Methods and Tools for Developing Decision Rules for Classifying Objects in Aerial Images

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Abstract—**Automatic processing and identification of objects in aerial images is in demand in a wide range of practical tasks, for example, in the land use control process. One of the popular approaches to automatic object detection is the object-based classification using decision rules considering various features of image objects. The effectiveness of this approach is largely determined by the reliability of the created decision rules. The purpose of this work is to increase the degree of automation of the process of analysis and search for decision rules by experts and users of aerial image processing systems. The proposed approach consists in the search for dependencies between feature sets, constraints, and the degree of reliability of the decision rules by converting quantitative feature values into qualitative ones based on histograms, fuzzy clustering of a training sample set, and identifying the "class–features" dependencies. We experimentally show that the proposed approach allows obtaining more reliable classification rules compared to the traditional method, in which the means of supporting the analysis process are limited.**

I. Introduction

The rapid development of technologies for remote sensing of the earth's surface has opened up great opportunities for increasing the efficiency of decision-making by state services, reducing the response time to emerging natural and man-made accidents, preventing undesirable scenarios of territory development, increasing the depth and accuracy of environmental management planning, and providing geoinformation support to companies and end users.

The key problem is the detection of objects in remotely sensed images. Manual labeling of objects in aerial images is a slow and expensive process, while automatic processing systems so far are able to produce acceptable results only under strictly defined conditions and require further improvement.

Currently, an approach based on artificial neural networks is widely used for detecting objects in images, which includes a training stage with the use of large amounts of marked data. The best results are shown by convolutional neural networks (CNNs) focused on mass-parallel computing systems. For example, in [1], a convolutional structure of the U-NET type [2] is used for detecting buildings in aerial images, the technologies that allow to run this structure on high-performance graphics processors are described, and the high efficiency of this detection model is shown on a set of high-resolution images. In [3], the task of automatic change detection in buildings by images sensed at different times is solved on the base of the Mask R-CNN and MS-FCN architectures. The problem of the formation of training datasets is noted and it is proposed to solve it by generating synthetic examples of changes.

An alternative to the deep machine learning approach is the geographic object-based image analysis (GEOBIA), the key principles of which are declared in the work [4]. In the GEOBIA paradigm, significant objects are extracted by the image segmentation procedure, object descriptions are formed by calculating such features as shape, color, texture, size, relationships with other objects, etc., and objects are classified into target categories. In the recent paper [5], the formation of a set of objects occurs by analyzing the spectral and spatial homogeneity of image pixels. Classification of extracted objects is first implemented using the nearest neighbor classifier, which is pre-trained on sample data, and then using decision rules. The focus of the work [6] is the search for the optimal parameter values for the image segmentation procedure, functions for estimating the shape of objects, as well as the formation of the most effective set of rules for capturing targets and discarding background objects.

The effectiveness of GEOBIA solutions is largely determined by the reliability of the created decision rules. The development of rules is a very difficult task, since it is necessary to ensure that the set of rules is not too large (to be controlled), and that the rules themselves have a good ability to generalize and allow as few erroneous classifications as possible. Traditionally, the rules are developed by an expert who creates combinations of various restrictions and evaluates the results of their application to a test set of image objects in an interactive mode. Such an approach is used, for example, in [7] for classifying urban garden territories. Using this approach, a set of finely tuned rules can be obtained. But in its pure form, the approach is very time-consuming and highly subjective.

The work [8] proposes a possible solution to the problem of automating the search for rules for classifying objects in satellite images. The rules are formed on the basis of supervised learning: using manually prepared training examples, an automatic synthesis of a decision tree is performed, from which the most reliable classification rules are then extracted by an expert. In [9], the search for the optimal subset of distinctive features for the target class of objects is performed statistically using training examples. To do this, the feature analysis tool SEaTH [10] is used. The idea of the method is to maximize the measure of paired separability of object classes among themselves.

In our opinion, the above approaches to searching for rules are not without drawbacks. In images of urban areas, even within the same object class, as a rule, one can find instances that differ significantly from each other. Therefore, the synthesis of a universal set of requirements that captures all the desired objects is difficult to implement in practice. In order for the automatically synthesized rules to be effective enough, it is necessary to create separate training datasets for each subclass of objects, which requires additional costs.

