The Random Neural Model and the Fuzzy Logic on Cognitive Maps

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Abstract

The purpose of this paper is to describe a fuzzy cognitive map based on the random neural network model, and to illustrate its application in the modeling of process. This model is based on the probability of activation of the neurons/concepts in the network. Our model carries out inferences via numerical calculation instead of symbolic deduction. The arcs define dynamic relationships between concepts and describe the causal procedures. We show how the random fuzzy cognitive map can reveal implications of models composed of dynamic processes. The experimental evaluation shows that our model provides similar results than previous fuzzy cognitive map with less iterations.

1. Introduction

Fuzzy Cognitive Maps (FCM) was proposed by Kosko to represent the causal relationship between concepts and analyze inference patterns [10, 12]. FCM is a hybrid method that lies in some sense between fuzzy systems and neural networks. So FCM represent knowledge in a symbolic manner and relates states, processes, policies, events, values and inputs in an analogous manner. FCMs are appropriate to explicit the knowledge and experience which has been accumulated for years on the operation of a complex system. FCM have gained considerable research interest and have been applied to many areas [6, 8, 12, 13, 14, 15, 16]. The Random Neural Network (RNN) has been proposed by Gelenbe in 1989 [9]. This model does not use a dynamic equation, but uses a scheme of interaction among neurons. It calculates the probability of activation of the neurons in the network. The RNN has been used to solve optimization and pattern recognition problems [1, 2, 3, 4]. The problem addressed in this paper concerns the proposition of a FCM, using the RNN. We describe the Random Fuzzy Cognitive Map (RFCM) and illustrate its application in the modeling of process. We shall use each neuron to model a concept. In our model, each concept is defined by a probability of activation, the relationships between the concepts are defined by positive or negative interrelation probabilities, and the procedure of how the cause takes effect is modeled by a dynamic system.

2. Theoretical Aspects

2.1. The Random Neural Network Model

The RNN model consists of a network of n neurons in which positive and negative signals circulate [9]. Each neuron accumulates signals as they arrive, and can fire if its total signal count at a given instant of time is positive. Firing then occurs at random according to an exponential distribution of constant rate, and signals are sent out to other neurons or to the outside of the network. Each neuron i of the network is represented at any time t by its input signal potential $k_i(t)$. Positive and negative signals have different roles in the network. A negative signal reduces by 1 the potential of the neuron to which it arrives (inhibition) or has no effect on the signal potential if it is already zero; while an arriving positive signal adds 1 to the neuron potential. Signals can either arrive to a neuron from the outside of the network or from other neurons. Each time a neuron fires, a signal leaves it depleting the total input potential of the neuron. A signal which leaves neuron i heads for neuron j with probability $p^+(i,j)$ as a positive signal (excitation), or as negative signal with probability $p^-(i,j)$ (inhibition), or it departs from the network with probability $d(i)$. External positive signals arrive to the i^{th} neuron according to a Poisson process of rate $\Lambda(i)$. External negative signals arrive to the i^{th} neuron according to a Poisson process of rate $\lambda(i)$. The rate at which neuron i fires is $r(i)$. The main property of this model is the excitation probability of a neuron i, $q(i)$, where:

$$q(i) = \lambda^+(i)/(r(i)+\lambda^-(i)) \qquad (1)$$

and,

$$\lambda^+(i) = \sum^n_{j=1} q(j)r(j)p^+(j,i)+\Lambda(i)$$

$$\lambda^-(i) = \sum^n_{j=1} q(j)r(j)p^-(j,i)+\lambda(i)$$

The synaptic weights for positive ($w^+(i,j)$) and negative ($w^-(i,j)$) signals are defined as:

