THE USE OF DECISION-MAKING CELLULAR AUTOMATA IN POST-CLASSIFICATION ANALYSES OF REMOTE SENSING IMAGES FOR URBAN GREEN DETECTION

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Abstract

Image classification is probably the most often used strategy for land cover detection in remote sensing applications. Typical approaches to supervised classification, like Maximum Likelihood method, are still developed as well as some other methods based on segmentation, pattern recognition, artificial intelligence, neural networks and object-based image analyses.
Density based clustering is one of undervalued methods for classification of remote sensing databases. The base of this approach is that image pixels are enclosed to one of the set of initially defined classes according to the number of similar pixels lying within predefined range of neighborhood of the pixel under consideration (in geometric and radiometric space). If surrounding pixels fulfill some criteria, they are connected to the same class. Sometimes better is to arrange image data first at the process of preliminary unsupervised classification. Than the described method acts the role of post-classification rearrangement treatment.
In the paper density-based post-classification segmentation method are described and results of very high resolution (VHR) satellite image classification are presented. The aim of classification has been selection of some classes of vegetables within urban environment. It is very important goal for managing sustainable development of present cities. Classification of remote sensing images can then serve as an efficient monitoring tool of the current state of scattered green areas.
The Decision-Making Cellular Automaton (DMCA) has been adapted as a tool to re-aggregate previously clustered image pixels. Cellular automata were successfully used by some researchers for image enhancement, filtering or classification. In this paper the iterative process of clustering is driven by CA with specific transition rule. The decision-making nature of CA arises from the type of criterion function and the set of their factors and constraints. The main decision factor is the number of pixels ascribed to one or several clusters within certain neighborhood of the pixel under consideration. The factors are also numbers of pixels recognized as a noise within the image objects or outside of them. Decisions are verified and extended in next iterations by criteria of density.
The method has been verified for urban green of different type, which has been recorded by QuickBird-2 imaging sensor. The results of the test are presented below.

The assessment of the results shows great potential capabilities of the method and is expected to be useful in further change detection analyses of land cover.

1. Introduction

One of the most important parts of common live of urban societies is monitoring of natural environment within cities (Lang et al., 2007). Authorities responsible for the state of nature should be assisted by autonomous institutions, among others by Remote Sensing (RS) community. The newest satellite imaging systems give huge abilities at the domain of fast detection of environment hazards. The advantages of RS are its non-invasive nature and fast gathering of information about vast areas. Also the ability to select green areas by image classification has great significance.

Despite of development of a great number of approaches to image classification, still new trials are being conducted and old techniques are evolved, especially toward automation of tracing changes. Among somewhat neglected, but efficient solutions is classification based on densities of points that have certain properties. In the image these are pixels at some radiometric features. The use of density-based methods defeated such limitations of distance-based methods as spherical range of clustered pixels and great sensitivity of noise.

Density-based methods base on grouping these pixels, at which direct neighborhood is certain number of points having specific features. In principle many various solutions are expansion of classic DBSCAN algorithm (Ester et al., 1996). The new approaches or modify the way of selection of core points of clusters, or treat various densities of points in different clusters (Ertöz et al., 2002) or adapt themselves to other specific features of elaborated data sets. In relation to images the vital significance has experiences of Ye et al. (2003), who investigated neighborhood separately for the image space (*SpatialEps*) and color space (*ColorEps*). Approach proposed by Dash et al. (2001) relies on combination of distance-based and density-based methods. They argue that such approach accelerates segmentation process and also eliminates the noise from clusters.

The area under consideration of presented work is a part of the city Poznan in Poland, known as ‘green city’ because of extensive park areas spread out in four main directions from the city center to the borders. Now the green areas are under great pressure to be built-up and they have to be monitored by local authority to save them and revitalize the most destroyed ones. Every three years new color aerial photographs have been taken and new orthophotomap is compiled. Now have also been collected very high resolution satellite (VHRS) images. To implement urban green monitoring the QuickBird-2 spectral image has been utilized. The image was preliminary orthorectified, pansharpened and calibrated to local coordinate system. Three parts of the scene containing urban green areas of various destinations have been chosen. They represent areas with decreased number of tall trees.

The solution for making urban green maps utilizes my own density-based segmentation approach in the image after unsupervised classification. Te task is resolved using cellular automaton, called DBCA/IS (Density Based Cellular Automaton for Image Segmentation). To the end of the paper, section 2 refers to similar classification approaches, section 3 describes my solution show tests which have been made. Section 4 resumes obtained results and formulates generalized conclusions.

