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Modeling Complex Adaptive Systems using Learning Fuzzy Cognitive Maps

Ahmed Tlili
Mentouri University
Constantine, Algeria

Salim Chikhi
Mentouri University
Constantine, Algeria

ABSTRACT

This paper presents Learning Fuzzy Cognitive Maps (LFCM) as a new paradigm, or approach, for modeling complex adaptive systems (CAS). This technique is the fusion of the advances of the fuzzy logic, formal neural network, and reinforcement learning where they are suitable for modeling systems in artificial life domain of CAS.The FCM structure is similar to a recurrent artificial neural network. The reinforcement learning (RL) gives the explicative frame of entities like environment changing adaptation. A mathematical adaptation of the Q-learning algorithm is discussed and we present in this work an inspired pseudo-hybridization algorithm Q-learning, mainly used in non-linear dynamic systems RL, and the Hebb law for the inference calculus introduced by the cognitive maps. The prey and predator simulation model is shown.

General Terms

Artificial life, fuzzy systems, reinforcement learning.

Keywords

Complex adaptive system, fuzzy cognitive maps, reinforcement learning.

1. INTRODUCTION

A Complex Adaptive System (CAS) is defined as a collection of entities or agents, merged in a dynamic environment, with simple rules of behavior and able to adapt to its environment by learning experiences. The overall adaptation to the environment appears through the local behavior of entities that is adaptive..

Found in nature, many biological and social systems are similar to the CAS: the immune system, bird flocks, the cell, insect colonies, brain, economic markets etc.... All these systems are characterized by their two key concepts, namely the emergence of global behavior, which is due to of the lack of centralized control and measuring self- organization adaptation to the environment by relative learning.

The multi-agent systems (MAS) and cellular automata (CA) are the only approaches, used by the community for modeling CAS. The MASs are criticized for their complexity, by against the CAs are also criticized for lack of environment.

Recently, many studies have using FCMs [1][2], to model complex systems where CASs are a special case, and have given encouraging results [3] [4]. In this paper we present an approach for modeling CASs based on FCM formalism augmented by the concept of reinforcement learning algorithm inspired Q-Learning, and linear weight adaptation method based on hebbian learning algorithm [5] developed for neural networks to achieve adaptation to new environmental conditions.

2. THEORY ASPECTS

2.1 Fuzzy cognitive maps

The term cognitive map (CM) appears for the first time in 1948's in article by E. Tolman [6] cognitive maps in rats and men to describe the abstract mental representation of space built by rats trained to navigate in the labyrinth. The term FCM (Fuzzy Cognitive Map) was introduced in 1986 by B. Kosko [2], to describe a simple extension of CMs by the combination of fuzzy logic and artificial neural networks. This robust combination given FCMs a structure similar to artificial recurrent neural networks (Artificial Recurrent Neural Network ARNN. FCMs (Figure 1) can describe the complex behavior of entities. They are represented as directed graphs whose nodes are concepts (classified into three types: sensory, motor and effectors) and the arcs represent causal relationships between these concepts. Each arc from one concept C_i to one concept C_j is associated with a weight w_{ij} reflecting a relationship of inhibition ($w_{ij} < 0$) or excitation ($w_{ij} > 0$). Each concept is associated with a degree of activation, represent's the state at time t, and can be modified over time. The dynamics of an FCM can be summarized in one cycle (from t to t +1) by updating the activations vector.

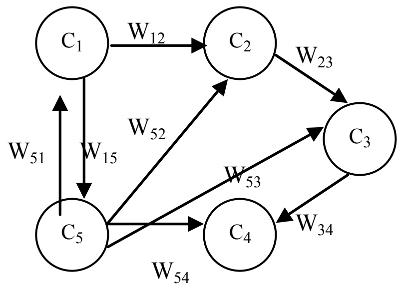


Fig 1: An FCM as a graph

The following gives a formal description of an FCM [7]. K denotes one of the rings $\mathbb{Z}$ or $\mathbb{R}$, by δ one of the numbers 0 or 1, for V one of the sets {0, 1}, {-1.0, 1}, or [-δ,a]. Let (n, t_0) ∈ IN² and k ∈ $\mathbb{R}^{*+}$. An FCM F is a sixfold (C, $\mathbf{A}$, W, A, f_a, R):

