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Performance Comparison of Methods for Tree Species Classification in Multispectral Images

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Introduction

Hyperspectral and multispectral imaging is a modern tool for solving different tasks [1] including forest inventory. When the images are obtained using high-resolution hyperspectral sensor deployed in the aircraft, it is possible to perform forest analysis on the individual tree level [2]. Another technology that complements spectral imaging for these purposes is that of LiDAR, providing means for obtaining height models of forest areas. One of the major inventory tasks is classification of tree species.

To perform classification from spectral images, relatively low number of not necessarily contiguous spectral bands within visible light and near infrared regions can be configured for acquisition by the hyperspectral sensor so that processed images are actually multispectral. To start with, coordinates of individual trees should be estimated and marked on the image first. This can be done by processing multispectral images, too, but LiDAR data are more suitable for the task [3], if available. However, joint use of LiDAR and multispectral data requires precise enough geocorrection so that both are properly mapped to the same spatial coordinates. For the methods analyzed in present study, it is assumed that LiDAR data are processed to provide coordinates of trees to be classified, and this processing is not considered here.

Depending of the forest type, number of species of interest may vary from 3 to more than 10. Various methods are developed for tree species classification [2, 4, 5], including fully automatic ones that do not exploit any prior data [5]. However, semiautomatic approaches are still more practicable and precise [6], relying on prior information about trees from different species identified during field work in forest or entered by the forestry specialist recognizing species of trees from their multispectral images by the shape of their crowns or using mapping of different spectral bands to RGB colors. In any case, those identified trees are used to form design sets of the classification algorithms. In this paper, we shall analyze performance of some practicable classification methods in terms of accuracy. Computer simulation of these methods was performed for that, using real multispectral image of the forest area in Latvia, together with field data collected about 270 trees from this area. Multispectral data were obtained in 13 spectral bands within the range of wavelengths from 400 nm to 950 nm, spatial resolution was 0.5 m on both axes. All input data were provided by the Institute for Environmental Solutions, Latvia (www.videsinstituts.lv).

Preprocessing

We shall denote the processed multispectral data set by X. It was obtained during a single overflight and represents the whole forest area of interest. Species of interest were pine, spruce, birch, oak and aspen, the percentage of other species was insignificant and they were ignored. We denote number of analyzed species by r.

Classification methods of individual trees were operating on subsets A_s of the data set, each representing an individual tree from one of the five mentioned species. The subsets were extracted from the surroundings of tree tops identified by the collected field data. We shall call the subset A_s an "envelope" containing pixels, i.e. p-dimensional (for the processed data, $p = 13$) data vectors $\boldsymbol{x} = (x_1, x_2, ..., x_p)^T$ of the s-th tree so that trees will be classified on the basis of their envelopes. Initial size of the envelopes $|A_s|$ was 20 pixels. At the beginning of classification, classes of k_i trees from i-th species ($i = \overline{1, r}$) were considered known in advance. Design sets X_i were formed from the envelopes of trees of i-th species selected in a random way. In practice, they should be formed to be as representative samples of i-th species as possible.

***k*-NN classifier using weighed Euclidean metric (*k*-NN)**

The first analyzed method was based on *k*-nearest neighbors algorithm [7] with weighed Euclidean distance

used as the distance metric. This method does not require any assumption about the probability distribution function of the population. Modified envelopes A_s' were used here, obtained from A_s by excluding darkest pixels, i.e. with component values related to green spectral band less than a certain threshold Δ relative to the brightest pixel of the envelope. As the experiments show, such truncation reduces error of this algorithm. Mean size of the modified envelopes $|A_s'|$ was ≥ 10.

The classifier used mean values of pixels within the envelope A_s' calculated at first

$$\hat{x}_s = \frac{1}{|A_s'|} \sum_{x \in A_s'} x. \tag{1}$$

The i-th design set $\hat{X}_i$ consists of k_i such mean values: $\hat{X}_i = \{\hat{x}_{i,1}, \ldots, \hat{x}_{i,k_i}\}$. The squared distance between the s-th tree and j-th tree within the i-th design set is computed then using the squared weighed Euclidean distance

$$d_E^2(\hat{x}_s, \hat{x}_{i,j}) = (\hat{x}_s - \hat{x}_{i,j})^T W (\hat{x}_s - \hat{x}_{i,j}), \tag{2}$$

where W is the diagonal matrix, with m-th diagonal element calculated as the inverse of a variance estimate for the m-th dimension of the data set X:

$$W = diag(1/\hat{\sigma}_1^2, \ldots, 1/\hat{\sigma}_p^2), \tag{3}$$

$$\hat{\sigma}_m^2 = \frac{1}{|X|-1} \sum_{x \in X} (x_m - \overline{X}_m)^2, \ m = \overline{1, p}, \tag{4}$$

$$\overline{X}_m = \frac{1}{|X|} \sum_{x \in X} x_m, \ m = \overline{1, p}. \tag{5}$$

