COMPARISON OF STATISTICAL METHODS AND NEURAL NETWORKS IN A POST-OBJECT CLASSIFICATION FOR FORESTRY REGISTRATION

Bobo Nordahl, Dr.Ing. student
Department of Surveying and Mapping
Norwegian University of Science and Technology, NTNU
N-7034 Trondheim, NORWAY
E-mail: Bobo.Nordahl@iko.unit.no

Commission VII, Working Group 3

KEY WORDS: Remote sensing, Forestry, SPOT, Neural Networks, Post-Object Classification

ABSTRACT

This paper presents a project where post-object classification has been used for forest stand registration. The classification method is divided in two steps where the first is pixel-specific and the second is object-based. In the pixel-specific classification, statistical and neural network classifications have been compared which is a particular focus of this paper. The stands from the previous forest inventory were used as objects in the second step. Ancillary data such as slope, aspect and stand with information such as boundaries and classes from the previous inventory, were combined with the image data. The project method is designed to prolong the forest inventory intervals rather than replace them in order to reduce the cost of forest management planning. The conclusion for the low productive areas is that they can not be classified with these methods. The result from the area which is dominated by medium-high site classes, indicated that homogeneous stands are better classified with a statistical classifier but a neural network classifier could perform a better result with heterogenous stands. After the object-based reclassification the differences are smaller. The results do not indicate that neural network classifier would be useful enough to this kind of forest stand classification.

1. INTRODUCTION

The aim of this study is to investigate the possibility of using remote sensing images in an alternative forestry inventory. The project focuses on the coniferous forests in a region in the middle of Norway (Trøndelag), with Norway spruce (Picea abies) and Scots pine (Pinus sylvestris). The initiative to start this project came from the local forestry authorities who wanted to reduce the high costs of the traditional inventories. It was presumed that the traditional stand forestry inventory could not be replaced but the intervals of 10 years could be prolonged to 20-25 years (the rotation age is 100 to 150 years). During these intervals, registrations with remote sensing images to update the previous forest inventory should be done.

Several other Nordic tests and projects that used remote sensing for forestry purposes have been studied. A method for stand delineation has been developed in the program named SKOGIS [Hagner 1990 and 1991], which could be used as a method to establish objects. The inductive approach using cluster analysis to explore the basic information in the satellite image is outlined in [Strand 1989]. The effect from varying reflection depending on topographical and background variations is handled in [Tharaldsen, Angeloff 1992]. A summary of some Nordic projects and an implementation of SKOGIS for a small-scale test have been carried out in [Kolstad 1993]. The main differences from Swedish and Finnish conditions are the hilly topography and the smaller average size of the stands in Trøndelag.

The project consist of three main parts:

-New inventory classes have to be established, based on what kind of forestry information at the stand level that could be separated in the image and what kind of information that is needed for forest management planning?

-What kind of ancillary data to be used has to be selected. Both to establish objects and to get information about the topography and other relevant stand information.

-An interpretation/classification method has to be established. Several methods for improving classifications have been tested in research projects during the last few years and some main areas are discussed in [Richards 1993]. When working with forest registration the stands should be a better classification unit than pixels and [Löcherbach 1992] summarized several advantages with object-based interpretation compared to pixel-based interpretation.

The first two parts are only roughly outlined in this paper.

For more details see [Nordahl, 1994 and 1995]. This paper focuses on the use of the classification method. A two-step post-object classification is used as classification method as seen in *Figure 1* (see also [Nordahl 1995 and 1996]). When the result was analyzed from this first phase of the project it was clear that many heterogeneous stands were wrongly classified. Signature patterns for these stands and their respectively training fields have complex structure that did not fit well with a statistical classifier.

At this stage a phase 2 was proposed to investigate the possibility to handle nonlinear signatures with the use of neural networks in the pixel-wise classification. Neural networks for remote sensing classification have been used in several projects with various results during recent years and some are summarized in [Dalen 1995]. A three-layer feed-forward neural network with standard back-propagation as training was used and compared with the result from the traditional statistical classification in the first pixel-based part.

