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Fuzzy cognitive map architectures for medical decision support systems

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Abstract

Medical decision support systems can provide assistance in crucial clinical judgments, particularly for inexperienced medical professionals. Fuzzy cognitive maps (FCMs) is a soft computing technique for modeling complex systems, which follows an approach similar to human reasoning and the human decision-making process. FCMs can successfully represent knowledge and human experience, introducing concepts to represent the essential elements and the cause and effect relationships among the concepts to model the behavior of any system. Medical decision systems are complex systems that can be decomposed to non-related and related subsystems and elements, where many factors have to be taken into consideration that may be complementary, contradictory, and competitive; these factors influence each other and determine the overall clinical decision with a different degree. Thus, FCMs are suitable for medical decision support systems and appropriate FCM architectures are proposed and developed as well as the corresponding examples from two medical disciplines, i.e. speech and language pathology and obstetrics, are described.

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1. Introduction

Any successful medical decision support system (MDSS) has to take into consideration a high amount of data and information from interdisciplinary sources (patient's records and history, doctors' physical examination and evaluation, laboratory tests, imaging tests, etc.). In general, the medical decision procedure is a complex one since, often, the medical data and information may be vague, conflicting, missing or not easy to interpret. Thus, MDSSs are complex systems consisting of non-related and related subsystems and elements, taking into consideration many factors that may be complementary, contradictory, and competitive; these factors influence each other and determine the overall decision with a different degree. It is apparent that medical decision support systems require a sophisticated modeling methodology that can handle all these challenges, while at the same time, is able to infer a decision. An advanced medical decision support system must be capable of extracting causal knowledge from the appropriate medical domain, building a causal knowledge base, and making inference through it.

Fuzzy cognitive maps (FCMs) are a powerful vehicle of causal knowledge representation and inference [1]. FCMs is a modeling and simulation methodology describing on an abstract conceptual representation any system. In fact, they are a computational intelligence modeling and inference methodology suitable for modeling complex systems and processes that are systems consisted of a great number of highly related and interconnected elements and subsystems.

Kosko [2] first introduced expanded cognitive maps in the engineering area to describe the cause and effect between concepts. This primitive FCM used crisp values $\{-1, 0, 1\}$ to describe causality and introduced concepts and dis-concepts to represent positive or negative concepts. Since then, FCMs have further developed, new methods have been proposed and they have been applied to many areas [3]. Recently, FCMs have been

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used successfully in the medical diagnosis and decision area; specifically, they have been used to model the complex process of radiotherapy [4], for differential diagnosis of specific language impairment [5] and for diagnosis and characterization for tumor grade [6].

Three FCM architectures suitable for medical decision support systems, as well as corresponding examples from medical disciplines are discussed in the subsequent sections. The first architecture is the Competitive FCM which is implemented for differential diagnosis of two language disorders. The second architecture is a distributed m-FCM and an example for the differential diagnosis of speech disorders is discussed. Thirdly, a hierarchical architecture for FCMs is presented and the use of this approach in an obstetrics decision support problem assisting obstetricians on how to proceed during labor is analyzed. Finally, conclusions are included and future directions are discussed.

2. Fuzzy cognitive maps

Fuzzy cognitive map is a soft computing technique that follows an approach similar to human reasoning and the human decision-making process. An FCM looks like a cognitive map, it consists of nodes (concepts) that illustrate the different aspects of the system's behavior. These nodes (concepts) interact with each other showing the dynamics of the model. Concepts may represent variables, states, events, trends, inputs and outputs, which are essential to model a system. The connection edges between concepts are directed and they indicate the direction of causal relationships while each weighted edge includes information on the type and the degree of the relationship between the interconnected concepts. Each connection is represented by a weight which has been inferred through a method based on fuzzy rules that describes the influence of one concept to another. This influence can be positive (a promoting effect) or negative (an inhibitory effect). The FCM development method is based on Fuzzy rules that can be either proposed by human experts and/or derived by knowledge extraction methods [3], in such a way that the accumulated experience and knowledge are integrated in the causal relationships between factors/characteristics/components of the process or system modeled [7].

2.1. Mathematical representation of fuzzy cognitive maps

The graphical illustration of an FCM is a signed directed graph with feedback, consisting of nodes and weighted arcs. Nodes of the graph stand for the concepts that are used to describe the behavior of the system and they are connected by signed and weighted arcs representing the causal relationships that exist between the concepts (Fig. 1).

