Fuzzy Cognitive Maps Structure for Medical Decision Support Systems

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Abstract Fuzzy Cognitive Maps (FCMs) are a soft computing technique that follows an approach similar to human reasoning and human decision-making process, considering them a valuable modeling and simulation methodology. FCMs can successfully represent knowledge and experience, introducing concepts for the essential elements and through the use of cause and effect relationships among the concepts Medical Decision Systems are complex systems consisting of irrelevant and relevant subsystems and elements, taking into consideration many factors that may be complementary, contradictory, and competitive; these factors influence each other and determine the overall diagnosis with a different degree. Thus, FCMs are suitable to model Medical Decision Support Systems and the appropriate FCM structures are developed as well as corresponding examples from two medical disciplines, i.e. speech and language pathology and obstetrics, are described.

1 Introduction

Fuzzy Cognitive Maps (FCMs) are a modeling and simulation methodology based on an abstract conceptual representation of any system. In fact, they are a computational intelligence modeling and inference methodology suitable for modeling complex processes and systems that are systems consisted of a great number of highly related and interconnected elements and subsystems. FCMs can successfully represent knowledge and experience, introducing concepts for the essential elements and through the use of cause and effect relationships among the concepts. They are used to develop models of aggregated behavior and inferring models that govern the components and interaction from large amount, possibly incomplete and uncertain data (Kosko 1992; Jang et al. 1997; Stylios and Groumpos 2000).

Medical Decision Systems have to consider a high amount of data and information from interdisciplinary sources (patient's records and information, doctors' physical examination and evaluation, laboratory tests, imaging tests etc) and, in addition to this, medical information may be vague, missing or not available. Furthermore the Medical Diagnosis procedure is a complex one, taking into consideration a variety of inputs in order to infer the final diagnosis. Medical Decision Systems are complex systems consisting of irrelevant and relevant subsystems and elements,

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taking into consideration many factors that may be complementary, contradictory, and competitive; these factors influence each other and determine the overall diagnosis with a different degree. It is apparent that Medical Decision Support Systems require a modeling tool that can handle all these challenges and at the same time to be 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 with it. FCM is as a major vehicle of causal knowledge representation and inference (Lee and Kim 1998).

Kosko (1986) 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 used concepts and dis-concepts in order to describe positive or negative concepts. The same period a first attempt to develop a generic system FCM for decision analysis proposed the POOL2 where both negative and positive assertions are weighted and kept separately based on the negative-positive-neutral (NPN) interval [-1,1] (Zhang et al. 1989), (Zhang et al. 1992).

FCMs attracted the interest of many researchers from different areas. FCMs were used to represent knowledge (Taber 1991), to model complex dynamical systems, such as social and psychological processes and organizational behavior (Craiger et al. 1996), and as an advanced artificial intelligence approach for engineering applications, (Jain 1997). FCMs were used for fault detection (Pelaez and Bowles 1996), and modelling process control and supervision of distributed systems (Stylios et al. 1999; Stylios and Groumpos 2004;). Other research efforts introduced FCMs to analyze urban areas (Xirogiannis et al. 2004), to represent the management of relationships among organizational members in airline service (Kang and Lee 2004) and to modeling software development project (Stach and Kurgan 2004; Stach et al. 2004). FCMs have been used for web-mining inference amplification (Lee et al. 2002) (Kakolyris et al. 2005). Finally, FCMs have been used successfully in the medical diagnosis and decision area; specifically, they have been used to model the complex process of radiotherapy (Papageorgiou et al. 2003), for differential diagnosis of specific language impairment (Georgopoulos et al. 2003) and for diagnosis and characterization for tumor grade (Papageorgiou et al. 2006).

An FCM is an interconnected network of concepts. Concepts 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 (Stylios et al. 1999).

This chapter describes FCM structures suitable for Medical Decision Support Systems as well as corresponding examples from medical disciplines. First, the Competitive FCM and its applicability in differential diagnosis of two language disorders is presented. Next a distributed m-FCM is described and an example for the differential diagnosis of a speech disorder is discussed. Finally, a hierarchical structure for FCMs is presented and the usage of this hierarchical approach in an obstetrics decision support problem supporting the obstetricians on how to proceed during labor is analyzed.

2 Fuzzy Cognitive Maps

FCMs are a soft computing technique that follows an approach similar to human reasoning and the human decision-making process. Soft computing methodologies have been investigated and proposed for the description and modeling of complex systems. 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. In the case of system modeling, the FCM is developed by human experts who operate/supervise/know the system and its behavior under different circumstances in such a way that the accumulated experience and knowledge are integrated in a causal relationship between factors/characteristics/components of the process or system modeled (Stylios and Groumpos 2004).

Fuzzy Cognitive Maps can be constructed either by actual experts or based on transforming expert knowledge from the literature. It is a knowledge-based methodology that utilizes the knowledge and experience of experts. It is accepted that the perceptions of experts create a subjective rather than objective model of the system. The main concern is to determine and describe which elements constitute the model and what elements influence other elements as well as the degree of this influence. There is an inference mechanism that describes the relations among elements as fuzzy causal relationships. Different values of influence are recommended and accepted; this is the main strength of this method. FCMs are ideal for knowledge and conceptual representation of complex systems in a soft computing way where the concepts of the system and their relationships are mainly fuzzy and not precisely estimated.

