ESTIMATION OF TREE SPECIES PROPORTIONS OF FOREST STANDS USING LASER SCANNING

Markus Törmä
Helsinki University of Technology
Institute of Photogrammetry and Remote Sensing
Otakaari 1, 02015 HUT, Finland
Tel: +358-9-451 3896, Fax: +358-9-465 077
Email: Markus.Torma@hut.fi

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ABSTRACT

Tree species proportions of forest stands were estimated using data measured by Toposys laser scanner. Employed estimation method was multilayer perceptron neural network with error back-propagation training algorithm. Measurements were divided into 2*2 m^2 squares and then those measurement which were higher than determined DTM were used to compute features. The purpose of extracted features were to determine and characterize the vertical distribution of measurements within squares. Four different featuresets were computed in order to test and compare different strategies to extract features. The estimation errors for those stands selected for training were really small but the estimation errors for other stands were considerably worse. When stands were classified according to dominant tree species, classification error for stands selected for training were nonexistent or small, but the classification errors for other stands were larger. Bad results may be due to small number of stand (79), but it also indicates that only 3D-coordinates are not enough to estimate stand tree species proportions. The alternatives to get better results are either classify single trees and compute tree species proportions from these or use also intensity information by using aerial images or laser which can measure intensity.

1. INTRODUCTION

Forest assessment deals with the methods of obtaining information on forest resources: estimation of growing stock, growth and health of the forest. That information is a basis for decisions of the forest industry, the official forest policy and the forest owners. For countries such as Finland, where 30 % of exports is based on forestry products and the percentage of the forest area (76 %) is the highest in the world, development of inventory methods are a necessity.

Typically, forests are operationally assessed with two scales: economic planning of forests at stand level (small-area inventory) and monitoring of forest resources at the national level (large-area inventory). The forest stand is a homogeneous forest area with respect to forest resources and treatments needed. Typical stand size, e.g. in Finland, is between 0.5 and 5 hectares. Conventionally, forest inventory data has been collected primarily by means of field surveys, which is both expensive and time-consuming. Important forest attributes, including stem volume per hectare and ratio of tree species, are then assessed to these stands by measuring sample plots and individual trees, and by using personal experience. Traditionally, the amount of forest cover and growing stock have been the most important parameters in forest inventory (Nyyssönen, 1993). During the last decades, due to increasing environmental consciousness, the importance of the information about tree species has increased because tree species have a great influence to biodiversity (Wilson, 1992).

Tree species classification has been made very successfully using large-scale (1:5000 or larger) aerial images (Needham et.al., 1987). The results with smaller scale images have been worse (Nyyssönen et.al., 1968, Gisnås, 1982). More recent studies have included different instruments such as AVIRIS (Martin et al. 1998), digital orthophotography (Duhaime et al., 1997), multispectral videography (Thomasson et al., 1994) or profiling radar (Törmä et.al, 1998). Due to the different methodologies and regional characteristics, detailed comparison is extremely difficult.

This paper studies the problem of obtaining tree species information of forest stands using laser scanning. First, the principle of laser scanning is introduced and the characteristics of study area and measurement campaign are discussed.

Then the proposed methodology to extract information from laser measurements and estimate tree species proportions of forest stands is presented. Finally, the results are discussed and some conclusions made.

2. LASER SCANNING

Laser scanning is a active remote sensing technique, which utilizes solid-state laser (Light Amplification by Stimulated Emission of Radiation) working typically within 500 - 1600 nm range as a radiation source. The most common technique to measure distance is pulse ranging where laser sends a short pulse of radiation and receiver receives the reflected pulse from a target (figure 1). The time difference between the transmitted and received pulse is used to determine the distance to target. Another technique is to measure the phase difference between the transmitted and received signal reflected from a target. This method is applied with lasers that continuously emit radiation and are called continuous wave lasers (Wehr et.al., 1999). When the position and attitude of the aircraft is known, then the measured distances can be converted into 3D-coordinates.

