Hopfield Neural Network for Microscopic Evacuation of Buildings

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Abstract: The problem of evacuation raised a lot of interest as its objective of saving lives is of an extreme importance. In this context, many researches supplied solutions allowing to plan the process of evacuation in case of disaster. Certain solutions took into account the behavior of the crowd, while others treated the evacuees in an independent way. For that purpose, we dedicate our study to this last type of evacuation, namely the microscopic evacuation. Our approach is based on the artificial neural networks which we considered capable of generating a human behavior thanks to their neuronal aspect. We proposed a solution capable of planning a microscopic evacuation of building by having recourse to Hopfield neural networks. We supplied an experimental study on the real cases of two hospitals. This study also brought a comparison of our model with another neuronal model for evacuation which is the self organizing map.

1 INTRODUCTION

Public areas such as schools, hospitals and shopping malls are buildings where there is generally an accumulation of persons. When everything is normal, people manage to reach the exit easily, once their need accomplished. However, when an unforeseen event like fire arrives, the access to the same exit becomes complicated. Indeed, the desperation, the speed of people, the time which is urgent and several other factors, make that the exit becomes harder and harder.

Naturally, if the building, the district or even the city is designed in a way that makes the evacuation process easier, more people could succeed to reach the safety places.

Many researches supplied solutions allowing to plan the process of evacuation in case of disaster. Certain solutions took into account the behavior of the crowd (Macroscopic evacuation), while others treated the evacuees in an independent way. For that purpose, we dedicate our study to this last type of evacuation, namely the microscopic evacuation. This kind of evacuation tends to propose the adequate itinerary of an evacuee according to the characteristics which define him in a panic situation.

In this context, we found that the neuronal aspect of artificial neural networks could be a good alternative to represent the human behavior in evacuation situations. However, only one type of artificial neural networks, namely the Self Organizing Map (SOM), treated the problem evacuation. For that purpose, we decided to investigate the track of Hopfield neural networks.

2 MICROSCOPIC EVACUATION OF BUILDINGS

Evacuation's essential aim is moving a population out of a dangerous place (an hypermarket, a work place and even a district or a city). Each evacuee is presented by some parameters like age, gender, or walking speed (Klupfel et al., 2000). According to these parameters, he would make his choice to move from one position to another. Naturally, simulating the occupants of one building behaviors would help in planning evacuation and preventing the loss of lives.

Indeed, architects and persons in charge must take the safety aspect into a high level of consideration and apply security measures. To be able of this, people behavior in trouble cases must be predicted in advance.

To realize such simulations, technical tools are required. In this context, different approaches handeled the problem. We essentially distinguished two big sectors in this domain; a sector treating the problem from a mathematical point of view, namely the cellular automata and the social forces, and another solving it using the artificial neural netwotks. We then

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decided to investigate this truck by focusing on Hopfield neural networks and trying to apply it to the evacuation field.

3 HOPFIELD NETWORK PRINCIPLE

Hopfield network is a very simple modeling of unsupervised neural network. It is simply a set of neurons fully connected with some strengths or weights; they have two possible states, on and off (Heaton, 2005).

However, Hopfield neurons could be classified into two logical layers.

- **Input Layer:** The layer containing the neurons which values have to be initialized and provided to the network.
- **Output Layer:** The layer of neurons which values are generated by the network.

Like all artificial neural networks, Hopfield neurons follow the different steps of figure 1 to provide an output. This output is retrieved by passing the Weighted Sum of Input (WSI) signals to the transfer function (Abraham, 2005).

