Augmented Fuzzy Cognitive Maps Supplemented with Case Based Reasoning for Advanced Medical Decision Support

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Abstract: Fuzzy Cognitive Maps (FCMs) have been used to design Decision Support Systems and particularly for medical informatics to develop Intelligent Diagnosis Systems. Even though they have been successfully used in many different areas, there are situations where incomplete and vague input information may present difficulty in reaching a decision. In this chapter the idea of using the Case Based Reasoning technique to augment FCMs is presented leading to the development of an Advanced Medical Decision Support System. This system is applied in the speech pathology area to diagnose language impairments..

1. Introduction

This chapter presents how the Soft Computing technique of Fuzzy Cognitive Maps (FCMs) can be combined with Case Based Reasoning methods in order to develop an Advanced Medical Decision Support System. FCM is a knowledge-based methodology suitable to describe and model complex systems and handle information from an abstract point of view (Kosko 1986). Soft computing techniques such as FCMs have been successfully used to model complex systems that involve discipline factors, states, variables, input, output, events and trends. FCM modeling can integrate and include in the decision-making process the partial influence of controversial factors, can take under consideration causal effect among factors and evaluate the influence from different sources, factors and other characteristics using fuzzy logic reasoning. Each one of the involved factors has a different degree of importance in determining (or influencing) the decision, which increases the complexity of the problem. Thus, soft computing methods are ideal for developing Decision Support systems in Medical Informatics where humans use mainly differential diagnosis based on fuzzy factors some of which are complementary, others similar and others conflicting, and all are taken into consideration when a decision is reached (Kasabov 1996, 2002; Zeleznikow and Nolan 2001).

Fuzzy Cognitive Maps develop a behavioral model of the system exploiting the experience and knowledge of experts. Fuzzy Cognitive Maps applicability in modeling complex systems has been successfully used in many different application areas (Stylios et al. 1999). An FCM is a signed fuzzy graph with feedback, consisting of concepts-nodes and weighted interconnections. Nodes of the graph stand for concepts that are used to describe main behavioral characteristics of the modeled system. Nodes are connected by signed and fuzzy weighted arcs representing the cause and effect relationship existing among concepts. Thus, an FCM is a fuzzy-graph structure, which allows systematic causal propagation, in particular forward and backward chaining (Stylios and Groumpos 2000). Fuzzy Cognitive Maps have been successfully used to develop a Decision Support System (FCM-DSS) for differential diagnosis (Georgopoulos et al. 2003), to determine the success of radiation therapy process estimating the final dose delivered to the target volume (Papageorgiou et al. 2003) and many other application areas. But there are cases where the input information is not adequate and FCM-DSS cannot discriminate and reach a decision; this surfaces the need of a mechanism to supplement the FCM-DSS.

In this research work we combine FCMs with methods and approaches that have been used for Case-Based Reasoning (CBR) (Noh et al. 2000; Kolodner et al. 1993). This is a successful methodology for managing implicit knowledge (Watson 1999; Lopez de Mantaras 2001), which has also been used in medical informatics (Schmidt et al. 1999, 2001). CBRs embed a considerable amount of previous solved instances of problems (cases). The problem solving experience is explicitly taken into account by storing past cases in a database (case base), and by suitably retrieving them when a new problem has to be tackled (Noh et al. 2000). It simply makes decisions on new cases by their similarity to old cases stored in its case-base rather than using some derivative representation, as is done for example in adaptive-type methodologies. But, if the new case has no match with the stored cases, the CBR has no solution. Similarly to FCMs, CBRs have been applied to medical diagnosis and patient treatment outcomes. Despite the limitations of CBRs, they are usually assumed to have a certain degree of richness of stored knowledge, and a certain degree of complexity due to the way they are organized.

This chapter is divided into 7 sections. Section 2 describes Fuzzy Cognitive Maps, how they model systems and how they are developed. Section 3 presents why Case Based Reasoning (CBS) is important in Medical Decision Systems and how CBR could be combined with FCMs. Section 4 proposes an algorithm to develop an Advanced Medical Decision System, implementing Case Base Reasoning to augment Competitive Fuzzy Cognitive Maps (CFCM); the CFVM developing algorithm is also presented. Section 5 presents an application of the proposed model to speech and language pathology and in section 6 the results of the example are presented. Finally section 7 concludes the chapter.

