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A new methodology for Decisions in Medical Informatics using fuzzy cognitive maps based on fuzzy rule-extraction techniques

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ABSTRACT

In this research work, a novel framework for the construction of augmented Fuzzy Cognitive Maps based on Fuzzy Rule-Extraction methods for decisions in medical informatics is investigated. Specifically, the issue of designing augmented Fuzzy Cognitive Maps combining knowledge from experts and knowledge from data in the form of fuzzy rules generated from rule-based knowledge discovery methods is explored. Fuzzy cognitive maps are knowledge-based techniques which combine elements of fuzzy logic and neural networks and work as artificial cognitive networks. The knowledge extraction methods used in this study extract the available knowledge from data in the form of fuzzy rules and insert them into the FCM, contributing to the development of a dynamic decision support system. The fuzzy rules, which derived by these extraction algorithms (such as fuzzy decision trees, association rule-based methods and neuro-fuzzy methods) are implemented to restructure the FCM model, producing new weights into the FCM model, that initially structured by experts. Concluding, our scope is to present a new methodology through a framework for decision making tasks using the soft computing technique of FCMs based on knowledge extraction methods. A well known medical decision making problem pertaining to the problem of radiotherapy treatment planning selection is presented to illustrate the application of the proposed framework and its functioning.

1. Introduction

This paper investigates a soft computing framework to handle different data types for decision support tasks in medical informatics. More specifically, it reports a methodology to construct an advanced framework implementing different knowledge extraction methods for the augmented construction of Fuzzy Cognitive Mapping Decision Support system in medicine.

Generally, a decision-making procedure is a complex process that has to take under consideration a variety of interrelated functions. In Medical Decision Support Systems (MDSS) we are not only interested on the accuracy and prediction of the results (as in classification and data mining techniques) but for the transparency and interpretability of the results from the medical practitioner who uses the MDSS in his daily clinical practice [1].

The a priori knowledge about a problem to be solved is frequently given in a symbolic, rule-based form. Extraction of knowledge from data, combining it with available symbolic knowledge, and refining the resulting knowledge-based expert systems is a great challenge for computational intelligence. Reasoning with logical rules is more acceptable to human users than the recommendations given by black box systems [2], because such reasoning is comprehensible, provides explanations, and may be validated by human inspection. It also increases confidence in the system, and may help to discover important relationships and combination of features, if the expressive power of rules is sufficient for that.

There are several methods proposed for logical rule generation combining different data types (machine learning, fuzzy decision trees, association rules, Bayesian networks, neural networks, pattern recognition techniques, hybrid computational intelligent algorithms) [3–7,15]. We have selected the more powerful of these algorithms for the knowledge extraction from data and development of the specific fuzzy rule base; some of the most frequently used rule generation algorithms are the neuron-fuzzy rule based algorithm, namely NEFCLASS, the fuzzy decision trees and the association rule based methods. It has been proved from the literature that these knowledge extraction algorithms give better rules (means appropriate for each specific problem) and keep the level of interpretability and accuracy in the decision making tasks [2,8–10].

In the area of analysis different data types, the interpretability and simplicity of fuzzy systems is the key advantage [9,11]. Fuzzy systems are not better function approximators or classifiers than other approaches. If we want to keep the model simple, the prediction is usually less accurate [12]. This means fuzzy systems should be used for data analysis, if an interpretable model is needed that

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can also be used to some extent for prediction. Furthermore, interpretability should not mean that anybody can understand a fuzzy system. It means that users, who are at least to some degree experts in the domain where the data analysis takes place, can understand the model. Obviously we cannot expect a lay person to understand a fuzzy system in a medical domain. It is important that the medical expert who uses the model should understand it [8].

During recent years, artificial intelligence techniques and expert systems have been used complementary to each other for medical decision support in a number of applications. The advantages of each one method have been taken into account in the new designed system making it (or developing) more powerful instruments to facilitate various tasks that require instant, accurate and reliable results.

Generally, Fuzzy cognitive maps are diagrams used as causal representations between knowledge/data to represent events relations. They are composed of nodes and edges, the former introducing the qualitative concepts of the analysis while the latter indicate the various causal relationships. Each concept node possesses a numeric state, which denotes the qualitative measure of its presence in the conceptual domain. Thus, a high numerical value indicates that the concept is strongly present in the analysis while a negative or zero value indicates that the concept is not currently active or relevant to the conceptual domain. Each strength of the causal relationship (that takes linguistic values), possesses a state that denotes the effect of a change in one concept/node affects other nodes, which in turn may affect other nodes.

FCMs, unlike data driven models, are built on human expertise. FCMs are usually constructed manually using extensive background knowledge about the system being modeled. It is essential to notice that the selection of FCM concepts (number and type of variables used in decision making), is a very important issue in model's design. Contrarily to current computerized support decision approaches which construct their diagnostic model only from available data, FCMs represent and model, the human knowledge and expertise in decision making.

In this study, FCM is developed combining knowledge from experts and data using rule extraction methods that generate meaningful fuzzy rules. Through this approach, one of the FCM problems that concern the FCM construction based explicitly on experts' assignments can be alleviated. This is a deficiency of the FCM model and till now only some investigations have been made towards this direction [13,14,19,21]. Most of the FCM models are constructed basically by experts' knowledge and this is a problem when there is also available knowledge from data sources that is useful and essential for the decision support. Furthermore, the performance of FCMs is known to be sensitive to the initial weight setting and architecture. This shortcoming could be alleviated by augmenting the FCM structure if a fuzzy rule base (IF-THEN rules) will be available. A number of knowledge extraction methods, fuzzy systems, neuro-fuzzy techniques, machine learning and other computational intelligence techniques [3–7,15] could be used for the generation of fuzzy rule base [4,16]. These methods extract the available knowledge from data in the form of fuzzy rules producing the respective fuzzy strengths of relationships (weights) and then insert them into the FCM-based decision support system.

Medical decision systems are complex systems that can be decomposed to non-related and related subsystems and elements, where many factors have to be taken into consideration that may be complementary, contradictory, and competitive; these factors influence each other and determine the overall clinical decision with a different degree. Thus, FCMs are suitable for medical Decision Support Systems by helping analyze the views and events that are carried on a medical subject with qualitative and quantitative methods and appropriate FCM architectures seem essential to be proposed and developed.

Few frameworks based on fuzzy cognitive maps for the task of reasoning and learning in medical decision systems have been proposed [17–25]. In these previous works, FCM based methods have been proposed for making decisions in external beam radiotherapy [17], for characterizing tumours' malignancy (urinary bladder and brain tumors) and a FCM grading tool, namely FCM-GT, was proposed for each case problem to classify the degree of tumour malignancy [19,22,23]. The FCM-GT was constructed from the available knowledge from histopathologists-experts and the cause-effect relationships among the concepts were trained using an unsupervised learning algorithm (for details see in [19,22,23]). Georgopoulos and Stylios proposed a new hybrid modeling methodology suitable for complex decision making processes, using complementary case based reasoning and competitive FCMs for the differential diagnosis problem from the speech pathology area [24]. Moreover, some appropriate FCM architectures were proposed and developed recently as well as the corresponding examples from two medical disciplines, i.e., speech and language pathology and obstetrics, were described [25].

