A Novel Approach on Constructed Dynamic Fuzzy Cognitive Maps Using Fuzzified Decision Trees and Knowledge-Extraction Techniques

Elpiniki I. Papageorgiou

Abstract. A novel approach for the construction of augmented Fuzzy Cognitive Maps based on data mining and knowledge-extraction methods has been investigated for decision making and classification tasks. Specifically, through this work, the issue of designing decision support systems based on fuzzy cognitive maps has been explored using fuzzified decision trees and other knowledge-extraction techniques. Fuzzy cognitive map is a knowledge-based technique that works as an artificial cognitive network inheriting the main aspects of cognitive maps and artificial neural networks. Decision trees, in the other hand, are well known intelligent techniques that extract rules from both symbolic and numeric data. Fuzzy theoretical techniques are used to fuzzify crisp decision trees in order to soften decision boundaries at decision nodes inherent in this type of trees. Comparisons between crisp decision trees and the fuzzified decision trees suggest that the later fuzzy tree is significantly more robust and produces a more balanced decision making. The new approach proposed in this paper could incorporate any type of knowledge extraction algorithm. Furthermore, through the knowledge extraction methods the useful knowledge from data can be extracted in the form of fuzzy rules and inserted those into the FCM, contributing to the development of a dynamic approach for decision support. The proposed approach is implemented in a well known medical decision making problem to preview the effectiveness.

Keywords: fuzzy cognitive maps, decision trees, fuzzy, neuro-fuzzy, data mining, causal paths, decision making.

1 Introduction

This chapter presents a soft computing procedure to handle different data types for decision support tasks in diverse scientific areas. The proposed methodology

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establishes an advanced framework by implementing different knowledge extraction methods for Fuzzy Cognitive Mapping (FCM) decision support.

Nowadays, the knowledge acquisition and representation constitutes a major knowledge engineering bottleneck. A large number of techniques in the field of artificial intelligence used to represent knowledge: production rules, decision trees, rule-based architectures semantic nets, frameworks, fuzzy logic, causal cognitive maps, among others. The decision trees gained popularity because of their conceptual transparency. The well-developed design methodology comes with efficient design techniques supporting their construction, i.e. (Quinlan, 1986; Sestino, and Dillon, 1991; Sison, and Chong, 1994). The decision trees generated by these methods were found useful in building knowledge-based expert systems. Due to the character of continuous attributes as well as various facets of uncertainty one has to take into consideration, there has been a visible trend to cope with the factor of fuzziness when carrying out learning from examples in the case of tree induction. In a nutshell, this trend gave rise to the name of fuzzy decision trees and has resulted in a series of development alternatives; i.e. (Mitra et al., 2002; Umano et al., 1994; Olaru, 2003). The incorporation of fuzzy sets (Pedrycz, and Sosnowski, 2000; Crockett et al., 2005; Ishibuchi et al., 1995; Janikow, 1998) into decision trees enables us to combine the uncertainty handling and approximate reasoning capabilities of the former with the comprehensibility and ease of application of the latter. Fuzzy decision trees (Janikow, 1998; 1999) assume that all domain attributes or linguistic variables have pre-defined fuzzy terms for each fuzzy attribute. Those could be determined in a data driven manner. The information gain measure, used for splitting a node, is modified for fuzzy representation and a pattern can have nonzero degree of matching to one or more leaves (Yuan, and Shaw, 1995; Weber, 1992).

One of the great challenges for computational intelligence is the knowledge extraction from data, combining it with available symbolic knowledge, and refining the resulting knowledge-based expert systems. The reasoning with symbolic-logical rules is more acceptable to human users than the recommendations given by black box systems (Zurada et al., 2004), because such reasoning is comprehensible, provides explanations, and may be validated by human inspection.

Fuzzy logic and causal cognitive maps, in the other hand, are some of the main topics of artificial intelligence on representation of knowledge and approximation of reasoning with uncertainty (Kosko, 1986). The choice of a particular technique is based on two main factors: the nature of the application and the user's skills. The fuzzy logic theory, based on representation of knowledge and approximation of reasoning with uncertainty, is very close to the expert's reasoning, and it is well known as artificial intelligence-based method, especially in the field of medical decision making. An outcome of this theory is fuzzy cognitive maps (Kosko, 1992).

Fuzzy cognitive maps (FCMs) are diagrams used as causal representations between knowledge/data to represent events relations. They are modeling methods based on knowledge and experience for describing particular domains using concepts (variables, states, inputs, outputs) and the relationships between them. They can be obtained by asking human experts to define the variables of the system and to identify fuzzy causal relationships among the variables using ‘if–then’ rules and thus producing fuzzy weights (Stylios and Groumpos 2004; Papageorgiou and Groumpos, 2005b). Human experts who supervise a system and know its behavior under different circumstances develop a FCM model in such a way that their accumulated experience and knowledge are integrated in the causal relationships between factors/characteristics (Groumpos and Stylios, 2000). It is a very convenient, simple, and powerful tool, which is used in numerous areas of application (Aguilar, 2005, Xirogiannis and Glykas 2004, Xirogiannis et al. 2007; Xirogiannis et al. 2008; Froelich et al. 2009; Sordo et al. 2008; Wei et al., 2009).

The performance of FCMs is known to be sensitive to the initial weight setting and architecture. This shortcoming can be alleviated and the FCM model can be augmented if a fuzzy rule base as well as new fuzzy relationships is available. A number of knowledge extraction techniques (i.e. machine learning, fuzzy decision trees, association rules, Bayesian networks, neural networks, pattern recognition techniques, hybrid computational intelligent algorithms) (Nauck et al., 1997; Au and Farm, 1999; Mitra and Hayashi, 2000; Zurada and Lozowski, 1996; Chen and Wei, 2002; Wells and Niederer, 1998) could be used for the generation of a fuzzy rule base (X. Liu et al., 1997; Mitra and Hayashi, 2000). These methods can extract the available knowledge from data in the form of fuzzy rules and thus insert them into the FCM system.

In the case of medical decision systems based on fuzzy cognitive maps only a few studies have been undertaken (Papageorgiou et al, 2003; Georgopoulos and Stylios, 2005; Papageorgiou et al. 2006a; Papageorgiou et al. 2006b; Papageorgiou et al., 2007; Papageorgiou et al., 2008; Georgopoulos and Stylios, 2008; Stylios et al., 2008). Few frameworks have been proposed such as the integrated two level structure for making decisions in external beam radiotherapy (Papageorgiou et al. 2003), a learning approach and an FCM based grading tool, namely FCM-GT for characterizing tumours’ malignancy (urinary bladder and brain tumors), (Papageorgiou et al. 2006a; Papageorgiou et al. 2008), an hybrid approach using complementary case based reasoning and competitive FCMs for the differential diagnosis problem from the speech pathology area (Georgopoulos and Stylios, 2008). Some appropriate FCM architectures were presented recently and applied to examples from two medical disciplines, i.e. speech and language pathology and obstetrics (Stylios et al., 2008). FCMs have been also used for pattern recognition and classification approaches (Papakostas et al., 2008, Froelich et al., 2009, Boutalis et al., 2009).

Most decision tree induction methods used for extracting knowledge in classification problems do not deal with cognitive uncertainties such as vagueness and ambiguity associated with human thinking and perception. Fuzzy decision trees represent classification knowledge more naturally to the way of human thinking and are more robust in tolerating imprecise, conflict, and missing information.

In this work, a new approach on constructing fuzzy cognitive maps combining knowledge from experts and from data using rule extraction methods is proposed. The explored knowledge extraction methods generate meaningful fuzzy linguistic weights incorporated to restructure and augment FCMs for decision support tasks.

The methodology is partly data driven and knowledge driven so some expert knowledge of the domain is required. The whole approach is applied to an FCM constructed to handle the complex problem of making decision on radiation therapy treatment.

The following sections are organized as: second section gives the necessary background information about fuzzy cognitive maps theory and development, as well as the knowledge extraction method of fuzzy decision trees for generating fuzzy rules. The third section is reserved for explanation of the developed fuzzy cognitive map based decision support system in medical informatics. Then the fourth section presents the application results of the proposed methodology for treatment planning selection of prostate cancer. Finally the last section gives the discussion for this proposed framework and outlines the conclusions.

2 Background of Proposed Approach

2.1 Main Aspects of Fuzzy Cognitive Maps

Fuzzy cognitive map is a causal knowledge-driven methodology for modeling complex decision systems, originated from the combination of fuzzy logic and neural networks (Kosko, 1986). An FCM describes the behavior of a knowledge-based system in terms of concepts; each concept represents an entity, a state, a variable, or a characteristic of the system (Kosko, 1992). FCM nodes are named by such concepts forming the set of concepts $C = \{C1,C2, . . . ,Cn\}$. Arcs (Cj,Ci) are oriented and represent causal links between concepts; that is how concept Cj causes concept Ci. Weights of arcs are associated with a weight value matrix $Wn{\cdot}n$, where each element of the matrix wji taking values in [-1, . . .,1] . Kosko has developed a fuzzy causal algebra that describes the causal propagation and combination of concepts in an FCM. The algebra depends only on the partial ordering P, the range set of the fuzzy causal edge function *e*, and on general fuzzy-graph properties (e.g., path connectivity). Kosko notes that this algebra can be used on any digraph knowledge representation scheme.

A causal path from some concept node *Ci* to concept node *Cj,* say *Ci---~Ck1, Ckl--~... Ckn, Ckn ---~Cj,* can be indicated by the sequence (i, *k, ... kn,j).* Then the indirect effect of *Ci* on *Cj* is the causality *C~I* imparts to *Cj* via the path *(i, kl . . . . . kn,j).* The total effect of *Ci* on *Cj* is the composite of all the indirect-effect causalities C~ imparts to *Cj.* If there is only one causal path from *Ci* to *Cj,* the total effect C~ imparts to *Cj* reduces to the indirect effect.

The indeterminacy can be removed with a numeric weighting scheme. A fuzzy causal algebra, and hence FCMs, bypasses the knowledge acquisition processing tradeoff.

