Automatic Identification of Individual Tree Crowns in Mixed Forests Using Fusion of LIDAR and Multispectral Data

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Abstract **– One of the most important steps in performing automated forest inventory at the individual tree level using remote sensing data is the identification of individual trees. The aim of this paper is to present a LIDAR and multispectral data fusion approach exploiting Template Matching (TM) method for individual tree identification and evaluate its accuracy comparing with single data source cases. Data fusion was achieved in two ways: 1) at pixel level combining data sets using principal components transform and wavelet decomposition, and 2) at feature level by combining intermediate results of the TM method. The best overall accuracy, namely 76%, was achieved by employing wavelet decomposition based data fusion; however this result does not outwork a lot the usage of LIDAR data set alone.**

Keywords **– identification of trees, multispectral imaging, LIDAR, template matching, data fusion.**

I. Introduction

Forests cover more than half of Latvian area and are one of the most important natural resources ensuring economy, well-being of the citizens and stability of the climate. Gathering accurate information (forest inventory) about qualitative and quantitative condition of forest areas is crucial for their sustainable management. An alternative to time consuming and financially expensive field measurements is an automatic extraction of forest inventory parameters using remote sensing data processing. The first step to perform automated forest inventory is identification of individual trees and their crowns. In practice, this task is non-trivial due to variations in forest spatial structure and limitations related with remote sensing data acquisition and characteristics. Once individual trees are identified (identification means finding treetops) and delineated (delineation means finding tree crown outlines), other forest inventory parameters like tree species, height and crown characteristics can be extracted.

The most common source of remote sensing data for forest inventory tasks at the individual tree level is airborne data [1], where frequently employed airborne data types are multispectral images and LIDAR(Light Imaging Detection and Ranging) data.

Multispectral images contain spectral information for each pixel which is important for identification of tree species and evaluation of forest health, but there is no information about the height structure of the forest. Significant problems in multispectral data processing for individual tree identification are related with spatial resolution. Individual tree distinction possibilities depend on the relationship between the spatial resolution and crown size. Coarse resolution (e.g. pixel size 0.5 m to 1 m) makes identification of smaller crowns impossible causing omission errors while very high resolution images (e.g. 0.05 m – 0.15 m) provides too much details causing commission errors [1]. Commission error characterizes how many other objects than trees are identified as trees while omission error shows how many tree objects are missed by tree identification method.

LIDAR data are obtained by transmitting laser pulses and recording reflected signals from the trees and ground surface called returns. They contain information about the 3-dimensional structure of the forest (tree height, tree profile etc.), but do not contain spectral information. Similarly to multispectral images, spatial resolution defined here as point density affects commission and omission errors. In addition, during investigation of forest stands with LIDAR technology, the following scenarios can occur instead of hitting the true treetop by a laser pulse: a) small trees close to larger ones can be ignored, b) laser returns may not hit the top of the tree, c) laser pulse may hit lower branches so that two tree tops are produced for one tree, d) in case of low density some trees can be ignored [2].

As far as one data type alone cannot provide full information about the forest inventory parameters and has specific limitations, it is important to research possibilities of LIDAR and multispectral data fusion for precise forestry. Data fusion can be referred to three different processing levels: pixel level combining measured physical parameters, feature level combining extracted parameters from various data sources and decision level, where data types are processed separately and the results are combined [3].

The aim of this paper is to present a data fusion approach exploiting Template Matching method for individual tree identification using LIDAR and multispectral data and evaluate its accuracy comparing with the single data source cases.

Data fusion in this study was performed at pixel and feature levels. Fusion of LIDAR and multispectral data was performed using principal component transform and wavelet decomposition. Fused data sets were employed then in Template Matching tests instead of original LIDAR and multispectral data sets. Template Matching itself was modified to enable multisource data input (fusion of intermediate results) and automatic generation of data independent templates.

