based on an estimated noise covariance matrix, de-correlates and rescales the noise in the data. This first step results in transformed data in which the noise has unit variance and no band-to-band correlations. The second step is a standard Principal Components transformation of the noise-whitened data. MNF bands are in a descending order of eigen values with almost no noise in the bands where the eigen values are near unity and below unity indicating signal-to-noise ratio (S/N) decreasing with decreasing order of MNF bands.

The second data set contains hyperspectral indices which were selected to estimate pigment, nitrogen, cellulose and water content in vegetation, and clay and iron content in soil.

Study area description

The study area is located in the Demmin region in north Germany (Figure 1). This is a previously mapped agricultural area, where the main land cover/ land use types are represented by agriculture and grassland farming, with intermixed forestry and urban areas. This area is used as an agricultural and multi-disciplinary test site, and is included in the Committeee on Earth Observation Satellites (CEOS) catalogue for calibration and validation sites.

Earth observation data

Images used in this study were acquired by the HyMap sensor flown by German Aerospace Center (DLR) on the 28th on July 2008, with spatial resolution of 4 m^2 and 126 channels covering the visible, NIR, SWIR regions of the solar spectrum from 450–2500 nm with a bandwidth of 15–20 nm. The images were corrected for radiometric (Richter, 1997) geometric (Schläpfer, Richter, 2000) and atmospheric influences (Richter, 2000).

The use of artificial neural networks

A multilayer, one-directional network was used for this work, trained using a supervised back-propagation method. The training process consists of determining the neuron connection weights to make the output signal from the network as close as possible to the expected one (Kavzoglu, Mather, 2003). The training data is a pair of vectors. The first (input) vector represents the structure, which the network is to recognize. The second (output) vector represents the pattern results corresponding to output data. The training aims, by adjusting the weights, to minimize the difference between the pattern vector, and the result generated by the network.

Input data sets

The first data set used for the classification contains the first 15 bands of a MNF transformation performed on HyMap imagery.

The second data set was prepared using a thematic approach to reduce the size of input data in classification using ANNs, and contains 7 hyperspectral geo-biophysical and -chemical indices. The selected indices are summarised in Table 1.

Table 1. Selected geobiophysical and -chemical indices

Parameter	Index	Formula	Author
Chlorophyll	Modified Normalized Difference 705 Index (mND705)	$\frac{R_{750} - R_{705}}{R_{750} + R_{705} - 2 * R_{445}}$	Sims, Gamon (2002)
Nitrogen	Normalized Difference Nitrogen Index (NDNI)	$\frac{\log \frac{1}{R_{1510}} - \log \frac{1}{R_{1680}}}{\log \frac{1}{R_{1510}} + \log \frac{1}{R_{1680}}}$	Serrano et al. (2002)
Cellulose	Cellulose Absorption Index (CAI)	$0.5 * (R_{2021} + R_{2213}) - R_{2100}$	Nagler et al. (2000)
Leaf water	Normalized Difference Water Index – MIR (NDWI-MIR)	$\frac{R_{860} - R_{2130}}{R_{860} + R_{2130}}$	Chen et al. (2005)
Density	Soil Adjusted Vegetation Index (SAVI)	$(1 + L) * \frac{R_{864} - R_{671}}{R_{864} + R_{671} + L}; L \in [0,1]$	Huete (1988)
Clay	Clay Index	$0.5 * (R_{2136} - R_{2240}) - R_{2195}$	DLR
Iron	Iron Index	$0.5 * (R_{780} - R_{1245}) - R_{920}$	DLR

Training and test data

Training and test data (used for validation of the training process) were chosen based on the reference crops map showed in figure 1b. These maps were kindly provided by the IG DEMMIN and DLR. Classification was performed on selected 7 crops classes: corn, winter rye, winter barley, winter wheat, winter rape, pastures and wasteland. The number of pixels for each class and data type is listed in Table 3.

Classification and post classification analysis

According to the characteristic of the data sets, classification in 4 parallel ways were performed: (1) 15 MNF bands, (2) 15 MNF bands with 3x3 textural window, (3) seven-index and (4) seven-index with 3x3 textural window. In all cases, the number of input neurons was defined by the number of input bands, so for data set with 7 hyperspectral indices 7 input nodes/neurones for classification were prepared, and for 15 MNF bands – 15 input neurones. In the second approach, using a sub pattern (textural) window the number of input bands was augmented by 9 (network performs a 3x3 pixel image convolution). To define the number of hidden nodes, the formula 2Ni+1 was used, where Ni means number of input bands (Kavzoglu, Mather, 2003). The learning parameters used for training the neural nets were: activation function – logistic, initial weight range – [-0,25, 0,25], learning rate – 0,2, number of training samples – 3000. The nets learning procedure was based on a training set, and an accuracy assessment on the test set. The accuracy assessment aims at standard procedures, which are based on an analysis of overall (ratio between correctly classified pixels to pixels that actually belong to this class), producer (percentage of a particular ground class correctly classified) user (percentage of a map class corresponding to the ground-truth class) accuracies and kappa coefficient (similarity of two maps, e.g. post classification and reference).

