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Novel Architecture for supporting medical decision making of different data types based on Fuzzy Cognitive Map Framework

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Abstract— **Medical problems involve different types of variables and data, which have to be processed, analyzed and synthesized in order to reach a decision and/or conclude to a diagnosis. Usually, information and data set are both symbolic and numeric but most of the well-known data analysis methods deal with only one kind of data. Even when fuzzy approaches are considered, which are not depended on the scales of variables, usually only numeric data is considered. The medical decision support methods usually are accessed in only one type of available data. Thus, sophisticated methods have been proposed such as integrated hybrid learning approaches to process symbolic and numeric data for the decision support tasks. Fuzzy Cognitive Maps (FCM) is an efficient modelling method, which is based on human knowledge and experience and it can handle with uncertainty and it is constructed by extracted knowledge in the form of fuzzy rules. The FCM model can be enhanced if a fuzzy rule base (IF-THEN rules) is available. This rule base could be derived by a number of machine learning and knowledge extraction methods. Here it is introduced a hybrid attempt to handle situations with different types of available medical and /or clinical data and with difficulty to handle them for decision support tasks using soft computing techniques.**

I. Introduction

IN THIS research work, a first trial to propose and construct a general architecture for advanced medical decision making is investigated based on Fuzzy Cognitive Map framework. Usually different types of data are available, which have to be combined and assessed in order to handle difficult and complex situations in medicine.

A decision-making procedure is a complex process that has to take under consideration a variety of interrelated measurements, procedures and functions. In Decision Support Systems (DSS) we are not only interested on the accuracy and prediction of the results (as in the case of classification and data mining techniques) but for the transparency and interpretability of the results from the medical-expert who uses the DSS in his daily clinical practice.

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The amount of available knowledge and information relevant to the decision making is huge even in the case of restricted medical subspecialities. For this amount of information, many clinicians may overlook or misinterpret abnormal findings because selection of relevant information is difficult [1, 2]. Health professionals are confronted today with many different types of information and computer systems, which are usually integrated with each other and are networked. They have access to huge amount of data and information, which are not easily understood and more difficulty interpreted especially when captured outside their original context.

The three main features that a DSS integrates are: medical knowledge which solves the disease cases, patient data with specific biomedical information of each patient, and specific advice for each case based on the medical knowledge and the patient data [2].

A large number of computational intelligence approaches to extract knowledge from databases, have been developed. New intelligent systems for data mining and knowledge processing are used in medical area for the tasks of diagnosis, prognosis, and treatment planning and decision support [3]. Frequently, machine learning systems are used to develop the knowledge bases of expert systems. Given a set of clinical cases that act as examples, a machine learning system can produce a systematic description of those clinical features that uniquely characterize the clinical conditions. This knowledge can be expressed in the form of simple rules, often used for decision making in medicine [4,5]. Researchers propose a consortium of methodologies that works synergistically so that to provide in one form or another flexible information processing capabilities to handle real life ambiguous situations [6].

Fuzzy Cognitive Maps (FCMs) are fuzzy digraphs that model causal flow between concepts [7]. FCM can be described as qualitative modelling that portrays how a given system operates. A qualitative model can be derived by describing the system in terms of its component variables and the causalities among them [7]. FCM can be obtained by asking people to define the variables of the system and to identify relationships among the variables using 'if–then' rules to justify the cause and effect relationship, and infer a linguistic weight for each connection [8, 15].

FCMs are dynamical systems, which have been used in many disciplines for easy comprehension of complex social systems and for decision-making [9-12]. Few frameworks based on fuzzy cognitive maps for the task of reasoning and learning have been proposed [13,14]. Furthermore, some FCM models have been proposed for medical decision support systems (see for example in [15-16]).

Traditionally, rule-based reasoning techniques are the most commonly used approach for knowledge reasoning and knowledge-based systems make decisions based on the rules and input states. However, rule-based reasoning is not powerful enough to model the situation in which there are complex relationships among the factors. Fuzzy Cognitive Map can be seen as a collection of the rules such that it not only concerns the relationships between the causes and effects, but also considers the relationships among the causes. Therefore, it provides a stronger reasoning ability than rule-based reasoning and it can be used to model complex relationships among different concepts.