$$w^+(i,j) = r(i)p^+(i,j)$$
$$w^-(i,j) = r(i)p^-(i,j)$$

and
$$r(i) = \Sigma^n_{j=1} [w^+(i,j) + w^-(i,j)]$$

2.2. Fuzzy Cognitive Maps

FCMs combine the robust properties of fuzzy logic and neural networks. At first, R. Axelord used cognitive maps as a formal way of representing social scientific knowledge and modeling decision making in social and political systems [5]. Then, B. Kosko enhanced cognitive maps considering fuzzy values for them [10, 12]. A FCM describes the behavior of a system in terms of concepts, each concept represents a state or a characteristic of the system. A FCM illustrates the whole system by a graph showing the cause and effect along concepts. Variable concepts are represented by nodes in a directed graph. The graph's edges are the casual influences between the concepts. The value of a node reflects the degree to which the concept is active in the system at a particular time. This value is a function of the sum of all incoming edges multiplied and the value of the originating concept at the immediately preceding state. The threshold function applied to the weighted sums can be fuzzy in nature. The causal relationships are expressed by either positive or negative signs and different weights.

In general, a FCM functions like associative neural networks. A FCM describes a system in a one-layer network which is used in unsupervised mode, whose neurons are assigned concept meanings and the interconnection weights represent relationships between these concepts. The fuzzy indicates that FCMs are often comprised of concepts that can be represented as fuzzy sets and the causal relations between the concepts can be fuzzy implications, conditional probabilities, etc. A directed edge E_{ij} from concept C_i to concept C_j measures how much C_i causes C_j. In simple FCMs, directional influences take on trivalent values {-1, 0, +1}, where −1 indicates a negative relationship, 0 no causality relationship, and +1 a positive relationship. In general, the edges E_{ij} can take values in the fuzzy causal interval [-1, 1] allowing degrees of causality to be represented: $E_{jk}>0$ indicates direct (positive) causality between concepts C_j and C_k. $E_{jk}<0$ indicates inverse (negative) causality between concepts C_j and C_k. $E_{jk}=0$ indicates no relationship between C_j and C_k.

Because the directional influences are presented as all-or-none relationships, FCMs provide qualitative as opposed to quantitative information about relationships. In FCM nomenclature, model implications are revealed by clamping variables and using an iterative vector-matrix multiplication procedure to assess the effects of these perturbations on the state of a model. A model implication converges to a global stability, an equilibrium in the state of the system. During the inference process, the sequence of patterns reveals the inference model. The simplicity of the FCM model consists in its mathematical representation and operation. So a FCM which consists of *n* concepts, is represented mathematically by a *n* state vector A, which gathers the values of the *n* concepts, and by a n*n weighted matrix E. Each element E_{ij} of the matrix indicates the value of the weight between concepts C_i and C_j. The activation level A_i for each concept C_i is calculated by the following rule:

$$A_i = f(\Sigma^n_{j=1} A_j E_{ji}) + A_i^{old} \quad (2)$$

A_i is the activation level of concept C_i at time t+1, A_j is the activation level of Concept C_j at time t, A_i^{old} is the activation level of concept C_i at time t, and *f* is a threshold function. A FCM can be used to answer a "what-if" question based on an initial scenario that is represented by a vector $S_0= \{s_i\}$, for i=1 ...n, where $s_i=1$ indicates that concept C_i holds completely in the initial state, and $s_i=0$ indicates that C_i does not hold in the initial state. Then, beginning with k=1 and $A=S_0$ we repeatedly compute A_i. This process continues until the system convergence (for example, when $A_i^{new}=A_i^{old}$). This is the resulting equilibrium vector, which provides the answer to the "what if" question.

The development of a FCM often occurs within a group context. That is, each expert provides its individual FCM matrix, which is then synthesized into a group FCM matrix. The group matrix (E^G) could be computed as:

$$E^G_{ji} = \max_t \left\{E^t_{ji}\right\}, \quad \forall \text{ t=1 to number of experts (NE).}$$

or (3)

$$E^G_{ji} = \sum_{t=1}^{NE} b_t E^t_{ji}$$

Where E^t_{ji} is the opinion of the expert *t* about the causal relationship among C_j and C_i, and b_t is the expert's opinion credibility weight.