Experts design and develop the fuzzy graph structure of the system, thus the FCM describes the perception of experts about the system. Experts determine the structure and the interconnections of the network using fuzzy conditional statements. Experts' concern is to describe whether one concept influences another. Cause and effect relations among concepts are the basis of expectations and this is important in every system trying to model and replicate brain-like intelligence. Experts use linguistic variables in order to describe the relationship among concepts, and then all the linguistic variables are combined and so the weights of the causal interconnections among concepts are concluded. The simplest FCMs act as asymmetrical networks of threshold or continuous concepts and converge to an equilibrium point or limit cycles. At this level, they differ from Neural Networks in the way they are developed as they are based on extracting knowledge from experts. FCMs have non-linear structure of their concepts and differ in their global feedback dynamics (Papageorgiou et al. 2004).

Given two events that are represented by two concepts A and B, in FCM terms, the main questions that have to be answered are:

i) Does event A cause B or vice versa?
ii) What is the strength of the causal relationship?

Causality plays a key role in any knowledge-based system. The issue of how to understand and interpret the existing cause and effect relations is central to any effort to design systems that have some human like intelligence. The main problems concerning causality in that context are the extraction and elicitation of causal knowledge, its representation and its use. In the general approach, causal information emerges from statistical data and information, by looking at data that occur simultaneously, but it is clear that the co occurrence of data, although most likely correlated, does not always mean that the data are causally linked.

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 one 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.

The value A_i of concept C_i expresses a degree, which is related to its corresponding physical value. Ateach simulation step, the value A_i of a concept C_i is

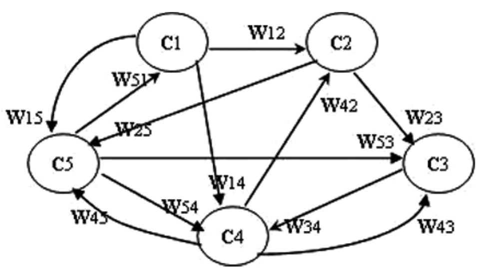

Fig. 1 The Fuzzy Cognitive Map model

calculated by computing the influence of other concepts C_j's on the specific concept C_i following the calculation rule:

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

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

2.2 *Method to Construct Fuzzy Cognitive Maps*

The development and construction method of FCMs has great importance to sufficiently model any system. The proposed method is dependent on a group of experts who operate, monitor, supervise the system. This methodology extracts the knowledge from the experts and exploits their experience of the system's model and behavior (Stylios and Groumpos 2000).

The group of experts determines the number and kind of concepts that comprise the FCM. An expert from his/her experience knows the main factors that describe the behavior of the system; each of these factors is represented by one concept of the FCM. Experts know which elements of the systems influence other elements; for the corresponding concepts they determine the negative or positive effect of a concept on the others, with a fuzzy degree of causation. In this way, an expert transforms his/her knowledge in a dynamic weighted graph, the FCM. Experts describe the existing relationship between the concepts and thus, justify their suggestions. Each expert determines the influence of one concept on another as "negative" or "positive" and then evaluates the degree of influence using a linguistic variable, such as "strong influence", "medium influence", "weak influence", 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 comprise nine variables. Using nine 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)*={negatively very strong, negatively strong, negatively medium, negatively weak, zero, positively weak,

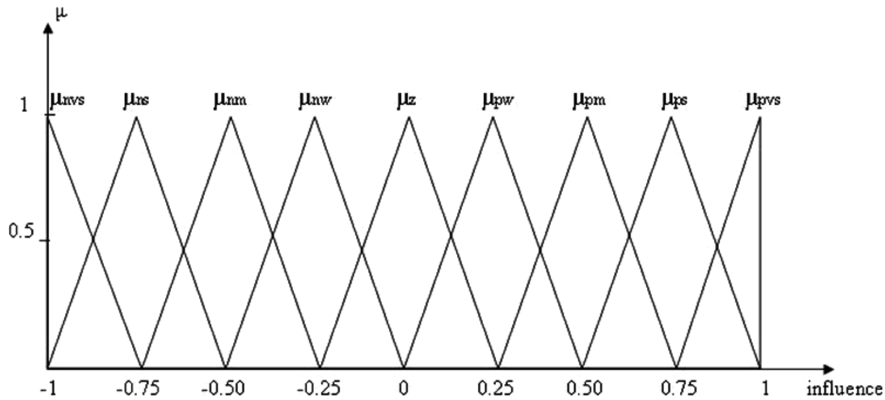

Fig. 2 Membership functions of the linguistic variable *Influence*

positively medium, positively strong and positively very strong}. The corresponding membership functions for these terms are shown in Fig. 2 and they are μ_{nvs}, μ_{ns}, μ_{nm}, μ_{nw}, μ_{z}, μ_{pw}, μ_{pm}, μ_{ps} and μ_{pvs}.

Thus, every expert describes each interconnection with a fuzzy linguistic variable from the set, which correspond to the relationship between the two concepts and determines the grade of causality between the two concepts. Then, all the proposed linguistic variables 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) (Lin & Lee 1996), 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 (Stylios and Groumpos 2004).

This FCM development approach utilizes the knowledge and experience of experts asking them to describe the existing causal relationship using Fuzzy rules. Since a knowledge base reflects its sources, it is critical to identify suitable knowledge sources, i.e. domain experts taking into account perceived expertise level. Each expert draws an FCM and these are easily combined, leading to the combined FCM being potentially stronger than an individual FCM because the information is derived from a multiplicity of sources, making point errors less likely (Stylios et al. 1999).

