Develop Fuzzy Cognitive Maps based on recorded data and information

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Abstract—**This work presents a novel integrated approach on how to develop Fuzzy Cognitive Maps combining human expert knowledge with existing recorded information and historical data. The proposed approach aims to extract information from unstructured data and to transform it into knowledge in the form of a FCM. The proposed approach still is dependent on experts but providing them with more information and supportive data, in the form of particular evidence-based information available in the literature in order to better justify their selections. The proposed approach is inherit to the FCM and its structure the extracted knowledge and it can be used to model a complex system such as the Medical Decision Support Systems .**

Keywords—Fuzzy Cognitive Maps, knowledge extraction, historical data, case based, soft computing

I. INTRODUCTION

Fuzzy Cognitive Maps (FCMs) [1][2] have been introduced to model causality among natural entities and they are widely used in many discipline application areas, achieving a great awareness as a soft computing modeling method for complex systems [3][4]. One main application of FCMs is their usage to infer and suggest decisions by applying a similar to human approach to abstractly describe any system through concepts (that stand for the main issues) and positive or negative weighted relationships among the concepts (describing the influence of one concept to another) [5][6].

Many different approaches have been proposed to develop and construct FCMs, mainly based only on human experts who are asked to determine the main concepts and design the conceptual FCM structure [7], which best models the operation of any complex system [5][8]. Other approaches were based on introduced simplified structures [9]; still others were based on exploiting quantitative existing historical data along with expert based approaches [10] or evolutionary development of FCMs [11]. There also is proposed, FCM development based on rule based among concepts including the dynamics of the system [12]. Another approach focused on the automatic determination of the membership functions and quantification of causalities [24]An additional proposed framework consisted of a representation level (the cognitive graph), an updating mechanism that receives feedback from the real system and a storage of the acquired knowledge throughout the operation. In that framework every node has its unique label and is characterized either as control, reference, output, simple and operation nodes [13].

In addition to the construction methodology either inherited during the developing procedure or later on, complementary learning algorithms have been applied. Learning algorithms influence mainly the way that the concepts update their values leading to different final values of concepts i.e. new converge states. Furthermore algorithms based on the Hebbian algorithm , have been proposed [14][15]; other algorithms come from the field of genetic algorithms [16], or other optimization techniques [17] in order to refine the FCM structure and achieve better performance. Learning algorithms are used to overcome the shortcomings that the traditional FCM present i.e. decreasing the human intervention by suggested automated FCM candidates; or by activating only the most relevant concepts every execution time; or by making models more transparent and dynamic [18]

Here, a new approach is proposed for developing Fuzzy Cognitive Map Medical Decision Support Systems (FCM-MDSS) mainly based on existing evidence-based information about a system that is published in relevant recognized sources along with the contribution from experts.

This paper includes section 2, where a general description of Fuzzy Cognitive Maps is presented. Section 3 describes the proposed algorithm for developing the FCM-MDSS. Section 4 concludes the paper briefly discussing the proposed approach and suggesting future directions.

II. FUZZY COGNITIVE MAPS

Fuzzy Cognitive Maps (FCMs) have been proposed for advanced modeling of complex systems, mainly because of their human-like reasoning approach. Since their introduction [1] FCMs have successfully been applied to a wide range of problems in various application domains, achieving recognition as a tool to model complex systems and every year the range of applications is increasing along with the number of publications. A particularly extended use of FCM has been for developing advanced diagnosis and other medicaldecision support systems.

FCMs are considered as a soft computing approach that aims to model systems and support decision-making procedures based on a reasoning approach in a human-like manner. As in most of the soft computing approaches, human knowledge and experience is inherited in the model through a human based designing and creation procedure and it is reflected in the FCM infrastructure itself. There have been proposed different Fuzzy Cognitive Map implementations, variants and modifications where they integrate aspects of fuzzy logic, neural networks, genetic algorithms, semantic networks, expert systems and they are usually supplemented with other soft and hard computing methodologies.

The general FCM illustration is a causal graphical representation consisting of interrelated concepts [1]. FCMs are fuzzy signed directed graphs permitting feedback, where the weighted edge w_{ij} from causal concept C_i to affected concept C_j describes the degree with which the first concept influences the latter, as is illustrated in Fig. 1.