Each concept is characterized by a number A_i that represents its value and it results from the transformation of the fuzzy real value of the system's variable, for which this concept stands, in the interval [0, 1]. Between concepts, there are three possible types of causal relationships that express the type of influence from a concept to the others. The weights of the arcs 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.

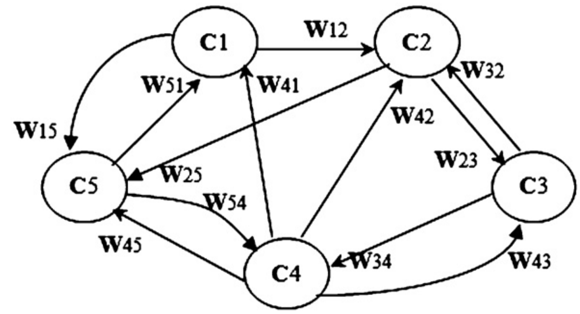

Fig. 1. The fuzzy cognitive map model.

The value A_i of concept C_i expresses the degree which corresponds to its physical value. At each 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:

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

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 determining its steepness. In this approach, the value $\lambda = 1$ has been used. This function is selected since the values A_i of the concepts, lie within [0, 1].

3. Medical decision support systems based on fuzzy cognitive maps

When medical experts are called upon to make a decision they take into consideration a variety of factors (concepts) giving each one a particular degree of importance (weight). Medical experts have a conceptual model in mind by which they process these factors and their degrees of importance, making comparisons, integrating the available information, and differentiating their importance, thus, finally reaching a decision out of a number of alternative potential decisions. Based on this approach, one can create a representation of the experts' knowledge using causal concept maps, which are developed by considering experts as the creators of the ‘‘map’’ that explicitly represents their expert knowledge drawn out as a diagram. In essence, this is an integrated interactive, graphic diagram of each expert’s mental model of his inference procedure to reach a decision. Concepts of the map are factors that are usually considered to reach a decision, as well as the potential decisions. In the graphical form of a cognitive map the concepts are the nodes. The ‘‘causal’’ component of these maps refers to the cause–effect relationships that hold between factors involved in the decision and the possible diagnosis and between the different factors themselves. The cause–effect relationships are connections between the nodes and are depicted in the graphical form as signed directed edges from one node (the causing concept) to another node (the affected concept). Given that the weighting in a human reasoning decision process almost never carries an exact numerical value, on the contrary, it carries a fuzzy (linguistic value), the appropriate modeling technique for developing medical decision support systems are fuzzy cognitive maps.

3.1. MDSS fuzzy cognitive map construction method

The method used to develop and construct a MDSS FCM has considerable importance in order to represent the medical decision procedure as accurately as possible. The methodology described here extracts the knowledge from the experts and exploits their experience of the process [8].

The appropriate medical experts, consisting in most cases of interdisciplinary teams, determine the number and kind of concepts that comprise the MDSS FCM. Each expert from his/her experience knows the main factors that contribute to the decision; each of these factors is represented by one concept of the FCM. The expert also understands potential influences and interactions between factors themselves or between factors and decisions, thus establishing the corresponding fuzzy degrees of causation between concepts. In this way, an expert’s knowledge is transformed into a dynamic weighted graph, the MDSS FCM. Experts describe the existing relationship between the concepts firstly, as ‘‘negative’’ or ‘‘positive’’ and secondly, as a degree of influence using a linguistic variable, such as ‘‘low’’, ‘‘medium’’, ‘‘high’’, etc.

More specifically, the causal interrelationships among concepts are 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 be comprised of eight variables. Using eight linguistic variables, an expert can describe in detail the influence of one concept on another and can discern between different degrees of influence. The nine variables used here are: T(influence) = {zero, very very low, very low, low, medium, high, very high, very very high, one}. The corresponding membership functions for these terms are shown in Fig. 2 and they are μ_{z}, μ_{vvl}, μ_{vl}, μ_{l}, μ_{m}, μ_{h}, μ_{vh}, μ_{vvh} and μ_0. A positive sign in front of the appropriate fuzzy value indicates positive causality while a negative sign indicates negative causality.

Once one expert describes each interconnection as above, then, all the proposed linguistic values for the same interconnection, suggested by experts, are aggregated using the SUM method and an overall linguistic weight is produced, which with the defuzzification method of center of gravity (COG) [9], is transformed to a numerical weight w_{ji}, belonging to the interval [−1, 1]. A detailed description of the development of FCM model is given in [7].