2. TEST AREA AND USED DATA

2.1 Test area

As test area the Steinkjer municipality forest, Ogndalsbruket (21 800 hectares with 8400 hectares productive forests) in North-Trøndelag was chosen. It has a representative variation for a "standard" forest in Trøndelag according to stand sizes, age and tree variations. The productive forest is the coniferous stands which are dominated by Norway spruce (Picea abies) and where Scots pine (Pinus sylvestris) has a smaller commercial volume.

In a control area of approximately 650 hectares field measurements were conducted to establish ground truths for analyzing the results. The height above sea level varied in the control area from 150 to 400m and the site classes from low to medium-high. Mainly outside of this control area there are a total of 45 training fields representing approximately 3500 pixels (=140 hectares) which had been registered [Nordahl,Kjellsen 1994].

2.2 Data used

As it was required to obtain an image from the maximum growth period when the spectral reflections are at their highest both from the conifer stands and from the broad-leaf trees in the conifer stands, we looked for an image in the period from mid of June to late July, from the same year as a recent forest inventory which was finished in 1991. A search of existing scenes led us to only one suitable, a SPOT2 XS scene from 24 July 1991 which was only slightly covered by clouds in the test area. Landsat TM with its higher spectral resolution specially in the infrared wavelengths is normally better suited for vegetation analysis. But SPOT XS with its higher geometrical resolution with 20x20m was interesting for classification at the resolution level of stands. As the test area contains a variation from almost sea level to mountain areas and we planned to combine the image with ancillary GIS-data, the scene was ordered with geometric precision correction by the use of a digital terrain model to UTM coordinate system.

The digital terrain model (DTM) was a standard product from the Norwegian mapping authority with medium density point data at approximately 90x90m (3x6"). A Kriging interpolation from this data-set was also used to calculate values for aspects and slopes for the image pixels. A 5m elevation map was constructed and visually compared with a 1:10 000 map to control the interpolation. In areas with a smooth topography the heights were normally correct within some meters and the aspects and slopes had negligible errors. Naturally the errors are largest in rapidly changing topography, but in our test area this is limited to small parts concerning only a few stands. Due to the sampling method of the original digital terrain model the errors in the interpolated DTM are at a minimum along 20m level lines on the 1:50 000 topographic map.

The previous forest inventory was from 1981 in 1:10 000 paper-copies from ortho-photomaps in the NGO coordinate system. Stand boundaries and connected attributes were digitized for the control area and for all field-checked stands with PC-Arc/Info. Transformation to UTM and then to the UNIX image processing system (ERDAS) was made. This resulted in one set with raster-data and one with vector-data.

3. METHOD

The inventory class system had been established after a process which started with an inductive approach [Strand 1989] for analyzing the image data. The class system got three criteria where the first was for size/age with one class for clear-cuts and three other classes. The second criterion was the average crown coverage of the stands in two classes. The third criterion was a two level division for the amount of broad-leaf trees in the coniferous stands. Out of these classes a total of 8-10 classes was used. When the significance dropped too low for the objects, the program looked if any of the above divisions were significant and let the object be classed into a more general super-class.

The ground truth training fields have been analyzed and divided into slope- and aspect-subclasses of the inventory classes. A total of approximately 40 subclasses out of the 8-10 inventory classes was used in the pixel-based classification. To handle the topographic effect in the image slope and aspect values have been normalized/weighted to the spectral depth of the image channels as separate channels instead of recalculating the image channels themselves. A maximum-likelihood classification was conducted on the 5 data channels consisting of the three SPOT-channels and two for the slope and aspect values.

3.1 Object-based post classification

An object-based approach was implemented to achieve a better result than the pixel-based interpretation gave. Object-based interpretation has several advantages compared to a pixel-based interpretation, as summarized by [Löcherbach 1992]. Object boundaries have also been used to reduce the effect from mixed pixels along the boundaries. How to establish the objects? Stands could be delineated with the information contents in the image by the use of the program SKOGIS [Hagner 1990 and 1991, and Kolstad 1993]. An other possibility was to use the stands in the 10 year old forest inventory. As the plan was to update the previous forest inventory an estimation of the reliability of the old boundaries was done. A comparison was made between the 1981 and 1991 inventories. Boundaries demarcating physical differences are normally unchanged except where forestry activities have changed them. The opposite was boundaries for administrative or planning reasons which could differ widely, but it seems to be of less importance from a classification point of view, as it was merely the same forests on both sides of these kinds of boundaries.

