TRANSFERABILITY OF ARTIFICIAL NEURAL NETWORKS FOR MAPPING LAND COVER OF REGIONAL AREAS WITH HIGH SPATIAL RESOLUTION IMAGERY

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ABSTRACT:

Accurate and frequently updated land cover maps of environmentally protected areas are necessary for the management of legislation programs governed by the EU, national authorities and local environmental schemes. This study has analysed the suitability of Artificial Neural Networks (ANN) for mapping and monitoring land cover over regional areas, such as National Parks, using both hard and soft classification approaches together with the high spatial resolution of multispectral Carterra™ Geo IKONOS imagery.
The study aimed to examine the transferability of remote sensing mapping algorithms over Northumberland National Park (NNP) located in Northern England. The ANNs were trained using ground data of eight different upland vegetation classes and applied to a multispectral IKONOS image of NNP. The ANNs applied consisted of a Multiple Layer Perceptron (MLP), using a conjugate gradient descent, and one hidden layer with a varying number of hidden nodes and combinations of weights. The transferability of ANNs was found to depend on the ability to generalise, which could be improved by applying early stopping in the training process, improving the accuracy of the validation data by an average of 15%. The classification accuracies for validation pixels of the training areas resulted in 80%, but decreased to less than 50% if evaluated against validation pixels acquired from different areas within NNP. Limitations and issues regarding the transferability of MLP ANNs were observed to be significant. Advanced ANN algorithms such as Support Vector Machines were required to enable the use of ANNs for mapping and monitoring land cover.

KURZFASSUNG:

Genaue und regelmäßig aktualisierte Karten von umweltgeschützten Gebieten sind notwendig für die Verwaltung von gesetzlichen Schutzmaßnahmen durchgeführt von der EU, bundesweiten und regionalen Umweltschutzprogrammen. Diese Studie hat die Eignung und Nutzbarkeit von künstlichen Netzwerken als Kartierungs- und Überwachungsmethode für regionale Gebiete analysiert. Dabei wurden softe und harte Klassifizierungsmethoden, zusammen mit hochauflösenden multispektralen Carterra™ Geo IKONOS Bildern, verwendet. Das Ziel der Studie war die Verbesserung der Übertragbarkeit von Kartierungsalgorithmen der Fernerkundung für das Gebiet des Northumberland Nationalparks im Norden Englands (GB). Die künstlichen Netzwerke wurden für acht verschiedene Hochlandsvegetationsklassen trainiert und auf multispektrale IKONOS Bilder angewendet. Die Gewichtskombinationen und die Anzahl der Neuronen des mittleren Layers wurde nach verschiedenen Literaturempfehlungen variiert. Die Übertragbarkeit von künstlichen Netzwerke wurde beeinflusst von ihrer Generalisierung. Diese konnte mit dem vorzeitigen Beenden des Trainingvorgangs verbessert werden und die Genauigkeit der Klassifizierung von Vergleichsdaten um 15% erhöht werden. Die Klassifikationsergebnissen für Pixels der Trainingsgebiete erreichten um die 80%, aber verschlechterten sich zu unter 50% für Pixels des IKONOS Bildes von andern Gebieten des Nationalparks. Die Studie zeigte Begrenzungen und Probleme bei der Übertragung von künstlichen Netzwerken auf.

1. INTRODUCTION

Environmentally protected areas are monitored by different legislation and management programmes introduced by the EU, national and local environmental management bodies, such as national park authorities. Such management schemes require by legislation the accurate and frequent mapping and monitoring of land cover, for example for upland vegetation found in national parks in the UK. Traditional mapping approaches, such as field surveys and the interpretation of aerial photography have been shown to be low in accuracy, time consuming and therefore expensive (Cherrill et al., 1994). Remote Sensing has been seen as a potential mapping methodology for the last 20 years but has until recently been limited in its spatial resolution (e.g. Landsat TM) in relation to the spatial variability of land cover, such as that of upland vegetation (Taylor et al., 1991). Additionally remote sensing has yet to be successfully applicable to monitoring schemes, allowing the transfer of mapping algorithms across geographical areas and multi-temporal imagery.
The development of high spatial resolution satellite imagery in the last five years has offered a new potential to map vegetation regularly and at a more suitable scale (Slater and Brown, 2000). However the classification of high spatial resolution IKONOS imagery using traditional remote sensing mapping algorithms, such as the Maximum Likelihood Classification, has been limited to accuracies ranging between 52% and 80%. This

paper will report on the analysis of the suitability and transferability of Artificial Neural Networks (ANN), using both mixed and unmixed pixels, as a remote sensing algorithm for mapping and monitoring land cover at regional areas together with the high spatial resolution of multispectral Carterra^{TM} Geo IKONOS imagery.