A simple fuzzy causal algebra is created by interpreting the indirect effect operator *I* as the minimum operator (min) and the total effect operator *T* as the maximum operator (max) on a partially ordered set P of causal values (Peláez and Bowles, 1996). Formally, let ~ be a causal concept space, and let e: ~ × ~ P be a fuzzy causal edge function, and assume that there are m-many causal paths from

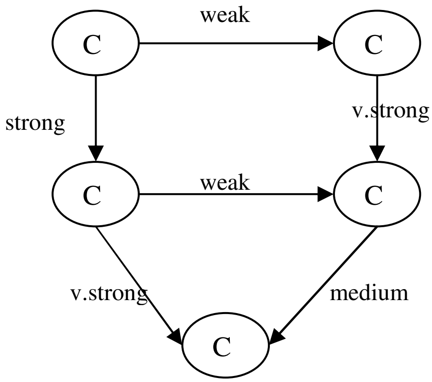

Fig. 1 A cognitive map with fuzzy labels at the edges

Ci to *Cj*: (i, k~ ..... k~, j) for 1 ~< r ~< m. Then let *Ir(Ci, Cj)* denote the indirect effect of concept *Ci* on concept *Cj* via the rth causal path, and let *T(i, Cj)* denote the total effect of *Ci* on *Cj* over all m causal paths. Then

I~(Ci,Cj)=min{e(Cp,Cp+,):(p,p+ 1) ~ (i,k~ . . . . . k,~,j) }

T(Ci,Cj)= max(Ir(Ci,Cj)) , where l <~r<~m

where p and p + 1 are contiguous left-to right path indices.

The indirect effect operation amounts to specifying the weakest causal link in a path and the total effect operation amounts to specifying the strongest of the weakest links (Kosko, 1992; Peláez and Bowles, 1996). For example, suppose the causal values are given by P = {none, weak, medium, strong, very strong} and the FCM is defined as in Figure 1. There are three causal paths from C1 to C5: path (C1, C3, C5), path (C1, C3, C4, C5) and path (C1, C2, C4, C5).

The three indirect effects of C1 on C5 are:

I1(C1,C5) = min {el3 , e35) = min {strong, v.strong} = strong
12 (C1 ,C5) = min{e13,e34,e45}= weak,
I3(C1,C5) = min{e12,e24,e45}= weak.
Hence, the total effect of C1 on C5 is:
T(C1,C5) = max {I1,(C1,C5), I2(C1,C5), I3(C1,C5) }
= max {strong, weak, weak} = strong.

– In words, C1 can be said to impart strong causality to C5.

FCMs display two distinct characteristics: firstly Nodes or concepts are also considered to be fuzzy, ie, each node is a fuzzy set, and can have an activity level to some degree from 0% to 100% and secondly, the causal relationships between nodes are fuzzified, a number is assigned to the causal link to express the degree of relationship between two concepts. The directed edge eij from the causal concept *Ci* to concept *Cj* measures how much *Ci* causes *Cj*. The edges *eij* take values from the fuzzy causal interval [-1, 1], *eij* = 0 indicates no causality; eij > 0 indicates a causal increase (ie *Cj* increases as *Ci* increases, and *Cj* decreases as Ci decreases); eij < 0 indicates causal decrease (ie, *Cj* decreases as *Ci* increases, and

Cj increases as *Ci* decreases). Word weights like '*little*' or '*somewhat*' can be used instead of numeric values (Groumpos and Stylios, 2000). An FCM can be described by a connection matrix and the activation levels of its nodes can be represented as a state vector, whereby simple vector-matrix operations allow extension to neural or dynamical systems techniques. FCMs can be subjected to an initial stimulus in the form of a state vector A representing the states of the system's variables.

At each simulation step, the value *Ai* of a concept *Ci* is calculated by computing the influence of other concepts *Cj*'s on the specific concept *Ci* following the calculation rule:

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

where $Ai^{(k+1)}$ is the value of concept *Ci* at simulation step $k+1$, $Aj^{(k)}$ is the value of concept *Cj* at simulation step *k*, e_{ji} is the weight of the interconnection from concept *Cj* to concept *Ci* and *f* is a sigmoid threshold function that have been selected since the values *Ai* of the concepts, lie within [0,1]:

$$f = \frac{1}{1+e^{-mx}} \tag{2}$$

The parameter *m* is a real positive number and *x* is the value $Ai^{(k)}$ on the equilibrium point. In this work we use m=5, because this value showed best results in previous works (Bueno & Salmeron, 2009). A concept is turned on or activated by making its vector element 1. New state vectors showing the effect of the activated concept are computed using method of successive substitution, i.e., by iteratively multiplying the previous state vector by the relational matrix using standard matrix multiplication.

For the construction of FCMs, experts of the specific domain problem develop a mental model manually based on their knowledge in related area. At first, they identify key domain issues or concepts. Secondly, they identify the causal relationships among these concepts and thirdly, they estimate causal relationships strengths. This achieved graph (FCM) shows not only the components and their relations but also the strengths. In fuzzy diagrams, the influence of a concept on the others is considered as "negative", "positive" or "neutral". All relations are expressed in fuzzy terms, e.g. very weak, weak, medium, strong and very strong.

In a simple FCM, all fuzzy variables are mapped into interval [-1, 1]. A simple way is to map fuzzy expression to numerical value in a range of [-1, 1]. For example, positively weak is mapped to 0.25, negatively medium to -0.5, positively strong to 0.75 (Stylios and Groumpos, 2004). Then, all the suggested by experts linguistic variables, are considered and an overall linguistic weight is obtained, which transformed to a numerical weight with the defuzzification method of Centre of Gravity (COG) (Jang, 1997).

The above situation shows that in many cases, to develop a FCM manually becomes very difficult and experts' intervention could not resolve the problem. Therefore, a systematic way should be found in order to bridge this gap. For example, designing a new method using data mining and knowledge extraction approaches from data could eliminate the existing weakness.

2.2 Fuzzy Rules and Linguistic Weight Generation by Using Knowledge Extraction Methods

The task of decision making, especially in medicine, is difficult and complex due to the huge amount of medical data and the different sources of medical information. Thus data mining and knowledge processing systems are used in medicine for the tasks of diagnosis, prognosis, treatment planning and decision support (Fayyad and Uthurusamy, 1996; Fayyad et al., 1996).

From the literature, a large number of knowledge extraction approaches have been found (Pal and Mitra, 1999; Zurada et al., 2004). Frequently, machine learning systems can be used to develop the knowledge bases used by expert systems. Given a set of clinical cases that act as examples, a machine learning system can produce a systematic description of those clinical features that uniquely characterize the clinical conditions. This knowledge can be expressed in the form of simple rules, often used for decision making in medicine (Nauck and Kruse, 1999).

Some known rule generation algorithms existing from the literature are: Subset (Fu, 1993), MoFN (Towel, Shavlik, 1994), X2R (Liu and Tan, 1998), C4.5 (Quinlan, 1993), FuNN (Kasabov, 1993), Rulex (Andrew and Geva, 1997), NEFCLASS (Nauck, 1997), fuzzy logical MLP (Mitra and Pal, 1994), Rough fuzzy MLP (Pal and Mitra, 2003). All of these functions and methodologies tried to discover knowledge from historical data. This knowledge represented in the form of rules most of the time.

In the medical field, it is preferable not to use black box approaches. The user should be able to understand the modeler and to evaluate its results. Fuzzy rule based systems are especially suitable, because they consist of simple linguistically interpretable rules and do not have some of the drawbacks of symbolic or crisp rule based classifiers. Among the wide range of possible approaches, the fuzzy decision trees based rule generation computing method was selected to extract the knowledge exploring causal paths and useful fuzzy rules.

2.2.1 Extraction Method Using Fuzzy Decision Trees

Fuzzy decision trees are an extension of the classical artificial intelligence concept of decision trees. The main fundamental difference between fuzzy and crisp trees is that with fuzzy trees, gradual transitions exist between attribute values (Pedrycz and Sosnowski, 2000). The reasoning process within the tree allows all rules to be fired to some degree, with the final crisp classification being the result of combining all membership grades. Modifications to the ID3 algorithm have been made for developing such trees (Sison and Chong, 1994, Umano et al., 2003, Olaru, 2003, Hayashi et al., 1998, Crockett et al., 2006). Sison and Chong (Sison and Chong, 1994) proposed a fuzzy version of ID3 which automatically generated a fuzzy rule base for a plant controller from a set of input–output data. Umano et al. (Umano et al., 2003) also proposed a new fuzzy ID3 algorithm. This algorithm generates an understandable fuzzy decision tree using fuzzy sets defined by the user. These fuzzy tree methodologies require the data to have been pre-fuzzified before the fuzzy decision trees are induced.

Recent work by Janikow involves the induction of fuzzy decision trees directly from data sets by the FID (Fuzzy Induction on Decision Tree) algorithm (Janikow, 1998; 1999). Janikow introduced the non fuzzy rules and the different kind of fuzzy rules (Janikow, 1998). In this point it is essential to refer that the data (real values) are partitioned into fuzzy sets by experts.

The following steps identify the proposed algorithm process based on FID algorithm:

Step 1: A fuzzy clustering algorithm is used for input domain partition. The supervised method takes into account the class labels during the clustering. Therefore the resulted partitions, the fuzzy membership functions (fuzzy sets) represent not only the distribution of data, but the distribution of the classes too.

Step 2: During a pre-pruning method the resulted partitions could analyze and combine the unduly overlapped fuzzy sets.

Step 3: The results of the pre-pruning step are input parameters (beside data) for the tree induction algorithm. The applied tree induction method is the FID algorithm by C. Z. Janikow.

Step 4: The fuzzy ID3 is used to extract rules which are then used for generating causal paths and the fuzzy rule base.

Step 5: While the FID algorithm could generate larger and complex decision tree as it is necessary, therefore a post pruning method is applied. The rule which yields the maximal fulfillment degree in the least number of cases is deleted.

This method provides causal paths and fuzzy rules for producing linguistic weights and thus building dynamic FCMs for decision support.