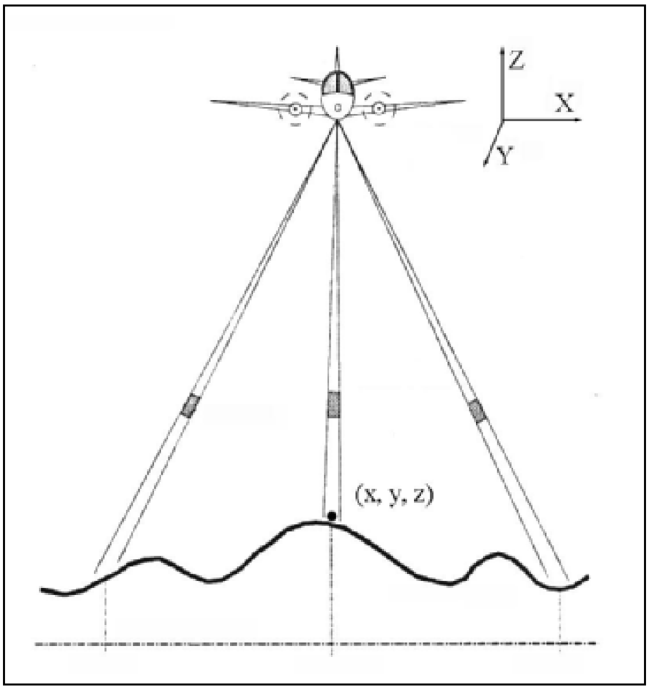

Figure 1: *The principle of laser scanning using pulse ranging method (Katzenbeisser, 1998).*

Depending on target, transmitted pulse is reflected back once or several times. If a target is heterogeneous within height direction like forest, some part of the pulse is reflected from tree top, stems and ground producing multiple echoes (figure 2). Usually, only the first or last echo is recorded, but there are systems capable of recording both first and last echoes or even multiple echoes in regular intervals. Some systems record also intensity information, in other words how the target has changed the pulse intensity and waveform. This can provide information for classification of the target (Baltsavias, 1999a).

Typically, laser system is operated using helicopter or aeroplane as a measurement platform and measurement height is less than 1000 metres. Laser scanning system includes following components (Baltsavias, 1999b):

* laser including transmitter and receiver, their optics, signal detector, amplifier, time counter;
* scanning system;
* positioning and navigation system including GPS-receiver and antennas, and INS attitude measurement system;
* computer system consisting of hardware and software to control the data acquisition.

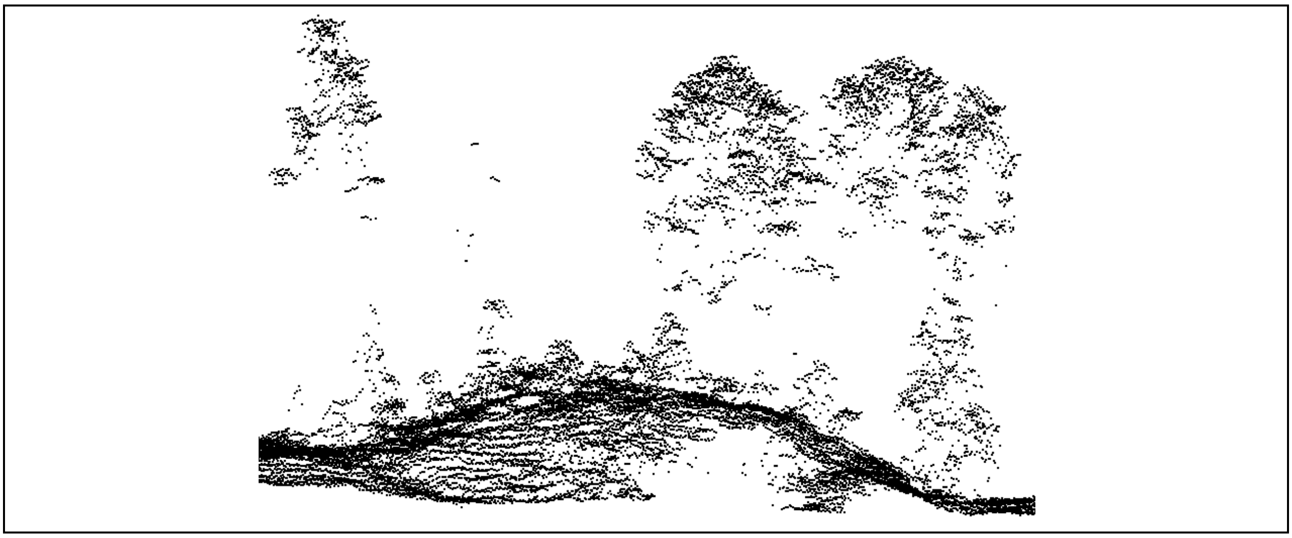

Figure 2: *Example of 3D points measured by laser scanning.*

The high measurement rate of laser scanning produces lots of 3D-coordinates from a target. The sampling density depends on the system and on the balance between flying speed, pulse rate, scan angle and flying height. The sampling pattern is determined by the used scanning method of the instrument, and it also depends on the flying path and its irregularities and topography of terrain. Depending on pulse rate, the sampling densities from 1000 m flying height usually vary from 1 point per 20 m^2 to 20 points per m^2 (Ackermann, 1999).

