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Complementary case-based reasoning and competitive fuzzy cognitive maps for advanced medical decisions

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Abstract This paper presents a new hybrid modeling methodology suitable for complex decision making processes. It extends previous work on competitive fuzzy cognitive maps for medical decision support systems by complementing them with case based reasoning 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 two decision support systems, one a differential diagnosis problem from the speech pathology area for the diagnosis of language impairments and the other for decision making choices in external beam radiation therapy.

Keywords Soft computing · Fuzzy cognitive maps · Case-based reasoning · Medical decision support systems

1 Introduction

Fuzzy cognitive maps (FCMs) and case-based reasoning (CBR) are two successful techniques for developing knowledge-based systems applied in a variety of different application domains. Both techniques are based on utilizing previous knowledge and experience to handle complexity and solve new problems. The main idea behind FCMs is the assumption that experts who supervise and control a system, posses a mental model on the behavior of any domain, which can be used successfully for any unprecedented problem (Kandasamy and Smarandache 2003). The main idea of CBR is the assumption that similar problems usually have similar solutions. FCMs rely on the general knowledge of a domain making associations along generalized relationships between domain descriptors, concepts and conclusions. On the other hand, CBR utilizes the specific knowledge on previously experienced concrete situations. Here a hybrid method consisting of the synergic combination of FCMs and CBR is proposed, such that, when the FCM model is unable to infer a solution, the CBR is called to modify the FCM model and finally, conclude to a decision.

Case-based reasoning is an 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 solutions. The CBR method is based on identifying the current problem, finding a past case similar to the new one, and using that case to suggest a solution to the current problem.

The FCMs are an illustrative causative representation for the description and modeling of complex systems. The FCMs model the world as a collection of classes and causal relations between classes, 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. 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 the FCM and the FCM developing methodology, i.e., by

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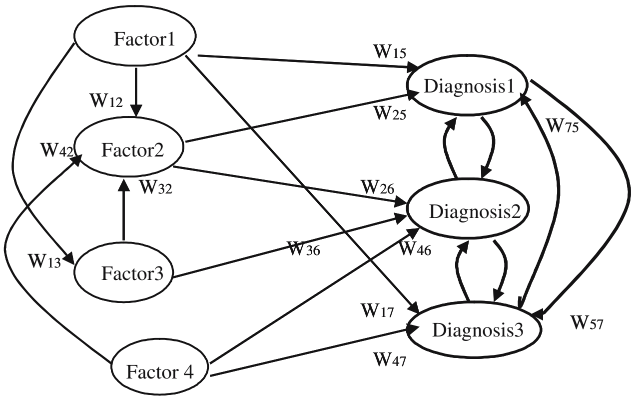

Fig. 1 A general medical decision support CFCM

using human experts who observe, monitor, supervise and know the operation of system and its behavior under different circumstances.

FCMs have been successfully used to develop a decision support system (FCM-DSS) for differential diagnosis (Georgopoulos et al. 2003), to determine the success of the radiation therapy process estimating the final dose delivered to the target volume (Papageorgiou et al. 2003) and many other applications. It must be mentioned that medical systems are complex systems involving inexact, uncertain, imprecise and ambiguous information (Sprogar et al. 2002). 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, the general knowledge built into FCM-DSS requires the contribution of the specific knowledge on some special cases using case-base reasoning.

2 Fuzzy cognitive maps for medical decision support systems

The FCMs have been used to model and develop medical decision support system (MDSS). A special type of FCM with advanced capabilities was introduced for medical diagnosis systems, i.e., the competitive fuzzy cognitive map (CFCM) (Georgopoulos et al. 2003; Georgopoulos and Stylios 2003, 2004), which consists of two main kinds of concepts: decision-concepts and factor-concepts. An example of a CFCM is illustrated in Fig. 1.

Each decision concept represents a single 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 have to conclude to only one diagnosis and then decide accordingly the treatment. The medical diagnosis procedure is a complex process that has to take under consideration a variety of interrelated factors and functions (Brasil et al. 2001). 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.

