Application of artificial neural network in non-destructive Compton scattering densitometry

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ABSTRACT

This study investigates the use of artificial neural networks (ANN) in Compton scattering densitometry. Samples with different densities were irradiated by gamma rays and the spectra of photons, scattered at 90°, were recorded by a NaI scintillator. These data were used to train the network and to validate its performance. After various training functions with different structures of layers were examined, by comparing the ANN predicted results with the experimental ones, the best algorithm was adopted for the ANN.

1. Introduction

Nondestructive testing (NDT) is a technique used to probe and sense material structure and properties without causing damage. It has a significant role in the modern industrial processes for evaluation and testing, reducing downtime and enhancing safety and productivity. Various types of NDT techniques have been developed [1–3]. Among the many available techniques, those based on gamma-ray radiation appear to be attractive in many applications, because they are most nondestructive and highly reliable. The density distribution of an unknown sample can be determined by detecting either transmitted or scattered gamma rays. Comparing the Compton scattering technique with the conventional transmission densitometry, the scattering technique has some advantages. First, the access to the sample from opposing sides is not needed and scanning of bulky materials and objects becomes possible. Second, this technique has greater sensitivity to density variations for low density materials [4]. Furthermore, we can obtain direct three-dimensional density images by using this technique [5].

To determine the electron density distribution from the measured energy spectrum of the scattered gamma-rays, several methods have been proposed in the literature. For example, Norton has proposed an analytical formula [6] and Arendtsz [7] has used an iteration method to process the experimental gamma spectra. In this work, we used an algorithm which is based on artificial neural networks (ANN). The neural network is a mathematical model inspired by the human brain which has the capacity to learn from a finite set of information. The ANN algorithm has the advantage of rapid density recognition when an appropriate primary training of the network is performed [8].

2. Material and method

2.1. Compton scattering densitometry

The Compton effect is one of the main processes by which energetic photons interact with matter. It refers to the scattering of photons by electrons when the binding energy of the electrons is much lower than the energy of incident photons. In such collisions, the photon loses an amount of energy that depends on the incident photon energy, $E_0$, and scattering angle, $\Theta$. The energy of the scattered gamma ray, $E$, is given by

$$E = \frac{E_0}{1 + \frac{E_0}{m_0c^2}(1 - \cos \Theta)}$$

(1)

where $m_0c^2$ is the rest-mass energy of electron. The angular distribution of the scattered gamma rays is predicted by the Klein–Nishina formula for differential scattering cross-section $d\sigma/d\Omega$ [9]:

$$\frac{d\sigma(E, \Theta)}{d\Omega} = \frac{r_0^2}{2} \left[ \frac{E}{E_0} \right]^2 \left[ \frac{E}{E_0} + E_0 - \sin^2 \Theta \right]$$

(2)

with $r_0$ as the classical electron radius. Using these relations, the intensity of photons reaching the detector after being scattered in
the target is given by

\[ I = I_0 N_A \rho Z/A \exp(-\mu_2 l_2) \frac{d\sigma(E, \theta_1)}{d\Omega} \exp(-\mu_1 l_1) \, dV \, d\Omega. \]  \hspace{1cm} (3)

Here \( I_0 \) is the incident photon flux with energy \( E_0 \), \( N_A \) is Avogadro’s number, \( \rho \) is the mass density and \( Z/A \) is the ratio of atomic number to the atomic mass of target material. The quantities \( \mu_1 \) and \( \mu_2 \) are the total attenuation coefficients (in \( \text{cm}^{-1} \)) of the target at energies \( E_0 \) and \( E \), respectively. \( l_1 \) and \( l_2 \) are lengths of the paths of the photons in the sample from the source to the scattering center and back to the detector, respectively. \( d\Omega \) is the element of solid angle in the direction of the detector and \( dV \) is the differential volume considered for the radiation and its interaction with the matter \([10]\).

For a fixed value of incident and scattered photon energies, the energy dependent terms in Eq. (3) will be constant and the number of counts recorded in the detector will be directly related to the mass density of the examined material. Therefore, it is practically possible to determine the local electron density of the target by designing proper collimators and recording the energy spectrum of the scattered photons.