2.2.2 A Generic Example Representing the Proposed Approach

A generic example of the causal knowledge-driven FCM model consisting of eight concepts and eleven interconnections among concepts, with fuzzy labels at the edges of connections, is depicted in Figure 2. This FCM will be restructured using the proposed methodology and the available knowledge from fuzzified decision trees. Only for implementation reason, we consider that the fuzzy decision tree presented in Figure 3 has been produced by using the fuzzified decision tree above method on the available data set.

The produced tree has a number of three paths for C1 to C8, two paths for C2 to C8, and one path of each one of the other concepts to C8, thus defining new interconnections and/or update the initial ones of the FCM model.

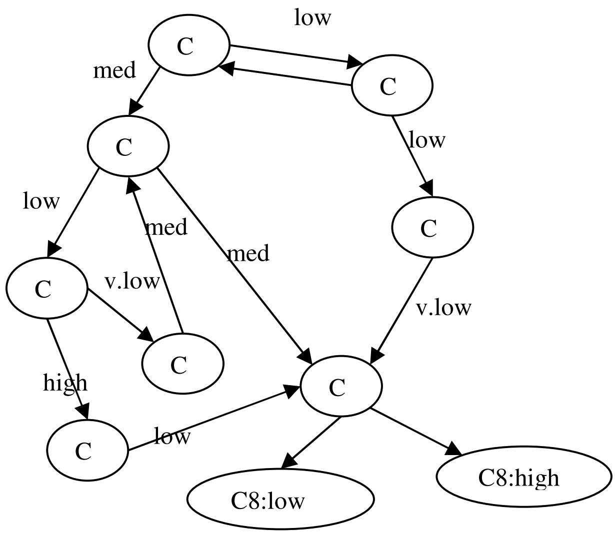

Fig. 2 Example FCM model with initial linguistic labels on interconnections (weights)

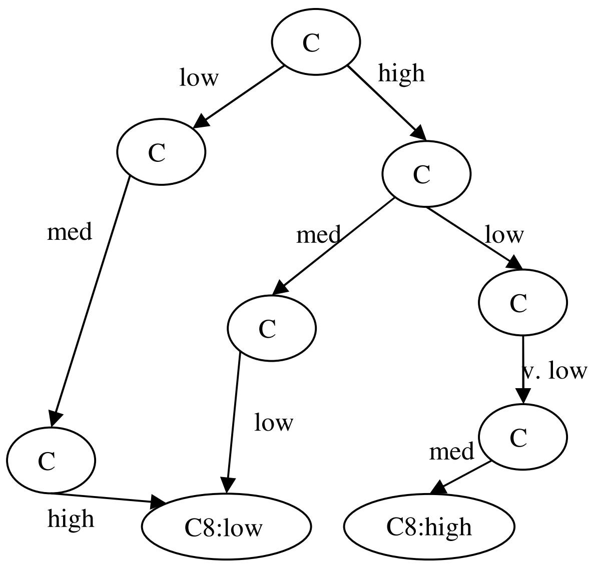

Fig. 3 Example Fuzzy decision tree induced from the data showing membership grades at each branch

Here, the causal effect of C1 to C8 is determined by taking the minimum of the attached labels of the individual paths. Let I1, I2 and I3 denote the effect of C1 to C8 through the paths 1 to 3 respectively, and e_{ij} be the label attached with edge from node i^{th} to node j^{th}. Then, to determine the total effect of C1 to C8, we take the maximum of paths I1 through I3 causal paths.

Path 1 from C1 to C8: c1→c3→ c6→ c8

I1(C1 to C8)=min(low, med, high)=low

Path 2 from C1 to C8:c1→c2→ c5→ c7 →c8

I2(C1 to C8)=min(high, low, v. low, med)=v. low

Path 3 from C1 to C8: c1→c2→ c4 →c8

I3(C1 to C8)=min(high, med, low)=low

Thus total effect of C1 to C8, denoted by T(C1,C8) is computed below:

T(C1,C8)=max{I1,I2,I3}=max{low, v. low, low}=*low*

– In words, C1 imparts *low* causality to C8.

To determine the total effect of C2 to C8, we take the maximum of paths I4 through I5.

Path 4 from C2 to C8: c2→ c5→ c7 →c8

I4(C2 to C8)=min(low, v.low, med)=v. low

Path 5 from C2 to C8: c2→ c4 →c8

I5(C2 to C8)=min(med, low)=low

Thus total effect of C2 to C8, denoted by T(C2,C8) is:

T(c2,c8)=max{I4,I5}=max{low, v. low}=*low*

– In words, C2 imparts *low* causality to C8.

Path 6 from C6 to C8: c6 →C8:

I6=high

To determine the total effect of C6 to C8, we take the maximum of path I6.

– In words, C6 imparts *high* causality to C8.

Path 7 from C4 to C8: c4 →c8:

I7=low

The total effect of C4 to C8 is determined by taking the maximum of path I7.

– In words, C4 imparts *low* causality to C8.

To determine the total effect of C5 to C8, we take the maximum of path I8.

Path 8 from C5 to C8: C5→ C7 →C8:

I8(C5 to C8)=min(v.low, med)=v.low

Thus total effect of C5 to C8, denoted by T(C5,C8) is computed:

T(C5,C8)=max{I8}=*v. low*

– In words, C5 imparts *v. low* causality to C8.

Summarizing, new causal paths describing the interconnections among concepts as well as some of the existed interconnections have been explored updating their initial values due to the above paths.

After the implementation of the investigating methodology, the FCM model was restructured and a new augmented FCM model was produced illustrated in Figure 4. Where each branch has fuzzy labels, fuzzy values derived from corresponding fuzzy sets as they have been initially prescribed by experts and data handle.

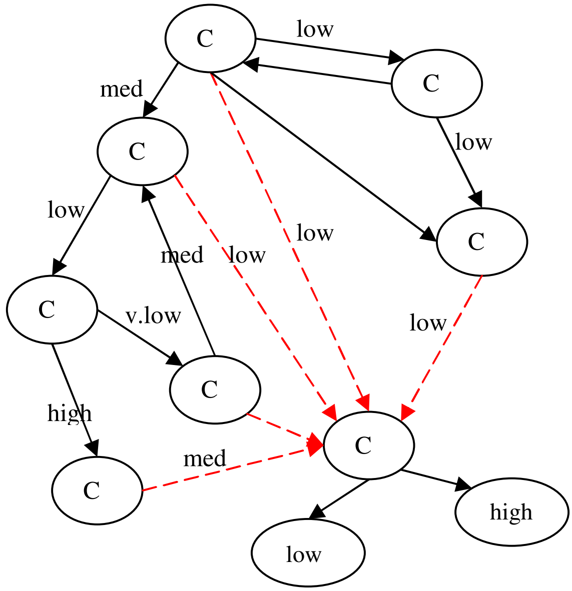

Fig. 4 The new restructured FCM model using the proposed approach

3 New Approach on Constructing Dynamic Fuzzy Cognitive Maps Using Knowledge Extraction Techniques

There is a necessity to propose a methodology and generally a framework for extracting fuzzy interconnections among attributes from available data using knowledge extraction techniques. Through the knowledge extraction methods, fuzzy linguistic interconnections could be identified to restructure the fuzzy cognitive map model thus producing a new dynamic FCM-based tool for decision support tasks. The proposed approach can incorporate any decision tree algorithm, but for the purpose of this work C4.5 has been chosen as it is a well-known and well-tested decision tree induction algorithm for classification problems (Quinlan, 2002). As it has already been stated, the central idea of the proposed method is to combine a fuzzy decision tree to extract the available knowledge of data and to generate fuzzy linguistic weights through causal paths. The resulted fuzzy relationships among leaf nodes are applied to restructure the FCM model. Among the different fuzzy inference techniques we selected for our approach the Zadeh's union and intersection parameters (see above section 2.1). The inference algorithm of FCMs remains the same and only the weight matrix multiplied with previous concept values was changed. Figure 5 illustrates the proposed process with the corresponding steps and final decision.

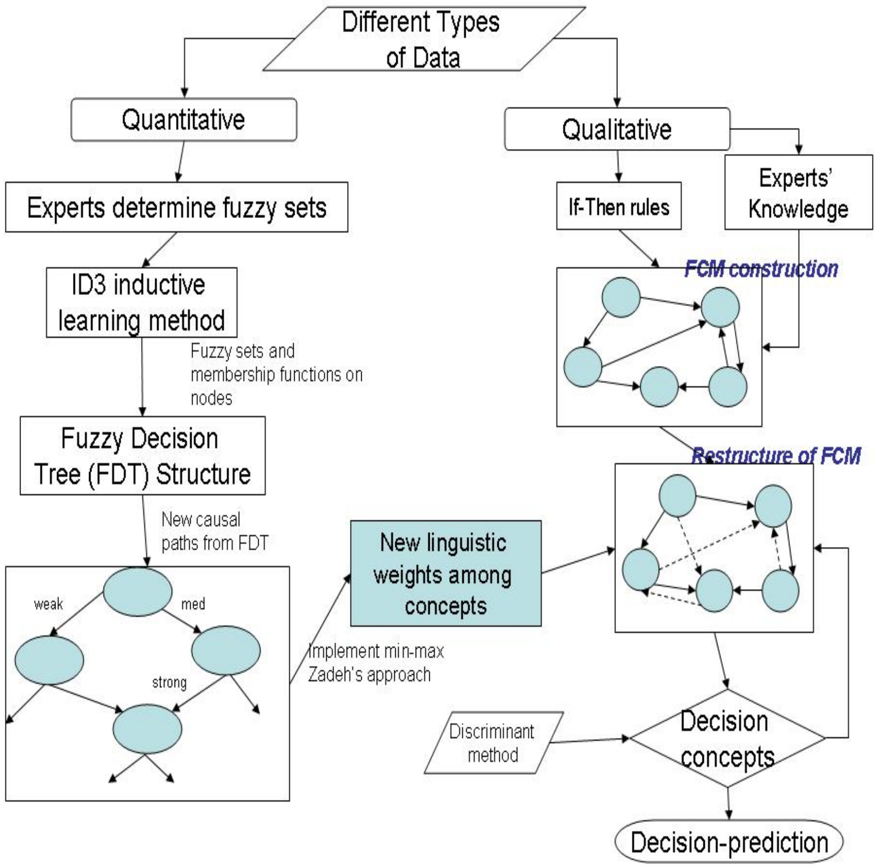

Fig. 5 New approach for constructing augmented FCMs by complementary use of fuzzy decision trees

The algorithmic approach for the restructure of FCM using fuzzy decision trees (and/or other knowledge extraction methods) is consisting on the following steps:

<u>Step 1:</u> For all the M experts, set credibility weight $b_k = 1$

<u>Step 2:</u> Each of the M experts is asked to suggest and describe each of the N concepts that comprise the FCM.

