Augmentative Fuzzy Cognitive Maps with Case Based Reasoning for Advanced Medical Diagnosis

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Abstract

This research work proposes the combination and integration of Fuzzy Cognitive Maps (FCMs) with Case Based Reasoning (CBR) Method to develop an Augmentative modeling method for Medical Decision Support Systems (MDSS). They are two complementary methods that are applied synergistically to support each other, when the FCM part of the MDSS cannot reach a decision, the CBR component heads the decision process. In this scenario the CBR leads to reconstruction of the FCM so that the Medical Decision Support System to easily reach a decision. This integration can successfully used for differential diagnosis in the speech pathology area for the diagnosis of language impairments.

Keywords: Fuzzy Cognitive Maps, Case Based Reasoning, Medical Decision Support System.

1. Introduction

Fuzzy Cognitive Maps (FCMs) and Case Based Reasoning (CBR) are two well known methods that have been applied successfully for developing knowledge-based systems in many different application domains. They are based on utilizing and exploiting existing knowledge and experience to handle and solve new problems. Human knowledge and experience on reasoning and decision making and diagnosis is reflected in the development method so that the infrastructure of FCMs emulates and models the human reasoning process. The complementary method of CBR utilizes a database approach to store the most important significant cases that are used as examples and comparisons are made to find a solution using the assumption that similar problems usually have similar solutions.

FCMs rely on specific human knowledge and system behavior making associations along generalized relationships between domain descriptors, concepts and conclusions. On the other hand, CBR is an expert approach to problem solving and learning, which instead of relying solely on general knowledge of a problem domain, utilizes the specific knowledge of previously experienced concrete problem situations and implicit solutions. Here a hybrid method consisting of the synergic combination of FCMs and CBR is proposed such that when the MDSS based on the FCM module is unable to infer a solution, the CBR module is called to modify the FCM module and finally the MDSS concludes to a decision.

The CBR method is based on identifying the current problem, finding a past case similar to new one, and using that case to suggest a solution to the current problem [1][2][3].

Fuzzy Cognitive Maps are an illustrative causative representation for the description and modeling of complex systems. FCMs model the behavior of a system 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, which reflects the general operation and behavior of a complex system. The core mechanism behind FCM is the interrelation among concepts that actually determine the FCM model. FCMs are fuzzy signed directed graphs permitting feedback, where the weighted edge 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 who have observed and know the operation of system and its behavior under different circumstances [4].

Fuzzy Cognitive Maps have been successfully used to develop a Decision Support Systems (FCM-DSS) for differential diagnosis [5], to determine the success of the radiation therapy process estimating the final dose delivered to the target volume [6] and many other applications. Particularly in the medical diagnosis and decision field, the main characteristics are complex involving inexact, uncertain, imprecise and ambiguous information [7]. Frequently for these kinds of problems, the available information and input may be inadequate and the FCM module of the MDSS cannot discriminate and reach a decision; this surfaces the need of a mechanism to supplement the FCM-DSS. This is the case where FCM-DSS based on general knowledge requires the contribution of the specific knowledge of some special cases using CBR.

2. Medical Decision Support Systems based on FCMs

Many methods are proposed to develop Medical Decision Support Systems (MDSS); FCMs have been successfully applied in this area [5][6]. An important type of MDSS is used in Diagnosis where Competitive Fuzzy Cognitive Maps (CFCM) have been developed and applied [8]. The CFCM consists of two main kinds of concepts: decision-concepts and factor-concepts. Fig.1 illustrates an example CFCM model used to perform medical decision/diagnosis. Here all the concepts of the FCM their causal relations are shown. The concepts interact with each other and determine the value of diagnosis-concepts of interest indicating the final diagnosis.