In this work, a new framework for constructing fuzzy cognitive mapping combining knowledge from experts and guidelines, and from data using rule extraction methods that generate meaningful fuzzy weights is proposed. The explored methodology is partly data driven and knowledge driven so some expert knowledge of the domain is required. The whole approach is applied to a clinical treatment simulation tool based on FCMs constructed to handle the complex problem of making decisions in radiation therapy treatment. The results of augmented fuzzy cognitive map-based decision support system (aFCM-DSS) are acceptable and encourage our research towards this type of decision support systems in medicine. Furthermore this system could benefit the students in medicine for their training in clinical routine.

This paper is organized as follows: the following second section gives the necessary background information about fuzzy cognitive maps theory and inference process. The third section presents the fuzzy rule-based generation methods through knowledge extraction. The forth section is reserved for explanation of the proposed integrated framework of fuzzy cognitive map based decision support system in medical informatics. Then the fifth section presents the application results of the proposed methodology for treatment planning selection of the prostate cancer case study. Finally, the sixth section depicts the discussion for this application and the last section outlines the conclusions.

2. Background of proposed approach

2.1. Fuzzy cognitive maps theory

Fuzzy Cognitive Maps (FCMs) are soft computing tools, which combine elements of fuzzy logic and neural networks. FCM theory was developed by Kosko [26,27] as an extension of cognitive maps by applying fuzzy causal functions with real numbers in $[-1, 1]$ to the connections. Kosko (1987) was also the first to determine the outcome of a FCM, as well as to model the effect of different policy options. They initially used for planning and decision-making in the fields of international relations, social systems modeling and the study of political developments in the context of such systems [28].

Strictly speaking, a Fuzzy Cognitive Map is a fuzzy diagram that describes the behavior of an intelligent system in terms of concepts; each concept represents an entity, a state, a variable, or a characteristic of the system [27]. FCM nodes are named by such concepts forming the set of concepts $C = \{C_1, C_2, \ldots, C_n\}$. 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

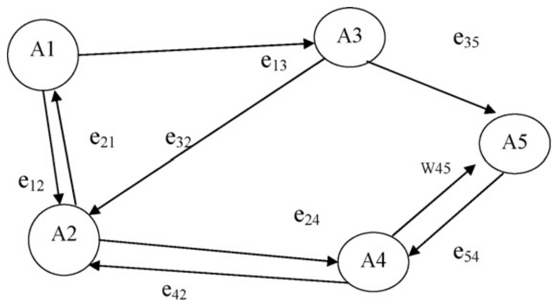

Fig. 1. A simple fuzzy cognitive map model.

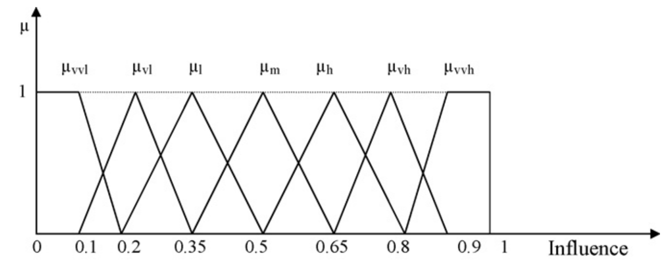

Fig. 2. The seven membership functions corresponding to each one of the seven linguistic variables.

a weight value matrix *En·n*, where each element of the matrix *eji* taking values in [−1, . . ., 1]; Thus, there are three types of weights: $e_{ij} = 0$ indicates no causality; $e_{ij} > 0$ indicates a causal increase (i.e., A_j increases as A_i increases, and A_j decreases as A_i decreases); $e_{ij} < 0$ indicates causal decrease (i.e., A_j decreases as A_i increases, and A_j increases as A_i decreases). Word weights like 'little' or 'somewhat' can be used instead of numeric values [29]. If the value of this link takes on discrete values in the set {−1, 0, 1}, it is called a simple or crisp FCM.

An FCM works in discrete steps [30]. When a strong positive correlation exists between the current state of a concept and that of another concept in a preceding period, we say that the former positively influences the latter, indicated by a positively weighted arrow directed from the causing to the influenced concept. By contrast, when a strong negative correlation exists, it reveals the existence of a negative causal relationship indicated by an arrow charged with a negative weight. Two conceptual nodes without a direct link are, obviously, independent. The interaction strengths are used to represent either 'expert opinion', semi-quantitative or quantitative data on the relative degree to which one variable influences another. The advantage of FCMs is that they are relatively easy to construct and parameterize and are capable of handling the full range of system feedback structure, including density-dependent effects. Fig. 1 illustrates a Fuzzy Cognitive Map model.

2.2. Constructing fuzzy cognitive map model

An FCM is usually constructed by a knowledge engineer who acquires domain knowledge from systems experts and uses that knowledge to define the concepts, causal directions and fuzzy values of the edges of the graph. Edge matrices resulting from interviews with multiple domain experts can be combined to yield an edge matrix that collectively encodes the background knowledge of the cause and effect relationships of a system [13].

Compared with other schemes for developing knowledge bases, such as the rule base in an expert system, the process of constructing an FCM is relatively simple. FCMs can be produced by experts manually or generated by other source of information computationally. The main steps in this process are as follows.

Step 1: Identification of key domain issues, factors or concepts.
Step 2: Identification of causal relationships among these concepts.
Step 3: Estimation of causal link strengths.

Knowledge engineers contributed as multiple domain experts develop an FCM or 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 directions (edges) among these concepts and thirdly, they estimate fuzzy values of the edges of the graph. This achieved graph (FCM) shows not only the components (concepts) and their relations but also the fuzzy 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.

Usually, a linguistic variable declared as *Influence,* is used to represent the causal interrelationships among concepts. Its term set *T*(influence), in most case studies, is suggested to comprise seven variables. Using seven linguistic variables, an expert can describe in detail the influence of one concept on another and can discern between different degrees of influence. The seven variables used here are: *T*(influence) = {very very low, very low, low, medium, high, very high, and very very high}. The corresponding memberships functions for these terms are shown in Fig. 2 and they are: μ_{vvl}, μ_{vl}, μ_l, μ_m, μ_h, μ_{vh} and μ_{vvh}.

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 [30]. 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) [31].

In general, when at least there is one knowledge engineer who has expertise in the area under studied, the manual procedures for developing FCM have occurred. However, there are some situations, where a FCM could not construct manually such as:

- There is no expert to define a FCM.
- The domain experts' knowledge is different with each other and they draw different FCMs.
- There are large amount of concepts and connections between them, which could not be drawn without mistakes.

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.

2.3. Fuzzy cognitive map inference

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. Once constructed, a FCM is then solved numerically to find the equilibrium value of variables (A_i), given any fixed boundary conditions (e.g. sustained press of a variable).

FCMs can be subjected to an initial stimulus in the form of a state vector $\boldsymbol{A}$ representing the states of the system's variables. The outcome of the constructed map can be determined by using matrix algebra where the vector of initial states of variables ($\boldsymbol{A}$) is multiplied with the adjacency matrix $\boldsymbol{E}$ of the FCM. The value of each concept is influenced by the values of the connected concepts with the corresponding causal weights and by its previous value. The concept values of nodes $C_1, C_2, \ldots, C_n$ (where n is the number of concepts in the problem domain) together represent the state vector $\boldsymbol{A}$. To let the system evolve, the state vector $\boldsymbol{A}$ is passed repeatedly through the FCM connection matrix $\boldsymbol{E}$. So the value A_i for each concept C_i is calculated by the following rule:

$$\mathbf{A}^{(k)} = f(\mathbf{A}^{(k-1)} + \sum \mathbf{A}^{(k-1)} \cdot \mathbf{E}) \tag{1}$$

or

$$A_i(k+1) = f(A_i(k) + \sum_{\substack{j \neq i \\ j=1}}^{N} (A_j(k) \cdot E_{ji}) \tag{2}$$

where $A_i^{(k+1)}$ is the value of concept C_i at simulation step k+1, $A_j^{(k)}$ is the value of concept C_j at step k, E_{ji} is the weight of the interconnection between concept C_j and concept C_i and f is a threshold (activation) function that squashes the result of the multiplication in the interval [0, 1].

