A COMPARISON OF URBAN AREA AGGREGATION IN SATELLITE IMAGES USING NEURAL NETWORKS, CELLULAR AUTOMATA AND MEDIAN FILTRATION

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ABSTRACT

Of the many existing methods for area aggregation a majority concern maps in vector format. In order to process raster data one has to convert them to vector, which is a laborious process introducing imprecision. The other choice is to use one of the aggregation methods native to raster format, some of which are related to image processing techniques.

The authors investigated some approaches to direct aggregation of area objects in raster maps: neural networks, cellular automata, and median filters. All the methods were programmed and applied to source data obtained from SPOT images. Neural networks possess several important qualities which often make them advantageous such as: independence of any implicit properties of data, their nature and magnitude, automatic learning of patterns, significant tolerance for incomplete and erroneous data, gradual degradation of performance in case of insufficient data and the ability to compute partial results. Cellular automata are discrete dynamical systems whose behavior is completely specified in terms of a local relation. The processing elements, each of which can be in one of a number of states, are organized in a uniform grid. At discrete time step each cell computes its new state from that of its close neighbors according to some rule. Thus, the system's laws are local and uniform. The median filter is a simple and often used algorithm for raster image processing. It is most often used for cleaning photographs, but also has the capability for aggregating area objects. The experiments conducted and the presented results show that all these approaches are useful, but accomplish slightly different goals.

1. INTRODUCTION

Of the many existing methods for area aggregation a majority concern maps in vector format. In order to process raster data one has to convert them to vector, which is a laborious process introducing imprecision. The other choice is to use one of the aggregation methods native to raster format, some of which are related to image processing techniques. The authors investigated a number of approaches to direct aggregation of urban area objects in raster maps. This includes: neural networks, cellular automata, and image processing algorithms.

Artificial neural networks are receiving increasing attention in cartography and GIS. They possess several important qualities which often make them advantageous such as: independence of any implicit properties of data, their nature and magnitude, automatic learning of patterns, significant tolerance for incomplete and erroneous data, gradual degradation of performance in case of insufficient data and the ability to compute partial results. The application of ANNs to generalization and, specifically, area aggregation is not very popular, but previous results obtained by the authors [1] among others, indicate this is a promising direction for their use.

On the other hand, the application of cellular automata to generalization is relatively new [2], [3]. Somewhat similar to neural networks, cellular automata are potentially large structures of simple computing elements whose behavior is completely specified in terms of local relations. Each cell of such an automaton can be in any of a number of states, and at each time step it makes a transition to another state, which is determined by the states of the cell and the cell's neighbors, and a local transition rule. This rule is usually uniform for the whole automaton and simple. It could also be more complex, depending on the source data and the goals of generalization. This brings cellular automata close to expert systems. In this paper only simple cellular automata were considered.

In this project a number of source raster images obtained from Spot satellite images and classified using the classical manual approach, have been subsequently processed for aggregation with both neural networks and cellular automata.

In order to compare the results obtained, as well as to evaluate the results in absolute terms, several models of such evaluation have been considered.

Additionally, the source data have been processed by a median filter, and the results added for reference and discussed. While neural networks and cellular automata are systems containing many computing elements operating in parallel on small localities, image processing algorithms such as median filter make image transformations which are also based on local properties. The goal of this comparison was to determine which aggregation processes can be properly accomplished by such a filter.

2. MAP GENERALIZATION CASE STUDY - AREA AGGREGATION IN VECTOR AND RASTER MAPS

Map generalization is still a hard problem in cartography. The traditional, manual approach requires skill and experience, and the computer tools for digital map generalization still require manual intervention while using subjective and imprecise evaluation criteria. Many approaches have been developed and studied: mathematical models, computer processing algorithms, artificial intelligence based methods, and others [4].