The purpose of this work is to increase the degree of automation of the process of analysis and search for decision rules by experts and users of aerial image processing systems.

To achieve this goal, we propose:

- principles for organizing classification rules;
- a tool for clustering objects automatically identified or specified by the expert based on feature vectors;
- an interface for generating qualitative feature values;
- methodology for developing classification rules using the above tools.

As a result of applying the proposed approach, the efficiency of the process of creating decision rules is increased in comparison with the traditional way, where the process of formulating the rules is random in nature and has a poorly predictable result. The results of an experimental study on aerial images of urban areas are presented.

II. PRINCIPLES FOR ORGANIZING CLASSIFICATION RULES

Our approach to the analysis of aerial images includes the following main phases:

1) Dividing the image into frames to improve the quality of color segmentation by increasing locality.

2) Color segmentation and determining the borders of color areas in each frame.

3) Merging color areas from neighboring frames along transition segments of the borders.

4) Splitting color segments into subregions in narrow "isthmuses".

5) Approximating edges of color areas by straight line segments and circular arcs.

6) Calculation of the features of areas. Translation of the quantitative values of the features into a qualitative form.

7) Detecting desired objects by means of classification rules.

The methods of color segmentation and increasing the relevance of color areas (phases 1–5) are discussed in detail in [11]. The process of forming a set of features of objects (phase 6) is described in detail in [12]. Below we provide extended comments on phase 7.

Classification of objects into target classes is performed in a stage-by-stage mode (iteratively). The number of classification stages is determined by the number of rule blocks existing in the rule base:

$$RulesDB = (B_i \mid i = 1..n).$$

Each block of rules is focused on identifying objects that have some common characteristics (features). The rule blocks have the following structure:

$$B = (m, C_0, <V_j = (C_j, r_j) \mid j = 1..k>),$$

where m is the label of a target class;

C_0 is a set of common requirements, may be empty;

V_j is a section of variable requirements;

C_j is a set of requirements from the variable section;

$r_j \in [0, 1]$ is the degree of reliability of the classification from the expert's point of view.

In order for the analyzed object to be assigned to class m, it must meet the requirements of the set C_0 and the requirements of one of the sets C_j. Variable sections represent variants of classification of a certain degree of reliability; within the block, these variants are ordered in descending order of the reliability value.

Requirements in C_0 and C_j can be atomic or compound. Atomic requirement is a restriction on the value of the feature, for example:

$$Tortuosity < Large,$$

where *Tortuosity* is the name of the feature, *Large* is the qualitative value of the feature.

A compound requirement is a combination of atomic requirements using logical connectives $\wedge$, $\vee$, $\neg$.

Since shape features are often distorted, for example, by shadows or overhanging crowns of trees, in the rule block, the selected main feature (for example, L-shaped, or rectangular, or pentagonal) is enhanced by various variants of additional features (for example, average width, straightness). In this case, the reliability may vary, in particular, due to the weakening of restrictions on the values of features. In addition, a rule block can be aimed at distinguishing subclasses of objects that differ in size or color, etc.

The applied principle of object classification based on rule blocks allows working with rules in an isolated way, well control the results of each individual rule (or group of rules), develop different strategies for detecting objects and evaluate their effectiveness in a step-by-step mode. From our point of view, this principle is ideal for finding new and improving existing rules using the object clustering tool, which we describe below.

III. OBJECT CLUSTERING TOOL

The applied clustering method is discussed in detail in [13] on the example of the problem of automatic grouping of machine parts by geometric and other parameters. The method belongs to the histogram-based class and is distinguished by the fact that it works with qualitative values of object parameters, which accelerates the clustering process and provides the user with extremely clear feedback.

Fig. 1 shows a window where the user performs clustering of image objects and analyzes the resulting clusters to find new or refine existing classification rules.

In this window, the user must first specify the features by which clustering of image objects will be performed.

Further, for each characteristic, it is necessary to set the rules for converting quantitative values into qualitative ones. Working with fuzzification rules takes place in a separate window, which is described in detail in Section IV.

By default, the entire set of objects present in the processed image is subject to clustering. However, it is possible to select only those objects that satisfy the necessary criteria, for example:

- “building”: at least 75% of the area of the object should be located on the true building (in accordance with the reference labeling);
- “classified as building”: as a result of automatic classification on the base of decision rules, the object was assigned to the class “building” with a greater reliability than to other classes;
- “remaining unclassified”: as a result of the classification, the object was not assigned to any class with sufficient reliability;
- as well as negation of each of the above requirements.

