Optimization of Fuzzy Cognitive Map Model in Clinical Radiotherapy Through Differential Evolution Algorithm

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Abstract: In this article, a Fuzzy Cognitive Map model used for the supervision and monitoring of the radiotherapy process, is optimized through the minimization of an objective function, using the Differential Evolution algorithm. The Differential Evolution algorithm is a Computational Intelligence technique and belongs to the fields of Evolutionary Computation. The proposed approach determines the appropriate values of the causal links (weights) of the Supervisor-Fuzzy Cognitive Map model of the system in order to succeed acceptable results for the radiation therapy. This method is useful for doctors-radiotherapists to manage a clinical case and make decisions for the successful or not of the radiotherapy.

Keywords: Fuzzy Cognitive Maps, Differential Evolution, Radiation Therapy, Optimization, Evolutionary Computation

1. Introduction

Soft Computing encompasses a range of techniques, namely fuzzy logic, neural network theory, genetic algorithms and probabilistic reasoning, generally grouped together to give solutions to specific problems or group of problems. Soft computing is an efficient technique that incorporates human knowledge effectively, deal with imprecision and uncertainty, and learns to adapt to unknown or changing environment for better performance [1].

Fuzzy Cognitive Map (FCM) is a soft computing technique and seems to be capable to deal with situations where the human reasoning process for any procedure includes uncertain descriptions. FCMs are used to exploit the knowledge and experience of experts on the description and modelling of the operation of a complex system. They are important modelling means for describing particular domains showing the concepts (factors) and the causal relationships between them [2].

The problem of radiotherapy is a very complex problem consisting of a large number of factors-parameters and contains uncertainty and fuzziness. Radiotherapists-doctors must take into consideration many different (complementary, similar or conflicting) factors, which influence the selection of the radiation dose and, consequently, the final result of the therapy. All these factors are usually incorporated in an optimization process, where the main objectives are to minimize the total amount of radiation at which the patient is exposed, maximize the minimum final radiation dose received by the tumour, minimize the radiation to critical structure(s) and healthy tissues, and produce acceptable dose distributions with the smallest computational effort [3].

FCMs can handle with enough precision the issues of uncertainty and fuzziness. So, FCMs have been proposed to model complex systems that involve different factors, states, variables, and events, integrating the influence of several controversial factors in the decision-making process [4].

Several algorithms and mathematical tools have been proposed and used for the optimization of radiation therapy treatment plans [5,6,7,8,9,10], but till today there have not been suggested other methods for the optimisation of the FCM model through the determination of the FCM causal links. In FCMs, the causal links among different factors are the main parameters that calculate the values of all causal concepts. The objective of this research is to introduce a methodology for determining the appropriate values of the FCM causal links, so as to succeed the goals of clinical radiotherapy.

Thus, an algorithm, the Differential Evolution (DE), coming from the fields of Evolutionary Computation, is employed for the determination of the optimum cause-effect relationships of the supervisor--FCM used in an established radiation therapy treatment planning system. The rest of this article is organized as follows: an introduction to the basic concepts of FCMs is given in Section 2, while a description of the FCM model for the supervision of the radiation therapy process is briefly described in Section 3. The DE algorithm and the proposed approach are presented in Section 4. The experimental results are reported in Section 5. The paper concludes with Section 6.

2. Overview of Fuzzy Cognitive Maps

FCMs were proposed by Kosko to represent the causal relationship between concepts and analyze inference patterns [2,11]. FCMs represent knowledge in a symbolic manner and relate states, processes, events, values and inputs in an analogous manner. Compared
either expert system or neural networks, it has several desirable properties such as: it is relatively easy to use for representing structured knowledge, and the inference can be computed by numeric matrix operation. The FCM structure can be viewed as a recurrent artificial neural network, where concepts are represented by nodes and causal relationships by weighted links connecting the neurons [11].

Nodes for the FCM stand for the concepts that are used to describe the behavior of the system and they are connected by signed and weighted arcs representing the causal relationships that exist between the concepts. These weighted interconnections represent the direction and degree with which concepts influence the value of the interconnected concepts. Fig. 1 illustrates a graphical representation of Fuzzy Cognitive Maps. It must be mentioned that all the values in the graph are fuzzy, so concepts take values in the range between [0,1] and the weights of the arcs are in the interval [-1,1].