The use of field boundaries for pre-object and post-object classification had been tested [Jansen, Van Amsterdam 1991], where the post-object method gave the best result. As shown in *Figure 1* a two-step object-based post classification was used. In the first phase (left-hand side) the pixel-based classification used a maximum likelihood statistical algorithm.

Also other inventory class information from the previous registration was registered (object attributes) and rules were implemented to have a knowledge-based control function. But they had not been fully used at this stage as not all of the inventory information were marked at same level on the whole map.

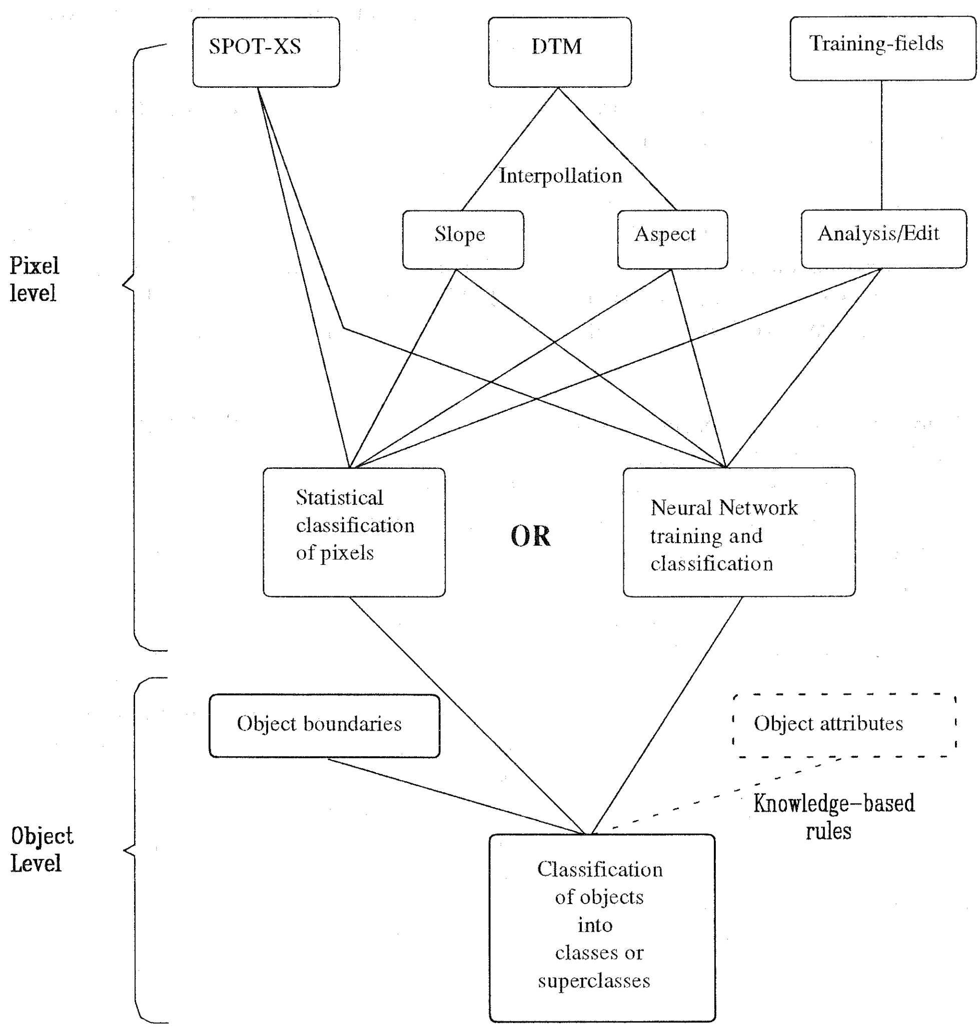

Figure 1. Flow chart for post-object classification

3.2 Neural network in pixel-wise classification

The main advantages with the neural network as a classifier, for this project was the ability to handle complex data patterns as it is nonlinear. In this case the complexity in the data patterns concerned the variation between the image channels on one hand versus the slope and aspect channels on the other hand. For some of the subclasses it has been noticed that signatures for the near-infrared channel and slope and aspect channels have spread and complex patterns, which had not been solved by the subclass division.