FCM have been used for decision analysis, for modeling and processing political knowledge, etc. [6, 7, 12, 16]. [14, 15] investigate the implementation of the FCM in distributed and control problems. A novel approach is the use of FCMs as a computationally inexpensive way to "program" the actors in a virtual world [7, 8, 11, 16].

3. Our Random Fuzzy Cognitive Maps (RFCM)

Our RFCM improves the conventional FCM by quantifying the probability of activation of the concepts and introducing a nonlinear dynamic function to the inference process. Similar to a FCM, concepts in RFCM can be causes or effects that collectively represent the system's state. The value of W_{ij} indicates how strongly concept C_i influences concept C_j. $W^+_{ij}>0$ and $W^-_{ij}=0$ if the relationship between the concepts C_i and C_j is direct, $W^-_{ij}>0$ and $W^+_{ij}=0$ if the relationship is inverse, or $W^+_{ij}=W^-_{ij}=0$ if doesn't exist a relationship among them. The quantitative concepts enable the inference of RFCM to be carried out via numeric calculations instead of symbol deduction. Quantitative concepts can also help to make the feedback mechanism realistic. A feedback is a very important mechanism that must be included in a causal model. For example, an army needs several battles to know the strength of its enemy before a decisive battle.

To calculate the state of a neuron on the RFCM (the probability of activation of a given concept C_j), the following expression is used:

$$q(j) = \min\{\lambda^+(j), \max\{r(j), \lambda^-(j)\}\} \quad (4)$$

where,
$$\lambda^+(j) = \max_{i=1,n}\{\min\{q(i), W^+(i,j)\}\}$$
$$\lambda^-(j) = \max_{i=1,n}\{\min\{q(i), W^-(i,j)\}\}$$

Such as, $\Lambda(j)=\lambda(i)=0$. In addition, the fire rate is

$$r(j) = \max_{i=1,n}\{W^+(i,j), W^-(i,j)\} \quad (5)$$

The general procedure of the RFCM is the following:

1. Design the configuration of the FCM. Experts determine the concepts and causality.
2. Initialize the number of neurons. The number of neurons is equal to the number of concepts.
3. Call the Learning phase
4. Call the Simulation phase.

3.1 The learning Procedure

In this phase we must define the weights. The weights are defined and/or update according to the next procedures:

- *Based on expert's opinion:* each expert defines its FCM and the global FCM is determined according to the equation (3). The next algorithm determines the weight from a group of experts.

1. If $i\neq j$ and if $E_{ij}>0$ then $W^+_{ij} = \max_{t=1,NE}\{E^t_{ij}\}$ and $W^-_{ij}=0$
2. If $i\neq j$ and if $E_{ij}<0$ then $W^-_{ij} = \max_{t=1,NE}\{E^t_{ij}\}$ and $W^+_{ij}=0$
3. If $i=j$ or if $E_{ij}=0$ then $W^+_{ij} = W^-_{ij} = 0$

The causal relationship (E_{ij}) is caught from each expert using the next table:

Symbolic value	Real Value
no relationship	0
Slight	0.2
Low	0.4
Somehow	0.6
Much	0.8
Direct	1

Table 1: Relationship between the concepts

- *Based on measured data:* In this case we have a set of measures about the system. This information is the input pattern:

$$M=\{D_1, \ldots, D_m\} = \{[d_1^1, d_1^2, \ldots, d_1^n], \ldots, [d_m^1, d_m^2, \ldots, d_m^n]\}$$

Where d_j^t is the value of the concept C_j measured at time *t*. In this case, our learning algorithm follows the next mechanism:

$$W^t_{ji} = W^{t-1}_{ji} + \eta\left(\Delta d^t_j \Delta d^t_i \Big/ \Delta^+ d^t_i \Delta^+ d^t_j\right)$$

where, $\Delta d^t_j = d^t_j - d^{t-1}_j$ $\qquad \Delta d^t_i = d^t_i - d^{t-1}_i$
$\Delta^+ d^t_j = d^t_j + d^{t-1}_j$ $\qquad \Delta^+ d^t_i = d^t_i + d^{t-1}_i$

and η is the learning rate. On this way we guarantee the values of W_{ij} in the interval [0, 1], where W_{ij} can be W^+_{ij} or W^-_{ij}.

