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Application of the artificial neural network for reconstructing the internal-structure image of a random medium by spatial characteristics of backscattered optical radiation

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***Abstract*. The feasibility of using an artificial neural network (ANN), which is the standard Matlab tool, for non-invasive (based on the data of backscattering) diagnostics of macro-inhomogeneities, localised at subsurface layers of the turbid strongly scattering medium was shown. The spatial and angle distribution of the backscattered optical radiation was calculated by using the Monte-Carlo method combining the modelling of effective optical paths and the use of statistical weights. It was shown that application of the backscattering method together with the ANN allows solving inverse problems for determining the average radius of the scattering particles and for reconstructing the images of structural elements within the medium with a high accuracy.**

Keywords: *artificial neural network, backscattering, Monte-Carlo method, optical tomography, multiple scattering.*

1. Introduction

Studies of the peculiarities of the optical radiation distribution within randomly-inhomogeneous highly scattering media, e.g. biotissues, are actively underway for recent decades [1, 2]. It has been shown that it is possible to reconstruct the images of macro-inhomogeneities embedded within the turbid strongly scattering media using the characteristics of scattered light [3]. A number of different methods of optical tomography (OT) based on the analysis of spatial and angle properties of scattered radiation has been proposed and developed [4]. The image in OT (known also as the inverse problem) can be reconstructed by using the diffusion approximation [5], the radiation transfer models [6, 7], statistical nonlinear algorithms [8], methods of average photon trajectories [9, 10], the method of finite elements [11], the Bayes method [12], the Monte-Carlo method [13] and others (see for details references in [4, 5]).

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Usually, the algorithms of image reconstruction are quite cumbersome, which leads to a considerable consumption of time and computer resources.

In the current paper we consider the feasibility of using the artificial neural network (ANN), which is the standard tool of Matlab, to visualise the macro-inhomogeneities in the near-surface area of a model medium.

2. Materials and methods

The ANN is of great interest for solving a number of different problems in optical diagnostics [14 – 17]. The ANN structure consists of a network of so-called artificial neurons (Figure 1), which are connected with each other with synapses [18]. The ultimate aim of the artificial neuron is to form a correct output signal depending on the input. The ANN changes itself by transforming the input signal in time and forms the required output parameters.

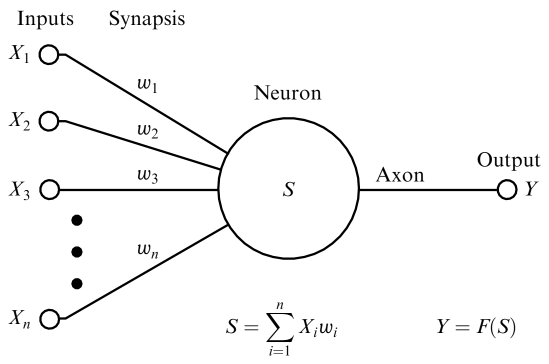

Figure 1. Schematic representation of the artificial neuron [18]: $X_1 - X_n$ – input parameters; $w_1 - w_n$ – weight coefficients; S – ANN activation function; Y – output.

The majority of ANNs require the process of multi-dimensional optimisation of parameters (e.g. 'network training'). There are different algorithms to implement this process [18]. While training, the ANN becomes tolerant to small variations in the inputs (e.g. noise, variations in inputs, etc.) and, consequently, produces a correct output. A trained ANN can be used then to solve analogous problems. Besides, the ANN is able to create an ideal output, i.e. the ability of abstracting [18], even if the inputs were corrupted.

In this paper, we used the Levenberg – Marquardt algorithm, which is ideal for networks with a small number of parameters and takes sufficiently short time to train an

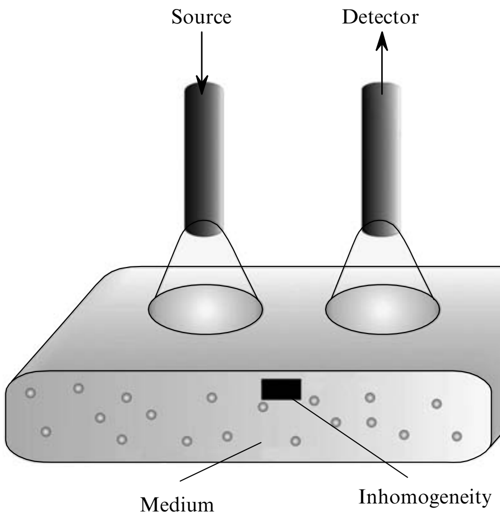

Figure 2. Scheme of the experimental setup. The medium surface is illuminated with a narrow beam of low-intensity continuous laser radiation, which is incident normally to the surface. Backscattered radiation is detected with a mobile fibre driven by a computer.

