

Prediction of the thickness of the compensator filter in radiation therapy using computational intelligence

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ARTICLE INFO

Article history:

Received 14 January 2014

Received in revised form

12 September 2014

Accepted 29 September 2014

Keywords:

Computational intelligence

Radiation therapy

Filter in radiation therapy

Thickness of the compensator

ABSTRACT

In this study, artificial neural networks (ANNs) and adaptive neuro-fuzzy inference system (ANFIS) are investigated to predict the thickness of the compensator filter in radiation therapy. In the proposed models, the input parameters are field size (S), off-axis distance, and relative dose (D/D₀), and the output is the thickness of the compensator. The obtained results show that the proposed ANN and ANFIS models are useful, reliable, and cheap tools to predict the thickness of the compensator filter in intensity-modulated radiation therapy.

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Introduction

Intensity-modulated radiation therapy (IMRT) is one of radiotherapy techniques in which a field of variable intensity is used. The IMRT is applied in 2 methods by using either multileaf collimators (MLCs) or compensator filters. The MLC techniques deliver an intensity-modulated photon field by either moving the collimator leaves during irradiation or by irradiating a sequence of static MLC ports. The former is often referred to as the dynamic MLC technique and the latter as the step-and-shoot MLC technique. MLC systems have limitations in spatial resolution or segmental dimensions.¹ The convenience and automatic application are the best advantages of MLC. Initially, compensators were used to merely compensate for the “missing tissue” in the actual patient geometry compared with a rectangular phantom. We use this technique as an alternative to the MLC techniques to deliver intensity-modulated treatments designed by a 3 dimensional treatment planning system.

The compensator resolution is limited by milling system, which, however, is higher than that of the MLC.^{2,3} The design of the compensator for each patient and field is a time-consuming task and is considered as the main defect of this technique.

To calculate the thickness of the compensator for delivering a given absorbed dose (D), the following equation is used:

$$T = -\frac{1}{\mu_{\text{eff}}} \ln(D/D_0) \quad (1)$$

where D/D₀ is the relative dose of the radiation transmitted through the compensator, T is the compensator thickness, and μ_{eff} is the effective attenuation coefficient of the compensator. The μ_{eff} depends on several parameters, including compensator thickness, field size, depth, and off-axis distance. The μ_{eff} depends on the cause of these parameters and is discussed in several articles.^{4–10} In this study, artificial neural networks (ANNs) and adaptive neuro-fuzzy inference system (ANFIS) are investigated to predict the thickness of the compensator filter in IMRT.

Methods and Materials

Measurements

The variation of the D/D₀ for the 6-MV photon beam of linac, with 0.69 tissue phantom ratio (20/10), Elekta SL 75/25, was measured in 10-cm depth of interest

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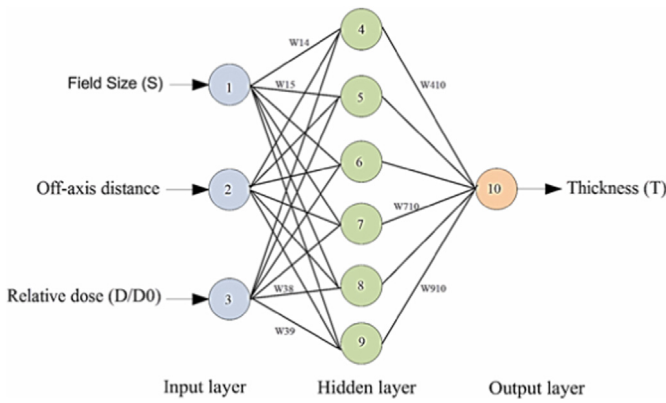


Fig. 1. The proposed MLP model. MLP = multilayer perceptron. (Color version of figure is available online.)

point at different clinical radiotherapy conditions.¹¹ The measurements were carried out by an RK dosimeter (IBA, Germany), with the nominal volume of 0.125 cm³ connected to a DOSE 1 electrometer (IBA, Germany). The measurements were carried out in RFA-300 plus phantom (IBA, Germany) in which the location of the dosimeter in the phantom is controlled by software (RF A plus version 5.2). All the measurements were carried out at source-to-surface distance of 100 cm. The compensator material was the cerrobend alloy (MCP 96) with density of 9.4 g/cm³. Various thicknesses of the compensator were investigated ranging from 0 to 6 cm with an increment of 0.5 cm over to 2-cm range and thereafter at 1-cm intervals.^{5–12} The D/D₀ values were measured for various square field size dimensions of 4, 6, 8, 10, 15, 20, and 25 cm. To investigate the effect of the off-axis distance on the D/D₀, at continuous 0.5-cm fixed intervals away from the center of the fields, the variation of the D/D₀ was measured for all the various thicknesses and field sizes.