The factor-concepts can be considered as inputs to the Decision Support System from patient data. These concepts may be observed symptoms, patient's medical history, experimental and laboratory tests etc, which are dynamically updated and changed. On the other hand, 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 Case-based reasoning in medical diagnosis

The CBR is an interesting artificial intelligence (AI) technique that has been applied in different domains, but mainly in medicine. It remembers stored cases and adapts old ones to derive a new solution for a new problem. The CBR reasoner can avoid previous mistakes, and can focus on the most important parts of a problem. The CBR approach to learning is very similar to human learning, such as people take into account and use past experiences to make future decisions (Schmidt et al. 1999).

Apart from these positive aspects, there are still a lot of open problems in CBR. The retrieval and selection of cases, is dependable since the operations of adaptation and evaluation will succeed only if the past cases are the relevant ones. An interesting issue is the matching problem, how to select the best case and most similar case from the data base, because in the CBR procedure, case matching is essential. Usually the case matching 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 significantly reduce the amount of work needed to solve the problem. Evaluation gives to the case-based reasoner feedback about whether or not the current case had been adequately solved in the past. Especially in medicine, adaptation can be a serious and tough problem, because cases often consist of an extremely large number of features.

Medicine is a rather suitable domain for application of CBR and especially for the development of medical decision support systems. These systems are based on experts and subjective knowledge, which is contained in cases. CBR has been successfully used in the medical domain because:

- Reasoning with cases corresponds to the decision making process of physicians.
- Incorporating current cases automatically updates the knowledge.
- Integration into the clinic communication system is easy (cases are routinely stored).

The CBR has been mainly applied in medicine for diagnostic and partly for therapeutic tasks because the 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.

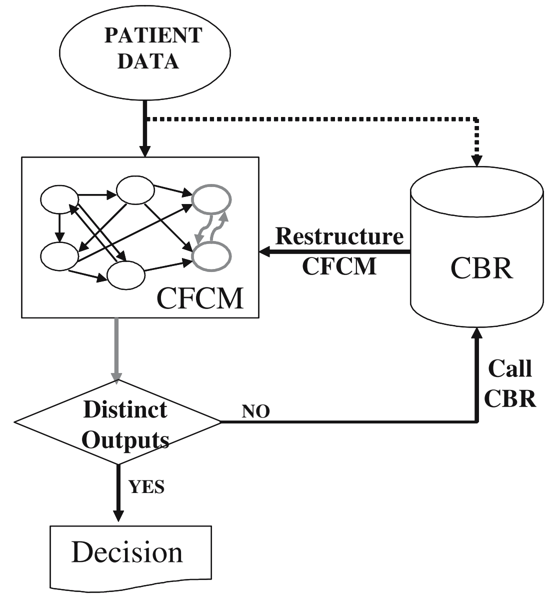

Fig. 2 The flowchart of CBR enhanced FCM algorithm for the advanced MDSS

4 An advanced Medical DSS based on FCM and CBR

It is analysed in the previous sections that both FCM and CBR 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 CBR; thus, a hybrid inferring methodology is proposed. When the CFCM has difficulty to infer a decision with great certainty, then the CBR is called to assist the CFCM, so that the hybrid MDSS can propose a decision.

Figure 2 diagrammatically shows the CBR 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 (Georgopoulos et al. 2003) 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 CBR component. The patient data is then input into the CBR leading to a nearest neighbor search between the patient data and stored cases. Once a case is found with the minimum distance from the patient case, its decision is used to update the CFCM.

5 Description of the complementary CBR-CFCM algorithm

The advanced medical decision support system CBR-CFCM based on the synergism of case-based reasoning and competitive fuzzy cognitive map (CFCM) techniques is implemented by the following proposed algorithm:

Step 1 First apply the CFCM algorithm described in Georgopoulos et al. (2003).

Step 2 The CFCM algorithm stops when nodes reach steady state, then measure difference between the values of competitive decision/diagnosis concepts.

Step 3 If the difference between the highest values of the decision/diagnosis concepts is more than 10%, THEN a decision/diagnosis is inferred so go to Step 7, ELSE activate Case Base.

Step 4 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 factors 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 proposed by Karacapilidis and Pappis (2000) and extended by Liao (2001) for a continuous universe (Dvořák and Šeda 2004):

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

where: $\mathrm{area}(A) = \int\limits_U \mu_A(x)\mathrm{d}x$

$$\mathrm{sim}(A, B) = S_{A,B} = \frac{\int\limits_U |\mu_A(x) - \mu_B(x)|\mathrm{d}x}{\int\limits_U (\mu_A(x) + \mu_B(x))\mathrm{d}x} \tag{2}$$

Step 5 Once a case of the case base has been identified with the highest similarity to the patient input data, the resulting decision/diagnosis of the CBR is returned to the CFCM. At this point, it is mentioned that the decision/diagnosis of CBR could be used itself as a result of the system, but there is a policy to double check the decision/diagnosis and so the CFCM is updated.

