Image segmentation using decision trees method

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Abstract: The image segmentation method aimed at segmentation of orthophoto maps is discussed. The method makes use of ID-3 algorithm by its adjustment for different types of land cover classification. The segmentation method proposed consists of some processing steps. It starts with the initial filtering, followed by the color quantization, and the decision tree building. The decision tree is used then as a classifier in the final segmentation step. To build the classifier some patterns made up of orthophoto maps and corresponding raster images segmented by an expert were prepared. The method was tested on the images not used for classifier building.

Keywords: image processing, decision trees, classification.

I. INTRODUCTION

The image segmentation algorithms play an important role in the image processing domain. These algorithms are often used as the preprocessing step to the following problems: object detection, object recognition, and object tracking. The image segmentation algorithms produce results that are observable in the form of homogenous regions within the image of interest, which are well separated.

In the paper the image segmentation method based on a decision trees building algorithm is discussed. This method is one of the common method used in inductive machine learning. The method is adjusted to detect different land cover classes in the orthophoto maps. In brief, an orthophoto or orthophotograph is an aerial photograph or satellite image that has been geometrically corrected to reflect real area geometry with a great accuracy. The land cover classes such as: urban areas, industrial areas, forests of some type, water, agriculture fields are concerned throughout the paper. The similar methods were successfully applied for hyper-spectral cement image segmentation [1], and object recognition [2].

The segmentation method proposed consists of some processing steps. It starts with initial filtering, followed by the color quantization and classifier building.

The initial filtering should reduce the noise appearing in the image and aggregate some local regions. Thus the low pass filtering can be used for that purpose. The color quantization step should reduce the computational upload of the decision trees building algorithm. The level of color quantization can be chosen arbitrary on the base of experiments performed. The classifier building should result with a set of rules organized in a decision tree structure. In our case the inputs were defined as pixels of orthophoto maps. For the training these inputs were accompanied with the corresponding pixels of orthophoto segmented by an expert. The classifier building step involves ID-3 algorithm which ends up with a set of decision rules [3, 4, 5]. The rules learned are used in the final segmentation step, where different land cover classes are detected and classified.

The paper presents details of the segmentation method proposed, accompanied with results of its use.

II. SEGMENATION SCHEMA

The ID-3 algorithm is one of the methods that employs decision trees to learn object classifications from labeled training instances. In general supervised learning relies on building classifier on the base of the input-output exemplary patterns provided by the trainer. The classifier after training should produce correctly the output pattern when excited with one of the given input patterns. Decision trees method is a special class of supervised learning. It belongs to the group of inductive learning techniques where given set of input-output pairs, $\{x_i, f(x_i)\}$, a hypothesis $h(x_i)$ is to be determined, such that $h(x_i) \approx f(x_i)$, $\forall i$. Thus, when trained, the function $h(x_i)$ is an approximation of classification function $f(x_i)$. Hence the decision tree can be used as a classifier which yields a decision on proper class assignment to the given input.

Formally, the decision tree is a tree with nodes representing conditions for the input attributes selection, and the branches representing different values of these attributes, and the leafs representing decisions (in our case the decisions are simply class labels which are obtained after training phase).

The main idea of ID-3 algorithm relies on spawning nodes in a recursive manner until a maximal tree is reached. The method is based on samples analysis, where each sample have to be described by the set of attributes of different values.

The main part of ID-3 algorithm is the criterion used for properties selection and nodes spawning. In this part the attributes' set entropy is minimized until the leaf of the tree is reached. The leaf reached represents the subset of instances belonging to the same class (which is characterized by the null entropy). The disadvantage of this strategy is the tendency of using often these properties, which quantity excides largely the quantity of other properties.

When the classifier has an output range that takes C different values, then entropy of S with respect to this C-wise classification will be:

$$Entropy(S) = \sum_{i=1}^{C} - P_i \log_2(P_i) \tag{1}$$

where P_i denotes the proportion of S belonging to class i, C – the number of all attributes of the set. Information gain results from the set division with respect to the single element A and is defined as:

$$G(S, A) = Entropy(S) - \sum_{v \in A} \frac{|S_v|}{|S|} Entropy(S_v) \tag{2}$$

where v – the value of the attribute A, S_v – set of instances with A having the value of v, S – the set of all instances.

For obtaining a decision tree with lesser number of nodes information gain of all attributes are measured and the nodes of the tree are expanded based on the order of the attributes, following the descending sequence of their information gain. Thus in each step of the ID-3 algorithm the current node is spawned into so many numbers of nodes as many values has the most informative property (this property maximally reduces entropy).