The cause and effect interconnection between two nodes $C_j$ and $C_i$ is described with the weight $w_{ji}$. There are three possible types of causal relationships between concepts:

1. $w_{ji} > 0$ which indicates positive causality between concepts $C_j$ and $C_i$. That is, an increase (decrease) in the value of $C_j$ leads to an increase (decrease) in the value of $C_i$.

2. $w_{ji} < 0$ which indicates negative causality between concepts $C_j$ and $C_i$. That is, an increase (decrease) in the value of $C_j$ leads to a decrease (increase) in the value of $C_i$.

3. $w_{ji} = 0$ which indicates no relationship between $C_j$ and $C_i$.

where $A_j^{(k+1)}$ is the value of concept $C_j$ at time $k+1$, $A_j^{(k)}$ is the value of concept $C_j$ at time $k$, $w_{ji}$ is the weight of the interconnection between concept $C_j$ and concept $C_i$ and $f$ is the sigmoid threshold function.

The methodology for developing FCMs is based on a group of experts who are asked to define concepts and describe relationships among concepts and use IF-THEN rules to justify the cause and effect relationship among concepts and infer a linguistic weight for each interconnection [12]. Every expert describes each one of the interconnection with a fuzzy rule; the inference of the rule is a linguistic variable, which describes the relationship between the two concepts according to everyone expert and determines the grade of causality between the two concepts.

Then the inferred linguistic weights suggested by the group of experts are composed and an overall linguistic weight is produced, which with the defuzzification method of Center of Area (CoA) [13], is transformed to a numerical weight $w_{ji}$, belonging to the interval [-1,1] and representing the overall suggestion of experts. Thus an initial matrix $w^{initial} = \{w_{ji}\}$, $i,j=1,...,N$, with $w_{ji} = 0$, $i=1,...,N$, is obtained.

Using the initial concept values, $A_{ji}$, the matrix $w^{initial}$ is used for the determination of the steady state of the FCM, through the application of equation (1).

Optimization procedures for FCM modelling have not been introduced and implemented in FCMs until now. An approach based on computational intelligence techniques and more specifically on Differential Evolution Algorithm, for optimisation of FCM model and structure, is introduced, presented and implemented in a clinical process problem.

### 3. FCM model for Supervising Radiation Therapy process

FCMs have been successfully applied to model the radiation therapy process and an established FCM model that supervises and evaluates the radiotherapy process is described briefly in this section, before the presentation of the proposed optimisation approach.

The radiation therapy procedure is a complex process where a great number of treatment variables have to be taken under consideration. The objective goal of radiotherapy is to deliver the highest dose to a volume shaped exactly with the tumour shape and to keep the dose level at the minimum value for healthy tissues and critical organs. The treatment planning is another complex problem a step before the final treatment execution, because of a number of intercontracting constraints. A large number of treatment variables take part according to each plan and each patient. The process of adjusting treatment variables and displaying the corresponding dose distribution is repeated till the objective criteria are considered optimized.

In order to achieve a good distribution of the radiation on the tumour, maximum amount of dose to the final

![Fig.1. A simple Fuzzy Cognitive Map model](image-url)
target volume, as well as to protect the healthy tissues and critical organs, different factors should be taken into consideration.

A FCM model consisting of 33 concepts (factor-concepts, selector-concepts and output-concepts) have been developed by Papageorgiou et al., for modelling the treatment planning and the dose distribution to the target volume, healthy tissues and critical organs [4]. Another model more abstract and generic have to be used in order to supervise the whole radiotherapy procedure, consisting of more abstract concepts representing the final parameters before the treatment execution. The Supervisor-FCM behaves as a human operator-doctor and represents what the doctor does when he takes a differential decision on the radiation therapy procedure.