Several formulas can be used as threshold function [32], and as the interval of concept is bivalent (i.e., the concepts belong to the interval [0, 1]), we propose the function $f(x)$:

$$f(x) = \frac{1}{(1 + \exp(-mx))} \tag{3}$$

where m is a real positive number and x is the value $A_i^{(k)}$ on the equilibrium point. In this work we use m = 1, because this value showed best results in previous works [32]. The threshold function is used to reduce unbounded weighted sum to a certain range. The normalization hinders quantitative analysis, but, at the same time, it allows for a comparative analysis of activation levels of the concepts.

A concept is turned on or activated by making its vector element 0 or 1 or a value in [0, 1]. A snapshot of the activation levels of all nodes at a particular iteration defines the system state. Initial state vector refers to the system state at the first iteration. 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 $\mathbf{A}^k = \mathbf{A}^{k-1} + \mathbf{A}^{k-1} \cdot \mathbf{E}$. Successive states are calculated by iterating making use of Eqs. (1) or (2). Eqs. (1) or (2) indicate that a FCM is free to interact; at every step of interaction every concept has a new value. The simulation outcomes directly depend on the type of threshold (transformation) function. Discrete output functions lead the simulation into either hidden pattern (fixed-point attractor) or limit cycle. The former term refers to a scenario, in which the state vector is kept unchanged after a certain number of iterations. Limit cycle describes a situation, in which the system keeps cycling between certain states. When the transformation (threshold) function is continuous, the system may produce fixed-point attractor, limit cycle, and chaotic attractor, in which case different state vectors are computed in successive iterations.

The iteration stops when a limit vector is reached, i.e., when $\mathbf{A}^k = \mathbf{A}^{k-1}$ or when $\mathbf{A}^k - \mathbf{A}^{k-1} \leq e$; where e is a residua, whose value depends on the application type (and in most applications is equal to 0.001).

The traditional FCM simulation algorithm (proposed by Kosko and expressed with Eqs. (1)–(2)) consists of a number of steps gathered at follows and is used to simulate a process by giving the necessary decisions about it.

(Step 1): Definition of the initial vector **A** that corresponds to the elements-concepts identified by experts' suggestions and available knowledge.

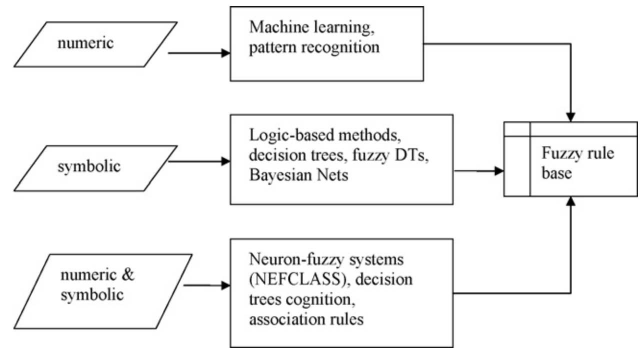

Fig. 3. Fuzzy rule base generated from different data types using knowledge extraction methods.

(Step 2): Multiply the initial vector **A** and the matrix $\boldsymbol{E}$ defined by experts by the Eq. (1).
(Step 3): The resultant vector **A** at time step k is updating using Eqs. (1)–(3).
(Step 4): This new vector $\mathbf{A}^k$ is considered as an initial vector in the next iteration.
(Step 5): Steps 2–4 are repeated until $\mathbf{A}^k - \mathbf{A}^{k-1} \leq e = 0.001$ (where e is a residua, describing the minimum error difference among the subsequent concepts) or $\mathbf{A}^k = \mathbf{A}^{k-1}$. Thus $\boldsymbol{A\_f} = \mathbf{A}^k$.

In each of the case study, an initial vector **A** is assigned (consisting of A_i values corresponding to each one of the 7 linguistic variables, concept C_i), representing the performed events at a given time of the process, and a final vector **A_f** is calculated at the steady state of the system, representing the last state that can be arrived at.

Recently, a rescaling has been suggested for the above traditional FCM inference process to avoid the conflicts emerge in cases where the initial values of concepts are 0 or 0.5 and especially for the cases where there is no any information about a concept-state or the physician does not know the initial state of the patient [33,34]. By this way, we overcome this problem and the new rescaled inference process is more reliable, yielding more exact and natural inference results than traditional FCMs. The proposed rescaling algorithm for FCM inference is presented in Appendix A.

3. Fuzzy rules and linguistic weight generation by using knowledge extraction methods

The huge amount of medical data and the different sources of medical information make the task of decision making difficult and complex. Data mining and knowledge processing systems are intelligent systems that used in medicine for the tasks of diagnosis, prognosis, treatment planning and decision support [11,35].

A large number of possible computational intelligence approaches extracting knowledge from databases, have been developed [2,9]. 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 [8].

Fig. 3 represents the computational intelligent methods for knowledge discovery that used to assess different data types in order to derive appropriate fuzzy rules for knowledge representation.

Some known rule generation algorithms existing from the literature are: Subset [36], MoFN [81], X2R [67], C4.5 [37], FuNN [38], Rulex [39], NEFCLASS [72], fuzzy logical MLP [40], Routh fuzzy

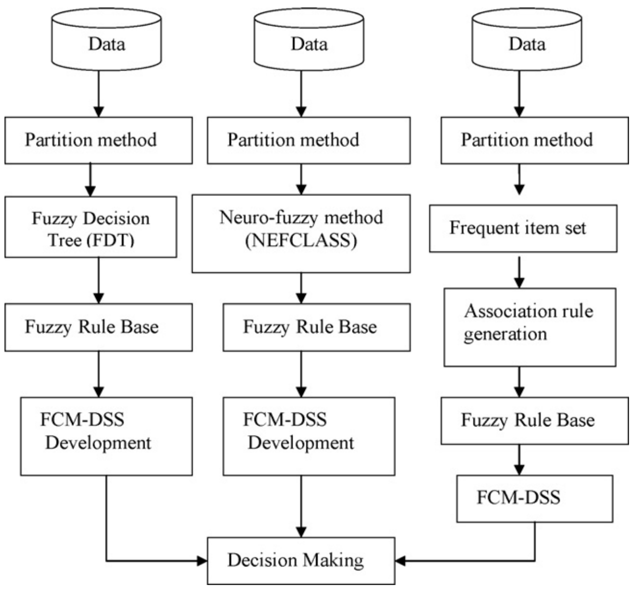

Fig. 4. Main steps of the neuron-fuzzy (center), fuzzy decision tree (left) and the association rule (right) based methods.

MLP [9]. 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 classifier and to evaluate its results. Fuzzy rule based classifiers 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 and construct a compact and useful fuzzy rule base.

3.1. Presentation of three rule-based extraction methods

3.1.1. 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 [41]. 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. Recent approaches to developing such trees were through modifications to the ID3 algorithm [42–44,82]. Sison and Chong [42] 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. (2003) also proposed a new fuzzy ID3 algorithm. This algorithm generates an understandable fuzzy decision tree using fuzzy sets defined by the user. The fuzzy tree methodologies proposed by [42,82] require the data to have been pre-fuzzified before the fuzzy decision trees are induced.