There is a disadvantages of ID-3 algorithm, which limits its very much for practical use. It is a requirement of the discrete features domain. Thus to use this algorithms for the continuous domain the values of parameters must be discrete. Most often this discretization is just the bracketing into some sections. It is allowed to provide some erroneous samples, or samples without all values known. The ID-3 based segmentation might provide different results for different discretization.

In our case the segmentation schema using decision trees was following. Inputs x_i for the decision tree building were defined as pixels of orthophoto map being segmented with such attributes as: colors – in the case of the aerial photo, or gray level values – in the case of the satellite image composed of different spectral channels. In general the inputs could be defined in other way, using local image statistics or applying filter bank to the image, etc. In the training phase of the algorithm the corresponding outputs for the given inputs were taken from the raster images segmented by an expert. The correct selection of attributes ranges in the attributes discretization guaranteed not complicated, readable segmentation results.

But before decision tree was built the image was filtered with low-pass Gaussian filter. High frequency elements were removed – these were the pixels with significant different colors intensities comparing with neighboring pixels. After this filtering the edges in the image were blurred. The filtering eliminated the noise in the image.

In the next step the input data quantization was done trough the simple pixels values bracketing. In that way the labels from limited set were assigned to each pixel of the original image. To limit the numbers of the resulting attributes the Fisher coefficient was calculated. This coefficient allows distinguishing the most informative attributes by providing information about class membership as follows:

$$F = \frac{\dfrac{1}{1 - \sum_{k=1}^{K} P_k^2} \sum_{k=1}^{K} \sum_{j=1}^{K} P_k P_j (\mu_k - \mu_j)}{\sum_{k=1}^{K} P_k V_k} \tag{3}$$

where D – inter-class dispersion, V – inner-class variance, V_k – variance in class k, P_k – probability distribution of the class k.

Finally, the input data were analyzed for inconsistency. The inconsistency happened when for the same values of input attributes different outputs were assigned. In such case majority voting was applied, and the contradicting samples were removed from the input set. The resulting input set was supplied to the ID-3 algorithm. The decision tree produced was used next for segmentation of the testing orthophoto, see Fig. 1. The processing schema shown in this figure follows the proposition of J. Jędrzejczyk and B. Śródka, described in the report from the project realized in the scope of "Computer knowledge processing" course at Wrocław University of Technology, Poland, 2007.

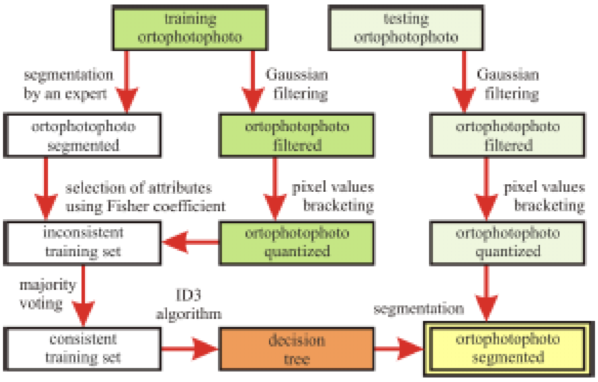

Fig.1. Schema of segmentation using decision tree method.

III. EXPERIMENTS RESULTS

The experiments were performed on orthophoto maps from Landsat satellite and produced by the TM (*Thematic Mapper*) scanner. The TM sensor records reflected electromagnetic energy from the visible to thermal infrared regions of the spectrum in 7 bands. The spatial resolution of TM images is 30x30 m for all bands except the thermal, which has 120x120 m resolution. The bands 3, 4, and 5 were used in the experiment.

The training orthophoto maps were produced with the aid of CORINE Program (*Coordination of Information on the Environment*) database and an expert knowledge. The original CORINE classification consists of twenty two classes of land use, but for the experiment the reference classification map was hand-created by an interpreter. The resulting reference map contained only 9 different classes of land use: buildings, family houses, fields, sands, meadows, forests, industrial areas, cultivation area, water. In the Fig.2 the set consisting of the training orthophoto map (shown in pseudo RGB colors with the following color – spectra band assignments: R = band 3, G = band 4, B = band 5) and the reference map segmented by an expert. This set was used to build the decision tree used later for segmentation. The description of similar experiments on the same can be found in [6, 7].