So, the supervisor process is modelled as a Fuzzy Cognitive Map that model, monitor and evaluates the whole process of radiation therapy. The supervisor-FCM is developed from expert’s knowledge, which actually supervises the process using the notion and values of tumor localization, patient positioning and the calculated dose from treatment planning system in order to determine the Final Dose. Also, experts suggest that human factors and machine factors take part in the determination of the Final Dose. These suggested concepts consist the supervisor-FCM.

The supervisor-FCM is consisted of 7 concepts to supervise the decision making process during the radiation therapy process and it is depicted on Figure 2. One more concept has been added in the initially suggested FCM-supervisor. This new concept represents the Quality Assurance (QA) of the whole radiotherapy process. QA of radiation therapy includes the whole range of procedures and technical systems for assuring that the quality parameters of the process are in accordance with the national and international standards (preset) like the International Standards Organization (ISO-standards). Treatment planning systems, imaging devices, simulators, treatment units, checks of beam quality and inhomogeneity, clinical dose measurements, etc., are part of the QA process.

Thus the concepts of FCM-supervisor are:

\( C_1: \) Tumor Localization. It is dependent on patient contour, sensitive critical organs and tumor volume. It embodies the value and influence of these three Factor-concepts that are concepts of first-level FCM.

\( C_2: \) Dose prescribed from Treatment Planning (TPD). This concept describes the delivered doses to target volume, normal tissues and critical organs that are calculated at the treatment planning model of the first level FCM.

\( C_3: \) Machine factors. This concept describes the equipment characteristics.

\( C_4: \) Human factors. A general concept describing the experience and knowledge of medical staff

\( C_5: \) Patient positioning and immobilization. This concept describes the cooperation of the patient with the doctors and the potential of follow instructions.

\( C_6: \) Quality Assurance (QA). Quality assurance includes demands on staff, the therapeutic procedures and the technical systems for complying with the preset standards.

\( C_7: \) Final Dose given to the target volume (FD). A measurement of the radiation dose received by the target tumor.

The methodology that was proposed in [12], was used to develop the FCM. The experts were asked to describe the relationships among concepts and they used IF-THEN rules to justify the effect relationship among concepts and inferred a linguistic weight for each interconnection [11]. The degree of the influence was represented by a member of the fuzzy set (positive very high, positive high, positive medium, positive weak, zero, negative weak, negative medium, negative low, negative very low).

The following connections among the above-described concepts of supervisor-FCM were suggested:

**Linkage 1:** Connects \( C_1 \) with \( C_6 \). It relates the tumour localization with the delivered final dose.

**Linkage 2:** Relates \( C_2 \) with the \( C_1 \); when the dose derived from treatment planning is high, the value of tumour localization increases at a small amount.

**Linkage 3:** Connects \( C_2 \) with \( C_7 \); when the dose from treatment planning is high, the final dose given to the patient will be also high.

**Linkage 4:** Relates \( C_3 \) with \( C_7 \); when the machine parameters increase the dose from treatment planning decreases.

**Linkage 5:** Connects \( C_3 \) with \( C_7 \); any change to machine parameters influences negatively the final dose given to target volume decreases.

**Linkage 6:** Relates \( C_4 \) with \( C_7 \); the human factors causes decrease in final dose.

**Linkage 7:** Connects \( C_4 \) with \( C_7 \); the presence of human factors causes decrease in patient positioning.

**Linkage 8:** Relates \( C_5 \) with \( C_7 \); any change on the patient positioning influences negatively the factors related to humans.

**Linkage 9:** Connects \( C_5 \) with \( C_7 \); when the patient positioning increases the final dose also increases.

**Linkage 10:** Connects \( C_6 \) with \( C_7 \); any change on the Quality Assurance (control) checks influence positively the treatment planning.

**Linkage 11:** Connects \( C_7 \) with \( C_7 \); any change on the Quality Assurance (control) checks influence positively the final dose.

**Linkage 12:** Connects \( C_7 \) with \( C_7 \); when the final dose reaches an upper value the patient positioning influenced positively.

**Linkage 13:** Connects \( C_7 \) with \( C_7 \); any change in final dose causes change in tumour localization.

**Linkage 14:** Connects \( C_7 \) with \( C_7 \); when the final dose increases to an acceptable value, the dose from treatment planning increases to a desired one.