Results

The best overall accuracy was achieved for 15 MNF bands trained with 3x3 sub pattern window (overall accuracy 92,5%, kappa coefficient 0,91) (table 2). In this case corn, winter barley and rape were classified significantly above 90%. The worst results, wasteland (85%) and winter rye (user accuracy 77%), are good as well. These same 15 MNF bands set without the textural window gave the worst results (70,1%) and in some cases (e.g. wasteland and winter rye) the user accuracy is below 40 %, which should be re-analysed. The classification based on soil and vegetation indices achieved overall accuracy 79–82%. Land use form analysis shows that generally indices, which were used for the classification, offers 8–9% worst results than MNF bands, because only corn and winter rape achieved accuracy better than 90%. Analysing the matrix error (Table 3), corn achieved a very good classification (99,1%).

The best resulting classification maps for each data set are shown in Figure 2, and corresponding accuracy assessment is displayed in Table 2. For the data set with 7 hyperspectral indices, better classification results are achieved by the neural structure without the sub patterns window. Corresponding for these results the error matrices is displayed in Table 3.

Table 2. Overall classification accuracy

Classes	Accuracy [%]							
	Seven-index		Seven-index with 3x3 window		15 MNF bands		15 MNF bands with 3x3 window	
	OA: 82.2		OA: 79.4		OA: 70.1		OA: 92.5	
	KC: 0.77		KC: 0.74		KC: 0.64		KC: 0.91	
	P	U	P	U	P	U	P	U
Corn	90.7	91.8	88.4	97.1	90.1	98.5	90.8	99.1
Winter rye	72.8	67.7	0.0	0.0	94.8	38.7	93.5	76.9
Winter barley	77.1	80.3	77.8	90.7	97.8	92.2	98.3	94.7
Winter wheat	81.5	81.5	96.8	66.6	0.0	0.0	85.3	97.2
Winter rape	83.6	90.9	94.4	94.4	94.4	87.2	96.3	98.7
Pastures	92.0	82.0	96.2	81.5	98.3	83.0	98.0	87.6
Wasteland	73.6	73.6	80.2	46.3	83.0	37.2	85.2	80.2

OA – Overall Accuracy, KC – Kappa Coefficient, P – Producer Accuracy, U – User`s Accuracy

Table 3. Error matrix (pixels) resulting from MNF data set classified with 3x3 sub pattern window

Classes	a	b	c	d	e	f	g	Total result class	Total training class	Pd. Acc. [%]
a-Corn	69859	514	2	59	5	21	19	70479	19782	90.8
b-Winter rye	108	75321	386	21732	32	143	246	97968	23030	93.5
c-Winter barley	215	309	89067	981	3073	54	381	94080	88333	98.3
d-Winter wheat	342	2862	5	143115	179	227	513	147243	125068	85.3
e-Winter rape	351	400	171	268	116221	46	355	117812	132547	96.3
f-Pastures	5019	643	522	1276	874	64937	898	74169	129732	98.0
g-Wasteland	1012	472	436	396	248	864	13847	17275	9376	85.2
Total Gr. Truth	76906	80521	90589	167827	120632	66292	16259	619026	OA= 92.5	
User's Acc. [%]	99.1	76.9	94.7	97.2	98.7	87.6	80.2			

Discussion and conclusion

In this paper, two different data sets for crop classification were used. For each data set a back-propagation algorithm was applied with different structure of input nodes (1x1 and 3x3 sub pattern windows) to analyse agricultural heterogeneity. The textural window has a direct impact for classification accuracy. The best results were obtained using MNF data and 3x3 sub pattern window, but accuracy assessment in any case of over 80% for data sets containing hyperspectral indices showed that these data can be also successfully used for crop classification.