II. RELATED WORK

Individual tree identification using LIDAR and multispectral data in Latvia has been researched by [4] and [5], however the data sets were used separately in these studies. Smits et. al. [4] concluded that Latvian forest conditions are complex for individual tree detection using remote sensing data as they contain mixed stands with high density. They achieved 92.3% accuracy by processing LIDAR data with mean point density 9 points/m^2 and multispectral data with spatial resolution 20 cm x 20 cm and using decision based data fusion. In case of data set equivalent to one presented in this paper, 73% accuracy was attained. In [5], treetops were identified from LIDAR data with mean point density of 4 points/m^2 and such density was considered as insufficient for the analysis of tree crown shapes. However accuracy assessment largely depends on the particular test case employed and comparison of accuracy achieved in different researches is inconvenient due to lack of publicly available test cases as noted by [6].

Summarizing previous researches in LIDAR and multispectral data fusion for individual tree delineation, two groups of methods can be identified: multi-feature approach and step-by-step approach.

Studies of [2], [7]-[10] employ the **multi-feature approach**. Following it, the LIDAR and multispectral data sets were resampled to one spatial resolution. Data specific features such as LIDAR metrics and spectral variables were calculated. Segmentation or object recognition algorithm was used then to analyze both LIDAR and multispectral features simultaneously and calculate the result.

Another approach is described in [11]-[14], namely a **step-by-step procedure**. Individual tree delineation was performed there using only LIDAR data features and multispectral data were incorporated to check and improve LIDAR results. Supervised classification methods were used for tree species classification and each LIDAR based tree crown was analyzed. If there was more than one tree species inside one crown then crown was delineated further by taking into account classification results.

Very original approach is presented by Popescu et. al. [15]. First, regression analysis was calculated to find the relations between tree height and diameter of tree crowns. Then they performed the maximum likelihood classification to identify tree species. Finally, tree height information was obtained from LIDAR and depending on height and tree species, variable-size-window tree delineation was performed.

In this paper multi-feature approach is evaluated based on Template Matching method. Template matching, introduced by [16] for forestry applications, is one of the most frequently used algorithms for individual tree identification using single data source [1]. Template matching has been extended by various researchers [17]-[19], but proposed modifications were mostly related to tree crown modeling procedure instead of the generalized LIDAR and multispectral data fusion.

III. STUDY SITE

Study site covers 500 m x 500 m large region and it is situated in north-eastern part of Latvia near Cesis (Fig. 1). This geographical area contains complex mixed forest structure with five dominant tree species: Norway spruce (*Picea abies (L.) Karst.*), Scots pine (*Pinus sylvestris L.*), Silver birch (*Betula pendula Roth*), Eurasian aspen (*Populus tremula L.*) and Grey alder (*Alnus incana (L.) Moench*). Stand age varies between 60-135 years, height between 25-28 meters and density 0.6-0.7 (quantitative measure of the area occupied by trees). Forest stands are natural and located on well-drained soil in a hilly landscape where only 10 % of forest stands have an understory.

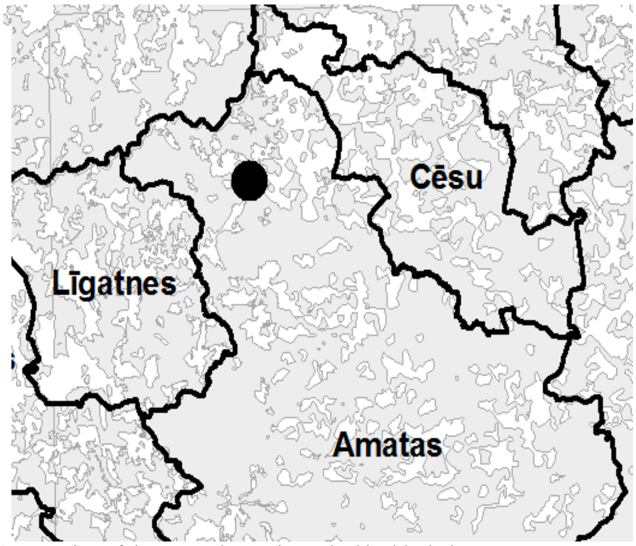

Fig. 1. Location of the research area is marked by black dot.