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 different degree of importance (weight). The description, characteristics and information of the factors they use may be complementary, similar, conflicting, vague, or even incomplete (Zeleznikow and Nolan 2001). 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. A well known approach for designing a medical decision support system involves the process of mapping experts' knowledge concerning the decision into a computer program's knowledge base. 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 the 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 decisions and between different the 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). Causal knowledge generally involves many interacting concepts that make them difficult to deal with, and for which analytical techniques are inadequate (Park and Kim 1995). A cognitive map is a technique adequate for dealing with interacting concepts (Chaib-draa and Desharnais 1998).

The type of cognitive maps proposed here for developing the medical decision support systems are Fuzzy Cognitive Maps. Where the values of the nodes themselves and the weightings of the connections are expressed using a fuzzy (linguistic value), such as those described in the previous section. This is an appropriate modeling technique for the medical decision support system since the weighting in a human reasoning decision process almost never carries an exact numerical value.

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. Especially for MDSS, FCMs have been successfully applied (Georgopoulos et al. 2003; Papageorgiou et al. 2003; Georgopoulos and Stylios 2005).

4 Competitive FCM for Medical Diagnosis

A specific type of MDSS for differential Diagnosis has been proposed where a new structure, the Competitive Fuzzy Cognitive Map (CFCM) is presented (Georgopoulos et al. 2003). The CFCM introduced the distinction of two main kinds of concepts: decision-concepts and factor-concepts. Figure 3 illustrates an example CFCM model which is used to perform medical decision/diagnosis, and includes both types of concepts of the FCM and the causal relations among them. All the

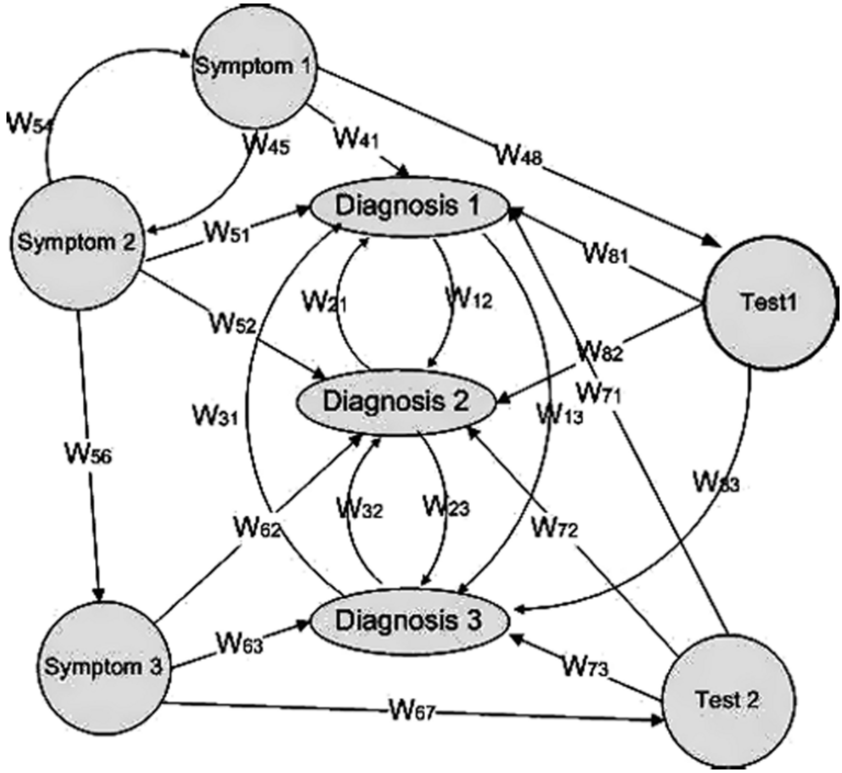

Fig. 3 A conceptual model for Medical Diagnosis

concepts can interact with each other and determine the value of diagnosis concepts that interest us thus indicating the final diagnosis.

In the CFCM model, each decision concept represents a single decision/diagnosis, which means that the decision concepts must be mutually exclusive because the MDSS intention is to infer always only one diagnosis. This is the case of most medical applications, where, according to symptoms, medical professionals have to conclude to only one diagnosis and then must determine, accordingly, the treatment. It is well known that the medical diagnosis procedure is a complex process that has to take under consideration a variety of interrelated factors, measurements and functions. This is the case of any real world diagnosis problem, where many different factors are taken into consideration. In carrying out any diagnosis procedure, some of these factors are complementary, others are similar and others conflicting, and most importantly, factors influence other factors.

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, FCM 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. Both are considered as important public health problems since they affect the lives of many individuals. Prevalence studies report percentages between 3% and 15% for dyslexia and 3% to 10% for SLI.

In general terms, developmental dyslexia is identified if a child has poor literacy skills despite adequate intelligence and opportunities to learn. SLI is diagnosed when oral language lags behind other areas of development for no apparent reason. 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.

Specifically, in several studies that have investigated the reading skills of children with SLI, literacy problems (high incidence of reading difficulties) have been documented at an early age of these children. Similarly, it has also been found that many dyslexic children show a history of language impairment.

