Extracting Material Information from the CT Numbers by Artificial Neural Networks for Use in the Monte Carlo Simulations of Different Tissue Types in Brachytherapy

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ABSTRACT

Background: The artificial neural networks (ANNs) are useful in solving nonlinear processes, without the need for mathematical models of the parameters. Since the relationship between the CT numbers and material compositions is not linear, ANN can be used for obtaining tissue density and composition.

Objective: The aim of this study is to utilize ANN for determination of the composition and mass density of different tissues to be used in Monte Carlo simulation in treatment planning of brachytherapy.

Methods: The ANN were used for mass density calibration. The density and composition of several human body tissues, along with their corresponding CT numbers are used as the training samples. Finally, when the ANN is trained, the neural network would give us the material information, i.e. mass density, electron density, and material composition, by entering the CT numbers of different tissues into the network as its input. The tissue compositions and densities predicted by the ANN for each CT number were compared with the real values of such parameters. The tissue parameters predicted by the ANN were used as the phantom materials for obtaining the dose at different distances from Pd-103 and Cs-137 brachytherapy sources. Finally, the doses at different distances of the real phantoms were compared with doses inside the phantoms predicted by Neural Network.

Results: According to the results of these studies, the Neural Network algorithm used in this investigation can be used for accurate prediction of the material compositions of different tissues. For example, it can give the mass densities of bone, muscle, and water with the percentage differences of 0.52%, -0.95%, and 0% respectively. Comparison of the dose distribution inside the water phantom predicted by ANN and the real water phantom shows a percentage difference of less than 0.66% and 2% for Cs-137 and Pd-103, respectively.

Conclusion: The results of this study indicate that the Artificial Neural Networks are applicable in determination of tissue density and material compositions from the CT images data, and the material compositions and density of the phantoms (bone, muscle, and water) obtained by this method can be used for material definition in Monte Carlo simulations.

Keywords

Artificial Neural Network, Treatment planning, Brachytherapy, CT number, Density calibration

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Introduction

The neurons in Artificial Neural Networks are mathematical, nonlinear operators computing the weighted sum of the inputs for production of individual outputs [1]. This sum is passed through the activation function, which is a non-linear function. The implementation of ANNs and Monte Carlo calculations in radiation therapy has increased recently. The ANNs have been used in automated image segmentation and in dose calculation, especially in the presence of tissue heterogeneities [2, 3]. The Monte Carlo method is one of the accurate methods for dose calculation in inhomogeneous medium [4, 5]. An accurate MC simulation requires accurate knowledge of phantom geometry and compositions. In modern radiation therapy, 3D cross sectional images, i.e. CT images, are used for obtaining patient geometry. The outlines of contours and internal structures can be determined either manually or on the basis of CT number distribution. The electron density of the tissue in each voxel of a CT image can be derived from the CT number of that voxel [1].

The precise extraction of material composition and density from CT images is essential in CT- based treatment planning and Monte Carlo simulations for performing inhomogeneity corrections. The purpose of this study is to investigate the applicability of ANNs in derivation of tissue density and composition from CT images, by comparing the MC calculated doses in the ANN predicted phantoms with those in the real phantoms.

Materials and Methods

Artificial Neural Network

Since the correlation of CT images information and tissue parameters, i.e. mass density and material composition, is non-linear, the artificial neural networks (ANN toolbox of MATLAB software) were used to learn the relationships between these two parameters. The density and composition of several tissues of the body, along with their corresponding CT numbers are used as the training samples. Finally, by entering the CT numbers of different tissues into the network as its input, the neural network would give us the material information, i.e. mass density, electron density, and material composition [1]. The optimum structure of this network chooses 3 hidden layers. Figure 1 shows the network topology. The predicted density and composition of different phantoms were then compared with those of real phantoms.

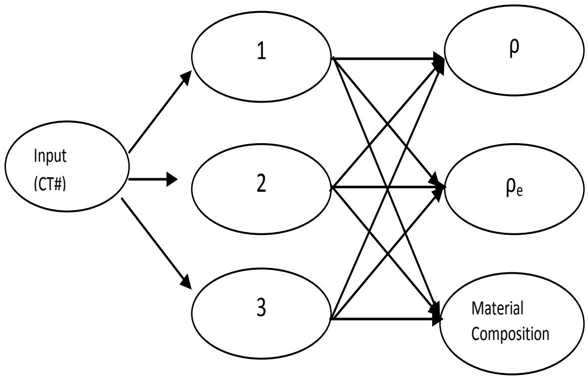

Figure 1: BP network structure

Monte Carlo simulations

The use of Monte Carlo methods for simulations in external radiotherapy and brachytherapy has increased recently [6, 7, 8]. The MC simulations have been accepted as a golden standard for dose calculation in radiation therapy. One of the advantages of this method is considering the effect of tissue inhomogenities for accurate dose calculation in treatment planning systems [4, 5].