Modeling approach

In this study, the computational intelligence models based on ANN and ANFIS to predict the thickness of the compensator filter in radiation therapy are presented. In the proposed models, the input parameters are field size (S), off-axis distance, and relative dose (D/D₀), and the output is the thickness of the compensator (T). The data set required for training and testing the proposed ANN and ANFIS models is obtained experimentally.⁴ For developing the ANN and ANFIS models, the experimental data are divided into 2 sets: training (approximately 78%) and testing (approximately 22%). MATLAB 7.0.4 software was used for training the proposed models. To obtain the best ANN and ANFIS models, various configurations have been constructed and tested.

ANN model

ANNs are a good way to handle the problems of modeling, prediction, and control.¹³ The fundamental processing element of ANN is a neuron that is capable of performing parallel computations for data processing and knowledge representation. The multilayer perceptron networks are the most widely used ANNs that consist of 1 input layer, 1 output layer, and 1 or more hidden layers with at least 1 neuron in each layer. Figure 1 shows the proposed ANN model for predicting the thickness of the compensator filter in IMRT. In Fig. 2, the output from i-th neuron of

Table 1
Specification of the proposed ANN model

Neural network	MLP
No. of neurons in the input layer	3
No. of neurons in the hidden layer	6
No. of neurons in the output layer	1
Learning rate	0.5
Number of epochs	300
Transfer function	Tansig

MLP = multilayer perceptron.

the hidden layer is given by

$$\beta_i = f \left(\sum_{k=1}^6 (x_k W_{ki}) + b_i \right), \quad i = 1, 2, 3 \quad (2)$$

where b_i is the bias term, W_{ki} is the weighting factor, and f is the activation function of the hidden layer. The output of the neuron in the output layer is given by

$$y = \sum_{k=1}^6 (\beta_k W_k) + b \quad (3)$$

Table 1 shows the specification of the proposed ANN model.

ANFIS model

ANFIS is a fuzzy inference system (FIS) implemented in the framework of ANNs, which has advantages of FIS and ANNs.^{14,15} Its FIS corresponds to a set of fuzzy IF-THEN rules that has learning capability to approximate nonlinear functions. Figure 2 shows the proposed ANFIS model for predicting the thickness of the compensator filter in IMRT. The layers of this ANFIS model are defined as follows:

Layer 1. The node functions of the layer 1 are given by

$$A_i(x) = \mu_{A_i}(x), \quad i = 1, 2, \dots, 20 \quad (4)$$

$$B_i(y) = \mu_{B_i}(y), \quad i = 1, 2, \dots, 20 \quad (5)$$

$$C_i(z) = \mu_{C_i}(z), \quad i = 1, 2, \dots, 20 \quad (6)$$

where x , y , and z are the inputs of the model, and $\mu_{A_i}(x)$, $\mu_{B_i}(y)$, and $\mu_{C_i}(z)$ are the fuzzy membership functions.

Layer 2. The output of this layer represents the firing strength of the each rule given by

$$W_i = A_i(x) \times B_i(y) \times C_i(z), \quad i = 1, 2, \dots, 20 \quad (7)$$

Layer 3. This layer estimates the ratio of the i-th rule's firing strengths to the sum of all rule's firing strengths as follows:

$$\bar{w}_i = \frac{W_i}{W_1 + W_2 + W_3}, \quad i = 1, 2, \dots, 20 \quad (8)$$

Layer 4. The output of layer 4 is given by

$$f_i = \bar{w}_i(p_i x + q_i y + r_i z + k_i), \quad i = 1, 2, \dots, 20 \quad (9)$$

where p_i , q_i , k_i , and r_i are called consequent parameters.

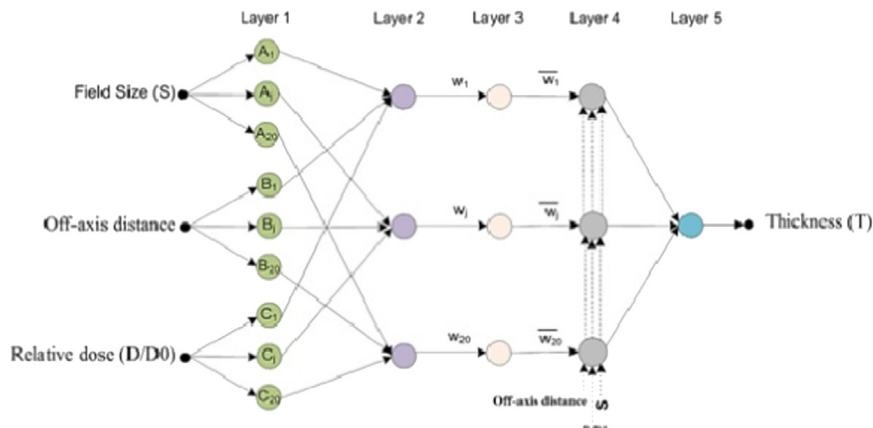


Fig. 2. ANFIS structure. (Color version of figure is available online.)

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