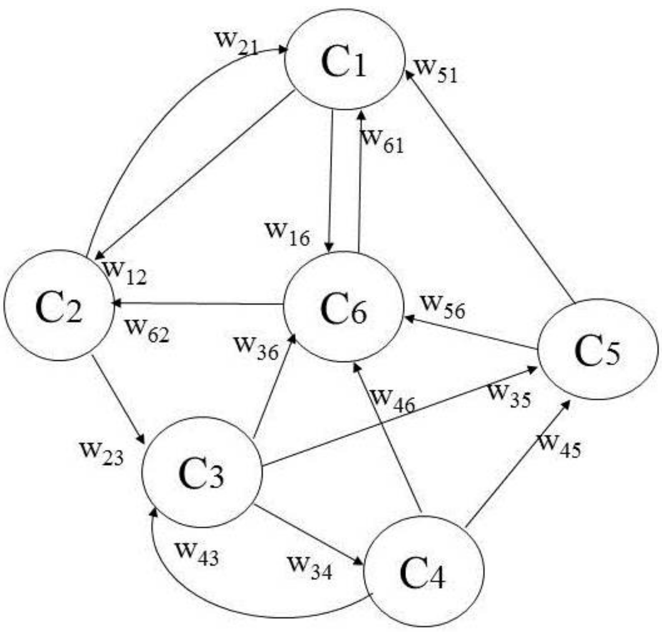

Fig.1. The Fuzzy Cognitive Map model.

The concepts of the Fuzzy Cognitive Model stand for the main characteristics comprising an abstract model of any system; each concept of the FCM represents a granular entity such as state, variable, input, output, event, action, goal, trend of the system that is modeled as an FCM. The value of every concept C_i is A_i and it results from the transformation of the real fuzzy value of the system's variable, for which this concept stands for, in the interval [0,1]. Thus, after the initial concept value is set, then this value is updated as it is computed through the interaction of the interconnected concepts with the corresponding weights. Generally, between two concepts there are three possible types of causal relationships that express the type of influence from one concept to the other. The weight of the arc between concept C_i and concept C_j could be positive ($W_{ij} > 0$) which means that an increase in the value of concept C_i leads to the increase of the value of concept C_j, and a decrease in the value of concept C_i leads to the decrease of the value of concept C_j. Or there is negative causality ($W_{ij} < 0$) which means that an increase in the value of concept C_i leads to the decrease of the value of concept C_j and vice versa.

The value A_i of concept C_i expresses the degree of its corresponding physical value. Fuzzy Cognitive Maps are used to model the behavior of a system; during the simulation step, the value A_i of a concept C_i is calculated by computing the influence of the interconnected concepts C_j's on the specific concept C_i following the calculation rule:

$$A_i^{(k+1)} = f(A_i^{(k)} + \sum_{\substack{j \neq i \\ j=1}}^{N} A_j^{(k)} \cdot w_{ji}) \tag{1}$$

where $A_i^{(k+1)}$ is the value of concept C_i at simulation step $k+1$, $A_j^{(k)}$ is the value of concept C_j at simulation step k, w_{ji} is the weight of the interconnection from concept C_j to concept C_i and f is the sigmoid threshold function:

$$f = \frac{1}{1+e^{-\lambda x}} \tag{2}$$

where $\lambda > 0$ is a parameter that determines its steepness. In this approach, the value $\lambda = 1$ has been used. This sigmoid function is selected since the values A_i of the concepts lie in the interval [0,1].

A. Fuzzy Cognitive Maps for Modeling complex systems

Fuzzy Cognitive Maps have been successfully used to model and describe complex systems. They are successfully able to handle situations where there is any number and kind of relationships as well as feedback between the main concepts. Thus, interrelations between criterion-concepts can be included in the proposed medical decision-support model. Such interconnections are shown in Fig. 2 where the "competitive" interconnections between decision concepts are also illustrated

A significant area of application of Fuzzy Cognitive Maps is the Decision Support systems and especially the Medical Decision Support System (MDSS), where FCM is used to infer a Diagnosis based on the information of the interconnected factors that determine the diagnosis. A specific type of FCM has been introduced for MDSS, the Competitive Fuzzy Cognitive Map (CFCM), which consists of two main types of concepts: diagnosis-concepts and factor-concepts. Fig.2 illustrates an example CFCM model that is used to perform medical diagnosis. Here the concepts of the FCM and the causal relations among them that influence concepts and determine the value of diagnosis concepts indicating final diagnosis are illustrated [19].