The criteria considered can be combined, thereby obtaining the necessary subset of objects of interest.

The user can specify the maximum number of clusters and the allowed distance between clusters. Smaller clusters are attached to the nearest heavier clusters until the number of clusters is reduced to the specified value. If the parameter is set to 0, the restriction is removed. The more clusters are formed, the more accurate, but less general dependencies are captured by each individual cluster. In the case of a small number of clusters, the degree of generalization is more noticeable, but, unfortunately, among the "good" objects there is a greater number of “bad” (“noisy”) ones.

After clustering is complete, a histogram appears in which each bar corresponds to one of the resulting clusters. Clusters are ordered in decreasing order of the number of objects in the cluster. The height of the bars can take one of the following interpretations (optional):

- number of objects;
- total area of objects;
- average area of objects;
- value of the completeness indicator, i.e. the percentage of coverage of reference objects;
- value of the accuracy index;
- value of the *IoU* metric that integrates completeness and accuracy.

The last three interpretation options are based on the calculation of evaluation indicators that characterize the degree of compliance of cluster objects with the reference labeling. From the point of view of compiling decision rules, the second and fourth interpretation options can be considered the most useful, since they show the potential contribution of each cluster to the final result of object detection.

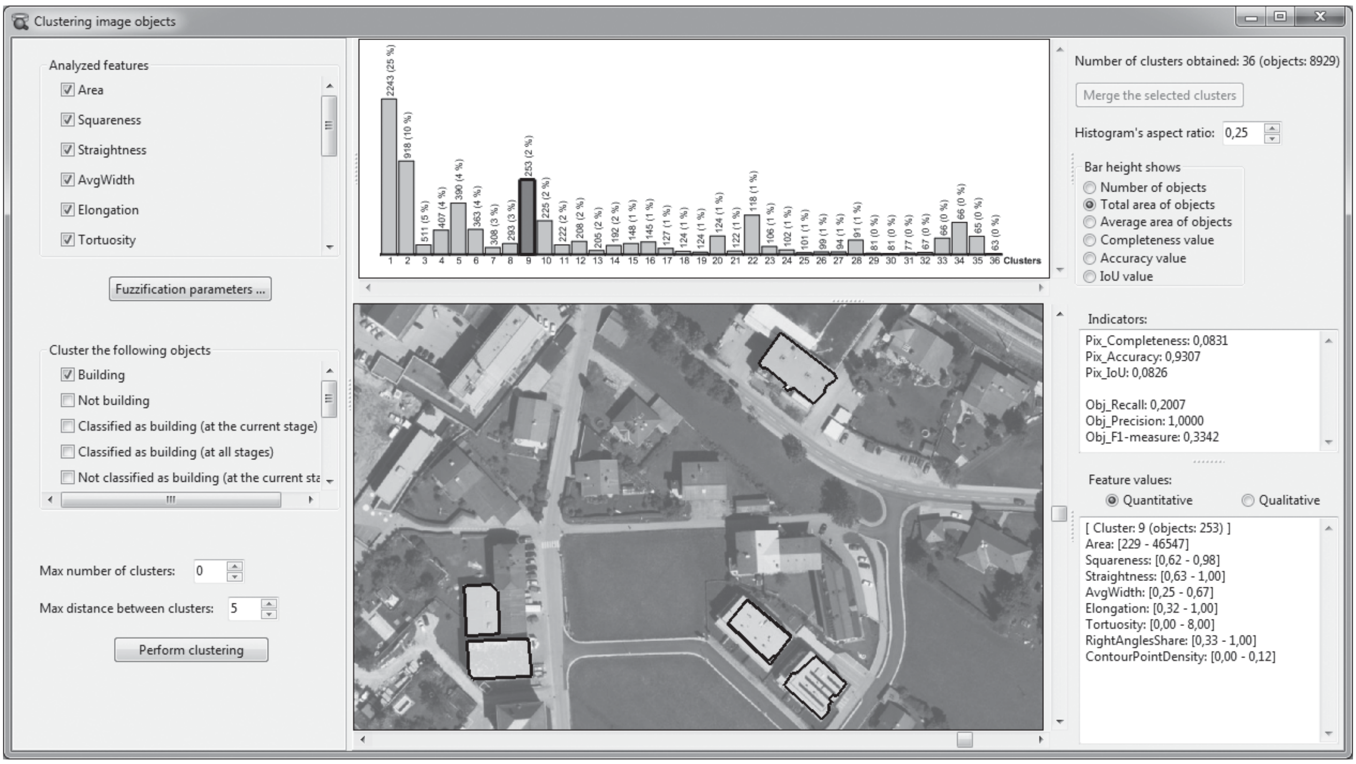


Fig. 1. Window for clustering image objects. 36 clusters were obtained. The cluster number 9 is selected, for which the following items are displayed: objects assigned to it, values of indicators of compliance of objects with the reference labeling, and ranges of values of object features.

By clicking on a bar of the histogram, all objects assigned to the corresponding cluster are displayed on the screen. The values of metrics characterizing the degree of correspondence of these objects to the reference labeling are also displayed. In addition, feature value ranges are displayed (in quantitative or qualitative form). If desired, the user can also see the distribution of objects by the range of a feature in a histogram form.

In the interface it is possible to select several clusters at a time to view their objects and parameters together, or combine them into a single cluster.

IV. Feature value fuzzification tool

The conversion of feature values from a quantitative form to a qualitative one takes place with the help of a tool based on the construction of distribution histograms.

Fig. 2 shows the program window where the rules for fuzzification of feature values are set. Initially, the user sees a histogram with a large number of equal ranges (Fig. 2*a*). This gives the user a general idea about the form of distribution. With this information in mind, the user reduces the number of ranges to the required number of qualitative values. For example, in Fig. 2*b*, the user defined ranges of six qualitative values of the straightness feature, which he or she considers sufficient for clustering. The program also has the ability to automatically generate target ranges by using the standard *k*-means method [14]. Automatically generated ranges can serve as a good starting point for fine-tuning of intervals.

By clicking on any bar of the histogram, the system shows all objects in the image for which the value of the feature falls into the range corresponding to this bar. In this way, the user evaluates the correctness of the created ranges.