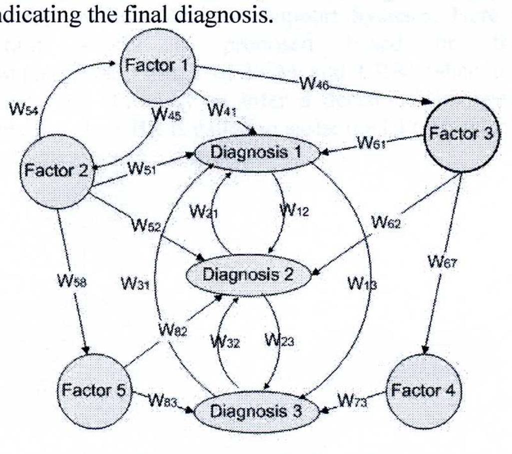

Fig.1.: A FCM model for Medical Diagnosis.

In the FCM 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 conclude to only one diagnosis and then decide accordingly concerning the treatment. It well known that medical 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 others conflicting, and the most importantly factors influence other factors.

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

3. CBR in Medical Diagnosis

An essential characteristic of Medical Diagnosis is that it is almost impossible to design an explicit model based on the human body's subsystem interactions to infer diagnosis. Thus, expert systems approaches, such as Case Based Reasoning (CBR), which belongs to Artificial Intelligence (AI) techniques are developed. CBR has also been applied in different application domains but mainly in medicine. The CBR approach utilizes stored significant cases and adapts old ones to derive a new solution for a new case. The CBR reasoner can avoid previous mistakes, and can focus on the most important parts of a problem. The CBR approach to inferring and learning is very similar to human reasoning and knowledge acquisition. Exactly the same as people take into account and use past experiences to take future decisions CBR follows the same principle [9].

Apart from these positive aspects, there are still a lot of open problems in CBR. The retrieval and selection of cases, since the operations of adaptation and evaluation will succeed only if the past cases are the relevant ones. In the matching problem is important to select the best case because it is necessary to be able to match cases. Usually the match cannot be perfect because the values of the comparable features are not exactly the same; there are missing values for some or even many of features. The adaptation/evaluation can reduce significantly the amount of work needed to solve the problem. Evaluation gives to the case-based reasoner feedback about whether or not the current case was solved adequately. Especially in medicine, adaptation can be a serious problem, because cases often consist of an extremely large number of features [10][11].

Medicine is a rather suitable domain for application of CBR and especially for development Medical Decision Support Systems. These systems are based on the experts and subjective knowledge, which is contained in cases. CBR has successfully used in medicine domain because:

- Reasoning with cases corresponds to the decision making process of physicians.

- Incorporating current cases obtains automatically updated parts of the knowledge.
- Integration into clinic communication system is easy (cases are routinely stored).

CBR has been mainly applied in medicine for diagnostic because human diagnosis process is the adaptation of an old case to fit a current problem. For diagnostic tasks cases are usually described by a list of syndromes or symptoms. These syndromes and symptoms are of different importance for typical cases, some are essential while an often occurrence of others may be only coincidental.

4. Hybrid Medical Diagnosis system based on the CFCM and CBR

Both FCM and CBR have been successfully used in medical domain to perform diagnosis tasks and develop Medical Decision Support Systems. Here a hybrid MDSS is proposed based on the complementary usage of FCM and CBR; when the CFCM has difficulty to infer a decision with great certainty, the CBR is called to assist the CFCM, which then can propose a diagnosis.