2. Fuzzy Cognitive Maps

Fuzzy Cognitive Maps (FCM) are a soft computing tool that is a result of the synergy of Fuzzy Logic and Neural Network methodologies and is based on the exploitation of the integrated experience of expert-scientists (Stylios et al. 1999). The graphical illustration of a FCM is a signed, weighted graph with feedback that consists of nodes and weighted arcs. Nodes of the graph are the concepts that correspond to variables, states, factors and other characteristics incorporated in the model, which describe the behavior of the system. Directed, signed and weighted arcs, which represent the causal relationships that exist between the concepts, interconnect the FCM concepts. Each concept represents a qualitative characteristic, state or variable of the system; concepts stand for events, actions, goals, values, and/or trends of the system being modeled as an FCM. Each concept is characterized by a numeric value that represents a quantitative measure of the concept's presence in the model. A high numeric value indicates the strong presence of a concept. The numeric value results from the transformation of the real value of the system's variable, for which this concept stands, to the interval [0,1]. All the values in the graph are fuzzy, so weights of the arcs are described with linguistic values that can be defuzzified and transformed to the interval [-1,1].

Between concepts, there are three possible types of causal relationships that express the type of influence of one concept on the others. The weight of an interconnection, denoted by W_{ij}, for the arc from concept C_i to concept C_j, can 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. When, there is no relationship from concept C_i to concept C_j, then $W_{ij}=0$ (Kosko 1991).

When the Fuzzy Cognitive Map starts to model the system, concepts take their initial values and then the system is simulated. At each step, the value of each concept is determined by the influence of the interconnected concepts on the corresponding weights:

$$A_i^t = f\Big(\sum_{\substack{j=1 \\ j\neq i}}^{n} A_j^{t-1} W_{ji} + A_i^{t-1}\Big) \qquad (1)$$

where A_i^t is the value of concept C_i at step t, A_{j-1}^t is the value of the interconnected concept C_j at step t-1, and W_{ji} is the weighted arc from C_j to C_i and f is a threshold function.

Fuzzy Cognitive Maps represent the human knowledge on the operation of the system, so in order to develop an FCM one expert is asked to do so; thus, FCMs rely on the exploitation of experts' experience on system's model and behavior. Experts determine the number and kind of concepts of FCM and the interrelation among concepts. Experts know the main factors that determine the behavior of the system, each one of these factors is represented by a concept. So an expert draws an FCM according to his experience, he determines the concepts, which for example stand for events, actions, goals, values, and trends of the system. The expert knows which elements of the system influence other elements; for the corresponding concepts he determines the negative or positive effect of one concept on the others, with a fuzzy degree of causation. The determination of the degree of casual relationship among concepts can be improved by the application of learning rules for choosing appropriate weights for the FCM (Kosko 1986). In this way, an expert decodes his own knowledge on the behavioral model of the system and transforms this knowledge in a weighted graph. After the construction of the map, the FCM starts to simulate the operation of the system and each concept interacts with other concepts.

The major advantage of fuzzy cognitive maps is that they can handle even incomplete or conflicting information. This is very important in the decision-making and diagnosis in the area of medical informatics. Especially, in the case of language/communication disorders it is very difficult to reach a conclusion and frequently important information may (Georgopoulos et al. 2003): i) be missing, ii) be unreliable, iii) be vague or conflicting, and/or iv) be difficult to integrate with other information.

3. Case Based Reasoning

Even though successful medical Decision Support FCMs have been developed (Georgopoulos et al. 2003; Papageorgiou et al. 2003), there are situations where the patient data to be input into the system presents a very rare configuration of symptoms where most of the nodes of the FCM would not be active. In other words, for example, although the FCM-Model of a Medical Decision Support System has been designed to include all possible symptoms and causative factors (nodes-concepts) and the relationship between them (weights) for some medical condition, there are particular situations where very few symptoms are available and are taken into consideration. Thus, in such a diagnosis or prognosis model Decision Support FCM, the decision would be made only using a very small subset of the concepts of the entire system. Such a system could lead to either an erroneous decision or difficulty in reaching stability since the weighting of the active nodes reflects only a small amount of the experts' stored knowledge.