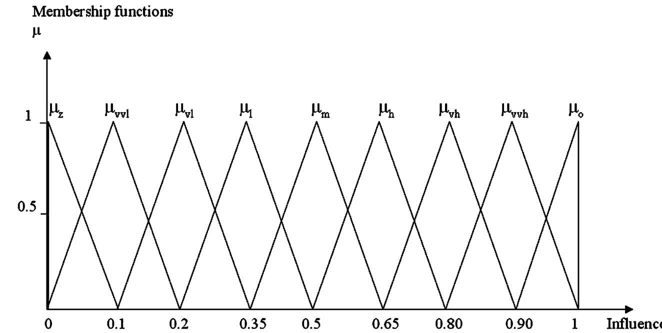

Fig. 2. Membership functions of the linguistic variable *Influence*.

In the following sections three MDSS FCM architectures are described which are based on the general construction method.

4. Competitive FCM for medical differential diagnosis

In a differential diagnosis MDSS where only one diagnosis is always inferred, a novel configuration, the competitive fuzzy cognitive map (CFCM) can be used [5]. The CFCM introduced the distinction of two main kinds of concepts: decision-concepts and factor-concepts. Fig. 3 illustrates an example CFCM model which is used to perform medical decision/

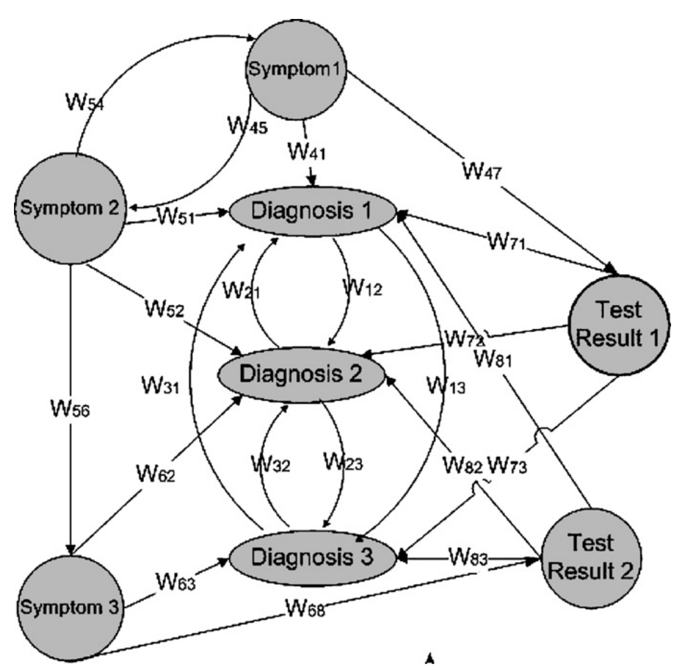

Fig. 3. A conceptual model for medical differential diagnosis.

Table 1
Weights between concepts for CFCM for dyslexia and specific language impairment

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17
C1	−1																
C2		−1															
C3	+VVH	+M–H							+L		+L			+L			+L
C4	+VH	+L–M															
C5	+VVH	+M–H				+L			+L								
C6	+VVH	+M–H			+L				+L								
C7	+H	+VVH	+L						+L	+L							
C8	+M–H	None[a]															
C9	+M-H	+VVH			+L		+L			+L				+L			
C10	+M	+VVH					+L		+L								
C11	+M	+L															
C12	+VVH	+VVH															
C13	+M-H	+VH															
C14	+M-H	+M															
C15	+M	CD							+L								+L
C16	+M	+M–H															
C17	+M–H	CD															

[a] No consistent and clear relationship was reported in the literature regarding the pragmatic aspects of language of children with dyslexia.

diagnosis, and includes both types of concepts of the FCM and the causal relations among them. All the concepts can interact with each other and determine the value of the diagnosis concepts, which are mutually exclusive, in order to indicate always a single diagnosis. This is the case in most medical applications, where, according to symptoms, medical professionals must conclude only one diagnosis and then determine the treatment, accordingly.