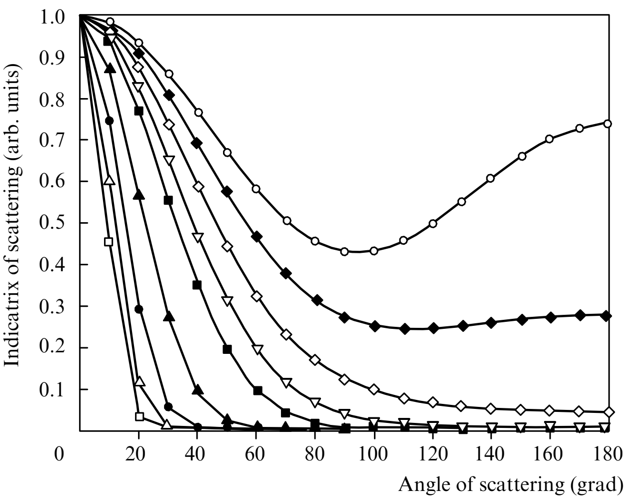

Figure 3. Indicatrix of scattering simulated according to the Mie theory for the scattering particles of diameter 0.15 (□), 0.25 (△), 0.35 (●), 0.45 (▲), 0.55 (■), 0.65 (▽), 0.75 (◇), 0.85 (◆) and 0.95 μm (○). Each curve corresponds to the input data of the ANN.

ANN. Optical parameters of the model medium were chosen in correspondence with typical parameters of biotissues [2, 19, 20]. The distribution of optical radiation within the medium and on its surface was simulated by using the Monte-Carlo method combining modelling of effective optical paths and the use of statistical weights [21, 22]. This algorithm, in the case of selecting the adequate parameters of the medium, makes it possible to imitate the detected signal with a high accuracy, taking into account the actual source – detector parameters used in the experiment.

The lay-out of the source and detector, which is realised in simulations, repeats the experiment schematically represented in Fig. 2. It is assumed that the local rectangular inhomogeneity with a high absorption coefficient $\mu_a = 4.5$ cm^{-1} within the medium significantly changes the spatial distribution of the backscattered radiation detected at the medium surface. The optical parameters of the medium are: the absorption coefficient $\mu_a = 0.7$ cm^{-1}, the scattering coefficient $\mu_s = 172$ cm^{-1}, the anisotropy factor $g = 0.95$, the refraction coefficient $n = 1.4$ [19]. The inhomogeneities with the size 3×3 and 2×4 mm are taken into account.

3. Results and discussion

To test the ANN algorithm we have used the scattering indicatrix calculated according to the Mie theory [23] for the scattering particles with a radius of 0.05 – 1 μm (Fig. 3) as the initial ANN training parameters to check the feasibility of the network for determining the average size of the scatterers. In this case, the ANN structure consisted of 30 neurons in the input layer and 2 neurons in the hidden layer. We have used three layers of neurons with the hyperbolic tangent activation function for the input and hidden layers and with the linear activation function for the output layer. The latter consisted of one neuron because of the uniqueness of the output paramter, i.e. the particle radius. The number of neurons in the layers was found experimentally for the case of a minimal error of ANN training and without overtraining.

The error of the ANN training calculated with the help of the regression analysis [18] significantly increases when the testing set comes outside the boundaries of the input data (Fig. 4), i.e. when the radius of particles is outside the