Medical applications most of the time are not covered by law explanations but doctors express their knowledge that are used instead of natural laws. A lot of approaches are focused on creating automatic detection and extraction of causal relations that outline the mechanism representing the deepest medical knowledge [23]. Actually, in any real world either diagnosis or decision problem, many different factors/criteria have to be taken into consideration. The various factors / criteria may be either complementary or independent, or similar ones and even others may be are conflicting. It is accepted that for the reaching of any decision/ diagnosis, all the factors/ criteria are taken into consideration since all of them influence the final diagnosis/decision.

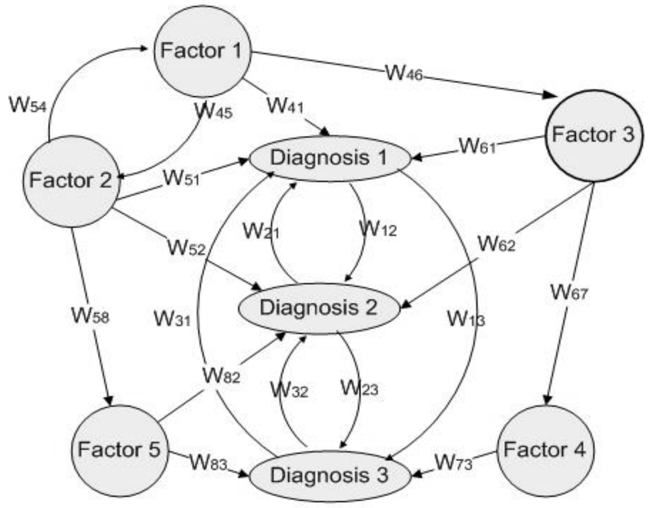

Fig. 2. A CFCM model for Medical Diagnosis.

III. ALGORITHM TO DEVELOP FUZZY COGNITIVE MAPS

As has been described in the previous sections, one of the major uses of FCM is modeling complex systems and especially Medical Decision Support Systems (MDSS). In a MDSS the FCM has to model the system and based on the values of concepts has to conclude to one decision/ diagnosis. This is achieved by the Competitive Fuzzy Cognitive Map (CFCM), where some concepts refer to the possible decision/ diagnosis and the values of these concepts are mutually exclusive and compete with each other [19][20]

A. Determining Concepts

An FCM development algorithm is proposed, based on the use of existent widely accepted evidence-based procedures, bibliographic and historical data. All these constitute the existing recorded information that has been transformed into knowledge through a hidden inference mechanism that correlates data, events, results and etc. Knowledge is usually gathered and presented in unstructured form increasing the difficulty to create adequate and useful representations. Such available unstructured knowledge has to be presented in a formal way in order to be easily transformed into a FCM format. Here -is assumed a general format of knowledge representation, where the FCM development algorithm is applied.

Let's assume that we would like to develop a model that describes any complex system and how a decision is inferred. This means that the different potential decisions that could be suggested are already known. Thus, a list with the possible decisions is available, which constitute the Decision-Concepts DC_j with j=1,..m.

Then, an extensive bibliographic search is applied on gathering evidence-based information from recognized sources of the relevant criterions that are taken into consideration in order to extrapolate any decision of the above mentioned DC_j concepts. So at the end all the possible Criterion Concepts CC_i i=1,..n. will be gathered that would lead to determine a DC_j. In such a way an aggregated extended Fuzzy Cognitive Map consisting of n+m concepts would be created, which usually most of the time is a very complicated model. This aggregated model includes either the rarest potential criterion concepts that could be of influence or very small degrees of influence on the decision concept.

An algorithm is proposed, here to determine both the essential decisions DC_j and the important criterions CC_i. The bibliographic search algorithm is based on ideas originating in data mining and text retrieval. We are looking for described cases where a decision was concluded based on some criteria. For each bibliographic reference and/or case, we record the case index #c, the final decisions DC_j and the criteria concepts CC_i based on which any decisions are made as it presented at Table I.

