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Applications of Artificial Neural Network to Building Statistical Models for Qualifying and Indexing Radiation Treatment Plans

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***Abstract*—**The main goal in this paper is to quantify the quality of different techniques for radiation treatment plans, a back-propagation artificial neural network (ANN) combined with biomedicine theory was used to model thirteen dosimetric parameters and to calculate two dosimetric indices. The correlations between dosimetric indices and quality of life were extracted as the features and used in the ANN model to make decisions in the clinic. The simulation results show that a trained multilayer back-propagation neural network model can help a doctor accept or reject a plan efficiently. In addition, the models are flexible and whenever a new treatment technique enters the market, the feature variables simply need to be imported and the model re-trained for it to be ready for use.

***Keywords*—**neural network, dosimetric index, radiation treatment, tumor

I. Introduction

NOWADAYS, the combination of biomedicine and information engineering is a major branch of research in the world. Radiation treatment plays an important role in curing cancer. Almost all kinds of cancer can be treated by medical radiation. High-energy X-rays or gamma rays are delivered at the tumor; however radiation also harms the normal tissue around the target. Each organ has its own constraints of radiation doses. If the radiation dose to an organ exceeds its limit, this will cause permanent injury or even death. In the opposite case, radiation treatment is ineffective if the delivered dose is lower to prevent damage to normal organs. Therefore, the technique of delivering the desired dose to the target and reducing it to a reasonable level on normal organs has been improved in the history of radiation treatment. In our research, we wish to study biomedicine signals and analyse the patient database by medical engineering. The statistical data collected from a department of radiation oncology are analyzed and compared; this helps engineers edit the program. In addition, we also wish to adopt modern algorithms to simulate the relationship between normal tissues and cancer.

II. Material and Method

In today’s treatment planning system, there are two commonly methods used to describe the distribution of radiation dose: the isodose curve and dose-volume histogram (DVH).

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However, if we wish to compare different treatment plans at the same time, the only way that this can be done is to evaluate plans based on a doctor’s experience. The disadvantages are the time taken and sometimes an improper decision being made. Fortunately, a neural network offers a faster and more precise way to compare treatment plans.

This research adopts the concept of dosimetric index and dosimetric parameters which include four evaluated parameters for treatment target, nine evaluated indices and two dosimetric parameters for normal tissue. In the next step, we choose three kinds of treatment plan to compare their quality with the specified dosimetric indices and parameters mentioned above. The first is a conventional seven-field intensity modulated radiotherapy (IMRT) plan. The next is an 18-field IMRT plan which offers a well-shaped dose distribution on the edge of targets but takes two to three times longer than the first. The latest technique which is so-called volumetric modulated arc therapy (VMAT) is the final plan. The neural network is well suited to constructing analytical modules because of its self-adaptive and powerful learning ability. Therefore, the calculated result of a neural network can be a reference as the doctor decides to reject or accept a treatment plan.

A. Dosimetric index and parameter

A case of nasopharyngeal cancer will be an example for describing the relationship between radiated volume of normal tissue and radiation dose around a tumor with some dosimetric indices and parameters. These indices and parameters are constructed by the neural network and its output is available when choosing a suitable conformity index and homogeneous index. These dosimetric parameters are defined as follows.

Dosimetric parameters: These parameters are obtained by the range of dose distributions on a tumour. The term V93 means that at least 97 percent of the volume of the tumour accepts 93 percent of the prescribed dose. V100 means that more than 95 percent of the volume of the tumour is covered by the total prescribed dose. The volume of the tumour receiving 110 percent of the prescribed dose is less than 20% which is defined as V110. Similarly, less than five percent of volume is radiated by 115 percent of the prescribed dose which is called V115 [1-2].