The factor-concepts can be considered as inputs to the MDSS such as patient data, observed symptoms, patient records, experimental and laboratory tests etc, which can be dynamically updated based on the system interaction, whereas the decision-concepts are considered as outputs where their estimated values outline the possible diagnosis for the patient. The factor-concepts can be interrelated and they partially influence the diagnosis. For such a situation, FCMs are suitable as their strength is their ability to describe systems and handle situations where there are feedback relationships and relationships between the factor-concepts. Such interconnections are shown in Fig. 3 where the ‘‘competitive’’ interconnections between the diagnosis concepts are also illustrated.

4.1. CFCM for dyslexia and specific language impairment

Dyslexia and specific language impairment (SLI) are frequent developmental disorders that may have a serious impact on an individual’s educational and psychosocial life. In general terms, developmental dyslexia is identified if a child has poor literacy skills despite adequate intelligence and opportunity to learn [10]. SLI is diagnosed when oral language lags behind other areas of development for no apparent reason [11]. Although, these two developmental disorders have separate and distinct definitions, they share many similar symptoms and characteristics that can make it difficult for clinicians to differentiate between them.

In the current differential diagnosis model there are two diagnosis concepts, i.e. the two disorders that are studied: concept 1 specific language impairment (SLI) and concept 2 dyslexia. The factor-concepts are considered as measurements that determine the result of the diagnosis in this model and they are

- concept 3 reduced lexical abilities;
- concept 4 decreased MLU;
- concept 5 problems in syntax;
- concept 6 problems in grammatical morphology;
- concept 7 impaired or limited phonological development;
- concept 8 impaired use of pragmatics;
- concept 9 reading difficulties;
- concept 10 problems in writing and spelling;
- concept 11 reduced ability of verbal language comprehension;
- concept 12 difference between verbal and nonverbal IQ;
- concept 13 heredity;
- concept 14 impaired sociability;
- concept 15 impaired mobility;
- concept 16 attention distraction;
- concept 17 reduced arithmetic ability.

The connections between the concepts are determined from Table 1 [12]. Four case studies from the literature are examined here, two on specific language impairment [13,14] and two on dyslexia [15,16] and, as experimental clinical cases to illustrate the differential diagnosis model. In Table 2 the factors used by the model in the diagnosis of each case are presented. In addition, the degree of occurrence of each factor in each case study is denoted with similar qualitative degrees of very very high, very high, high, medium, low, very low, and 0. The designation of weight ‘‘NR’’ in Table 2 indicates that the factor is not reported in the particular case and a value of zero is used in the computational model and ‘‘CD’’ is case dependent.

Table 2
Initial factor-concept fuzzy values for four cases

Factor-concepts	Case 1	Case 2	Case 3	Case 4
C3	VVH	VVH	M	VVH
C4	NR	VVH	NR	NR
C5	VVH	H	M	VH
C6	VH	VH	M	NR
C7	0	L	VVH	VVH
C8	L	VVH	0	0
C9	0	NR	VVH	VVH
C10	0	NR	VVH	VVH
C11	0	VH	H	H
C12	H	VVH	0	VH
C13	H	0	NR	NR
C14	-M	0	M	0
C15	0	0	M to H	NR
C16	0	0	VVH	NR
C17	0	NR	M	NR

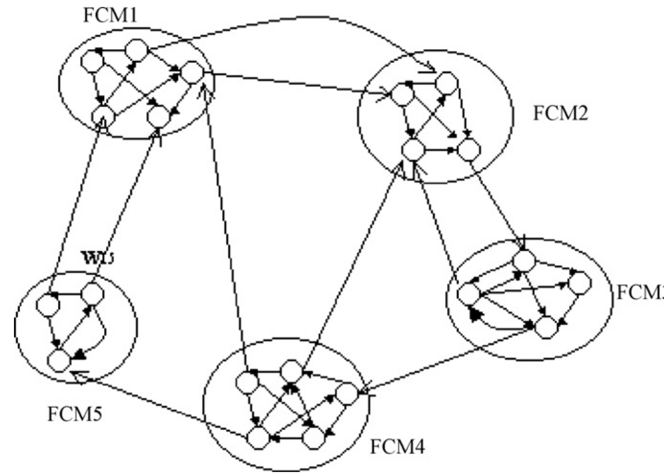

Fig. 4. The distributed m-FCM model.