Step 6 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 each one decision/diagnosis (Georgopoulos et al. 2003). Thus, according to the diagnosis of CBR, the corresponding critical factor concepts are used to inhibit the connections of those factors to the other competitive decisions by a small percentage according to the function:

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

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; where 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.

Step 7 The final decision/diagnosis is the concept with the highest value.

The purpose of lateral inhibition is to enhance differences between different decisions/diagnoses and to emphasize boundaries (Georgopoulos 1997) thus, leading to the single "winner" (Krekelberg and Kok 1992) decision/diagnosis.

6 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 (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 making the CFCM an attractive solution of this differential diagnosis problem (Georgopoulos et al. 2003). 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 (Leonard 2000).

The 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 language 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 (Kamhi and Catts 1986; NICHCY 2004). 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 (Georgopoulos et al. 2003), fundamental factors that are common 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 1. The factors within each disorder were taken into consideration in a comparative way for 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 1 Values for speech and language pathology example

Attributes	Example
1. Reduced lexical abilities	Medium–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 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	–

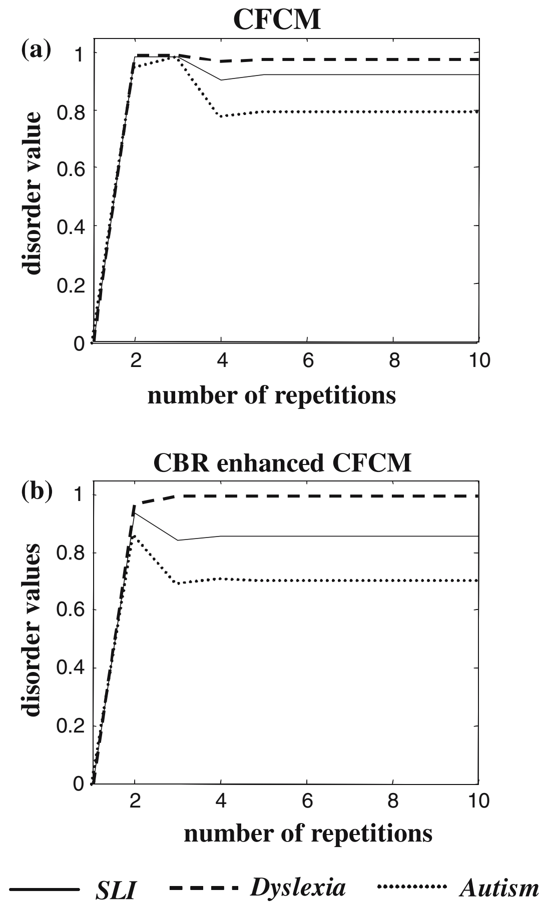

Fig. 3 Comparison of results of 10 iterations of the two algorithms for the example

As an example to the complementary CBR-CFCM, we consider an input case, which is described with the initial values for the factors, as shown in Table 1. 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 (Georgopoulos et al. 2003) and the CBR enhanced CFCM model described here can be obtained. If we use the input information of Table 1 in the CFCM model, after four simulation iterations, equilibrium is reached where decision concepts have the values:

$$\text{SLI} = 0.9189 \quad \text{Dyslexia} = 0.9737 \quad \text{Autism} = 0.7964$$

It is apparent, that two of the three possible diagnoses (SLI and Dyslexia) have high values and their difference of 5.6% 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 CBR enhanced CFCM model. According to the proposed algorithm, with the same input case the distinction between SLI and Dyslexia decisions is "No" leading to the activation of the CBR component in the MDSS. Then a comparison of this input case to the stored cases in the case-base of the CBR is performed, based on the similarity measures described above. Here, the cases that are retrieved and run are only those with a diagnosis of SLI or Dyslexia, since there is a greater than 10% difference between the diagnosis of Autism and the others. Then the stored case with highest similarity is found based on Eq. (2). The retrieved case has a diagnosis of Dyslexia. The attributes of this case are then used to laterally inhibit the weights of the connections of the factor concepts to the other two diagnoses, following Eq. (3), according to the algorithm presented.