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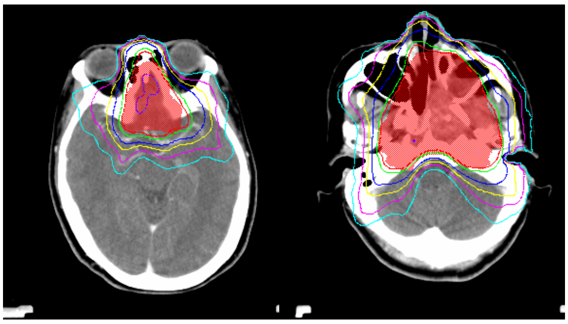
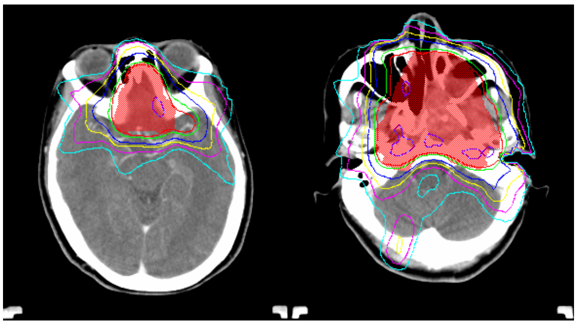
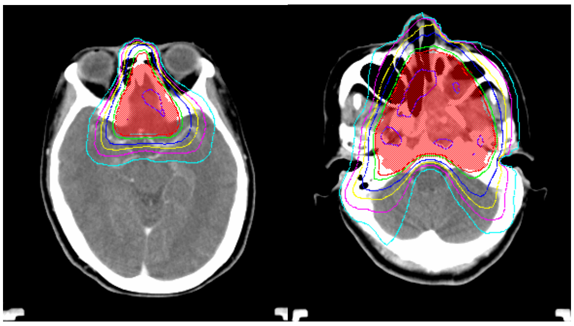


(a) The 18-field IMRT is the ideal case of distribution of radiation dose.



(b)The simulated result of a 7-field IMRT plan.



(c) The dose distribution of a VMAT plan.

Fig.1 The practical treatment data is the target value of simulation.

Dosimetric indices: The conformity index is defined as the degree to which the radiated volume of a tumor matches its physical volume. If the value is greater than one, which means the treatment area is larger than the physical one. In the opposite sense, the value is less than one. The distribution of radiation dose within a tumor is known as the homogeneous index. Fig. 1 shows the distribution of radiation dose and the red area denotes the treatment target. The penetrated depth of the radiation beam is determined by organs and by the thickness along its travelling path in a body. When a specific treatment plan is set up, sometimes we need to prevent critical organs from receiving a radiation dose. This is because some organs are sensitive to radiation, such as the spinal cord, brain stem, lymph nodes, etc. Therefore, we have to carefully manage the angles from which the radiation is directed and this gives the desired isodose curves shown as colored solid curves in Fig. 1.

A treatment plan has many treatment indices to qualify it and it always takes time for a doctor or technician to evaluate the quality of a treatment plan according to these indices. In Table 1, there are 15 parameters to be evaluated for the treatment index in each row.

Today's planning systems show the treatment indices by DVH as in Fig. 2. Each color denotes a specific treatment index and there are three different shaped lines for each color which denote three different treatment plans, respectively. In nasopharyngeal cases, there could be more than ten critical organs that need to be considered. One critical organ has 13 dosimetric parameters and two dosimetric indices to be evaluated. Then we can imagine how complex the problem becomes if three or more plans are taken into consideration..

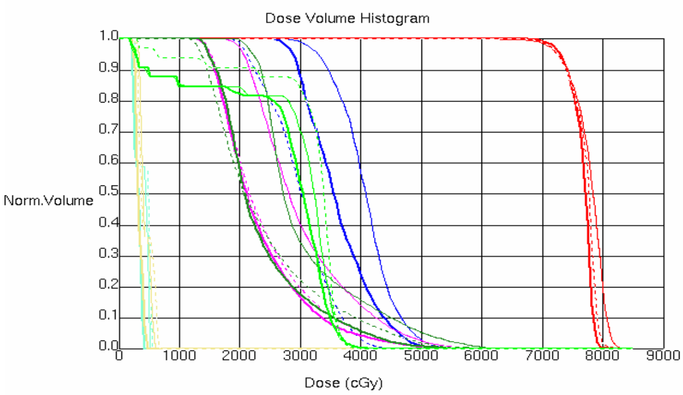


Fig.2 A dose-volume histogram (DVH)

B. Models of Neural Network

The back-propagation algorithm is one of the most commonly used algorithms in neural networks because it is easy to extend and use [3-7].

A neural network is an adaptive network that has powerful learning ability and can handle complex nonlinear problems. After training the weights, the network's output can reach the target value rapidly [3, 5, 8-12]. Fig.3 shows the flow-chart of training a neural network.