Results showed that in all four cases, even though some of the information was incomplete, the outcome given by the model agreed with the published diagnosis:

Case 1: concept 1 (SLI) = 0.9659	concept 2 (dyslexia) = 0.8975
Case 2: concept 1 (SLI) = 0.9394	concept 2 (dyslexia) = 0.8540
Case 3: concept 1 (SLI) = 0.9302	concept 2 (dyslexia) = 0.9634
Case 4: concept 1 (SLI) = 0.9287	concept 2 (dyslexia) = 0.9620

That is in all four cases, the correct diagnosis was concluded: SLI, SLI, dyslexia, and dyslexia, respectively. In the two cases of dyslexia the largest-final diagnosis, even though correct, differed by a relatively small amount from the other diagnosis (SLI) which points out the difficulty in differential diagnoses of the two disorders.

5. Distributed m-FCM for medical diagnosis

A common approach proposed for modeling large complex system is based on the decomposition into subsystems [17,18]. But usually decomposition is not easily applicable, especially, when subsystems have common elements that prohibit the simplified approach of summing up the individual components behavior. We follow the same direction in using FCMs to model complex medical decision support systems where every subsystem is modeled by an FCM. With the proposed perspective for the modeling and analysis of complex systems, each component of the infrastructure constitutes a part of the intricate web that forms the overall infrastructure [19].

Here the case where multiple infrastructures are connected as ‘‘systems of systems’’ is considered. A fuzzy cognitive map is used to model each subsystem and the complex system is modeled with the interacting fuzzy cognitive maps. FCMs communicate with each other as they operate in a common environment, receiving inputs from other FCMs and transmitting outputs to them. The links between two FCMs have the meaning that a concept of one FCM influences or is correlated to the state-concept of the other. This distributed multiple m-FCM is shown in Fig. 4. FCMs are connected at multiple points through a wide variety of mechanisms, represented by bi-directional relationship existing between states of any pair of FCMs, that is, FCM_k depends on FCM_l through some links, and probably FCM_l depends on FCM_k through other links. There are multiple connections among FCMs such as feedback and feed forward paths, and intricate and branching topologies. The connections create an intricate web, depending on the weights that characterize the links. Interdependencies among FCMs increase the overall complexity of the ‘‘system to systems’’.

Fig. 4 illustrates a combined distributed fuzzy cognitive map, which aggregates five FCM models for the five subsystems of the complex system. Among the subsystems and thus, among the FCM models, there are interdependencies that are illustrated as interconnections between concepts belonging to different FCMs, where each FCM can be easily modeled [7].

5.1. Distributed m-FCM for differential diagnosis of dysarthria and apraxia of speech

Dysarthria is the term used to describe a group of disorders of oral communication resulting from disturbances in muscle control over the speech production mechanism due to damage to the central or peripheral nervous system [20,21]. Neurological impairment in the form of paralysis, weakness, or lack of co-ordination of the muscles that support speech production, can result in different forms of dysarthria. Darley et al. [20,21] identified seven forms of dysarthria: spastic, flaccid, ataxic, hypokinetic, hyperkinetic chorea, hyperkinetic dystonia, and mixed dysarthrias. Apraxia of speech is defined as ‘‘a neurogenic speech disorder resulting from impairment of the capacity to program sensorimotor commands for the positioning and movement of muscles for the volitional production of speech [22].

The differentiation between the dysarthria types can be a challenging task for a speech and language pathologist (SLP), since many speech and oral motor characteristics of the dysarthrias are overlapping. Additionally, despite the fact that the distinction between AOS (apraxia of speech) and dysarthrias is usually an easier process, differentiation between AOS and ataxic dysarthria or the establishment of a co-occurrence of both AOS and a dysarthria type can be challenging as well [22]. One of

