

ADJUSTMENT AND PREDICTION OF X-RAY MACHINE FACTORS BASED ON NEURAL ARTIFICIAL INTELLIGENCE

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Since the discovery of X-rays, their use in examination has become an integral part of medical diagnostic radiology. The use of X-rays is harmful to human beings but recent technological advances and regulatory constraints have made the medical X-rays much safer than they were at the beginning of the 20th century. However, the potential benefits of the engineered safety features can not be fully realized unless the operators are aware of these safety features. The aim of this work is to adjust and predict X-ray machine factors (current and voltage) using neural artificial network in order to obtain effective dose within the range of dose limitation system and assure radiological safety.

INTRODUCTION

The first X-ray device was discovered accidentally by the German scientist Wilhelm Roentgen (1845-1923) in 1895. He found that a cathode-ray tube emitted invisible rays that could penetrate paper and wood. The rays caused a screen of fluorescent material several yards away to glow. Roentgen used his device to examine the bone structure of the human hand. This machine was really just a modified cathode-ray tube. True X-ray machines were not invented for several years.

Upon their discovery in 1895, X-rays were advertised as the new scientific wonder and were seized upon by entertainers. Circus patrons could view their own skeletons and were given pictures of their own bony hands wearing silhouetted jewelry. Many people were fascinated by this discovery.

The most important application of X-rays has been its use in medicine. This importance was recognized almost immediately after Roentgen's findings were

published in 1895. Within weeks of its first demonstration, an X-ray machine was used in America to diagnose bone fractures.

X-rays are waves of electromagnetic energy. They behave in much the same way as light rays, but at much shorter wavelengths. When directed at a target, X-rays can often pass through the substance uninterrupted, especially when it is of low density. Higher density targets (like the human body) will reflect or absorb the X-rays. They do this because there is less space between the atoms for the short waves to pass through. Thus, an X-ray image shows dark areas where the rays traveled completely through the target (such as with flesh). It shows light areas where the rays were blocked by dense material (such as bone) [1].

In this paper, an artificial Neural Network has been applied to adjust the X-Ray machine, instead of technician experience, in order to obtain effective dose within the range of dose limitation system and assure radiological safety.

MODERN X-RAY MACHINES

Modern medical X-ray machines have been grouped into two categories: those that generate "hard" X-rays and those that generate "soft" X-rays. Soft X-rays are the kind used to photograph bones and internal organs. They operate at a relatively low frequency and, unless they are repeated too often, cause little damage to tissues.

Hard X-rays are very high frequency rays. They are designed to destroy the molecules within specific cells, thus destroying tissue. Hard X-rays are used in radiotherapy, a treatment for cancer. The high voltage necessary to generate hard X-rays is usually produced using cyclotrons or synchrotrons. These machines are variations of particle accelerators [2].

ARTIFICIAL NEURON MODELS

Computational neurobiologists have constructed very elaborate computer models of neurons in order to run detailed simulations of particular circuits in the brain. As Computer Scientists, we are more interested in the general properties of neural networks, independent of how they are actually "implemented" in the brain. This means that we can use much simpler, abstract "neurons", which (hopefully) capture the essence of neural computation even if they leave out much of the details of how biological neurons work.

People have implemented model neurons in hardware as electronic circuits, often integrated on VLSI chips. Remember though that computers run much faster than brains - we can therefore run fairly large networks of simple model neurons as

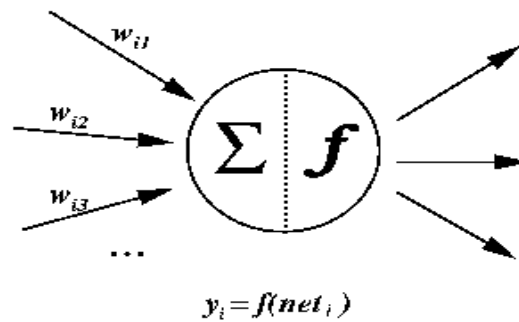
software simulations in reasonable time. This has obvious advantages over having to use special "neural" computer hardware [3] and [5]

Simple Artificial Neuron

Basic computational element (model neuron) is often called a **node** or **unit**. It receives input from some other units, or perhaps from an external source. Each input has an associated **weight** w , which can be modified so as to model synaptic learning. The unit computes some function f of the weighted sum of its inputs:

$$y_i = f\left(\sum_j w_{ij} y_j\right)$$

Its output, in turn, can serve as input to other units.