Table1. Knowledge base with referred cases for decision making

#c	Decision Concepts DC_j	Criteria Concepts CC_i
1	DC^1_j j=1,..m.	CC^1_i i=1,..n
2	DC^2_j j=1,..m.	CC^2_i i=1,..n
	…..	…..
K	DC^k_j j=1,..m.	CC^k_i i=1,..n

It is apparent that in order to build a wide model, the higher the available referenced cases k the better. But on the other hand, it is important not to have a very broad pool of cases that actually correspond to any kind of decisions. Thus, a new case will be added to the knowledge base KB, and updating the corresponding list of Decision Concepts DC_j and Criterion Concepts CC_i , with the following algorithm :

Step 0: *Start with Case c_1 Record DC^l_j and CC_i*
Step 1 *Examine new Case c_k*

Step 2 *IF the new* $\{DC_j^k \subseteq$ *(of all the existing the* $DC_j\}$ *OR the new* DC_j^k *increases the kind and number of the existing - Decisions* DC_j *by* $\leq 10\%$, *THEN update the* DC_j^k *and* CC_i^k *; increase the number of case* c_k *k=k+1 and go to step 1.*

step 3 *IF the new* $\{CC_i^k \subseteq$ *(of all the existing the* CC_i *) OR the* CC_i^k *increases the kind and number of the existing Criteria* CC_i^k *by* $\leq 10\%$ *THEN update the* DC_j^k *and the* CC_i^k *increase the number of case* c_k *k=k+1 and go to step 1.*

This algorithm adds to the Knowledge Base KB a new case, when it refers to exactly the same existing decisions or slightly increases them by up 10% regardless of the criteria of the new case. Alternatively, a new case is added, when the criteria are exactly the same or different by less than 10% of the existing criteria regardless of the decision.

It is expected that the Knowledge Base KB, will result with either a limited number of cases or with numerous recorded cases. Here, we assume that the overall recorded number of cases is restricted, which is the first situation. Thus, it is possible to ask for the support of human experts on the particular application area.

B. Determining Criterion participation

Usually, when humans conclude to a decision, they don't take into consideration all the possible criteria, but focus on the most important ones. This is a general procedure, which is dependent on the specific conditions per case; that means the same human decision maker, in another case may select another set of essential criteria to infer his decisions.

Based on the developed KB, we are going to determine the ***participation*** for every Criterion/ concept CC_i , which is used to determine the participation of the specific criterion to the final FCM based on the following formula:

$$p_i = (\text{\# of cases considering the criterion } CC_i)/(\text{ total number of cases}). \quad (3)$$

After having built the KB, we are going to apply a simple procedure to integrate all the cases into a distinct number of cases. Our intention is to have as many cases as is the number of Decision Concepts DC_j i.e. $k = j$

We are gathering all Decision Concepts DC_j, but we are including in the augmentative case only the Criterion/ concept CC_i with $p_i \geq 0{,}65$ as we want to include all the essential criteria and not to have a loose FCM with many and possible overlapping criteria.

Then, we will reconstruct the Knowledge Base KB, where there is a district number of cases. For this -new KB, we determine the ***importance weight*** for every Criterion/ concept CC_i , which is used to determine the influence of the specific criteria to the final decision based on the following formula:

$$iw_i = (\text{\# of cases considering the criterion } CC_i)/(\text{ total number of cases}). \quad (4)$$

C. Determining weights

After gathering all the available information and knowledge in the Knowledge Base and its integration into a distinct number of cases, we have to produce the Fuzzy Cognitive Map and determine the corresponding weights among concepts. For this procedure, we are going to ask for the support of experts who are going to infer the ***specific weight-*** sw_{ij}^k [21]. The ***specific weight-*** sw_{ij}^k is a weight describing the "influence to specific decision" by the related criterion. It has been introduced to represent how much the specific criteria leads towards a specific decision. The procedure to calculate the sw is the following: every expert examining a case, considers certain criteria as important for the specific decision; he is asked to present the degree with which the specific criteria leads to the specific decision for this case. Every expert describes the degree of influence of one criterion towards a decision, using a linguistic variable, such as "strong influence", "medium influence", "weak influence", etc.