Thus, there is a modified CFCM which runs again for the same input data and after 4 simulation iterations reaches an equilibrium region, where the values of decision concepts are:

$$\text{SLI} = 0.8495 \quad \text{Dyslexia} = 0.9933 \quad \text{Autism} = 0.6798$$

so that the new difference between SLI and Dyslexia is 14.48% leading to a more confident diagnosis. 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 Fig. 3 which shows the result of ten iterations of the CFCM and complementary CBR-CFCM for the input example of Table 1.

With this simple example, it 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 led to the diagnosis of the most probable disorder.

7 Example from external beam radiation therapy

Radiation therapy is the application of ionizing radiation in the therapy of pathological illness and elimination of infected cells (Khan 1994). The majority of radiation therapy applications are related to the use of photons or electrons in the therapy of cancer patients. Most of the methods of determining in advance the distribution of the radiation dosage are based on measurements done in water. The inhomogeneity of the tissue in the human body is taken into consideration in the calculation of the dosage using empirical methods. Before any treatment planning for a patient with radiation therapy, it is inherently necessary to know how a tumor will be controlled by irradiation and how surrounding healthy tissue is likely to be adversely affected by the applied radiation dose.

A large number of treatment techniques have been developed to allow a true optimization of the delivered dose distribution in radiation therapy. The most important clinical requirement of most optimization techniques is to be able to deliver strongly nonuniform beams on the patient from arbitrary directions. For very complex tumors the number of beams required to eradicate the tumor without severe injury to normal tissues is quite high, to accurately make the three-dimensional dose distribution conform to the target volume. For simpler target geometries, fewer beams are sufficient, and in many cases with small tumors the classical uniform rectangular beams will do nicely. A number of new treatment techniques, from narrow beam robot mounted linear accelerators through fan beam devices using linear multileaf collimation in rotary gantries, to the most flexible external beam devices with scanned electron and photon beams and/or dynamic multileaf collimation available over the whole treatment field are now rapidly coming into clinical use. Also, calculating doses to radiotherapy patients involves a trade-off between computation time and accuracy.

The kind, nature and number of the parameter-factors that have to be taken under consideration in determining the radiation treatment bring up the fuzziness, the complexity and the uncertainty of the model. All these are characteristics and qualities that lead to the use of soft computing techniques for decision making such as FCMs. Since a number of the decisions that must be made in the process represent mutually exclusive decisions, competitive nodes are used for those decisions, i.e., such concepts are made up of two or three competitive subnodes, respectively, as shown subsequently:

- C1: Type of radiation. This concept represents three discrete values (three competitive nodes C1a, C1b, C1c).
- C2: Quality of radiation. This concept represents the quality of radiation, so it takes continuous values.
- C3: Size of radiation field(s). The size of radiation field is categorized into five fuzzy categories.
- C4: Single or multiple field combinations. This concept represents two discrete conditions (two competitive nodes C4a, C4b).
- C5: Beam direction(s).
- C6: Weight of each radiation field. It represents the percentage of each field.
- C7: Stationary versus rotation—isocentric—beam therapy. This concept represents two discrete conditions.
- C8: SSD (used in nonisocentric techniques).
- C9: Wedge filters. This concept takes fuzzy values representing the degree of the applied filters.
- C10: Cerrobend blocks versus multileaf collimators. This concept represents two discrete conditions (two competitive nodes C10a, C10b).
- C11: Compensating filter or bolus. This concept represents two discrete conditions (two competitive nodes C11a, C11b).
- C12: Patient immobilization. This concept represents discrete conditions.
- C13: 2D versus conformal (3D) radiotherapy. This concept represents two discrete conditions (two competitive nodes C13a, C13b).
- C14: Depth of tumor. This concept can be scaled in five fuzzy values.
- C15: Size of tumor. This concept can be scaled in seven fuzzy values.
- C16: Shape of tumor. This concept represents the degree of irregularities scaled in three fuzzy values.
- C17: Location of tumor—size of cross section.
- C18: Regional metastasis of tumor. This concept can be scaled in five fuzzy values.
- C19: Type of tissue(s) included in irradiated volume—inhomogeneities. This concept represents the degree of inhomogeneity scaled in four fuzzy values.
- C20: Dose uniformity within target volume. The most important concept taking desired almost fixed value.
- C21: Isodose of 90% surrounding treatment volume. The most important concept taking almost desired fixed value.
- C22: Radiation sensitive organs within irradiated volume. This concept represents the abutting on sensitive organs scaled in 3 fuzzy values.
- C23: Skin sparing. This concept can be scaled in five fuzzy values.
- C24: Patient thickness. This concept can be scaled in five fuzzy values.
- C25: Patient contour. This concept can be scaled in five fuzzy values.