At the same time there are fast growing repositories of basic maps and even faster growing demand for thematic maps in GIS systems, and changing requirements from the users. The existing computer software packages to assist in map generalization give cartographers the means to speedup and automate this process. One notable such package is the Intergraph's DynaGEN, incorporating the idea of amplified intelligence [5]. It contains a collection of generalization operators, according to the generalization model of McMaster and Shea [6], each with a number of options and parameters. These operators constitute smaller, more specialized and easier to apply generalization processes. Examples of such operators are: elimination of specific map elements, which are irrelevant at the target map scale, and area aggregation (amalgamation) merging adjoining, or very close areas of the same class, into one larger area.

These techniques are particularly relevant with respect to vector maps with their many attributes for map elements. Different approaches are useful for maps in raster format. Techniques based on cartographic knowledge and artificial intelligence are of limited use here because of a much smaller set of attributes available in raster maps. Most techniques developed for raster map generalization are based on image processing algorithms [7-9].

3. ARTIFICIAL NEURAL NETWORKS IN CARTOGRAPHY

The history of artificial neural networks and the ideas of neurocomputers started in 1940-ies with the investigation of information processing in the nervous systems of humans and animals, especially in the brain. The efforts to mathematically describe the principles of the operation of a single nerve cell, and their groups, were the basis on which the theory of artificial neural networks was developed [10].

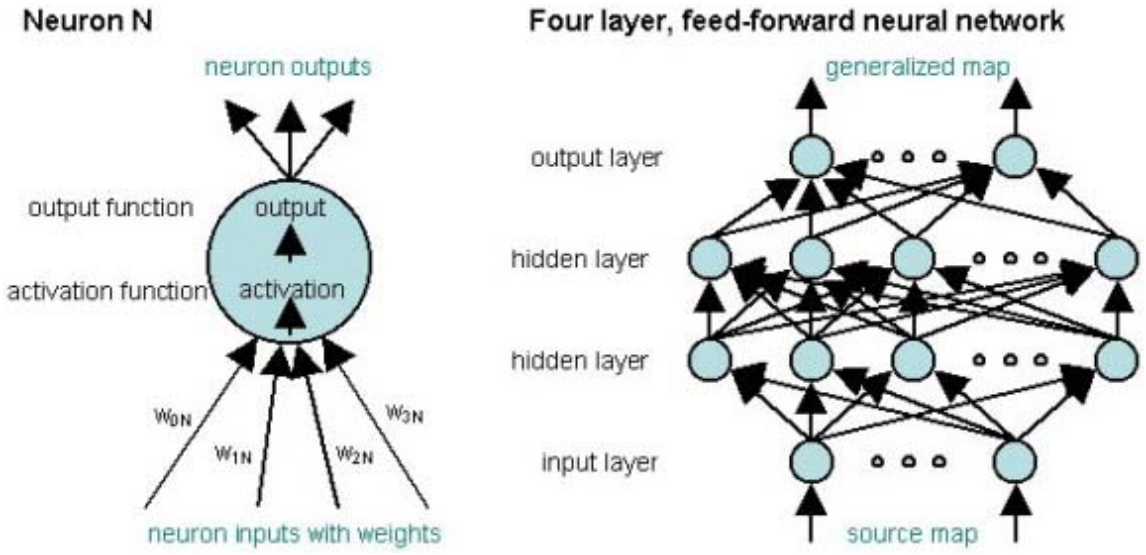


Figure 1. Neuron model and a feed-forward network of neurons

ANNs consist of simple processing elements called neurons, connected into networks by links passing signals from one neuron to another. Neurons receive signals from a number of other neurons and combine them according to some simple formula, called the activation function, which may be a weighted sum of the input signals. Also associated with each neuron is an output function that computes the neuron output signal based on the computed value of the activation

function (Figure 1). The output function is often a nonlinear function, a sigmoid function, or one of many other possibilities. The output signals computed by the neurons are propagated through the network in a one-way fashion, the so-called feed-forward networks, or can make feedback loops, in Hopfield networks.

There are many proposed models for ANNs and there are strong mathematical foundations supporting their operation and properties. Also associated with the specific network models are learning algorithms which make possible to adjust the network parameters, the connection weights and others, based on signals generated for test input data. This way, ANNs can learn some processing scheme based only on test data presented to it during network training. Training can be supervised, in which test data have input and output parts, and the network is expected to learn the association between those, to be able to compute the output part for any input set fed to it during normal operation. On the other hand, unsupervised training presents single data sets to the network, expecting it to learn the patterns in the training data, so the network would be able to recognize and accept or reject data during normal operation.