2.2. Experimental setup

In this work, a point source of \(^{137}\text{Cs}\) (gamma ray energy: 662 keV, strength: 5 mCi) with stainless-steel cylindrical encapsulation has been employed. The thickness of the capsule is sufficient to absorb all the beta particles and 32 keV K X-rays emitted due to internal conversion processes. For mc2-range sources, the solid angle subtended by the detector at the inspection point must be kept large in order to increase the geometrical detection efficiency, and consequently to minimize the statistical error of the measurement. But, the solid angle should be increased in such a way that it does not allow the energy dispersion of the scattered photons (i.e. the variation in the scattering angle \( \Delta\theta \) must be kept sufficiently small). All these conditions can be achieved by using a specially designed rectangular collimator in front of the detector. The collimator consists of two identical rectangular lead bricks each of dimensions of 100 mm \( \times \) 50 mm \( \times \) 2 mm. The 5 mm spacing between the bricks forms a window of 5 mm width and 100 mm height and 2 mm depth along the direction of gamma ray arrival. This rectangular window eliminates all photons except those scattered almost at 90° with respect to the incident photons. An additional pinhole lead collimator, with a hole diameter of 5 mm, is used in front of the point source to restrict the original gamma rays to the inspection voxel inside the target. Both the voxel-source and the voxel-detector distances are fixed at 6 cm. The dimensions of the scattering voxel are defined by the incident beam diameter and the detector’s slit size. In this experiment the scattering voxel size is about 100 mm\(^3\).

The gamma photons scattered from the target were detected by a 3 in. \( \times \) 3 in. NaI (TI) scintillation detector placed at a scattering angle of 90°. The detector was properly shielded with lead to minimize the background radiation. The geometry and shielding arrangement of the experimental setup is shown in Fig. 1. Energy spectra of the scattered photons were recorded by a PC-based ATOMTEX Multi Channel Analyzer (MCA), and were used as the input to the artificial neural network (ANN) analysis.

2.3. Artificial neural network

Artificial neural network (ANN) is a programming method based on brain emulation, and is used extensively in the artificial intelligence problems from simple pattern-recognition tasks to advanced symbolic manipulation \([11–14]\). The ANN operates in two phases: (i) the training phase in which, by modeling use of a training algorithm, the ANN is supposed to learn features (behavior, patterns, etc.) from a given set of examples (the training set) and (ii) the working phase in which the trained ANN is used to respond to new (real-world) situations. In the first phase, to train the network, available data should be divided into three subsets. The first subset is the training set, which is used to train the network. The second subset is the validation set, which is used to estimate the possible errors during the training process. The third subset is the testing data set, which is only used to obtain the overall accuracy of the network and to compare the performance of various network structures. In order to understand whether the ANN is making a reasonable prediction, the test data, which has not been previously presented to the network, is used and results are checked carefully.

Different statistical methods have been used to make comparisons between values predicted by the ANN (output) and measured ones (target). The mean square error (MSE) gives the dispersion of the experimental data and is defined as \([15,16]\)

\[ \text{MSE} = \frac{1}{n} \sum_{i=1}^{n} (t_i - o_i)^2. \]  \hspace{1cm} (4)

Also the mean percentage error is defined as

\[ \text{MPE} = \frac{1}{n} \sum_{i=1}^{n} \left( \frac{t_i - o_i}{t_i} \right) \times 100, \]  \hspace{1cm} (5)

and the absolute fraction of variance, a statistical indicator that can be applied to multiple regression analysis, is determined from

\[ R^2 = 1 - \frac{\sum_{i=1}^{n} (t_i - o_i)^2}{\sum_{i=1}^{n} (t_i - \bar{t})^2}. \]  \hspace{1cm} (6)

which ranges between 0 and 1. The values closer to 1 indicate a very good fit, while the values closer to 0 indicate a poor fit. In the above equations, \( t_i \) and \( o_i \) are the target and output values, respectively, and \( n \) is the number of samples.