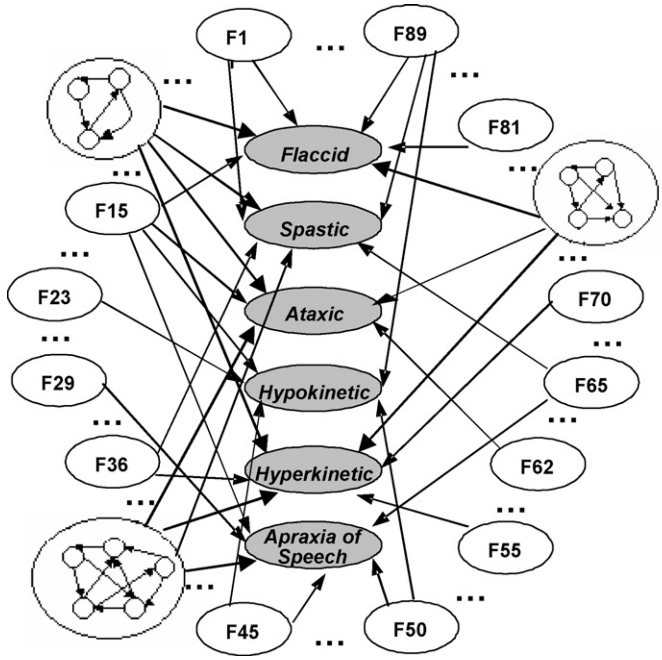

Fig. 5. Diagram of differential diagnosis distributed system of dysarthria and apraxia of speech.

the most widely used and accepted systems for the differential diagnosis of the dysarthria types is the DAB system or the Darley et al. [20,21] system which has some difficulties associated with its use since there are too many parameters to remember, overlapping symptoms, etc.

In the distributed m-FCM differential diagnosis system developed 89 factors were used as the factor-concepts. Of these 31 were oral motor characteristics and 58 were speech characteristics (see [22] for a complete set of the factors used). Since some of these factors can be grouped together given that they represent separate assessment procedures, certain FCM subsystems can be developed so as a distributed m-FCM diagnosis model is developed. For example, ''voice quality assessment'' can include nasality of speech, hoarseness, breathiness, voice tremor, strained voice, voice breaks, diplophonia in the DAB system. A fuzzy cognitive map subsystem with these factors can provide a value for the concept voice quality in the FCM of Fig. 5. Similarly, the concept ''voice pitch'' consists of another FCM system with concepts such as low pitch, high pitch, pitch breaks, and monopitch. Thus, in the distributed m-FCM model for the differential diagnosis system of dysarthria and apraxia of speech, shown in Fig. 5 the results of subsystem FCMs used for various assessments are aggregated into one combined distributed fuzzy cognitive map. Table 3 represents an example of some of the weights between factors and diagnoses since it is not possible to show all 89 factors here and their connection to each of the seven possible diagnoses. It is important to note that the diagnosis FCM here is not a CFCM since there can be co-occurrence of more than one dysarthria, as well as dysarthria and apraxia. This can be observed in Table 4 where there is a comparison of diagnosis provided by a speech and language pathologist (SLP) and the dysarthria–apraxia distributed m-FCM DSS for four patient cases where the bold values indicate the final diagnoses.

6. Hierarchical architecture for obstetric decision

A knowledge-based system is more suited to accomplish tasks when the nature of the problems and solutions is not well defined or not known beforehand. In medical applications there are situations involving a significant number of variable factors such as changing characteristics, unexpected disturbances, different combinations of fault and alarm situations, where the approach of knowledge-based system has certain advantages and flexibility which make such method particularly attractive for complex systems.

A hierarchical architecture is proposed where the m-FCM can be used to model the supervisor, which is the medical

Table 3
Examples of fuzzy values of weights between factor-concepts and diagnosis concept

Factor	Flaccid dys.	Spastic dys.	Ataxic dys.	Hypokinetic dys.	Hyperkinetic dys.	Apraxia of speech
Head tremor	0	0	M	M	M	0
Dysphagia	M	M	0	M	M	0
Drooling	M	M	0	M	0	0
Voice quality	M to H	M to H	L to M	M to H	M to H	0
Distorted vowels	0	0	H	0	H	M
...	...	...	...	...	...	...

Table 4
Comparison of diagnosis provided by speech and language therapist and dysarthria–apraxia distributed FCM DSS

Actual diagnosis of case by SLP	Output values of distributed FCM differential diagnostic system-resulting diagnosis					
	Flaccid dys.	Spastic dys.	Ataxic dys.	Hypokinetic dys.	Hyperkinetic dys.	Apraxia of speech
Case 1 ataxic dys.	0.5622	0.8081	**0.9170**	0.5000	0.8355	0.6225
Case 2 flaccid dys.	**0.9284**	0.6900	0.5156	0.6514	0.5312	0.5312
Case 3 AOS	0.5467	0.7432	0.8936	0.7186	0.8727	**0.9975**
Case 4 mixed dys.	0.5101	**0.9272**	**0.9487**	0.6934	0.8222	0.5248

