Genetic Algorithm Enhanced Fuzzy Cognitive Maps for Medical Diagnosis

Chrysostomos D. Stylios and Voula C. Georgopoulos

***Abstract*— This paper presents a new hybrid modeling methodology for the Complex Decision Making processes. It extends previous work on Competitive Fuzzy Cognitive Maps for Medical Decision Support Systems by complementing them with Genetic Algorithms Methods. The synergy of these methodologies is accomplished by a new proposed algorithm that leads to more dependable Advanced Medical Decision Support Systems that are suitable to handle situations where the decisions are not clearly distinct. The methodology developed here is applied successfully to model and test a differential diagnosis problem from the speech pathology area for the diagnosis of language impairments.**

I. Introduction

BOTH Fuzzy Cognitive Maps (FCMs) and Genetic Algorithms (Gas) have been successfully employed for developing intelligent systems, which have been applied effectively in many different application domains. Both techniques incorporate knowledge, experience and historical information and data in order to handle and solve new problems. Knowledge and experience is reflected in the developing procedure and the infrastructure of FCMs which are suitable to model the reasoning process on making desicions or, more specifically in the medical field, for reaching a diagnosis. On the other hand, GAs belong to adaptive methods exploiting existing data which are mainly used to solve search and optimization problems. They originate from the genetic processes of biological organisms.

FCMs rely on the expert knowledge of a domain making associations along generalized relationships between domain descriptors, concepts and conclusions.

Genetic algorithms (GAs) represent an advanced methodology based on a random selection within a defined search space to solve a problem.

Fuzzy Cognitive Maps are an illustrative causative representation for the description and modeling of complex systems. Fuzzy Cognitive Maps model the world as a collection of concepts and causal relations between concepts based on the experience and knowledge of experts. An FCM draws a causal graphical representation to model the behavior of any system; it consists of interrelated concepts [1]. FCMs are fuzzy signed directed graphs permitting feedback, where the weighted edge w_{ij} from causal concept C_i to affected concept C_j describes how much the first concept influences the latter. The human experience and knowledge on the operation of the system is embedded in the structure of FCM and the FCM developing methodology, i.e., by using human experts that have observed and know the operation of system and its behavior under different circumstances.

Fuzzy Cognitive Maps have been successfully used to develop a Decision Support System (FCM-DSS) for differential diagnosis [2], to determine the success of the radiation therapy process estimating the final dose delivered to the target volume [3] and many other applications. But medical systems are complex systems involving inexact, uncertain, imprecise and ambiguous information [4].

However, there are problems 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. For such systems exploitation of the optimization properties of Genetic Algorithms for selected weighted edges w_{ij} of the FCM-DSS may lead to more confident decisions.

This paper is organized in seven sections including this introduction. The next two sections discuss FCMs and GAs, respectively, for medical decision support. Section 4 discusses the synergy of FCMs and GAs leading to an advanced Medical DSS while Section 5 presents the algorithm for the GA-enhanced FCM DSS. Section 6 shows an implementation of the algorithm and finally section 7 offers conclusions.

II. Fuzzy Cognitive Maps for Medical Decision Support

Fuzzy Cognitive Maps have been used to develop Medical Decision Support System (MDSS). A specific type for Medical Diagnosis is the Competitive Fuzzy Cognitive Map (CFCM) [5-6] and it consists of two main types of concepts: diagnosis-concepts and factor-concepts. Figure1 illustrates an example CFCM model which is used to perform medical diagnosis. Here the concepts of the FCM and the causal relations among them that influence concepts and determine the value of diagnosis concepts indicating final diagnosis are illustrated.