The main application of laser scanning seems to be DTM generation, especially in forested areas. Due to high measurement rate, it is useful in applications where high accuracy and dense sampling is required, e.g. DTM generation and volume calculations for open mines or mapping of electrical transmission lines. Depending on used wavelength, laser scanning can be used to make bathymetric maps up to 70 m. Within urban areas, laser scanning can be used to measure buildings and other structures in order to generate 3D city models (Wehr et.al., 1999).

Laser scanning system used in this study was build by Toposys. It is pulse modulated laser with fiber optic line scanner. The advantage of this kind of scanning system is that the transmitting and receiving optics are identical. An identical fiber line array is mounted in the focal plane of the receiving and transmitting lenses. By means of two rotating mirrors, each fiber in the transmitting and receiving path is scanned sequentially and synchronously. These mirrors relay the light either from the central fiber to a fiber of the fiber array mounted in a circle around the central fiber or the other way around from the array to the central fiber. Due to small aperture of the fibers, small moving mechanical parts are required and high scanning speeds achieved. Fiber array has 128 fibers and scan angle 14 degrees, so the across-track spacing of measurements is 0.4 - 1.9 m depending on flying height. Along track spacing of measurements is 0.06 - 0.13 m and these values lead to point density 5 - 25 points per m^2. Instrument measures the first or last pulse without any intensity information (Wehr et.al., 1999, Baltsavias, 1999b).

3. TEST AREA AND MEASUREMENTS

Tuusula test area is located in southern Finland, some 30 km north from Helsinki. The land-use of test area consists of forested areas like deciduous, coniferous and mixed forests growing in peat covered or mineral soil and open areas like forest clear-cuts, agricultural fields and lakes. There are 210 forest stands and stand wise forest inventory was made during summer 1995 (Hyyppä, 1999). The measured forest parameters include stem volume, basal area, tree species proportions (weighted by stem volume) and ground type. The main tree species are pine, spruce and birch, the proportion of other deciduous trees is very small. The stands are rather small, the mean area was 2.4 ha varying from 0.2 ha to 14.0 ha. The stem volume is largest in spruce stands and smallest in birch stands. Likewise the most usual development class of spruce stands are advanced thinning or mature stands, as birch stands are advanced saplings or young thinning stands.

The laser scanner campaign was carried out on 2-3 September 1998. TopoSys-1 laser scanner was installed in the local aircraft provided by FM-kartta OY. Three DGPS receivers were employed to record the carrying platform position: one on board the aircraft, and two ground reference GPS stations (the first as basic receiver, the second for backup). Three flight lines using first pulse mode were flown from the altitude of 400 m resulting the swath width approximately 100 m. Also two flight lines using last pulse mode were flown from the altitude of 800 m, but this data was not used in this study (Hyyppä, 2000).

Flight lines covered 79 forest stands (mean size 2.6 ha, varying 0.3 - 14.0 ha), 40 were pine dominated (mean size 3.3 ha, varying 0.4 - 14.0 ha), 19 spruce (mean size 2.3 ha, varying 0.8 - 6.1 ha) and 20 birch (mean size 1.4 ha, varying 0.3 - 5.3 ha). The soil of stands was mostly mineral soil, but there were some pine dominated stands with peat covered soil. The most usual development classes of pine were young thinning or mature stand, spruce were mature stands and birch were advanced saplings or young thinning stands.

4. PREPROCESSING AND FEATURE EXTRACTION

4.1 Preprocessing

The transformation of measured distances to 3D-coordinates was made by Toposys. The whole dataset consisting of three flight lines contained over 15 million points, so dataset was divided to smaller parts in order to speed up processing. Data measured using first pulse mode was used in this study. There was slight translation between laser-measurements and ground truth data, so ground truth was georeferenced to same coordinate system as laser measurements.