More specifically, the causal interrelationship from one criterion / concept towards a decision/ concept is declared using the variable *Influence* which is interpreted as a linguistic variable taking values in the universe U=[-1,1]. Its term set *T(influence)* is suggested to comprise nine variables so that to permit the experts to explicitly describe the degree of influence. Actually using nine linguistic variables, an expert can describe in detail the influence of criterion concept towards a decision concept and can discern between different degrees of influence. If -more than 9 linguistic variables are used, it would quite difficult for an expert to decide on the influence and on the other hand, if the number of linguistic variables is too small a simplified influence will be described. The nine variables that are used: *T(influence)*={negatively very strong, negatively strong, negatively medium, negatively weak, zero, positively weak, positively medium, positively strong and positively very strong}. The corresponding membership functions for these terms are shown in Figure 3 and they are $\mu_{nvs}, \mu_{ns}, \mu_{nm}, \mu_{nw}, \mu_{z}, \mu_{pw}, \mu_{pm}, \mu_{ps}$ and μ_{pvs}. The nine linguistic variables allow the experts to better define the degrees of influence. The proposed triangular membership functions permit the human expert to select the central degree of influence from one concept to the other and additionally, they allow a high degree of overlapping between the linguistic weights that every expert selects.

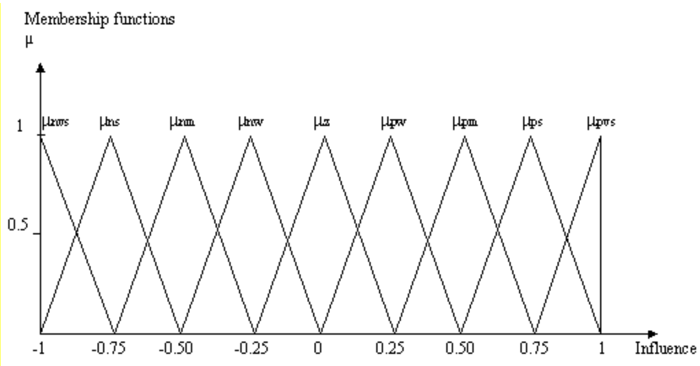

Fig. 3. Membership functions of the linguistic variable *Influence*

Thus, every expert describes the ***specific weight*** sw_{ij} of each interconnection with a fuzzy linguistic variable from the above mentioned set, which stands for the relationship between the two concepts and determines the grade of causality between the two concepts. Then, all the proposed linguistic weights for one interconnection suggested by experts, are aggregated using the SUM method and an overall linguistic weight is produced. The overall linguistic weight with the defuzzification method of Center Of Gravity (COG), is transformed to a numerical weight sw_{ij}^{k}, belonging to the interval [-1, 1].

D. Aggregate Fuzzy Cognitive Maps

Actually for every single case of the KB, the group of experts took into consideration the proposed Decision Concepts DC_j and Criteria Concepts CC_i and so experts suggested and determined the ***specific weight*** sw_{ij}^{k}.

Then, in order to produce an integrated overall Fuzzy Cognitive Map, the overall weight describing the influence from one criterion concept towards a decision concept is calculated using the form:

$$w_{ij} = \mathrm{sgn}(sw)\left(l_1 * iw_i + \sum_{k=1}^{n} l_2 * \left| sw_{ij}^{k} \right| \right) \qquad (5)$$

where the two parameters l_1, l_2 are introduced to represent the participation of the ***importance weight*** iw and the ***specific weight*** sw_{ij}^{k} ,on the overall weight describing the influence of every factor concept towards the decision/diagnosis concept. It is mentioned that the value of w_{ij} has to be normalized in the interval [-1, 1], where the weight takes values.

IV. CONCLUSIONS

Fuzzy Cognitive Maps is a soft computing approach that can successfully handle vagueness and imprecision that characterizes any real system. Most importantantly, FCMs can abstractly represent and infer decisions in a way similar to human reasoning. Since its introduction, it has been used widely to model and describe complex systems and it has been successfully applied to various application areas mainly to model , simulate the operation and provide decisions and suggestions

A lot of effort has been placed in order to propose more generic development approaches for FCMs, utilizing all available methods from knowledge representation, computational intelligence algorithms to provide learning abilities to the FCM, genetic algorithms to automatically select weights optimization based approaches and many others.

Here is proposed a new structural algorithm for the construction of FCMs utilizing existing bibliographic resources and references along with the support of experts. The proposed algorithm enhance the classical fuzzy based approaches for developing FCMs with historical data and information leading to a more advanced approach. This algorithm is suitable for developing FCMs for decision support systems and it reduces the dependence on human factor since it relies on evidence based practice. Future research will focus on applying the algorithm to a real problem, develop the FCM and compare its performance with other similar approaches.

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