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978-1-4244-1819-0/08/$25.00©2008 IEEE

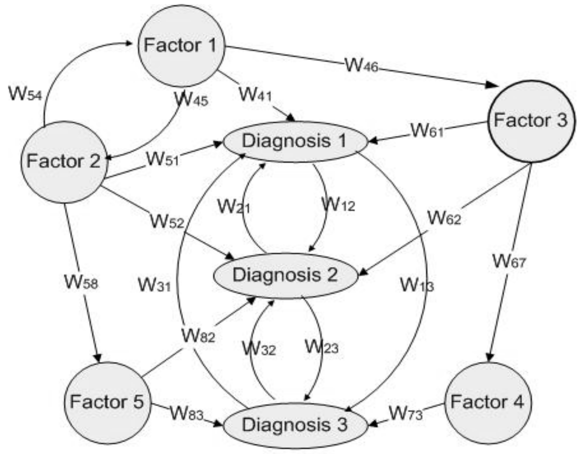

Fig. 1. A CFCM model for Medical Diagnosis.

Each decision concept represents a single 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 general diagnosis procedure is a complex process that has to take under consideration a variety of interrelated factors and functions. Usually, in any real world diagnosis problem, many different factors are taken into consideration. In accomplishing any diagnosis process, some of these factors are complementary, others are similar and even others are conflicting.

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. Such interconnections are shown in Fig. 1 where the "competitive" interconnections between diagnosis concepts are also illustrated.

III. Genetic Algorithms

Genetic algorithm (GAs), based on the genetic evolution of a species were introduced by Holland [7]. They are adaptive methods, based on the genetic processes of biological organisms, which may be used to solve search and optimization problems. Potential solutions to specific problems are encoded using simple data structures similar to chromosomes. These chromosomes make up an initial population where each individual chromosome is assigned a "fitness score" according to how good a solution to the problem it is. The higher the fitness score the more opportunity they have to produce "offspring" through mechanisms of mutation, selection and crossover as defined in [8] retaining some desirable properties from the parents. In this way, the population members cover the search space based on selection rules and parameters specified and convergence towards the optimal solution occurs, with a tendency to detect local optima and ultimately to find the global optimum. Genetic algorithms are particularly effective for problems where i) the cost function or its gradient are not defined analytically, ii) the cost function has many local minima, iii) there is a large number of variables is large, or iv) there is requirement for application of many and/or complex constraints.

Originally, genetic algorithm populations were only binary valued but other coding types have been considered, such as Real Coded Genetic Algorithms (RCGA) [9], for optimization problems of parameters with variables in continuous or discontinuous domains. The theory and workings of genetic algorithms is beyond of the scope of this paper and can be found in [10].

Genetic Algorithms have been successfully employed to Fuzzy Cognitive Maps by Stach et al. [11-15] to optimize the learning process.

Genetic Algorithms have also been successfully used for Medical Decision Support either alone [4] or in combination with other techniques, particularly in the area of diagnosis [16-19]. GAs are designed to evaluate existing potential solutions as well to generate new (improved) solutions to a problem for evaluation. Thus, GAs can improve the quality of decision making.

The following section discusses the synergy of the two techniques as Medical Decision Support systems.

IV. An Advanced Medical DSS Based on FCMs and GAs

It is concluded from the previous sections that both FCM and GA techniques have been successfully used in the medical domain to perform diagnosis tasks and develop Medical Decision Support Systems. Here, an advanced MDSS is proposed based on the complementary use of FCMs and GA that constitutes an advanced hybrid inferring methodology. When the CFCM has difficulty to infer a decision with great certainty, then the GA is called to assist the CFCM, so that the hybrid MDSS can propose a diagnosis.