More recent work by Janikow involves the induction of fuzzy decision trees directly from data sets by the FID algorithm [45,46]. The [46] takes a detailed introduction about the non fuzzy rules and the different kind of fuzzy rules.

In this point it is essential to refer that the data (real values) are partitioned into fuzzy sets by experts.

This approach (Fig. 4, on the left) consists on the following steps:

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 (Fuzzy Induction on Decision Tree) 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.

3.1.2. Extraction method using fuzzy association rule

The association rule mining algorithms are the most frequently used data mining tools in rule extraction besides the others methods. A large number of methods have been developed [6,15,47,48,61] but two main steps are common in most of them. The mining starts with frequent item set searching (it is defined first in paper [49] then association rules are generated from the large item sets. The selection of an appropriate algorithm depends on the structure (sparse, dense) and the size of the analyzed database. Additionally the application area influences also notable the suitable methods.

The fuzzy association rule-based method proposed by Agrawal et al. [49] is selected in this study and the following steps depict the proposed approach:

Step 1: A partitioning method, applying a fuzzy clustering algorithm to determine trapezoidal fuzzy membership functions for each attributes, is used to get discrete data elements on continuous attributes.
Step 2: The membership values determine the supports of the items. Thus, the frequent item sets are searched easily. The searching of the larger item sets is based on the a*priori*-principle [49].
Step 3: The association rules with class label in the consequent part are generated from the frequent item sets.
Step 4: A correlation measure selects the classification rules determine most the results of prediction. Only the positive correlated, above the average rules are stored in the rule base. These rules are called important rules.
Step 5: The unnecessary complex, redundant and conflict rules are searched during a post-pruning method [50]. The selected rules are removed from the rule base, therefore only the most important and most confidential rules could be use for FCM decision making tasks.

3.1.3. Fuzzy rule extraction using neuro-fuzzy based algorithm

The neuro-fuzzy based method selected for our task (Fig. 4) is consisted on the following steps:

Step 1: In the first step a partitioning method is needed to get discrete data elements on continuous attributes. The applied method is a fuzzy clustering algorithm to determine trapezoidal fuzzy membership functions for each attribute (two fuzzy sets were considered for NEFCLASS). The fuzzy clustering toolbox proposed by Abonyi et al., using the Gath-Geva clustering algorithm was used (more details can be found in [48,51]).

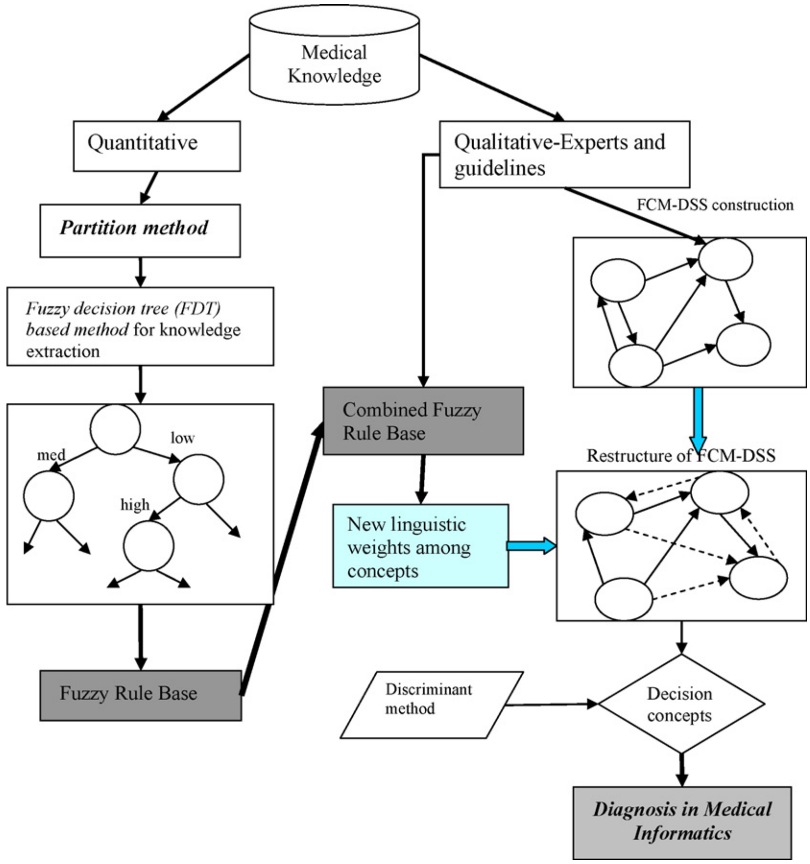

Fig. 5. Main steps of the rule-extraction based methods for fuzzy rule base generation and development of FCM-DSS.

Step 2: The user sets the maximum number of rules to n. The NEFCLASS approach is analyzed and transformed by a rule learning algorithm into a fuzzy rule base.
Step 3: The fuzzy rule learning algorithm processes the training data and determines the best consequent for a rule by a performance measure. In addition, the algorithm tries to reduce the size of the rule base by selecting only a number of rules depending on their performance.
Step 4: A post pruning process that deletes the unnecessary long rules is implemented.

In this study investigated how soft computing techniques could discover that kind of knowledge (in the form of fuzzy rules), and implement this, complementary with experts' knowledge, for developing augmented Fuzzy Cognitive Map for decision support in medical informatics. It selected the fuzzy decision tree (FDT) algorithm for fuzzy rule extraction as the more powerful of these algorithms for the knowledge extraction from data and development of the specific fuzzy rule base (illustrated in Fig. 5); it has been proved through our approach and due to the specific type of data, that gives better rules and keeps the level of interpretability for the decision making [3,4].

In the following section, the development process of the augmented Fuzzy Cognitive Map Decision Support System in Medical Informatics based on the FDT algorithm for rule extraction from data is described.

4. New framework design for augmented fuzzy cognitive map decision support system in medical informatics

There is a necessity to develop a framework extracting fuzzy interconnections among attributes from available data using knowledge extraction techniques and then insert these fuzzy linguistic interconnections to restructure the fuzzy cognitive map model producing a new augmented FCM tool for medical decision making (aFCM-DSS). The framework 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 [37]. As it has already been stated, the central idea of the proposed method was to combine any rule-based extraction method to extract the available knowledge of data and to generate fuzzy linguistic weights through causal paths. The resulted fuzzy relationships among leaf nodes are translated to fuzzy causal paths with the corresponding linguistic weights applied to restructure the FCM-DSS model.

The derived aFCM-DSS model is subsequently trained using an unsupervised learning algorithm (i.e., the nonlinear hebbian learning algorithm (Papageorgiou et al., 2005a)) to achieve improved decision accuracy and interpretability. Then, a simple discriminant method is used for the characterization of output concepts of the aFCM-DSS. According to the desired values of output concepts, the grading tool based on augmented FCM-DSS reaches a decision about the grading process and the degree of tumour malignancy (for details see e.g. in [19,22,23].