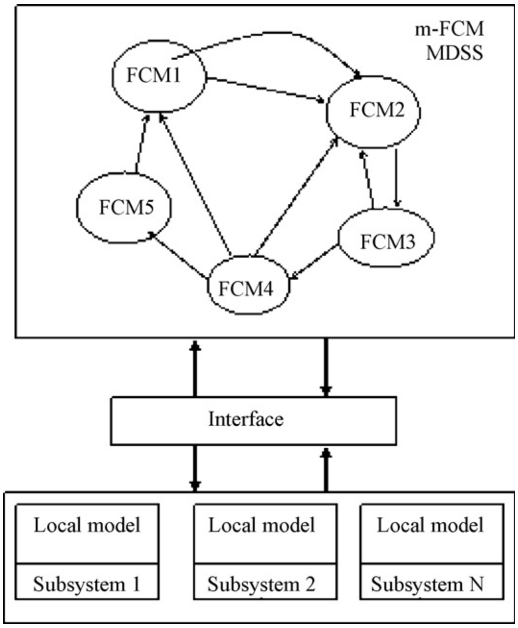

Fig. 6. The hierarchical architecture with the m-FCM for medical decision support systems.

decision support systems (Fig. 6). The m-FCM consists of concepts representing each one of the FCM modeling discipline sources (patient's records and information, doctors' physical examination and evaluation, laboratory tests, imaging tests, etc.). In addition there are other concepts representing issues for emergency behavior, estimation and overall decision and etc. The m-FCM is an integrated model of the complex system and it represents the relationships among the subsystems and their models while inferring the final decision by evaluating all the information from them.

Consequently, the m-FCM system has a generic purpose, it receives information from all the subsystems in order to accomplish a task, it makes decisions and it can plan strategically. This m-FCM uses a more abstract representation, general knowledge, and adaptation heuristics.

6.1. Two-level architecture for decision support during labor

During the crucial period of labor, obstetricians evaluate the whole situation, they take into consideration a variety of factors, they interpret and evaluate the fetal heart rate (FHR) signal and they continuously reconsider regarding the procedure of the delivery. Obstetricians have to determine whether they will proceed with a Caesarian section or a natural delivery based on the physical measurements, FHR and the intepretation of and other essential indications and measurements.

Cardiotocography was introduced into obstetrics practice and it has been widely used for antepartum and intrapartum fetal surveillance. Cardiotocogram (CTG) consists of two distinct signals, i.e. the recording of instantaneous fetal heart rate (FHR) and uterine activity (UA), which are two biosignals. FHR variability is believed to reflect the interactions between the sympathetic nervous system (SNS) and the parasympathetic nervous system (PSNS) of the fetus. Considerable research efforts have been made to process, evaluate and categorise FHR either as suspecious, or pathological or normal. There have been proposed integrated methods based on support vector machines, wavelets and other computational intelligence techniques to interpet the FHR [23].

Here, the development of a fuzzy cognitive map to model the way by which the obstetrician makes a decision for a normal delivery or a Caesarian section is investigated. This is an online procedure where the obstetrician evaluates whether either the woman or the fetus are at serious risk and thus, he/she has to intervene, stopping the physiological delivery and perform a Caesarian section or to continue with natural delivery.

The main parameters, that the obstetrician evaluates, constitute the nine concepts of the FCM model:

- concept 1 decision for normal delivery;
- concept 2 decision for caesarian section;
- concept 3 fetus heart rate (FHR) evaluation;
- concept 4 presence of meconium;
- concept 5 time duration of labor;
- concept 6 bishop score;
- concept 7 quantity of the medicine oxytocine given;
- concept 8 contractions of the uterine;
- concept 9 hypertension.

Experienced obstetricians have estimated the degree of influence from one concept to another as presented in Table 5. Then the obstetrics fuzzy cognitive map model is constructed,

Table 5
Relationships among concepts representing by fuzzy values in obstetrics example

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
C_1	–	–	–	–	–	–	–	–	–
C_2	–	–	–	–	–	–	–	–	–
C_3	Very high (normal)	Very high (pathological)	–	–	–	High	–	–	–
C_4	Low	High	–	–	High	–	–	–	–
C_5	High (<8h)	High (>8h)	–	Medium	–	Medium	–	–	–
C_6	Medium	High	–	–	Medium	–	Medium	–	–
C_7	–	–	–	–	–	Medium	–	Medium	Medium
C_8	–	–	–	–	–	–	Medium	–	–
C_9	–	–	–	–	–	–	Low	–	–