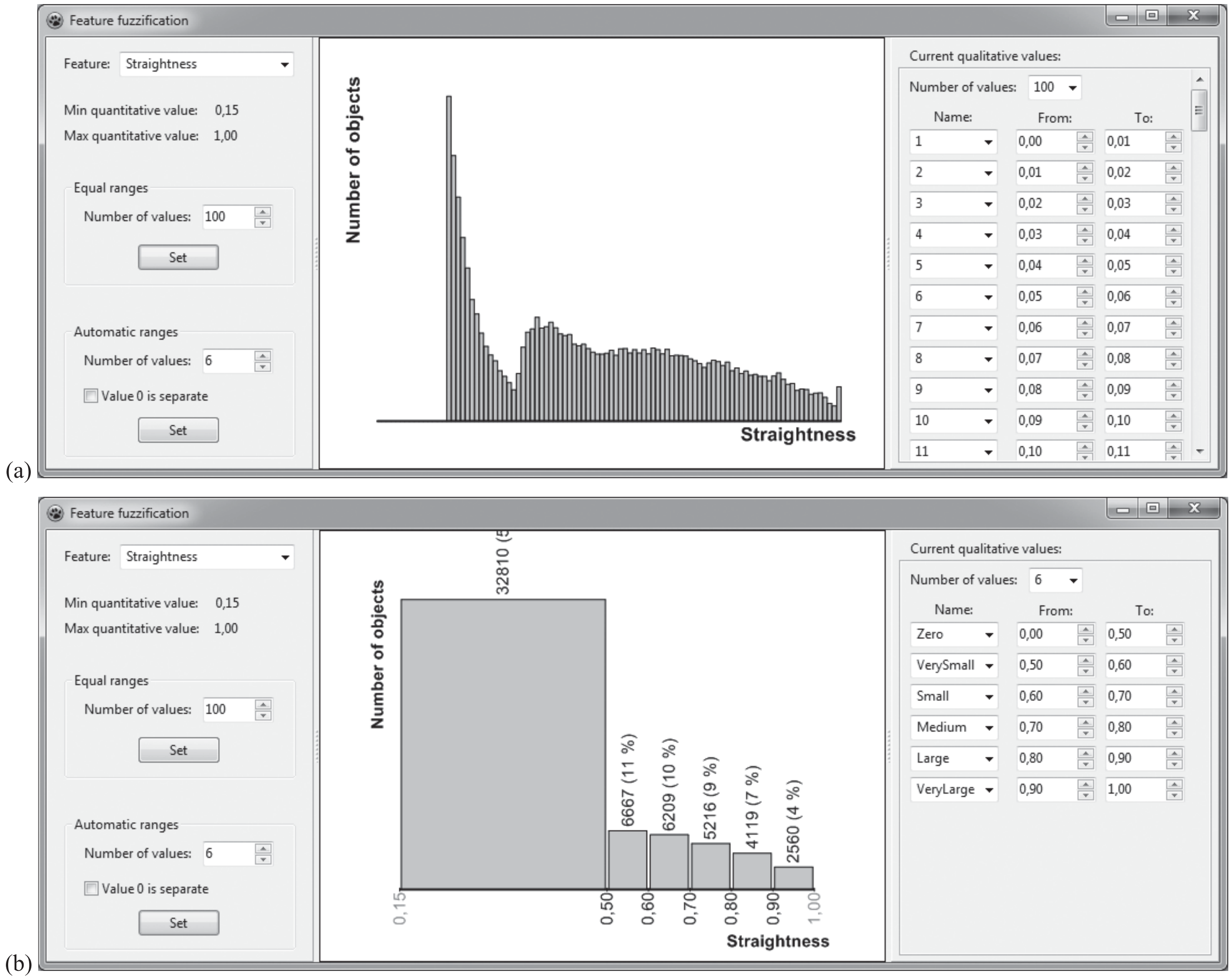


Fig. 2. Window for fuzzification of feature values: (a) the original histogram with a large number of ranges of equal width; (b) the histogram for six qualitative values

V. Methodology for Developing Decision Rules

In general, searching for decision rules is an iterative process. The proposed methodology covers both the process of creating rules from scratch and refining previously formed rules.

The process of developing decision rules in the proposed system is shown in Algorithm 1.

Algorithm 1 General algorithm for developing decision rules

Input: I – one of the most representative images, F – set of feature names, V – validation image set.
Output: *RulesDB* – decision rule base.
1: $RulesDB = \varnothing$
2: [$L = CreateTargetObjectsLabeling(I)$]
3: $A = ExtractColorAreas(I)$
4: $A^C = ClassifyAreas(Areas, RulesDB)$
5: $O = SelectObjectsToBeClustered(A, A^C, L)$, $O \subseteq A$
6: $F2 = SelectFeatures(F)$, $F2 \subseteq F$
7: $P1 = SetFuzzificationParams(F2, A)$
8: $P2 = SetClusteringParams()$
9: $C = PerformClustering(O, F2, P1, P2)$
10: $H = CreateClustersHistogram(C)$
11: $SortClusters(H, C)$
12: **Loop by clusters** (C_i):
  12.1: $VisualizeClusterObjects(C_i)$
  12.2: $EvaluateVisually(C_i)$
    If $(\neg\, Target(C_i)) \vee (\neg\, SimilarShapes(C_i))$
    Then $Exclude(C_i)$, continue
  12.3: $\langle F^N, F^D\rangle = AnalyzeFeatureValues(C_i, F)$.
  12.4: $B = CreateRule(F^D, C_i)$
  12.5: $p = EvaluateDetectionAccuracy(V, B)$
    If $Sufficient(p)$
    Then $AssignReliability(B, p)$
    Else $Exclude(C_i)$, continue
  12.6: $RulesDB = RulesDB \cup B$
13: $IoU = EvaluateOverallDetectionRate(V, RulesDB)$
14: **If** $Sufficient(IoU)$ **Then** stop **Else** goto 2

At step 2, the user prepares the reference labeling for the target object class (optional).

In step 3, the system extracts color areas from the image by performing color segmentation and applying a number of procedures to improve the edges of color segments (splitting in narrow places, approximation, etc.). More details on this process can be found in [11].

In step 4, the system classifies the image regions according to the rules created in the previous iterations of the algorithm.

At step 5, the user selects the areas to be subjected to cluster analysis by setting the necessary criteria described in Section III.