In the current differential diagnosis model there are two diagnosis concepts, i.e. the two disorders that are studied: Concept 1 Dyslexia and Concept 2 Specific Language Impairment (SLI). Two types of factors are the factor-concepts that 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

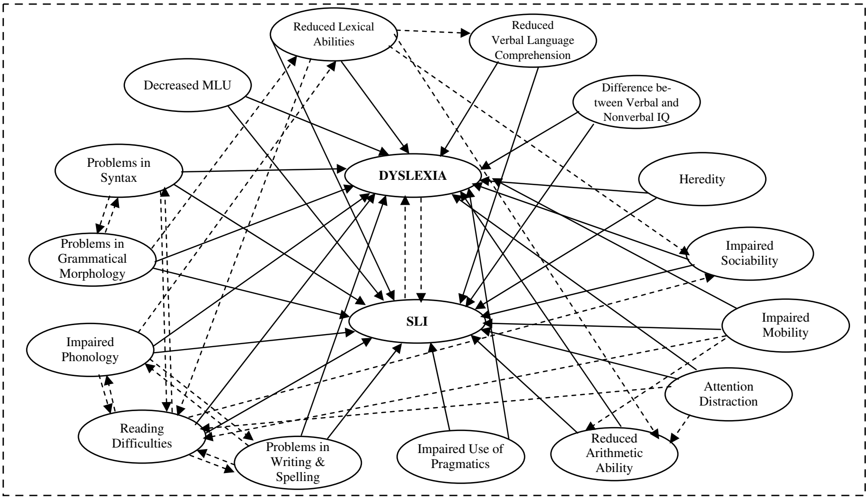

Fig. 4 Fuzzy Cognitive Map Differential Diagnosis of Dyslexia and SLI

The connections between the concepts are shown in Fig. 4 by arcs. However, due to limited space the sign and weights of the connections are not shown in Fig. 4, but can be determined from Table 1 (Malandraki and Georgopoulos 2006).

Four case studies from the literature are examined here, two on Dyslexia (Psychcorp 2005; Pierson 1999) and two on SLI (Van der Lely 1997; McGregor and Appel 2002), as experimental clinical cases that were used to run the differential diagnosis model. Three of the cases were school-age children and one was a preschool child.

Table 1 Weights between Factor and Disorder concepts

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17
C1		-1															
C2	−1																
C3	+ M-H	+ VVH							+L		+L			+L			+L
C4	+ L-M	+VH															
C5	+ M-H	+ VVH				+L			+L								
C6	+ M-H	+ VVH			+L				+L								
C7	+VVH	+ H	+L						+L	+L							
C8	NONE *	+M-H															
C9	+VVH	+M-H			+L		+L			+L				+L			
C10	+VVH	+M					+L		+L								
C11	+ L	+M															
C12	+VVH	+VVH															
C13	+VH	+M-H															
C14	+M	+M-H															
C15	CD	+M							+L								+L
C16	+M-H	+M															
C17	CD	+M-H															

*No consistent and clear relationship was reported in the literature regarding the pragmatic aspects of language of children with dyslexia

Details on the history and the assessment results of these cases can be found in Psychcorp 2005, Pierson, 1999, Van der Lely 1997 and McGregor and Appel 2002.

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.

Table 2 Initial Factor Concept Fuzzy Values for Four Cases

Factor-Concepts	Case 1	Case 2	Case 3	Case 4
Reduced Lexical Abilities	Very very high	Very very high	Medium	Very very high
Decreased MLU	NR	Very very high	NR	NR
Problems in Syntax	Very very high	High	Medium	Very high
Problems in Grammatical Morphology	Very high	Very high	Medium	NR
Impaired or Limited Phonological development	0	Low	Very very high	Very very high
Impaired Use of Pragmatics	Low	Very very high	0	0
Reading Difficulties	0	NR	Very very high	Very very high
Difficulties in writing and Spelling	0	NR	Very very high	Very very high
Reduced Ability of Verbal Language Comprehension	0	Very high	High	High
Difference between Verbal and Nonverbal IQ	High	Very very high	0	Very high
Heredity	High	0	NR	NR
Impaired Sociability	- Medium	0	Medium	0
Impaired Mobility	0	0	Medium to high	NR
Attention Distraction	0	0	Very very high	NR
Reduced Arithmetic Ability	0	NR	Medium	NR

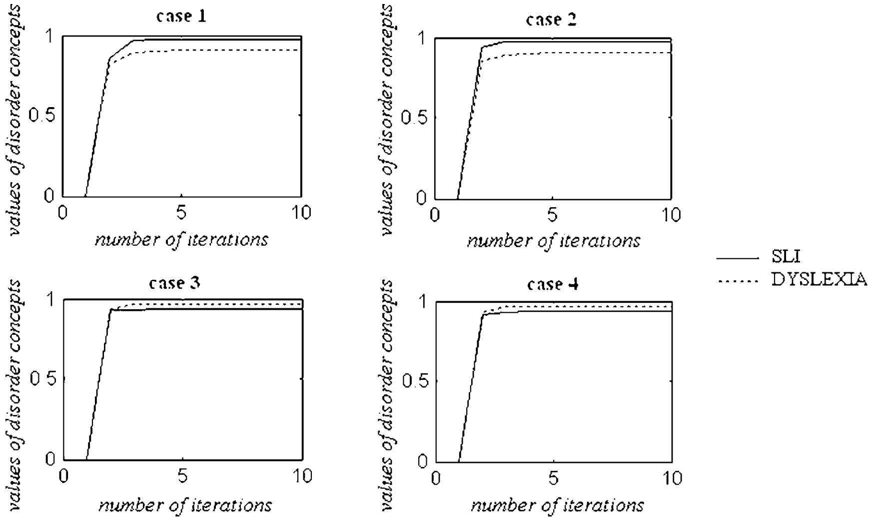

Fig. 5 Output nodes (disorder concepts) of differential diagnosis FCM for Dyslexia and SLI for four known cases