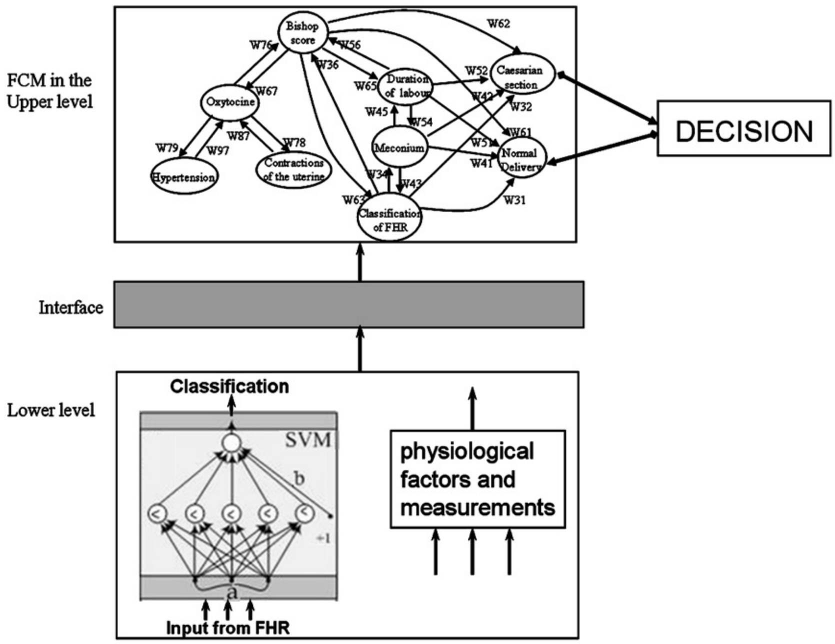

Fig. 7. The two-level architecture for decision support during labor.

which is illustrated at the upper level of the architecture for decision-making during labor (Fig. 7).

At each step, values of concepts are calculated according to the influence from interconnected concepts. Some concepts can have only external input such as the concept C_3 (FHR), which stand for the evaluation and classification of FHR, which is performed at the lower level by the support vector machine [24]. The interactions among concepts will change values of concepts. New values of some concepts may mean some action from the obstetrician; as an example, a new value for oxytocine requires pharmaceutical action to the woman. When the system reaches the steady state, the value of the concept for natural delivery and value of the concept for Caesarian section have to be mutually exclusive and only one suggestion will be the outcome of the system. Thus, the FCM in the upper level is a CFCM, as shown in Fig. 7.

In the two-level architecture presented, at the lower level there are either simple sensors or more advanced systems such as the FHR classification system based on support vector machines. Information from the lower level is transformed in suitable form through the interface and this information is transmitted to the FCM on the upper level. This supervisor FCM will infer a final suggestion to the obstetrician on how to proceed with the labor.

7. Conclusion

The area of medical diagnosis and medical decision support is characterized by complexity requiring the investigation of new advanced methods for modeling and development of sophisticated systems. Medical decision support systems (MDSSs) have attracted the interest of many researchers and still considerable efforts are under way. MDSSs must adequately take into consideration the needs of medical practitioners. The novel MDSS fuzzy cognitive map architectures described here are developed with appropriate medical experts from interdisciplinary background and are based on human reasoning approaches.

Three novel types of fuzzy cognitive map (FCM) architectures suitable for medical decision support systems were presented: (a) the competitive FCM, suitable when a single out of many possible diagnoses must be reached, (b) a distributed m-FCM for complex medical decision support system where a large number of interacting factors are involved, and (c) a hierarchical architecture with the m-FCM where it receives information from all the subsystems in order to accomplish a task, it makes decisions and it can plan strategically. For each architecture, a corresponding example of the FCM is described performing a medical decision support function. The real examples are successful applications of the architectures in the fields of language pathology, speech pathology, and obstetrics illustrating the potential of the FCM models in enhancing clinical judgments.

It is expected that the proposed FCM architectures for MDSS will be further evaluated for the previously described application areas and the results of the evaluation will help us to select the best architecture and further improve it. Clinicians have to evaluate the usefulness, applicability and user friendliness of each of the developed tools before promoting them available for incorporation into clinical practice. Additionally, the implementation of the proposed architectures in other areas of medical decision support will be investigated.

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