Timed-Fuzzy Cognitive Maps: An overview

Evangelia Bourgani
Dept. of Computer Science & Engineering,
University of Ioannina,
Ioannina, Greece
Email: ebourgani@gmail.com

Chrysostomos D. Stylios
Dept. of Computer Engineering,
Technological Educational Institute of Epirus,
Artas, Greece.
Email: stylios@teiep.gr

George Manis
Dept. of Computer Science & Engineering,
University of Ioannina,
Ioannina, Greece
Email: manis@cs.uoi.gr

Voula C. Georgopoulos
School of Health and Welfare Professions,
TEI of Western Greece,
Patras, Greece
Email: voulacg@gmail.com

***Abstract*— Fuzzy Cognitive Maps have been widely used for modeling complex systems but time and evolution of the system has not sufficiently been illustrated and taken into consideration within the FCM model. Time is a substantial aspect for any application because factors determining the behavior of the system evolve over time; they affect and change the route of any evolution of the system. This work further explains and justifies Timed Fuzzy Cognitive Maps (T-FCMs), an extension of the known soft computing technique of FCMs that can handle uncertainty to infer a result. T-FCM has been introduced to take into consideration the time evolution of any system and it provides intermediate modeling results. This work also introduces the combination of T-FCMs with Hidden Markov Model (HMM) to create an integrated system which always reach a decision, as HMM are called in the case that T-FCM do not converge to an acceptable state and HMM suggests the most probable state (decision-concept).**

Keywords— Timed-Fuzzy Cognitive Maps; Hidden Markov Model; Soft Computing; modeling; Decision Support Systems

I. INTRODUCTION

Nowadays systems are characterized by high complexity. This results from the fact that they should be more complex in order to approximate better real world systems. Real world problems consist of many and various factors that can be complementary, contradictory and competitive. Decision Support Systems can provide assistance during the process of decision making, which involves the comparison and selection of the best (or optimal) decision. FCMs have been used successfully to develop Decision Support Systems (DSS). The major advantage of FCMs is that they can handle even incomplete or conflicting information. This is essential in almost any field, where experts should take many factors under consideration before they can reach a decision.

Fuzzy Cognitive Map (FCM) is a soft computing modeling technique for complex systems, which originated from the combination of Fuzzy Logic and Neural Networks. It was introduced [1] as an extension to Cognitive Maps [2] They are a graphical representation for the description and modeling of the behavior and operation of a system. FCM supports the causal knowledge reasoning process and belongs to neuro-fuzzy systems that aim at solving decision making and modeling problems. FCM resembles human reasoning; it relies on the human expert knowledge for a domain, making associations along generalized relationships between domain descriptors concepts and conclusions. It models any real world system as a collection of concepts and causal relations between concepts [3].

The graphical representation consists of interrelated concepts. FCMs are dynamical, fuzzy signed directed graphs, permitting feedback, where the weighted edge w_{ij} from causal concept C_i to affected concept C_j describes the amount by which the first concept influences the latter, as is illustrated in Fig. 1. Experts design and develop the structure of the system, including the nodes that represent the key factors of the system operation. They determine the way of network's interconnections, using linguistic variables to describe the relationships among concepts. Then all the variables are combined and the weights are determined. Learning methods and historical data lead to an equilibrium point [4], [5].

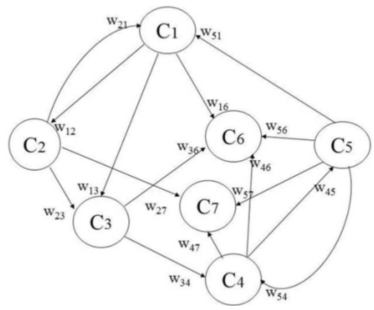

Fig. 1. The Fuzzy Cognitive Map model

FCMs have been applied to various fields. They have been used to model and simulate many problems that require decision making or classification or prediction/checking of scenarios. Thus, many extensions of the basic FCM model and combinations with other technologies are used in order to better approximate real world problems [6]. Until now, the concept of time has been used in limited cases [7], [8], [9]. For many fields, time is a vital concept for the evolution of a case. In the medical field, for example, time can change the final result in any given moment. For this reason, T-FCM tries to insert the concept of time and base the evolution of a case on previous time units. Also, it lets the user intervene on the overall procedure, by changing values during the time units, while the intermediate results illustrate the evolution of a case during the time.