The proposed approach was composed of three main phases. At first, extract fuzzy association rules from related historical data using fuzzy rule generation methods [48,52], secondly, transform into FCM causal knowledge based, and thirdly inference amplification using unsupervised learning algorithms for FCMs and a simple discrimination method for the final decision. The inference algorithm of FCMs remains the same and only the weight matrix multiplied with previous concept values was changed. Fig. 6 illustrates the proposed framework with the corresponding steps and final decision. Fig. 6, as illustrates the steps of the generic frame-

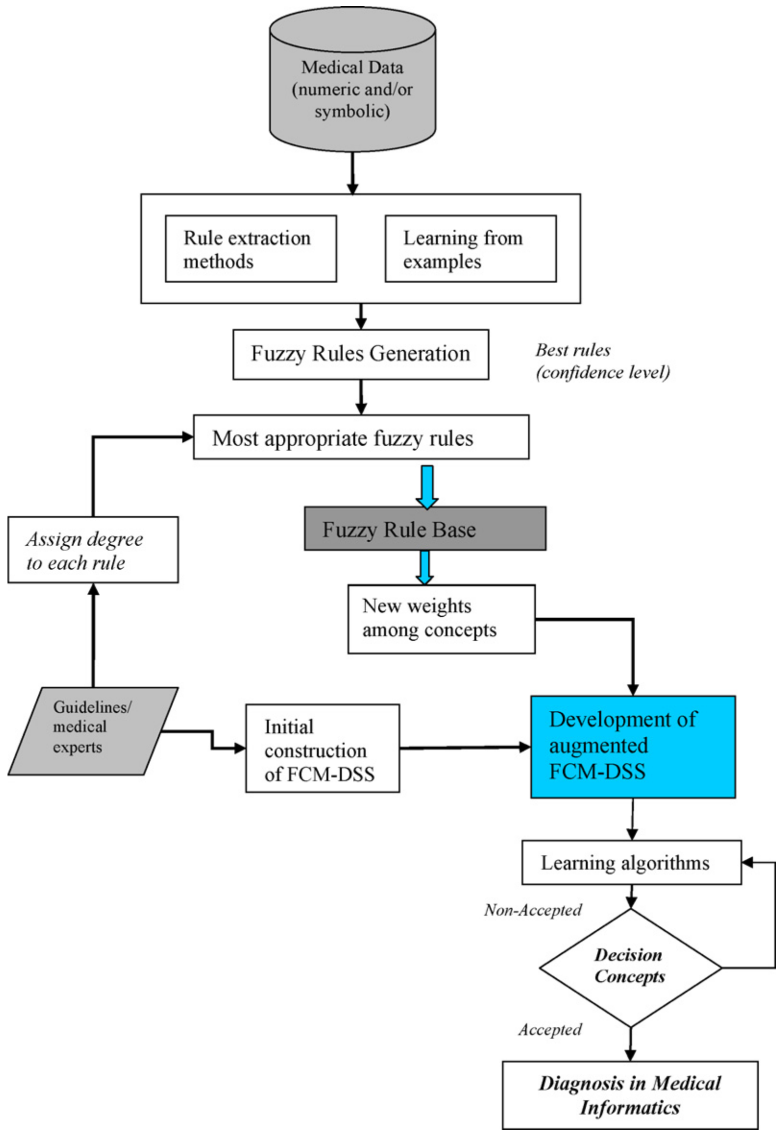

Fig. 6. Flowchart of the generic framework for the construction of aFCM-DSS for diagnosis in medical informatics.

work is different from Fig. 5 which is concentrated only on the FDT technique for producing augmented FCM tools.

The generic framework of the proposed algorithmic approach (as depicted in Fig. 6) using knowledge extraction methods and thus producing augmented FCM-based DSS for medical informatics, comprises of the following steps:

1st Step: Division of the input and output spaces (desired input–output pairs) into fuzzy regions. Assume that each input–output variable lies in a domain interval. Divide each domain interval into $2N+1$ regions (fuzzy sets) according to the meaning and differentiability of each variable (N is the number of variables). The shape of each membership function used can be triangular or trapezoidal (both types of membership functions can be handled by FCMs).

2nd Step: (a) Generation of fuzzy rules from given data pairs, and (b) implementation of rule extraction methods for fuzzy rule base construction.

In this step, at first, determine the degrees of given input–output data pairs and thus obtain one rule from one pair of desired input–output data [52]. The rules generated in this way are "and" rules. Second, rule extraction methods and more specific fuzzy rule extraction methods such as FDTs, are implemented into the data base to derive fuzzy rules. Finally, a fuzzy rule based is constructed which at next steps is combined with the linguistic knowledge from experts. (For the problems considered in this work, i.e., generating fuzzy rules from numerical data, only "and" rules are required since the antecedents are different components of a single input vector) [51,52,75].

3rd Step: Medical doctors/knowledge experts assign a degree to each rule from the derived fuzzy rules. Since there are usually lots of data pairs, and each data pair generates one rule, it is highly probable that there will be some conflicting rules. We often have some a priori information about data pairs. For example, if we let an expert check given data pairs, the expert may suggest that some are very useful and crucial, but others are very unlikely and may be caused just by measurements errors. We can therefore assign a degree to each data pair that represents experts' beliefs of its usefulness.

4th Step: Creation of a combined Fuzzy Rule Base.

A combined fuzzy rule base is composed of assigned rules from either that generated from numerical data and/or linguistic rules. (*We assume that a linguistic rule also has a degree that is assigned by the human expert and reflects the experts' belief of the importance* *of the rule*). In this way, both numerical and linguistic information are codified into a common framework-the combined fuzzy rule base.

5th Step: Experts/medical doctors suggest rules and relationships among factors/parameters/variables to develop the FCM-DSS model based on their initial *a priori* information. In this point, a preliminary FCM-DSS is developed using methodology described in [17], considering the main factors and their cause–effect relationships of the system.

6th Step: Determination of the aFCM-DSS based on the combined Fuzzy Rule Base. An augmented FCM based decision support system for medical diagnosis is determined by using new available knowledge about the interrelationships and interdependencies among factors/parameters/variables of the FCM-DSS model from the combined fuzzy rule base.

7th Step: Implementing learning algorithms (i.e., unsupervised, evolutionary, etc.) into FCM-DSS process to update and strength the weighted relationships. The learning techniques are used to fine-tune the cause–effect relationships of the augmented FCM-DSS model. These methods are efficient algorithms for improving the FCM operation and successful simulation in desired regions. This step is elective according to the problem's data availability for learning FCMs [73,74,79].

8th Step: Distinction of decision-concepts giving final decision. In this step, the values of decision concepts (outputs) are calculated and the final decision is reached according to the experts' a priori knowledge, and/or related protocols and conditions.

The proposed approach for medical decision making using aFCM-DSS is a tool to support user in constructing a decision support system for medical applications. The new technique has three major advantages. First, the rules derived from knowledge extraction method (i.e., fuzzy decision tree technique proposed for our case studies) have a simple and direct interpretation and are introduced in the initially constructed by experts FCM model to update its operation and structure. For example, a produced rule can be: If the *variable 1* (input variable) has *feature A* Then the *variable 2* (output variable) has *feature B*.

Second, the procedure that introduces the fuzzy rules evidences into an FCM also specifies the weight assignment through new cause–effect relationships (linguistic weights) among the FCM decision tool concepts. The framework has embedded a feedback process for the re-structure of the initially development of aFCM-DSS through the insertion of the best fuzzy rules extracting from different techniques of soft computing. Third, this technique fares better in respect to the transparency of the results, easily implementation and low time consuming, than each one of data mining and the inductive learning techniques.

Using the above algorithm, someone can use knowledge extraction techniques (i.e., fuzzy decision trees) to pass available knowledge into FCM reconstructed by causal paths and strengths of relationships (weights) through fuzzy rules. Furthermore, knowledge engineers (contribute as domain experts) might determine fuzzy sets and fuzzy membership functions for each problem and these fuzzy sets could be used into the fuzzy decision tree algorithm due to compatibility reasons.