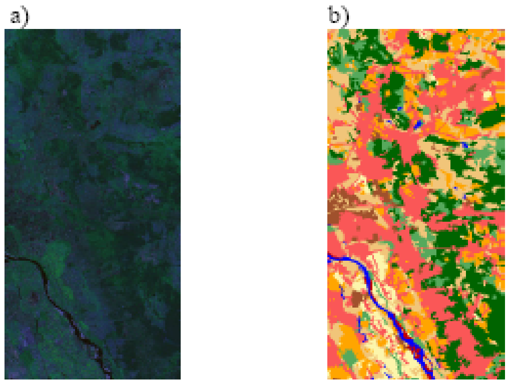

Fig.2. Training set for the classifier building: a) orthophoto shown in pseudo RGB colors with the following color assignments: R = band 3, G = band 4, B = band 5, b) orthophoto segmented by an expert.

The results of segmentation can be observed in the Fig.3. Part a) of this figure contains the satellite image being processed in pseudo RGB colors with the same color assignments as in Fig.2. Part b) represents the reference image created by an expert – this image is given for the segmentation results evaluation only. Part c) contains segmented image obtained for the discretization of the processed attributes (i.e. intensities of pixel colors) into 5 sections and Gaussian filtering parameterized by the mask size 5x5 and σ=0.3.

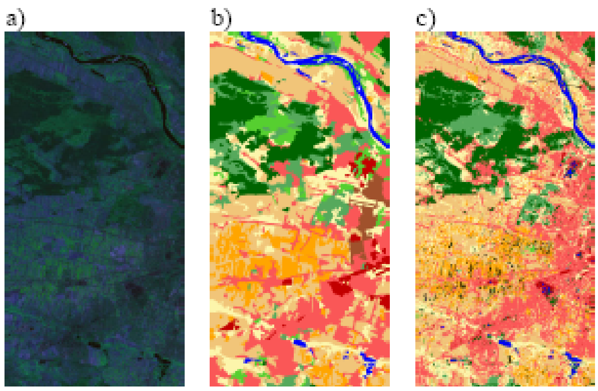

Fig.3. Segmentation using decision tree method: a) satellite image being processed shown in pseudo RGB colors b) reference image created by an expert, c) segmentation results for the discretization of the attributes into 5 sections and Gaussian filter parameterized by the mask size 5x5 and σ=0.3.

The results of segmentation of the same satellite image filtered with different Gaussian filter parameters settings are shown in the Fig.4. The parameters of Gaussian filter were following: a) mask 5x5, σ=0.3, b) mask 5x5, σ=3.5 c) mask 9x9, σ=3.5. It can be observed, that after segmentation some pixels stayed unclassified. Such pixels are easily visible in the Fig.4a) as black dots. The reason is that there was inconsistency in the testing set, i.e. the decision tree build in the training phase did not cover completely the parameters domain of the testing set. Thus there was a lack of proper rule in the decision tree produced.

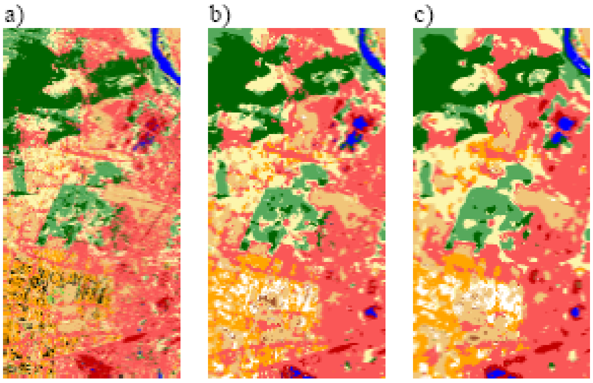

Fig.4. Segmentation results for the discretization of the attributes into 5 sections and different Gaussian filter parameters choices: a) mask 5x5, σ=0.3, b) mask 5x5, σ=3.5 c) mask 9x9, σ=3.5.

VI. CONCLUSION

The classifier was trained with the patterns made up of orthophoto maps and corresponding raster images segmented by an expert. After training some orthophoto maps were processed with the classifier built. The experiment showed that the method proposed can be successfully used for the land cover classes segmentation.

For the correctness of the method it is important to provide most representative and well prepared training set as an input to the ID-3 algorithm. Moreover, the decision tree can not be constructed correctly, if the original orthophoto map and the orthophoto map segmented by an expert does not match. The preprocessing steps might also influence the results of segmentation. More wider mask of the Gaussian filter and its kernel, more merged the results of segmentation are. But region merging might remove some tiny details of the image and thus segmentation accuracy on the region borders might be poor.

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