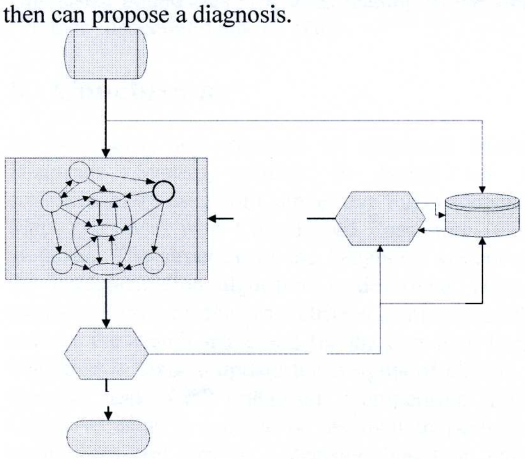

Fig. 2: The flowchart of CBR enhanced FCM algorithm for the advanced MDSS

Figure 2 diagrammatically shows the CBR enhanced CFCM Medical Diagnosis System. Here the patient data is input to the CFCM and the factor concepts take their initial values. Patient information are experimental results, test results, physical examinations and other descriptions symptoms and measurements of physical qualities, which are described in fuzzy linguistic weights and are transformed in numerical weight in the range [0,1] where concepts of CFCM take values. The CFCM runs according to algorithm described in [5] and when an equilibrium region is reached the CFCM ceases to interact. Then the values of diagnosis concepts are examined if there is a distinct diagnosis or not. A distinct outcome is inferred if the value of a decision concept is leading to the others for over 10%, then the leading diagnosis is the suggested decision. Otherwise, when the % difference between the two leading diagnoses is less than 10%, then the comparison made in the "Distinct Outputs" box leads to a "NO" result activation of the CBR component. The patient data is then input into the CBR leading to a nearest neighbor search between patient data and stored cases. Once a case is found, with the minimum distance from the patient case, its diagnosis is used to update the CFCM.

5. The Complementary use of CFCM and CBR

An algorithm is proposed to run inside the Medical Diagnosis System based on the synergism of CBR and CFCM techniques:

- First apply the CFCM methodology [5].When the CFCM methodology stops, compare the crisp values of diagnosis concepts. If the difference between the highest values of the decision/diagnosis concepts is less than 10%, activate Case Based Reasoning.
- Find minimum difference between input patient data (input case) and stored cases. The comparison is performed only for cases in the case-base with decisions/diagnoses corresponding to the two highest valued decision/diagnosis concepts of the CFCM. It must be mentioned that this is a new criterion that reduces the search space of cases and minimizes the required time. The similarity between the fuzzy factor attributes of the input case and the stored cases in the database are based on the similarity measures for fuzzy sets in a discrete universe [12] and extended by Liao [13] for a continuous universe [14]:

$$sim(A,B) = M_{A,B} = \frac{area(A \cap B)}{area(A \cup B)} \quad (1)$$

where: $area(A) = \int_U \mu_A(x)dx$

$$sim(A,B) = S_{A,B} = \frac{\int_U |\mu_A(x) - \mu_B(x)|dx}{\int_U (\mu_A(x) + \mu_B(x))dx} \quad (2)$$

- Once a case has been identified with the highest similarity to the patient input data, the resulting decision/diagnosis of the CBR is returned to the CFCM. It is mentioned that the diagnosis of CBR could itself be used but there is a policy to double check the diagnosis and so the CFCM is updated.
- At the CFCM an updating of weights based on the CBR results occurs according to lateral inhibition. Lateral inhibition is used in neural networks so that strong signals can inhibit weak signals. Usually, in all the diagnosis systems there are attributes (factor concepts) whose values are

considered critical for the each one decision/diagnosis [5]. Thus, according to the diagnosis of CBR, the corresponding critical factor concepts are used to inhibit the connections of those factors to the other diagnosis by a small percentage according to the function:

$$w_{lk}(new) = w_{lk}(old)(1 - \eta|w_{lc}|) \qquad (3)$$

where:

l refers to factor concepts that are critical factors for the decision/diagnosis that is the same as the case result of the CBR.

c is the decision/diagnosis concept that is the same as the case result of the CBR

w_{lk} is the weight from factor concept l to decision concept k and k includes all the other decision/diagnosis concepts except for the concept c.

w_{lc} is the weight from factor concept l to decision concept c

η is a small number between 0 and 0.5 giving the percent inhibition

The purpose of lateral inhibition is to enhance differences between different decisions/diagnoses and emphasize boundaries [15] thus, leading to the single "winner" decision/diagnosis [16].