- $C = \{C_1, \ldots, C_n\}$ is the set of n concepts forming the nodes of a graph.
- $A \subset C \times C$ is the set of arcs (C_i, C_j) oriented from C_i to C_j.
- $W: C \times C \rightarrow K$

$(C_i, C_j) \rightarrow W_{ij}$ is a function of $C \times C$ to *IR* associating a weight W_{ij} to a pair of concepts (C_i, C_j), with $W_{ij} = 0$ if $(C_i, C_j) \notin A$, or W_{ij} equal to the weight of the edge if $(C_i, C_j) \in A$. Note that $W(C \times C) = (W_{ij}) \in K^{n \times n}$ is a matrix of M_n *(IR)*.

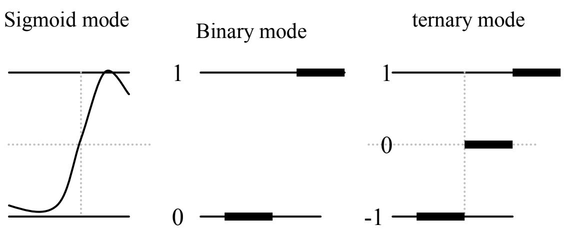
- $A: C \rightarrow V^n$

  $C_i \rightarrow a_i$ is a function that maps each concept C_i to the sequence of its activation degree at the moment $t \in$ IN, a_i (t) $\in V$ is its degree of activation at the moment *t*. We Note $a\ (t) = [(a_i\ (t))_{\ i\ \in\ [[1,\ n]]}]^{T}$ the vector of activations at the moment *t*.

- $f_a \in (IR^{n})^{N}$ is a sequence of vectors of forced activations such as for $i \in [1, n]$ and $t \geq t_0$ is the forced activation of the concept C_i at the moment t.

- *(R)* is a recurrence relationship on $t \geq t_0$ between $a_i\ (t+1)$, $a_i(t)$ and f_{ai} (*t*) for $i \in [1,n]$ indicating the dynamics of the map *F*.

$$\begin{cases} (R): \ \forall i \in [1, n], \forall t \geq t_0, \\ a_i\ (t_0) = 0 \\ a_i\ (t+1) = \sigma[g_i(f_{\ ai}(t), \sum_{j \in [1,n]} W_{ij}\ a_j(t))] \end{cases}$$



f (x) = 1/(1+e^{-x}) **f (x) = 1 si x ≥k** **f (x) = 1 si x≥k**

0 si x ≤k **0 si x = k**

-1 si x≤k

Fig 2. Cognitive maps' standardizing function.

The Mode represented by the function f is to reduce the value of concepts within the range of values taken as the area and can be either binary, ternary and sigmoid. The value of each concept is calculated with original formula proposed by Kosko [2]:

$$A^{(\kappa+1)} = f(\ \Sigma\ A^{(\kappa)}.\ \omega\ ) \qquad (1)$$

Other alternatives involve taking into account the past history of concepts and jointly proposed the following equation:

$$A^{(\kappa+1)} = f(A^{(\kappa)} + \Sigma\ A^{(\kappa)}.\omega) \qquad (2)$$

The Algorithm 1 shows the steps to follow for the calculation of the next input vector .

Algorithm 1: Calculation of the output vector

Step 1: Read the input vector $A^{(\kappa)}$ and weight matrix W.
Step 2: Calculate the output vector $A^{(\kappa+1)}$:
$A^{(\kappa+1)} = f(\Sigma\ A^{(\kappa)}.\ \omega\ )$
Step 3: Apply the transfer function f to the output vector $A^{(\kappa+1)}$
Step 4: verify the conditions of termination of the algorithm

2.2. Reinforcement Learning (RL)

The Markov Decision Processes (MDP) defines the formal framework of reinforcement learning [8]. More formally, an MDP process is defined by:

- S, a finite set of states. s Є S
- A, a finite set of actions in state s. a Є A(s)
- r, a reward function. r(s, a) Є R
- P, the probability of transition from one state to another depending on the selected action P (s '| s, a) = P_a(s, s').