A novel architecture for a FCM-based framework for decision support in medical systems is proposed in order to combine different data types through a number of available knowledge extraction methods.

II. Brief Description of Fuzzy Cognitive Mapping

An FCM is a digraph structured as a collection of nodes and arcs. Nodes, called concepts, are system variables; their values change over time. Connections among concepts, the arcs or edges of the graph represent causality. That is, a weighted directed edge that connects concept C_0 to C_1, pointing from C_0 to C_1, tells that C_0 causes C_1. An edge may connect any concept to any other concept. An edge may also connect a concept to itself, indicating that the future value of the concepts depends on the concept's current value. Each concept, or node, has a strength value traditionally ranging from 0 (no strength) to 1 (full strength). The 0 to 1 range is arbitrary, and some users prefer bipolar values ranging from -1 for maximum negative representation, through 0, for ambivalence, to +1, for maximum positive representation.

An FCM is a data system in which the collection of current concept values represents the current overall system-concept status. At each time increment, the next value of each dependent system concept is calculated from the current concept and edge values. Several techniques are available for calculating concept values of a system. The most common one is a normalized sum of products. The first step is to take the product of each source concept value and connecting edge value, and then sum these products and normalize the result into the range of allowable concept values. The purpose is to cause sums greater than one, which can occur when several products are summed, to be monotonically mapped into the 1 (or 0 to 1) range. Appropriate normalizing functions are those based on the sigmoid function popular in neural networks [6]. The links in the FCM can be redefined as continuously varying functions to reflect this information.

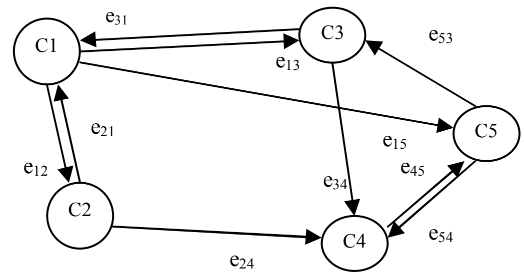

Fig.1. A simple Fuzzy Cognitive Map with 5 nodes and 10 weighted arcs

The runtime operation of an FCM consists of calculating the next value of each concept in the FCM structure from the current concept and edge values. The value A_i of a concept C_i is calculated by computing the influence of other concepts C_i's on the specific concept C_i following the calculation rule:

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

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, e_{ji} is the weight of the interconnection from concept C_j to concept C_i and f is a sigmoid threshold function [7]. FCM acts as an asymmetrical network and converges to limit cycles.

Experts develop the FCM as a mental model, manually based on their knowledge in the area under study. At first, they identify key domain issues or concepts. Secondly, they identify the causal relationships among these concepts and thirdly, they estimate causal relationships strengths. The FCM graph shows not only the components and their relations but also the strengths.