MC simulation of brachytherapy sources

After prediction of the material densities and compositions by ANN, homogeneous spherical phantoms of each material (bone, muscle, and water) were simulated by MCNP4c Monte Carlo code. The dose values at different distances from Cs-137 and Pd-103 sources in different phantoms were obtained by MCNP5 Monte Carlo code. The output of the ANNs was also used for material and density definitions in MCNP5 Monte Carlo simulations for obtaining the dose distribution around brachytherapy sources.

Pd-103 source

The Pd-103 source (Model Best2335) has

been simulated in this investigation [9]. This source contains a 5 mm long titanium capsule, at the center of which is a cylindrical tungsten x-ray marker. Three spherical polymer resins coated with Pd-103, having a density of 1.00 g/cm3 exist at each end of the x-ray marker. In this study, the dose distribution around this source has been obtained using MCNP4C Monte Carlo code in real muscle phantom and muscle phantom predicted by Artificial Neural Networks. To perform the MC simulations, the Pd-103 source was considered inside a water phantom with dimensions of 30×30×30 cm3. The energy spectrum used for simulation of Pd-103 was obtained from TG43U1 formalism [10]. Small spherical tally cells with 0.05 mm radius were defined at different distances on the transverse plane of the source (θ-90°). The energy flux was obtained using tally type *F4. The results were then multiplied by energy dependent mass energy absorption coefficients and the average photon per disintegration (0.77 for Pd-103 source) to obtain the dose rate per source particle at each distance from the source center. The energy cut offs for both electron and photon were set to 5 keV. The active length of this source is 4.55 mm for calculation of geometry function (G(r, θ)) and radial dose function ($g_L(r)$) of the source, according to equations 1 and 2. The simulation of Pd-103 was repeated one more time in a cubical phantom made up of water with density and material composition predicted by ANNs. Finally, the dose values at different points on the transverse plane of Pd-103 source were compared in real and predicted phantoms.

$$(1) \qquad G_L(r,\theta)=\begin{cases}\dfrac{\beta}{Lr\sin\theta}\, if\,\theta\neq 0^\circ\\ (r^2-L^2/4)^{-1}\, if\,\theta=0^\circ\end{cases}$$

$$(2) \qquad g_L(r)=\frac{\dot{D}(r,\theta_0)}{\dot{D}(r_0,\theta_0)}\frac{G_L(r_0,\theta_0)}{G_L(r,\theta_0)}$$

^{137}Cs Source

The simulations performed for Pd-103 low energy source were repeated for Cs-137 high energy source in different phantoms of water, bone, and muscle. The Selectron (Nucletron BV, Netherland) is low dose rate- Medium Dose Rate (LDR- MDR) remote afterloading system used in gynecological brachytherapy. In this system a mixture of several Cs-137 spherical Active sources (A) (supplied by Amersham corporation) along with several Non-active (N) (dummy) pellets of the same dimensions (2.5mm overall diameter) are inserted in the applicator set [11, 12, 13]. In this study, dose at different distances from a single active source inside the applicator, on the transverse plane of the applicator has been obtained using MCNP5 Monte Carlo code in real and ANN predicted phantoms of muscle, bone, and water. It should be mentioned that the electron and photon cutoff energies were set to 5 keV. The energy of Cs-137 source was considered as 662 keV, and tally type F6 was used for dose calculation purpose. The radial dose function $g_p(r)$ of the single active pellet was obtained by considering the spherical pellet as point source and calculating the geometry function as inverse square law (see equations 3 and 4).

$$(3) \qquad G_p(r,\theta)=\frac{1}{r^2}$$

$$(4) \qquad g_p(r)=\frac{\dot{D}(r,\theta_0)}{\dot{D}(r_0,\theta_0)}\frac{G_p(r_0,\theta_0)}{G_p(r,\theta_0)}$$

Results

ANN Results

The results indicate that Artificial Neural Network (ANN) can predict the densities and material compositions of different tissues precisely. For example, it can give the mass densities of bone, water, and muscle with the percentage differences of 0.52%, -0.95%, and 0% respectively. The percentage differences between real and predicted electron densities are of 0%, -0.96%, and 1% for bone, muscle and water respectively. Table 1, shows the real and predicted values of mass and electron densities and the percentage differences between real and ANN predicted values.