In an earlier work [1] we have constructed a neural network to investigate the possibility of applying this approach to the amalgamation of nearby buildings, typical in the process of map generalization when converting to a lower scale. Area feature amalgamation needs to take into account the relations of nearby objects, so two-dimensional areas of some size have to be considered in making the aggregation decisions. Therefore, the set of inputs to the neural network was determined to be a two-dimensional array of neurons processing the corresponding elements (pixels) of a map. The goal was to accomplish a complete amalgamation, without any need to select the map fragments or parameter values. The network training was performed by presenting the network with original raster maps of different sizes together with their generalized versions. The set of such map pairs contained many various examples of local generalization.

4. CELLULAR AUTOMATA

The essence of cellular automata, constitute parallel calculations - the result of application of the local rule of cellular automata is characterization of the global structure of result image. The initial cellar configuration, which is a kind of cellar map containing the initial state of each of the cellars, evolves in next iterations on the basis of transformation rule. The significant influence on the results of the process has the number of neighbors used in the process of calculation of the state of the cell - so called definition of the surrounding (Picture 2) and the number of calculation iterations. The central cell does not belong to its own surrounding. The greater is the number of the neighbors used (and greater number of iterations) the clearer are the effects of evolution of automata. Updated values of singular cells become then the material for the changes in the next iteration.

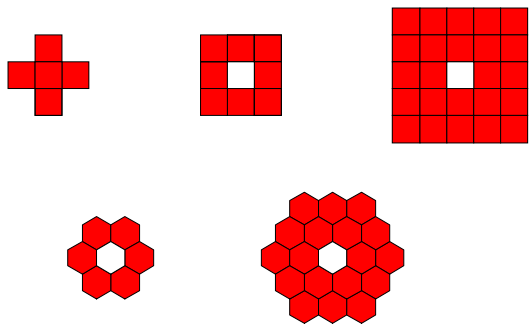


Figure 2. Cellular automata: von Neumann, Moore, expanded Moore, hexagonal, and expanded hexagonal surroundings defined on a two-dimensional cell network.

The cellular automata are applied in mathematics, chemistry, physics, social sciences and geography. Wilkinson [3] used the cellular automata, defined on orthogonal grid with the von Neumann and Moore surrounding, for the generalization of classified satellite image of the Lisbon Bay. The results achieved in this research were very interesting despite the fact that only the simplest function of the automata transformation was used. Olszewski [2] applied hexagonal cellular automata of complex rule for generalization of the map of land cover using the classification of CORINE Land Cover. The achieved results indicate that cellular automata can generalize very complex, global spatial formulas with the use of simple rules of change of local reach. This method enables the aggregation of multi-state spatial data on the basis of deterministic and stochastic rules of changes

According to Wolfram [11] cellular automata are able to perform the parallel calculations of any complexity and each process (both natural and man-made) might be modeled with the use of cellular automata of a given - simple or complex rule.

Definition of the cellular automata is given by:

- a network of cells $\{i\}$ of a D-dimension space,
- a set S_i of possible states of single cells,
- a rule defining the state of a cell at time $(t+1)$ which depends on its state, and the state of the cells that surround it, at time t.

5. MEDIAN FILTRATION

The median filter is a very simple and popular nonlinear image processing filter belonging to the class of statistical filters. It determines the value of each image element based on the values of the elements in the immediate vicinity of the element in question, and setting this value to the median of the values of all the elements. The results obtained depend on the radius taken to define the "vicinity". In practice, for digital images most often square areas of sizes 3x3, 5x5, 7x7, and so on, are taken, with the processed element in the center of the square. Median filters are often used to eliminate "noise" since it ignores the absolute values of the elements noticeably different from the elements in their environment, and sets the new value for such elements according to the "majority vote" of their neighbors. When image has a lot of noise of some specific size, it can be eliminated by applying the median filter with the square size set larger than the noise.