Using a CBR-augmented FCM Decision support system, as shown in Figure 1, in such situations, the decisions support system would draw upon cases that are maximally similar according to distance measures and would use the CBR subsystem to generate a sub-FCM emphasizing the nodes activated by the patient data and thus redistributing the causal weightings between the concept-nodes.

The advantage of CBR-augmented FCMs lies in the ability to represent rare occurrences of medical conditions/symptoms, which may not be adequately represented in an FCM due to its design methodology, which is dependent on human experts and learning algorithms (Georgopoulos and Stylios 2003).

There are a variety of approaches that determine the similarity between an input case and the stored cases. Some similarity measures rely on only the shared features between input and stored cases (Rosch and Mervis 1975) whereas others determine similarity by adding up the features that are shared and subtracting the features that are not shared between the input case and each stored case (Tversky 1977). The most common techniques used in CBR diagnostic systems are based on nearest-neighbor retrieval since it is a simple approach that computes the similarity between stored cases and an input case based on weight features. The similarity of the problem (input case) to a case in the case-library for each case attribute is determined. This measure may be multiplied by a weighting factor. The weighted sum of the similarity of all attributes provides a measure of the similarity of each case in the library to the input case, as given by (Noh et al. 2000; Kolodner et al. 1993):

$$Similarity(I,R) = \frac{\sum_{i=1}^{m} f(I_i, R_i) \times w_i}{\sum_{i=1}^{m} w_i} \quad (2)$$

where I is the input case; R the retrieved case; m the number of attributes in each case; i an individual attribute from 1 to m; f a similarity function for attribute i in cases I and R; and w the importance weighting of attribute i. This calculation is repeated for every case in the case library to rank cases by similarity to the input. The normalization is used so that similarity values fall within a range of zero to one, where zero is totally dissimilar and one is an exact match (Watson 1999).

Since the CBRs are used to augment FCMs, linguistic variables are used to represent the attributes of each case in the CBR and the similarity measures are calculated based on fuzzy combination rules, according to well-defined operators called triangular norms (Watson 1999; Lopez de Mantaras 2001).

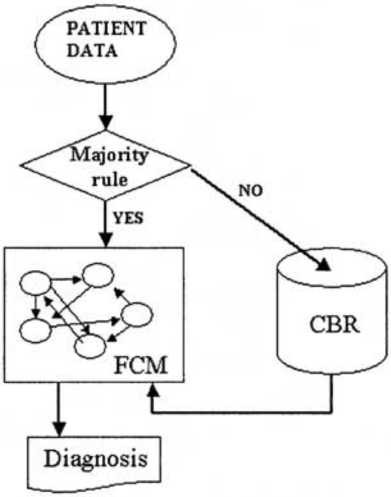

Figure 1. Schematic illustration of CBR augmented FCM.

4. Algorithm to augment CFCM combined with CBR

In this research a special type of Fuzzy Cognitive Maps is used in conjunction with CBR methods to develop a Medical Decision Support System (MDSS). This type is called a Competitive Fuzzy Cognitive Map (CFCM) and it consists of two main kinds of concepts:

- the n decision-concepts
- the m factor-concepts

Each one of the decision concepts stands for one decision/diagnosis, which means that these concepts must be mutually exclusive if our intention is to infer always only one diagnosis. This is the case of most medical applications, where, according to symptoms, medical professionals conclude to only one diagnosis and then decide accordingly concerning the treatment.

The factor-concepts can be considered as inputs of the DSS from 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.

However, the real strength of FCMs is their ability to describe systems and handle situations where there are feedback relationships and relationships between the factor concepts. Thus, interrelations between factor-concepts can be included in the proposed medical decision-support model.