At step 6, the user selects a subset of the features by which objects should be clustered. Initially, it is advisable to involve all the available features, and then along the way the user can experiment with excluding some of the features from consideration.

At step 7, the user sets the parameters of fuzzification of the values of the selected features using the tool described in Section IV. Features should be fazzified into 4-6 qualitative values.

At step 8, the user sets the clustering parameters: the maximum number of clusters and the allowed distance between clusters. At the initial stage, it is preferable to form a small number of clusters (5-10); later, if necessary, the target number of clusters can be gradually increased.

At step 9, the system clusters objects, and at the next step (10), it builds a histogram of the resulting clusters.

In step 11, the user determines the order of cluster analysis. It is recommended to consider clusters in descending order of the contribution that a single cluster makes to the coverage of the target set of objects of interest.

In step 12.1, the system displays the objects of the current analyzed cluster to the user, and in step 12.2, the user performs a visual analysis of these objects. The fact that objects have strong similarities in the shape of the border suggests that the cluster is useful. If no obvious regularities of the shape are observed or objects are not target or have a little significance (for example, small details such as chimneys on roofs or narrow color areas along the boundaries of buildings), then the cluster can be immediately excluded from consideration.

In step 12.3, the user analyzes the ranges of feature values within the cluster. If the value varies widely enough, then the feature is neutral for this cluster ($\in F^N$). Otherwise, the feature is distinctive ($\in F^D$) and must be included in the decision rule in step 12.4.

At step 12.5, the accuracy of the created rule on the verification images is evaluated. If the rule classifies objects with an insufficient degree of accuracy, then exclude the current cluster from consideration. Otherwise, if the accuracy of the solutions is acceptable, set the system-calculated value of the accuracy index as the rule's reliability and add it to the base of decision rules. Even if the reliability of the rule is not very high, the rule may be useful, since at the final phase it is possible to perform case-based clarification of questionable objects; in order to reduce the analysis space, the case-based clarification process considers only those objects that have already been assigned to a certain class, but with not very high reliability.

At step 12.6, the user inserts the created rule into the rule base. Either simple addition or replacement/modification of a previously created rule takes place. If there are related clusters in which the neutral features are the same and the distinctive features are adjacent, they can be combined to create a more general decision rule.

In step 13, the system performs a quantitative assessment of the overall quality of object detection based on the resulting rule base.

Finally, at step 14, depending on the obtained semantic classification quality assessment, either the rule development process is completed or a new iteration of the algorithm is initiated. In the new iteration, other objects and/or features can be considered, and other values of clusterization parameters can be applied. Vague clusters containing objects of different types can be subjected to repeated (hierarchical) clustering in order to identify more specific subgroups of objects. The focus can be shifted to a different target class of objects.

Note that steps 3, 4, 9, 10, and 13 are carried out by the system fully automatically without any user intervention.

VI. Experiments

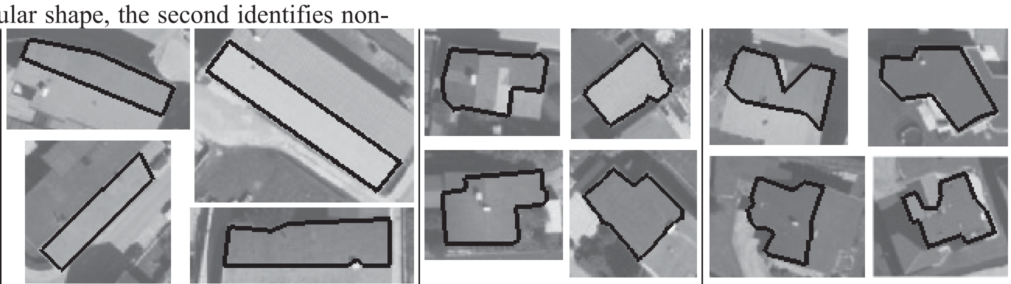
An experimental study of the effectiveness of the proposed approach was performed on publicly available data from the Inria Aerial Image Labeling benchmark [15, 16], on a group of West Tyrol images.

In the process of creating decision rules, one aerial image of size 5000×5000 and the corresponding reference pixel-wise labeling of buildings were used. This data served as a training sample.