<u>Step 3:</u> For all the ordered pair of concepts (*Ci* and *Cj*) each k^{th} of the M experts is asked to make the following statement (using an if-then rule):

IF the value of concept *Ci* {increases, decreases, is stable} **THEN** causes value of concept *Cj* to {increase, decrease, nothing} **THUS** the influence of concept *Ci* on concept *Cj* is *T(Ci,Cj)*

Through this step a number of linguistic weights have been assigned by experts.

<u>Step 4:</u> If quantitative data (numeric or symbolic) are available, the approach of using fuzzified crisp decision trees (presented in above section 2.1) is

implemented into the data set to derive the available structure of fuzzy decision trees and the fuzzy labels in the branches *Di*.

Step 5: From the created fuzzy decision trees, a number of causal paths among the branches *i*, connecting leaf nodes *Di* to *Dj*, is determined. These causal paths transferred in FCM model as fuzzy rules between interconnecting concepts *Ci* to *Cj*, through a number of direct positive relationships.

Step 6: Using the fuzzy causal algebra, an indirect effect operator *I* used as the minimum operator (min) on an ordered set *P* of causal values. The simple fuzzy causal algebra is created by interpreting the indirect effect operator *I* as the minimum operator (min) on the set *P* of fuzzy values, corresponding to the respective causal paths among the FCM concepts. Then the max operator *T* is applied to the resulted effect operators *I*, and a new linguistic weight produced among *Ci* and *Cj*. The overall linguistic weight is the sum of the path products. Thus a new inferred fuzzy weight is assigned between the concepts *Ci* and *Cj*.

Step 7: Aggregate all the linguistic weights both produced by experts and knowledge extraction methods, using the SUM method where the membership function μ suggested by k^{th} expert is multiplied by the corresponding credibility weight b_k. Use the COG defuzzification method to calculate the numerical weight e_{ij} for every interconnection.

Step 8: IF there is an ordered concept pair not examined go to step 3, ELSE construct the weight matrix $\boldsymbol{E}$ whose are the defuzzified weights e_{ij}.

END.

Using the above algorithm, someone could use fuzzy decision trees (and/or other knowledge extraction techniques) to pass available knowledge into FCM reconstructed by causal paths through fuzzy rules. Experts construct fuzzy sets and fuzzy membership functions for each problem and these fuzzy sets are used into the fuzzy decision tree algorithm due to compatibility reasons. This happens in the case of FCMs to derive the respective linguistic variables and then make the necessary comparisons.

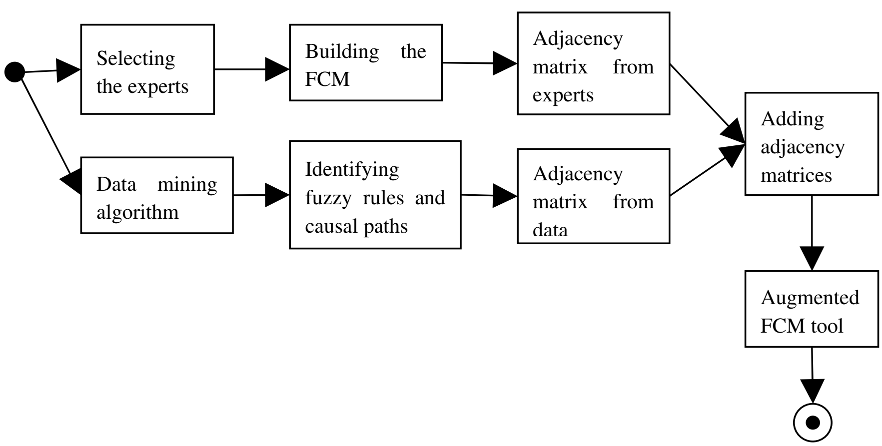

Fig. 6 Basic steps for building an augmented FCM tool

The causal paths of the leaf nodes used to determine new causal paths and weights in the FCM model. Thus the FCM model was augmented as new direct and indirect relationships among concepts determined. The basic stages for building augmented FCMs are given in Figure 6.

4 Application of the Proposed Framework into FCM-DSS in Radiotherapy

Radiotherapy is the application of ionizing radiation to cure patients suffering from cancer (and/or other diseases) and to eliminate infected cells, alone or combined with other modalities. The aim of radiation therapy is to design and perform a treatment plan on how to deliver a precisely measured dose of radiation to the defined tumor volume with as minimal damage as possible to the surrounding healthy tissue.

In a previous work, a decision making system for radiation therapy based on human knowledge and experience was developed by Papageorgiou et al., 2003. That system was consisted of a two-level hierarchical structure where an FCM in each level was created producing an advanced decision-making system. The lower-level FCM modeled the treatment planning, taking into consideration all the factors and treatment variables as well as their influences (CTST-FCM). The upper-level FCM modeled the procedure of the treatment execution and calculated the optimal final dose for radiation treatment. The upper level FCM supervised and evaluated the whole radiation therapy process. The proposed two-level integrated structure for supervising the procedure before treatment execution seems a rather realistic approach to the complex decision making process in radiation therapy.

As it has already been stated, the central idea of the proposed technique is to combine different data driven methods to extract the available knowledge from data and to generate causal paths through fuzzy rules by determining new linguistic weights. The resulted linguistic weights are applied to construct an augmented FCM-based clinical treatment simulation tool (new CTST-FCM) used for decisions in radiation treatment planning. According to the desired values of output concepts, the augmented FCM-DSS reaches a decision about the acceptance of treatment planning technique.

At this point, according to the guidelines (AAPM and ICRU protocols) and radiotherapists' opinions for the most important variables taken under consideration (in order to achieve a good distribution of the radiation on the tumor, as well as to protect the healthy tissues), as well as to minimize the complexity of the presented model, five factor concepts and eight selector-concepts were selected to determine the system performance through the calculation of output concepts. Thus, a new CTST-FCM model that represents the radiotherapy treatment planning procedure according to the test packages, guidelines and radiotherapists' opinions is designed and illustrated in Figure 7.

The number of concepts has been reduced to 16 concepts thus to avoid the complexity of the previously developed CTST-FCM model and to be more clear the proposed technique to no specialist readers. Concepts F-C1 to F-C5 are the

Factor-concepts, that represent the depth of tumor, the size of tumor, the shape of tumor, the type of the irradiation and the amount of patient thickness irradiated. Concepts S-C1 to S-C8 are the Selector-concepts, representing size of radiation field, multiple field arrangements, beam directions, dose distribution from each field, stationery vs. rotation-isocentric beam therapy, field modification, patient immobilizing and use of 2D or 3D conformal technique, respectively. The concepts OUT-C1 to OUT-C3 are the three Output-concepts. Table 1 gathers these respective concepts. The value of the OUT-C1 represents the amount of dose applied to mean Clinical Target Volume (CTV), which have to be larger than the 90% of the amount of prescribed dose to the tumor. The value of concept OUT-C2 represents the amount of the surrounding healthy tissues' volume received a dose, which have to be as less as possible, less than the 5% of volume received the prescribed dose and the value of concept OUT-C3 represents the amount of organs at risk volume received a dose, which have to be less than the 10% of volume received the prescribed dose (Khan, 1994; ICRU Report 50).

Table 1 Description and Type of new CTST-FCM concepts

Concepts	Description	Number & Type of values scaled
F-C 1	Accuracy of depth of tumor	Five fuzzy
F-C 2	Size of tumor	Seven fuzzy (very small, small, positive small, medium, negative large, large, very large)
F-C 3	Shape of tumor	Three fuzzy (small, medium, large)
F-C 4	Type of irradiated tissues-presence of inhomogeneities	Five fuzzy
F-C 5	Amount of patient thickness irradiated	Five fuzzy
S-C 1	Size of radiation field	Five fuzzy
S-C 2	Single or multiple field arrangements	Two discrete
S-C 3	Beam direction(s) (angles of beam orientation)	converted to Five fuzzy
S-C 4	Dose distribution from individual field	Two fuzzy
S-C 5	Stationery vs. rotation-isocentric beam therapy	Two discrete
S-C 6	Field modification (no field modification, blocks, wedges, filters and multileaf-collimator shaping blocks)	Five discrete
S-C 7	Patient immobilization	Three discrete
S-C 8	Use of 2D or 3D conformal technique	Two discrete
Out-C 1	Dose given to treatment volume (must be within accepted limits)	Five fuzzy
Out-C 2	Amount of irradiated volume of healthy tissues	Five fuzzy
Out-C 3	Amount of irradiated volume of sensitive organs (organs at risk)	Five fuzzy

