Risk Assessment in Urban Planning for Disaster Management Using Kohonen Self Organizing Feature Map Neural Network

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ABSTRACT

Natural disasters have crucial effects on safety and economy of urban areas. Scientists, managers and decision makers face with different problems for optimum management after the disasters. It is clear that traditional statistical analyses of analog geospatial data cannot efficiently help in control a huge natural disaster. To overcome these problems, geospatial information systems (GIS) can be widely used. Providing a risk appraisal map for different urban areas can effectively help managers for better rescue planning after a disaster occurrence.

This paper presents a model using the Kohonen self organizing feature map (SOFM) neural networks for automating the most crucial step of mass appraisal which is known as neighborhood development. The model uses benefits criteria such as the distance from dangerous utilities as well as cost criteria such as distance from hospitals to determine the degree of survival risk. SOFM neural network is learned using a large number of sample data to provide acceptable results. The model is then used to generate the survival risk map in parts of Tehran, capital of Iran.

1. INTRODUCTION

Disaster management is an important problem in the urban management. Risks of survival after occurrence of natural disasters have more negative social impacts than the damages in the affected zones. Because disasters can affect geostrategic stability and international safety, developed countries invest a huge amount of funds to manage these risks (Rodríguez et al. 2009).

Factors such as climate change and the growing population density of many cities and countries are putting more and more people throughout the world at risk of suffering from natural disasters (Milly et al. 2002). Recent tragic events such as the April 2009 L'Aquila earthquake in Italy or Hurricane Katrina in 2005 remind us that, even inside developed countries, there exist many population groups which are vulnerable to the impact of adverse natural phenomena (Morrow. 1999).

Natural disasters have consequences not only for the population, which is directly affected but also for all the society. They can also have profound implications for large sectors of the economy and the political system of the affected region, especially in developing countries illustrate that the impact of a disaster in a region, if not managed properly, can produce political and social instability (Olsen et al. 2003).

The investigations on disaster management usually employ the data of before and after the event to determine the amount of destruction. Satellite images, aerial images, altimetry data and digital maps are usually used in the research. These researches have focused on comparing the affected area before and after occurrence of disaster, so they use both pre and post data to detect damaged buildings and determine their disaster extents. The data for pre event occurrence are not always available; therefore using these methods leads to some problems. Hence, it is necessary to investigate some methods that just use the data of after the incident to evaluate the damages (Ahadzadeh et al. 2008).

This paper investigates a solution using the Kohonen self organizing feature map (SOFM) neural networks for automating the most crucial step of mass appraisal which is known as neighborhood development, used to generate a value map for part of Tehran.

GIS and neural networks are two separate, potentially complementary systems that can be used to improve decision-making (Eksteen 2010).

2. BASIC PRINCIPLES

2.1. Artificial Neural Networks

Artificial Neural Networks (ANNs) have been considered as systems or mathematical models that work in such a way that imitates the human brain (Lin and Lee 1996; Thurston 2002).

They work in a way that resembles human intelligence in order to solve problems. ANNs learn by some examples to extract information within a data set. The model of the neural network is like synapses in the human brain which consists of a series of processing units which are collectively connected (Thurston 2002).

ANN is being touted as the future wave in the computing (Anderson and McNeill 1992). ANN is a unique system that is different to other systems. For example, some traditional artificial intelligence (AI) and statistical solutions rely on and require a priori information to be able to solve problems. However, unlike these two approaches, because ANNs work based on self-learning mechanisms, they do not need any a priori assumptions to solve a problem. ANNs will learn any regularities or patterns that may exist in the available data set to form a relationship.

One of the aspects that differentiate a neural network from others is its architecture. This architecture represents the pattern of connection between nodes, its method of determining the connection weights, and the activation function (Haykin 1999). Two ways of determining neural networks architecture are the number of layers (includes single layer, bi-layer, and multi-layer), and the direction of information flow and processing (includes feed-forward and recurrent). One network that provides good performance with regard to input-output function approximation such as forecasting is multi-layer perceptrons (MLPs). This network is a multi-layer feed-forward networks, which is trained with a back-propagation learning algorithm. A typical multi-layer feed-forward network (as seen in Figure 1) has input layers, hidden layers, and output layers (Lin and Lee 1996). The input layers have the main function of receiving inputs and then buffering the input signals. The signals from the input layers are then transmitted to hidden layers, particularly hidden neurons or hidden units. The function of hidden neurons is to intervene between the external input and the network output in some useful manner.

