

ROAD NETWORK DETECTION BY GROWING NEURON GAS

Arpad Barsi

Department of Photogrammetry and Geoinformatics Budapest University of Technology and
Economics Budapest, Hungary- barsi@eik.bme.hu

Commission III Working Group III/5

KEY WORDS: neural network, image analysis, self-organization

ABSTRACT:

The growing neuron gas (GNG) algorithm is an excellent self-organization tool, which efficiently combines the graph and neural network techniques. The gas formation starts with two connected neurons and during the training both the neurons (nodes) and their connections are iteratively added. The most relevant advantage of this technology is that it forms the final graph structure considering the input data points regarding the control parameters, but without the strict requirement of any prior hypothesis of the graph. Although the graph nodes can represent data points of any arbitrary number of dimensions, in this specific application they are taken as two-dimensional ones. The data points derived by simple image processing operations, like thresholding the intensity values and by other similar low-level segmentation techniques. The algorithm is fast and can handle even larger set of data points. The paper gives an overview about the main self-organizing and unsupervised neural network techniques. It's followed by the description of the growing neuron gas algorithm, and then its application in road network detection is presented. The illustration of the proposed method with aerial and satellite imagery also contains accuracy and performance analysis, of course in comparison with other detection methodologies.

1. INTRODUCTION

Neural networks are currently accepted analyzing tools in data processing, also in digital image analysis. The unsupervised networks have some basic automatism which prognoses rapid spreading. The self-organization is a special type in the unsupervised network group.

The paper will give a short overview about the three main types of self-organizing neural techniques, a presentation of their simple algorithmic backgrounds, then the description of the test areas and the performed experiments are followed, and it has been finished with the results and conclusion. The main point of the paper is the most flexible self-organizing methodology.

Because both aerial and satellite imagery is used in the tests, the presented techniques can be taken as generally suitable ones for remote sensing image analysis.

2. BASICS OF SELF-ORGANIZING NEURAL NETWORKS

2.1. Self-organizing maps (SOM)

The self-organizing (feature) map technique was developed by T. Kohonen as a special case of unsupervised learning technique [Kohonen2001]. The network has a neuron lattice; in most cases it is a regular rectangular or hexagonal grid. The learning rule is very simple: it is the winner-takes-all rule. The neurons of the network have weights, stored in a vector \mathbf{m} . The input data points – also organized into a vector, called \mathbf{x} – are shown to the network, where a winner is firstly selected:

$$c = \arg \min_i \left(\left\| \mathbf{x} - \mathbf{m}_i \right\| \right) \quad (1)$$

Then the weights of the winner and its neighboring neurons have been increased from epoch $t+1$ based on epoch t :

$$\mathbf{m}_i(t+1) = \mathbf{m}_i(t) + h_{ci}(t) \cdot [\mathbf{x} - \mathbf{m}_i(t)] \quad (2)$$

where considering the neighborhood $N_c(t)$

$$h_{ci}(t) = \begin{cases} \alpha(t) & i \in N_c(t) \\ 0 & \text{otherwise} \end{cases} \quad (3)$$

Usually $\alpha(t)$ is a simple, e.g. linear decreasing function.

The training has two phases: a most raw “ordering” and fine “tuning”. The algorithm is the same for both phases, only the parameter sets are differing.

The application of SOM is widely spread from analyzing speech to images [Kohonen2001]. Data mining takes SOM as a basic technique, too [Kohonen2001].

2.2. Self-organizing neuron graph (SONG)

The self-organizing neuron graph technique is a generalization of SOM's by introducing graphs for describing the neuron structure. The basic learning rule has been kept, only the graph feature must be considered, therefore the processing is started by a generalized neighborhood analysis, which is used in propagating the weight update for the winner's neighborhood. The neighborhood is taken by generalized adjacency (\mathbf{A}) of graphs [Barsi2003a]:

$$h_{ci}(t) = \begin{cases} \alpha(t) & \mathbf{A}_{ci} < a(t) \\ 0 & \text{otherwise} \end{cases} \quad (4)$$

The working style of SONG technique requires a hypothetical neural network structure, which can be from e.g. existing maps or template description for any image object.

The author of the current paper has published different studies on the self-organizing neuron graph technique [Barsi2003a, Barsi2003b].

2.3. Growing neuron gas (GNG)

The third neural self-organizing method has been developed by B. Fritzke in 1997 [Fritzke1998]. The basic idea is to create a neural network by continuously maintained network structure.