Table 2 The linguistic values of fuzzy weights influence from Concepts C14–C34 towards Concepts C1–C13 in radiotherapy CFCM

	C14	C15	C16	C17	C18	C19	C20	C21	C22	C23	C24	C25	C26	C27	C28	C29	C30	C31	C32	C33	C34
C1	VH	VH	M	H	M	VH	H	H	H	H	ML	L	H	H	0	ML	H	M	0	0	0
C2	VH	VH	M	H	VH	VH	VH	VH	VH	VH	H	M	VH	VH	0	0	H	M	0	0	0
C3	H	VH	H	ML	VH	ML	H	VH	H	VH	M	0	VH	VH	0	0	0	H	0	0	0
C4	H	H	H	H	H	H	VH	VH	M	VH	H	0	M	H	H	H	0	H	VH	0	0
C5	M	L	H	M	VH	H	H	H	VH	VH	H	H	VH	H	0	0	0	H	0	H	0
C6	M	H	H	H	H	H	VH	VH	VH	H	H	H	VH	M	0	0	0	H	M	0	0
C7	H	H	M	M	0	M	L	0	M	L	L	VH	L	L	L	0	0	ML	0	VH	0
C8	H	H	0	VH	M	M	VH	H	H	H	M	ML	H	H	H	0	0	L	0	0	0
C9	VH	H	M	0	0	0	VH	H	VH	H	VH	H	VH	H	L	0	0	M	0	0	VH
C10	ML	H	H	H	0	M	0	0	ML	M	0	0	M	M	VH	VH	VH	VH	0	0	0
C11	0	0	0	H	0	0	VH	H	H	H	H	VH	H	H	0	0	M	0	0	0	0
C12	M	H	0	VH	0	0	M	0	VH	0	0	0	H	0	M	M	0	H	0	0	0
C13	0	M	VH	0	0	H	VH	VH	VH	H	0	H	VH	0	VH	VH	VH	VH	0	0	0

C26: Damage to healthy tissue in irradiated volume. This concept can be scaled in three fuzzy values.
C27: Scattered radiation received by patient. This concept can be scaled in five fuzzy values.
C28: Repeatability–flexibility of treatment setup. This concept can be scaled in three fuzzy values.
C29: Time required for treatment procedure or planning. This concept can be scaled in five fuzzy values.
C30: Cost of equipment, shielding and space. This concept can be scaled in five fuzzy values.
C31: Almost perfect match of beam to target volume. This concept can be scaled in three fuzzy values.
C32: Edge effect. Value of this concept can be scaled in three fuzzy values.
C33: Tumor position regarding center of contour cross section. Value of this concept can be scaled in three fuzzy values.
C34: Irradiation of one side of skin surface.

Concepts C1 to C13 are the output concepts and concepts C14 to C34 are the input concepts. The values of the output concepts will determine, for example, what type and/or energy of radiation is chosen, whether there are multiple or single fields, if wedge filters are used. Table 2 illustrates the causal relationship between output concepts and input concepts of the competitive fuzzy cognitive map (Stylios et al. 2001). The rows correspond to output concepts and the columns to input concepts.

In order to achieve a good distribution of the radiation on the tumor, as well as to protect the healthy tissues, the following should be taken into consideration: (a) selection of appropriate size of the radiation field, (b) increase of entry points of the beam (more than one radiation field), (c) selection of appropriate beam directions, (d) Selection of weight of each field (dose contribution from individual fields), (e) selection of appropriate quality, i.e., energy and type of radiation (X-rays, γ-rays, electrons), (f) modification of field with cerrobend blocks or multileaf collimators and/or wedge filters, (g) processing of the outline of the patient with addition of compensating filter or bolus in place of the missing tissue, (h) SSD (Source to Skin Distance) used in stationary nonisocentric techniques, (i) use of isocentric stationary beam therapy versus isocentric rotation therapy, (j) patient immobilization and (k) use of conformal (3D) instead of conventional (2D) radiotherapy whenever possible. At the present time many institutions still use treatment plans produced in a 2D cross section of the patient and the treatment machines which deliver the radiation use only square/rectangular fields since they are limited by the collimator design. This means that the high dose treatment volume is usually approximately cylindrical for the circular target areas used on 2D plans and rectangular volumes for square/rectangular target areas (Aird 1989). Thus, interactions with appropriate fuzzy weights exist between output concepts.