2. Density-based classification approaches and BDCCA

2.1. Basics on density-based image classification

Monitoring of urban green and its valuation with the use of RS methods were the subject of investigations of Lang et al. (2007). They and most other authors use aerial photographs rather than satellite images, because they are more detailed and their acquisition is more flexible. Photographs are also reach historical resource, so they are useful to trace long-term changes within natural environment (Carmel & Kadmon, 1998). Unfortunately photographs usually don't have infrared layer, which is the base for indexing of green objects. Important growth came up when very high resolution satellite (VHRS) images appeared. They provide spatial resolution above 1 m, and 4-band with 11-bit spectral resolution, including NIR band, so they are huge source of data about terrain objects.

There are many articles concerning detection of objects on VHRS images. Among others on Hannover Workshop 2005 Zhang and Fraser (2005) presented automated VHRS registration method for change detection and Leitloff et al. (2005) used them to detect vehicle queues. The latest represents works concerning precision positioning of objects only a bit greater than pixel size. Similar works concern detection trees (Suarez, 2003). In order to detect clusters of trees I adapted the method called DCMA (Decision-Making Cellular Automata), which in fact is post-classification procedure for aggregation image objects having common set of selected features. Similar approach was used for post-classification aggregation by Dash et al. (2001) as well as Wang and Hamilton (2003).

The core of density-based methods is counting surrounding pixels that fulfill certain criteria. According to the algorithm DBSCAN introduced by Ester et al. (1996) the *neighborhood* is defined by the circle at the radius ε. When the number of positively identified points exceed lower threshold *MinPts*, then the central point is marked as *core point* of a new cluster. If there are next similar pixels behind the range ε, than borders of the cluster extends. The problem are pixels within the cluster, that don't fulfill the condition of affiliation, and also some points fulfilling the conditions but encircled by not enough number of similar pixels. In such cases it is necessary to use next criterion which assign these pixels to suitable cluster. The points from the second part are called border points and they are connected to the cluster only when they are *density reachable* (e.g. if they are connected with some core points by the string of *directly density reachable* points).

The tasks that base on the neighborhood can be effectively realized by the use of Cellular Automata (CA), which in simply way resolves complex solutions. According to the definition of CA, the goal of automaton is to set certain *state* to central *cell*, when adjacent cells satisfy certain criterion called *transition rule*. Standard definition of neighborhood uses 3x3 mask of von Neumann or Moore, but masks can have different sizes (Kocabas & Dragicevic, 2004) or shapes, not always regular. Some authors expand neighborhood including global information. Moreover, there were investigated various criteria to detect state of environment and also numerous rules had been defined to change cell states, what sometimes led algorithms to much complex form. In such solutions authors rather used tables of transition rules. Among others Sullivan and Knight (2004) and Hernández et al. (2007) elaborated CA models of fire front spreading, basing on the theories of fire behavior. Another complex task resolved by CA was developed by Prusinkiewicz (2000) in order to simulate plants and plant ecosystems. In his models roots, branches and lives 'are growing up' in the way dependent on the place (under or above the ground), time (the age of the tree), environment (access to the sun and water), season and so on.

In my method cellular automaton has classic form, e.g. extended Moore neighborhood, finite range of the cell states and deterministic transition rules. It works on empty raster space and information layers play role of its environment. In the work (Wyczalek, 2005) I described theoretic frame and results attained during test works, and in (Wyczalek 2006) I discussed results of tests made in the VHRS image of QuickBird. The method is investigated towards including GIS layers into common environment to serve as data for decision making.

2.1. Density-based clustering cellular automata

The aim of cellular automata that classify the image according to density-based clustering rules is to select one or more classes of land cover. The task is qualified as post-classification ordering algorithm, like AGGREGATION. As a clustering method is used DBSCAN, described by Ester et al. (1996) and cited by Wang & Hamilton (2003), Ye et al. (2004) and other authors.

In order to solve above formulated task, there were adopted terms extending theory of DBCSAN. They are:

1) Any source of spatial information that enclose the area of influence of CA and have spatially oriented descriptive attributes can state the environment of automata. In particular the environment is an image (resampled to the lattice of CA) that has grey values adequate to spectral response of terrain objects (radiometric features). The environment can also be the set of any RS data and also vector or raster data gathered from spatial data bases;
2) ε^N-neighborhood of the cell A_{ij} is the group of cells defined as Von Neumann- or Moore-neighborhood of N^{th} degree (N means the distance from the central point to the border counting in pixels);
3) The behavior of the automaton is its response on detected properties of the environment at a spatial range of ε^N, which effect is change of its state. The vital initial factor is ability to detect environment by CA. The values of recognized features serve as arguments of transition rule which is responsible for behavior of CA. It is necessary to state, that CA affect only on its central cell, and the transition rule acts according to multicriteria analyses;
4) The sensitivity of CA is its ability to recognize the state of environment at the range of its neighborhood. In practice transition rule can recognize only that properties of environment, which are defined in its set of metadata.