In addition to this, another important quality of the proposed FCM for medical decision support system is that it includes connections (arcs) between the decision-concepts (outputs) themselves. These are not cause-effect connections, but inhibitory connections. These decision concepts must "compete" against each other in order for only one of them to dominate and be considered the correct decision (e.g. diagnosis with the highest probability). Here a new idea is proposed for achieving this "competition" between concepts. The interaction of each of these nodes with the others should have a very high negative weight (even -1). This implies that the higher the value of a given node, this should lead to a lowering of the value of competing nodes, i.e. strong inhibition.

Another novel consideration is that in the FCM in which there are nodes that do not accept feedback, it is important not to allow the values of those nodes to change. In order for this to be achieved, a check should be made of each node to examine if it accepts inputs from other nodes. If not, then a self-feedback value of the node should be set at 1 and the value of that node after each repetition should remain the same. In this case at equation (1), only the second term inside the parenthesis is non-zero.

4.1 The CFCM algorithm

Therefore, the following algorithm is proposed, which describes how to develop a Competitive Fuzzy Cognitive Map (CFCM), which is suitable for decision support systems:

- Set values A_i of nodes according to the input factors involved in the decision process. These values are described using fuzzy linguistic degrees similar to: i.e. none, very-very low, very low, low, medium, high, very high, and very-very high. These linguistic degrees are around to the numerical weights 0, 10%, 20%, 35%, 50%, 65%, 80%, and 90%, respectively, as shown by the membership functions of Figure 2. The decision-concepts are given the initial value of 0 because there is no initial diagnosis.
- The connection weights between the factor-concepts and the decision-concepts are taking their initial values. These connection linguistic weights have been proposed by experts who inferred them using IF THEN rules (Stylios et al. 1999). For the current research, the linguistic weights are defuzzified and transformed in the range are between 0 and 1. Then these numerical weights are then placed in a matrix W of size $(n+m)$x$(n+m)$. The values in the first n columns correspond to the weighted connections from all the concepts towards the n decision-concepts. The values in the remaining m columns correspond to the weighted connections from all the concepts towards the factor-concepts. Also included in this matrix are the -1 weight values for competition between output decision concepts, as described earlier.
- Use equation (1) to calculate the updated value of each concept, where the sigmoid nonlinearity ensures that values of concepts are between 0 and 1 by the implementation of the unipolar sigmoid:

$$f(x) = \frac{1}{1+e^{-\lambda x}} \qquad (3)$$

  where $\lambda \succ 0$ determines the steepness of the sigmoid.
- Repeat steps until equilibrium has been reached and the values of concepts no longer change
- The procedure stops and the final values of the decision-concepts are found, the maximum of which is the chosen decision.

4.2 Algorithm to combine CFCM along with CBR

In the Competitive Fuzzy Cognitive Map (CFCM) model, which is used for medical decision support there are some factors that are considered most important and are the main factors determining a particular decision-diagnosis. These factors are called Critical Factor Concepts and they are dependent on the specific application. When experts develop the CFCM for an application, they determine factor-concepts and the decision-concepts; they are also asked to select among the factor-concepts, the Critical Factor Concepts that are more prevalent in the assigning of the diagnoses. Critical Factor Concepts play important role in reaching any decision but the most important is that the lack of information on a number of them may forbid any decision.

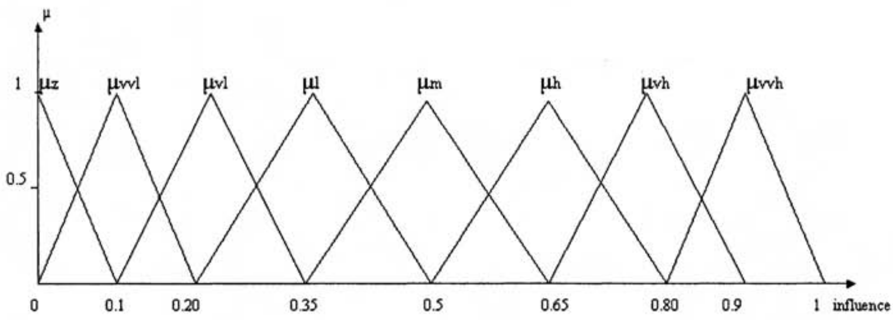

Figure 2. Membership functions

Therefore, when the patient input is entered into the system a logical majority operation rule is applied. The logical majority rule operation is applied to the total of all Critical Factors involved in the decision. This means that if the majority of the Critical Factors for all the possible decision outcomes are activated then the inputs are provided to the Competitive FCM (CFCM) Decision System, otherwise the CBR is called upon. This is shown in Figure 1 where a decision box is included.