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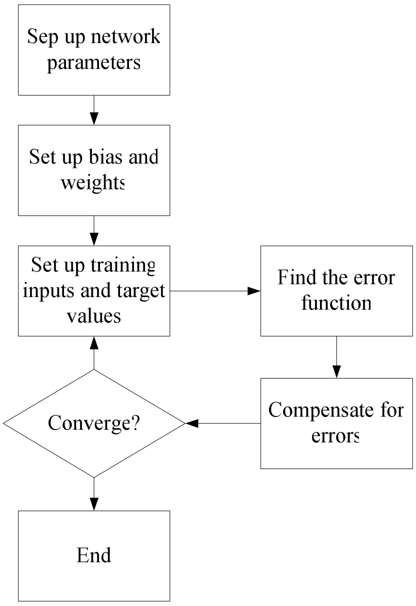

Fig.3 Flow-chart for training a neural network

A multilayer network consists of three layers: the input, hidden and output layers. A three-layer neural network is shown in Fig. 4 [13]. We can see that the neurons in different layers connect to each other through axons with different weights. The weight is sometimes called a memory unit in which the training results can be stored [14]. The training result converges to the target value rapidly if the input and output data are complete [15].

The outputs of each layer are the inputs of the next in a multilayer network which is shown as follows:

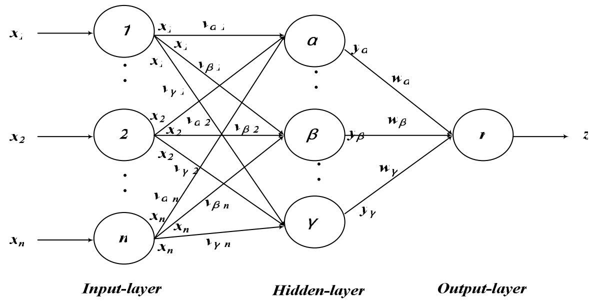

Fig. 4 Framework of a three-layer neural network

TABLE I DOSIMETRIC PARAMETERS

Pt no	PTV				Organ									Index	
	V_{93}	V_{100}	V_{110}	V_{115}	SC	BS	Rt parotid	Lt parotid	lens	Rt eye	Lt eye	oral	mandible	CI	HI
1	99.40	99.17	0.42	0.42	44.79	52.08	24.56	24.99	4.90	11.17	11.68	26.11	23.35	1.50	1.04
2	99.22	98.70	0.12	0.12	43.61	55.40	21.41	20.40	4.73	10.34	9.31	32.75	27.45	1.65	1.04
3	98.34	99.30	4.59	0.07	44.79	54.03	29.01	29.00	5.27	26.42	8.36	37.78	37.42	1.51	1.06
4	98.13	97.28	3.80	0.17	43.60	53.27	27.55	30.24	5.02	19.21	10.51	33.08	36.48	1.35	1.06
5	98.98	98.43	12.86	0.47	46.70	55.20	29.01	18.39	4.90	14.26	12.86	34.17	28.57	1.33	1.12
6	99.80	97.90	9.54	0.47	48.20	56.70	27.55	22.63	4.73	11.83	20.29	35.36	29.78	1.34	1.12
7	98.20	99.17	24.99	3.70	41.20	50.47	19.57	28.30	4.76	18.10	13.24	44.98	23.35	1.33	1.13
8	99.60	98.70	21.41	2.42	41.83	52.92	19.98	27.50	4.70	15.78	6.47	42.13	27.45	1.34	1.15
9	97.60	98.96	11.04	2.65	46.20	54.80	29.56	21.36	10.30	23.40	10.22	44.35	59.49	1.51	1.04
10	98.20	97.36	10.78	1.78	45.60	55.20	28.56	21.44	14.60	20.30	9.69	47.59	53.50	1.35	1.04

Pt= patient, PTV=Planned Target volume; CI=Conformal Index; HI= Homogeneous Index; SC=Spinal cord; BS=brain stem;

$$a^{m+1} = f^{m+1}(W^{m+1}a^m + b^{m+1}), m = 0,2,...,M-1 \quad (1)$$

where M denotes the number of layers.

The output of a hidden layer is represented in the following:

$$a^k = W_p + b^k \quad (2)$$

In Eq. (4), b is the bias and p is the input of a neuron. The weight between any two neurons is denoted by W [9]. The input of the first layer is

$$a^o = p \quad (3)$$

and the output of the last layer is

$$a = a^M \quad (4)$$

The back-propagation algorithm is a generalized mean-squared algorithm which adopts the mean-squared error (MSE) as its performance index. The following is a series of training data.

$$\{p_1, t_1\}, \{p_2, t_2\}, \{p_3, t_3\}, ..., \{p_n, t_n\} \quad (5)$$

where p_n and t_n denote the input and target value respectively.