Table 1: Comparison of real values of mass and electron density with the predicted values by ANN.

		Predicted value	Real value	% difference
bone	ρe	1.78	1.78	0%
	ρ	1.91	1.92	0.52%
muscle	ρe	1.05	1.04	-0.96%
	ρ	1.06	1.05	-0.95%
water	ρe	0.99	1.00	1%
	ρ	1.00	1.00	0%

Monte Carlo dosimetry results

The percentage difference between the dose inside real and predicted muscle, bone, and water phantoms around the Cs-137 source are shown in Figures 2 to 4. The maximum, minimum, and average values of percentage difference in dose are shown in Table 2. As it is obvious from the Table, the maximum percentage difference in MC calculated doses is less than 0.66%. Comparing the dose distribution inside the water phantom predicted by Artificial Neural Networks and the real water phantom shows a percentage difference of less than 0.66% and 2% for Cs-137 and Pd-103 respectively. The percentage dose difference between real and predicted water phantoms is shown in Figure 5. Figures 6 and 7 compare the radial dose function (g(r)) of Pd-103 and Cs-137 brachytherapy source in real and predicted water phantoms.

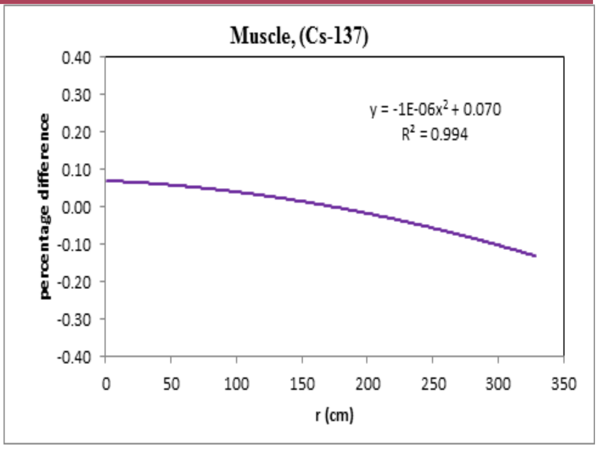

Figure 2: : The percentage difference between the dose around the Cs-137 in real and predicted muscle phantoms.

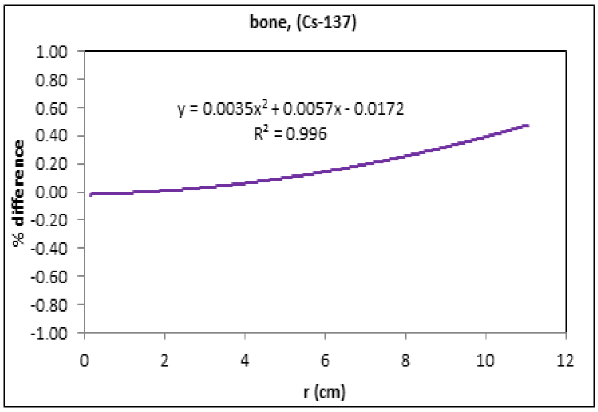

Figure 3: : The percentage difference between the dose around the Cs-137 in real and predicted bone phantoms.

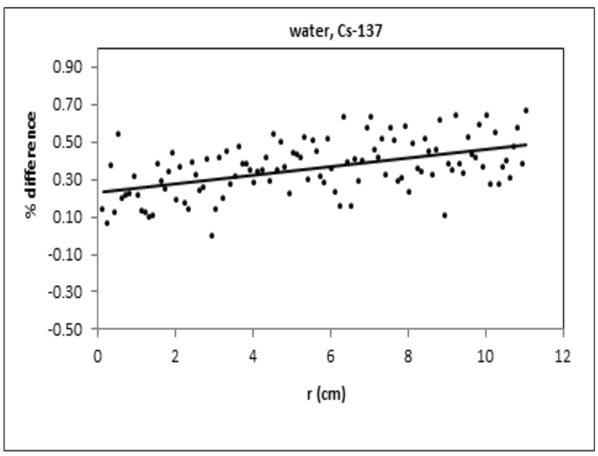

Figure 4: : The percentage difference between the dose around the Cs-137 in real and predicted water phantoms.

