Medical decision making through fuzzy computational intelligent approaches

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A new approach for the construction of Fuzzy Cognitive Maps augmented by knowledge through fuzzy rule-extraction methods for medical decision making is investigated. This new approach develops an augmented Fuzzy Cognitive Mapping based Decision Support System combining knowledge from experts and knowledge from data in the form of fuzzy rules generated from rule-based knowledge discovery methods. Fuzzy Cognitive Mapping (FCM) is a fuzzy modeling methodology based on exploiting knowledge and experience from experts. The FCM accompanied with knowledge extraction and computational intelligent techniques, contribute to the development of a decision support system in medical informatics. The proposed approach is implemented in a well-known medical problem for assessment of treatment planning decision process in radiotherapy.

1. Introduction

This paper investigates a fuzzy computational intelligent 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 a fuzzy knowledge extraction method for the design of Fuzzy Cognitive Mapping decision support system in medicine.

Fuzzy Cognitive Map (FCM) is a soft computing technique used for causal knowledge acquisition and supporting causal knowledge reasoning process. FCM permits the necessary cycles for knowledge expression within their feedback framework of systems. FCMs are useful methods for exploring and evaluating the impact of inputs on dynamical systems that involve a set of objects such as processes, policies, events and values as well as the causal relationships between those objects.

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.

In this study, FCM is developed combining knowledge from experts and from data, using rule extraction methods that generate meaningful fuzzy rules. 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 enhanced if a fuzzy rule base (IF-THEN rules) is available. A number of knowledge extraction techniques such as, fuzzy systems, neurofuzzy, machine learning and other computational intelligence techniques used for the generation of fuzzy rule base [3,4]. These methods extract the available knowledge from data in the form of fuzzy rules and insert them into the FCM based decision support system.

Few frameworks based on fuzzy cognitive maps for the task of reasoning and learning in medical decision systems have been proposed [5-8]. This paper investigates a new approach to address the complex problem of medical decision making that applied to the radiation therapy treatment planning problem for making decisions on ionizing radiation.

2. Fuzzy Cognitive Map theory

Fuzzy cognitive maps (FCMs) are simple, yet powerful tool for modeling and simulation of dynamic systems. They were originally introduced by Kosko [9] as an extension of cognitive maps. The main advantage of FCMs lies in their straightforward graph representation, which consists of nodes connected by edges. Nodes correspond to concepts or variables within given domain of application, whereas directed edges reflect mutual relationship between concepts. Each edge is associated with a weight value from the range [-1,1] that expresses both the type and strength of given relationship. Negative value indicates prohibitory effect that source concept exerts on the destination one, Positive value indicates a promoting effect. The zero value denotes no causal relationship between two concepts. The graph representation can be equivalently denoted by a square matrix, called *connection matrix*. It accumulates all weight values for edges between corresponding concepts. Figure 1 shows an example of FCM model that concerns public city health issues [10].

During simulation, FCM iteratively calculates its state that is represented by a *state* vector $\boldsymbol{A}$, which consists of all nodes values (A_i) at given iteration. Value of each node is determined based on values of nodes that exert influence on the given node, i.e. nodes that are connected to this node. These values are multiplied by corresponding connction matrix E_{ij} and the sum of these products is taken as the input to a transformation function *f.* So, the value *Ai* of each concept C_i is calculated by the following rule:

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

The purpose of using the function *f* is to normalize the node value, usually to the range [0,1]. As a result, each node can be defined as active (value of 1), inactive (value of 0), or active to a certain degree (value between 0 and 1) [11].

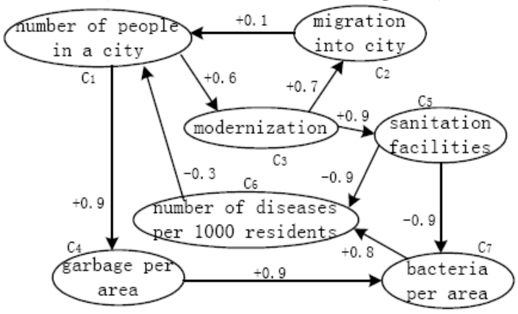

Fig. 2: An example of FCM model for public city health

Compared with other schemes for developing knowledge bases, such as the rule base in an expert system, the process of constructing an FCM might seem relatively simple. FCMs can produced by expert manually or generate by other source of information computationally. Experts develop a mental model (graph) 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 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. Then, the proposed linguistic variables suggested by experts, are aggregated using the SUM method and an overall linguistic weight is produced, which with the defuzzification method of Center of Gravity, is transformed to numerical weight e_{ji} . A detailed description on the FCM development is given in [8].

Although developing an FCM manually might seem simple, it is in fact difficult because the knowledge from experts is not enough and there is difficulty to handle knowledge from different sources of information. 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 and enhance the FCM structure.

3. Generation of Fuzzy Rules using knowledge based 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 [12,13].

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. Among the wide range of possible approaches, the fuzzy decision tree based rule generation computing method was selected to extract the knowledge and construct a compact and useful fuzzy rule base.

3.1 Extraction method using fuzzy decision trees

Fuzzy decision trees exploit the popularity of decision tree algorithms for practical knowledge acquisition and the representative power of the fuzzy technology. They are extensions of Quinlan ID3 trees, with the tree-building routine modified to utilize fuzzy instead of strict domains, and with new inferences combining fuzzy defuzzification with the inductive methodology. Fuzzy decision trees represent the discovered rules most natural for human (for example thanks to the linguistic variables). As ID3 trees, they require that real-valued and multi-valued domains be partitioned prior to tree construction.