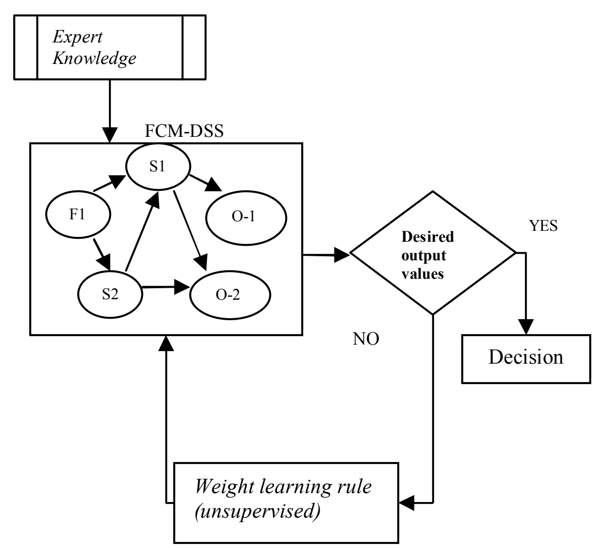

Fig. 2. Decision making using a simple FCM-DSS

A group of experts can be utilized to improve the results. All experts are asked to determine the relevant factors in a brain storm meeting. They discuss about main characteristics of the system, for example, number and kinds of concepts and relation between nodes, which are in the FCM. Then, they determine the structure and the interconnections of the network using fuzzy conditional statements or fuzzy rules. Each expert may draw his own individual FCM, which can be different from the others. In order to deal with these diagrams, the assigned weights by each expert can be considered and a new FCM will be constructed by all experts. Thus, this constructed FCM will represent the knowledge and experience of all related experts [8]. The weighted interconnections in the FCM architecture play an important role and the method used to adjust the weights in the process of training is called the learning rule [17].

The process of decision making is a complex one as it has to take under consideration a variety of interrelated functions. A simple FCM-DSS model for diagnosis could be consisted of 3 kinds of concepts: the concepts that represent the **Factor**-concepts, which are either laboratory tests and measurements, or observations of the doctor and other information on patient status [15]. The values of **Factor**-concept s interact and influence the values of **Selector**-concepts. **Selector-**concepts represent some intermediate conclusions. The **Selector-**concepts influence the **Output-**concepts that conclude the decision. The FCM-DSS model can include all the factors and symptoms that can infer a decision, along with the existing causal relationships among Factor-concepts because factors may are interdependable and/or sometimes the existence or lack of a factor require the existence or lack of another.

In the above figure of the simple FCM-DSS, Factor-concepts influence Selector-concepts and the value of each Selector-concept can subsequently influence the degree of the Output-concept (O-i) of the FCM. This FCM model is an abstract conceptual model of what a doctor does when he make a decision; he reaches some intermediate inferences based on the inputs taking into consideration all the related symptoms, and then according to the intermediate Selector-concepts values he determines his final decision that in the FCM model are presented as Output-concepts. The decision of this process of decision making based on FCM-DSS is taken under the desired values of Output-concepts.

III. DESIGN OF GENERIC FRAMEWORK FOR MEDICAL DECISION MAKING

The central idea of the proposed technique is to propose an architecture, which can combine different data types and extract the inhered knowledge from them, within the FCM-DSS. The derived FCM-DSS model is subsequently trained using an unsupervised learning algorithm to enhance its decision accuracy and interpretability capabilities.

There is a necessity to develop architecture for medical decision making based on FCM framework. The FCM framework, as a knowledge based technique, can be enhanced by including new fuzzy rules extracted from the available medical knowledge. In Figure 3, the previously described FCM-DSS framework has been developed by inserting the best fuzzy rules derived from knowledge processing methods.

Fuzzy Cognitive Map can be seen as a collection of the rules such that it not only concerns the relationships between the causes and effects, but also considers the relationships among the causes. Therefore, it provides a stronger reasoning ability than rule-based reasoning and it is used to model complex relationships among different concepts.

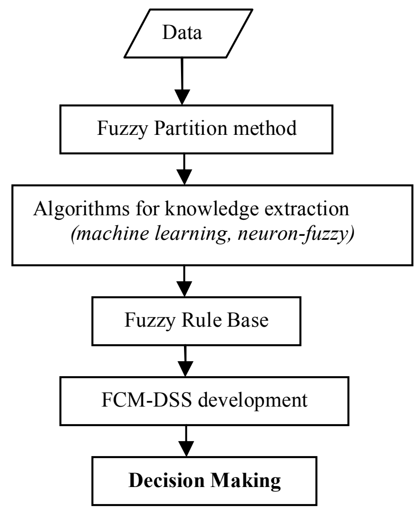

Fig. 3. Fuzzy rule base available from FCM-DSS development

The synergism of neural and fuzzy techniques leads to a symbiotic relationship in which fuzzy systems provide a powerful framework for expert knowledge representation, while neural networks provide learning capabilities and exceptional suitability for computationally efficient hardware implementations [18]. The significance of this integration becomes even more apparent by considering their disparities. For example, when data is treated as collections of objects encapsulated by linguistic labels they lend themselves to symbolic processing via rule-based operations, while by referring to the definitions of the linguistic labels their membership functions are also suitable for numeric processing. The neuro–fuzzy approaches are powerful providing flexible information processing capability by devising methodologies and algorithms on a massively parallel system for representation and recognition of real-life ambiguous situations forms [18,19].