4.2 Feature extraction

The purpose of feature extraction was to arrange and transform the measured 3D-coordinates so that different tree species would be separable and estimation process possible. Measurements were divided into 2*2 m^2 squares and then those measurement which were higher than determined DTM were used to compute features. The purpose of features were to determine and characterize the vertical distribution of measurements within square (or pixel). Four different featuresets were computed in order to test and compare different strategies to extract features.

4.2.1 Generation of DTM: First task was to extract elevation model, in other words to determine the ground height. This was done by dividing measurements into 2*2 m^2 pixels and searching the lowest height. The size of pixel was large in order to make certain that at least some of measurements would come from ground. Then gaps (shadow areas) were filled if there were at least six pixels in the 8-neighborhood with measurements. The height of the gap was determined by using the mean height of the neighbors. Finally, DTM was median filtered using 3*3 window in order to decrease the effect of trees and erroneous measurements.

4.2.2 Featuresets: Features were computed for 2*2 m^2 pixels corresponding to DTM pixels. Pixel was selected for processing is it was thought to represent trees (difference between DTM and the highest height at least 1.5 m) and there were enough measurements (8 or more). Measurement was taken into processing if it was at least as high as corresponding DTM height and at the same time the height of DTM was subtracted from measurement. Four different featuresets were computed, which tried to characterize the vertical distribution of measurements:

Featureset A
1. Height of the trees within pixel.
2. The mean height of the lowest quarter of heights within pixel.
3. The deviation of the lowest quarter of heights within pixel.
4. The mean height of the second lowest quarter of heights within pixel.
5. The deviation of the second lowest quarter of heights within pixel.
6. The mean height of the second highest quarter of heights within pixel.
7. The deviation of the second highest quarter of heights within pixel.
8. The mean height of the highest quarter of heights within pixel.
9. The deviation of the highest quarter of heights within pixel.

Featureset B
1. Height of the trees within pixel.
2. The mean height.
3. The deviation of the heights.
4. Height corresponding to lowest 25% heights divided by height of the trees.
5. Height corresponding to lowest 50% heights (median height) divided by height of the trees.
6. Height corresponding to lowest 75% heights divided by height of the trees.

Featureset C
1. Height of the trees within pixel.
2. Height corresponding to lowest 16% heights divided by height of the trees.
3. Height corresponding to lowest 34% heights divided by height of the trees.
4. Height corresponding to lowest 50% heights (median height) divided by height of the trees.
5. Height corresponding to lowest 66% heights divided by height of the trees.
6. Height corresponding to lowest 84% heights divided by height of the trees.

Featureset D
1. Height of the trees within pixel.
2. The mean height.
3. The deviation of the heights.
4. Number of heights within the lowest quarter divided by number of heights within pixel.
5. Number of heights within the second lowest quarter divided by number of heights within pixel.
6. Number of heights within the second highest quarter divided by number of heights within pixel.
7. Number of heights within the highest quarter divided by number of heights within pixel.

5. ESTIMATION OF TREE SPECIES PROPORTIONS

The estimation of tree species proportions was performed using multilayer perceptron neural network (Widrow et.al., 1995) with error backpropagation training algorithm (Werbos, 1995). During the training process, input patterns (i.e. extracted features) and corresponding desired output patterns (i.e. tree species proportions) are presented to neural network. The purpose of error backpropagation algorithm is to adjust the weights so that the squared error between computed output patterns and desired output patterns is minimized. Computer software called Stuttgart Neural Network Simulator (SNNS) was used in this study. The aim of the network is to perform nonlinear regression between extracted features and corresponding tree species proportions. Network configurations (number of neurons in different layers) were based on Kolmogorov's theorem (Kurkova, 1995). The size of the network for featureset A was 9-19-3 neurons in different layers, for featureset B and C 6-13-3 and featureset D 7-15-3.

Training data was acquired by computing feature vectors from selected forest stands. The criteria for selection were large size and that the proportion of the dominant tree species was more than 80%. There were 25 stands selected, which 10 were pine dominated stands, 8 spruce and 7 pine. Because of small number of stands and for the need for large training data, 50 feature vectors taken randomly from each stand were averaged and this was repeated several times. In the end, there were about 1000 vectors in the training data. The purpose of the methodology is that training data represents the same statistical distribution as the mean values of forest stands, but they are at the same time statistically independent. The mean values computed from forest stands were used as test data.