With respect to building aggregation in raster maps the median filter can be taken to be the simplest aggregating algorithm, since it eliminates area features not surrounded by a sufficient number of other such features, and fills-in the gaps between other such area features, when they are located sufficiently close to one another. The motivation for making a comparison experiment between the above approaches, significantly more involved both in terms of the underlying theory and in the amount of computation, was to find out whether it is possible to arrive at similar results by a much simpler algorithm, and what would be the relative correspondence between: the degree of aggregation to which a neural network has been trained, the size of the aggregating cellular automaton, and the square size of the median filter.

6. THE EXPERIMENTS

The starting point for aggregation method comparison was a SPOT satellite image of the suburbs of the city of Warsaw with mostly single-family buildings. All the individual buildings were first classified and set in red. The buildings extracted from a section of that image were used as input data for the experiments:

- median filtration with mask sizes of: 3x3 up to 25x25
- cellular automata of Moore type with 8 and 24 neighbors
- feed-forward neural networks.

Thus prepared input data have also been used, after digitalization and vectorization, with vector aggregation algorithms of the DynaGEN system to create a reference for the result evaluation.

6.1 Median Filtration

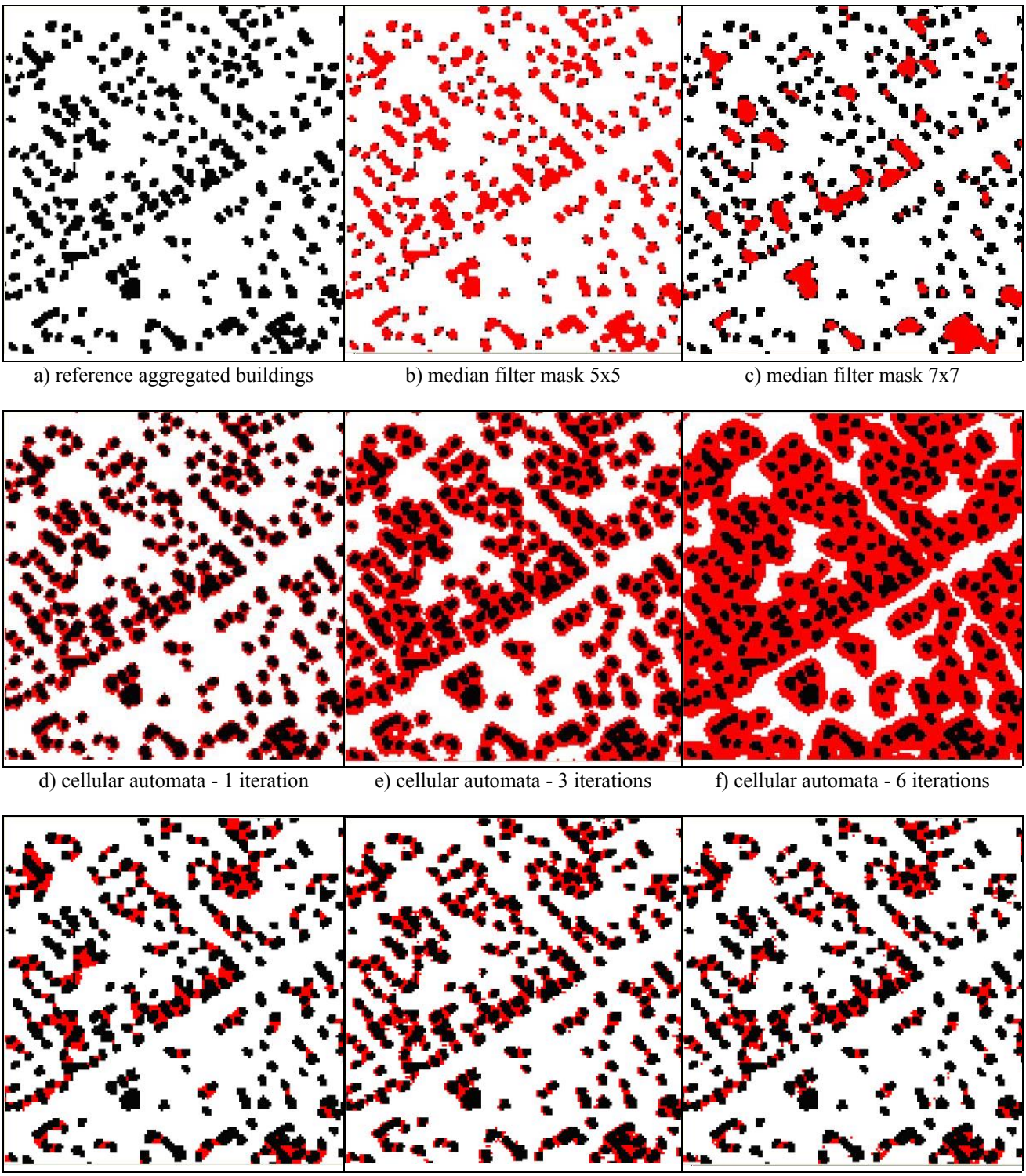
Processing has been performed using the image processing program xv. The results of median filtration are shown in (Figures 3a-c). As can be see in these images, the smallest mask size of 3x3 gives only a low level of aggregation (Figure 3b). Increasing the mask size (mask size 7x7, Figure 3c) gives not only a higher level of aggregation in densely built-up areas, but also increasing levels of elimination in more sparse areas. While elimination is also an element of generalization, in the aggregation process it is undesirable.