When, the CBR is called, the input values describing the problem under examination are compared to the cases stored in the CBR and the case with the highest similarity is selected. Then, the CFCM is updated according to the case with the highest similarity, i.e. in the CFCM only the concepts corresponding to the information of the similar case in CBR are included. Then the updated CFCM is used to suggest a decision/diagnosis, which combines expert's knowledge (CFCM) and previous tested cases (CBR), thus, leading to a more reliable decision. It should be noted that this step is actually performed before the update rule of equation (1) is applied for the first time.

Figure 3 illustrates the implementation of the combination algorithm and the effect that it has in the structure of FCM. Part 3.a of the figure presents the CFCM that was initially developed to suggest one of the three different diagnoses, which are represented by the three striped concepts in the center of CFCM (Georgopoulos et al. 2003). Figure 3.b illustrates an intermediate stage, when the majority rule does not apply, so the CBR is called and a similar case is found in the case base. Thus, updating of the connections between CFCM concepts occurs; that actually means that some weights become zero and the corresponding concepts do not play any role in the decision. Therefore, for this specific case, the concepts with zero influence are removed as is depicted in figure 3.c and only the remaining concepts are used to provide the decision. It should be mentioned that for the next forthcoming problem the CFCM is restored to its initial structure.

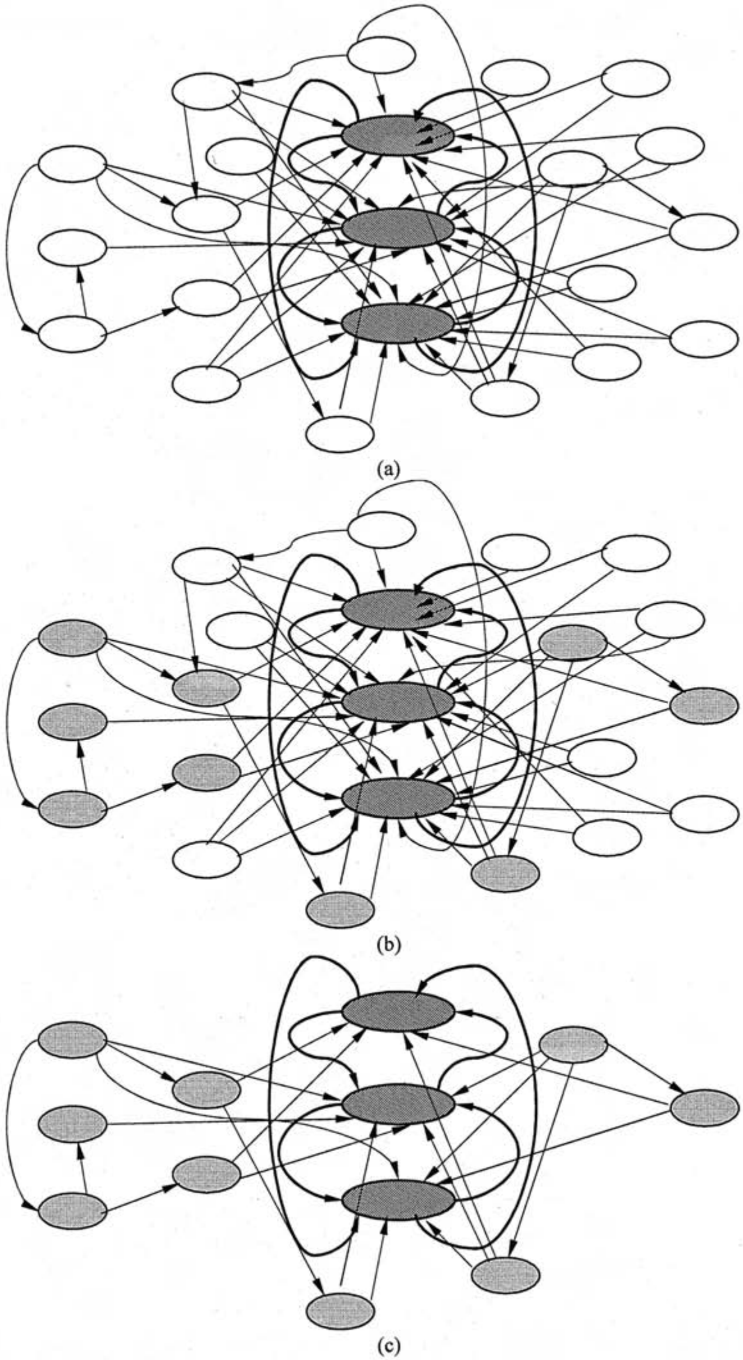

Figure 3 a, b, c. The evolution of CFCM structure based on information from case-base for a specific problem

Even though CBR Augmented CFCM and creates an advanced Medical Decision Support Systems (MDSS); this MDSS is required to perform such distinct tasks as diagnosis, therapy advice and time course analysis, that it would be too ambitious to attempt to propose a general prototype tool that can handle all these tasks. Therefore, as an example, in this chapter we discuss a single but complex diagnostic task. This was chosen since in such medical DSS system the reasoning of the medical professionals is of outmost importance to be taken into account, and this is achieved in the Augmented FCM-CBR. Also, the evaluation required to be carried on a patient for such a case requires inputs from pediatricians, ear-nose-throat specialists, psychologists, as well as of course speech pathologists. The example of an Augmented CFCM developed in the next section is from Speech and Language Pathology. It is a Differential Diagnostic System for Specific Language Impairment, Autism and Dyslexia. This is an extension of the CFCM, which was developed in (Georgopoulos et al. 2003).