After the determination of the linkages among concepts, three radiotherapists-doctors (experts) suggested the fuzzy linguistic variables for the weights of the linkages, and through the corresponding
membership functions [4], the bounds for these weights have been defined:

\[
0.3 \leq w_{17} \leq 0.5, 0.2 \leq w_{21} \leq 0.4, \\
0.5 \leq w_{27} \leq 0.8, -0.5 \leq w_{2} \leq -0.2, \\
-0.5 \leq w_{7} \leq 0, -0.5 \leq w_{4} \leq -0.2, \\
-0.6 \leq w_{7} \leq -0.2, -0.6 \leq w_{8} \leq 0, \\
0.4 \leq w_{7} \leq 0.8, 0.5 \leq w_{6} \leq 0.75, \\
0.5 \leq w_{6} \leq 0.7, 0 \leq w_{71} \leq 0.4, \\
0.5 \leq w_{72} \leq 0.9, 0.5 \leq w_{75} \leq 0.9
\]

These linguistic variables were defuzzified and transformed in numerical weights using the construction methodology of FCMs. Thus, the following weight matrix for the supervisor-FCM was produced:

\[
W^{initial} = 
\begin{bmatrix}
0 & 0 & 0 & 0 & 0 & 0 & 0.5 \\
0.4 & 0 & 0 & 0 & 0 & 0 & 0.6 \\
0 & -0.3 & 0 & 0 & 0 & 0 & -0.25 \\
0 & 0 & 0 & -0.3 & 0 & 0 & -0.3 \\
0 & 0 & -0.4 & 0 & 0 & 0 & 0.6 \\
0.55 & 0 & 0 & 0 & 0 & 0.5 & 0 \\
0.3 & 0.7 & 0 & 0.55 & 0 & 0 & 0
\end{bmatrix}
\]

The obtained supervisor-FCM is illustrated in Fig. 2.

![Fig. 2. Supervisory Fuzzy Cognitive Map for decision-making process](image)

Also, the three radiotherapists-doctors determined the desired limits for the parameters TPD and FD, which represent the Treatment Planning Dose and the Final Dose respectively, and they are the control objectives of the supervisor-FCM. These desired limits are:

\[
0.90 \leq FD \leq 0.98, \\
0.85 \leq TPD \leq 0.95
\]

The objective criteria are defined by the related ICRU and IAEA protocols [14,15,16]. The supervisor-FCM evaluates the success or failure of the treatment by monitoring the values of FD and TPD concepts. Successful treatment corresponds to values of the final dose and dose from treatment planning that lie within the desired bounds. These values identify the supervisor model [15]. The supervisor-FCM has been incorporated to an integrated two-level hierarchical decision making system for the description and determination of the specific treatment outcome and for the scheduling of the treatment process before its treatment execution [4]. Thus, optimizing the supervisor-FCM, i.e., detecting the weights that correspond to the maximum values of the concepts FD and TPD, within their prespecified ranges, the result is an enhanced control system which models the radiotherapy procedure more accurately and makes decision-making more reliable. In this way the supervisor-FCM models, supervises and controls the parameters of the radiotherapy planning systems and more generally the whole procedure.

4. The Differential Evolution Algorithm

The Differential Evolution (DE) [17] is a stochastic optimization algorithm that, although not inspired by natural evolution procedures, operates in a way similar to that of Evolutionary Computation (EC) techniques.

In this work, we use the Differential Evolution algorithms, which can be easily implemented and they are computationally inexpensive, since their memory and CPU speed requirements are low [18]. Moreover, they do not require gradient information of the objective function under consideration, but only its values, and they use only primitive mathematical operators. DE algorithms can also handle non-differentiable, nonlinear and multimodal objective functions efficiently, and require few easily chosen control parameters. Experimental results have shown that DE algorithms have good convergence properties and outperform other evolutionary algorithms [19,20,21].

The DE algorithm used here, has been developed by Storn and Price [22]. Applying DE algorithms for FCM learning, the same process for Artificial Neural Network (ANN) training is used, starting with a specific number (N) of n-dimensional weight vectors, as initial population, and evolve them over time; N is fixed throughout the training process and the weight population is initialised by perturbing the appropriate solution provided by the initial weight matrix.