1.2. Artificial Neural Networks in Remote Sensing

Artificial Neural Networks have been applied to several remote sensing studies often resulting in higher or equal mapping accuracies than achieved with traditional classification methodologies or mixture modelling (Benediktsson et al., 1990; Foody et al., 1995; Atkinson et al., 1997). An advantage of ANNs is the ability to generalise, and they do not require end-member spectras for soft classifications approaches (Lippmann, 1987; Heppner et al., 1990; Atkinson and Tatnall, 1997; Foody et al., 1997). It has also been found that ANN require less training data than traditional remote sensing classification approaches, such as Maximum Likelihood classification (Heppner et al., 1990). However, remote sensing applications of ANNs have tended to use simple data sets consisting of few pixels and land cover classes (Bernard, 1998). The generalisation ability of ANNs has been found to be limited, as ANNs tend to be overfitted to the training data (Wilkinson, 1997). Additionally, the fine scale spectral variation and low number of pixels available for training in comparison to the number of pixels within the image have caused difficulties in applying ANN to high spatial resolution imagery. In previous studies, the transferability over large geographical areas has been found to be limited and dependent on the ability of the ANN to generalise (Egmont-Petersen et al., 2002). This study therefore aims to examine the ability of ANNs to transfer trained knowledge, acquired by a classifier on one area, to classify unseen data across large geographical areas and potentially multi-temporal imagery.

2. METHODOLOGY

2.1. Study area

The study area was located in the Northumberland National Park (NNP) in Northern England (UK). The NNP is one of the eleven English and Welsh National Parks and is valued for its biodiversity and wildlife. It is covered mainly by upland vegetation, such as bracken, heather moorland (approximately 20% of England's upland vegetation resources) and blanket bog (approx. 18 % of England's resource) (ERDP, 2000). These resources are a significant proportion of the worldwide resources, as almost 15% of the world's blanket bog can be found in Britain (RSPB, 2000; Backshall et al., 2001). However, the increasing pressure of changes in the environment and in management practices have impacted the status, composition and extent of important vegetation habitats and resulted in significant changes in the extent of upland communities and their biodiversity (Tallis, 1985). The requirement for new monitoring and management schemes and the high spatial variation of upland vegetation made the NNP an ideal test site for this study. The specific site covered by the IKONOS imagery is the British Ministry of Defence's (MoD) Otterburn Training Area (OTA). The Otterburn range is located in the centre of NNP and covers 229 square km, approximately 20% of the Park area.

2.2. Image and ground data acquisition

A Carterra^{TM} Geo IKONOS image, recorded on 2nd September 2002, was acquired for the majority of the OTA. The image was georeferenced to the British National Grid (BNG) using 18 GPS ground control points, resulting in a Root Mean Squared (RMS) error of 2.57 m. Corrections for relief displacement, caused by the altitude range of the imagery of 500 m, were also carried out, (Hanley and Fraser, 2001). Further details of the geometric and atmospheric corrections applied to the image may be found in (Mehner et al., 2003; Mehner et al., in press).

Ground survey data offered the only source of providing information on the surface land cover distribution. Several GPS field campaigns using the kinematic Leica GPS 500 system were carried out along different transects across the imagery. Sample points were recorded at least every metre yielding 3D coordinates and the vegetation type attribute. The GPS coordinates were transformed to BNG and thereby referenced with the imagery. The number of measurements per class for each pixel was used as a guide to calculate the land cover distribution of each pixel. The number of mixed pixels applied were however much smaller than pure pixels, reflecting the true spatial variation of land cover found at the test site.

Two transects were located within the same geographical area (training site), while the third transect was carried out at a site 5 km away (remote site). Both areas are similar in terms of vegetation types and altitude and are relatively flat, thus the spectral variation due to anisotropic reflectance effects was minimised. Initially the ANNs were trained using data, both mixed and unmixed pixels, from the training site and then applied to the remote site to test the performance of ANNs when classifying unseen data of a different geographical location.

2.3. Artificial Neural Network design and training considerations

The ability of an ANN to classify unseen data successfully and thereby transfer its trained knowledge dependent on its ability to generalise (Haykin, 1999). The generalisation of an ANN is influenced by several parameters, which require an optimal choice.