The FCM-DSS could be created by rules derived from data using association rules or neuron-fuzzy methods to create rule bases. This model can be constructed combining knowledge from the available data sets and from experts. Figure 4 represents the processing methods of data sets to extract the available knowledge into a fuzzy rule base.

The proposed architecture for medical decision making using FCM is not supposed to function as an automated process to create a fuzzy classification system, but as a tool to support user. Some of the advantages of this approach are: (a) the fuzzy rules derived from the knowledge extraction, data mining and pattern recognition techniques have a simple and direct interpretation and introduced in the initial FCM model to update its operation and structure, (b) the approach that introduces the fuzzy rules evidences into an FCM also specifies the weight assignment through new cause-effect relationships among the FCM-DSS concepts and (c) the results are transparent and interpretable from the medical expert-doctor than each one of data mining techniques.

Due to the specific needs of the decision support tasks, a generic architecture based on FCM framework has proposed to handle the different types of uncertainty in medical knowledge and to extract this knowledge by producing a fuzzy rule base (see Figure 4). The approach has embedded a feedback process for the re-structure of the initially development of FCM framework for decision support through the insertion of the best fuzzy rules extracting from different methods of pattern, recognition, data mining, soft computing.

This is a first attempt to propose a generic architecture, which may have some model limitations, but there is not yet any concrete application of the proposed approach in medical decision making. It is ongoing research and this approach will be applied to real medical problems.

Some issues under investigation are: a) If not enough information is available, the approach could not be more efficient than other decision making methods and should be complemented by other methods b) The outcomes may be dependent on the attentiveness of the analysts about the knowledge extraction methods.

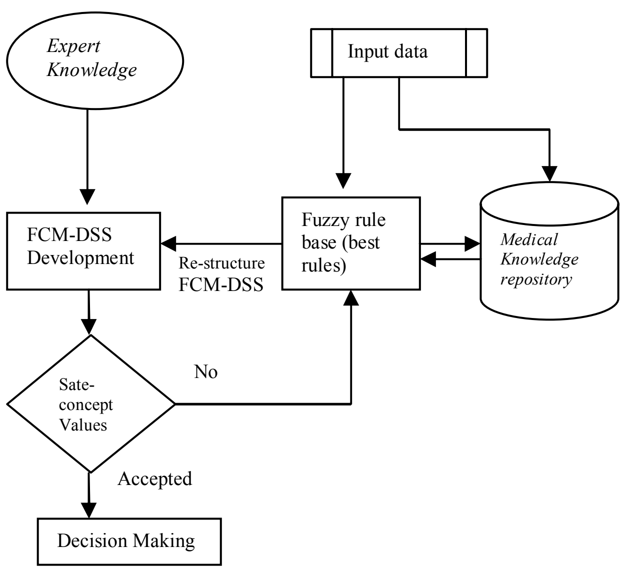

Fig. 4. Generic Architecture for FCM-DSS of Medical Decision Making

IV. Conclusion

A new architecture for supporting medical decision making based on Fuzzy Cognitive Maps have been proposed here, including knowledge extraction methods for different data types, fuzzy rules handling and insertion into FCM-DSS. The distinguishing feature of this architecture of FCM-DSS is its integration of different data types that could efficiently handle the available knowledge from many different sources of information.

There is a great interest in medical decision support area, which examines new architectures that would extend the cognitive capacities of DSS to meet the necessities of real applications. In this work, no detailed specifications or comprehensive guidance have been produced but the main idea is highlighted and is future intensive.

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