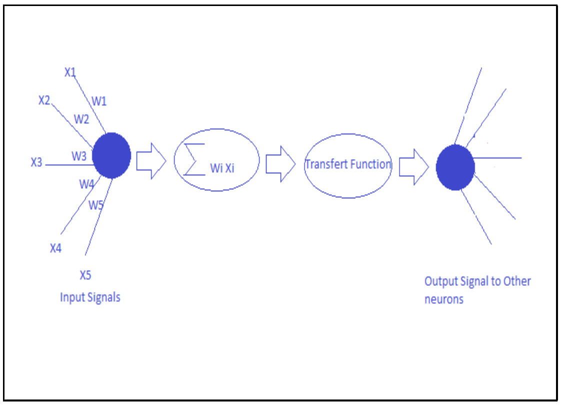

Figure 1: Artificial neuron.

This WSI value is the sum of the multiplication of each synapses' weight with its corresponding signal. In fact, WSI value is calculated basing on the neurons connected to the considered node following equation (1) where w_i is the weight between current neuron and neuron i, x_i is the input coming from neuron i.

$$WSI = \sum_i w_i x_i \quad (1)$$

This sum is passed to a transfer function to decide whether to activate the neuron or not. Like a biological neuron, the artificial neuron is inactive until a WSI value is reached .

Hopfield networks are based on an auto-associative memory concept. Like the brain, they are able to store some memories that can be later recovered when the network is provided with only a part of the information. For example, a smell, a colour or a situation makes us remember special persons or some childhood memories. Also, Hopfield networks work can complete information from corrupted or incomplete data.

Hopfield networks were widely used in optimization problems like the traveller salesman (Letchford et al., 2011) and the n-queens problem (Letavec and Ruggiero, 2002) and in pattern recognition (Yu, 2003),(Pandey et al., 2010). However, it was never used in the field of microscopic evacuation.

4 A HOPFIELD MODELING FOR EVACUATION PROBLEM

In the microscopic evacuation problem we have to present two essential information; the input which is the evacuee's parameters as well as the output described by the itinerary he would follow.

We then opted for an architecture which allows the distinction between the various data, those of input and those of output; we subdivided the network into two layers, an input layer which values are provided to the network and an output layer that the network generates. Both layers where combined to form one vector as shown in figure 2.

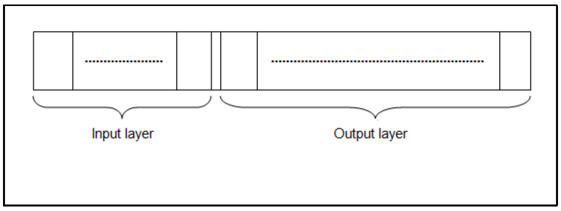

Figure 2: The vector modeling.

The input part of the vector have to be initialized and the output part is provided by the network.

4.1 Input Layer

The input layer is a description of the evacuee's characteristics that would make us guess the path he would follow. Each parameter is defined by a neuron having a state that takes the value 1 if the condition is true and -1 if it is false.

After a prerequisite study of different researches in the evacuation field, we decided to retain some parameters that almost all the studies showed effective in egress process. Later, these parameters will be validated in the experimental phase, where we could decide of their usefulness in our model.

- **Age**
  The category of age to which the evacuee belongs. This factor would influence the evacuee behavior as experience and advanced years of life make him more able to choose the best road.
- **Gender**
  Men and women generally don't think in the same way and have different psychological characteristics, especially in disaster situations.
- **Fire Experience (FE)**
  The evacuee behavior would be influenced by his experience in confronting egress situation as it would help him in having this quality to react and to keep control of the situation.
- **Familiarity with the Building (FB)**
  When the evacuee knows the building well, the egress process would be easier to him as he already knows the direction to exit.
- **Starting Position (SP)**
  We also have to specify the starting position of the evacuee that must be kept firing in every time step of the execution.

As Hopfield model doesn't allow to provide data having integer values, each parameter could only be on true, having the value 1 or -1 otherwise.

To train the network, we choose a set of instances of input neurons to which we assigned the corresponding and logical itineraries. The number of training patterns should not exceed 14% the number of nodes in the network. Each pattern represents a specific person, having some characteristics and the itinerary he took to exit the building.