When the network is active, it starts to adjust its bias and weights and tries to minimize the mean-squared error.

$$F(x) = E[e^2] = E[(t-a)^2] \tag{6}$$

where x denotes the error vector. If the network has multiple outputs, then Eq. (6) can be rewritten in quadratic vector form:

$$F(x) = E[e^T e] = E[(t-a)^T (t-a)] \tag{7}$$

Furthermore, we can use the steepest decent method to find the weight and bias of the network.

$$w_{i,j}^m (k+1) = w_{i,j}^m (k) - \alpha \frac{\partial \hat{F}}{\partial w_{i,j}^m} \tag{8}$$

$$b_i^m (k+1) = b_i^m (k) - \alpha \frac{\partial \hat{F}}{\partial b_i^m} \tag{9}$$

The coefficient α is the learning rate which is related to the number of converged steps of the algorithm. The relationship between iteration and MSE is shown in Fig. 5.

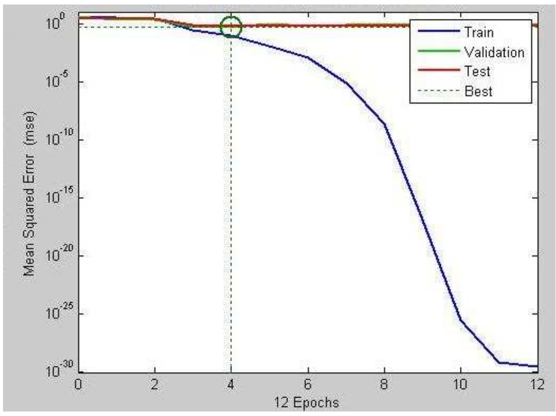

Fig. 5 Relationship between iteration and MSE

The neural network is a self-adaptive model and it also uses the steepest descent algorithm to optimize the training model. Furthermore, the MSE and delta law can be used together to make it converge faster. The equations are described below.

$$\delta^k = d - a^k \tag{10}$$

$$\Delta W^k = 2L\delta^k p^T, W^{k+1} = W^k + \Delta W^k \tag{11}$$

$$\Delta b_k = 2L\delta^k, b^{k+1} = b^k + \Delta b^k \tag{12}$$

The symbol δ is the differential of b. The vector b is obtained when the initial value of every neuron is zero. The symbols a and Δb denote the outputs. Finally the coefficients L and k are the learning rate that affects the iteration steps and convergent speed. The variation of the gradient, momentum and iteration are depicted in Fig. 6.

III. Results

The trained results can be classified into six levels, in Fig. 7, each colour denotes a different qualified level in the treatment plans. As seen in the result shown in Fig. 7, the more training sets that were used in the network, the more precise the outputs obtained.

The simulated results in Fig. 8 show that the discrepancy between outputs and targets is small. In other words, the adaptive ability of the neural network is excellent. In the past, treatment plans were qualified by experience. But now, we have devised a completely new method for doing this with fewer misses and greater precision. It is also convenient for updating the system. If the treatment indices and dosimetric parameters are given, the network can again be trained.

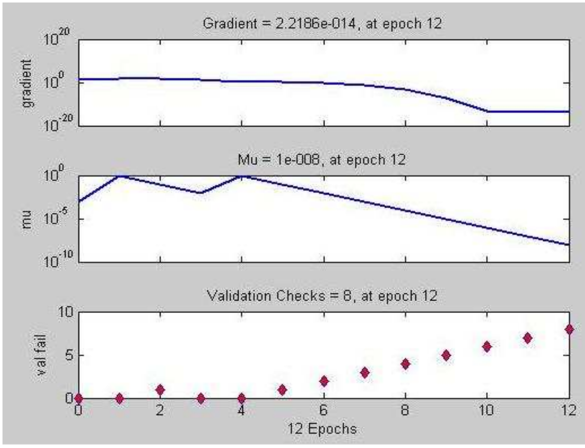

Fig. 6 Variation of the gradient, momentum and iteration

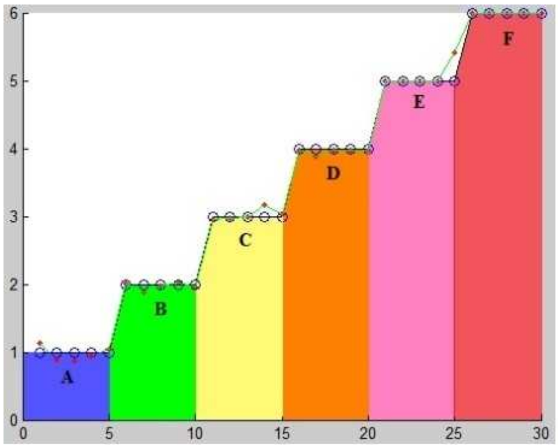

Fig. 7 The vertical axis denotes the level of a treatment plan and the horizontal axis denotes inputs