The different networks were trained using training data and the mean values of the forest stands were used as test data. There were two sets of mean values, one was computed from stands selected for training and other independent set included the mean values from the other stands. The training process was repeated several times for each network to find suitable parameters. After training, the tree species proportions were estimated.

Estimated proportions were compared to ground truth and following descriptive values were computed: the mean of the error (*ME*), the mean of the squared error (*MSE*), the mean of the maximum difference (*MMD*), the overall accuracy of the main tree species classification and average accuracies for each tree species. The error for forest stand is defined as follows:

$$E = \sum_{i=1}^{3} | e_i - c_i | , \tag{1}$$

where e_i is the estimated tree species proportion of tree species i, c_i is the correct tree species proportion of tree species i and tree species are: $i = 1$ is pine, $i = 2$ is spruce and $i = 3$ is birch. The squared error for forest stand is defined as:

$$SE = \sum_{i=1}^{3} (e_i - c_i)^2. \tag{2}$$

The maximum difference is defined as:

$$MD = \mathop{MAX}_{i=1}^{3} | e_i - c_i | . \tag{3}$$

The forest stands were also classified according to their dominant tree species and error matrix was computed. The overall accuracy is the probability of correct classification (Sotkas et.al., 1992):

$$OA = \frac{100 * \sum_{i=1}^{m} EM_{ii}}{n}, \tag{4}$$

where n is number of feature vectors used to compute error matrix, m is number of classes and EM_{ii} is diagonal element of error matrix. The average accuracy of class i is the probability that pixel belonging to class i taken randomly from reference data has also same class i as corresponding pixel in classified data and pixel taken randomly from classified data belonging to class i has same class i as corresponding pixel in reference data:

$$AA_i = \frac{2 * EM_{ii}}{\sum_{j=1}^{m} EM_{ji} + \sum_{k=1}^{m} EM_{ik}}. \qquad \textbf{(5)}$$

6. RESULTS

The best estimation results acquired with different featuresets are represented in table 1 (stands selected for training) and table 2 (other stands). In each case, the estimation errors for those stands selected for training were really small but the estimation errors for other stands were considerably worse. The featureset A performed best and featureset D worst, but in each case the estimation errors for other stands were large. There was no correlation with stand characteristics (development class, soil, etc.) and largest estimation errors, but it seems that this methodology works rather badly when the tree species of stand are mixed. Errors are much smaller for those stands where there are one clearly dominant tree species.

When stands were classified according to dominant tree species, classification error for stands selected for training were nonexistent or small, but the classification errors for other stands were larger. Table 3 represents the overall and the average accuracies for different tree species for other stands. The best classification accuracy 59.3% of other stands was achieved with featuresets A and B, and the worst (48.1%) with featureset D. Tree species pine and spruce were classified best, but also in this cases average accuracy was only 66% at its best.

7. CONCLUSIONS

The presented methodology to estimate the tree species proportions of forest stands do not seem to work well. The estimation errors and dominant tree species classification errors were high for test data, especially when compared to results acquired with profiling radar (Törmä et.al., 1998). This may be due to small number of stands (79), but also indicates that only 3D-coordinates are not enough to estimate stand tree species proportions. The alternatives to get better results are either to classify single trees and compute tree species proportions from these or to use also intensity information by using aerial images or laser which can measure intensity.

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Table 1: *The best estimation results acquired with different featuresets, when the mean values of the features of those forest stands used as training data were used for testing.*

	Featureset A	Featureset B	Featureset C	Featureset D
Mean error	0.07	0.05	0.13	0.11
Mean squared error	0.01	0.00	0.07	0.05
Mean of maximum difference	0.04	0.03	0.09	0.06

Table 1: *The best estimation results acquired with different featuresets, when the mean values of the features of other forest stands were used for testing.*

	Featureset A	Featureset B	Featureset C	Featureset D
Mean error	0.89	0.95	0.92	1.04
Mean squared error	0.52	0.59	0.59	0.68
Mean of maximum difference	0.44	0.47	0.46	0.52

Table 3: *The overall accuracies (OA) and average accuracies of tree species classes of dominant tree species classification for different featuresets. These results were acquired by using thse stands which were not used in training as test data.*

	Featureset A	Featureset B	Featureset C	Featureset D
OA	59.3%	59.3%	57.4%	48.1%
AA pine	64.2%	66.7%	66.7%	49.0%
AA spruce	64.5%	60.0%	56.3%	60.6%
AA birch	41.7%	41.7%	31.6%	30.8%