Table 2: : Minimum, maximum, and average percentage dose difference in real phantoms and predicted ones for Cs-137 brachytherapy source.

	Minimum	Maximum	Average
bone	0.1621%	0.4523%	0.0009%
water	0.3588%	0.6646%	0.0025%
muscle	0.1400%	0.5086%	0.0006%

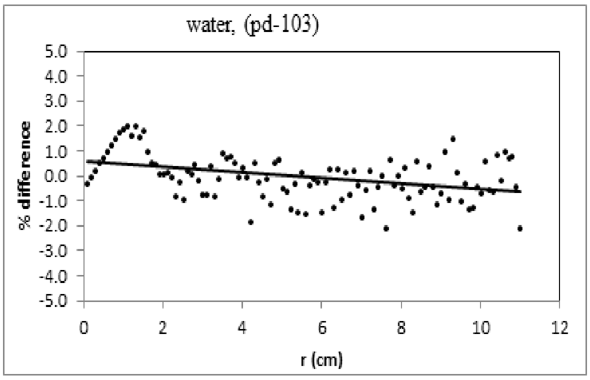

Figure 5: : The percentage difference between the dose around the Pd-103 in real and predicted muscle phantoms.

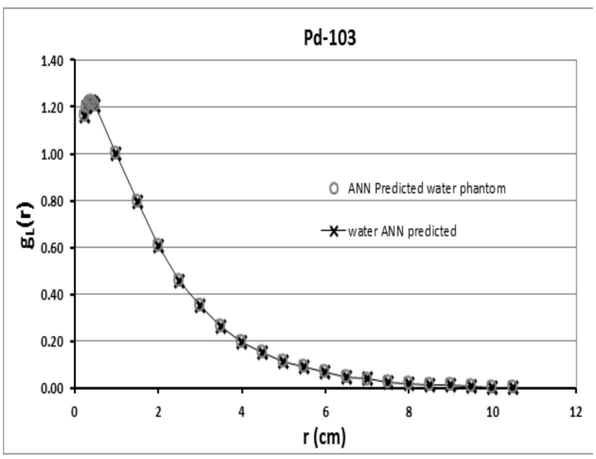

Figure 6: : Comparison of Radial dose function ($g_L(r)$) of Pd-103 brachytherapy source in real and predicted water phantom.

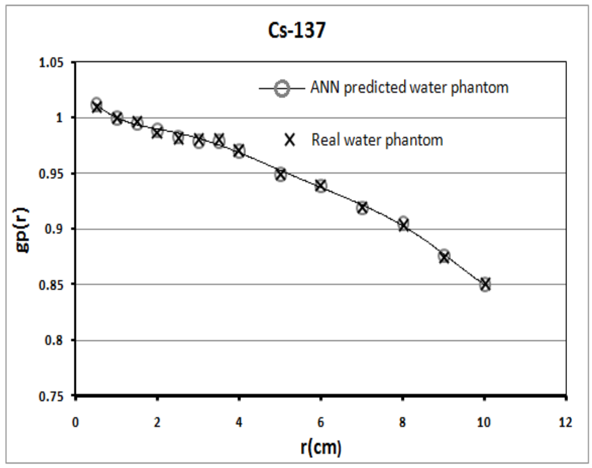

Figure 7: :Comparison of Radial dose function ($g_P(r)$) of a single Cs-137 pellet source in real and predicted water phantom

Conclusion

The applicability of artificial Neural Network for extracting the tissue properties, i.e. density, and composition, is studied in this investigation. For this purpose, the atomic composition, density and CT number of several tissues were used for training the ANN using the ANN toolbox of MATLAB. The trained network was then used for extracting tissue information from the CT numbers. The results of this study indicate that the Artificial Neural Network trained in this study can accurately predict the mass and electron density and material composition of this phantom.

To verify the accuracy of ANN predictions, the MC calculated dose distribution inside real water, bone, and muscle phantoms is compared by the dose distribution in ANN predicted water phantom. The results of MC simulations show that ANN are applicable in determination of tissue parameters from the CT images data and the material properties obtained by this method can be used for material definition in Monte Carlo simulations.

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