6.2 Cellular Automata

Two kinds of the surrounding of the cell determining the operation of automata were used in the research:

- Moore surrounding using 8 neighbors of the cell,
- expanded Moore surrounding using 24 neighbors of the cell.

The greater the number of neighbors taken into account, the clearer are the effects of automata aggregation. For both types of cellular automata the aggregation functions were applied which resulted in aggregation of the neighboring pixels in subsequent iterations. The operation of automata (with a settled type of neighborhood) are defined by two parameters: minimal number of the cells of certain type (buildings) necessary for the change of state of the central cells, and the number of iterations.



a) reference aggregated buildings b) median filter mask 5x5 c) median filter mask 7x7

d) cellular automata - 1 iteration e) cellular automata - 3 iterations f) cellular automata - 6 iterations

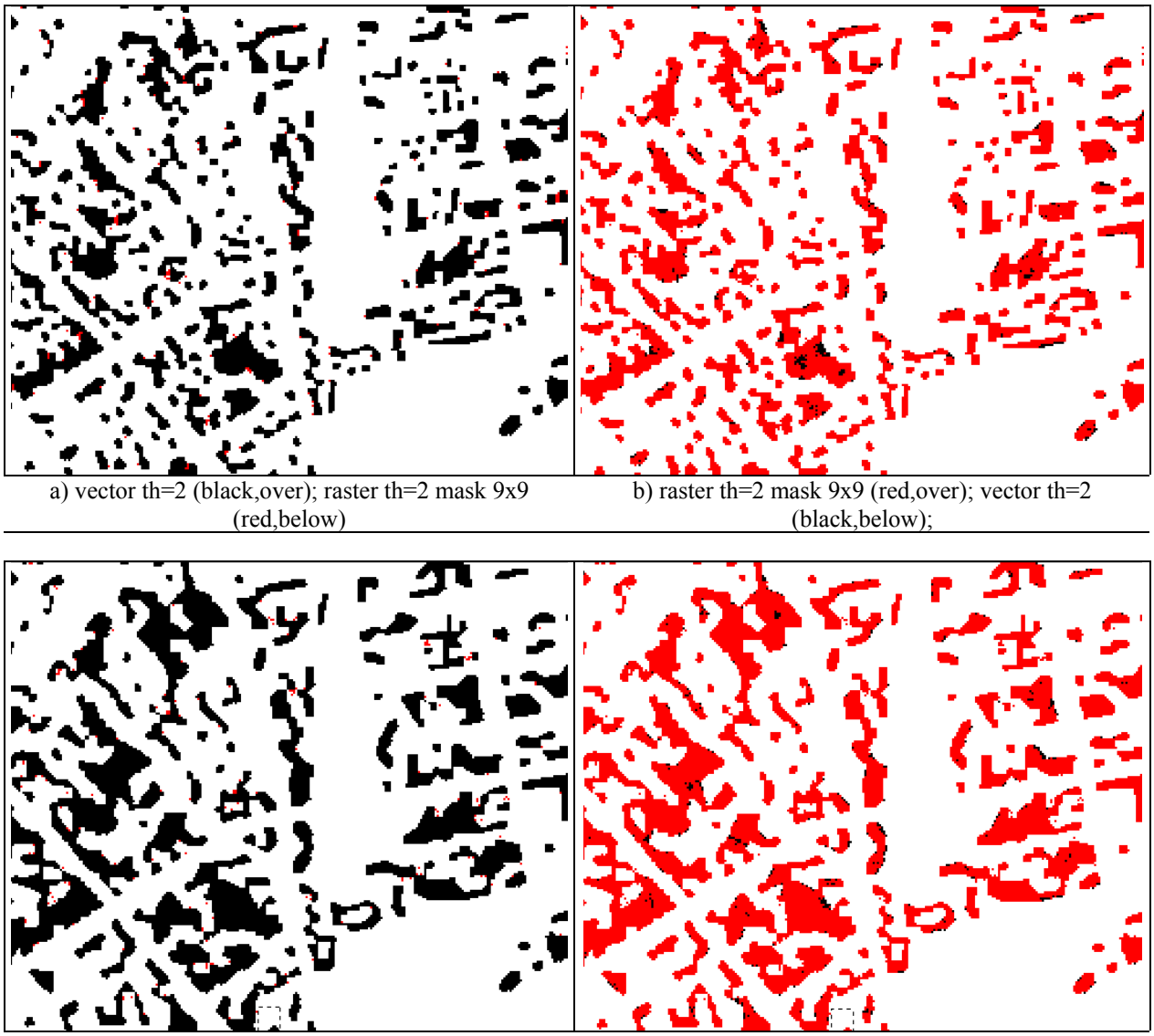
g) vector th=2 h) ANN th= 2, mask=5x5 i) ANN th=2, mask 9x9

Figure 3. Raster map aggregation, black color – original buildings from the satellite image, red color – aggregated buildings; b and c – aggregated buildings (red) are on top of the originals (black), d, e, f, g, h, and i – aggregated buildings (red) are below the originals (black).

Because of the relatively simple structure of source data (two elementary states: buildings and lack of buildings) the number of iterations used in the experiments was small, not more than 10 (Figures 3d-f). The increase of the number of iterations causes reinforcement of the effect of aggregation leading to the total deformation of data. The most essential parameter