In respect to the resulting set of unsupervised classification automaton is able to sum pixels ascribed to particular classes and to assign to its central point the state of the core point, border point or noise, and also to group these points into clusters.
The metadata necessary to recognize image contain only the number of classes. In order to select individual class of land use the method needs to show some training areas. It can be done automatically, using GIS tools or by hand (using points, lines or polygons). Therefore, the procedure of action contain following steps:

1) the starting state of CA is the state of cells within learning areas;
2) in the first iteration (and eventually all another) automaton recognize learning pixels in the image and sum each cluster individually in order to ascribe the status of core points;
3) in the following iteration automaton mark all pixels that fulfill density criteria as the core points;
4) in next steps remaining pixels are added to adequate classes (and are labeled as ‘associated points’ when are surrounding by suitable number of core points), or removed from its own class when in their neighborhood is not enough amount of core points (and then are labeled as ‘dispersed’);
5) iterations repeat to the time when the process of transitions stops.

The final image of the space of automaton consists of clusters of core or associated points, and also some dispersed pixels and the noise. Because of the ability of automaton to detect various properties of environment, it is possible to enrich the algorithm by detection of vegetation index (NDVI, SAVI) or other additional information useful to make a choice. The combination of detection of few properties is similar to multicriteria analyze.

3. Practical tests

3.1. Testing fields

The method has been tested on a part of QuickBird image registered 01-06-2003 (image number 1010010001F23F01) at ideal atmospheric conditions. Analyzed fragments have size of 1000x1000 pixels and contain (1°) urban forest with the lake and some athletic objects, (2°) the park with dense complexes of trees and some meadows crossing by a net of walks, (3°) river banks with clumps of trees or bushes and garden plots. The images consist of 4 spectral bands and had been ortho-rectified, Pansharpened and transformed to local coordinate system. These operations as well as initial K-means classification had been done in program PCI geomatica, release 9.1.7. Final images have 16 strongly correlated classes dispersed in whole images. In order to allocate compact segments of particular types of land cover, e.g. trees, the higher described CA procedure has been carried out using own computer program.

3.2. Stages of elaboration

Consecutive steps of computation are illustrated in Figure 1. Result of non-supervised classification (a) serves as learning field for density based algorithm. After first step core cells appeared (b) and each next step adds neighboring cells (c) and remove sole core points. Each step moves closer to expected result of classification (d, e, f). Algorithm finishes its work after reaching declared threshold of number growth of pixels linked to the class in one step.

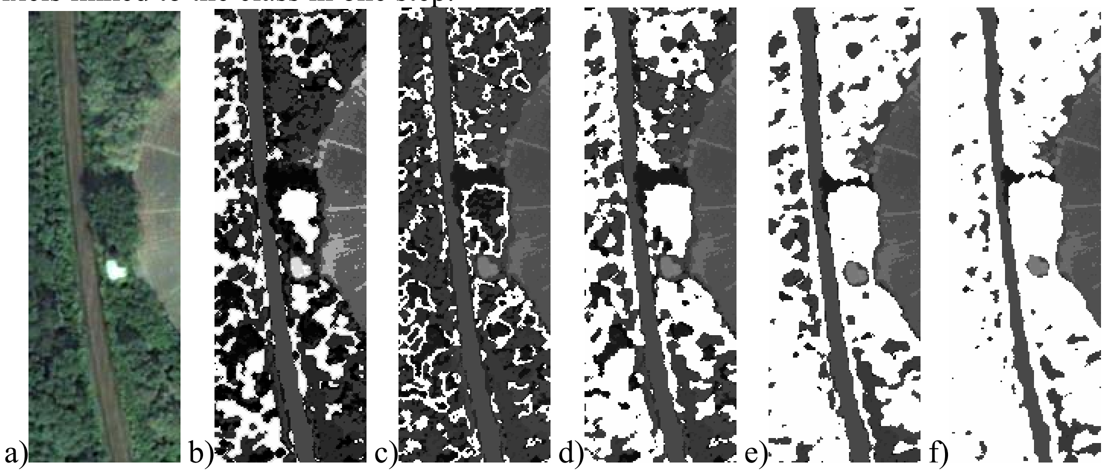


Fig. 1. Stages of aggregation pixels to a class ‘TREES’ on multispectral QuickBird image using Density Based Classification Cellular Automaton (description in text).

Figures 3-5 show results of classification for described 3 types of urban green landscapes – image classified by K-means method (left) and resulting state of DBCCA work (right).