Results showed that for all four cases, even though some of the information was incomplete, the outcome given by the model agreed with the published diagnosis. That is in all four cases, the correct diagnosis was concluded: SLI, SLI, Dyslexia, and Dyslexia, respectively (Fig. 5). 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

For the case of a large complex system a common known approach is the decomposition into subsystems, which is a well known technique that has been used extensively on conventional approaches (Mesarovic et al. 1970), (Siljak 1979). But this decomposition is not easily applicable 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. 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 (Stylios 2002).

The case where multiple infrastructures are connected as “systems of systems” is considered. A Fuzzy Cognitive Map models 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 linkage between two FCMs has the meaning that one state-concept of one FCM influences or is correlated to the state-concept of the other. This distributed multiple m-FCM is shown in Fig. 6. FCMs are connected at multiple points through a wide variety of mechanisms, representing 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 linkages. Interdependencies among FCMs increase the overall complexity of the "system to systems".

Figure 6 illustrates an 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 (Stylios and Groumpos 2004).

5.1 Distributed m-FCM for Differential Diagnosis of Dysarthria and Apraxia of Speech

Dysarthria is the term 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 (Darley et al. 1969a, 1969b). Dysarthrias are associated with certain neurologic and very debilitating disorders, such as Parkinson's disease, Huntington's disease, Multiple Sclerosis,ALS

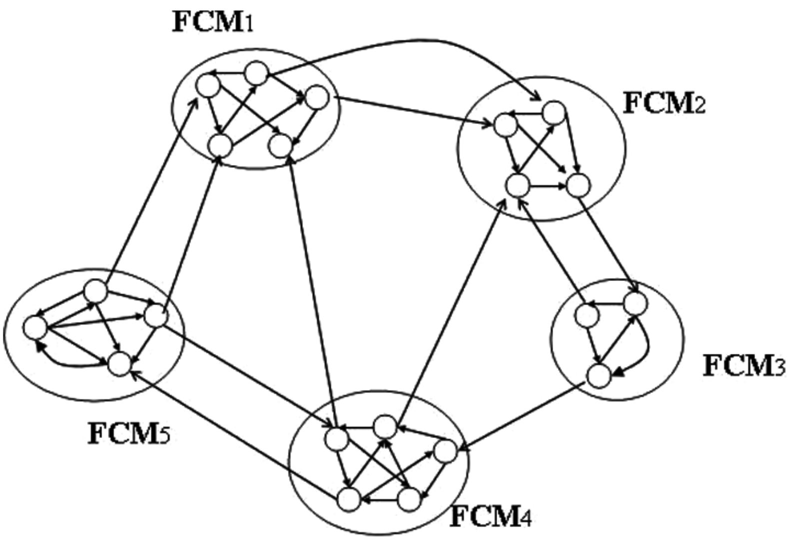

Fig. 6 The Distributed m-FCM model

(Lou Gehrig's Disease) Disease, Cerebral Palsy, Brain Tumors, Stroke, Certain Types of Brain Surgery, etc. Neurological impairment in the form of paralysis, weakness, or lack of coordination of the muscles that support speech production, can result in different forms of dysarthria. Darley et al. (Darley et al. 1969a, 1969b) identified seven forms of dysarthria: spastic, flaccid, ataxic, hypokinetic, hyperkinetic chorea, hyperkinetic dystonia, and mixed dysarthrias. The most common types of mixed dysarthrias can be: flaccid-spastic, ataxic-spastic, hypokinetic-spastic, ataxic-flaccid-spastic, and hyperkinetic-hypokinetic.

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. It can occur without significant weakness or neuromuscular slowness, and in the absence of disturbances of conscious thought or language" (Duffy 1995). Although apraxia of speech is controversial, most definitions of the disorder refer to impairment in programming, planning, or sequencing the movements of speech.

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 (Duffy 1995) . One of the most widely used and accepted systems for the differential diagnosis of the dysarthria types is the DAB system or the Darley, Aronson and Brown (Darley et al. 1969a, 1969b) system which has some difficulties associated with its use since there are too many parameters to remember, overlapping symptoms etc.

Characteristics of the specific type of dysarthria is important in treatment design, since clinicians working with patients with dysarthria must make a variety of decisions including: what aspects of the disorder will be responsive to treatment, what type of intervention and how much intervention is needed and when to undertake intervention, etc.