of this method is the minimal number of cells of "buildings" type appearing in the surrounding of the central cell, necessary for the aggregation of data (e.g. 14 out of 24 for the expanded Moore surrounding). A choice of either too small or too great number of cells causes the automaton to deform the data unacceptably. The best results have been achieved for the rule 8/24 and 1 iteration (minimum 8 cells out of 24 neighbors of the central cell necessary in the given iteration for the aggregation of data), and for the rule 3/8 and 3 iterations.

6.3 Neural networks

Three-layer feed-forward neural networks used in the experiment were constructed and trained as described in [1] using the SNNS (Stuttgart Neural Network Simulator [12]). The input layer was the processing mask with sizes ranging in different experiments from 5x5 to 19x19, and the output layer was always the single middle-point neuron. The networks were trained with reference data aggregated using distance thresholds corresponding to two and four pixels in raster maps (Figure 4). Also, several different threshold values for neuron analog output discrimination we considered. As demonstrated in the earlier paper cited above, there is a correlation between the distance threshold tolerance applied, and the neural network mask size. As can be seen in Figure 4, the best aggregation results were obtained for the two-pixel distance threshold and 9x9 mask size, and for the four-pixel distance threshold and the 11x11 mask size.



a) vector th=2 (black,over); raster th=2 mask 9x9 (red,below)

b) raster th=2 mask 9x9 (red,over); vector th=2 (black,below);

c) vector th=4 (black,over); raster th=4 mask 11x11 (red,below)