The problem is to find an optimal policy of actions that achieves the goal by maximizing the rewards, starting from any initial state. At each iteration, the agent being in the state chooses an action, according to these outputs the environment sends either award or a penalty to the agent shown by the following formula: $r_i = h\ (s_i, a_i, s_{i+1})$.

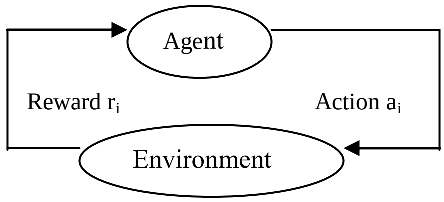


Fig 3 : Agent-environment Interaction in reienforcement learning

To find the total cost, which is represented by the formula $\Sigma\ h(s_i,a_i\ ,s_{i+1})$, the costs are accumulated at each iteration of the system. In [9] the expected reward is weighted by the parameter γ and becomes $\Sigma\ \gamma\ h\ (s_i,a_i,s_{i+1})$ with $0 \leq \gamma \leq 1$. The RL is to find a policy or an optimal strategy π *, among the different π possible strategies in the selection of the action. Q-Learning algorithm [8] is to introduce a quality function Q represents a value for each state-action pair and Q^{π} (s, a) is to strengthen estimate when starting from state s, executing action a by following a policy π: $Q^{\pi}(s, a) = E\ \Sigma\gamma r_i$ and Q*(s, a) is the optimal state-action pair by following policy π* if $Q^*(s, a) = \max Q^{\pi}(s, a)$ and if we reach the $Q^*(s_i, a_i)$ for each pair state-action then we say that the agent can reach the goal starting from any initial state . Initially, the Q values are initialized most cases to 0 and the value of Q is updated by the equation:

$$Q^{k+1}(s_i\ ,a_i) = Q^{k}\ (s_i\ ,a_i) + \alpha[h(s_i,a_i\ ,s_{i+1}) + \gamma \arg\max(Q^{k}(s_{i+1,}a)) - Q^{n}\ (s_i\ ,a_i)] \qquad (2)$$

α is called learning parameter.

3. THE ADAPTATION OF LFCM

The CASs [10] are distinguished from other systems by their dynamic improvements in current policy for each interaction with the environment. So this is a local building that does not require an assessment of the overall strategy. This observation leads us to overlook the value of the quality function Q in step (i+1). This translates mathematically by: $Q^n(s_{i+1}, a) = 0$ and therefore equation (2) of the function Q becomes as follows:

$$Q^{\kappa+1}(s_i, a_i) = Q^{\kappa}(s_i, a_i) + \alpha\,[r_i - Q^{\kappa}(s_i, ai)] \qquad (3)$$

The following pseudo code provides an update of the value of Q function:

If r = 1 / / Award

$$Q^{\kappa+1}(s_i, a_i) = Q^{\kappa}(s_i, a_i) + \alpha[1- Q^{\kappa}(s_i, a_i)]$$

If r = 0 / / Penalty

$$Q^{\kappa+1}(s_i, a_i) = (1 - \alpha)\, Q^{\kappa}(s_i, a_i)$$

In our approach, if the states are represented after fuzzyfication by the concepts inputs or sensory concepts, the output vector is represented by the set of output concepts or effectors concepts that represent actions to perform in the environment after defuzzyfication. The motors concepts are the decision-making mechanism.