Figure 2 diagrammatically shows the GA enhanced CFCM Medical Decision Support Model. Here the patient data is input to the CFCM and the factor concepts take their initial values from this input data. Patient information are experimental results, test results, physical examinations and other descriptions of symptoms and measurements of physical qualities. This information can be described either in numerical values or in fuzzy linguistic weights which are then transformed into a numerical weight in the range [0,1], i.e. the allowable values for the CFCM concepts. The CFCM runs according to the algorithm described in [2] and when an equilibrium region is reached the CFCM ceases to interact. Then the values of the decision/diagnosis concepts are examined to determine if there is a distinct decision/diagnosis or not. A distinct outcome is inferred, if the value of a decision concept is surpassing the others by at least 10%. In this case the leading competitive node is the suggested decision. Otherwise, when the percent difference between the two leading competitive nodes is less than 10%, then the comparison made in the "Distinct Outputs" box leads to a "NO" result, activating the GA component. The GA component is used to "manipulate" weights that are not directly associated with the two "leading" decision/diagnosis concepts. The weight vectors for each concept make up a real-coded chromosome which is allowed to mutate/reproduce as long as the weights associated with the "leading" decision/diagnosis concepts are not affected. The new weight matrix resulting is used to run the CFCM. If one of the two "leading" decision/diagnosis concepts is not the result of the new CFCM or if again the 10% rule above is not met, then the new chromosomes are discarded. Otherwise, the new result (interim inferred decision) is recorded, "chromosome" weights are kept as part of the population and the algorithm is repeated for a large number of iterations. The final decision is the decision with the highest probability as a result of the iterations. The detailed algorithm is discussed in the next section.

V. Description of the Complementary GA-CFCM Algorithm

The Advanced Medical Decision Support System GA-CFCM based on the synergism of Genetic Algorithms and Competitive Fuzzy Cognitive Map (CFCM) techniques is implemented by the following proposed algorithm:

Step1. First apply the CFCM algorithm described in [2].

Step 2 When the CFCM algorithm drives concepts to reach steady state, measure the difference between the values of competitive decision/diagnosis concepts.

Step3 If the difference between the highest values of the decision/diagnosis concepts is more than 10%, THEN a decision/diagnosis is inferred, which is reflected in the concept with the highest value – go to Step 6. ELSE activate Genetic Algorithm.

Step 4 For all factors that are not critical for the two decision/ diagnosis concepts, allow the weights w_{ij} *to change based on mutations, crossover, and inversion to form new "offspring" weights for the noncritical factors.*

Step 5 Run the FCM based on the new values, if the two decision/diagnosis concepts having the highest values are not the same as before, OR IF the difference between the highest values of the decision/diagnosis concepts is less than 10%, discard new weights, repeat Step 4. ELSE IF the difference between the highest values of the decision/diagnosis concepts is more than 10%, THEN an intermediate decision/diagnosis is inferred which is recorded. Repeat Step 4 – this step is iterated1000 times.

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Step 6. Final Decision/diagnosis is either the result of Step 3 OR, if GA-CFCM was activated, the intermediate inferred decision with the highest probability as a result of 1000 iterations of steps 4 and 5.

VI. Example from Speech and Language Pathology

Specific Language Impairment (SLI) is a language disorder that cannot be easily diagnosed because it has similar characteristics to other language disorders. Research has shown that almost 160 factors can be taken into account in the diagnosis of SLI [20] and there is no widely accepted method of identifying children with SLI [21]. This implies that the differential diagnosis of SLI with respect to other disorders, which have similar characteristics, is a very difficult procedure making the CFCM an attractive solution of this differential diagnosis problem [2]. Findings in the literature have shown that severe cases of dyslexia and mild cases of autism are disorders, whose diagnoses often have been confused with the diagnosis of SLI [22].

SLI is a significant disorder of spoken language ability which 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 [23-24]. 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.

In a previous work [2], fundamental factors that may appear in all three disorders with different frequency and severity in most cases were identified. The considered factors are either causative factors and/or symptoms of the disorders and are those shown in the first column of Table I. 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 using fuzzy variables: a) Very-very important, b) very important, c) important, d) medium, e) not very important, and f) minimally important. These criteria were represented in the Competitive Fuzzy Cognitive Map Differential Diagnosis Model that was developed as the fuzzy weight with which each factor influences every one of the three diagnoses.

Table I. Values for Speech and Language Pathology Example

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

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

Based on the algorithm presented above, a diagnosis for this input case using the CFCM model that was developed in [2] and the GA-enhanced CFCM model described here can be obtained and compared.