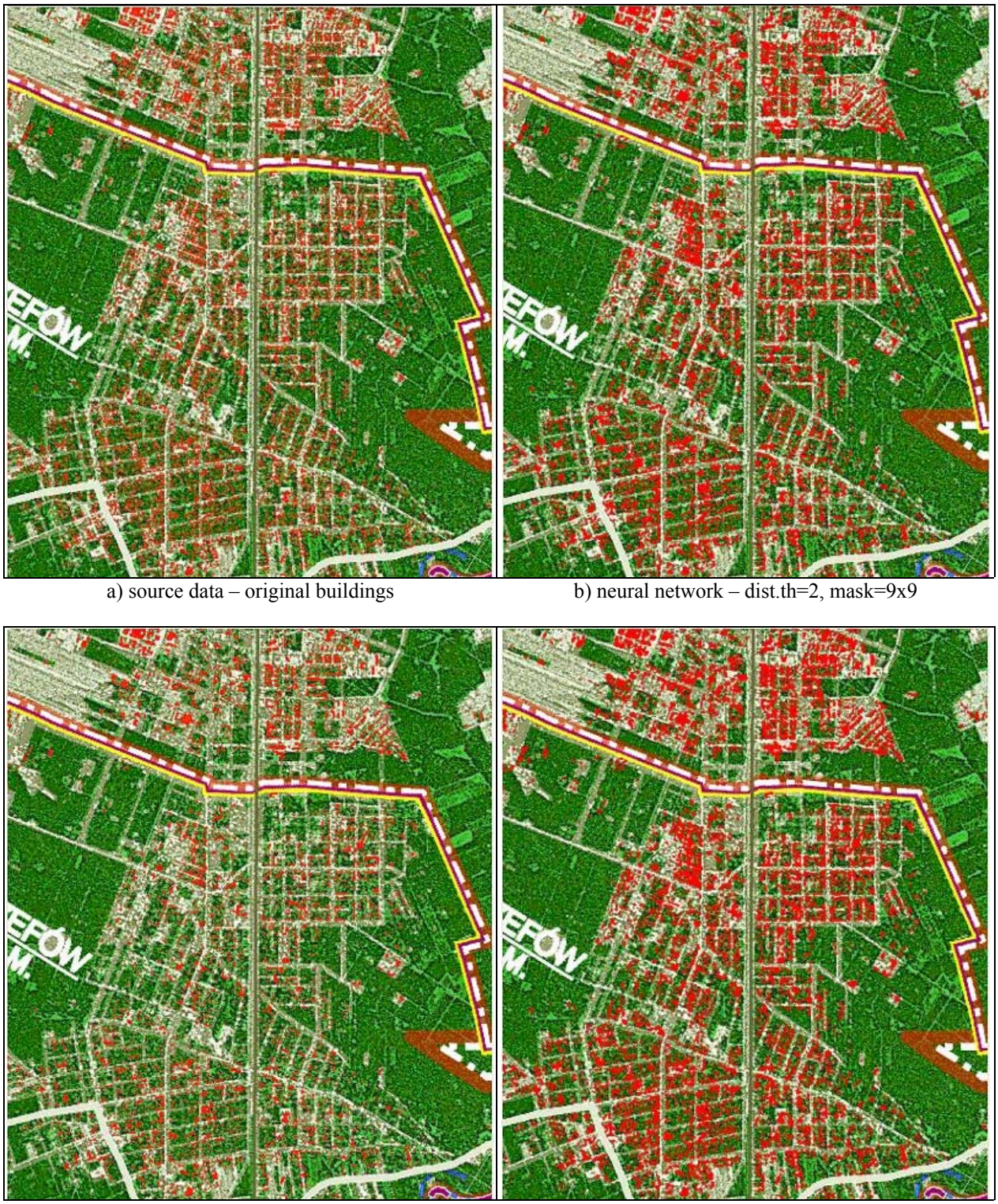
d) raster th=4 mask 11x11 (red,over); vector th=4 (black,below)

Figure 4. Difference between vector mode aggregation (DynaGen) and the ANNs: black color – vector mode results, red color – ANN results.