In this work, section two presents an overview of Timed-Fuzzy Cognitive Maps, which is further explained and justified and it introduces a detailed designing and learning methodology. Section three proposed an integrated system based on the synergy of Hidden Markov Models (HMMs) with T-FCMs, which is used for the cases that the model does not conclude to a clear decision. Section four concludes the paper and proposes future directions.

II. TIMED-FUZZY COGNITIVE MAP

A. *Timed-FCM Design*

Timed-FCMs have been introduced in works [10] and [11]. The block diagram presented at Fig.2 describes the main steps that should be followed in order to design a T-FCM

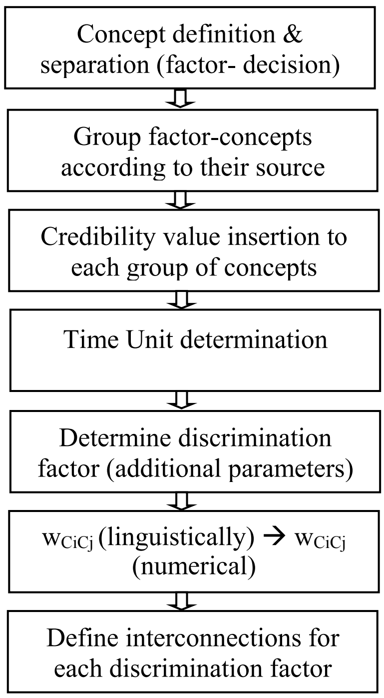

Fig. 2. Block diagram of T-FCM design

As in most of the cases of Soft Computing approaches, the T-FCM design and construction demands expert interference. However, the gathering of concepts for creation a model requires extensive professional experience, literature review, long time detailed observation so that to include each and every source that would appeared and/or could possibly be seen. The model can incorporate the information of various sources. The validity of each source is determined by introducing and determining a corresponding credibility factor. Thus, the concepts are gathered into groups according to their origin, i.e. if a concept originates from literature this will belong to the group with the highest credibility value, while if it comes from an observation of a non-professional will belong to group with the lowest credibility value. In this way, the concepts will be extra-weighed according to their origin and the suitable importance will be given to the participating concepts.

In the next step, experts will define the time unit for every concept evaluating the ability of the smallest change. Taking into account even the smallest change, it will be able to follow the real evolution of a case. Afterwards, experts have to define the additional parameters/characteristics where every combination of parameters corresponds to a unique case/model and actually develops a unique modified version of the FCM. These parameters are exterior factors that may seem not affecting the overall procedure, but they are substantial for characterizing a case and define the changes over time. The values of parameters, γ_p, are binary and characterize if a parameter is activated or not. However, even if these parameters lead to a more specified model, they also increase the complexity of the method. This means that there are 2^p different cases/situations, which correspond to their own FCM model and their evaluation over time. Table 1 illustrates the possible situations.

TABLE I. DISCRIMINATION PARAMETER

Discrimination parameter	**Additional Parameters ($\gamma_1,\gamma_2,\ldots\gamma_p$)**
m_0	000….0
m_1	100….0
m_2	010….0
m…	111.....1

The final steps demand the definition of interconnection weights for each discrimination parameter m_k and for each time unit.

The main steps of the algorithm for constructing a T-FCM [10] and [11] are summarized to the following:

Step 1: Concepts are gathered determined by experts and other sources.

Step 2: Concepts are grouped according to their origin.

Step 3: Credibility weight values are assigned for each group –based on their experience.

Step 4: Experts determine time unit. Time unit will be the smallest time that evens a small change at a concept value could take place. That is the time required when starting from an initial state (S_t) to transient to a new one (S_{new}) state.