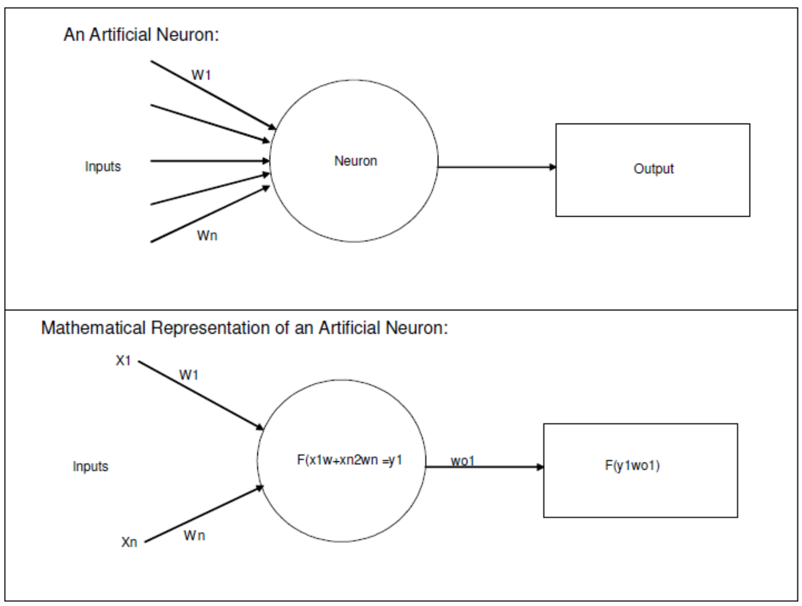

Figure 1. Basics elements of an ANN (Saha 2003)

2.2 Self-Organizing Feature Maps

Self-organizing feature maps (SOFM) learn to classify input vectors according to how they are grouped in the input space. They differ from competitive layers in that neighboring neurons in the self-organizing map which learn to recognize neighboring sections of the input space. Thus, self-organizing maps learn both the distribution (as do competitive layers) and topology of the input vectors they are trained on.

The neurons in the layer of an SOFM are arranged originally in physical positions according to a topology function. Distances between neurons are calculated from their positions with a distance function.

Here a self-organizing feature map network identifies a winning neuron i* using the same procedure as employed by a competitive layer. However, instead of updating only the winning neuron, all neurons within a certain neighborhood Ni* (d) of the winning neuron are updated, using the Kohonen rule. Specifically, all such neurons i Ni*(d) are adjusted as follows:

$${}_iw(q) = w(q-1) + \alpha(p(q) - \ {}_iw(q-1) \qquad (1)$$

Or

$${}_iw(q) = (1-\alpha)\,{}_iW(q-1) + \alpha p(q) \qquad (2)$$

Where α is a learning rate, q is the training index number, and w is the neuron in the neighborhood of the winning neuron (which has the same dimension of p).

Here the neighborhood Ni* (d) contains the indices for all of the neurons that lie within a radius d of the winning neuron i*.

$$N_i(d) = \{j, d_{ij} \leq d\}$$

Thus, when a vector p is presented, the weights of the winning neuron and its close neighbors move toward p. Consequently, after many presentations, neighboring neurons have learned vectors similar to each other.
Another version of SOFM training, called the batch algorithm, presents the whole data set to the network before any weights are updated. The algorithm then determines a winning neuron for each input vector. Each weight vector then moves to the average position of all of the input vectors for which it is a winner, or for which it is in the neighborhood of a winner.
To illustrate the concept of neighborhoods, consider the Figure 2.

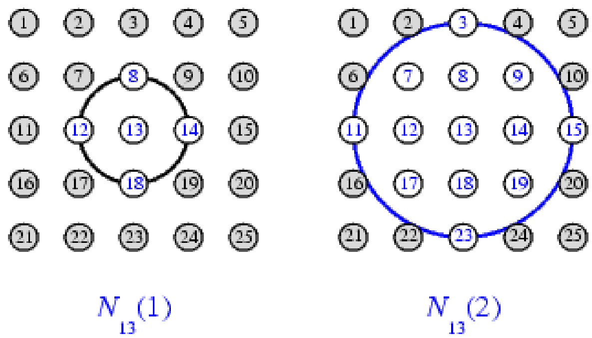

Figure 2. The left diagram shows a two-dimensional neighborhood of radius d = 1 around neuron 13. The right diagram shows a neighborhood of radius d = 2

The architecture for this SOFM is shown in Figure 3.
This architecture is like that of a competitive network, except that no bias is used here. The competitive transfer function produces a^1 for output element a^1 corresponding to i*, the winning neuron. All other output elements in a^1 are 0.
Now, however, as described above, neurons close to the winning neuron are updated along with the winning neuron. it can be selected from various topologies of the neurons. Similarly, it can be selected from various distance expressions to calculate neurons that are close to the winning neuron.