In this approach, the FDT algorithm is considered as the most easy and efficient approach due to the type of data for the problem of radiation therapy. The FDT algorithm proposed by Janikow (1999) seems to be the more efficient one for our case problem, after a number of experiments and simulations that have been done for this, providing fuzzy rule base that can be used to build advanced FCM-DSS systems. As a result, an appropriate aFCM-DSS for decision making tasks in medical informatics explored and in the next section it was applied in clinical radiation treatment planning simulation approach.

5. Illustrative application and results of augmented FCM-DSS based on fuzzy rule extraction methods for radiation therapy decision making

In a previous work, a decision making system for radiation therapy based on human knowledge and experience was developed by [17] and evaluated by respective radiotherapy guidelines. The radiation therapy is applied to patients suffering from cancerous diseases (and/or other diseases) and to eliminate infected cells, alone or combined with other modalities [53]. Its goal is "*to design and perform a treatment plan on how to deliver a precisely desired dose of radiation to the defined tumor volume with as minimal damage as possible to the surrounding healthy tissue*", according to Khan [53]. The results of a successful treatment using ionizing radiation are the damage of cancer cells, thus high quality of patient life, and prolongation of survival.

That system, previously published, 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 (namely 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 (namely Supervisor-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 [17].

As it has already been stated, the central idea of the proposed framework is to use known and efficient data driven methods for extracting the available knowledge from data and determining new linguistic weights through fuzzy rules. 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-decision concepts, the aFCM-DSS reaches a decision about the acceptance or not of the selected treatment planning technique.

At this point, according to the AAPM protocols [54] and opinions of radiotherapists-physicians (medical domain experts) for the most important factors that should be taken into consideration (in order to achieve a good distribution of the radiation on the tumor, as well as to protect the healthy tissues), five factor concepts and eight selector-concepts were selected with discrete and fuzzy values for the determination of the output concepts. Now, a new CTST-FCM model that represents the radiotherapy treatment planning procedure according to the test packages, protocols and radiotherapists' opinions is designed and illustrated in Fig. 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 rep-

Table 1
Description and type of the new CTST-FCM concepts.

Concepts	Description	Number & type of values scaled
F-C1	Accuracy of depth of tumor	Five fuzzy
F-C2	Size of tumor	Seven fuzzy (very small, small, positive small, medium, negative large, large, very large)
F-C3	Shape of tumor	Three fuzzy (small, medium, large)
F-C4	Type of irradiated tissues-presence of inhomogeneities	Five fuzzy
F-C5	Amount of patient thickness irradiated	Five fuzzy
S-C1	Size of radiation field	Five fuzzy
S-C2	Single or multiple field arrangements	Two discrete
S-C3	Beam direction(s) (angles of beam orientation)	converted to Five fuzzy
S-C4	Dose distribution from individual field	Two fuzzy
S-C5	Stationery vs. rotation-isocentric beam therapy	Two discrete
S-C6	Field modification (no field modification, blocks, wedges, filters and multileaf-collimator shaping blocks)	Five discrete
S-C7	Patient immobilization	Three discrete
S-C8	Use of 2D or 3D conformal technique	Two discrete
Out-C1	Dose given to treatment volume (must be within accepted limits)	Five fuzzy
Out-C2	Amount of irradiated volume of healthy tissues	Five fuzzy
Out-C3	Amount of irradiated volume of sensitive organs (organs at risk)	Five fuzzy

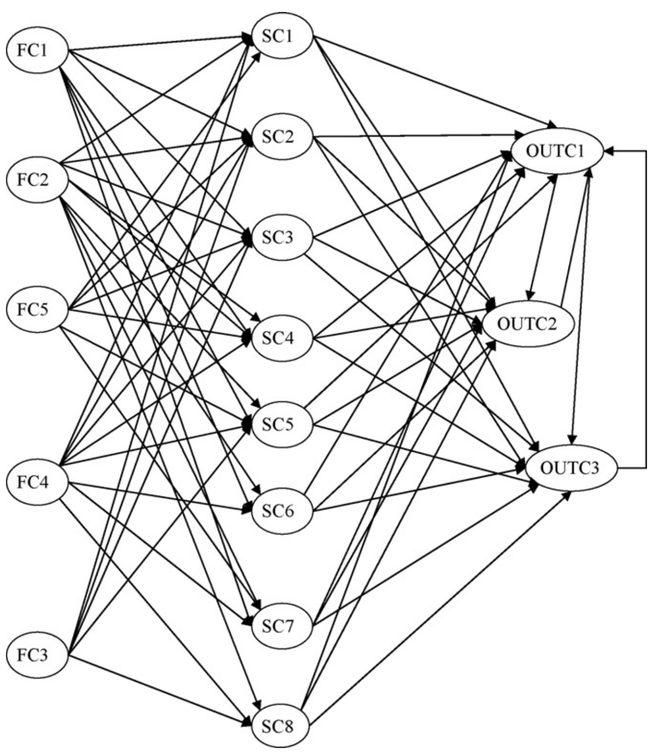

Fig. 7. The new CTST-FCM tool for decision making in radiotherapy.

resents the amount of organs at risk volume received a dose, which have to be less than the 10% of volume received the prescribed dose [53,62]. These factors and the acceptable values of Output-concepts satisfying the performance criteria were described analytically in [17].

Table 2
Linguistic values among F-Cs and S-Cs of new CTST-FCM.

Factors/selectors	S-C1	S-C2	S-C3	S-C4	S-C5	S-C6	S-C7	S-C8
F-C1	H	H	L	M	H	H	VL	0
F-C2	H	H	VL	M	M	M	H	M
F-C3	H	H	M	0	M	0	0	VH
F-C4	VL	H	M	M	M	M	0	H
F-C5	M	H	H	H	VL	M	M	0

After the description of new CTST-FCM concepts, the design of FCM-DSS model continues with the determination of fuzzy sets for each one concept variable. The experts-radiotherapists 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 Fig. 8.

For this case problem in medicine, the FDT algorithm was used to generate the fuzzy rule base combined with the knowledge from physicians and guidelines because only this algorithmic method could handle the available type of data, considering both fuzzy values and discrete values for the concepts.

Two case studies 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 proposed framework using the fuzzy decision tree knowledge extraction method. In the first case, the 3-D conformal technique consisting of six-field arrangement was selected and in the second one the conventional four-field box technique. Radiotherapy physicians and medical physicists choose and specified, the fuzzy membership functions for the weights for each scenario as well as the fuzzy rules according to their knowledge for each treatment planning procedure. The linguistic values of fuzzy weights between factor and selector concepts for the new CTST-FCM are given in Table 2, while in Table 3 the numerical weights between

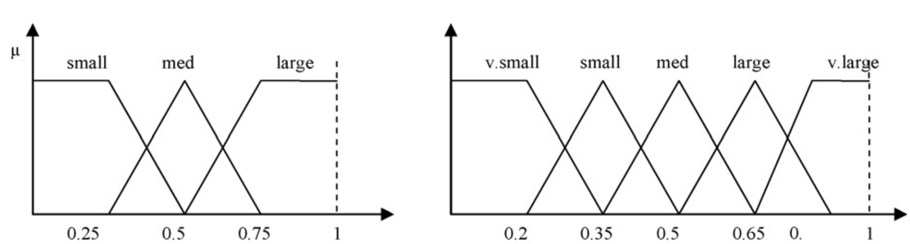

Fig. 8. Partitions (fuzzy trapezoidal membership functions) for F-C3 and S-C1 determined by a priori knowledge from radiotherapists-experts.