Let’s now describe briefly the version of DE algorithm used here. For each weight vector \( w_i^{(k)} \) the new vector called mutant vector \( v_i^{(k+1)} \) is generated according to the following relation:

\[
v_i^{(k+1)} = w_i^{(k)} + \mu (w_{best}^{(k)} - w_i^{(k)} + w_{r1} - w_{r2}),
\]

for \( i = 1, \ldots, NP \), where \( w_{best}^{(k)} \) is the best population member of the previous iteration, \( \mu > 0 \) is a real parameter (mutation constant) which regulates the contribution of the difference between weight vectors, and \( w_{r1}, w_{r2} \) are weight vectors randomly chosen from the population with \( r1, r2 \in \{1,2,\ldots,i-1,i+1,\ldots,N\} \),
i.e. $r_1, r_2$ are random integers mutually different from the running index $i$. Aiming at decreasing the diversity of the weight vectors further, the crossover-type operation yields the so-called trial vector, $u^{(k+1)}_i$, $i = 1, \ldots, N$. This operation works as follows: the mutant weight vectors ($v^{(k+1)}_i$, $i=1,\ldots,N$) are mixed with the "target" vectors, $w^{(k+1)}_i$, $i=1,\ldots,N$. Specifically we randomly choose a real number $r$ in the interval $[0,1]$ for each component $j$, $j=1,2,\ldots,n$, of the $v^{(k+1)}_i$. This number is compared with $CR \in [0,1]$ (crossover constant), and if $r \leq CR$ then the $j$-th component of the trial vector $u^{(k+1)}_i$ gets the value of the $j$-th component of the mutant vector $v^{(k+1)}_i$; otherwise, it gets the value of the $j$-th component of the target vector, $w^{(k+1)}_i$. The trial vector is accepted for the next generation if and only if it reduces the value of the following proposed fitness function $f()$; otherwise the old value, $w^{(k)}_i$, is retained.

This last operation is the selection and, due to the moving “optimum” nature of the differential evolution task, it ensures that the fitness function $f()$ starts steadily decreasing at some iteration.

The structure of the DE algorithm in pseudocode form is shown in Fig. 3.

The purpose is to determine the appropriate values of the weights of the FCM that produce a desired behavior of the system. The determination of the weights is of major significance and it contributes towards the establishment of FCMs as a robust methodology, and improves the performance of FCMs.

### "Differential Evolution Algorithm"

- **Step 1b**: Initialize the DE population in the neighbourhood of $w^m$ and within the suggested weight ranges (constraints).
- **Step 2b**: Repeat for each input concept state $(k)$.
- **Step 3b**: For $i=1$ to $NP$
- **Step 4b**: MUTATION ($w^{(k)}_i$) → Mutant Vector
- **Step 5b**: CROSSOVER (Mutant Vector) → Trial Vector
- **Step 6b**: If $f$(Trial Vector) $\leq f(w^{(k)}_i)$, accept Trial Vector for the next generation.
- **Step 7b**: End For
- **Step 8b**: Until the termination condition is met.

Fig. 3. The Differential Evolution Algorithm

### 4.1 The Proposed Approach

The detection of the optimum FCM’s weights that correspond to the maximum value of the parameters $FD$ (final dose) and $TPD$ (dose prescribed from the treatment planning), within prescribed ranges, is the important task. The parameters $FD$ and $TPD$ are determined as the desired output concepts. For this purpose, the DE algorithm has been used for the optimization of the supervisor-FCM, through the minimization of an objective function.

More specifically, the DE algorithm evolves a population of individuals each of which consists of a weight matrix describing the degree of causal relationships between the concepts of Figure 2. The initial generation contains weight matrices with randomly selected values from the weight ranges, which derived from the fuzzy linguistic variables suggested initially by experts. The evolution of the individuals is performed with the help of the FCM model, which computes the final values of output concepts through equation (1).