3.2 The Simulation phase

Once constructed the RFCM of a specific system, we can perform qualitative simulations of the system. The RFCM can be used like an auto-associative memory. In this way, when we present a pattern to the network, the network will iterate until generate an output close to the information keeps. This phase consists on the iteration of the system until the system convergence. The input is an initial state $S_0=\{s_1, \ldots, s_n\}$, such as $q^0(1)=s_1, \ldots, q^0(n)=s_n$ and $s_i\in[0, 1]$ (set of initial values of the concepts ($S_0=Q^0$)). The output $Q^m=\{q^m(1), \ldots, q^m(n)\}$is the prediction of the RFCM such as *m* is the number of the iteration when the system converge. The algorithm of this phase is:

1. Read input state Q^0
2. Calculate the fire rate r(i) according to the equation (5)
3. Until system convergence
   3.1 Calculate q(i) according to the equation (4)

4. Experiments

In this section we illustrate the RFCM application. A RFCM of a particular system consists of a graph representing the relevant causal relationships. A discrete time simulation is performed by iteratively applying the equation (4) to the state vector of the graph. At the beginning, we must define an initial vector of concept states, and the simulation halts if an equilibrium state is reached. To test the quality of our approach, we compare it with the Kozko binary FCM [8, 9, 15, 16, 22].

4.1 First Experiment: model of property theft in a community

Consider the RFCM shown in figure 1. This map attempts to model property theft in a community [16]. The concepts chosen are:

- Opportunity (C_1): physical access to property, availability of burglary tools, etc.
- Community involvement (C_2): town watch, communication between neighbors, crime reports in local news.
- Police presence (C_3): the visible presence of uniformed officers on a regular basis.
- Punishment (C_4): a measure of the reliability and certainty of punishment for crimes.
- Criminal intent (C_5): the presence of persons intending to commit theft.
- Presence of property (C_6): the visible presence of goods desired by thieves.
- Theft (C_7): actual taking of property.

Note the first two concepts are abstractions of a variety of lesser entities in the domain of interest. The presence of property strongly influences criminal intent, theft, and opportunity. Police presence and community involvement deter theft, and sure punishment deters the formation of criminal intent. Property owners respond to theft by forgoing purchases and hiding goods (i.e., the negative causal link between theft and opportunity), and calling for additional police patrols (i.e., the positive causal link between theft and police presence).

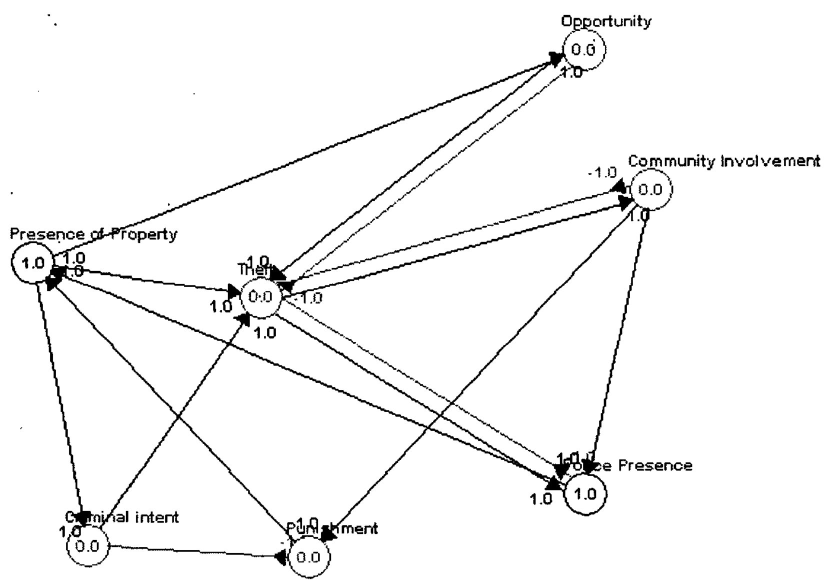

Figure 1: Crime and Punishment RFCM

The table 2 presents the results for the initial states (0 0 1 0 0 1 0).