IV. DATA SETS

Remote sensing data were acquired on June 13, 2008 using airborne pulse LIDAR system ALTM Gemini from Optech and multispectral sensor CASI-1500 from ITRES. Data acquisition was performed from 10:34 till 10:36 a.m. with average flight height 1050 m and ground speed 100 knots. Solar elevation was from 55.95° - 55.65° and solar azimuth from 185°-191°.

Multispectral data were obtained from 13 bands covering visible light and near infrared part of the electromagnetic spectrum (398.7nm - 971.3nm) with spatial resolution 0.5m x 0.5m.

LIDAR data were acquired with the following parameters: laser repetition rate – 167 kHz, scan frequency – 50 Hz, scanning angle +- 20 degrees and mean point density – 4 points/m^2.

Field data of 270 trees from the same area were also acquired for the algorithm validation purposes. Clearly recognizable trees in multispectral images were selected for the study; their coordinates were obtained using high precision GPS and tree species information was gathered. Inspected trees are located in 6 clusters tending to cover chosen areas continuously.

V. METHODS

Data fusion in this study is achieved in two manners:

1. LIDAR and multispectral **data are transformed to a fused data set** using principal component transform and wavelet data fusion (pixel level data fusion) before passing them to Template Matching.
2. LIDAR and multispectral data are processed and **intermediate results are fused** during implementation of Template Matching (pixel level feature fusion).

A. Data processing

Preparation of LIDAR CHM

Both multispectral and LIDAR data have to be projected on a unified coordinate grid to perform data fusion at pixel level. Spatial resolution of the grid was chosen as a spatial resolution of multispectral image – 0.5m x 0.5m. LIDAR data were processed as follows:

1. Digital Terrain Model (DTM) was calculated by filtering ground points according to [20].
2. Digital Surface Model (DSM) was calculated by filtering highest returns of LIDAR pulse.
3. Canopy Height Model (CHM) was calculated by subtracting DTM from DSM.
4. CHM was interpolated on regular grid with cell ground size 0.5 x 0.5 m.
5. Order-statistic maximum spatial filter of size 3x3 was applied to reduce impact of returns which are reflected from understory or lower branches of the tree to emphasize the shape of tree crowns.

Principal components

Principal component (PC) transform is a common mathematical procedure that converts a set of partially correlated images to a set of linearly uncorrelated images (for more details refer to [21]).

In this context, principal component transform was employed to perform data fusion. A fused data set was created by putting LIDAR CHM and 3 multispectral bands: R (red), G (green), NIR (near infrared) in one data set and calculating principal components of this set. Since multispectral data values and CHM values span various intervals of values, histogram equalization was chosen as a method to avoid domination of one data set.

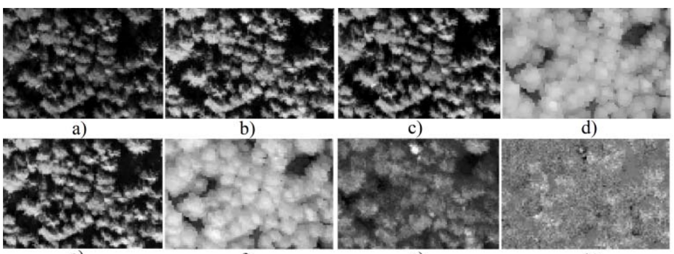

Fig. 2. a) NIR, b) R, c) G, d) LIDAR CHM, e) PC1, f) PC2, g) PC3, h) PC4.

Figure 2 shows an example of original data and calculated transformed data. Images corresponding to first principal components (like PC1, PC2 in Fig. 2) contain the most significant information while images of the last PCs contain small details and noise (like PC3, PC4 in Fig. 2). Hereafter the term "principal component" will be referred to the transformed image corresponding to the given principal component.