Fig. 3 shows examples of clusters that were formed by the system. It can be seen that the corresponding first rule focuses on buildings of a rectangular shape, the second identifies non-convex objects containing external and internal right angles, and the third retrieves parts of buildings of a non-trivial configuration. The completeness and accuracy indicators were calculated relative to the reference labeling, which was performed without subclassing.

During the experiment, the expert created a total of 18 rules for the class of buildings and 17 rules for other classes of objects (shadow, greenery, road, other). All these rules were organized in the form of 16 rule blocks.

Fig. 4 shows an example of an aerial image from a test set and the results of automatic building detection in it. Light gray pixels are pixels of objects assigned to the building class, which are also marked as buildings in the reference labeling (True Positives). Dark gray pixels belong to objects that were classified as buildings, but do not belong to buildings in the labeling (False Positives). White pixels relate to the target buildings that the system did not detect (False Negatives).



Area	[Medium - VeryLarge]	[VerySmall - Large]	[VerySmall - Large]
Squareness	[Medium - VeryLarge]	[Medium - VeryLarge]	[Small - Large]
Straightness	[Small - VeryLarge]	[Zero - Medium]	[Zero - Medium]
AvgWidth	[Small - Large]	[Small - VeryLarge]	[Medium - VeryLarge]
Elongation	[Medium - VeryLarge]	[Zero - Small]	[Zero - Small]
RightAnglesShare	[Medium - VeryLarge]	[Medium - VeryLarge]	[Zero - Medium]

Fig. 3. Examples of clusters, based on the analysis of which the expert creates decision rules. The rule created by the expert on the basis of the first cluster detects buildings with a completeness of 0.05 and an accuracy of 0.92. The performance indicators of the rule based on the second cluster are the following: completeness 0.13, accuracy 0.83. The rule corresponding to the third cluster has the following influence on the result of building detection: completeness 0.25, accuracy 0.73.

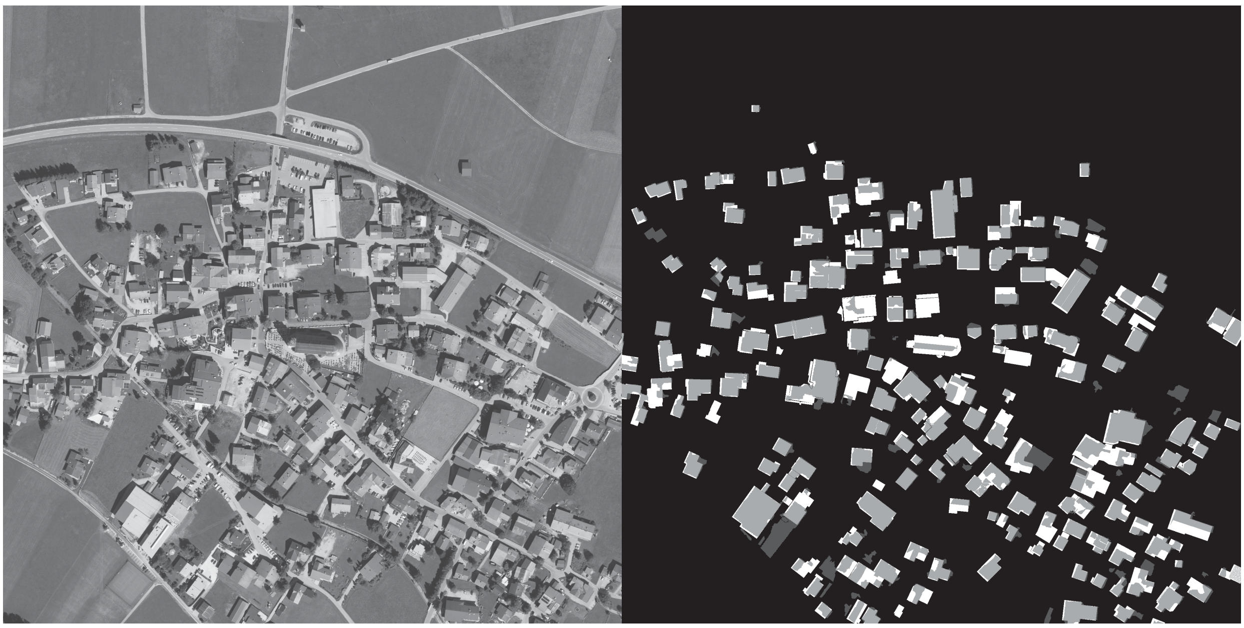


Fig. 4. An example of automatic building detection. On the left is the original image. On the right are the semantic classification results (true positive pixels are light gray, false positive pixels are dark gray, and false negative pixels are white).