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Streszczenie

Celem opracowania jest porównanie wyników klasyfikacji upraw uzyskanych ze zdjęć hiperspektralnych HyMap. Teren badań znajduje się w rolniczym regionie Demmin w północnych Niemczech. Do klasyfikacji wykorzystano dwa zestawy danych: 1) obrazy po transformacji Minimum Noise Fraction (MNF) oraz 2) mapy wskaźników roślinnych i glebowych. Transformacja MNF polega na redukcji wymiarów przestrzeni spektralnej (kompresji danych) i składa się z dwóch kaskadowych transformacji. Pierwszy etap polega na dekorelacji szumu, a drugi to standardowa transformacja PCA przeprowadzona na danych po oddzieleniu szumu. W rezultacie powstają nowe kanały, które uszeregowane są od największej do najmniejszej wariancji, przez co do dalszych prac mogą być wykorzystane najbardziej przydatne informacje. Drugi zestaw danych zawiera utworzone na podstawie obrazu hiperspektralnego wskaźniki roślinne i glebowe. Definiują one zawartość pigmentów, azotu, celulozy oraz wody w roślinność, a także iłu i żelaza w glebie.

Klasyfikacja przeprowadzona została z wykorzystaniem sztucznych sieci neuronowych. Wykorzystano do tego celu oprogramowanie Stuttgart Neural Network Simulator (SNNS). Zastosowano sieć wielowarstwową, jednokierunkową, uczoną z użyciem metody wstecznej propagacji błędów (back-propagation errors). Klasyfikacje obu zestawów danych wykonano z zastosowaniem dwóch typów struktury neuronów w warstwie wejściowej. Pierwszy typ to struktura standardowa, gdzie liczba neuronów wejściowych odpowiada liczbie wykorzystywanych kanałów obrazowych. Druga struktura zaprojektowana została poprzez zdefiniowanie okna maski w postaci macierzy 3x3 piksele, dzięki czemu do procesu klasyfikacji włączona została informacja o teksturze badanego obiektu. Najlepszą dokładność całkowitą klasyfikacji wynoszącą 92,5% oszacowano dla zestawu zawierającego kanały wynikowe transformacji MNF i przeprowadzonej z wykorzystaniem struktury sieci odpowiadającej masce 3x3 piksele. Dla zestawu danych składającego się ze wskaźników roślinnych i glebowych dokładność klasyfikacji wyniosła około 80% w obydwu zastosowanych strukturach sieci.

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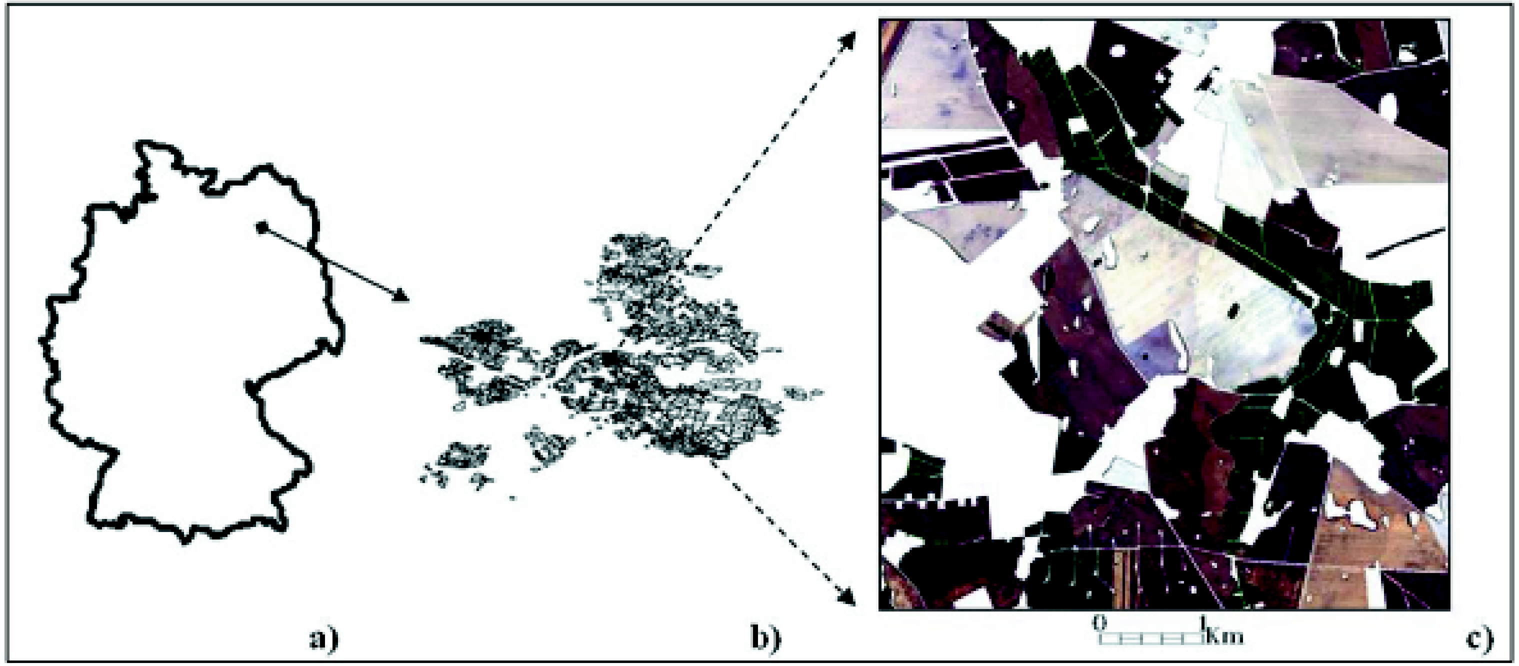