4.2 Output Layer

This layer of the network represents the different compartments of the building. If the area is visited in the road the evacuee chooses, the corresponding neuron will be activated. All the neurons of the output layer are initialized to 0 except the starting point which is initialized to 1 and kept in this state during all the iterations of the process.

Figure 3 shows the resulting networks with its both layers.

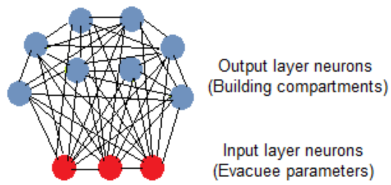

Figure 3: The resulting network.

5 CASE STUDIES OF BUILDING EVACUATION IN THE CASE OF FIRE

In order to apply the problem of evacuation on a real situation, we will test the network behavior in the case of two hospital buildings.

5.1 Case of the Second Floor of the Tunisian Children Hospital

This floor of the building constituted the neurons of the output layer. We supposed that the fire is located in the transfer room. In table 1 we find the legend of the different sectors of the building.

Table 1: Legend of the building areas.

Neuron name	Description
Sri	Septic room number i
Laui	Laundry number i
offi	Office number i
SR	Room of Rest
Row	Row
CM/W	Cloak rooms Men/ Women
Rt	Transfer room
TP	Technical premise i
STE	Sterilization
Was	Washing
ELE	Elevator
Gri	Guard room number i
CiPi	Corridor number i part i
exti	Exit number i

The itinerary of each person will appear as red colored neurons while inactive neurons will remain blue. For example, the evacuee of figure 4 took the itinerary sr2-sas1-c1p3-off2-off3-off2-c1p3-rt2-c2p2-ext3.

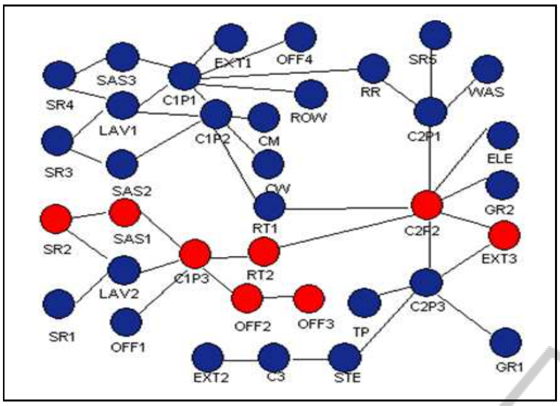

Figure 4: An example of output of the Hopfield network.

For the learning phase, we tried to choose profiles as exhaustivly as possible because of the constraint of limited number of patterns. To validate the training phase, we must be sure of the stability of all the learned pattern. Meaning that if we provide the network with an input layer of one learned pattern, the generated output must be identical to the learned one. We reached a threshold of 14 patterns, after which the network showed a high level of error.

This restriction of number of patterns could be explained by the imminence of correlation between the learned vectors every time we exceed a certain number of patterns.

We then choose 50 different profiles to test the network. Each generated itinerary was compared to the logical expected one in the validation set to retrieve the error rate of the network. The network accomplished the tests with an error rate of 10% which is a satisfying result. Furthermore, the network converged after less than 50 epochs.

5.1.1 Experimental Results and Interpretations

One of the aims of our solution to evacuation problem is to analyze the building architecture. We found a lot of disparity in the tendency of the evacuees to visit certain compartments.

Figure 5 shows the number of times each compartment was visited in the evacuation of our sample of 50 persons. We notice for instance that the second part of corridor2 and the third part of corridor 1 are very frequently visited by evacuees.

Thus, it would be useful to widen them to remedy the congestion, to put plans indicating the exit on their walls and to place security cameras there to supervise the situation. Another precaution to take is to put obstacles in places of congestion to separate the crowd.

Figure 6 shows the probability of taking the shortest path according to each parameter.