2.3.1. Design The classification performance of an ANN is influenced by its design depending on a choice of several parameters, such as the number of hidden nodes and learning algorithms (Haykin, 1999). The most common type of ANN used in remote sensing is the Multilayer Perceptron (MLP), which was also chosen for this study (Lippmann, 1987; Lees, 1996; Atkinson and Tatnall, 1997). MLPs have shown to be a suitable ANN design for many remote sensing applications (Lees, 1996). MLPs consist of three different kinds of layers: input layer, hidden layer and output layer. The number of nodes in the input layer is determined by the number of input bands, which is: four IKONOS bands - blue, green, red and near-infrared - as well as the Normalized Difference Vegetation Index (NDVI), calculated to enhance the spectral separability (Figure 1). The number of output nodes is dependent upon the number of land cover classes in the classification scheme: in this case eight different upland vegetation classes, such as *Calluna vulgaris*, Mire and *Molinia Cearula* (Figure 1) were considered.

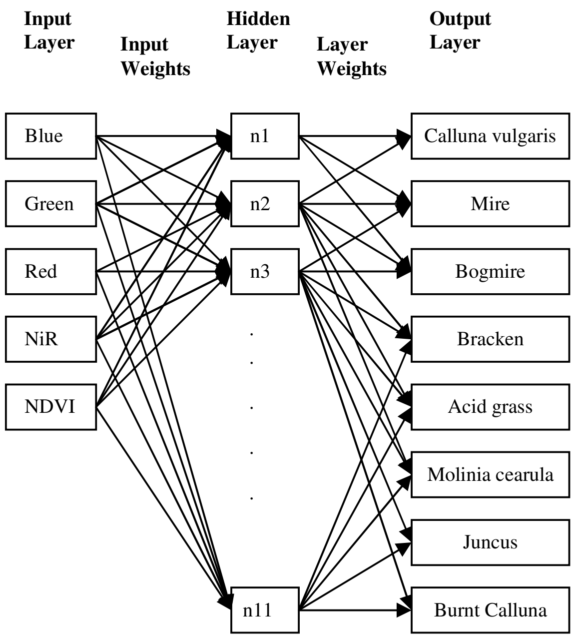

Figure 1. Example of an ANN as applied in this study, consisting of five input nodes, each connected to eleven hidden nodes, which are linked with each one of the eight output classes.

No universally applicable rule concerning the optimal number of hidden layers and number of hidden nodes exists (Kavzoglu and Mather, 1999). Most applications therefore apply extensive and time-intensive trial and error tests to determine the optimal design for each study, also known as structural stabilisation (Bishop, 1995; Openshaw and Openshaw, 1997). In this study the number of hidden nodes was calculated following three literature recommendations. The method (Equation 1a) suggested by (Atkinson et al., 1997) used only the number of input bands (n), whereas (Dunne and Campbell, 1994) recommended a formula considering only the number of output bands (m) (Equation 1b). The third method (Equation 1c) by (Miller et al., 1995) consisted of both parameters to calculate the number of hidden nodes:

No. of hidden nodes= $2n+1$ (Atkinson et al., 1997) (1a)

No. of hidden nodes = $\binom{m}{2}$ (Dunne and Campbell, 1994) (1b)

No. of hidden nodes = $2\sqrt{n}+m$ (Miller et al., 1995) (1c)

Following these recommendations, ANNs consisting of 11 (Atkinson et al., 1997), 28 (Dunne and Campbell, 1994) and 12 (Miller et al., 1995) hidden nodes were created. The network training was carried out using the conjugate gradient algorithm, which requires no definition of additional parameters, such as momentum and learning rate for the gradient descent algorithm. The activation function was the 'tanh' function leading to quicker convergence than the sigmoid activation function (Bishop, 1995).

2.3.2. ANN weights Beside the design, the network performance depends upon the choice of initial weights. Weights connecting the nodes between each layer (Figure 1) are initially assigned randomly and adjusted during the learning process to minimise the global error. The influence of the assignment of random weights was considered in this study by initialising each neural network 10 times, each time with a different combination of weights.

2.3.3. Training data The characteristics of the training data have to represent the whole data set. Statistical parameters of all classes, including standard deviation and deviation from the mean, were calculated for all pixels. The deviation from the mean was used as a guideline to include border and core pixels in the training dataset. The integration of border pixels, covering the whole spectral range of each class is needed to allow the networks to learn the full characteristics of the responding land cover classes (Foody, 1999). The data set of the training site was separated into 2/3 training data and 1/3 validation data, consisting of 1363 pixels and 714 pixels respectively for the OTA classification.