5. Application to Speech and Language Pathology

Despite the numerous studies that have been conducted since the first half of the 19th century (Leonard 2000), Specific Language Impairment (SLI) remains a language disorder that cannot be easily diagnosed because it has similar characteristics to other disorders. Research has shown that almost 160 factors can be taken into account in the diagnosis of SLI (Tallal et al. 1985) and there is no widely accepted method of identifying children with SLI (Krasswski and Plante 1997). This implies that the differential diagnosis of SLI with respect to other disorders, which have similar characteristics, is a very difficult procedure. Therefore, it was necessary to develop a model of differential diagnosis of SLI that would aid the specialist in the diagnosis and suggest to him/her a possible diagnosis. Findings in the literature have shown that both dyslexia and autism are disorders, whose diagnoses often have been confused with the diagnosis of SLI (Leonard 2000). Particularly, the data has initially lead to the assumption that SLI cases are confused either with severe cases of dyslexia or with mild cases of autism.

SLI is a significant disorder of spoken language ability that is not accompanied by mental retardation, frank neurological damage or hearing impairment. Children with SLI face a wide variety of problems both on language and cognitive levels.

Dyslexia, or otherwise, specific or developmental dyslexia, constitutes a disorder of children that appears as a difficulty in the acquisition of reading ability, despite their mental abilities, the adequate school training or the positive social environment. *Autism* is a developmental disorder and pathologically it is defined as an interruption or a regression at a premature level of a person's development. The main idea in autism is the impaired or limited relation that exists between the autistic person and its environment

Some basic factors that appear in all three disorders with different frequency and severity in most cases were included in this study. The considered factors are either causative factors or symptoms of the disorders. The factors within each disorder were taken into consideration in a comparative way in the development of the model. The significance of each factor as a diagnostic criterion is defined with the following fuzzy variables: a) Very-very important, b) very important, c) important, d) medium, e) not very important, and f) minimally important. These criteria are represented in the Competitive Fuzzy Cognitive Map Differential Diagnosis Model as the fuzzy weight with which each factor influences every one of the three diagnoses. The advanced MDSS consisted of CFCM and CBR is shown in Figure 4.