Table 3
Weight values between F-Cs and S-Cs for new CTST-FCM after deffuzification 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

Table 4
Numerical weights among F-Cs, S-Cs and OUT-Cs of new CTST-aFCM 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

factor and selector concepts are depicted after the defuzzification process.

Then, using the experimental data derived from measurements (that had been done in Tubingen University Hospital [55]), 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 presented only examples of them and for simulations only those selected 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 fuzzy weights suggested by experts produce the new augmented CTST-FCM simulation tool (namely CTST-aFCM) for radiation therapy, which has new strengths-weights among concepts and assigns new decisions and treatment planning suggestions.

In each of the test cases, 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 14th, 15th and 16th value of this vector are the final values of decision concepts. The inference algorithm used to obtain the final vector **A_f** has been described in Section 2.3.

5.1. First case study

For the first case study, the conformal radiotherapy was selected. Multiple CT-based external contours define the patient anatomy and isocentric beam therapy was used [53]. Beam weights were different for the six fields, and blocks, wedges were 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 knowledge and the measured experimental data, the initial values of concepts and weights of interconnections between S-Cs and OUT-Cs are assigned. Table 4 gathers the numerical weights among Factor-concepts, Selector-concepts, and Output-concepts, of new CTST-aFCM (which illustrated in Fig. 9). The new linguistic weights which have been converted to numerical weights after defuzzification, derived from combined knowledge from radiotherapists-experts and data.

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

$$\boldsymbol{A}_1 = [\,0.6 \quad 0.7 \quad 0.6 \quad 0.6 \quad 0.6 \quad 0.4 \quad 0.65 \quad 0.7 \quad 0.45 \quad 0.6 \quad 0.6 \quad 0.5 \quad 0.6 \quad 0 \quad 0 \quad 0\,]$$

The initial values of the three output concepts have been set equal to 0 because no information exists for these state concepts. Through the inference process described in Section 2.3 the new CTST-aFCM starts to interact and simulate the radiation procedure. New values of concepts are calculated after eight simulation steps

Table 5
Numerical weights among F-Cs, S-Cs and OUT-Cs of new CTST-aFCM for the second 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	0.6	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

and the final vector $\boldsymbol{A}_1$**_final** is assigned.

$$A_1\_final = [\ 0.6000\quad 0.7000\quad 0.6000\quad 0.6000\quad 0.6000\quad 0.7811\quad 0.7961\quad 0.6785\quad 0.8178\quad 0.8368\quad 0.8424\quad 0.6667\quad 0.6937\quad 0.9786\quad 0.0386\quad 0.0453\ ]$$

This vector gives the calculated values of concepts in the equilibrium region. 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, outlined with the following values of OUT-Cs: for OUT-C1 is 0.9786, for OUT-C2 is 0.0386 and for OUT-C3 is 0.0453. Based on the performance criteria – guidelines and protocols [54,62] the calculated values of output (decision) concepts are accepted. The calculated value of OUT-C1 means that the target volume receives the 97.86% of the amount of the prescribed dose, which is accepted. The value of OUT-C2 that represents the received dose of the surrounding healthy tissues' volume means that the 3.86% of the volume of healthy tissues receives the prescribed dose of 81 Gy. The value of OUT-C3 that represents the amount of the critical organ's volume (bladder and rectum) and is equal to 0.0453, means that the 4.53% of the volume receives the prescribed dose, which is accepted because a volume less than the 10% of volume of organs at risk is accepted to receive a prescribed dose. After this discussion it is obvious that the new CTST-aFCM model, with the linguistic weights and treatment variables (concepts) defined by experts and medical data, reach a set of values that satisfy the performance criteria. The investigated treatment planning technique can be executed with acceptable results for the patient treatment.

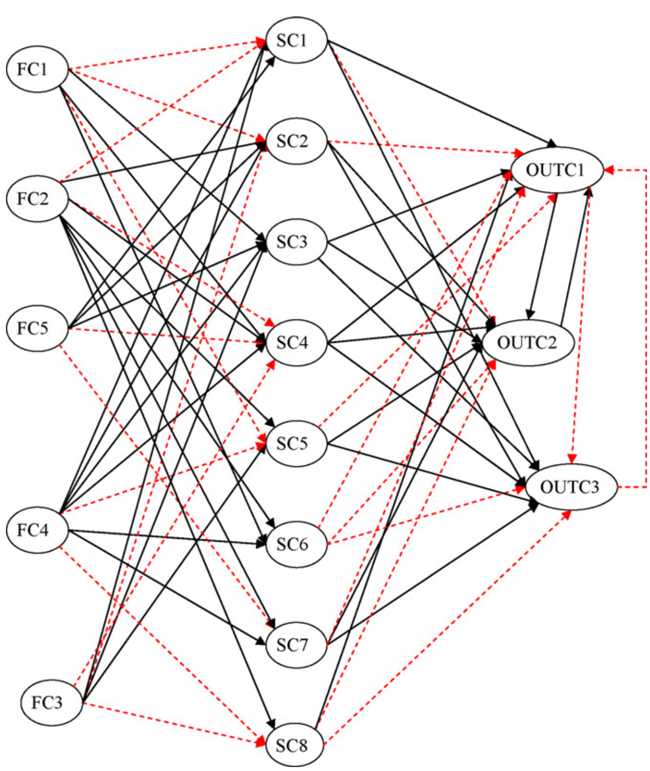

Fig. 9. The new CTST-aFCM tool for decision making in radiotherapy after combining knowledge from experts and data (the broken lines are the new weight values).

5.2. Second case study

In the second case study, the conventional four-field box technique was implemented for the prostate cancer treatment. This technique was consisted of a four-field box arrangement with gantry angles 0, 90, 180, and 270. The isocentric beam therapy was considered [53,58]. Beam weights had the same value for four fields and no blocks, wedges, collimator settings, and compensating filters were used. For this case, as a different treatment technique used, the produced CTST-aFCM was reconstructed which means that the cause–effect relationships and weights have been reassigned not only from radiotherapists' suggestions and guidelines but also from data knowledge extracted by the rule extraction tech-

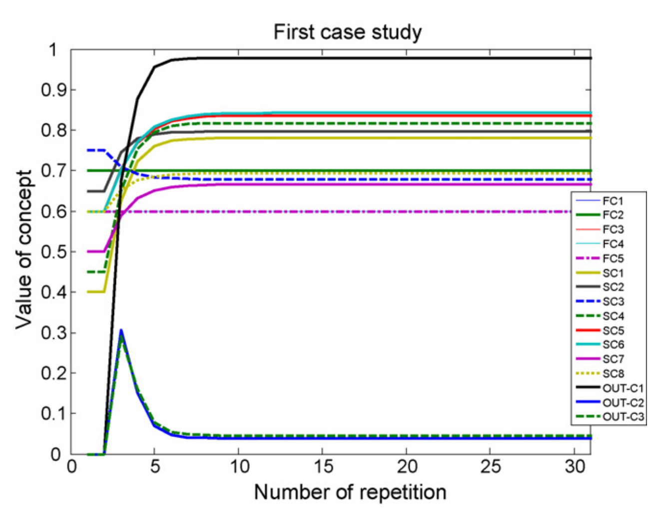

Fig. 10. Variation of values of 16 concepts for the new CTST-aFCM for the first case study for eight simulation steps.