For the differential diagnosis of dysarthia an m-FCM system is developed, it is consisted of 89 factors. These factors are divided: 31 concepts represent oral-motor characteristics and 58 the speech characteristics (See (Duffy 1995) for a complete set of the factors used). But some of these factors can be grouped together since they represent separate assessment procedures, thus certain FCM subsystems can be developed and so the most suitable approach is the distributed m-FCM diagnosis model. For example, "voice quality assessment" can include nasality of speech, hoarseness, breathiness, voice tremor, strained voice, voice breaks, diplophonia. A fuzzy cognitive map subsystem with these factors can provide a value for the concept voice quality in the FCM of Fig. 7. Similarly, the concept "voice pitch" is represented by another FCM subsystem with concepts such as low pitch, high pitch, pitch breaks, and monopitch. Thus, the distributed m-FCM model for the Differential Diagnosis System of Dysarthria and Apraxia of Speech, shown in Fig. 7 is a hierarchical one where the results of subsystem FCMs used for various assessments are fed into the supervisor "upper FCM". The connection between the output concepts of the lower FCMs to the output concepts of the upper ones can have values of

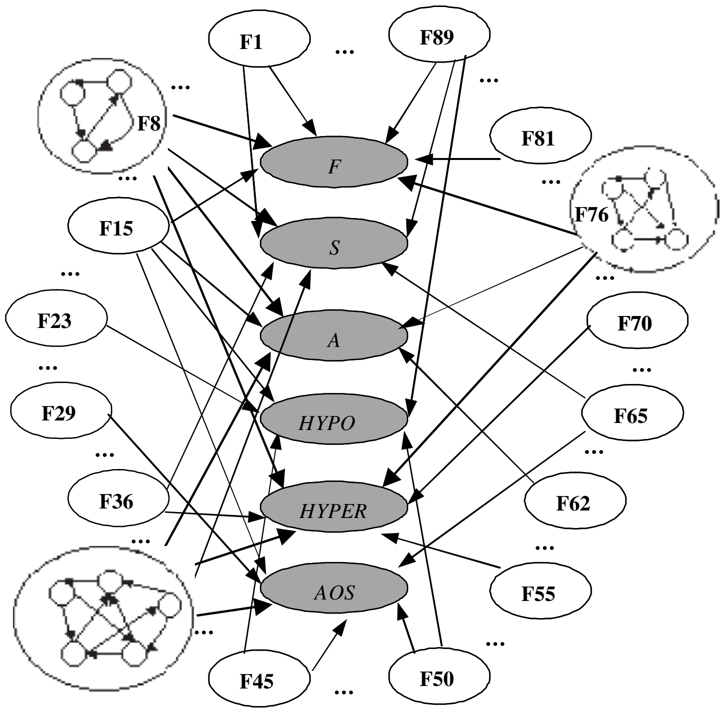

Fig. 7 Diagram of Differential Diagnosis Hierarchical System of Dysarthria and Apraxia of Speech

low (L), medium (M), high (H), near zero (0) etc. Table 3 illustrates an example of some of the weights between factors and diagnoses since it is not possible to show the whole table with the 89 factors and their connection to each of the 7 possible diagnoses would be quite complex. It is mentioned that the diagnosis m-FCM here is not a CFCM because there is not 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.

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
Dysphagia	M	M	0	M	M	0
Hyperactive gag	0	H	0	0	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
Irregular AMRs	0	0	H	0	H	0
….	….	….	….	….	….	….

Table 4 Comparison of Diagnosis Provided by SLP and Dysarthria-Apraxia FCM DSS

Initial Diagnosis of Case by SLP	Output Values of Differential Diagnostic System Resulting Diagnosis					
	Flaccid Dys.	Spastic Dys.	Ataxic Dys.	Hypok. Dys.	Hyperk. 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

7 Hierarchical Structure for Medical Decision Support System

A knowledge based methodology is more suited to accomplish complex tasks when the nature of the tasks, systems, 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 and suitable for complex systems.

Medical Decision Support systems may have a large number of operating rules and constraints requiring complex logic methods. Knowledge based systems have considerable potential for successful applications requiring synthetic and abstract logic, such as decision making, diagnosis, alarm management.

A hierarchical structure is proposed where the m-FCM can be used to model the supervisor, which is the Medical Decision Support Systems (Fig. 8). The m-FCM consists of concepts representing each one of the FCM modeling various 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, aggregated and abstract model of the complex system and it represents the relationships among the subsystems and the procedure for 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.

7.1 Two-level Structure 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 FHR signal and they continuously reconsider regarding the procedure of the delivery. Obstetricians have to determine whether they will proceed with a Caesarian section

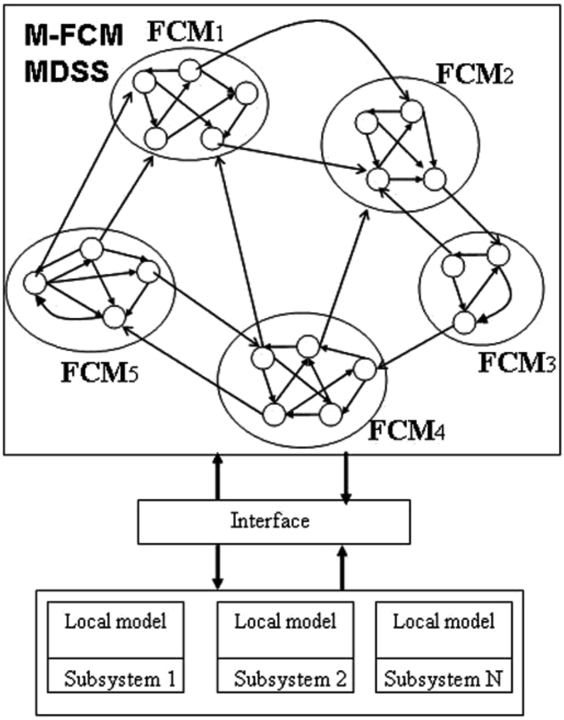

Fig. 8 The hierarchical structure with the m-FCM for Medical Decision Support Systems

or a natural delivery based on the physical measurements, and the intepretation of Fetal Heart Rate (FHR) 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 (Georgoulas et al., 2006a; 2006b).