2.3.4. Training amount The amount of training applied to an ANN influences its ability to generalise (Bishop, 1995). The longer the network is trained, the more the danger increases that the ANN becomes 'overfitted' to its training data, thereby reducing its ability to generalise (Atkinson and Tatnall, 1997; Benediktsson and Sveinsson, 1997). The training process can be stopped according to one of the following user defined options (Bishop, 1995):

- after a fixed number of epochs
- after a certain CPU time
- when a minimum error function is reached
- after minimum gradient is reached and learning per epoch is only marginal
- when the error value of validation datasets starts to increase (cross-validation).

In most remote sensing applications the first approach is used, training the ANN for a user defined fixed number of epochs. However results in a previous study showed that generalisation was significantly affected by such an approach (Mehner et al., 2003). The longer the training process was carried out, the higher the accuracy of the training data, showing a good fit of the ANN model between input and output data. However it caused the loss of generalisation, resulting in a decrease of accuracy of the validation data of up to 15 % (Mehner et al., 2003). This study applied early stopping as criteria for the amount of training carried out. Early stopping utilises cross-validation to stop the training process when the Mean Squared Error (mse) of the validation data starts to increase (Bishop, 1995; Duda et al., 2001). It allows maximum generalisation and prevents the network from becoming overfitted to the training data.

3. Results and Discussion

The overall accuracy was calculated for all pixels, mixed and unmixed, using the rank matrix (Bernard, 1998). The rank matrix is a modified traditional confusion matrix, as it calculates the accuracy based on the correctly classified positions and classes.

The training of the ANNs using early stopping resulted in different numbers of epochs for each ANN, depending on the initialised random weights. Early stopping enabled the ANNs to generalise and thereby classify the validation data to accuracies similar to the accuracies of the training data.

3.1. Classification accuracy of training and validation data

The trained ANNs were applied to classify the training data and validation data of the training site. For both data sets overall accuracies of the same magnitude were achieved for all networks, independent of the number of hidden nodes. Additionally the overall accuracies were found to be comparable to the accuracies of the Maximum Likelihood classification. The overall accuracies ranged from 57% to 77.4% for the training data and from 55.2% to 76.1% for the validation data of the training site of all ANNs. The highest overall accuracy of the validation data of the training site was 76.1%. This showed that the ANNs had resulted in a high generalisation ability, enabling them to classify unseen data of the same area as the training data to a high accuracy. On the other hand the choice of random weights influenced the performance of the neural networks more strongly than the choice of hidden nodes (Figure 2 and 3). Differences in accuracy of up to 15% of both training and validation data (ANN F vs. ANN G) were found between ANNs consisting of different initialising weights (Figure 2). Therefore different sets of random weights should be applied to each ANN within one study to determine the optimal ANN for the application.

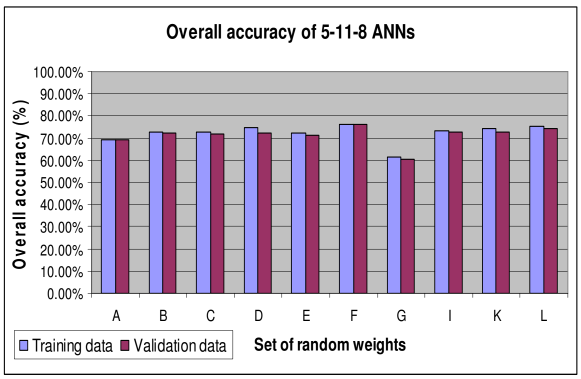

Figure 2. Overall classification accuracy of training (blue) and validation (red) data of the training site for the ANN consisting of 11 hidden nodes.

3.2. Overall accuracy of the classification of the remote site

The trained ANNs were applied to pixels from the remote site to investigate the ability of the ANNs to classify unseen data. The data of the remote site consisted of 384 mixed and unmixed pixels, being of similar vegetation cover, but had not been integrated in the training process. The averaged overall accuracy of the remote site data for the three different ANN designs was 21.6% (11), 19.1% (28) and 21.7%% (12 hidden nodes) (Figure 3). This showed a significant decrease in classification accuracy. The highest overall accuracy of the transferability data was 27.3% for a ANN (ANN G) consisting 28 hidden nodes. However even the highest accuracy of the remote site data achieved was far below expectations, indicating a poor classification performance. The generalisation and knowledge of the ANN gained at the training site was not sufficient to classify pixels of a remote part of the image. Modifications and improvements of the ANN classification were therefore required.