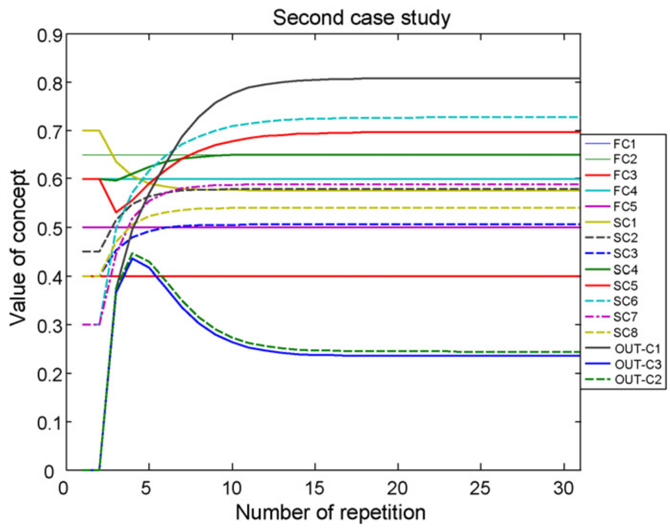

Fig. 11. Variation of values of 16 concepts of new CTST-aFCM for the second case study, with the classical treatment planning case.

nique of fuzzy decision trees. For this treatment technique, 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 determined in Table 5. If we compare Table 5 with Table 4 that gathers the weights for the first case, we will see that some interconnections have different values. This happens due to the different knowledge assigned by experts and data for this case study.

The initial vector for this particular treatment technique is formed:

$$\boldsymbol{A}_2 = [\,0.5 \quad 0.65 \quad 0.4 \quad 0.6 \quad 0.5 \quad 0.75 \quad 0.45 \quad 0.4 \quad 0.6 \quad 0.55 \quad 0.3 \quad 0.3 \quad 0.4 \quad 0 \quad 0 \quad 0\,]$$

Considering the updated FCM inference process, the inference of the radiotherapy procedure for this case starts. The new CTST-aFCM model, with the new modified weight matrix, simulates the radiotherapy process. New values of concepts are calculated after 10 simulation steps and the final vector $\boldsymbol{A}_2$_**final** is assigned.

$$\boldsymbol{A}_2\_\boldsymbol{final} = [\,0.5000 \quad 0.6500 \quad 0.4000 \quad 0.6000 \quad 0.5000 \quad 0.5763 \quad 0.5787 \quad 0.5050 \quad 0.6499 \quad 0.6963 \quad 0.7268 \quad 0.5881 \quad 0.5398 \quad 0.8072 \quad 0.2348 \quad 0.2437\,]$$

The final values of OUT-Cs are as follows: for OUT-C1, 0.8072; for OUT-C2, 0.2348; and for OUT-C3, 0.2437 (as depicted in Fig. 11). These values for OUT-C1, OUT-C2 and OUT-C3 are not accepted according to related protocols [54,62]. If these suggested values for Output-concepts were adopted, the patient would receive a smaller amount of dose to the target volume and a larger amount of dose than the desired one on the normal tissues and sensitive organs.

6. Discussion

The aFCM-DSS, which in the selected problem is the new CTST-aFCM for radiation therapy, has been designed not only by radiotherapists-experts' suggestions and guidelines but also by knowledge extracted from fuzzy decision tree-based rule extraction technique. The rule extraction algorithm was used to enrich in knowledge the appropriate rule base, thus producing a dynamic support system which works efficiently.

The new CTST-aFCM model is depicted in Fig. 9, where the modified relationships and new weights are shown by red line. 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-FCM weights have been changed according to the new knowledge inserted from the fuzzy rules.

Essentially, the main task 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 linguistic weights not only determined by radiotherapists-experts' suggestions but from data knowledge, has a dynamic feature and is a less complex model which works sufficiently. This radiation therapy decision making tool can adapt its knowledge from available data and not only from physicians opinions and enhance its operation. 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.

Our scope of this study was not to compare the proposed approach with other FCM approaches or other methodologies for medical decision support systems, but to explore and present a new framework for making decision in medical informatics based on FCMs not only constructed by experts but partially developed from extracting knowledge from data. Also, an implementation change in the FCM inference algorithm has been presented and used for the FCM simulations process by giving reliable results and overcoming some of the traditional FCM simulation algorithm.

In our opinion using this fuzzy rule based decision support system in the education process provides a more useful environment for the physicians and students than huge, hard-covered materials. Furthermore, this type of aFCM-DSS and the related process could be used as education aimed in selection of treatment planning techniques and is user friendly for physicians and training medical students. In an upcoming work, other knowledge extraction algorithms will be implemented in a number of different case studies and in other application areas beyond medicine.

7. Conclusion

In this paper, we have identified the need and conveyed our vision for a new generic type of Decision Support Systems based on the soft computing technique of Fuzzy Cognitive Maps and fuzzy rule extraction methods. The distinguishing feature of such augmented FCM-DSS is its situations with different data types and to handle the available knowledge from many different sources of information. A generic architecture for such system has been proposed including knowledge extraction methods for different data types, inserting new relationships-linguistic weights into the FCM-DSS, thus producing an augmented FCM-DSS.

The scope of the proposed methodology was not to achieve better accuracies or results compared with other FCM approaches, but to introduce a novel framework based on the aFCM-DSS that enhanced by fuzzy rules extracted by data. The new decision support tool is simple, less complex, easy of use and low time consuming to be accepted for medical applications. The distinguishing feature of such aFCM-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.

The main advantages of the proposed augmented FCM-DSS are the following:

- Combination of knowledge from experts and data to enhance the knowledge-based system.
- Fuzzy rule base generation from data using rule extraction methods.
- Simplicity and linguistic interpretability.
- Handling uncertainty.
- Independed on the size and type of data.

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.

Through the results, the prospective performance of the decision support framework based on FCMs is emerged and encourage us continue towards the direction on combing knowledge from data and from experts and guidelines for making decisions contributing to more “intelligent” systems.

Appendix A.

For the sake of convenience of explaining the proposed inference algorithm, let us describe only some main aspects and thus presenting the rescaled mathematical formulation for FCM inference process.

Generally, the FCM network works with truth values in the range $[-1, 1]$ whereas the input/output should be truth values in the range $[0, 1]$. This is perfectly feasible and all that is needed is a translation between both i.e., t_internal = 2 × t_external − 1.

This change can be implemented with the following mathematical equation: $\mathbf{A} = (2\mathbf{A} - 1) + (2\mathbf{A} - 1) \cdot \mathbf{E}$.

Thus, a new simulation function has been determined, substituting the initial Eqs. (1) and (2), with Eqs. (4) and (5), respectively:

$$\mathbf{A} = f((2\mathbf{A} - 1) + (2\mathbf{A} - 1) \cdot \mathbf{E}) \tag{4}$$

or

$$A_i(k+1) = f((2A_i(k) - 1) + \sum_{\substack{j \neq i \\ j=1}}^{N} (2A_j(k) - 1) \cdot E_{ji}) \tag{5}$$

Using the above inference algorithm, the final vector ***A*_*f*** is also obtained. The decision concepts of the final vector **A_f** are assessed and clarify the final decision of the specific decision support system.

By this implementation change, we have solved the problem with the initial zero values of concepts which through the threshold function, at second iteration step, take the value of 0.5. There is a conflict with the initial values of nodes 0.5 and the results were not reliable for those different cases for initial values of concepts. This rescaling have been experimented for a large number of FCM modules, making enough simulations through many different test cases-scenarios for the radiation therapy problem, thus the results were more reliable than those using the traditional FCM propagation algorithm.

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