The value of Q is designed to instruct the agent to consider optimally its historical past. If the agent is in a state already visited, with a Q value in the table of values, it will be directly exploited to move to the next state, otherwise it will explore the possible actions in this state according to their respective probabilities. The exploration of the actions is accompanied by an update of their probabilities according to the linear scheme [11]:

If r = 1 / / Award

$$P^{\kappa+1}(s_i, a_i) = P^{\kappa}(s_i, a_i) + \beta\,(1 - P^{\kappa}(s_i, a_i))$$

If r = 0 / / Penalty

$$P^{\kappa+1}(s_i, a_i) = (1-\beta)\, P^{\kappa}(s_i, a_i)$$

4. THE PROPOSED APPROACH

Based on the theoretical aspects described above, the pseudo code of Algorithm 2 summarizes our approach.

Algorithm 2 : Pseudo code of the proposed appoach

Step 1: Read the vector $A^{(k)}$ and weight matrix W

Step 2: Calculate the output vector $A^{(k+1)}$:
$A^{(k+1)} = f(A^{(k)} + \Sigma\, A^{(k)}.\, W)$

Step 3: Apply the transfer function f to the output vector $A^{(k+1)}$

Step 4: Among the active concepts choose the one that has the highest value of the function Q, if not probability

Step 5: calculate the new output vector (output concepts) $A^{(k+1)}$

Step 6: Depending on the response to the environment:

If r = 1 / / Award

(Updating the probability P_{ij} and the Q value)

$$Q^{\kappa+1}(s_i, a_i) = Q^{\kappa}(s_i, a_i) + \alpha\,[1 – Q^{\kappa}(s_i, a_i)]$$

$$W^{\kappa+1}(C_i,C_j) = W^{\kappa}(C_i,C_j)$$

$$P^{\kappa+1}(a_i) = P^{\kappa}(a_i) + \beta\,[1 - P^{\kappa}(a_i)]$$

If r = o / / Penalty

(Updating the probability P_{ij}, the weight of the connection and the value of Q)

$$Q^{k+1}(s_i, a_i)) = (1- \alpha)\, Q^{k}(s_i, a_i)$$

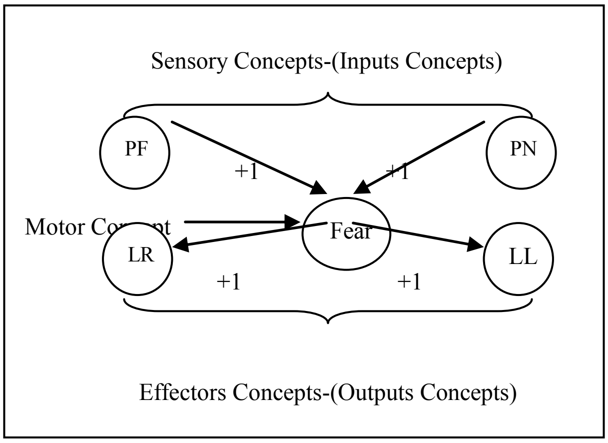
$$W^{\kappa+1}(C_i,C_j) = W^{\kappa}(C_i,C_j) + \eta\,[1 - W^{\kappa}(C_i,C_j)]$$

$$P^{\kappa+1}(a_i) = (1-\beta)\, P^{\kappa}(a_i)$$

Step 7: If the termination conditions are realized Stop. Otherwise go to Step 2

5. THE PREY AND PREDATOR MODEL SIMULATION

It is assumed that the prey in a presence of a predator has only two actions to be taken for escape. Leak to the right (LR) and Leak to the left (LL). The use of probabilities of actions and values of the function Q provide a compromise between exploration and exploitation of actions. An FCM to represent this model in the theoretical framework of FCMs can be outlined as follows:



$$W = \begin{array}{c|ccccc} & C_1 & C_2 & C_3 & C_4 & C_5 \\ \hline C_1 & 0 & 0 & +1 & 0 & 0 \\ C_2 & 0 & 0 & +1 & 0 & 0 \\ C_3 & 0 & 0 & 0 & +1 & +1 \\ C_4 & 0 & 0 & 0 & 0 & 0 \\ C_5 & 0 & 0 & 0 & 0 & 0 \end{array}$$