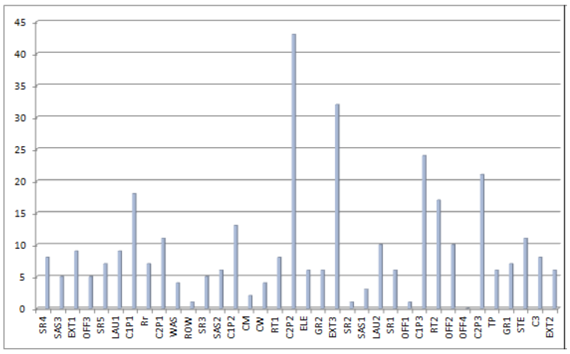

Figure 5: Number of visits to each compartment.

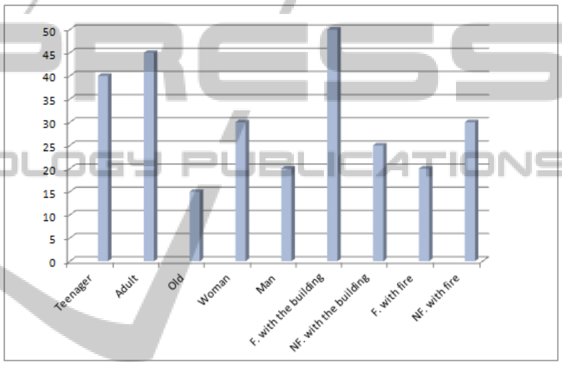

Figure 6: Percentage of taking the shortest path.

People familiar with the building are more likely to take the shortest path while old people are generally not able to take the best alternative as only 15% out of them guessed the best itinerary.

5.1.2 Sensitivity Analysis

In this phase of the work, we have to validate our choice of input parameters by analyzing the effectiveness of each of them in the network behavior.

For every given parameter, we made disturbances on its value while keeping all the other parameters fixed. We took 20 profiles for each parameter and made the variation noticing the number of times output changes.

The results of the tests gave the statistics illustrated in figure 7. This figure shows the percentage of times where the output changes when we only change the value of one of the parameters.

All of the model's parameters were effective, as the variation rate exceeded 50% for all of them. However the degree of effectiveness changed from one parameter to the other.

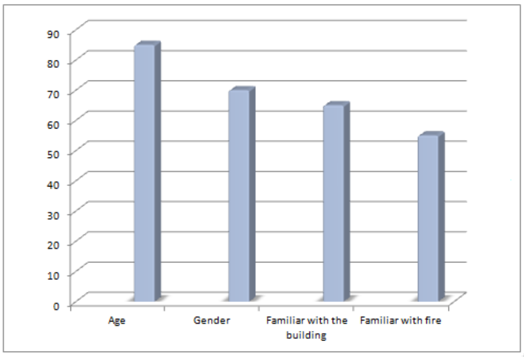

Figure 7: Variation rate.

5.2 Case Study of the First Floor of Cardiology Department of Charles Nicole Hospital

The experimental study will concern a building bigger than the floor of the children hospital studied in the previous section in order to test, in the same time, the sensitivity of the Hopfield model to the dimensions of the building.

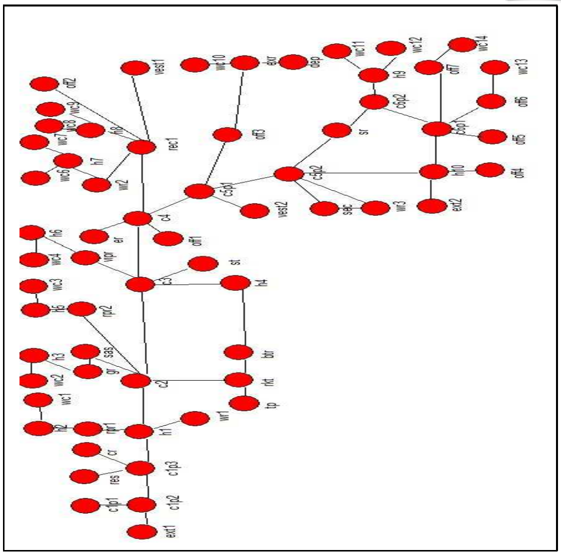

Figure 8: Network output corresponding to the first floor of cardiology department of Charles Nicole hospital.