- The weighted sum

$$\sum_j w_{ij} y_j$$

is called the **net input** to unit i , often written net_i .

Note that w_{ij} refers to the weight from unit j to unit i (not the other way around).

- The function f is the unit's **activation function**. In the simplest case, f is the identity function, and the unit's output is just its net input. This is called a **linear unit** [3].

Biological Neural Network

The biological neural network serves as a natural engineering example of a working, intelligent information processor. As a result of millions of years of evolution, the brain has evolved into a compact, optimum package of computing power capable of dealing with the myriad situations that it can run into. The power of the biological brain lies both in its unsurmountable flexibility and massive parallelism.

A neuron is the fundamental unit of a biological neural network. A neuron is made up of a nucleus, a cell body (soma), dendrites and an axon. The cell body and the enclosed nucleus do not play a significant role in the processing of incoming and outgoing data. Rather, the cell body is a place for the mechanisms that provide the cell its energy and cause the activation of the cell. Dendrites receive the signals from other neurons. The axon transmits the signal to other neurons. At the junction of the signal-sending axon and the signal-receiving dendrite lies a small gap called a synapse.

As the neurons learn to react to certain signals, the synaptic connections between neurons either get stronger or weaker. The strength of the synaptic connection determines how strong the receiving neuron finds the signal. The signals from different neurons are thus weighted differently based on the strength of the synaptic connections. If the total effect of all the received signals is adequate, the neuron is activated and it will begin to send a signal to the other neurons via its axon.

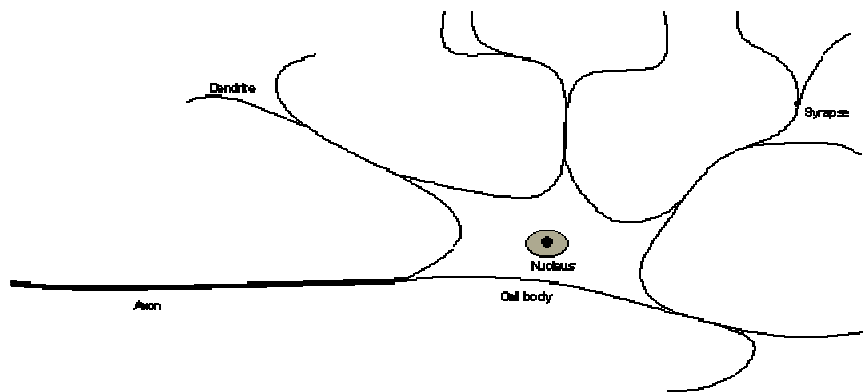


Figure 1. Biological neuron

Neurons that are connected with each other with synaptic connections constitute a biological neural network. The human brain consists of about 100 billion interconnected neurons. A single neuron has 1000 to 10,000 connections with other neurons [4].

Artificial Neural Networks

An artificial neural network (ANN) is either a hardware implementation or a computer program which strives to simulate the information processing capabilities of its biological exemplar. ANNs are typically composed of a great number of interconnected artificial neurons. The artificial neurons are simplified models of their biological counterparts.

The typical characteristics of ANNs differ very much from what is normally expected of a computer. These new properties include adaptive learning, self-organization, error tolerance, real-time operation and parallel information processing.

Learning in the context of ANNs means, that the network can adopt different behavior on the basis of the data that is given to the network. Unlike telling the network how to react to each data vector separately, as would be the case in the conventional programming, the network itself is able to find properties from the presented data. The network learning can be continued as new data becomes available. Learning is thus adaptive.

As data is given to the ANN, it organizes its structure to reflect the properties of the given data. In most ANN models, the term self-organization refers to the determination of the connection strengths between neurons. The way the internal structure of an ANN is altered is determined by the used learning algorithm. Several distinct neural network models can be distinguished both from their internal architecture and from the learning algorithms that they use.