These networks compute their results by making a single pass over all the pixels in an image and computing the output values taking into account the pixels' immediate neighborhood, according to the specific mask size of a network. The results, as expected, show a good aggregation ability corresponding to the level the specific network was trained to, at the same time producing some amount of "noise", i.e. spurious "in" pixels in random pattern.

7. SUMMARY

The main observation from all the experiments performed is that all techniques achieve some degree of area aggregation, and so can all potentially be useful for specific purposes. It is also true, that all these techniques have different features (Figure 5).



a) source data – original buildings

b) neural network – dist.th=2, mask=9x9

c) median filter – mask=5x5

d) cellular automaton – 1 iteration, 24 neighbors

Figure 5. Aggregation results: a) source data, b) neural network processed, c) median filter processed, d) cellular automaton processed.

Median filtration aggregates and eliminates at the same time, so can be most useful for areas of compact build-up. A disadvantage of the median filter is its lack of a “threshold” parameter, which would allow selecting the level of build-

up, different than 50% as in median, above each aggregation takes place. A useful modification would be to introduce such a parameter leading to a statistical "voting" filter with modifiable threshold level. Such a filter would be equivalent to a single-iteration cellular automaton with the state transition rule such as used in these experiments.

With cellular automata the degree of aggregation increases with the number of iterations. The aggregated areas have well-defined, sharp outlines. However, the apparent side effect is an exaggeration of the aggregation effect. It is present with both surrounding types considered, and increases with the number of iterations performed. This suggests, that a simple generic aggregation effect is achieved after only a few iterations, sometimes only one, which reduces the cellular automaton to a functional filter.

The neural networks mostly compute what they have been trained to and the results obtained exhibit a high similarity to the reference image. There is no undesired elimination or exaggeration. However, the outlines are not well defined and the image is speckled with noise effects. The images thus obtained are suitable for on-line viewing, especially when the result is viewed in smaller scale, such as after map generalization. But the resulting images are not acceptable for publication.

The visual selection of best results shows a correlation between the processing mask size and the distance threshold parameter used in creating the training data. In other words, there is an optimal network size for the desired aggregation level, and using too small or too large input layer size gives sub optimal results. For the network output threshold value, in most cases the visually best result was obtained with the value of 0.7

It should be noted, that some errors incurred in the neural network approach result from the raster-vector and vector-raster conversions applied in creating the training data for the network and the reference image for result comparison.

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Biography

Associate Professor Metternicht has 14 years of experience in the production and management of spatial information for land degradation and agriculture-related applications. Her MSc in Geoinformatics (The Netherlands) and PhD in applications of remote sensing and GISystems to the mapping of land cover and land degradation, with emphasis on salinisation and soil erosion processes (University of Gent, Belgium) have furnished her with the skills and expertise that she has continued developing since her appointment as Associate Professor in Cartography and Remote Sensing at Curtin University. In addition to funding received from the Australian Research Council, A/Prof Metternicht has been recipient of awards and research grants by the Australian Academy of Science (1999), the Chinese Academy of Sciences (1999), the Science and Technology Agency of Japan (2001), the Rural Industries Research and Development Corporation (1997), the Netherlands Fellowship Program (1991-96), the European Association of Remote Sensing Laboratories (1993), the European Community (1995) and the American State Organisation (1989). In 1998 A/Prof Metternicht was awarded the Dean's Medallion for distinguished research at Curtin University.

Dr Metternicht is Principal Investigator on the Envisat Program of the European Space Agency, active member of the ICA commission on Mapping from satellite imagery, and editor of the International Cartographic Association Newsletter. She has also served as on the Western Australia Land Information System (WALIS) Advisory Committee, being member of the Australian Mapping Sciences Institute, the IEEE Geoscience and Remote Sensing Society, the Remote Sensing and Photogrammetry Association of Australia and the Remote Sensing Society (UK). Her research interests include agricultural remote sensing, spatial analysis and modelling for land use/cover and land degradation mapping and monitoring and change detection, with emphasis on the use of fuzzy logic, and advanced remote sensing classifiers.