Step 5: Experts determine the values of additional parameters that correspond to unique cases.

Step 6: Experts will define weights per time unit linguistically. They determine the weight between two concepts (w_{CiCj}) linguistically, all the linguistic values corresponding one interconnection are aggregated, an overall fuzzy weight is produced which is then transformed into a numerical value, using fuzzy logic based approaches.

$$w_{CiCj}\,(\text{linguistically}) \rightarrow w_{CiCj}\,(\text{numerical})$$

This procedure is repeated for each possible activated discrimination factor m in Eq. (1)

$$w_{m,t,ij} = [w_{m_0,t_1,ij}, w_{m_0,t_2,ij}, \ldots, w_{m_0,t_n,ij}, w_{m_1,t_1,ij}, \ldots, w_{m_1,t_n,ij}, w_{m_n,t_1,ij}, w_{m_n,t_2,ij}, \ldots, w_{m_n,t_n,ij}] \quad (1)$$

and each $w_{\gamma,t,ij} \in [-1,1]$

This procedure will define for each discrimination factor the corresponding interconnections among the FCM's concepts.

Step 7: for $m_k = m_0$ or m_1, or… m_k and for $t = t_0, t_1, \ldots t_n$ the interconnections $d^t_{m,t,ij}$ among concepts will be dependent on the weight, case m and the corresponding time unit. Thus, for a time unit the weighted interconnection between two concepts will be given by equation (2):

$$d^t_{m_k,t,w_{ij}} = f\left(\sum_{\substack{i \neq j \\ j=1}}^{j=N} d^t_{m_k,t,w_{ij}}\right) = f(w, m_k, t, C_i, C_j) \quad (2)$$

Apart from the T-FCM construction, the training of the T-FCM so that to better modify the weights is required along with taking into consideration the FCM convergence.

T-FCM main aspect is the introduction of time for the evolution of case/model so that T-FCM create more efficient models that could be used for various applications. The selection of time unit is determined by the experts and has to correspond to the specific application. The construction of the T-FCM model includes determining the concepts, weight-interconnections, time unit and discrimination factor by experts.

B. *Timed-FCM Learning*

A learning approach of the model is proposed which is based on known FCM training approached but with some new enhancements so that to take into account the time unit and the individual characteristics of the case/model under investigation. Thus, in T-FCM model we insert the aspect of time in the calculation of the next concept value and this time unit plays a significant role during the training.

Specifically, the value A_i of the concept C_i expresses the degree of its corresponding physical value at each simulation step, the value A_i of a concept C_i is calculated by computing the influence of other concepts C_j's on the specific concept C_i on a specific time unit for a specific discrimination factor combinations following the calculation rule (3):

$$A_i^{k+1}(t) = f\left(A_i^k(t-1) + \sum_{t=1}^{t-1} \sum_{\substack{j \neq i \\ j=1}}^{n} A_j^k(t-1) d^t_{m,t,w_{ij}}), m \right) \quad (3)$$

where A_i^{k+1} (t) is the value of concept C_i at simulation step k+1 for a time unit, A_j^k(t-1) the value of the interconnected concept C_j at simulation step k, $d^t_{m,t,ij}$ is the weight of the interconnection between concept C_j and C_i for the discrimination factor m , and f is a sigmoid threshold function:

$$f = \frac{1}{1 + e^{-\lambda x}}, \quad (4)$$

where $\lambda > 0$ is a parameter that determines its steepness

For a case $m=m_0$, there are calculated the corresponding values for a specific case and they would be constant during the overall procedure. This value is a combination of binary values which is determined based on the discrimination parameter and is activated by the user. The final value of m renders the under investigation case (m_0) as unique. The value of *m* will determine the evolution of the model for $m=m_0$. This results from the fact that *m* takes value in the initial state of procedure and individualizes each case-study.