Error tolerance is an important aspect of an ANN. It refers to the network's ability to model the essential features of the given data. In other words, an ANN is capable of finding a generalization for the data. This powerful characteristic makes it possible to process new, imperfect and distorted data with neural networks.

Due to the parallel nature of the information processing in ANNs, real-time operation becomes possible. Basically, three entities characterize an ANN:

1. The network topology, or interconnection of neural 'units'
2. The characteristics of individual units or artificial neurons
3. The strategy for pattern learning or training [4] and [6]

STRUCTURE OF THE ANN

The artificial neural networks can be classified according to the structure that they exhibit. Figure 2 represents four commonly used neural network structures.

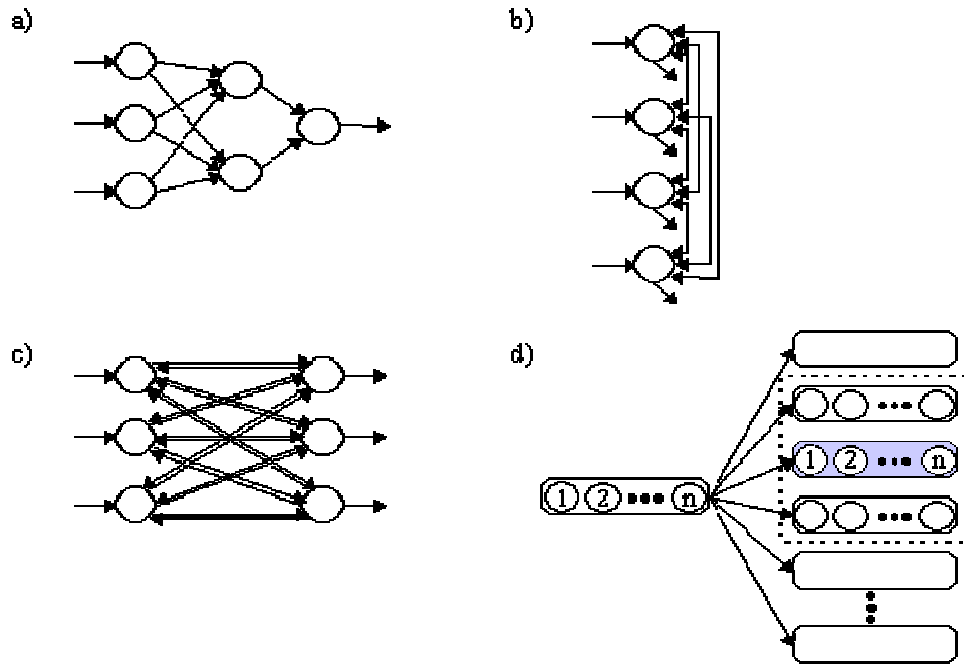


Figure 2. Different ANN structures. a) Multi-layered feed-forward network, b) single-layered fully connected network and c) two-layered feed-forward/feed-backward network

Figure 2. a) represents the structure of a multi-layered feed-forward network. The neurons in this ANN model are grouped in layers which are connected to the direction of the passing signal (from left to right in this case). There are no lateral connections within each layer and also no feed-backward connections within the network. The best-known ANN of this type is the perceptron network.

Figure 2. b) depicts a single-layered fully connected network model where each neuron is laterally connected to all neighbouring neurons in the layer. In this ANN model, all neurons are both input and output neurons. The best-known ANN of this type is the Hopfield network.

Figure 2. c) demonstrates the connections in a two-layered feed-forward/ feed-backward network. The layers in this ANN model are connected to both directions. As a pattern is presented to the network, it 'resonates' a certain number of times between the layers before a response is received from the output layer. The best-known ANN of this type is the Adaptive Resonance Theory (ART) network. [4] and [6]

RESULTS AND DISCUSSIONS

An artificial neural network has been applied using back-propagation method. Neural networks with classical three layer structure have been used for predicting voltage and current needed for x-ray machine adjustment. In the first step, the training data includes weight, age, voltage and current for many people have been fed to the neural artificial intelligence program. In the second step, the input data includes weight, age and the program must predict the voltage and current regarding the weight and age for each person.