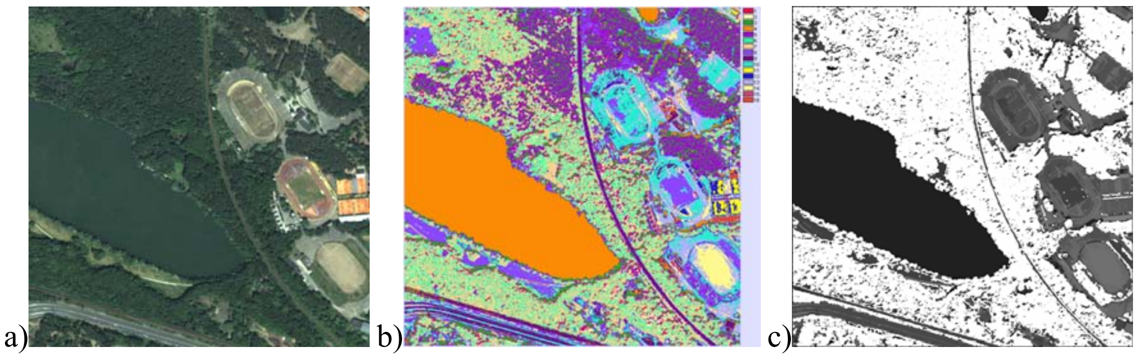
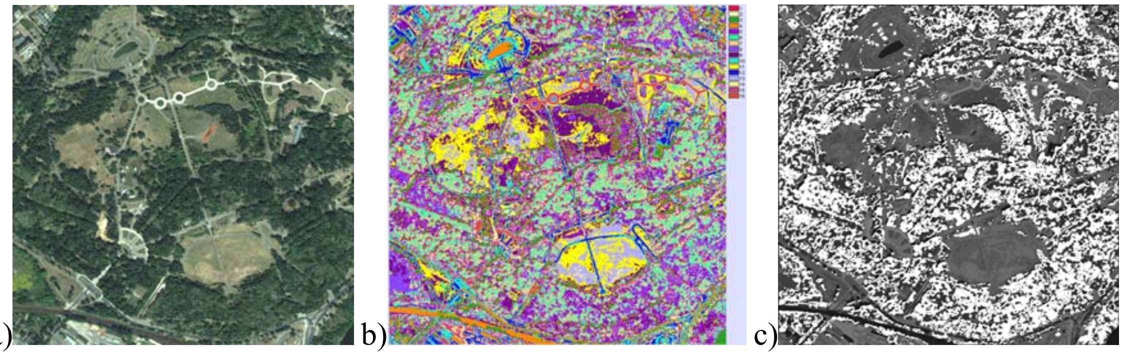
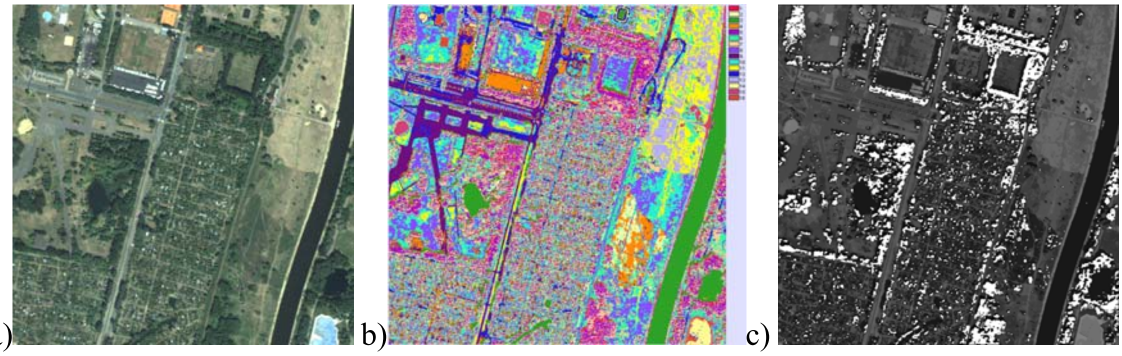


Fig. 2. Grouping pixels to class ‘TREES’ in satellite image of forested area: a) RGB composition, b) image classified with non-supervised method, c) result of using DBCCA aggregation procedure (white places).



a) b) c)

Fig. 3. Result of grouping pixels to class 'TREES' in satellite image of the park.



a) b) c)

Fig. 4. Result of grouping pixels to class 'TREES' in satellite image of river bank and gardens (excluding other types of green as grass, vegetables, bushes and fruit-trees).

4. Results and conclusions

Figures 2-4 presents the phases of the work of DBCCA, beginning from indication of training data in non-supervised classified image, through selection of core points and also associated and dispersed points, till to tree groups iterative compilation. Test show great ability of described classification method. Now the computer program is investigated and tested, especially from the angle of uncertainty and sensitivity analyses.

As a conclusion it can be stated, that elaborated algorithm comes true as post-classification aggregation method for forested areas, and it can select tree clusters according to established criteria. Tests conducted for various types of land cover allow to expect wider range of usefulness of the method.

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6. Referencies

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