Quantitative evaluation of the effectiveness of the proposed approach was performed using the *IoU* (*Intersection over Union*) indicator, which comprehensively characterizes the overall quality of object detection. This indicator is widely used in the tasks of semantic image segmentation [17]. It also has an alternative name – the Jaccard index. This indicator is calculated at the pixel level as follows:

$$IoU = |P \cap G| / |P \cup G|,$$

where P is the pixel set of automatically extracted objects; G is the pixel set of ground truth objects.

Table I presents the *IoU* values for neural network methods, for our system in the conditions when the rules are created by the user in the traditional way, and, finally, for our system in the conditions of application of the tools and methodological support proposed in this work.

TABLE I. EFFECTIVENESS OF BUILDING DETECTION METHODS

Method	IoU
FCN [15]	46.86
Skip [15]	54.91
MLP [15]	57.95
Our system without support means [11]	53.13
Our system with the use of the presented tools and methodology	58.16

Thus, the mechanisms proposed in this paper allow to form a more effective set of decision rules. The quality of building detection was increased by 5%, which is a noticeable change.

The new rule base obtained using the presented methodology captures a larger number of targets and produces fewer false classifications relative to the previous rule base, which was formed intuitively.

In the traditional workflow, the expert himself determines which subclasses of objects should be recognized in the image (for example, among buildings: rectangular, L-shaped, elongated, etc.). Unfortunately, the expert's view of subclasses is often idealized and not entirely consistent with the actual areas automatically extracted from the image. As is known [18, 19], when performing image segmentation, problems of insufficiency, excessiveness and inaccuracy of segmentation often arise in practice. Therefore, there is a semantic gap [20] between the categories that the expert uses when creating classification rules and the actual image data. As a result, the formed rules affect only the most exemplary instances of objects. On the contrary, in the proposed approach, generated clusters represent real subclasses of objects rather than abstract ones. The rules created on the basis of the resulting clusters are more relevant to the actual image data and, therefore, work more effectively.

In the related approaches, for example, [8], it cannot be said that the decision support process is organized quite flexibly, clearly and conveniently. In particular, decision trees generated in [8] take up a lot of space (both vertically and horizontally), and because of this, it is quite difficult and inconvenient to analyze them. Adjustable parameters are only the decision tree induction algorithm (ID3, GID3, etc.) and its technical thresholds (confidence level, tolerance level, etc.). In our system, the user is provided with more developed and comfortable tools to support decision-making.

A certain disadvantage is the need to set parameters for fuzzification of feature values. This slightly increases the overall labor costs of the process. On the other hand, the expert can set the fuzzification parameters once and then use them repeatedly.

VII. CONCLUSION

At the stage of setting up GEOBIA systems for a series of aerial images, experts are faced with the problem of finding the optimal set of rules for classifying image objects. In order to simplify the solution of this problem, an approach to automating the search for classification rules is proposed, which allows the expert to base his decisions on the results of fuzzy clustering of objects using a set of parameters, reveal hidden patterns in the data, and evaluate the reliability of the created rules.

The approach consists in the iterative search for dependencies between features, constraints, and the degree of reliability of classification rules based on them. To support decision-making, the expert is provided with convenient and visual tools:

- for fuzzification of features based on histograms of the distribution of values;
- for clustering image objects according to the selected set of features;
- for creating diagrams of the distribution of objects across clusters and descriptions of objects belonging to the selected cluster;
- for assigning a degree of confidence to the obtained rules based on completeness and accuracy indicators.

The advantage of the approach is that the presence of a reference labeling of target objects, although recommended, is not mandatory. Clustering can be performed on all objects of the image, and not just on the target ones. Due to the stage-by-stage (iterative) organization of the process of searching for decision rules, the system allows to build more in-depth class hierarchies. Such applications of the toolkit distinguish the proposed approach from related approaches.

The work extends the GEOBIA area with new means of supporting decisions made by users and experts.

Further, it is supposed to investigate methods for calculating the weight of features and fully automatic search for decision rules.

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