Input	Kosko FCM	RFCM	Iteration
0 0 1 0 0 1 0	0 0 1 0 0 1 0	0 0.2 0.6 0.2 0.8 0.2	1
	1 0 0 0 1 1 0	0 0.6 0.6 0 0.8 0.8 0.4	2
	1 0 0 0 1 0 1	0.8 0 0 0.2 0.2 1 0.8	3
	0 1 1 0 0 0 1	0.2 1 0.8 0 0.8 0.2 1	4
	0 1 1 1 0 1 0		5
	1 0 1 1 0 1 0		6
	1 0 0 0 0 1 1		7
	0 1 1 0 1 0 1		8

Table 2: The results for the second experiment.

We define the starting state S_0=(0, 0, 1, 0, 0, 1, 0) i.e., police and valuable property are present, but all other concepts are inactive. We then obtain the discrete time series show on the second and third columns of the table 3. The system stabilizes to the state S_7 (Kozko model) or state S_4 (RFCM). We can interpret this state (0 1 1 0 1 0 1) as follows: the community responds to the increase in theft by removing opportunity, calling for increased police patrols, and taking mutual aid measures, but criminal intent is increasing and theft continues. The previous state (1 0 0 0 0 1 1) to the equilibrium state can be interpreted as (S_6 on the Kozko model and S_3 on the RFCM): theft occurs, but declining interest has led to diminished prosecution and police activity. The criminal intent conceptual node may be interpreted as the wide-spread formation of criminal intent. Early incidents encourage additional thieves.

4.3 Second experiment: Virtual Worlds

Dickerson and Kosko proposed a novel use for FCMs [8, 11, 12, 16]. They employed a system of three interacting FCMs to create a virtual reality environment populated by dolphins, fish, and sharks. The use of FCMs proved to be a computationally inexpensive means of encoding behavior. This sparked the idea of using FCMs in training environments. [16] refines the Dickerson and Kosko's approach to be used the FCM to model the "soft" elements of an environment in concert with an expert system capturing the procedural or doctrinal – "hard" elements of the environment. In their paper, they present a FCM modeling a squad of soldiers in combat. This map is shown in Figure 2. The concepts in this map are:

- Cluster (C_1): the tendency of individual soldiers to close with their peers for support.
- Proximity of enemy (C_2): the observed presence of hostile forces within firing range.
- Receive fire (C_3): taking fire from hostile forces.
- Presence of authority (C_4): command and control inputs from the squad leader.
- Fire weapons (C_5): the state in which the squad fires on the enemy.
- Peer visibility (C_6): the ability of any given soldier to observe his peers.
- Spread out (C_7): dispersion of the squad.
- Take cover (C_8): the squad seeking shelter from hostile fire.
- Advance (C_9): the squad proceeding in the planned direction of travel with the intent of engaging any encountered enemy forces.
- Fatigue (C_{10}): physical weakness of the squad members.