After the determination of the discrimination parameter the T-FCM training stage follows. The convergence of T-FCM will result either to a steady-state which will give a 'clear' value or an infinitive loop without equilibrium point. Whether we have a clear decision or not is also determined by what is defined as accepted by the users. This means that the user should define the value of $\Delta_{DecisionDistance}$, which depicts the sufficient distance among all the decision concepts in order to regard a decision as an acceptable one or not. In case that the learning does not result to an acceptable one or the learning method does not reach to equilibrium point HMM can be used. Using HMM model, the integrated model will infer a final result which will be based on probabilities.

The main steps for T-FCM learning are summarized to the following algorithm:

Step 1: User sets the initial values of additional parameters, so that the under investigation case be defined.

Step 2: Start state (A_0). For i =1,…N expert characterizes linguistically the initial value of every concept.

$$A_0 = C_i(t_0)$$

Step 3: For t=1,…,N the value A_i of the concept C_i for a specific discrimination factor m=m_0 at k+1 step is calculated using (3)

Step 4: Start simulation running per time unit, presenting the result for each time span. The defined time unit is taken into consideration for each application and field. This means that the results per time unit are adaptable on each change and influence, eliminating the case of wrong decision.

Step 5: The simulation will stop when the values of the Decision Concepts that correspond to the possible decisions will have sufficient difference between them. This difference depends on the nature of problem and the required decision-making procedure. A decision will be acceptable if the distance among decision concepts will be greater than a pre-defined as acceptable value (e)

$$|\Delta_{DecisionDistance}| \geq e$$

Step 6: If $\Delta_{DecisionDistance}$ is not under the acceptable range or the overall procedure results in a infinitive loop without a clear decision, then Hidden Markov Model (HMM) have to be called in order to provide more information and support the selection of reaching a decision.

The calculation procedure provides intermediate results. For each time unit, the T-FCM gives a result based on the initial state that the user has inserted. The user can change the values of concepts for each time unit, if s/he justifies as necessary because a state has change unexpectedly. During this procedure the user can interfere on the results by increasing or eliminating or removing concepts and as result interconnections, rendering the system a dynamic one. It allows the change, increase, decrease or elimination of some interconnections.

However, it is possible that the system may not to converge to a ‘clear’ decision [12]. For this occasion, Hidden Markov Models (HMMs) is called so that to select among the T-FCM decision concepts and give the most possible final result.

III. Synergy of T-FCM and HMM in Convergence Procedure

Hidden Markov Models (HMMs) are well-known for their effectiveness in modeling the correlations among adjacent symbols, domains, or events, and they have been extensively used in various fields, especially in speech recognition [13], digital signal processing and telecommunications. HMM can be viewed as a specific instance of the state space model in which the latent variables are states [14]. HMMs were introduced by Baum et al. [15], where they were viewed as statistical models and could be considered as a Markov model whose states cannot be explicitly observed. However, HMMs has been applied to various fields apart from speech recognition [16]. They have been used for speech synthesis [17], machine translation [18], activity recognition [19] and for many other applications.

In this work, we introduce the use of HMMs in combination with T-FCM. The HMM will be called in the occasion of non-convergence of the T-FCM model or when the difference between the values of decisions concepts is not sufficient to identify the winning concept. If the results do not show a clear decision, HMMs are called in order to calculate the probability of the observation sequence given the T-FCM model. This method will lead to select the most probable decision when it is hard to reach one clear decision, based on the basic FCM procedure [3],[20] and [21].

HMMs have been used for various cases and applications and they are well-known for solving three basic problems [22]: evaluation problems, decoding problems and learning problems.