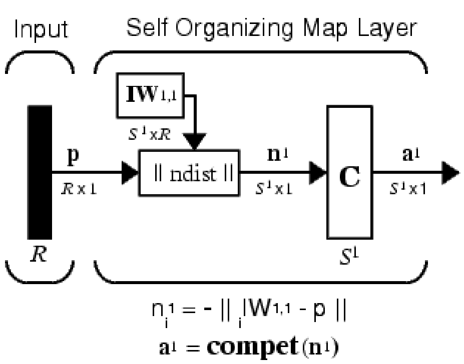

Figure 3. The architecture for SOFM (Eksteen 2010)

4. METHODOLOGY

The lack of basic statistical data and risk values could be overcome through effective utilization of location specifications. KSOMs utilization as is proposed to handle these data about location.

A two dimensional KSOFM with hexagonal cells is proposed in this paper for definition of the desired KSOFM. The number of neurons would be determined by calculation of an overall estimation about the number of clusters in data defined using K-Mean approach, a trade-off between the required resolution, generalization, and existing related segmentations (e.g. Census districts). Then the dimensions of network (rows and columns) would be defined asymmetrically based on the extent of our case study. A number of steps were carried out during the model development process. These are shown schematically in Figure 4.
The proposed spatial factors for this research are: (1) supplied basic services; (2) access to street; (3) street frontage; (4) usable open area, (5) distance to buildings capable for temporary settlement, (6) distance to health services, (7) recreational areas, (8) access to highways, (9) areas away from dangerous utilities such as gas stations, (10) distance from fire stations, (11) open spaces, (12) quality of buildings, (13) neighborhood land-uses and (14) topography. These data were generated through GIS based approaches like point in polygon, polygon in polygon and network analysis.
The output of the feeding data into the designed KSOFM will be a map which represents comparable blocks, considering the mentioned issues about the required contiguity and homogeneity for neighborhoods resulted from segmentation.

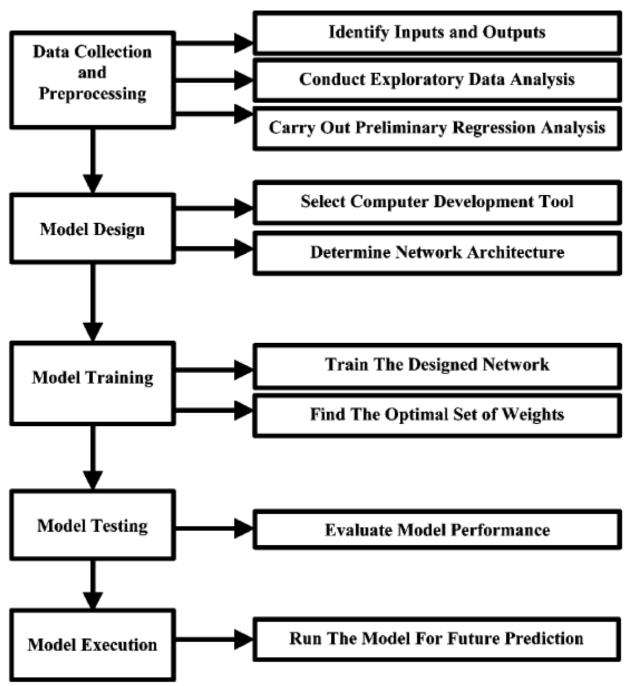

Figure 4. Steps of model development process (Hamed et al. 2004)

5. CASE STUDY

The proposed methodology is applied for Tehran, the capital of Iran. There are mainly aged structures in many parts of Tehran that would increase the risk of distortion by occurring a disaster.
The methodology is applied in parts of Tehran which contains about 6000 blocks spread into about 20 census districts. These data were extracted from 1:2,000 maps, produced by Iranian

National Cartographic Center (NCC). Then required spatial factors were calculated within a GIS environment.

The KSOM network which is used here is constructed in Matlab 7.8. Besides, 40 neurons were proposed for the network considering the result of using K-Mean approach, then an asymmetric 14×5 network constructed for the analysis. This hexagonal network was trained by data extracted from the 5000 block. The training executed in two phases as ordering and tuning phase. The training phase began by 0.8 learning rate within the first 1000 epochs (ordering phase) and continued the remaining epochs with 0.02 learning rate and 1 neighborhood distance for 6500 epochs (tuning phase) which is defined as the sum of row and width of network multiplied by 500 (13*500). The trained network is fed and simulated by the mentioned block and their relevant winner neurons are defined. The map was classified into 10 degree of risks using the learned network as illustrated in Figure 5.

6. CONCLUSION

Disasters have crucial effects on safety and economy of urban areas. Due to the importance of disaster management, the use of new methods for database management and information extraction is unavoidable. This research is conducted to overcome deficiencies caused by a natural disaster in Tehran. A straight toward approach is introduced as development of a value map using ANNs as a partial solution for risk segmentation.
Using this method caused an increase in block value precision in risk assessment.