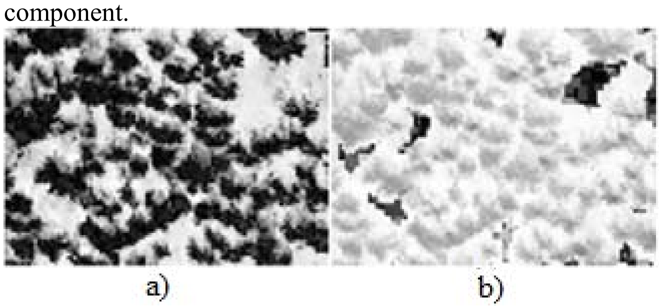

Fig. 3. Absolute difference between original data and principal components. Highest changes are denoted by brighter pixel intensity, while smaller changes by darker pixel intensity: a) NIR - PC1, b) LIDAR CHM-PC2.

Visual analysis show that first two principal components tend to copy multispectral and CHM data. Performing subtraction (see Fig. 3) emphasizes changes made to the data set: some features are exchanged between CHM and multispectral data sets. Test data set of PC1 and PC2 was employed for Template Matching experiments.

Wavelet data fusion

Another approach evaluated to fuse CHM and multispectral data was wavelet decomposition based data fusion. "The main idea of image fusion using wavelets is to merge the wavelet decompositions of the two original images using fusion methods applied to approximations coefficients and details coefficients " [22]. In this study, multispectral NIR band (as suggested by [1]) and CHM images are decomposed using Daubechies wavelet with order 2 and fusion is performed by merging first 3 layers of wavelet package decomposition. For more information refer to [21]. Figure 4 shows the example of fused data set for Template matching tests.

Fig. 4. Multispectral NIR band and LIDAR CHM fused data set by wavelet decomposition based fusion.

B. Template Matching (TM) method

The main concept of template matching is to slide a template over the image and to seek the best match. Template is a sample image which characterizes how the tree crown looks like in the remote sensing data under different conditions. Pseudo code below summarizes algorithmic details of TM.

Pseudocode for TM (modification for data fusion)
INPUT: *remoteSensingData*, *templates*, *templateSize*, *threshold* BEGIN: 1. FOR EACH *template* in *templates* 2. FOR EACH *size* in *templateSize* *3. FOR EACH dataSet in remoteSensingData* 4. Calculate normalized correlation coefficient matrix *g(dataSet)* for *dataSet* and *template* according to equation (2) 5. END FOR EACH dataSet 6. Sum all coefficient values for corresponding pixel in *g* and calculate average: *g2=average(g, along third dimension)* 7. *g3=g2>threshold* 8. Find local maximum values of *g2* for *g3* and save them as *coordinates* 9. END FOR EACH *size* 10. END FOR EACH *template* 11. Filter multiple responses in *coordinates* OUTPUT: *coordinates*

Template matching is performed using the following steps.

1. Preparing the template

Template is a generalized sample how the tree would look like in the given remote sensing data under specified conditions.

During this study, two template sets were tested: automatically generated templates and templates selected manually from the image. Since the aim of the template is to simulate a tree crown in specified remote sensing data, it is usually unique for each remote sensing data set. However spatial resolution of multispectral and LIDAR data allows to test some generalizations like automatically generated templates.

For LIDAR and multispectral sets, a template is generated automatically as a normalized Gaussian filter:

$$h(a,a) = \frac{e^{\frac{-2a^2}{2\sigma^2}}}{\sum_a \sum_a e^{\frac{-2a^2}{2\sigma^2}}} \qquad (1)$$

where a – filter size;

σ – standard deviation.

Figures 5, 6 show examples of automatically generated templates with varying standard deviation and filter size. Filter size allows simulating tree crown size and standard deviation controls slope of the tree crown.