Fig 4 : FCM's escape behavior of prey against its predator and W matrix link

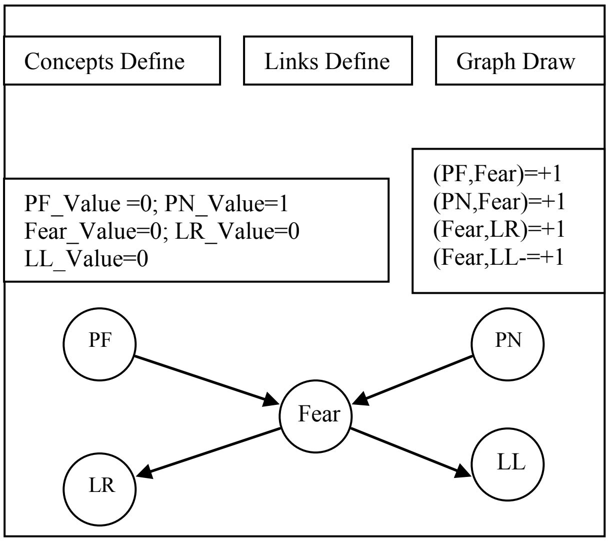


Fig 5: Main view of LFCM tools

Concepts C_1, (PF) for the Predator Far, and C_2, (PN) Predator Near, are the inputs sensory concepts. The concepts C_4 (LR), Leak Right, and C_5 (LL), Left Leak, are taken as effectors outputs concepts and concept C_3 (Fear) is a concept motor. The FCM (Figure 3) has four edges and five concepts with links excitatory (+1) of 'NP' to 'Fear' and 'Fear' to 'LR' and 'LL', and linked inhibitor (-1) of 'PF' to ' fear' . Activation of sensory concepts NP and PF fuzzyfication is achieved by the distance to the predator, while the defuzzification gives to escape a recession velocity for this agent.

The concept is active if its value is 1, otherwise it is inactive (binary mode). It is given an initial activation vector A = (0 1 0 0 0). Table 1 show's the values $P(a_i)$ of the probabilities of actions and values of the function Q updated at each iteration. Table 2 gives the output vector for all iterations in response to the environment.

Table 1. Action probabilities and Q-Function values

a_i	$P(a_i)$	$Q(s_i, a_i)$	value
LL	0.5	(NP,LL)	0
LR	0.5	(PF,LR)	0

Table 2. Output Vector

Inputs	Output vector	Iteration
(0 1 0 0 0)	0 1 0 0 0	1
	0 1 1 0 0	2
	0 1 1 1 1	3
	0 1 1 1 0	4

At iteration n ° 3 the prey is facing a situation where it has two possible actions, represented by the active concepts C_4 and C_5, but must choose one among them and this choice is guided either by the value of function Q, if the state is already visited, or by the value of the probability of the action if the first pass in this state.

6. Related work

We have selected two axes to compare our approach with the approaches used by the different teams in the field of intelligent modeling of dynamic systems. The first concerns the graphical representation and the second axis concerns the mathematical description of the studied system.

1. The FCMs graphical representation can view the structure of the studied system in the form of concept (node) that represent a state, a propriety or other characteristic of the modeled system, connected by causal relationships that determine the nature of the action exerted on each other concepts which it is connected. This graphical representation can develop relatively simple and readable models something that is not found in the AMAS theory [12] and in the cellular automata field [13].

2. The FCMs mathematical foundations [4] can express the behavior of the investigated system in algebraic form. The future state of the system is derived by simply applying algebraic methods represented here by the multiplying the current state vector with the causal links matrix and the result of the operation gives a new state vector to be used as an input for the nest step.

7. ACKNOWLEDGMENTS

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8. CONCLUSION

The complexity and criticism raised by the community in the field of modeling CASs by MASs and CAs, led us to seek another approach, which is contained in same concepts inspired by the area of life. In psychology behavior is generally related to the concepts of emotions, perceptions and sensations. These key concepts of life can be supported by FCMs. CASs are therefore in the field of artificial life more than other areas of computing. The area of FCMs, despite the improvement made by different research teams in the world, remains an area dense, low-unified.

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