6. Conclusions

In this paper, we proposed an advanced Medical Diagnosis System, which is based on the complementary usage of Competitive Fuzzy Cognitive Maps (CFCMs) with Case Based Reasoning (CBR) methods. The structure of the Diagnosis system and the implementation algorithm is described. Here, a second criterion for the case retrieval is introduced that reduces the search space and for the first time lateral inhibition is used to update the weights of CFCM. In essence, this CBR-Enhanced 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).

7. References

[1] J.L. Kolodner. Case-based Reasoning. San Francisco: Morgan Kaufmann 1993

[2] M. M. Veloso and A. Aamodt (Eds.). Case-based reasoning research and development. Lec. Notes in Artificial Intell.. Berlin: Springer-Verlag, 1995.

[3] S. Wess, K. Althoff and M. Richter (Eds.) Topics in case-based reaoning. Berlin:Springer-Verlag, 1994.

[4] C. D. Stylios and P.P. Groumpos, V. C Georgopoulos. "An Fuzzy Cognitive Maps Approach to Process Control Systems" *J. Advanced Computational Intelligence*, Vol. 3, No. 5, pp.409-417, 1999.

[5] VC Georgopoulos , GA Malandraki, and CD Stylios CD. "A fuzzy cognitive map approach to differential diagnosis of specific language impairment". *J A.Ie in Medicine.* Vol. 29, pp. 261–278, 2003

[6] E. Papageorgiou, C Stylios, and P. Groumpos. "An integrated two-level hierarchical system for decision making in radiation therapy using fuzzy cognitive maps". *IEEE Transactions on Biomedical Engineering.* Vol. 50, pp.1326-1339, 2003.

[7] M. Sprogar, M. Lenic and S. Alayon. "Evolution in medical decision-making". *Journ of Medical Systems, V*ol. 26 No. 5, pp. 479-89, 2002.

[8] VC Georgopoulos and CD Stylios. "Augmented fuzzy cognitive maps supplemented with case based reasoning for advanced medical decision support". *Soft Computing for Information Processing and Analysis Enhancing the Power of the Information Technology.* M. Nikravesh, et al. (Eds), 2004.

[9] R. Schmidt, B. Pollwein, L. Gierl . "Experiences with Case-based Reasoning Methods and prototypes for Medical Knowledge-based Systems". *In: W. Horn et al. (Eds):AIMDM'99, LNAI 1620*, pp. 124-132, 1999.

[10] J.P. Haton, M. Keane and M. Manago (Eds). Advances in case-based reasoning: Second European workshop. Berlin: Springer-Verlag, 1995

[11] R. Schank, C. Riesbeck and A. Kass. Inside case-based explanation. Hillsdale:Erlbaum, 1994

[12] N. Karacapilidis and C. Pappis . "Computer-supported collaborative argumentation and fuzzy similarity measures in multiple criteria decision making". *Computers & Operations Research.* Vol. 27, pp. 653-671, 2000.

[13] T. W. Liao. "Classification and coding approaches to part family formation under a fuzzy environment". *Fuzzy Sets and Systems.* Vol. 122, pp. 425-441, 2001.

[14] J. Dvořák and M. Šeda. "Comparison of Fuzzy Similarity Measures". *Proc. of 3rd International Conference APLIMAT 2004,* Slovak Technical University, Bratislava, Slovakia, pp. 387-392, 2004

[15] V. C. Georgopoulos. "A proposed electro-optical implementation of lateral inhibition with phase-only filters". *Microwave and Optical Technology Letters.* Vol. 15, pp. 98-102, 1997.

[16] B. Krekelberg, and J. N. Kok. "A lateral inhibition neural network that emulates a winner-takes-all algorithm". RUU-CS (no. 92-46). Utrecht., 1992

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