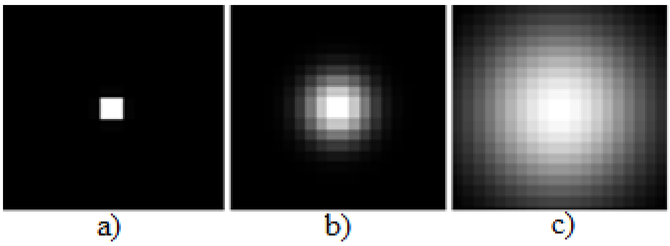

Fig. 5. Gaussian filters of fixed size but varying standard deviation: a) σ=0.5, b) σ=2, c) σ=5.5.

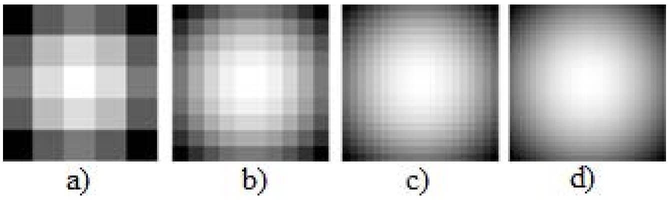

Fig. 6. Gaussian filters with fixed σ=2, but with varying size a) 5 x 5, b) 10 x 10, c) 20 x 20, d) 30 x 30 pixels.

Another template set is formed by selecting sample trees manually in the image. For evaluation 9 trees where selected: 3 pine trees, 3 spruce trees, 2 birches and 2 aspens. Figure 7 shows an example of tree crown templates selected from images. Selection is stored as binary mask and appropriate template is obtained by performing remote sensing image multiplication with binary mask at the same spatial resolution. Since a template must be smaller than the image itself to perform correct correlation procedure, templates are automatically cropped using a bounding box extracted from the connected components of binary image.

Once the templates are selected and cropped, different tree sizes are obtained by resizing images using nearest neighbor interpolation.

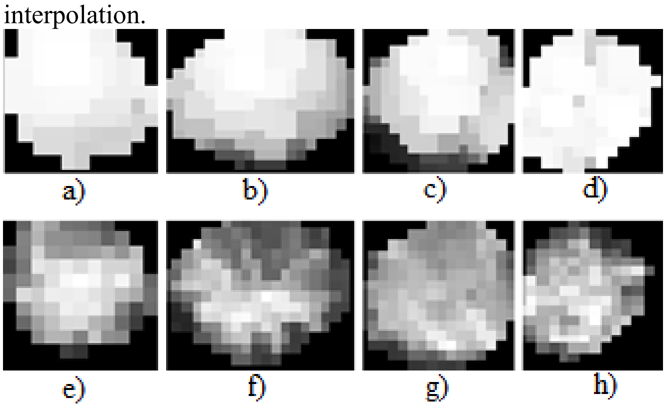

Fig. 7. Template examples: a) pine in CHM, b) spruce in CHM, c) birch in CHM, d) aspen in CHM, e) pine in NIR, f) spruce in NIR, g) birch in NIR, h) aspen in NIR.

2. Performing correlation

Matches between remote sensing images and templates are assessed by the correlation procedure. Normalized correlation coefficient is calculated for each image *f* and template *w* using expression:

$$\gamma(x,y) = \frac{\sum_{s,t}[w(s,t)-\overline{w}][f(x+s,y+t)-\overline{f}_{xy}]}{\sqrt{\sum_{s,t}[w(s,t)-\overline{w}]^2 \sum_{s,t}[f(x+s,y+t)-\overline{f}_{xy}]^2}} \qquad (2)$$

where $\overline{w}$- average value of the elements of the template;

$\overline{f}_{xy}$- the average value of the image in the region, where *f* and *w* overlap;

s, t, - summation variables chosen such that the image and the template overlap [21].