The randomly selected data point is compared to all gas neurons – their distances are calculated by e.g. Euclidean norm –, a winner and a second winner is selected, then their connection is checked. If they didn't have any, a new one is created. Then the quadratic distance of the data point and the winners are derived together with their weight update, which is a function of the computed distance. The ages of all connections are increased, followed by the remove of all overaged edges. If a neuron would lose all connection, it is also deleted. The overaging is controlled by a given age limit. The next phase is the update of the worst network segment: the neuron of the highest accumulated error is selected with its neighbor of highest error, and a new unit is established, of course with connections with the neighborhood [Fritzke1998]. Thereafter an error vector is calculated.

The network is growing in every controlled step, where the network error the highest. The above described operations are repeated till a stop condition is fulfilled (e.g. iteration step limit).

The algorithm starts with two connected neurons, and neurons and their connections are added progressively. The technique acts practically without any prior hypothesis or knowledge on the analyzed phenomena. The algorithm can manage also disjunct structures.

3. IMAGE ANALYSES BY SELF-ORGANIZATION TECHNIQUES

3.1. Image data sets

The above mentioned computational models have been tested on several data sets. Two of them were used for introducing growing neural networks; now only these latter two images are showed. Both data sets have high geometric resolution and are covering urban areas, where roads are significant man-made objects. The extraction of roads can be done either by their axe line (skeleton) or even by their bounding edges. The first data set has practically no elevation influence, because it's of a flat terrain, while the second one covers a hilly region.

The first one is a color aerial image taken by a Wild frame camera (Fig. 1). The image has a high geometric resolution of about 0.2 m per pixel, where the radiometric resolution takes 24 bits. The image was taken on analogue film, which was scanned to be able to be processed by digital photogrammetric techniques.

The second data set has been captures directly digitally: it is a cut-off from a Quickbird scene covering the Gödöllő hills (eastern of Budapest). The image (see a detail in Fig. 2) has the standard geometric resolution of 0.6 m (panchromatic band), and 2.4 m (multispectral band). The purchased bundle product has the three visible channels (RGB), the near infrared channel and the panchromatic one. Prior to the processing a resolution merge was performed by the method of the principal

components. The resulting radiometric resolution is 24 bits. The image has been captured on 13/10/2005.



Figure 1. Digital aerial image example



Figure 2. Quickbird image example (Band 1)

3.2. Executing the analyses

The aerial image (Fig. 1) was preprocessed by band-wise intensity threshold and a growing neural gas of 200 neurons analyzed it in 80 000 epochs with a neuron insertion rate was 100 (every 100 epochs had add a new neuron). The highest connection age factor was 50. The maximal connection age was 90, the error decrease was 0.5, and the weight update coefficient took 0.05. The results chapter contains the fitted neural gas to the image (Fig. 3).

The pre-hypothesis of processing of satellite images was proven by a Quickbird scenario (Fig. 2). The image has only a single spectral band (for this example the first, blue band was chosen, because it had the best quality. Another image data sources are – theoretically – usable, but their prior test is really suggested. Because of the initial random neuron positions, the whole iterative procedure can be different, when several repetitions are performing. Of course, if a stable state is the goal, many restarts are needed, followed by an evaluation, as the model errors are checked and the current version is qualified. Having many results, the best can easily be found automatically [Barsi2008].

The implementation was written in Mathworks Matlab Version 7.5 under the operating system Windows XP.

4. RESULTS

The growing neural gas has been evaluated on aerial image and a satellite image. The former one could find most of the streets, but two false alarms are also produced: there are two unreal blobs (disjunct graphs), which aren't part of the street network. Other image parts (like the main roads) could be found in excellent quality. This result has proven the ability of this cutting-edge technology not only on artificial image patterns, but also real photographed images.

As one can notice, the detected road network needs some manual correction, but the general quality is good. The founding is strongly correlated with the existing data points; that's why several road segments are mapped so dense. Its counterpart can also be seen: in the upper right corner of the image the arc hasn't been detected exactly, because there was a lack of adequate data (the drawback effect of using simple image processing as prior step!).



Figure 3. Growing Neural Gas has produced this road network based on simple image operations

The last test contained the digital satellite imagery of Quickbird. This example was the worst of all tested one. The reason could be the low contrast, so the exact data pixels weren't found by the previously executed processing. The road network is only partly reconstructed, although the two connecting roads are motorway and a rural main road.