IV. Conclusions

In our research, we try to combine the biomedicine and computer engineering together. As the simulated results, a well-trained neural network is suitable to evaluate treatment plans. It can help us to classify and qualify the numerous data in a rapid and reliable way. All we need to do is to collect the related data and to train the network.

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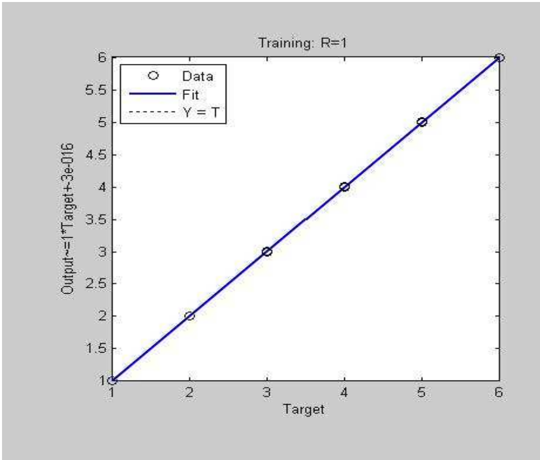
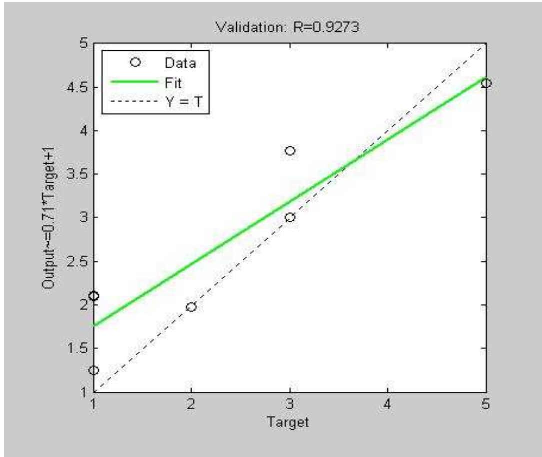
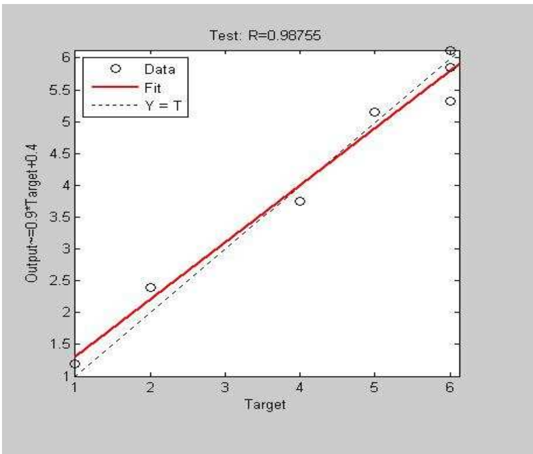


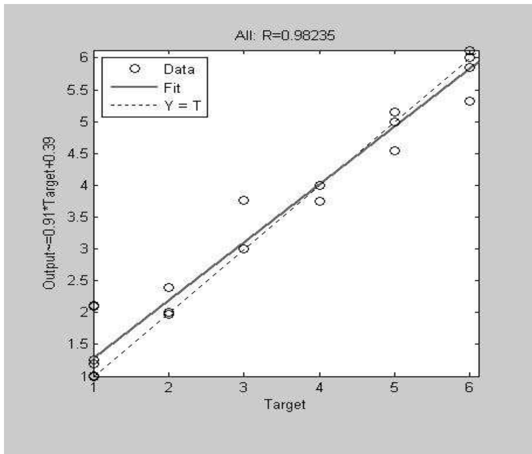
(a) R= 1



(b) R=0.9273



(b)R=0.9875



(d) R=0.9823

Fig. 8 Dispersion between the outputs and targets

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