The species of the s-th tree is determined using the "voting" principle within k smallest squared distances observed for all design sets combined, i.e. from the most frequent value of i among the k smallest squared distances $d_E^2(\hat{x}_s, \hat{x}_{i,j}), \ j = \overline{1, k_i}, \ i = \overline{1, r}$. If more than one species got the observed maximum number of "votes", then the tree was classified as a representative of species with smallest mean distance among these k distances among species with maximum number of "votes". Number of nearest neighbors was $k = 4$.

Bayes classifier using single pixels (BP)

The other three classification methods were designed on the basis of hypothesis that multispectral data of each species can be interpreted as a sample realization from the p-dimensional universe with Gaussian distribution, i.e. i-th species is represented by a universe X^i with multidimensional mean value $EX^i = \mu_i$ and covariance matrix $Cov(X^i) = \Sigma_i$. Estimates of these parameters are calculated from the pixels in design set according to expressions:

$$\hat{\mu}_i = \frac{1}{|X_i|} \sum_{x \in X_i} x, \ i = \overline{1, r}, \tag{6}$$

$$\hat{\Sigma}_i = \frac{1}{|X_i|-1} \sum_{x \in X_i} (x - \hat{\mu}_i)(x - \hat{\mu}_i)^T, \ i = \overline{1, r}, \tag{7}$$

where $X_i = A_{i,1} \cup A_{i,2} \cup \ldots \cup A_{i,k_i}$ and $A_{i,j}$ is the envelope of j-th tree in i-th design set.

As every envelope A_s consists of 20 p-dimensional vectors, this guarantees (not absolutely, of course), that the matrices $\hat{\Sigma}_i$ are not singular.

With estimates of $\hat{\mu}_i$ and $\hat{\Sigma}_i$ in place, we can write an estimate of the probability density of the universe X^i

$$\hat{f}_i(x) = (2\pi)^{-\frac{p}{2}} |\hat{\Sigma}_i|^{-\frac{1}{2}} \exp\left(-\frac{1}{2}(x - \hat{\mu}_i)^T \hat{\Sigma}_i^{-1}(x - \hat{\mu}_i)\right), \tag{8}$$

where $|\hat{\Sigma}_i|$ is the determinant of the matrix $\hat{\Sigma}_i$.

As the incidence probabilities of tree species were unknown, the classification was defined as follows: vector $x \in A_s$ was classified as a representative of i-th species if, for each $j = \overline{1, r}$, the condition $\hat{f}_i(x) \geq \hat{f}_j(x)$ holds. This classifier minimizes the mean error probability in case of equal prior probabilities, $\hat{\mu}_i = \mu_i$ and $\hat{\Sigma}_i = \Sigma_i$. To classify a tree related with envelope A_s, a supplementary rule was used: A_s was classified as an envelope of i-th species if the majority of vectors $x \in A_s$ were classified as representatives of i-th species. If it was impossible to determine species in such way, then species with minimum squared Mahalanobis distance between the design set and mean value of the envelope:

$$d_M^2 = (\hat{x}_s - \hat{\mu}_i)^T \hat{\Sigma}_i^{-1}(\hat{x}_s - \hat{\mu}_i), \tag{9}$$

$$\hat{x}_s = \frac{1}{|A_s|} \sum_{x \in A_s} x \tag{10}$$

were detected.

Bayes classifier using mean values of envelopes (BM)

This is a variation of the classification algorithm described above, designed by replacing classification of pixels $x \in A_s$ with classification of their mean values within the envelope (10).

In this case, supplementary rule defined above is not needed. This algorithm is less time-consuming than BP.

Two-stage Bayes classifier (BP2)

This classification algorithm exploits two consequent classification stages. It applies the same major rule as BM first, but considers the first classification procedure as clusterization that is performed within the whole set $X = \bigcup_s A_s$ or a sufficiently wide subset of X. The

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clusters $X'_1, X'_2, \ldots, X'_r$ obtained at the first stage are used to recalculate estimates of parameters $\boldsymbol{\mu}_i$ and $\boldsymbol{\Sigma}_i$ of the universes $\boldsymbol{X}^i$, i.e. initial estimate $\hat{\boldsymbol{\mu}}_i$ is replaced after first clustering by

$$\hat{\boldsymbol{\mu}}'_i = \frac{1}{|X'_i|} \sum_{\boldsymbol{x} \in X'_i} \boldsymbol{x}, \ i = \overline{1, r}, \quad (11)$$

where $\hat{\boldsymbol{\Sigma}}_i$ is replaced by

$$\hat{\boldsymbol{\Sigma}}'_i = \frac{1}{|X'_i| - 1} \sum_{\boldsymbol{x} \in X'_i} (\boldsymbol{x} - \hat{\boldsymbol{\mu}}'_i)(\boldsymbol{x} - \hat{\boldsymbol{\mu}}'_i)^T, \ i = \overline{1, r}, . \quad (12)$$