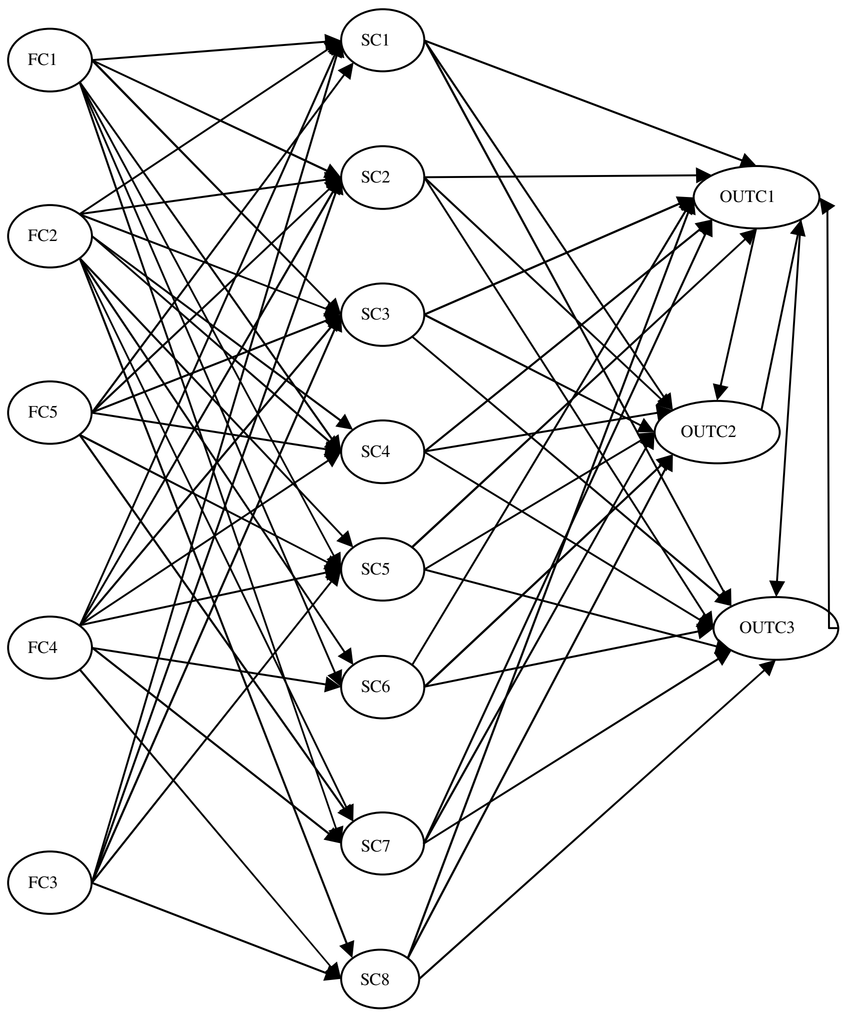

Fig. 7 The new CTST-FCM tool for decision making in radiotherapy

After the description of new CTST-FCM concepts, the design of FCM model continues with the determination of fuzzy sets for each one concept variable. The radiotherapists that work as experts specified the fuzzy membership functions for the fuzzy values of factor concepts, selector concepts and output concepts. For the factor concept F-C3 and selector concept S-C1 (size of radiation field) the experts proposed the fuzzy membership functions illustrated in Figure 8.

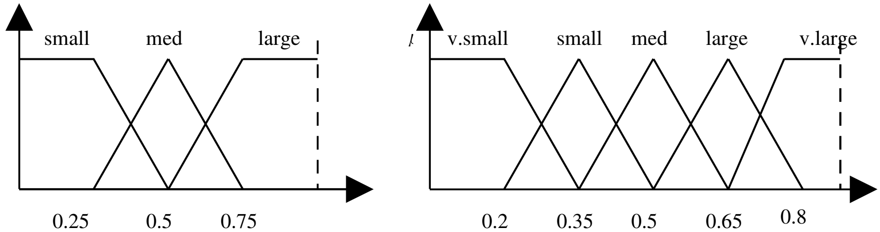

Fig. 8 Partitions (fuzzy trapezoidal membership functions) for F-C3 and S-C1 determined by a priori knowledge from radiotherapists-experts

Then, using the experimental data derived from measurements (Papageorgiou, 2000)), for the initial values of concepts and implementing the knowledge extraction method of fuzzy decision trees, a large set of fuzzy rules among the related concepts were derived. Some of the fuzzy rules that considered important to the decision making approach were selected from the fuzzy decision tree-based rule extraction technique according to the test packages and experimental data. Some example rules are presented at follows:

If F-C1 is medium Then S-C1 is high
If F-C1 is medium Then S-C2 is very high
If F-C2 is high Then S-C1 is high
If F-C2 is small and F-C3 is small Then S-C1 is very high
If S-C4 is 1 and S-C6 is medium Then F-C5 is very high
If F-C1 is small and F-C2 is small Then S-C3 is small

In this point, due to the large number of fuzzy rules produced by the fuzzy decision tree algorithm, we selected only those which differ from the initially suggested by experts and used for the reconstruction of the augmented CTST-FCM in radiation treatment planning. These rules accompanied by rules suggested by experts produce the new CTST-aFCM simulation tool for radiation therapy, which has new strengths among concepts and assigns new decisions and treatment planning suggestions.

5 Results on Implementing the Proposed Approach in Radiotherapy Process

After construction of new CTST-FCM tool for giving a decision about the acceptance or no of the radiotherapy process, a number of scenarios have been introduced and the decision making capabilities of the technique are presented by simulating these scenarios and finding the predicted outcomes according to the available data. Two scenarios for the problem of prostate cancer therapy were considered using the new CTST-FCM model, which consists of 16 concepts and 64 interconnections among concepts, in order to test the validity of the model. In each of the test scenarios we have an initial vector **A**, representing the presented events at a given time of the process, and a final vector **A**_f, representing the last state that can be arrived at.

The final vector **A**_f is the last vector produced in convergence region and the 14^{th}, 15^{th} and 16^{th} value of this vector are the final values of decision concepts.

The algorithm used to obtain the final vector **A**_f is consisting on the following steps:

(1) Definition of the initial vector **A** that corresponds to the elements identified in Table 1.

(2) Multiply the initial vector **A** and the matrix **E** defined by experts by the eq. (1), as indicated by the respective Tables of each case study.

(3) The resultant vector is updating using eqs. (1)–(2).

(4) This new vector is considered as an initial vector in the next iteration.

(5) Steps 2–4 are repeated until $\mathbf{A}^{k} - \mathbf{A}^{k-1} \leq e = 0.001$.

The FCM performance is illustrated by means of simulation of the following two case scenarios in radiotherapy process.

In the first scenario, the 3-D conformal technique consisting of six-field arrangement is suggested and in the second one the conventional four-field box radiation technique. Radiotherapy physicians and medical physicists choose and specified, in our previous study, the fuzzy membership functions for the weights for each case study as well as the fuzzy rules according to their knowledge for each treatment planning procedure. The numerical values of weights between factor and selector concepts for the new CTST-aFCM are summarized after the defuzzification process and are depicted in Table 2.

Table 2 Weight values between F-Cs and S-Cs for new CTST-aFCM after defuzzification process

Factors/ Selectors	S-C1	S-C2	S-C3	S-C4	S-C5	S-C6	S-C7	S-C8
F-C1	0.6	0.62	0.4	0.4	0.6	0.6	0.2	0
F-C2	0.7	0.6	0.2	0.53	0.55	0.5	0.6	0.5
F-C3	0.6	0.63	0.45	0	0.4	0	0	0.7
F-C4	0.32	0.6	0.5	0.55	0.47	0.5	0	0.6
F-C5	0.5	0.6	0.6	0.6	0.2	0.5	0.5	0

For the first case study, the conformal radiotherapy was selected. Multiple CT-based external contours define the patient anatomy and isocentric beam therapy is used (Khan, 1994). Beam weights are different for the six fields, and blocks, wedges are used. The specific characteristics of conformal therapy determine the values of concepts and weights interconnections of new CTST-aFCM model. So, the S-C2 takes the value of six-field number; S-C1 has the value of “small-size” for radiation field that means that the influence of S-C1 and S-C2 toward OUT-Cs is great. In the same way the S-C3 and S-C4 have great influence at OUT-Cs because different beam directions and weights of radiation beams are used. The S-C5 takes the discrete value of isocentric beam therapy. Concept S-C6 takes values for the selected blocks and/or wedges, influencing the OUT-Cs. The S-C7 takes a value for accurate patient positioning and the S-C8 takes the discrete value of 3-D radiotherapy.

Considering the above and the measured experimental data, the initial values of concepts and weights of interconnections between S-Cs and OUT-Cs are suggested. Table 3 gathers the numerical weights among Factor-concepts, Selector-concepts, and Output-concepts, of new CTST-aFCM for the first case study, as they identified from combined knowledge from experts and data. The new CTST-aFCM model is presented in Figure 9, where the modified relationships are shown by red line.

Table 3 Numerical weights among F-Cs, S-Cs and OUT-Cs of new CTST-FCM for the first case, as they derived from combined knowledge from experts and data

Concepts	S-C3	S-C4	S-C5	S-C6	S-C7	S-C8	S-C9	S-C10	OUT-C1	OUT-C2	OUT-C3
F-C1	0.7	0.75	0.4	0.4	0.65	0.6	0	0	0	0	0
F-C2	0.75	0.6	0	0.6	0.55	0.5	0.6	0.5	0	0	0
F-C3	0.6	0.7	0.45	0.2	0.4	0	0	0.75	0	0	0
F-C4	0.25	0.6	0.5	0.55	0.4	0.5	0	0.4	0	0	0
F-C5	0.5	0.6	0.6	0.5	0.2	0.5	0.6	0	0	0	0
S-C1	0	0	0	0	0	0	0	0	0.4	-0.4	-0.4
S-C2	0	0	0	0.5	0	0	0	0	0.3	-0.5	-0.4
S-C3	0	0	0	0	0	0	0	0	0.4	-0.3	-0.3
S-C4	0	0	0	0	0	0	0	0	0.4	-0.4	-0.4
S-C5	0	0	0	0	0	0.7	0	0	0.3	-0.3	-0.3
S-C6	0	0	0	0	0.6	0	0	0	0.4	-0.4	-0.4
S-C7	0	0	0	0	0	0	0	0	0.5	-0.5	-0.5
S-C8	0	0	0	0	0	0	0	0	0.6	-0.5	-0.5
OUT-C1	0	0	0	0	0	0	0	0	0	-0.6	-0.5
OUT-C2	0	0	0	0	0	0	0	0	-0.7	0	0
OUT-C3	0	0	0	0	0	0	0	0	-0.6	0	0

The following initial vector is formed for this particular treatment technique:

$\mathbf{A_1}$= *[0.6 0.5 0.5 0.6 0.6 0.4 0.65 0.7 0.45 0.6 0.6 0.5 0.6 0.5 0.5 0.5].*

Through the simulation algorithm described above, the resulting CTST-FCM starts to interact and simulates the radiation procedure. New values of concepts were calculated after 8 simulation steps. Fig. 10 illustrates the values of concepts for eight simulation steps, where is concluded that after the 5th simulation step FCM reaches an equilibrium region. The following vector gives the calculated values of concepts in the equilibrium region.