The value of the normalized correlation coefficient ranges from [-1, 1] and a high value indicates a good match between the image *f* and template *w* centered at coordinates *(x,y)*. Figure 8 shows an example of normalized correlation coefficient image.

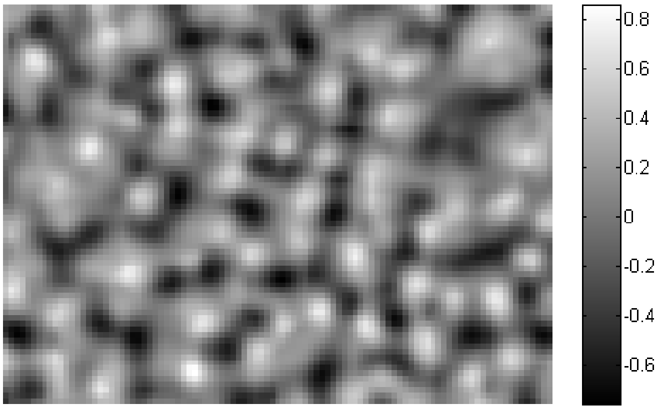

Fig. 8. Normalized correlation coefficient image calculated using Fig. 2 d) and 10 x 10 Gaussian filter with σ=2 as a template.

If more than one data set are employed, correlation coefficients are calculated for each data set separately and average values of correlation coefficients are calculated before proceeding to the next step.

3. Finding treetop locations

Correlation coefficient image is thresholded using empirical threshold to locate areas with the best match. For the sake of generalization of template matching, threshold is the most important internal parameter defining tolerance of acceptable matches. Lower threshold value allows accepting as a match less similar objects to the template allowing generalizing template, but the main drawback here is increased commission errors. Empirical evaluation of the optimal threshold value is shown in Results section. Once the correlation coefficient image is thresholded, tree coordinates are assumed to be in the pixel location where the maximum correlation is achieved, so that connected components are extracted from the thresholded image and coordinates of local maximum for each connected component is calculated.

4. Filtering responses

Larger tree crowns also responds on smaller templates resulting in multiple responses with small bias in coordinates. These biased responses for each tree are filtered by selecting each response and searching for neighbor points with bias in coordinates smaller than 1 ground meter. Only the point with higher correlation coefficient passes this test, other neighbors are deleted from the results.

VI. Results

Accuracy is assessed by measuring commission and omission errors. Commission error can be expressed as the number of false positive responses and omission error is replaced by an accuracy as a percentage (P) of correctly identified (true positives TP) trees in the area. These results are obtained by visually evaluating TM results and field measurements together with aerial data.

True positives are calculated by taking field measurements as a reference while false positives are more subjective characteristic inspected by visual assessment.

Another subjective measurement is introduced for the reference: true positives by visual inspection. This characteristic depends on viewer and it is included only for the comparison.

Experiments were performed using default correlation coefficient value of 0.45 and default template sizes from 3 m to 20 m (ground size). Figure 9 shows empirical estimation of threshold value by performing experiment with CHM and fixed size Gaussian template (σ=2, size 10 x 10). True positives were counted for each threshold value and threshold with maximum number of true positives was chosen for forming the results.

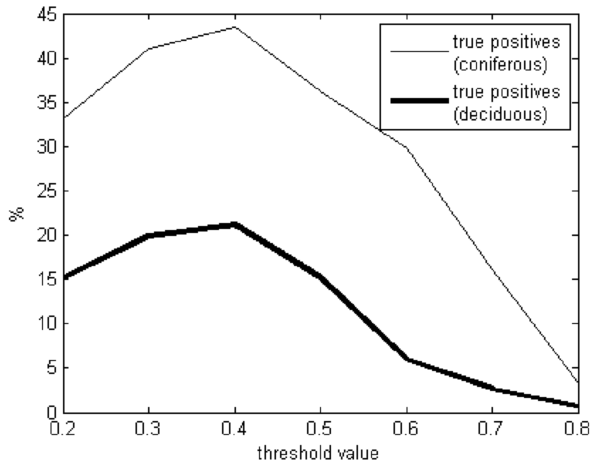

Fig. 9. Dependecy of accuracy for the test case with fixed Gaussian template size on threshold value.