Table I shows the information for four case examples stored in the Fuzzy CBR Database used to augment the CFCM Differential Diagnosis system. The first case in the Table is a case with SLI as the final diagnosis, the second and third cases with Dyslexia as a diagnosis, and the fourth case has a diagnosis of autism. The names of the attributes of the CBR are the same as the Factor-Concepts of the CFCM. The critical factors for each disorder have been defined in our previous work (Georgopoulos et al. 2003), as having weightings of very-very high. These are the attributes of Table I, 1, 2, 3, and 9 for SLI, attributes 4, 6, and 9 for Dyslexia and 1, 2, 3, 5, 7, 8, 11, 12, 13, and 15 for Autism. Thus, non-critical factors for all 3 disorders are only 10 and 14 and are not included in the majority test performed in the beginning of the CBR-Augmented CFCM algorithm (i.e. the majority rule imposed here would require *majority=(critical factors)/2 + 1* which in our case is *8* factor-concepts).

It should be noted that the CBR that includes cases of Table I is a general one concerning differential diagnosis of SLI/Dyslexia/Autism and does not only include cases for which the majority rule does not apply.

6. Example

As an example we consider an input case, which is described with the initial values for the factors as shown in Table II. These values are based on the patient's history and test results.

We can try to obtain a diagnosis for this input case using the CFCM model that was developed in (Georgopoulos et al. 2003) and the CBR augmented CFCM model proposed here. If we use the input information of Table II in the CFCM model, after simulation equilibrium is reached where decision concepts have the values:

$$SLI = 0.8700 \quad Dyslexia = 0.6550 \quad Autism = 0.8989$$

It is apparent, that two of the three possible diagnoses have values very close each other and so it is difficult to suggest a diagnosis.

Then, we test the same input case for the CBR Augmented CFCM. This input case does not meet the majority rule, so the CBR component in the MDSS is activated. Then a comparison of this input case to the stored cases in the case-base of CBR is performed. When a good match is found, the attributes of the case found in the CBR are used to reconstruct the CFCM. Then this reconstructed CFCM is run and it reaches the following equilibrium:

SLI= 0.8763 *Dyslexia*=0. 6878 *Autism*=0. 9526

It is obvious that the concept of 'Autism' dominates over values of 'SLI' and 'Dyslexia' concepts and thus the diagnosis of Autism is proposed for this case.

With this simple example, is suggested that a sufficient MDSS model was developed which, under constraints, processes the information about a case in such a way that out of three possible diagnoses we are lead to the diagnosis of the most probable disorder.

Table I. Sample Clinical Cases Stored in Fuzzy CBR used to Augment FCM

Attributes	Case 1	Case 2	Case 3	Case 4
1. Reduced Lexical Abilities	VERY - VERY HIGH	HIGH	MEDIUM	VERY HIGH
2. Problems in Syntax	VERY-VERY HIGH	HIGH	HIGH	VERY-VERY HIGH
3. Problems in Grammatical Morphology	VERY HIGH	HIGH	HIGH	VERY-VERY HIGH
4. Impaired or Limited Phonological Development	HIGH	MEDIUM	HIGH	VERY HIGH
5. Impaired Use of Pragmatics	MEDIUM	0	0	VERY-VERY HIGH
6. Reading Difficulties	0	MEDIUM	VERY-VERY HIGH	-HIGH
7. Echolalia	0	0	0	VERY HIGH
8. Reduced Ability of Verbal Language Comprehension	0	0	0	VERY-VERY HIGH
9. Difference between Verbal - Nonverbal IQ	HIGH	HIGH	HIGH	0
10. Heredity	0	0	0	0
11. Impaired Sociability	MEDIUM	0	VERY LOW	VERY-VERY HIGH
12. Impaired Mobility	MEDIUM	0	LOW	VERY HIGH
13. Attention Distraction	0	0	LOW	VERY HIGH
14. Reduced Arithmetic Ability	MEDIUM	0	MEDIUM	-HIGH
15. Limited Use of Symbolic Play	0	0	0	VERY-VERY HIGH