A_1_f= [*0.6590 0.6590 0.6590 0.6590 0.6590 0.9420 0.9568 0.8988 0.9412 0.9515 0.9585 0.8357 0.8770 0.9813 0.0203 0.0336].*

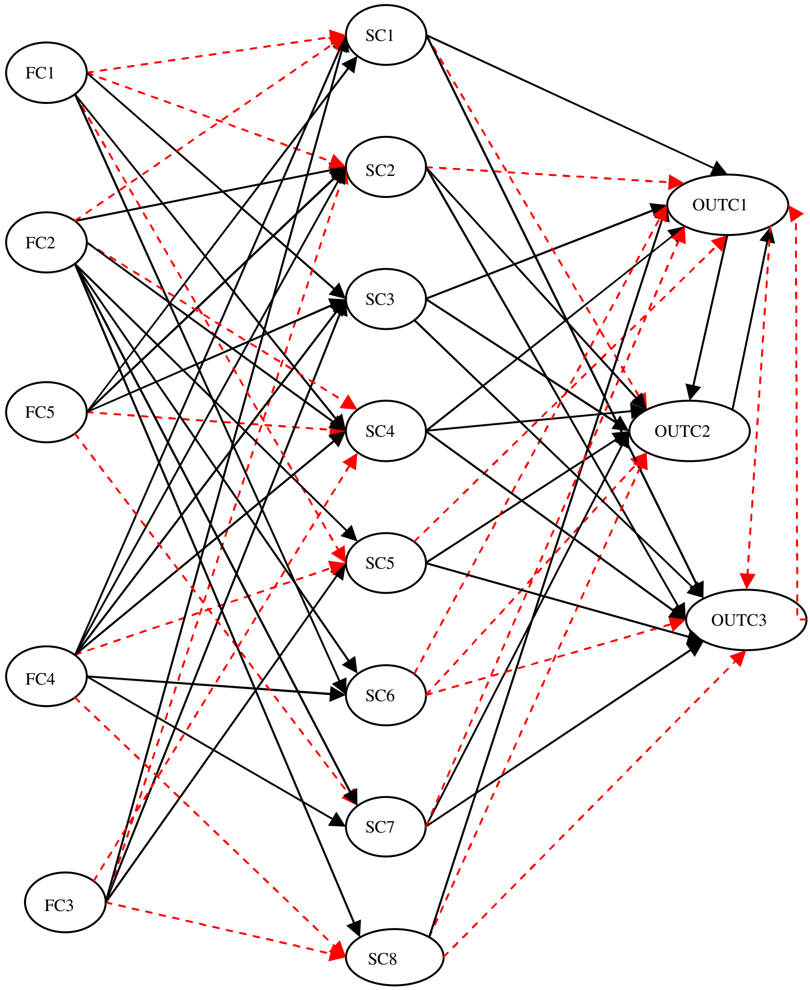

Fig. 9 The new CTST-aFCM tool for decision making in radiotherapy after combining knowledge from experts and data (the broken lines are the new weight values)

At the equilibrium point, the following values of OUT-Cs are: for OUT-C1 is 0.9813, for OUT-C2 is 0.0201 and for OUT-C3 is 0.0336. Based on the referred protocols (AAPM, 1995; ICRU Report 50), the calculated values of output concepts are accepted. The calculated value of OUT-C1 is 0.981, which means that the CTV receives the 98% of the amount of the prescribed dose, which is

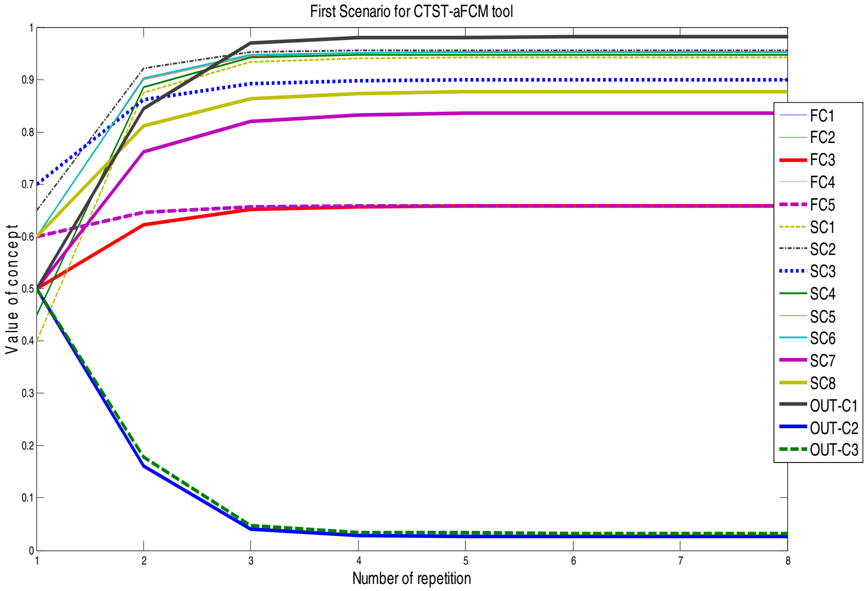

Fig. 10 Variation of values of 16 concepts for the new CTST-aFCM for the first case study for eight simulation steps

accepted. The value of OUT-C2 that represents the amount of the surrounding healthy tissues' volume received a dose was found equal to 0.0201, so the 2.01% of the volume of healthy tissues receives the prescribed dose, and the OUT-C3 was found equal to 3.36% of the dose received from organs at risk.

In the second scenario, the conventional four-field box technique is implemented for the prostate cancer treatment. This technique is consisted of a four-field box arrangement with gantry angles 0, 90, 180, and 270. For this case, the new CTST-FCM was reconstructed which means that the cause-effect relationships and weights have been reassigned not only from radiotherapists' suggestions but also from data knowledge using the proposed rule extraction technique. For this case, the Selector-concept S-C2 has the value of four-field number; S-C1 has the value of "large-size" of radiation field, which means that the influence of S-C1 and S-C2 toward OUT-Cs is very low. In the same way, the S-C3 and S-C4 have lower influence on OUT-Cs because different beam directions and weights of radiation beams are used. The S-C5 takes the discrete value of isocentric beam therapy and has the same influence on OUT-Cs as the above conformal treatment case. S-C6 has zero influence on OUT-Cs because no blocks (and/or no wedges and any filters) are selected for this treatment case. The S-C7 takes a low value for no accurate patient positioning and the S-C8 takes the discrete value of 2-D radiotherapy. The numerical weights among F-Cs, S-Cs and OUT-Cs, of new CTST-aFCM for the second case study, are given in Table 4.

Table 4 Numerical weights among F-Cs, S-Cs and OUT-Cs of new CTST-FCM for the second case

Concepts	S-C3	S-C4	S-C5	S-C6	S-C7	S-C8	S-C9	S-C10	OUT-C1	OUT-C2	OUT-C3
F-C1	0.7	0.75	0.4	0.4	0.6	0.6	0	0	0	0	0
F-C2	0.75	0.6	0	0.6	0.55	0.5	0.6	0.5	0	0	0
F-C3	0.6	0.7	0.45	0.2	0.4	0	0	0.75	0	0	0
F-C4	0.25	0.6	0.5	0.5	0.4	0.5	0	0.4	0	0	0
F-C5	0.5	0.6	0.6	0.5	0.2	0.5	0.6	0	0	0	0
S-C1	0	0	0	0	0	0	0	0	0.3	-0.4	-0.3
S-C2	0	0	0	0.5	0	0	0	0	0.25	-0.5	-0.4
S-C3	0	0	0	0	0	0	0	0	0.3	-0.3	-0.3
S-C4	0	0	0	0	0	0	0	0	0.25	-0.2	-0.2
S-C5	0	0	0	0	0	0.7	0	0	0.3	-0.3	-0.3
S-C6	0	0	0	0	0.6	0	0	0	0.2	0	0
S-C7	0	0	0	0	0	0	0	0	0.4	-0.3	-0.3
S-C8	0	0	0	0	0	0	0	0	0.4	-0.4	-0.4
OUT-C1	0	0	0	0	0	0	0	0	0	-0.4	-0.4
OUT-C2	0	0	0	0	0	0	0	0	-0.7	0	0
OUT-C3	0	0	0	0	0	0	0	0	-0.6	0	0

Using this new CTST-aFCM model, with the new modified weight matrix, the simulation of the radiotherapy procedure for this case starts with the following initial values of concepts:

$\mathbf{A_2} = [0.5\ 0.48\ \ 0.4\ 0.6\ 0.5\ 0.7\ \ 0.45\ 0.4\ \ 0.6\ \ 0.6\ 0.3\ \ 0.2\ \ 0.4\ \ 0.4\ \ 0.2\ 0.2].$

Through the simulation algorithm described above, the resulting CTST-aFCM simulates the radiation procedure and converges to a steady point after 8 simulation steps. Fig. 11 illustrates the values of concepts for eight simulation steps, where is concluded that after the 5th simulation step FCM reaches an equilibrium region. The following vector gives the calculated values of concepts in the equilibrium region:

$\mathbf{A_2\_f} = [\ 0.6590\quad 0.6590\quad 0.6590\quad 0.6590\quad 0.6590\quad 0.9420\quad 0.9568\quad 0.8988\quad 0.9412\quad 0.9515\quad 0.9585\quad 0.8357\quad 0.8770\quad 0.9541\quad 0.0754\quad 0.0910].$

The final values of OUT-Cs are as follows: for OUT-C1, 0.9541; for OUT-C2, 0.0754; and for OUT-C3, 0.0910. These values for OUT-C2 and OUT-C3 are not accepted according to related protocols and task groups (AAPM, 1995; ICRU Report 50).