TM method does not show clearly visible commission errors, however this statement is partially subjective due to burdened visual analysis because of spatial resolution and occurrence of dense stands.

Table I summarizes the results for different data sets and Fig. 10 shows an example of the results for wavelet fused data set and manually selected template.

TABLE I
ACCURACY ASSESSMENT OF TM FOR DIFFERENT DATA SETS.

Total number of trees inspected in field: **279** Number of coniferous trees: **124** Number of deciduous trees: **151** Number of dry trees: **4**			
Test case	TP/(P)	TP/(P) (coniferous)	TP/(P) (deciduous)
CHM, visual inspection	164/ (59%)	92/ (74%)	72/ (48%)
NIR, visual inspection	163/ (58%)	88/ (71%)	75/ (50%)
CHM, Gaussian template	156/ (56%)	86/ (69%)	70/ (46%)
NIR, Gaussian template	139/ (50%)	73/ (59%)	66/ (44%)
CHM, selected template	199/ (71%)	101/ (81%)	98/ (65%)

NIR, selected template	178/ (69%)	85/ (69%)	93/ (62%)
PC1, PC2 selected template	141/ (51%)	49/ (40%)	92/ (61%)
Wavelet fused, selected template	212/ (76%)	91/ (73%)	121/ (96%)
CHM, NIR, selected template	205/ (73%)	104/ (84%)	101/ (67%)
CHM, NIR, PC1, PC2, Wavelet fused, selected template	186/ (67%)	96/ (77%)	109/ (72%)

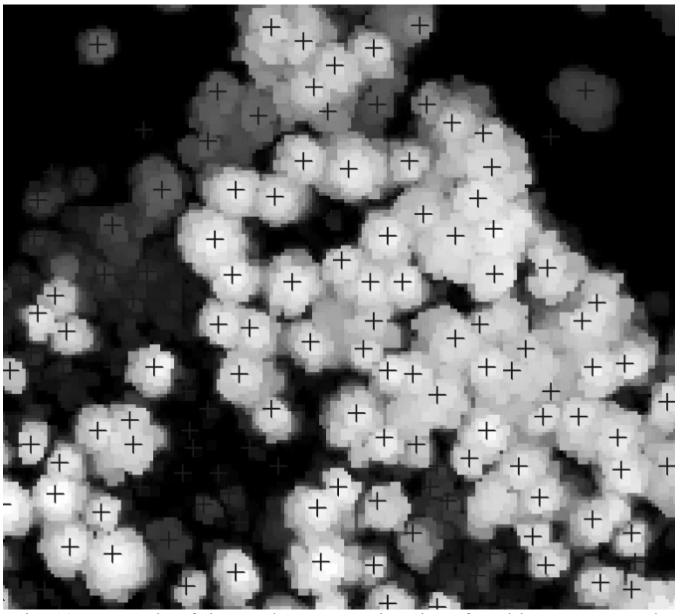

Fig. 10. Example of the results. Treetop locations found by TM are marked by "+".

VII. Discussion and Conclusions

Template matching method for LIDAR and multispectral data fusion was considered in this article. Results obtained from fused data sets using principal component transform and wavelet decomposition were evaluated to perform comparison with single data source cases. The main advantages of TM are related to the algorithm generalizability: TM can be easily adjusted to different data sources by manual selection of templates and setting of tolerance for the correlation coefficient (threshold value). In addition, TM is also robust against commission errors meanwhile it tends to underestimate the number of tree crowns. Omission errors could be reduced by sophisticating template generation procedure (requiring remote sensing metadata input) or by extending the database of manually selected templates. However these recommendations would reduce the simplicity of the TM modification shown in this paper by increasing computational complexity and introducing need for user input. Experiments showed that the performance of the algorithm using 9 arbitrary selected samples from the same image and default internal parameters (template size and threshold value) is equivalent to the accuracy achieved by [4]. Even with automatically generated Gaussian template half of the trees in the test area were recognized. This option could be useful for the first estimation of stand level forest inventory parameters without requiring additional input from the user.