The second stage was performed using the major and supplementary rules as described for the BP method, i.e. elements of the set A_s were classified according to the following rule: $\boldsymbol{x} \in A_s$ is classified as representative of i-th species, if for all $j = \overline{1, r}$

$$|\hat{\boldsymbol{\Sigma}}'_i|^{-\frac{1}{2}} \exp\left(-\frac{1}{2}(\boldsymbol{x} - \hat{\boldsymbol{\mu}}'_i)^T \hat{\boldsymbol{\Sigma}}'^{-1}_i (\boldsymbol{x} - \hat{\boldsymbol{\mu}}'_i)\right) \geq$$

$$\geq |\hat{\boldsymbol{\Sigma}}'_j|^{-\frac{1}{2}} \exp\left(-\frac{1}{2}(\boldsymbol{x} - \hat{\boldsymbol{\mu}}'_j)^T \hat{\boldsymbol{\Sigma}}'^{-1}_j (\boldsymbol{x} - \hat{\boldsymbol{\mu}}'_j)\right). \quad (13)$$

Classification accuracy

Performance of the described classification algorithms was tested against the multispectral data of 270 individual trees from the region with coordinates obtained by field work. Only trees from 5 species of interest were included in this analysis set. For each method, 30 experiments were perfor-med with design set formed from N randomly selected trees for each species, $N = \overline{1, 20}$. Trees not included in de-sign sets were considered unknown and number of correct-ly classified trees was calculated against these trees only.

Obtained mean percentage of correctly classified trees for each algorithm is presented in Fig.1.
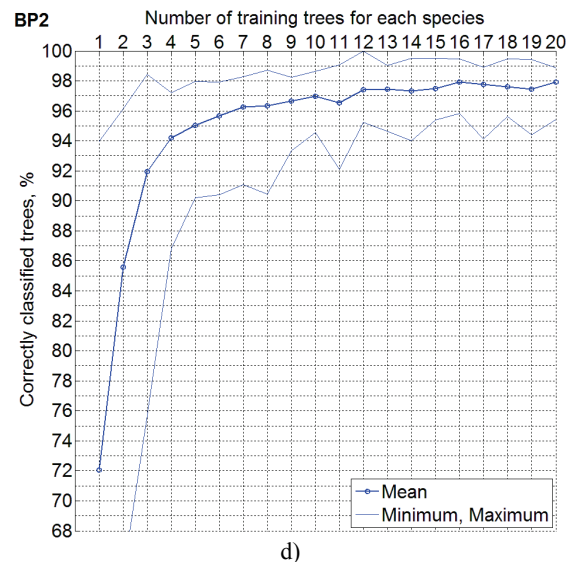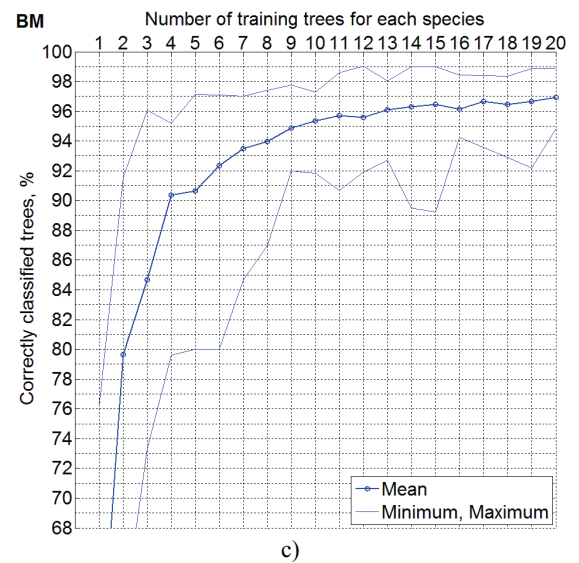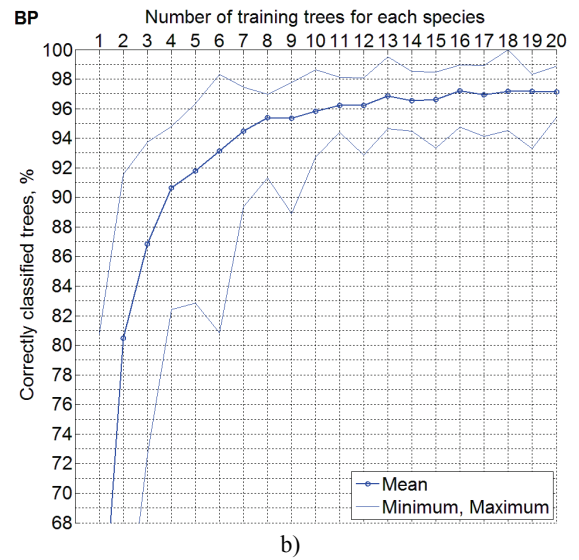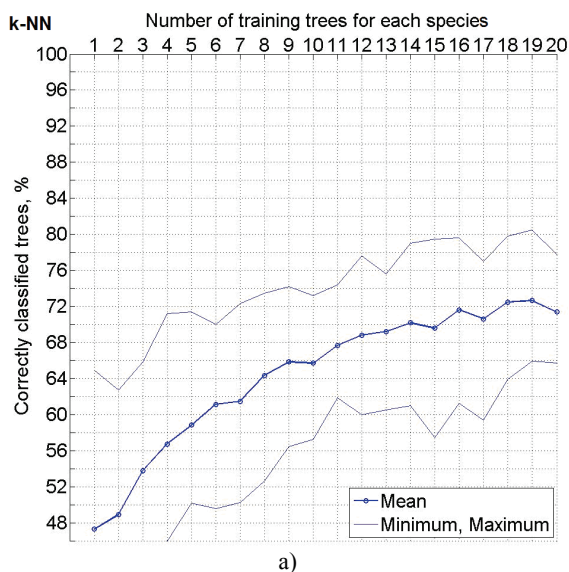
a)