The same subclasses of the training fields that were used with the maximum likelihood classifier were used to train the neural network. The values for the 5 input channels were normalized to a range between 0 and 1 in order to speed convergence to the minimum error point in the network. An equal number of pixels in each class would have given the Neural network its recommended balanced data sets. But because of the comparison of the methods exactly the same data sets are used.

Several tests with different combinations of learning-factors number of nodes in the hidden layer were conducted in the standard back-propagation training process. The settings of the variables are plausible and the guidelines from other projects only partly gave the same results. When it comes to the learning factor there are different recommendations in the literature. We got best convergence with a decreasing learning factor from approximately 4 to 0.1 for net with moderate number nodes in the hidden layer. But for larger net with around 100 hidden nodes a stable low (0.5) learning factor seems to give the best training result. Among others Skidmore et al. 1994 pointed out that even if the percentage of correctly classified training patterns has a slight tendency to grow as the number of hidden nodes is increased. There is an almost opposite tendency for the percentage of correctly classified test data that indicates an optimal number of hidden nodes as being quite low.

A "program" called Stuttgart Neural Network Simulator (SNNS) was used to conduct the neural network classification . SNNS is distributed by the University of Stuttgart as 'Free Software', for more information see the User Manual [Zell et al. 1994]. A three-layer feed-forward net with 5 input nodes, 100 nodes in the hidden layer and 10 output nodes was found to give the best training results and thereby used in the classification.

3.2.1 Training results from Neural Networks. Dalen 1995 has done some tests with the same training data sets as used in this project. He got an overall training result of 86% and for the individual classes a result from 65-95%. This best result was achieved with a network with 20 hidden nodes. He used 1200 iterations where the learning factor decreased from 4.0 down to 0.1. For his limited test data sets the overall results were 12% and the total of all stands in the individual classes ranges from 0-51% correctly classified. In these data sets there is no separation into areas with low and medium-high site classes as been done in section 4.

In this project the same training data sets were used, but for the test data all the coniferous stands in the control area were used. For nets with moderate number of nodes in the hidden layer the best result was for a net with 25 hidden nodes. The result for this net was 86% correctly trained when only the highest "score" counts (winner takes all). This was achieved after 1050 iterations with a decreasing learning factor.

As complex signature patterns necessitated the examination of neural networks, larger nets with more hidden nodes were also tested. The best training results was achieved after approximately 10000 iterations and 45 hours on a "Sun Sparc-station LX". The training-results was over 91% correctly trained (winner takes all) or over 87% if the 40-20-40 method is used in the training analysis.

4. RESULTS AND DISCUSSIONS

First the results from phase 1 with the maximum-likelihood classifier in the post-object classification are presented. The coniferous stands in the control area have to be divided into two groups to get any meaningful analysis at all. In one group that consists of areas with mainly low-productive stands (low site classes), hardly any of the stands were correctly classified. The spectral reflections in these stands are totally dominated by the background vegetation and the trees are too spread to make a dominating influence on the reflection signals.

The other group consists of stands with medium-high site classes and here the results are better. The total classification accuracy in this area is approximately 50% in the correct class, 30% in the correct super-class and 20% wrongly classified after the post-object classification. Among the stands that were not correctly classified are almost all the small stands. The rest of the wrongly classified stands are dominated by "spectral" heterogeneous stands. Many of these have physical variations in topography, crown coverage and/or amount of broad-leaf trees.

The pixel-based classification results are given here for two interesting groups of stands: homogeneous and heterogenous stands in the area dominated by medium-high site classes. For the homogeneous stands 70-95% are correctly classified and for the problematic heterogeneous stands they vary from 5 to 30%. These heterogeneous stands with complex signature patterns (see Section 3.2) were the direct reason for phase 2.