Figure 1. a – location of study area, b – with digitized reference crops map, c – masked HyMap imagery covering area of study

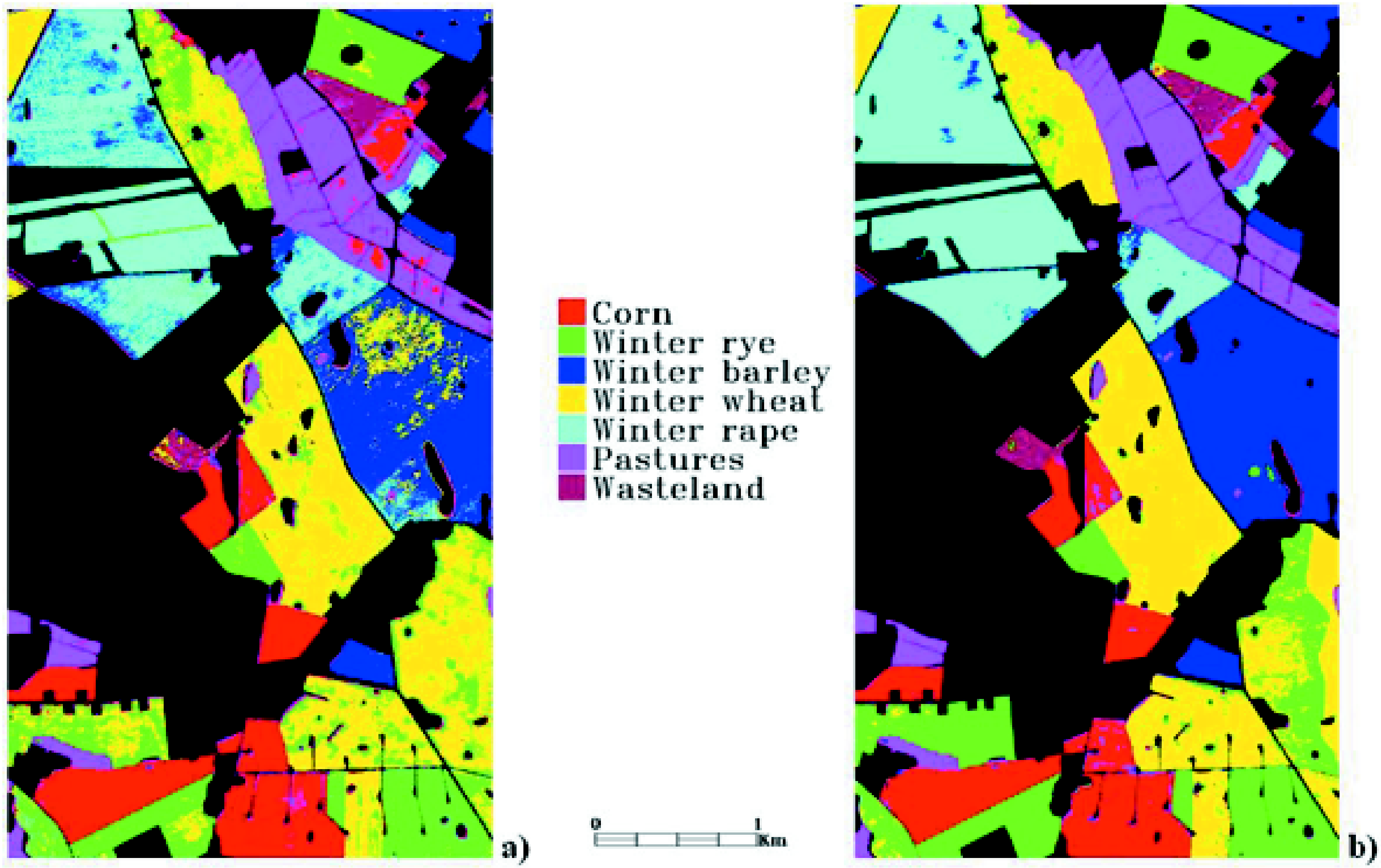

Figure 2. The best post classification maps achieved for each data sets: a – seven-index map, b – 15 MNF bands with 3x3 window