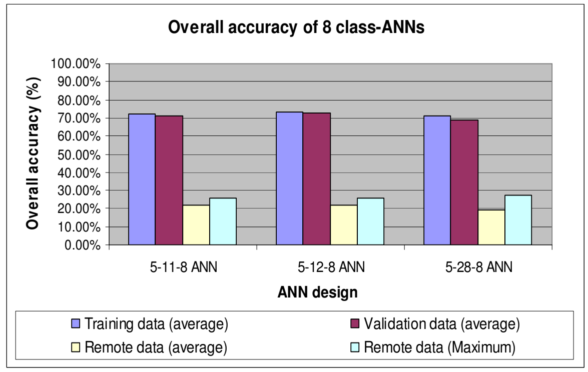

Figure 3. Averaged overall classification accuracy of training (blue), validation (brown), remote site (yellow) data and maximum overall classification (turquoise) for the remote site data (light blue), shown for all ANN designs.

3.3. Adding a geographical label to the data

The ANN training process was repeated but with modifications of the training data. Some pixels of the remote site (156 pixels) were integrated in the training process, but being much lower in number than the original training data. Additionally a geographical label was added as input band referring to the test site of the pixel. The label of 1 was given to pixels of the training site and 2 to pixels of the remote site. All ANNs were retrained, partly consisting of a new number of hidden nodes depending on the 6 input bands, applying again early stopping. The overall accuracy of the training and validation data of the training site was similar to the accuracies of the original training process. The averaged overall accuracy ranged between 31.6% and 78% for the training data and between 33.3% and 74.9% for the validation data (Figure 4).

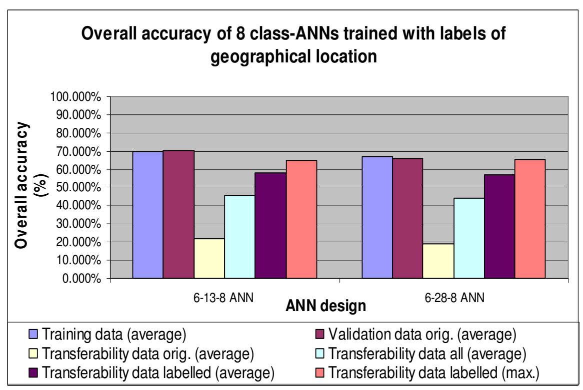

Figure 4. Averaged overall accuracy of the training (blue), validation (brown), original remote site (yellow) data and averaged accuracy (red) and maximum overall accuracy (green) of remote site data, when training data included geographical label.

A big improvement in classification accuracy was however found for pixels of the remote test site. The overall accuracy of the remote site ranged between 25.1% and 65.3% for the ANNs trained with a geographical label. The highest accuracy of all three ANN designs, being 64.9% (13 hidden nodes) and 65.3% (28 hidden nodes), which was of the same magnitude as the overall accuracy of the validation data of the training site. The overall classification accuracies achieved using a geographical label were of the same magnitude as other remote sensing studies, highlighting the potential of ANNs to classify vegetation of a high spatial variation. In the example of the ANNs consisting of 28 hidden nodes, overall accuracies were calculated for both approaches. On average the overall accuracy of the remote site data increased by 38%, e.g. for ANN E from 22.6% to 64.4%. It showed that the generalisation ability and thereby performance of the ANN could be improved by adding additional data to the training process. The integration of geographic label also comes as no additionally cost and provides a simple option to improve the classification performance significantly.

4. Conclusion

This study analysed the suitability of Artificial Neural Networks as mapping methodology for regional areas. The ANNs were trained using limited amounts of training data of one site of the image. The trained ANNs classified the training and validation data of the training site to accuracies comparable to the traditional Maximum Likelihood classification. However when the ANNs were applied to unseen data of a remote testsite the overall accuracy significantly decreased. The ANNs performed poorly and did not result in a generalisation ability high enough to transfer the learned knowledge to unseen data. The performance of the ANNs could be improved if additional information of each site, in this case a geographical label, was added. It increased the overall classification accuracy of the unseen data of the remote site to the same magnitude as of the validation data of the training site. It was concluded that ANNs as classification methodology across regional areas, and therefore also as multi-temporal approach, had failed to perform.

On the other hand it was concluded that the specific characteristics of upland vegetation influenced the generalisation ability of the ANNs. Upland vegetation consists of a high spatial variation, resulting in a spectral variability of land cover classes depending on the topographic location and interaction of different upland species.

Simplified ANN classification schemes promise a higher transferability. More research is needed to improve the transferability of ANNs as classification methodology. The choice of more ancillary data or incremental learning offer new opportunities to improve its application across large geographical areas and as multi-temporal classification approach.

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