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 caesarean 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 caesarean section or to continue with natural delivery.

The main parameters that the obstetrician evaluates are:

a) Interpretation of CTG

Cardiotocogram (CTG) has great importance and it is an essential main factor in the decision system and it is represented in the FCM as a concept for FHR and a concept for uterine contractions UA. The interpretation and classification of the FHR is essential; various advanced techniques have been proposed to classify FHR based on Computational Intelligence Techniques such as Wavelets and Support Vector Machines (Georgoulas et al. 2006b). The FHR is classified as normal, suspicious or pathological.

b) Bishop score

The Bishop score describes the potential and condition of the woman to deliver naturally. Having a cervical dilatation less than 3 and a pathological FHR means that the physician does not expect this woman to have a normal labor.

c) Uterine contractions

Uterine contractions (UCs) are the second parameter that obstetrician takes into consideration. The Obstetrician evaluates UCs' intensity and frequency and whether UCs are automatically or induced by the medicine oxytocine. The decelerations of the FHR are evaluated in conjuction with the uterine contractions. Obstetricians adjust the pharmaceutical dose of oxytocine or even to stop it when there are prolonged, severe or repetitive decelerations as a first action before thinking to perform a caesarean section.

d) Presence of meconium

The presence of meconium is a physical measurement. It is an indication of stress to the fetus and it leads many times to abnormal FHR

e) Duration of labor

Duration of labor is also a critical factor, as it is known that labor is a continuous stressful situation for the fetus. We can reduce the duration of the labor adjusting the pharmaceutical dose of oxytocine when contractions of the uterine are not satisfactory or there is no improvement in the Bishop score taking into account that the FHR monitoring is normal.

f) Oxytocine

This is the quantity of the medicine Oxytocine, that the pregnant woman has received.

In case of a suspicious FHR, obstetricians have to stop the oxytocine, wait for 20 minutes and if the FHR is strongly pathological, they continue with other examinations, testing the pH of fetal head. Because fetal scalp blood sampling for pH and blood gas assessment is an invasive technique, its use is not widespread and obstetricians usually prefer in the case of a pathological FHR to perform a Caesarean section. This is the critical point where the clinician needs an expert system to help him to distinguish between physiological stress and pathological distress and to decide whether he can wait for a normal labor or must immediately perform a Caesarean section.

FHR evaluation is a main concern during labor but another main concern for obstetricians is the Bishop score. The Bishop score describes the physiological findings from the fetus and the mother and it describes the labor in five stages. The Bishop score represents another main concept on the Fuzzy Cognitive Map.

The wide use of oxytocine during labor interferes with the Bishop score and the uterine contractions, although in women with hypertension during pregnancy or labor, oxytocine is eliminated. It is also clear, though, that we adjust the pharmaceutical dose (oxytocine) to the uterine contractions.

The duration of labor is also a critical point to the experts, as it is known that labor is a continuous state of stress to the fetus. As the time go by, obstetricians expect that the Bishop score is improved by the contractions of the uterine or the use of the oxytocine, otherwise they cannot wait especially when the FHR is a suspicious one and obstetricians have to perform a Caesarian section in order not to put fetus at risk.

Another factor that is taking under consideration is the presence of Meconium. When the outcome of the FHR is pathological, the presence of Meconium is highly considered in the decision of proceed to a Caesarian section. Thus another factor-concept of the Fuzzy Cognitive Map is the presence and quantity of Meconium.

Experienced obstetricians take into consideration all these factors during labor. Obstetricians exploiting their clinical experience developed the following Fuzzy Cognitive Map that is depicted on Fig. 9. Their knowledge on managing the labor was utilized and representing in the concepts of the FCM and the weighted interconnections among them.

The FCM model consists of 9 concepts:

Concept 1	Decision for Normal Delivery
Concept 2	Decision for Caesarian section
Concept 3	Fetus Heard Rate (FHR)
Concept 4	Presence of Meconium
Concept 5	Time duration of labor
Concept 6	Bishop score
Concept 7	Oxytocine
Concept 8	Contractions of the uterine
Concept 9	Hypertension

The relationships among concepts are represented by the corresponding weights. So the influence from concept C_i towards concept C_j is presented by the weight W_{ij}.