The results from the neural network part in phase 2 and the comparisons here are given for the same two groups of stands. Stands that are "spectral" homogenetic have a lower correct classification rate of 34-53% compared with the 70-95% for the statistical classification . Some of the "spectral" heterogeneous stands are better classified with the neural network, but they still have too low classification rate (4-43%) to be compared with the 5-30% in phase 1.

After the object-classification of the stands the differences are smaller. For the homogeneous stands two were changed from the correct classes. But for the heterogeneous stands a few more stands were put into the correct super class with the neural network classification.

In the low-productive forest area none of the methods are useful depending on the dominating background-reflection. Small stands are another group that are not suitable for this kind of classification with the sensors we have available today.

5. CONCLUSIONS AND REMARKS

The results do not indicate that neural network classifier would be useful enough to this kind of forest stand classification. Especially when considering the problem of setting the variables for a non-specialist, the time consumption and the lack of confidence in the results when the behavior sometimes seems to be unpredictable.

Out of 17 tests with larger neural networks (with 50 to 100 nodes and from 30 minutes to 50 hours iteration time) only two seem to reach some kind of global minimum. The other test ends up with a high average system error. For the best training results there are no intermediary results stored so it had not been tested to see if it was overtrained as is indicated by [Skidmore et al. 1994] among others.

ACKNOWLEDGEMENTS

Special thanks are directed to the initiator of the project Assistant Professor Asbjörn Kjellsen, North-Trøndelag College for his encouraging support.

REFERENCES:

Dalen, Ø 1995. Bruk av neurale nettverk for fjernmålingsklassifikasjon. Project report at The Norwegian Institute of Technology, Department of Surveying and Mapping.

Hagner, O. 1990. Computer aided forest stand delineation and inventory based on satellite remote sensing. Proceedings SNS/IUFRO, Umeå, Feb. 1990.

Hagner, O. 1991. A prototype GIS/remote sensing work station for forest map revision and updating. Proceedings(?) SNS/JCR-LFA, Copenhagen 1991.

Jansen, L.L.F., J. Van Amsterdam. 1991. An Object-Based Approach to the classification of remotely sensed images. Proceedings IGARSS, Espoo, Finland 1991.

Kolstad, J. 1993. Bruk av fjernmålte data i skogbruksplanlegging og eiendomsforvaltning. Partial-report 1a-c, Norskog, Norway, Feb. 1993.

Löcherbach, T 1992. Interpretation of aerial and satellite images. Course compendium Institut für Photogrammetrie, Universität Bonn, First course in digital photogrammetry, Bonn, Germany, Oct. 1992.

Nordahl, B. A, Kjellsen. 1994. Fjernmålingsprosjektet, Tolkning og praktisk anvendelse av en SPOT satellittscene i skogbruket. Preliminary report:NTDH, Steinkjer, Norway May 1994.

Nordahl, B. 1995. Integration of SPOT-XS Data with Ancillary Data in a Postobject Classification for Forestry Registration. Proceedings ScanGIS'95, Trondheim,Norway.

Nordahl, B. 1996. Skogregistrering med SPOT-Opptak - Project-rapport. Proceedings NKTF Kartdagene 1996 Beitostølen, Norway.

Richards, J.A 1993. Remote sensing digital image analysis - an introduction, second, revised and enlarged edition. Springer-Verlag. Chapter 8 part II and Chapter 12.

Skidmore, A.K, W. Brinkhof, J.Delaney 1994. Using Neural Networks To Analyse Spatial Data. 7th Australasian Remote Sensing Conference Proceedings :Poster and Post-deadline, Melbourne 1994

Strand, G-H.1989. Remote sensing of forest - An inductive approach. Norwegian Computing Center report no. 824, 1989.

Tharaldesen, C., M. Angeloff 1992. Kartlegging av bjørkeskogen i Vang kommune ved hjelp av satellitt. NIJOS-report, Norway, July 1992.

Zell, A., et al. 1994. SNNS User Manual, Version 3.3. University of Stuttgart, IPVR Report, No.3/94.