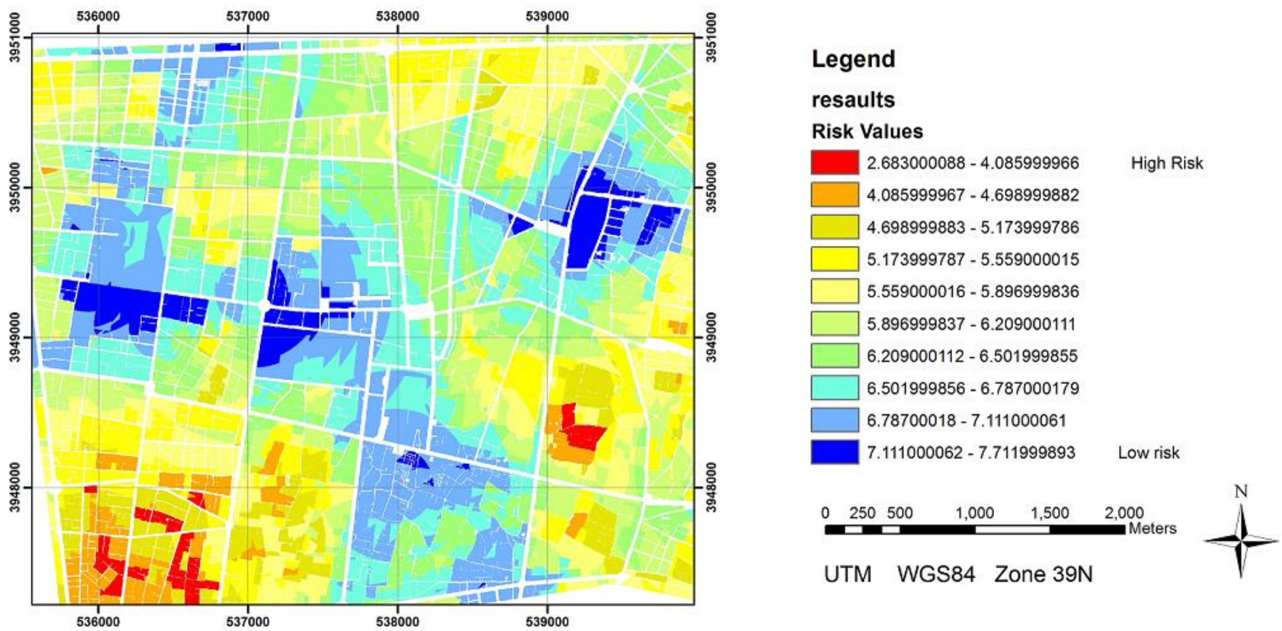

Figure 5. Block value map for risk analysis in part of Tehran (region 5 and 6)

7. REFERENCES

1-Ahadzadeh, S., Valadanzouj, M., Sadeghian, S., Ahmadi, S., 2008. Detection of damaged buildings after an earthquake using artificial neural network algorithm. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences. Vol. XXXVII. Part B8. Beijing.*

2-Anderson, D., and McNeill, G. 1992. *Artificial neural networks technology*. A DACS State-of-the-Art Report. New York: Kaman Sciences Corporation.

3-Eksteen, S., 2010. Integration of Geographical Information Systems and Artificial Neural Networks to Improve Spatial Decision Making. MSc Thesis submitted to The University of Pretoria.

4-Hamed, M. M., Khalafallah, M. G., and Hassanien, E. A. 2004. Prediction of wastewater treatment plant performance using artificial neural networks. *Environmental Modeling & Software,* 19, pp. 919–928.

5-Haykin, S., 1999. *Neural networks: A Comprehensive foundation. second ed*. New Jersey: Prentice Hall Inc.

6-Lin, C. T., and Lee, C. S. G. 1996. *Neural Fuzzy Systems*. New Jersey: Prentice Hall Inc.

7-Milly, P. C., Wetherald, R. T., Dunne, K. A., and Delworth, T. L., 2002. Increasing risk of great floods in a changing climate. *Nature*, 415, pp. 514–517.

8-Morrow, B. H., 1999. Identifying and mapping community vulnerability. *Disasters*, 23(1), pp. 1–18.

9-Olsen, G. R., Carstensen, N., and Hoyen, K., 2003. Humanitarian crisis: what determines the level of emergency assistance? Media coverage, donor interest and the aid business. *Disasters*, 27(2), pp. 109–26.

10-Rodriguez, J. T., Vitoriano, B. Montero, J. in press. A general methodology for data-based rule building and its application to natural disaster management. *Computers and Operation Research.*

11-Saha, A., 2003. Introduction to artificial Neural Network Models. http://www.geocities.com/adotsaha/NNinExcel.html (accessed March 2008).

12-Thurston, J. 2002. GIS & artificial neural networks: Does your GIS think?. http://www.integralgis.com/articles/ Neural%20Networks.pdf (accesses April 5, 2003).