The objective function, of each individual weight matrix $WM_i$, can be straightforwardly defined as:

$$f(WM_i) = -FD(WM_i) - TPD(WM_i)$$

where $FD(WM_i)$ and $TPD(WM_i)$ are the values of the final dose and the dose prescribed from the treatment planning, respectively, that correspond to the weight matrix $WM_i$. The minus signs are used to transform the maximization problem to its equivalent minimization problem. Thus, the main optimisation problem under consideration is the minimization of the objective function $f(WM_i)$, such that the constraints of equations (3) and (4) hold.

The weight matrix $WM$ can, in general, be represented by a vector, which consists of the rows of $WM$ in turn, excluding the elements of the main diagonal, $w_{11}, \ldots, w_{NN}$, which are by definition equal to zero:

$$WM = [w_{12}, \ldots, w_{1N}, w_{21}, \ldots, w_{2N}, \ldots, w_{N1}, \ldots, w_{NN}]$$

In the supervisor-FCM, the experts determined only 14 linkages, as it is described in section 3, and thus, the corresponding minimization problem is 14-dimensional.

The fuzzy linguistic variables, describing the cause-effect relationships among the concepts, are taken into consideration in the optimization process. These weight ranges, given in eq. (2), are used as constraints for the parameter vector $WM$, in the following experiments.

### 5. Simulation Results

First, before the implementation and testing of the proposed DE algorithm, we apply the typical eq. (1) to find the final state of the iterations in the previously described radiotherapy problem. The initial values of concepts given in vector $A^0 = [0.4 0.67 0.3 0.25 0.32 0.4 0.35]$. These values and the initial weight matrix $w^m$ are used in eq. (1) to calculate the equilibrium of the process. After 10 iteration steps the equilibrium state is reached and Fig. 4 gives the subsequent values of calculated concepts. It is observed that the values of concepts $C_1$ and $C_3$, in final state, are equal to the values 0.8033 and 0.89 which are out of the suggested desired regions in equations (3) and (4). Then we continue implementing the DE algorithm.
It is clear that the values of $C_2$ and $C_7$ lie within the desired regions defined by equations (3) and (4), while the weights fulfill the ranges posed initially by the group of experts. This supports the claim that the obtained solution is the true optimal solution. Some of the weights have changed significantly their values from the initial ones in order to succeed the desired output values of concepts.

After simulation results, we remark that there is a very high positive influence of the concept $C_1$ (final dose) to the concept $C_2$ (dose prescribed from the treatment planning) as well as to the concept $C_3$ (patient positioning). This means that if we succeed to deliver the maximum dose to the target volume, then the initial calculated dose from treatment planning is the desired and the same happens with the patient positioning. It must be mentioned that the estimated weights take their optimum values at the edges of the suggested bounds. The optimal values of "Final Dose" and "Dose Prescribed from the Treatment Planning" are acceptable according to the ICRU, IAEA protocols [14,15], optimizing the whole treatment process. Thus, radiotherapists can follow the suggested values and the treatment will be executed with successful results. The proposed approach is efficient and very useful for the FCM-controlled clinical radiotherapy process.

The recalculation of all weights that participate in the simulation process constitutes the most important drawback of the simple FCM model as initially determined by experts-doctors. Its importance to the doctors-radiotherapists is underlined by the fact that they will be able to introduce clinical cases based on a range of accepted values for the output concepts of the model.

6. Conclusions

The Fuzzy Cognitive Map model, which supervises and monitors the whole radiotherapy procedure, was optimized using the Differential Evolution algorithm. This model resulted in a sophisticated decision support system. The proposed algorithm determined the optimal weight matrix for the supervisor-FCM model with the synchronously satisfaction of the objective criteria.

An hybrid system consisting of the FCM and the computational intelligence technique of DE has been proposed in this work to determine the optimum values for weights in order to succeed the radiotherapy treatment. The hybrid system simulated the radiotherapy procedure successfully and produced results that are very descriptive of the actual cases. Thus, this hybrid system can be a reliable tool in the hands of doctors and medical physicists aiming at managing a clinical case or solving treatment problems in radiotherapy.

Future work will focus on the optimization of more complex models and especially of the generic hierarchical system in all levels and aspects of radiotherapy.

References


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