Table 1. The data of chest X-ray after simulation with the developed programme regarding current.

Age	Weight (kg)	Current (mA)	
		Data Collected For Chest	Program Prediction
0.55	6	0.05	0.0491
5	15	0.06	0.0598
5.5	17	0.06	0.0627
7	20	0.07	0.0685
8	30	0.07	0.0692
12	31	0.05	0.0504
0.8	8	0.06	0.0597
5.5	15	0.06	0.0586
6	19	0.05	0.0587
7.5	22	0.07	0.0688
9	29	0.07	0.0693
11	31	0.06	0.0608

P value is 0.87915 (> 0.05) with no significance difference.

The input data for chest X-ray including age and weight for different persons have been fed to the neural network. The neural network has predicted the machine adjustment (mA) as illustrated in table 1 for chest X-ray and table 3 for abdomen X-ray. Also neural network has predicted the machine adjustment (kV) as illustrated in table 2 for chest X-ray and table 4 for abdomen x-ray. Comparing Neural network

prediction for X-ray machine adjustment (mA) and (kV) for chest X-ray with the data collected for different person it has been found that there is no difference as shown in figure 3 and 4 for chest X-ray and figure 5 and 6 for abdomen X-ray. The results given by neural artificial intelligence program can be used to adjust the machine for better performance even with the lack of operator experience.

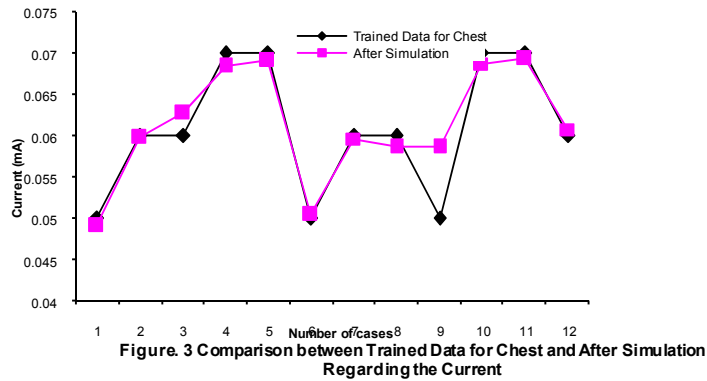


Table 2. The data of chest X-Ray after simulation with the developed program regarding voltage.

Age	Weight (kg)	Voltage (kV)	
		Data Collected for Chest	After Simulation
0.55	6	50	49.9177
5	15	50	50.7843
5.5	17	52	51.1368
7	20	52	52.1474
8	30	55	55.386
12	31	58	57.9825
0.8	8	51	51.1087
5.5	15	50	50.2453
6	19	51	51.1462
7.5	22	53	52.8476
9	29	55	55.1821
11	31	57	57.2553

P value is 0.934475 (> 0.05) with no significance difference.

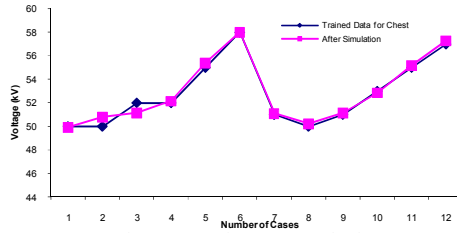


Figure.4 Comparison of Trained Data for Chest and Data After Simulation Regarding the Voltage

Table 3. The data of abdomen X-Ray after simulation with the developed program regarding current.