Consider the N state discrete model with M possible outputs. Formally, an HMM is defined by the following parameters:

1. Finite set of N hidden states: S= {S_1;S_2;…;S_N}
2. Distinct observation symbols per state, can be seen as physical output of the system;
$$V = \{V_1, V_2, \ldots, V_M\}$$
3. The transition matrix ‘A’, represents the probability of going from state Si to state Sj;
$$A = \{a_{ij};\, j = 1, \ldots, N\}$$
$$a_{ij} = P[q_{t+1} = Sj \mid q_t = S_i],\ 1 \leq i, j \leq N$$
$$with\ a_{ij} \geqslant 0\ and \sum_{j=1}^{N} a_{ij} = 1$$
4. The initial state probability vector ‘π’, represents probabilities of initial states;
$$\pi = \{\pi_i\}\, i = 1, \ldots, N$$
$$\pi_i = P[q_1 = Si] \quad i = 1, \ldots, N$$
$$with \quad \pi_i \geqslant 0\ and\ \sum_{i=1}^{N} \pi_i = 1$$

5. Observation symbol probability distribution matrix 'B', represents the probability of producing observation *k* at time *t* in state S_i;

$$B = \{bj(O_t)\} \quad O_t = k$$

$$b_j(O_t) = P[V_k \quad at \quad t \mid q_t = S_j] \quad j = 1, 2, ..., N$$

$$k = 1, 2, ..., N$$

Here, we will apply the known as second type of problem, that is, the decoding problem. It can be described as: Given a model λ and a sequence of observations $O=O_1, O_2, \ldots, O_N$, what is the most likely state sequence in the model that produced the observations?

We propose to apply HMMs when FCM has reached its finite state, but the distance among the decision concepts is not enough distinct to determine the winning concept. In this case, HMM will take action in order to indicate the most probable state. Using Hidden Markov Models, the system will select the most probable state given the T-FCM model and the sequence of observations. The sequence of observations $O=O_1, O_2, \ldots, O_N$ set to be the concepts-factors at the time that system has reached to the final state. The result of this action will give us the most probable state sequence (decision-concept) that could come from the given observation sequences.

IV. Conclusion

In this work, we describe in detail how the T-FCM model is built, which takes into consideration the aspect of time in modeling a system. Time is essential for many problems in order to approximate better real situations. Timed-FCM takes into consideration the evolution of a case, inserting parameters that makes the model case-sensitive and developing a model for each case-study unique. The combination of these parameters is determined and indicated by the discrimination factor. The construction of T-FCM is mainly based on the discrimination factor, which can route to the various evolution of a problem. Timed-FCM incorporates the time by determining, in each time step, the dependence of time among the concepts and quantifying this dependence. The described method gives the opportunity to make a transparent and dynamic system, that could be changed by the user at each time step. Also, its initial state (case) is determining by the user who sets and determines the exterior parameters of the problem according to the under-investigation case. T-FCM generates intermediate results corresponding to the time units and the evolution of the system. This lets the user to judge the result and change the selection of parameters if it is necessary.

However, the proposed method (T-FCM) may conclude to a non-convergent state in which no 'clear' decision can be made from the existing results. For overcoming this situation, this work also proposes the combination of T-FCMs with the HMM. In this way, T-FCMs are combined with HMM in order to suggest a decision based on a probabilistic approach. This method will propose the most probable decision-concept based on the observation states (concept-factor values) at their last steady state. This combination will always lead to a decision, even if the T-FCM did not manage to reach a clear-acceptable one.

In future work, we will further enhance the proposed method and we implement it to develop a Medical Decision Support System, which would be an assistant tool for the medical doctors as a diagnosis tool.

Acknowledgment

This work was supported by the National funds allocated by the Greek General Secretarial of Research and Development project 2006SE01330025 as continuation of FP7–PEOPLE–IAPP–2009, Grant Agreement No. 251589, Acronym: SAIL

References

[1] Bart Kosko, "Fuzzy Cognitive Maps," International Journal of Man-Machine Studies,24, pp. 65-75, 1986.

[2] R. Axelrod, Structure of Decision: the cognitive maps of political elites. NJ: Princeton, 1976.