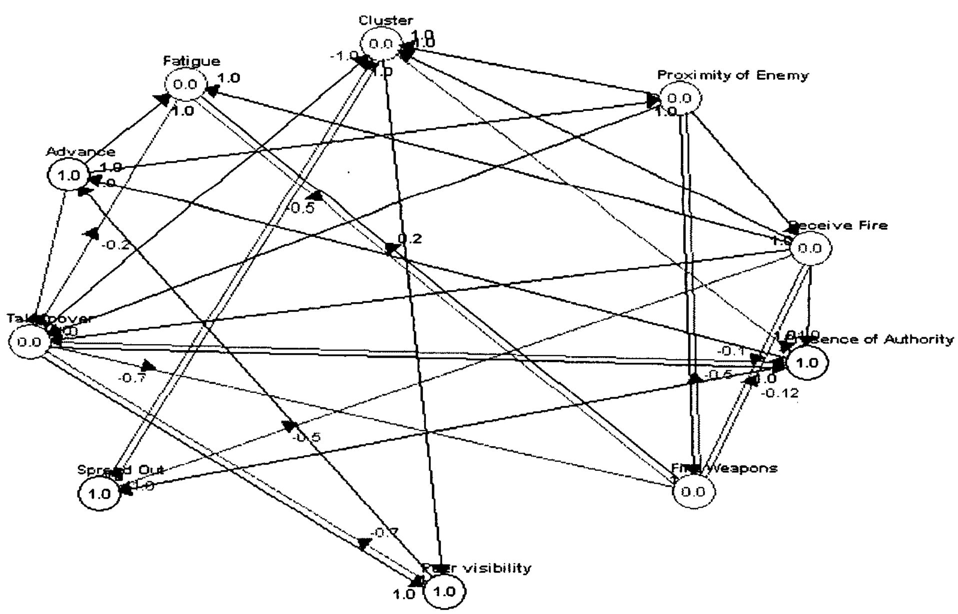

Figure 2: Virtual squad of soldiers RFCM

In the hybrid system we suggest, the presence of authority concept would be replaced by an input from an expert system programmed with the enemy's small unit infantry doctrine and prevailing conditions. Similarly, the proximity of the enemy would be an input based on the battlefield map and programmed enemy locations. Here, however, we give them initial inputs and allow them to vary according to operation of the FCM. The table 3 presents the results for the initial states 0 0 0 1 0 1 1 0 1 0.

Input	Kosko FCM	RCM	Iteration
0001011010	0001011010	0.8 1 0 0.6 0.2 1 0.4 0.2 1 0.8	1
	1111010101	1 0.8 0.8 0.6 0.8 0.2 0 0.8 1 0.8	2
	1011010110		3
	1101010011		4
	0110110011		5
	1111100111		6

Table 3: results for the virtual word experiment.

In the case of the RFCM, the state (0.8, 1, 0, 0.6, 0.2, 1, 0.4, 0.2, 1, 0.8) indicates they lose contact and cease firing, but their protective measures have emboldened them to leave cover and resume the advance. Next (the equilibrium state (1, 0.8, 0.8, 0.6, 0.8, 0.2, 0, 0.8, 1, 0.8)), the squad leader reasserts his authority and restores order to the advance. This is reasonable system operation and suggests the feasibility of FCMs as simple mechanisms for modeling inexact behavior that is difficult to capture with formal methods.

5. Conclusions

In this paper, we have proposed a FCM based on the Random Neural Model, the RFCM. We have shown that this model can efficiently work as associative memory. This model is a useful method in complex system modeling, which will help experts get "smarter". We do not observe any inconsistent behavior of our RFCM with respect to the previous FCMs. Our RFCM exhibit a number of desirable properties that make it attractive: i) Provide qualitative information about the inferences in complex social dynamic models. ii) Can represent an unlimited number of reciprocal relationships. iii) Has different learning approaches. iv) Can model both mediator and moderator relationships. v) Facility the modeling of dynamic, time-evolving phenomena and process. vi) Has a high adaptability to any inference with feedback.

Another important characteristic is its simplicity, the result of each RFCM's cycles is computed from the equation (4). Most of the computations are intrinsically parallel and can be implemented on SIMD or MIMD architectures. Further on, we will study the utilization of the RFCM in modeling the behavior of distributed systems and dynamic systems. In addition, we will test an unsupervised learning approach.

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