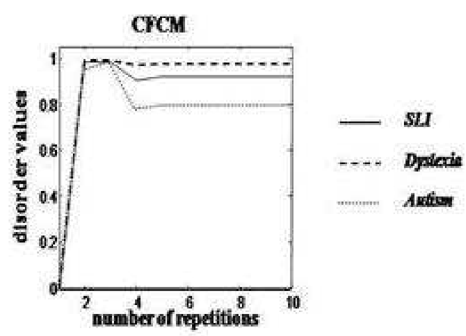

Fig. 3 Result of the CFCM for SLI, Dyslexia and Autism, which reaches equilibrium after 4 iterations, but not a 'confident' decision

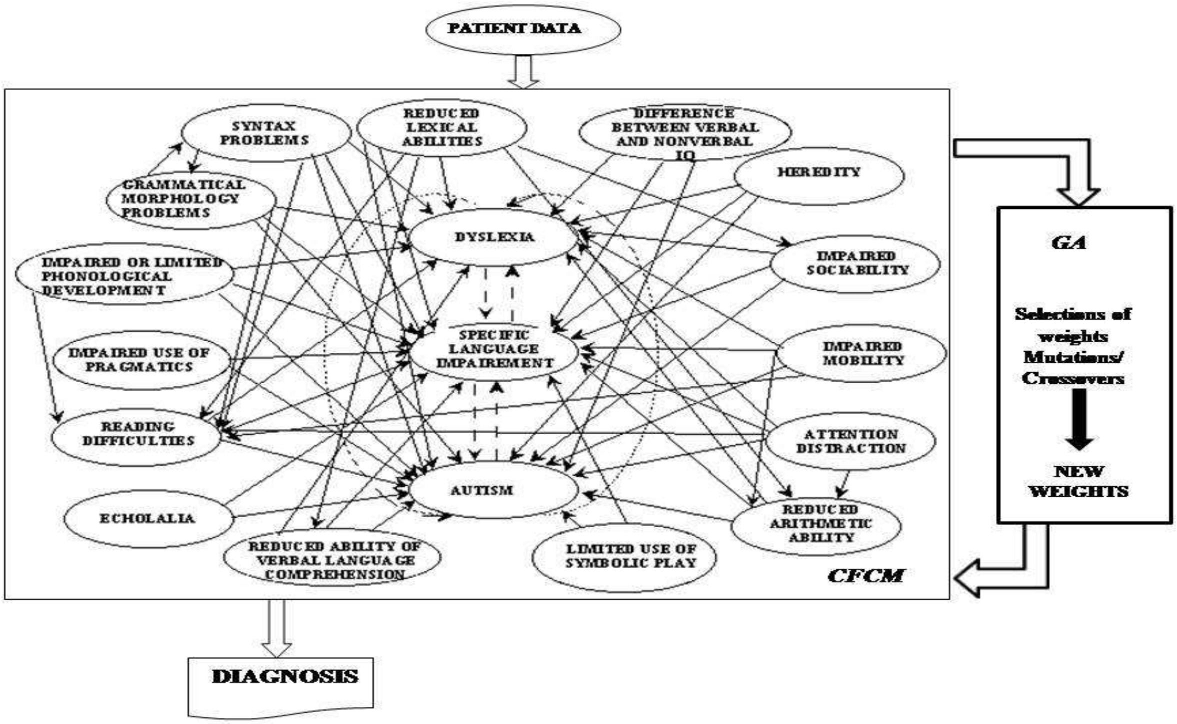

Fig. 4 Genetic Algorithm Enhanced Competitive Fuzzy Cognitive Map for SLI

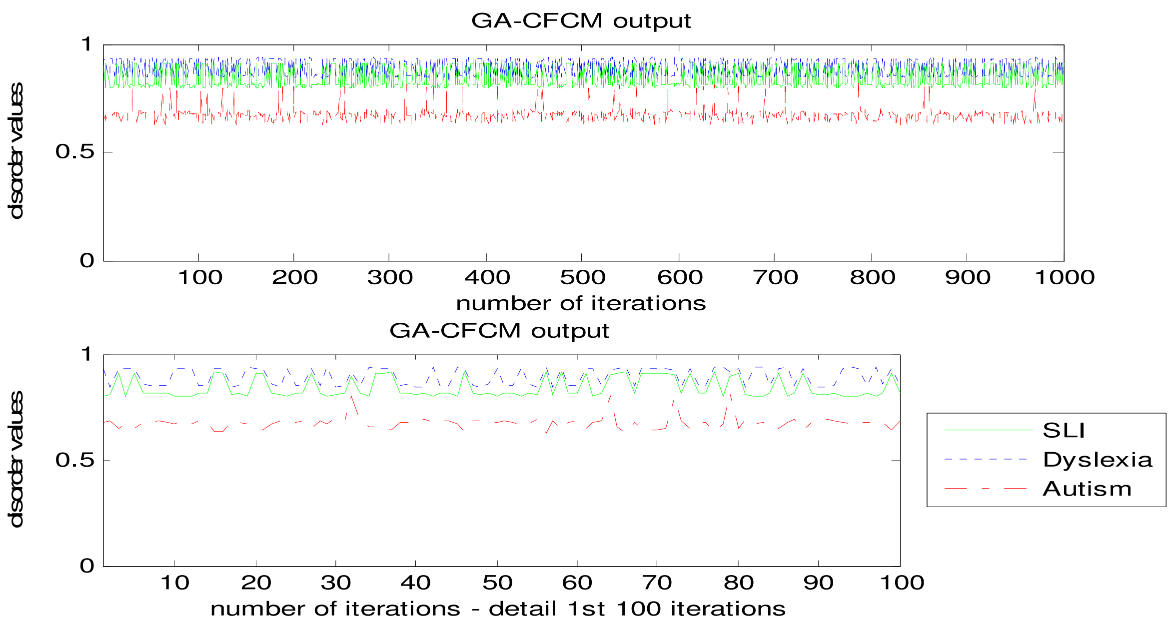

Fig. 5 Result of the GA-enhanced CFCM after 1000 iterations as well as detail showing the first 100 iterations

If we use the input information of Table I in the CFCM model, after 4 simulation iterations, equilibrium is reached where decision concepts have the values:

$SLI= 0.9281 \quad Dyslexia=0.9645 \quad Autism=0.7935$

It is apparent, that two of the three possible diagnoses (SLI and Dyslexia) have high values and their difference of 3.8% is less than 10%. Thus, the CFCM cannot support the diagnosis of Dyslexia, which has the highest value, without additional information.

Then, we test the same input data for the GA-Enhanced CFCM model, shown in block diagram form in Figure 4. According to the proposed algorithm, with this input case the distinction between SLI and Dyslexia decisions is "No" leading to the activation of the GA component in the MDSS.

The GA-CFCM through updating of the noncritical weights of the CFCM (the critical weights were those associated directly with the nodes SLI and Dyslexia) results in a probability of Dyslexia p= 0.9451 for the iterations of the algorithm where there is a difference greater than 10% between the leading two decision concepts. This leads to a more confident diagnosis, since due to the GA-FCM none of the outcomes were 'Autism' and 'SLI' has a probability of p=0.0549 for the iterations where there is a "clear" decision. Thus, it is obvious that the concept of 'Dyslexia' dominates over the values of 'SLI' and 'Autism' concepts and thus, the diagnosis of Dyslexia is proposed for this case.

This can also be seen in Figure 5 which shows the result of 1000 iterations of the GA-CFCM for the input example of Table I, as well as the detail for the first 100 iterations.

I. Conclusion

With this simple example, it is suggested that a sufficient MDSS model was developed which, under constraints, processes the information about a patient in such a way that out of three possible diagnoses we are lead to the diagnosis of the most probable disorder. Here a novel hybrid methodology is proposed to develop Medical Decision Support Systems. This hybrid technique is based on two complementary techniques FCMs and GAs in order to overcome the situation where one technique does not infer a unique decision/diagnosis. This promising approach will be tested on other decision support problems where the possible outcomes are more than three increasing the complexity of the problem.

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