Age	Weight (kg)	Current (mA)	
		Data Collected for Abdomin	After Simulation
1	9	0.07	0.0426
1	10	0.07	0.1117
2	11	0.15	0.1808
7	15	0.3	0.2361
10	45	0.3	0.319
2	13	0.06	0.0628
0.8	8	0.2	0.2763
3	15	0.15	0.1652
5	19	0.25	0.2449
7.5	22	0.3	0.3021

P value is 0.807313 (> 0.05) with no significance difference

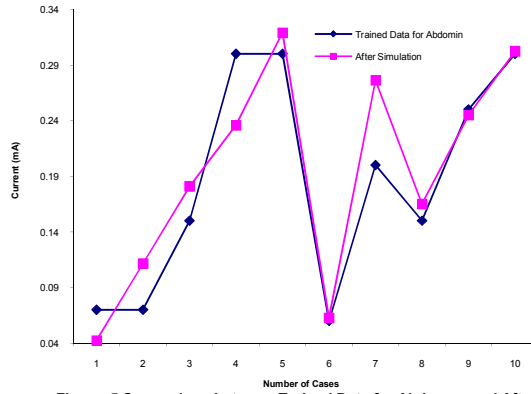


Figure. 5 Comparison between Trained Data for Abdomin and After Simulation Regarding the Current

Table 4. The data of abdomen X-Ray after simulation with the developed program regarding voltage.

Age	Weight (kg)	Voltage (kV)	
		Data Collected for Abdomin	After Simulation
1	9	50	50.0004
1	10	55	54.9994
2	11	60	59.9995
7	15	64	64.0008
10	45	70	69.9997
2	13	61	61.2217
0.8	8	66	65.9892
3	15	71	70.9992
5	19	53	53.0003
7.5	22	55	54.9988

P value is 0.994914 (> 0.05) with no significance difference

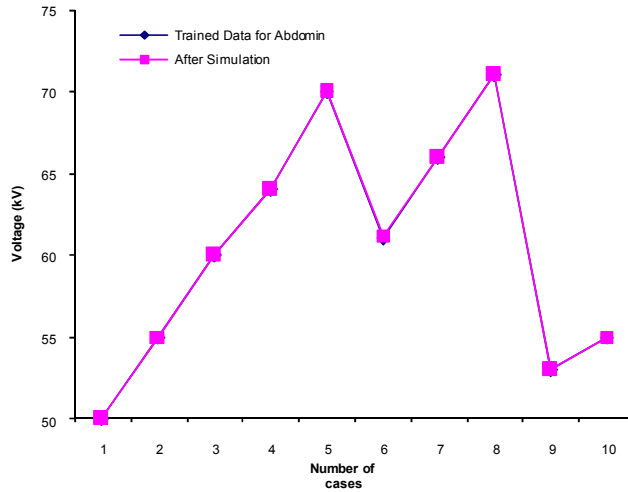


Figure.6 Comparison of Trained Data for Abdomen and Data After Simulation Regarding the Voltage

The developed program has shown a very high degree of accuracy and it adjusts and predicts the x-ray machine factors which could prevent human errors.

CONCLUSION

The artificial neural network technique has proved its efficiency in adjusting the X-ray machine to give the effective dose limitation for chest and abdomen. The applied program showed that the value of the calculated P is >0.05 . This value indicates that the trained data of chest and abdomen are in good agreement with that after simulation and assumes the radiological safety.

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ضبط و التنبؤ بعوامل جهاز الأشعة السينية باستخدام الذكاء الاصطناعي العصبي

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المركز القومي للأمان النووي و الرقابة الإشعاعية - هيئة الطاقة الذرية - مصر

منذ إكتشاف أشعة إكس يعد إستخدامها في الفحص عاملاً أساسياً للأشعة التشخيصية الطبية. وعلى الرغم من أن إستخدام أشعة إكس ضار بالإنسان إلا أن التكنولوجيا الحديثة والتنظيمات المشددة جعلت من الإستخدام الطبي لأشعة إكس أكثر أماناً مما كانت عليه في بداية القرن العشرين. مع ذلك فإن التأثيرات الأولية لمظاهر الأمان الهندسي لا يمكن إستيفاؤها إلا إذا كان المشغل على وعي بهذه المظاهر. يهدف هذا البحث لضبط وتوقع عوامل تشغيل جهاز أشعة إكس (التيار و الفولت) بإستخدام الذكاء الاصطناعي الشبكي للحصول على جرعة فعالة ضمن حدود نظام الجرعات و تحقيق الأمان الإشعاعي.