Table II. Values for example

Attributes	Example
1. Reduced Lexical Abilities	HIGH
2. Problems in Syntax	HIGH
3. Problems in Grammatical Morphology	VERY HIGH
4. Impaired or Limited Phonological Development	-
5. Impaired Use of Pragmatics	-
6. Reading Difficulties	-
7. Echolalia	-
8. Reduced Ability of Verbal Language Comprehension	MEDIUM
9. Difference between Verbal - Nonverbal IQ	MEDIUM
10. Heredity	-
11. Impaired Sociability	MEDIUM
12. Impaired Mobility	-
13. Attention Distraction	-
14. Reduced Arithmetic Ability	-
15. Limited Use of Symbolic Play	LOW

7. Conclusions

In this chapter, we described an advanced Medical Decision Support System (MDSS) which is based on the augmentation of Competitive Fuzzy Cognitive Map (CFCM) with Case Based Reasoning (CBR) methods. The proposed Decision System of CBR-Augmented Competitive FCM is applied and tested as a Medical Decision System for Speech and Language Disorders. For one problem case the CBR-Augmented Competitive FCM is compared with the simple CFCM and the results show the advantages of the new proposed system. In essence, this CBR-Augmented Competitive Fuzzy Cognitive Map is capable on its own to perform a comparison and lead to a decision based on expert knowledge and experience (structure of CFCM) and well known tested previous cases (CBR).

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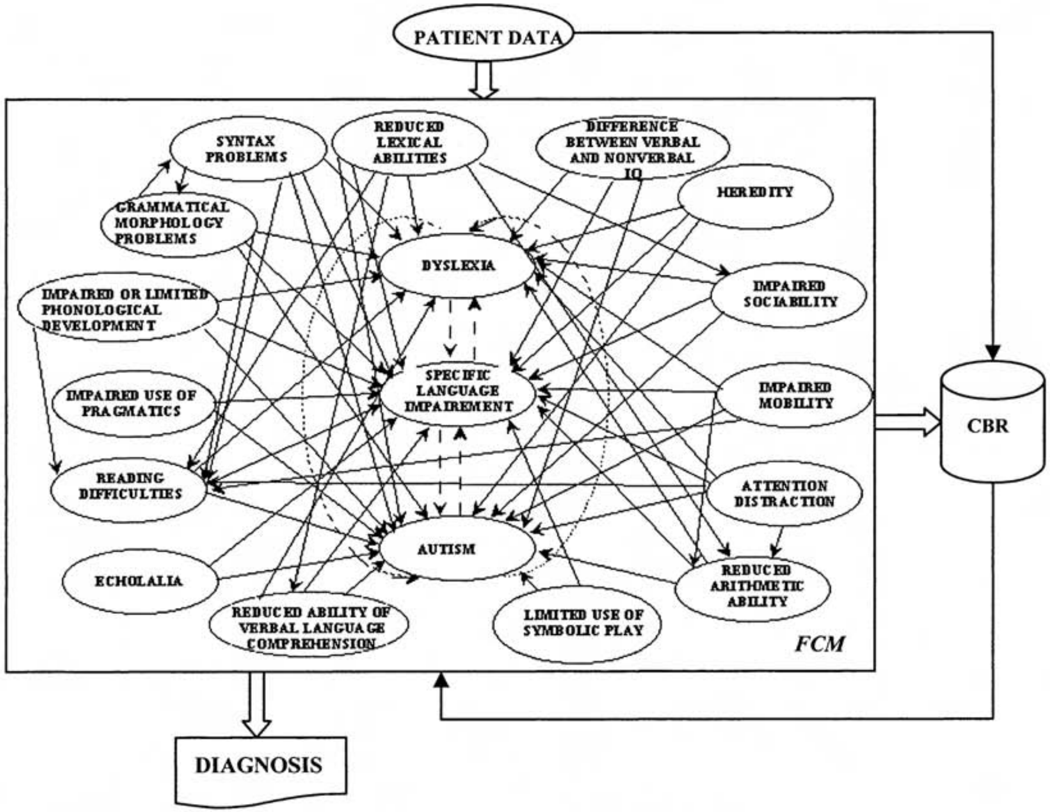

Figure 4. An abstract illustration with a view of the CBR augmented CFCM.