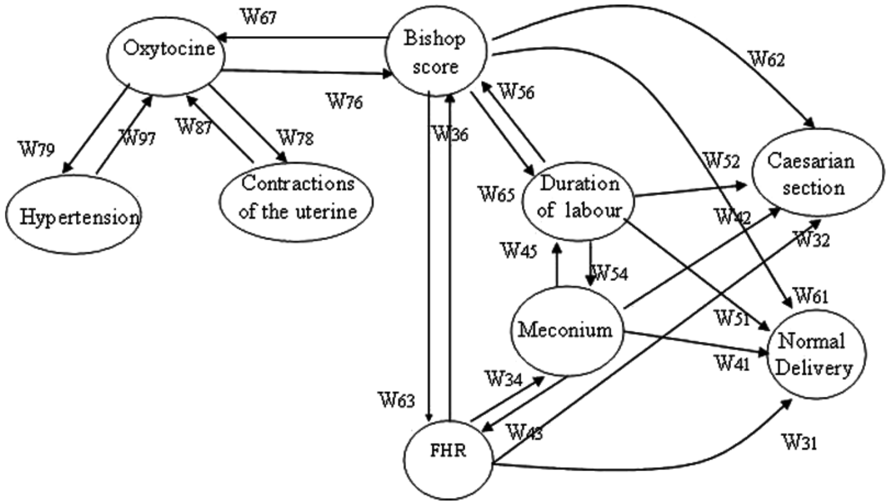

Fig. 9 Fuzzy Cognitive Map model for decision during labor

Experienced obstetricians have estimated the degree of influence from one concept to another and it is presented in Table 5. Linguistic values of interconnections are suggested by experts and are transformed in numerical weights.

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 (Georgoulas et al. 2006a). The interactions among concepts change values of concepts. New values of some concepts may require some action from the obstetrician; as an example, a new value for oxytocine concept means descrease or increase of the 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

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	-	-

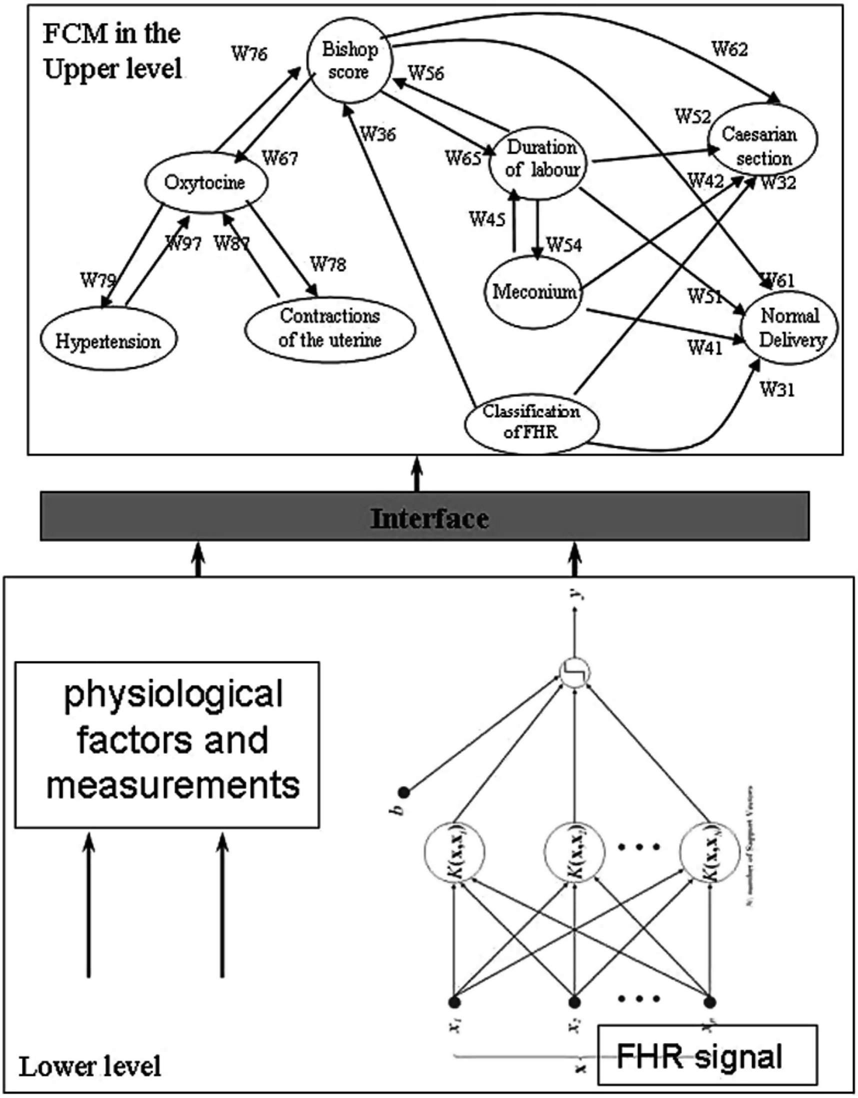

Fig. 10 The two-level structure for Decision Support during labour

be mutually exclusive and only one suggestion will be the outcome of the system. Thus, the FCM is the upper level is a CFCM, as shown in Fig. 10.

It is apparent that labor is a complex situation where the obstetrician has to consider a variety of factors and to make an on line decision on how to proceed with the delivery. It is a crucial decision, for the health of both the fetus and the mother. On the other hand, it is extremely hard to make decisions. Thus a two-level structure is proposed, where 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

This chapter describes three novel types of Fuzzy Cognitive Map (FCM) structures suitable for Medical Decision Support Systems. The three structures are: a) the Competitive FCM, suitable when a single out of different possible diagnoses must be reached, b) a distributed m-FCM as complex medical decision support system where a large number of interacting factors are involved, and c) a hierarchical structure where the m-FCM receives information from all the subsystems in order to accomplish the task of making decisions. For each structure a corresponding example of the FCM is described performing medical decision support. The real examples presented here, are successful applications of the proposed methodologies and structures in the fields of speech pathology, language pathology, and obstetrics.

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