The new explored CTST-aFCM model seems to be a less complex but dynamic model working efficiently with less number of concepts and weights and especially with weights identified by knowledge extracted from fuzzy decision

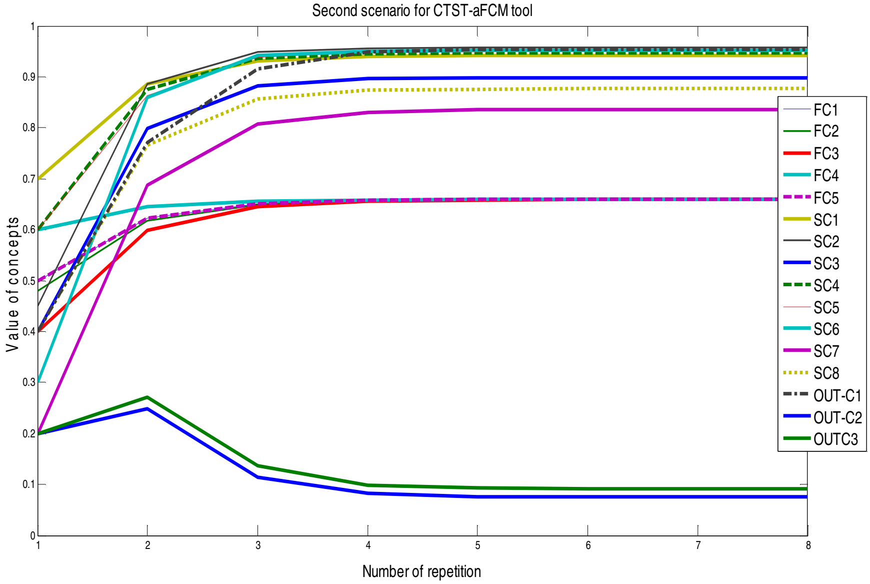

Fig. 11 Variation of values of 16 concepts of new CTST-aFCM for the second case study, with the classical treatment planning case

tree-based rule extraction technique. This tool for making decisions in radiation therapy can adapt its knowledge from available data and not only from experts' opinions. Thus, through the proposed approach, an acceptable decision is succeeded and the new CTST-aFCM tool is less time consuming and easy for use from no specialists.

6 Discussion and Conclusions

In this chapter, a novel approach on producing dynamic FCM-DSS combining knowledge extracted from the available data sets using a data mining algorithm and from guidelines has been explored and a medical application giving meaningful results has been depicted. The proposed approach was based partly on fuzzy rules derived from data using fuzzy decision tree rule extraction algorithm and on the experts' knowledge. All the available knowledge from data was used to enrich the FCM which works as a knowledge-based decision making model.

The produced CTST-aFCM was constructed combining knowledge from the available fuzzy rule base created by knowledge exploiting by experts, guidelines and data, using rule extraction methods for producing fuzzy rules. In this point, due to the large number of fuzzy rules produced by the fuzzy decision tree algorithm, we selected only those which differ from the initially suggested by experts and used for the construction of the CTST-aFCM in radiation treatment planning. Thus, some of the initial CTST-aFCM weights could be changed according to the new knowledge inserted from the fuzzy rules.

Pinpointing, the main goal of this work is to represent a different dynamic approach for construction of augmented FCM-based decision support tools rather to compare with other decision support systems. The new CTST-aFCM model with less number of concepts and weights and especially with weights not only determined by guidelines and radiotherapists-experts' suggestions but also using fuzzy rules extracted through fuzzy decision tree technique, is a dynamic and less complex model which works efficiently. Through the proposed approach was proven that the decision making tool can adapt its knowledge not only using experts' opinions and medical guidelines but also using the available data. Thus, an acceptable decision can be succeeded and the new CTST-aFCM tool is less time consuming and easy for use from no specialists.

In our opinion, revival of interest in DSS research crucially depends on new frameworks and architectures that would extend the cognitive capacities of DSS to meet the real world. We hope that our work points in this direction. Furthermore, the aim of the proposed methodology was not to achieve better accuracies or to present a better classifier, but to introduce a novel framework for FCM-DSS enhancement by fuzzy rule base constructed by efficient extraction of knowledge methods. The new decision support tool is simple, less complex, transparent and interpretable to be accepted for medical applications. The distinguishing feature of such dynamic FCM-DSS is its situations with large amount of data, not enough knowledge from experts and difficulty to handle the available knowledge from many different sources of information.

As disadvantages could be referred the following:

- If not enough information is available, the approach can not be more efficient than other decision making methods and should be complemented by other intelligent methods
- Its outcomes are dependent on the attentiveness of the analysts about the knowledge extraction methods.

Summarizing in this chapter, a novel approach for the construction of dynamic FCMs for inference and decision making is presented. The fuzzy weights and causal paths, which derived by using fuzzy decision tree induction algorithm for this data set, were incorporating to construct the new CTST-aFCM producing acceptable decisions not only based on experts' suggestions. In the future, other rule-extraction methods for decision support in medical domain will be investigated. Furthermore, the proposed methodology will be implemented in other medical problems which have been handled till today using only knowledge from data or from experts, as well as in other scientific domains with large amount of available data and information sources.

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References

AAPM Report No. 55, Radiation Treatment planning dosimetry verification. American Association of Physicists in Medicine. Report of Task Group 23 of the Radiation Therapy Committee. American Institution of Physics, Woodbury (1995)

Au, W.-H., Chan, K.C.C.: FARM: A data mining system for discovering fuzzy association rules. In: Proc. of the 8th IEEE International Conference on Fuzzy Systems, Seoul, Korea, August 22-25, pp. 1217–1222 (1999)

Aguilar, J.: A survey about fuzzy cognitive maps papers. International Journal of Computational Cognition 3(2), 27–33 (2005)

Alam, R., Ibbott, G.S., Pourang, R., Nath, R.: Application of AAPM Radiation Therapy Committee Task Group 23 test package for comparison of two treatment planning systems for photon external beam radiotherapy. Med. Phys. 24, 2043–2054 (1997)

Boutalis, Y., Kottas, T.L., Christodoulou, M.: Adaptive estimation of fuzzy cognitive maps with proven stability and parameter convergence. IEEE Transactions on Fuzzy Systems 17(4), 874–889 (2009)

Bueno, S., Salmeron, J.L.: Benchmarking main activation functions in fuzzy cognitive maps. Expert Systems with Applications 36(3), 5221–5229 (2009)

Chen, G., Wei, Q.: Fuzzy association rules and the extended mining algorithms. Information Sciences 147, 201–228 (2002)

Crockett, K., Bandar, Z., Mclean, D., O'Shea, J.: On constructing a fuzzy inference framework using crisp decision trees. Fuzzy Sets and Systems 157, 2809–2832 (2006)

Fayyad, U.M., Piatetsky-Shapiro, G., Smyth, P., Uthurusamy, R.: Advances in Knowledge Discovery and Data Mining. AAAI/MIT Press, Menlo Park (1996)

Fayyad, U., Uthurusamy, R.: Data mining and knowledge discovery in databases. Commun. ACM 39, 24–27 (1996)

Froelich, W., Wakulicz-Deja, A.: Predictive Capabilities of Adaptive and Evolutionary Fuzzy Cognitive Maps - A Comparative Study. In: Nguyen, N.T., Szczerbicki, E. (eds.) Intel. Sys. for Know. Management. SCI, vol. 252, pp. 153–174. Springer, Berlin (2009)

Froelich, W., Wakulicz-Deja, A.: Mining temporal medical data using adaptive fuzzy cognitive maps. In: Proceedings - 2009 2nd Conference on Human System Interactions, HSI 2009, pp. 16–23 (2009) art. no. 5090946

Fu, L.M.: Knowledge-Based Connectionism for Revising Domain Theories. IEEE Trans. on Systems, Man, and Cybernetics 23(l), 173–182 (1993)

Gath, G., Geva, A.B.: Unsupervised optimal fuzzy clustering. IEEE Transactions on Pattern Analysis and Machine Intelligence 7, 773–781 (1989)

Georgopoulos, V.C., Stylios, C.D.: Complementary case-based reasoning and competitive fuzzy cognitive maps for advanced medical decisions. Soft Computing 12, 191–199 (2008)

Georgopoulos, V.C., Stylios, C.D.: Augmented Fuzzy Cognitive Maps Supplemented with Case Base Reasoning for Advanced Medical Decision Support. In: Nikravesh, M., Zadeh, L.A., Kacprzyk, J. (eds.) Soft Computing for Information Processing and Analysis Enhancing the Power of the Information Technology. Studies in Fuzziness and Soft Computing, pp. 391–405. Springer, Heidelberg (2005) ISBN: 3-540-22930-2

Hayashi, Y., Maeda, T., Bastian, A., Jain, L.C.: Generation of fuzzy decision trees by fuzzy ID3 with adjusting mechanism of and/or operators. In: Proc. of Int. Conf. Fuzzy Syst., pp. 681–685 (1998)

ICRU Report 50, Prescribing, recording and reporting photon beam therapy. International Commission on Radiation Units and Measurements, Washington (1993)

Ishibuchi, H., Nozaki, K., Yamamoto, N., Tanaka, N.: Selecting fuzzy if–then rules for classification problems using genetic algorithms. IEEE Trans. Fuzzy Systems 3(3), 260–270 (1995)

Janikow, C.Z.: Fuzzy decision trees: issues and methods. IEEE Trans. Systems Man and Cybernetics 28(1), 1–14 (1998)

Janikow, C.Z.: Fuzzy partitioning with FID3.1. In: Proceedings of the 18th International Conference of the North American Fuzzy Information Society, pp. 467–471 (1999)

Janikow, C.Z.: Fuzzy Decision Trees Manual, free version for Fuzzy Decision Trees (1998) `http://www.cs.umsl.edu/Faculty/janikow/janikow.html`.