When the CFCM is run for a particular case, the results of the competitive nodes C1a, C1b, C1c and C10a, C10b, as shown in Fig. 4, reach close values. Since the decisions for the output nodes in external beam radiotherapy are of high critical importance, the CBR-enhanced CFCM is applied which concludes to the final choices as shown in Fig. 5.

8 Conclusions

In this paper, we proposed an advanced medical decision support system (MDSS) which is based on the complementary

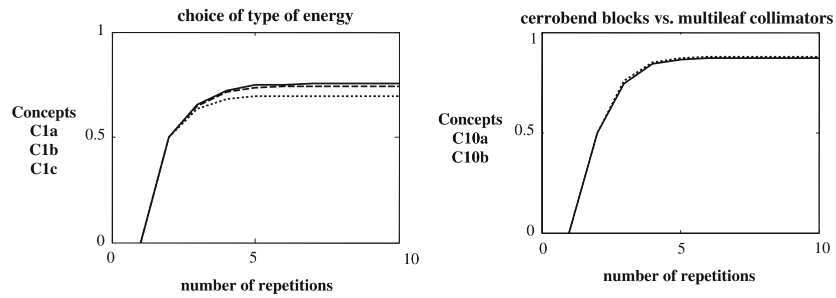

Fig. 4 The results of the competitive nodes C1a,C1b, C1c and C10a, C10b with the use of CFCM algorithm

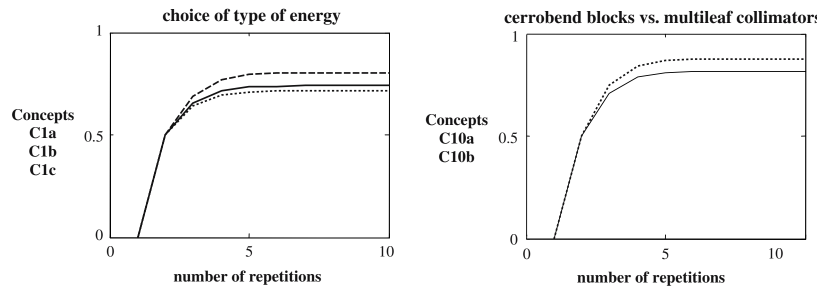

Fig. 5 The results of the competitive nodes C1a,C1b, C1c and C10a, C10b with the use of CBR enhanced CFCM algorithm

usage of competitive fuzzy cognitive maps (CFCMs) with case-based reasoning (CBR) methods, and thus, was developed the CBR-enhanced CFCM system for medical diagnosis. The structure of the MDSS and the implementation algorithm is described in detail. The proposed methodology introduces, a second criterion for the case retrieval which reduces the search space and for the first time lateral inhibition is used to update the weights of CFCM. The proposed decision system of CBR-enhanced CFCM is applied and tested for two medical decision problems. It develops a differential diagnosis model in speech and language pathology for language disorders and the second application is an external beam radiotherapy decision support system. Case examples from each field are examined and presented where the CBR-enhanced CFCM is compared with the simple CFCM and the results show the advantages of the new proposed system.

The integration of fuzzy cognitive maps and case-based reasoning for medical decision support systems shows that in cases where competitive fuzzy cognitive maps on their own do not provide clearly distinct decisions, the assistance from CBR leads to unambiguous decisions. The importance of the results for the clinician, in both example areas discussed, is significant when taking into consideration the trend for evidence-based practice (EBP) in medicine. EBP is the conscientious, explicit, and judicious use of current best evidence in making decisions about the care of individual patients. It is the integration of best research evidence with clinical expertise and patient values (Sackett et al. 2000). Thus, FCM together with CBR provide such integration where expert knowledge and research results are represented by the one and patient cases by the other. In essence, the proposed methodology of CBR-enhanced competitive fuzzy cognitive maps 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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