Till recently years, many fuzzy decision tree induction algorithms have been introduced [14,15]. The work in [15] 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 two different ways: (a) define linguistic values based on experts' knowledge into a range or (b) based on variable behavior data where it is possible to determine the number and the shape of sets. This approach 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 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 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 compact fuzzy rule base that can be used for building FCM-DSS.

4. Presentation of the proposed approach and application example

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 fuzzy If-Then rules. The resulted fuzzy rule base is applied to construct an augmented FCM based clinical treatment simulation tool (CTST-FCM) used for decisions in radiation treatment planning. Then, a simple discriminant method is used for the characterization of output concepts of the resulting FCM-DSS. According to the desired values of output concepts, the augmented FCM-DSS reaches a decision about the acceptance of treatment planning technique.

In our approach, the FDTs algorithm is used because of the type of data for the problem of radiation therapy. The fuzzy decision tree algorithm proposed by Janikow [15] is an efficient one, providing fuzzy rule base that can be used to build advance FCM-DSS systems.

4.1 Application problem

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 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 system based on human knowledge and experience had been proposed and developed by Papageorgiou et al., 2003. A two-level hierarchical structure with a FCM in each level had been created producing an Advanced Decision-Making System. The lower-level FCM modeled the treatment planning, taking into consideration all the factors and treatment variables and their influence. 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.

At this point, according to the AAPM protocols [16] and opinions of radiotherapists-doctors 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 FCM model that represents the radiotherapy treatment planning procedure according to the test packages, protocols and radiotherapists' opinions is designed and the new CTST-FCM is given in Figure 2.

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. 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 [16].

After the description of CTST-FCM concepts, the design of FCM model continues with the determination of fuzzy sets for each one concept variable. For example, the FC2 has three fuzzy sets. Next, each expert was asked to define the degree of influence among the concepts using an if-then rule, as presented in [8].

Then the fuzzy decision tree algorithm was implemented to the initial clinical data and measurements and a set of fuzzy rules were produced. 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 of these 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 augmented CTST-FCM simulation tool for radiation therapy, which has new relationships among concepts and assigns new decisions and treatment planning suggestions.

5. Results and discussion of augmented FCM-DSS in radiotherapy

Two case studies for the problem of prostate cancer therapy will be 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 the first case the 3-D conformal technique consisting of six-field arrangement is suggested and in the second one the conventional four-field box 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 weights between factor and selector concepts for the new CTST-FCM are given in Table 1 after the defuzzification process.

Table 1. 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

For the first case study, the conformal radiotherapy was selected with the following characteristics: 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.

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

A_1=[0.6 0.55 0.55 0.6 0.6 0.4 0.65 0.7 0.45 0.6 0.6 0.5 0.6 0.5 0.5 0.45].

Using the eq. (1), the resulting CTST-FCM starts to interact and simulates the radiation procedure. New values of concepts were calculated after 8 simulation steps. The following vector gives the calculated values of concepts in the equilibrium region.

A1_new=[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].

In the steady state, 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 [18,19], 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 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.

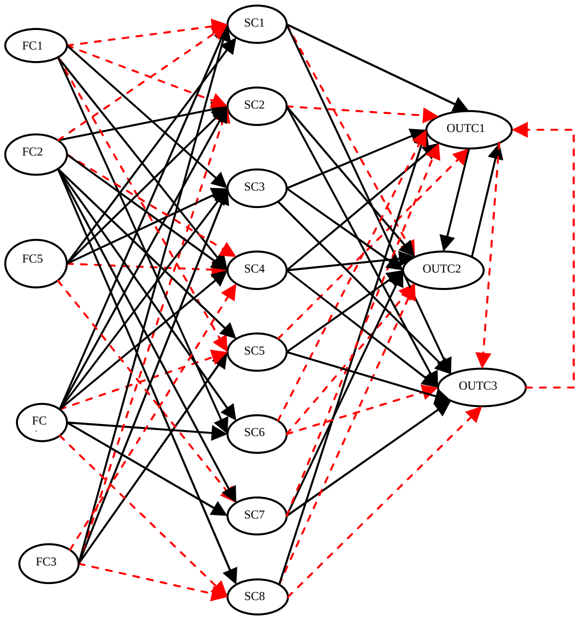

Fig. 2. The new CTST-FCM tool for decision making in radiotherapy after combining knowledge from experts and data (the broken lines are the new or changed weight values)

In the second case study, 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-FCM for the second case study, are given in Table 2.

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

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]

The final values of OUT-Cs are as follows: for OUT-C1, 0.9533; for OUT-C2, 0.0830; and for OUT-C3, 0.1133 (illustrated in the following vector A2_new).

A2_new=[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 0.9533 0.0830 0.1133].

These values for OUT-C2 and OUT-C3 are not accepted according to related protocols [16].

Table 2. 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

The new augmented CTST-FCM model, with less number of concepts and weights and especially with weights not only determined by radiotherapists-experts' suggestions but also by knowledge extracted from fuzzy decision tree-based rule extraction technique, is a dynamic and less complex model which works efficiently. This radiation therapy decision making tool 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-FCM tool is less time consuming and easy for use from no specialists.

Conclusion

In this investigation, a different dynamic approach for construction of FCM-based decision support tools presented. The main goal of the proposed methodology was not to achieve better accuracies or to present a better classifier, but to investigate an efficient enhancement of FCM-DSS accompanied by fuzzy rule base that has constructed by sufficient extraction of knowledge methods. The new decision support tool seems simple, no time consuming and less complex to be accepted for medical applications. The distinguishing feature of such augmented 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. In our opinion using this fuzzy rule based decision support system in the physicians' education process provides a more useful environment for the students than huge, hard-covered materials.

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