The building of the first floor of the cardiology department of Charles Nicole hospital contains 63 areas. The different areas of the building were considered as neurons composing the network showed in figure 8.

The maximum number of patterns accepted in the learning process was 18 patterns. After the learning phase, we tested both networks with 30 different profiles.

5.2.1 Experimental Results and Interpretations

The network succeeded in acheiving 23 % of error in less than 50 time steps. However, we noticed that the model's performance decreased comparing to the previous case study as the number of compartments increased.

When the number of compartments of the tested building increased of 27 areas comparing to the building tested in previous section, the number of maximum learned patterns didn't increased proportionally. In fact, we were only allowed to add 4 patterns, reaching the total number of 18 learned patterns.

In the example of 36 areas, the 14 allowed patterns were able to give the network the sufficient knowledge which permits it to generate intelligent and correct roads. However, in this example, the 18 learned profiles weren't able to cover the 63 neurons of the network for different times. To be as exhaustive as possible, we were obliged to place the evacuees of the learning set in distant areas in order to visit the totality of the neurons. The majority of the neurons were then visited only one time in the learning process. As a result, the outputs of the tests were very sensitive to the starting position.

6 HOPFIELD VS. SELF ORGANIZING MAP (SOM) FOR EVACUATION

After adapting Hopfield networks to the problem of microscopic evacuation of buildings, we thought of pushing the study to a comparison with another neural network model. Both belonging to unsupervised learning type of neural networks, Hopfield and SOM for evacuation were the object of a comparative study basing on the SOM model proposed in (Ben Salem et al., 2011).

We begun by a theoretical comparison that showed that Hopfield was simpler and easier in its processing way. We then moved to a practical comparison. In tables 2 and 3 we find the results of the comparison in the case of the two Hospitals quoted previously.

Table 2: Comparison results in the case of the second floor of children hospital.

	Hopfield	Som
Patterns number	14	50
Error rate	23 %	16%
Time steps	50	2500

Table 3: Comparison results in the case of the first floor of Charles Nicole hospital.

	Hopfield	Som
Patterns number	18	18
Error rate	23 %	36%
Time steps	50	350

The results of the tests were in the favor of Hopfield as they showed respectable error rates and rapidity in convergence time of Hopfield comparing to SOM. Hopfield also provided more logical and intelligent results.

In fact, we noticed that SOM tends to an illogical generation of the shortest path even when it hasn't to do it.

7 CONCLUSIONS

The problem of evacuation is an important subject of actuality which was the object of a lot of interest in the research's field. This paper dealt with the microscopic type of evacuation which focuses on the behavior of each evacuee during the egress process.

We carried our interest on Hopfield neural networks known by their simple architecture and their effectiveness in different domains especially the domain of pattern recognition and combinatory optimization. The model is based on an auto-associative memory concept which permits to recover any learned information providing the network with a respectable degree of intelligence.

We proposed a model able to intelligently draw evacuee's itineraries in a building, where there is a panic situation, according to some characteristics. The parameters we thought effective in getting the evacuee behavior are his age category, his gender, his familiarity with the building, his fire experience and his starting position.

To lighten our model's contribution in artificial neural network approaches for evacuation, we supplied a comparative study between our model and SOM model proposed in (Ben Salem et al., 2011). Hopfield gave largely better results than SOM. It conserved its rapidity quality adding to it the accomplishment of a better rate of error than SOM.

Even if Hopfield networks succeeded in simulating the evacuation process, the model could be improved by including other factors as the time of evacuation and the speed of people.

It would be also interesting to improve the quality of the learning set as we could deepen it by taking the opinion of sociologists and specialists of human behavior.

Finally, it would be promising to enlarge Hopfield capacity of learning.

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