3. Results and discussions

The energy spectra of the photons scattered from targets with different densities, which were recorded by a NaI scintillator, were used to train the neural network. The success of neural network modeling depends on the selection of the proper training function and the physical structure of the network. But there is no definite method to choose the appropriate training function and the optimal number of hidden layers. In this work, the network is trained with five training functions, namely BFG (quasi-Newton
back-propagation), CGB (conjugate gradient back-propagation with Powell–Beale restarts), CGP (conjugate gradient back-propagation with Polak–Ribière updates), LM (Levenberg–Marquardt back-propagation) and SCG (scaled conjugate gradient back-propagation); and the errors (MSE, $R^2$ and MPE) were compared [13]. Table 1 illustrates the behavior of the networks for different training functions and the number of hidden layers and neurons; here the $\text{tansig}$ transfer function was used for hidden layers and the $\text{purelin}$ transfer function was used for the output layer. The network’s input and output were taken to be the intensity of detected photons and the target density, respectively. Since we were interested in predicting only one quantity (density), in the output layer only one neuron has been used.

The computed results show that the Levenberg–Marquardt algorithm with three hidden layers (three neurons in the first layer, five neurons in the second layer and nine neurons in third layer) has provided the least errors. Moreover, it has higher stability and faster convergence rate than the other training algorithms. Therefore, it was selected for the ANN modeling.

Table 2 demonstrates the number of detected photons, real and predicted densities of the materials used in the training phase. Fig. 2 illustrates the MSE values of training, data validation and test processes for the Levenberg–Marquardt algorithm. From 15th iteration onward, where the final mean-square error is minimized ($\text{MSE} = 0.0009$), the most accurate and stable validation performance occurs. Therefore, the training was stopped after 15 iterations for the Levenberg–Marquardt algorithm. It can be seen from the figure that after 15 iterations the amount of the MSE parameter for test and train subsets is also small enough.

![Fig. 2. Training, validation and test mean squared errors for the Levenberg-Marquardt algorithm. The best MSE value of 0.0008754 for validation performance occurs at iteration 15.](image)

![Fig. 3. The experimental (real) density values of the samples vs the ANN predictions.](image)
After the training process had been finished, the next step was to compare the predicted values from the ANN model with the experimental values. Some new samples of different materials were prepared and the intensity of detected photons was recorded. Table 3 shows the predicted densities for these materials using the ANN method.

Accuracy of the ANN model was evaluated on the basis of the regression analysis between the predicted parameters and the experimental values. Fig. 5 shows a straight line indicating perfect prediction with 95% confidence bounds [16]. The ANN predicted parameters were compared with the experimental values and the MSE value of 0.0002 has been achieved.

\[
\begin{align*}
\rho^2 & = \frac{\sum_{i=1}^{n}(t_i - C_0)^2}{\sum_{i=1}^{n}(t_i - \bar{T})^2} \\
\end{align*}
\]

where \(\bar{T}\) is the mean value of target density. It ranges from 0 to 1 and the best predictions are obtained for \(\rho^2 = 1\) [17]. In this work, the value of \(\rho^2 = 0.9974\) clearly shows the validity of our approach.

### 4. Conclusions

We have shown that the ANN method is an attractive alternative to classical analytical and iterative techniques in Compton scattering densitometry. The neural network approach does not require a priori knowledge about the geometrical property or any initial guess on the density of the examined sample. Among different training functions, the Levenberg–Marquardt algorithm with three hidden layers showed a fast convergence rate with a small error.

### References


### Table 3

<table>
<thead>
<tr>
<th>Matter</th>
<th>Number of detected photons (in 5 min)</th>
<th>Density (ANN) (g/cm³)</th>
<th>Density (real) (g/cm³)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mg</td>
<td>10,712 (103)</td>
<td>1.77 (3)</td>
<td>1.73</td>
</tr>
<tr>
<td>S</td>
<td>12,263 (111)</td>
<td>2.04 (2)</td>
<td>2.06</td>
</tr>
<tr>
<td>Sc</td>
<td>15,792 (126)</td>
<td>3.09 (5)</td>
<td>2.91</td>
</tr>
<tr>
<td>Va</td>
<td>22,272 (149)</td>
<td>5.91 (11)</td>
<td>6.10</td>
</tr>
<tr>
<td>Cr</td>
<td>22,805 (151)</td>
<td>7.07 (23)</td>
<td>7.39</td>
</tr>
<tr>
<td>Fe</td>
<td>23,101 (152)</td>
<td>8.00 (18)</td>
<td>7.87</td>
</tr>
</tbody>
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