Jang, J.S.R., Sun, C.T., Mizutani, E.: Neuro-Fuzzy & Soft Computing. Prentice-Hall, Upper Saddle River (1997)

Jang, L.: Soft Computing Techniques in Knowledge-Based Intelligent Engineering Systems: Approaches and Applications. Studies in Fuzziness and Soft Computing, vol. 10. Springer, Heidelberg (1997)

Khan, F.: The Physics of Radiation Therapy, 2nd edn. Williams & Wilkins, Baltimore (1994)

Kosko, B.: Fuzzy Cognitive Maps. Int. J. Man-Machine Studies 24, 65–75 (1986)

Kosko, B.: Neural Networks and Fuzzy Systems. Prentice-Hall, New Jersey (1992)

Kurgan, L.A., Musilek, P.: A Survey on Knowledge Discovery and Data mining processes. The Knowledge Engineering Review 21(1), 1–24 (2006)

Lee, K.C., Kim, H.S.: A Causal Knowledge-Driven Inference Engine for Expert System. In: Proc. of the 31st Hawaii International Conference on System Science, January 6-9, vol. 1(1), pp. 284–293 (1998)

Liu, H., Tan, S.T.: X2R: A Fast Rule Generator. In: Proc of IEEE Inter. Conf. on Systems, Man & Cybernetics, Vancouver, Canada (October 1995)

Liu, X., Cohen, P., Berthold, M.R.: IDA 1997. LNCS, vol. 1280. Springer, Heidelberg (1997)

Lozowski, A., Zurada, J.M.: Extraction of linguistic rules from data via neural networks and fuzzy approximation. In: Cloete, J., Zurada, J.M. (eds.) Knowledge-Based Neurocomputing. The MIT Press, Cambridge (2000)

Miao, Y., Liu, Z.Q.: On causal inference in fuzzy cognitive maps. IEEE Transactions on Fuzzy Systems 8, 107–119 (2000)

Mitra, S., Konwar, K.M., Sankar, K.P.: Fuzzy decision tree, linguistic rules and fuzzy knowledge-based network: generation and evaluation. IEEE Trans. Syst. Man Cybern. Part C: Appl. Rev. 32(4), 328–339 (2002)

Mitra, S., Hayashi, Y.: Neuro-Fuzzy rule generation: Survey in soft computing. IEEE Trans Neural Networks 11(3), 748–760 (2000)

Nauck, D., Klawonn, F., Kruse, R.: Foundations of neuro-fuzzy systems. Wiley, Chichester (1997)

Nauck, D., Kruse, R.: Obtaining interpretable fuzzy classification rules from medical data. Artificial Intelligence in Medicin 16(2), 149–169 (1999)

Nauck, D.: NEFCLASS toolbox (1997), `http://fuzzy.cs.uni-magdeburg.de/nefclass/`

Olaru, C.W.: A complete fuzzy decision tree technique. Fuzzy Sets and Systems 138, 221–254 (2003)

Pach, F.P., Abonyi, J.: Association Rule and Decision Tree based Methods for Fuzzy Rule Base Generation. Transactions on Engineering, Computing and Technology 13 (2006) ISSN 1305-5313

Pal, S.K., Mitra, S.: Neuro-Fuzzy Pattern Recognition: Methods in Soft Computing. Wiley, New York (1999)

Papageorgiou, E., Stylios, C., Groumpos, P.: An Integrated Two-Level Hierarchical Decision Making System based on Fuzzy Cognitive Maps (FCMs). IEEE Trans. Biomed. Engin. 50(12), 1326–1339 (2003)

Papageorgiou, E.I.: A model for dose calculation in treatment planning using pencil beam kernels. MSc. Thesis, Medical University Hospital of Patras, Greece (June 2000)

Papageorgiou, E.I., Groumpos, P.P.: A weight adaptation method for fine-tuning Fuzzy Cognitive Map causal links. Soft Computing 9, 846–857 (2005a)

Papageorgiou, E.I., Groumpos, P.P.: A new hybrid learning algorithm for Fuzzy Cognitive Maps learning. Applied Soft Computing 5, 409–431 (2005b)

Papageorgiou, E.I., Spyridonos, P., Ravazoula, P., Stylios, C.D., Groumpos, P.P., Nikiforidis, G.: Advanced Soft Computing Diagnosis Method for Tumor Grading. Artificial Intelligence in Medicine 36(1), 59–70 (2006a)

Papageorgiou, E.I., Stylios, C.D., Groumpos, P.P.: A Combined Fuzzy Cognitive Map and Decision Trees Model for Medical Decision Making. In: Proceedings of the 28th IEEE EMBS Annual Intern. Conference in Medicine and Biology Society, EMBS 2006, New York, USA, 30 August-3 September, pp. 6117–6120 (2006b)

Papageorgiou, E.I., Groumpos, P.P.: Neuro-fuzzy, fuzzy decision tree and association rule based methods for fuzzy cognitive map grading process. In: Proceedings of International Conference on Computational Intelligence in MEDicine, CIMED 2007, Plymouth, UK, July 25-27 (2007) (CD-ROM)

Papageorgiou, E.I., Spyridonos, P., Glotsos, D., Stylios, C.D., Ravazoula, P., Nikiforidis, G., Groumpos, P.P.: Brain tumour characterization using the soft computing technique of fuzzy cognitive maps. Applied Soft Computing 8, 820–828 (2008)

Papageorgiou, E.I., Papandrianos, N., Apostolopoulos, D., Vassilakos, P.: Fuzzy Cognitive Map based Decision Support System for thyroid diagnosis management. In: Zurada, J.M., Yen, G.G., Wang, J. (eds.) Computational Intelligence: Research Frontiers. LNCS, vol. 5050, pp. 1204–1211. Springer, Heidelberg (2008)

Papakostas, G.A., Boutalis, Y.S., Koulouriotis, D.E., Mertzios, B.G.: Fuzzy cognitive maps for pattern recognition applications. International Journal of Pattern Recognition and Artificial Intelligence 22(8), 1461–1486 (2008)

Pedrycz, W., Sosnowski, A.: Designing decision trees with the use of fuzzy granulation. IEEE Trans. Syst. Man Cybern. A 30, 151–159 (2000)

Peláez, C.E., Bowles, J.B.: Using fuzzy cognitive maps as a system model for failure modes and effects analysis. Information Sciences 88, 177–199 (1996)

Quinlan, J.R.: Decision trees and decision making. IEEE Trans System, Man and Cybernetics 20(2), 339–346 (1990)

Quinlan, J.R.: C4.5: Programs for machine learning. Morgan Kaufmann, San Mateo (1993)

Quinlan, J.R.: Is C5.0 better than C4.5 (2002), `http://www.rulequest.com/see5-comparison.html`

Sestino, S., Dillon, T.: Using single-layered neural networks for the extraction of conjunctive rules and hierarchical classifications. J. Appl. Intell. 1, 157–173 (1991)

Sison, L., Chong, E.: Fuzzy modeling by induction and pruning of decision trees. In: IEEE Symposium on Intelligent Control, U.S.A., pp. 166–171 (1994)

Sordo, M., Vaidya, S., Jain, L.C.: An introduction to computational intelligence in healthcare: New directions. Studies in Computational Intelligence 107, 1–26 (2008)

Stach, W., Kurgan, L., Petrycz, W.: A Framework for a novel scalable FCM learning method. In: Proceedings of the 2007 Symposium on Human-Centric Computing and Data Processing (HCDP 2007), Canada, February 21 - 23, pp. 13–14 (2007)

Stylios, C.D., Georgopoulos, V.C., Malandraki, G.A., Chouliara, S.: Fuzzy cognitive map architectures for medical decision support systems. Appl. Soft Comput. 8(3), 1243–1251 (2008)

Stylios, C.D., Groumpos, P.P.: Modeling Fuzzy Cognitive Maps. IEEE Transactions on Systems, Man, and Cybernetics, Part A 34, 155–162 (2004)

Taber, R., Yager, R., Helgason, C.M.: Quantization Effects on the Equilibrium Behavior of Combined Fuzzy Cognitive Maps. International Journal of Intelligent Systems 22, 181–202 (2007)

Towell, G., Shavlik, J.: Extracting Refined Rules from Knowledge-Based Neural Networks. Machine Learning 131, 71–101 (1993)

Umano, M., Okamoto, H., Hatono, I., Tamura, H.: Generation of fuzzy decision trees by fuzzy ID3 algorithm and its application to diagnosis by gas in oil. In: Japan–U.S.A. Symposium, pp. 1445–1450 (1994)

Weber, R.: Fuzzy ID3: a class of methods for automatic knowledge acquisition. In: 2nd International Conference on Fuzzy Logic and Neural Networks, Iizuka, Japan, pp. 265–268 (1992)

Wei, Z., Baowen, S., Yanchun, Z.: Design of inference model based on activation for fuzzy cognitive map. In: 2009 International Workshop on Intelligent Systems and Applications, ISA 2009 (2009) art. no. 5072819

Wells, D., Niederer, J.: A Medical Expert System approach using Artificial Neural Networks for standardized treatment planning. Int. J. Radiat. Oncol. Biol. Phys. 41(1), 173–182 (1998)

Xirogiannis, G., Chytas, P., Glykas, M., Valiris, G.: Intelligent impact assessment of HRM to the shareholder value. Expert Systems with Applications 35(4), 2017–2031 (2008)

Xirogiannis, G., Stefanou, J., Glykas, M.: A fuzzy cognitive map approach to support urban design. Expert Systems with Applications 26(2), 257–268 (2004)

Xirogiannis, G., Glykas, M.: Intelligent Modeling of e-Business Maturity. Expert Systems with Applications 32/2, 687–702 (2007)

Yuan, Y., Shaw, M.J.: Induction of fuzzy decision trees. Fuzzy Sets Systems 69, 125–139 (1995)

Zurada, J.M., Duch, W., Setiono, R.: Computational intelligence methods for rule-based data understanding. In: Proc. of the IEEE International Conference on Neural Networks, vol. 92(5), pp. 771–805 (2004)

Zurada, J.M., Lozowski, A.: Generating linguistic rules from data using neuro-fuzzy framework. In: Proc. 4th Intern. Conf. on Soft. Computing (IIZUKA 1996), Iizuka, Fukuoda, Japan, pp. 618–621 (1996)