b)

c)

d)

Fig. 1. Classification accuracy of analyzed methods (a–d)

Conclusions

We found that the two-stage Bayes classifier in general provides the smallest error rate. This algorithm can

produce up to 94% correctly classified cases even with only one carefully selected tree in each design set, and up to 98,5% correctly classified trees with 3 trees in each design set.

k-NN classifier produced very weak results, in average only 72% trees were correctly classified using 20 trees in each design set. We obtained about 80% maximum correct classification rate for this algorithm. This number decreases as number of trees in design set decreases.

Other classifiers showed slightly weaker result than the two-stage classifier. Bayes classifier using single pixels featured slightly better performance than Bayes classifier processing mean values of envelopes. Whatever, when design sets' sizes are small, it is more preferable to choose a two-stage classifier or classifier with more than two stages designed on the basis of the same idea as BP2.

The results show that the average correct classification rate of up to 97-98% can be achieved by application of methods based on Bayes rules. However, these results are obtained in idealistic conditions. In real practice, a number of obstructive factors will influence the classification process and correct classification rate will be lower.

Our results also show that selection of reliable design sets has a dramatic influence on classification results especially then design sets' sizes are small. This means that further effort is needed to develop reliable selection procedures of trees for the design set.

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R. Dinuls, A. Lorencs, I. Mednieks. Performance Comparison of Methods for Tree Species Classification in Multispectral Images // Electronics and Electrical Engineering. – Kaunas: Technologija, 2011. – No. 5(111). – P. 119–122.

A number of methods for classification of individual trees in high resolution multispectral images have been developed. The paper provides comparative analysis of some practicable methods of such type. Classification accuracy into 5 species was tested by computer simulations with real multispectral data obtained using airborne hyperspectral sensor. Coordinates and species of individual trees were supplied for testing by field work. It is shown that classification accuracy better than 97 % can be reached by more sophisticated methods in favorable conditions. Presented results can be used to choose a classification method appropriate for the particular forest inventory task. Ill. 1, bibl. 7 (in English; abstracts in English and Lithuanian).

R. Dinuls, A. Lorencs, I. Mednieks. Multipleksinio vaizdavimo metodo, taikomo medžio rūšiai atpažinti efektyvumas // Elektronika ir elektrotechnika. – Kaunas: Technologija, 2011. – Nr. 5(111). – P. 119–122.

Pateikiami medžio rūšių klasifikavimo multispektrinio vaizdavimo metodais pranašumai ir trūkumai. Klasifikavimo tikslumas patikrintas su penkiomis medžių rūšimis taikant kompiuterinį modeliavimą. Medžių rūšys ir koordinatės buvo papildomai patikrintos natūriniais bandymais. 3 % klasifikavimo paklaida užtikrinama tik esant normalioms gamtos sąlygoms. Pasiūlytasis metodas geriausiai tinka konkrečioms miško rūšims. Il. 1, bibl. 7 (anglų kalba; santraukos anglų ir lietuvių k.).