Comparing the results of data fusion is not straight forward. Despite that the overall accuracy was higher for the wavelet fused data set, corresponding accuracy for the coniferous is higher for LIDAR CHM data set alone. Accuracy improvements and data fusion tests could be extended by performing fusion at the decision level and by integrating supervised classification results of tree species.

The most significant problems of tree identification was caused by spatial resolution of multispectral and LIDAR data as well as forest characteristics. Research area includes very dense deciduous stands where tree crowns overlap violating assumption that the canopy surface can be described as a mountainous structure. Spatial resolution also introduces the main threat of validity in accuracy assessment: significant part of the trees cannot be distinguished visually and field measurements do not ensure the presence of information about all trees in the region so that a small portion of commission errors can be ignored during the manual accuracy assessment. Obvious commission errors were not noticed but in the future studies it could be suggested to separate hardly classifiable responses in the individual group and analyze the worst case scenario where all unknown responses are considered as commission errors.

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Linda Gulbe, Ints Mednieks. Automātiska atsevišķu koku vainagu identifikācija jaukta tipa mežos, izmantojot LIDAR un multispektrālo datu kopīgu apstrādi

Attīstoties tālizpētes datu iegūšanas tehnoloģijām, arvien lielāku popularitāti mežsaimniecībā iegūst mežu inventarizācija individuālu koku līmenī, izmantojot no lidmašīnas iegūtu datu apstrādi. Lai to realizētu, viens no svarīgākajiem soļiem ir automātiska atsevišķu koku identifikācija. Šī raksta mērķis ir parādīt pieeju LIDAR un multispektrālo datu kopīgai apstrādei, izmantojot šablonu salīdzināšanas metodi un novērtēt šīs pieejas precizitāti individuālu koku identifikācijā, salīdzinot ar viena sensora datiem. Datu kopīga apstrāde tiek realizēta divos veidos: 1) dati tiek apvienoti vienā datu komplektā, izmantojot galveno komponentu transformāciju un maiņviļņu dekompozīcijas apvienošanu, un 2) tiek veikta šablonu salīdzināšanas metodes starprezultātu apvienošana algoritmā. Augstāka kopējā precizitāte tika sasniegta, izmantojot uz maiņviļņu dekompozīciju balstītu datu kopīgu apstrādi: 76%, taču šis rezultāts ievērojami nepārsniedz LIDAR rezultātus: 71%.

Линда Гулбе, Интс Медниекс. **Автоматическая идентификация отдельных крон деревьев в смешанных лесах, используя совместную обработку данных LIDAR и мультиспектральных данных.**

При развитии технологий дистанционного зондирования в лесном хозяйстве все большую популярность приобретает инвентаризация лесов на уровне индивидуальных деревьев, используя обработку данных, полученных из самолета. Чтобы это можно было реализовать, одним из важнейших шагов является автоматическая идентификация отдельных деревьев. Цель настоящей статьи - показать подход к совместной обработке LIDAR и мультиспектральных данных, используя метод сравнения шаблонов и оценить точность этого подхода в идентификации индивидуальных деревьев, сравнивая с данными одного сенсора. Общая обработка данных реализуется в двух видах: данные объединяются в комплект, используя объединение метода главных компонент и вейвлет-преобразования и объединение промежуточных результатов в алгоритм метода сравнения шаблонов. Самая высокая общая точность достигается, используя совместную обработку данных, базированную на вейвлет-преобразовании: 76%, но эти результаты ненамного лучше, чем результаты LIDAR: 71%.