[3] C. D. Stylios and P.P. Groumpos, "Modeling Complex Systems Using Fuzzy Cognitive Maps," in *IEEE Transactions on Systems, Man and Cybernetics: Part A Systems and Humans.*, vol. 34, 2004, pp. 155-162

[4] E. Papageorgiou, C. D. Stylios and P. Groumpos "Active Hebbian Learning Algorithm to train Fuzzy Cognitive Maps," *Int. journal of Approximate Reasoning*, vol. 37, pp. 219-249, 2004

[5] E. Papageorgiou, C. D. Stylios and P. Groumpos, "Unsupervised Learning Techniques for Fine-Tuning Fuzzy Cognitive Map Causal Links," *Int. Journal of Human Computer Studies* , vol. 64, pp. 727-743, 2006.

[6] M. Hagiwara, "Extended fuzzy cognitive maps," in *Fuzzy Systems,IEEE International Conference*, San Diego, CA, 1992, pp. 795 - 801.

[7] K. S. Park, "Fuzzy cognitive maps considering time relationships," *Computer Studies*, vol. 42, pp. 157-168, 1995.

[8] J. P. Carvalho and J. A. Tomé, "Rule Based Fuzzy Cognitive Maps- Fuzzy Causal Relations," *Computational Intelligence for Modelling, Control and Automation*, 1999.

[9] Y. Miao, Z.-Q. Liu, C. K. Siew, and C. Y. Miao, "Dynamical Cognitive Network—an Extension of Fuzzy Cognitive Map," *IEEE TRANSACTIONS ON FUZZY SYSTEMS*, vol. 9, pp. 760-770, October 2001.

[10] E. Bourgani, C. D. Stylios, G. Manis, and V. C. Georgopoulos, "Integrated Approach for Developing Timed Fuzzy Cognitive Maps," in *Advances in Intelligent Systems and Computing, Intelligent Systems'2014*, Warsaw, Poland, 2014, pp. 193-204.

[11] E. Bourgani, C.D. Stylios, G. Manis, and V.C. Georgopoulos, "Timed Fuzzy Cognitive Maps," in *IEEE International Conference on Fuzzy Systems FUZZ-IEEE 2015*, Istanbul, Turkey, August 2-2015, pp. 1-6.

[12] V. Georgopoulos and C. Stylios, "Complementary case-based reasoning and competitive Fuzzy cognitive maps for advanced medical decisions," in *Soft Computing*, vol. 12, 2008, pp. 191-199.

[13] L.R. Rabiner, "A tutorial on hidden Markov models and selected applications in speech recognition," in *Proc. IEEE*, 1989, pp. 257–286.

[14] Rakesh Dugad and U.B. Desai, "A tutorial on Hidden Markov Models," Technical Report SPANN 96.1, May 1996.

[15] Leonard E. Baum and Ted Petrie, "Statistical Inference for Probabilistic Functions of Finite State Markov Chains," in *The Annals of Mathematical Statistics 37, no. 6*, 1966, pp. 1554-63.

[16] G. Gravier, G. Potamianos, and C. Neti, "Asynchrony modeling for audio-visual speech recognition," in *Human Lang. Techn. Conf. (HLT)*, San Diego, 2002, pp. 1-6

[17] C. Champion and S.M. Houghton, "Application of continuous state Hidden Markov Models to a classical problem in speech recognition," in *Computer Speech and Language* , 2015, pp. 347–364.

[18] M.R. Costa-jussàa and J.A.R. Fonollosa, "Latest trends in hybrid machine translation and its applications," in *Computer Speech and Language*, 2015, pp. 3-10.

[19] M. Vieira, D.R. Faria, and U. Nunes, "Real-time Application for Monitoring Human Daily Activity and Risk Situations in Robot-Assisted Living," in *Robot 2015: Second Iberian Robotics Conference*.: Springer International Publishing, 2015, pp. 449-461.

[20] Bart Kosko, "Fuzzy Cognitive Maps," *International Journal of Man-Machine Studies,24*, pp. 65-75, 1986.

[21] R. Axelrod, *Structure of Decision: the cognitive maps of political elites*. NJ: Princeton, 1976.

[22] L. R. Rabiner and B, H. Juang, "An Introduction to Hidden Markov Models," *IEEE ASSP MAGAZINE* , pp. 1-16, January 1986.