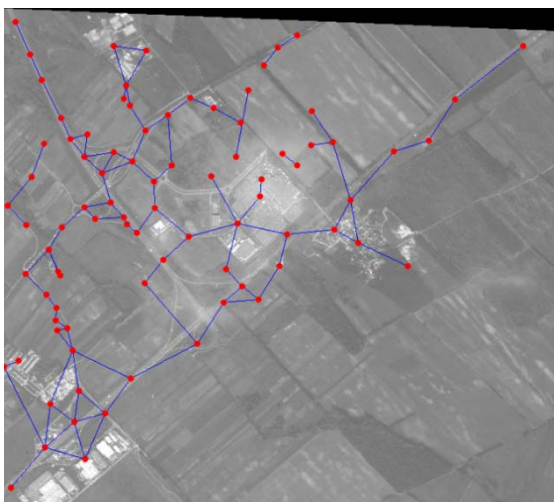


Figure 4. High-resolution satellite image analysis by growing neural gas. Gödöllő Hills, Hungary

One possible reason can also be the relatively high number of data points: the image cutoff was 5884×5241 pixels, where the data set was established by simple thresholding. (This operation was kept during the whole testing, because it is very simple, and the most relevant advantages of the connecting methods can be seen so.)

5. CONCLUSION

The self-organizing techniques can also be implemented by neural networks. The neural self-organizing methods have three main representatives:

- SOM, where a general winner-takes-all rule controls the neurons' weight (in our geometric case, the position)
- SONG, where the SOM technique has been generalized by the combination of SOM computational model with undirected cycle free graphs and the topology is fixed
- GNG, where the network topology is being created during the training.

The SOM methodology has long "history" in data analysis and computer science, also in data mining, which can inspire the image analysis efforts. The parameterization of SOM networks can be quickly set, the computation is really fast. These advantages forecast further photogrammetric and remote sensing applications.

SONG is a special SOM implementation, where a prior knowledge or at least hypothesis is needed. This can be taken from a manual evaluation of the first image in a series, and then the next images can be analyzed and evaluated automatically. Initial hypothesis can be taken from practical point of view: e.g. searching for image object having fixed topology can successfully supported by the SONG algorithm. Because it is the generalization of the SOM technique, its software representation can manage also the SOM usage.

GNG has the most freedom in topology, because this self-organizing method varies not only the neuron positions, but also their relations, their connection. This flexibility means that the gas will produce in all cases an output, but it shall be tested and evaluated critically. The last Quickbird application has the message that pure novel neural methods cannot serve with high quality maps. Of course, if enough suitable data points are available (like in Fig. 3), this technique can figure out the possible data structure (in this case the road network) based on few parameters (like number of neurons and epochs, connection age).

Future experiments are planned with the combination of sophisticated image analyzing techniques, like image enhancements and filtering, special edge detection operators, image classifications [Duda2001, Gonzalez2004] and then the grouping can be replaced by the presented self-organization technology.

All of the described neural computational models were applied in two dimensions, but the distance calculation phase can be much general: it can be interpreted and therefore used in n-dimensional space, e.g. in considering multispectral or even hyperspectral image information.

ACKNOWLEDGEMENT

The author wants to express his special thank to the Project GVOP financed by the Hungarian government under the identifier GVOP-3.1.1.-2004-05-0406/3.0.

REFERENCES

- Barsi, A., 2003a. Neural Self-Organization Using Graphs, *Machine Learning and Data Mining in Pattern Recognition, Lecture Notes in Computer Science, Vol. 2734, Springer Verlag, Heidelberg*, pp. 343-352
- Barsi, A., 2003b. Graph Based Neural Self-Organization in Analyzing Remotely Sensed Images, *Proceedings of the IEEE International Geoscience and Remote Sensing Symposium (IGARSS) 2003, Toulouse, Vol. VI*, pp. 3937-3939
- Barsi, A., 2008. 3D Road Database, *GVOP Research Report*, Budapest
- Demuth, H., Beale, M., 1998. Neural Network Toolbox, *Matlab User's Guide*, The MathWorks, Natick
- Doucette, P., Agouris, P., Musavi, M., Stefanidis, A., 2000. Road centerline vectorization by self-organized mapping, *International Archives of Photogrammetry and Remote Sensing*, 33(Part 3A):240-247
- Duda, R.O., Hart, P.E., Stork, D.G., 2001. Pattern Classification, *Wiley Interscience*, New York
- Fayyad, U.M., Piatetsky-Shapiro, G., Smyth, P., Uthurusamy, R., (Eds) 1996. Advances in Knowledge Discovery and Data Mining, *AAAI Press/MIT Press*, Menlo Park
- Fritzke, B., 1998. Vektorbasierte Neuronale Netze, *Habilitationsschrift, Shaker Verlag, Dresden*
- Gonzalez, R.C., Woods, R.E., Eddins, S.L., 2004. Digital Image Processing Using MATLAB, *Pearson Prentice Hall*, Upper Saddle River
- Kohonen, T., 2001. Self-Organizing Maps, *Springer Verlag, Berlin*
- Ladai, A.D., Barsi, A., 2007. Analyzing automatic satellite image classification in desert area in Sudan, *Periodica Polytechnica*, Budapest, in press