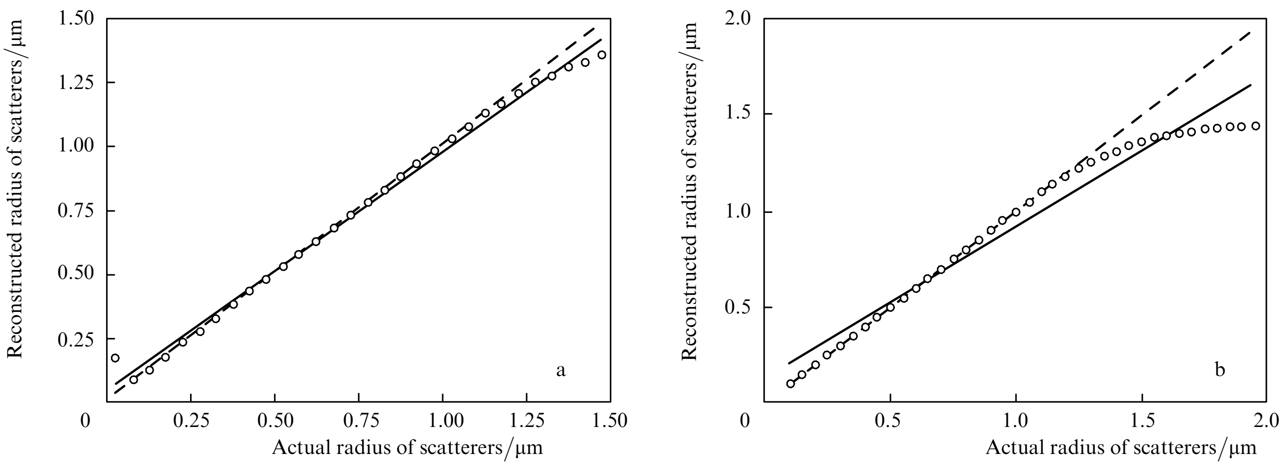

Figure 4. Regressional analysis of the comparison of the results of the ANN simulation (○) and actual size of scattering particles (- - -) used in the training set. The radius of scattering particles changes in the range 0.03 – 1.5 μm (a) and 0.1 – 2 μm (b) with a step of 0.05 μm. The solid line shows the linear interpolation of the distribution of particles' dimensions restored with the ANN.

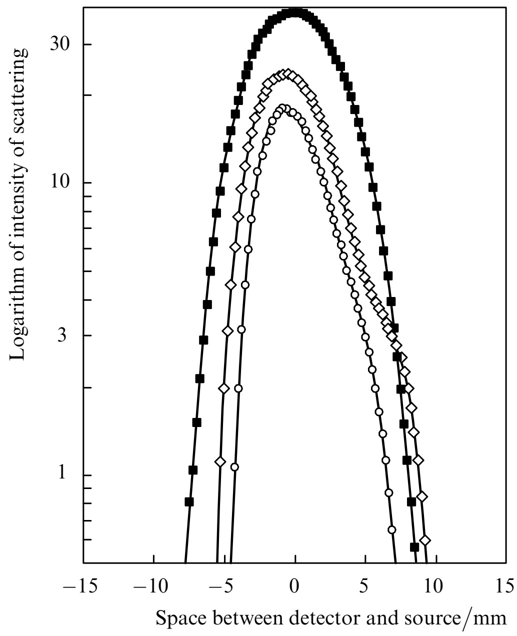

Figure 5. Intensity distribution of backscattered radiation on the surface of the medium in the absence of the inhomogeneity (■) and in the presence of the 3 × 3-mm absorbing inhomogeneity located at a depth 3 mm (○) and the 2 × 4-mm absorbing inhomogeneity located at a depth 5 mm (◇).

range 0.05 – 1 μm and the regression coefficient R decreases from 0.9 to 0.7. Thus, based on the scattering indicatrix, the ANN can be used to restore the dimensions of scattering particles but only within the limits of slight variations in the input set. Otherwise, the reliability of the obtained results will significantly decrease. To avoid the above mentioned limitation more training parameters should be used. Note that the particles with a radius less than 0.2 μm have the scattering indicatrix similar to the Rayleigh one; their characteristics are poorly determined by the angle dependence. To determine the size of the particles with a radius larger than 1 μm, it is useful to apply a small-angle scattering indicatrix.

We have used the Monte-Carlo method to simulate the spatial/angle distribution of backscattered radiation on the surface of the medium and to create training parameters for ANN in the case of strong anisotropy scattering which is typical for the majority of biotissues [21, 22]. The influence of the inhomogeneity on the intensity distribution of backscattered light was considered. Figure 5 presents the results of simulations of the spatial/angle distribution of radiation on the medium surface for different localisation and dimensions of the inhomogeneity and in its absence. The absorbing inhomogeneity is located at the depths 3 or 5 mm. It is assumed that the model imitates the structure of the biotissue in the case of a normal tissue and abnormal changes, e.g. the tumour [19, 20]. We have used the

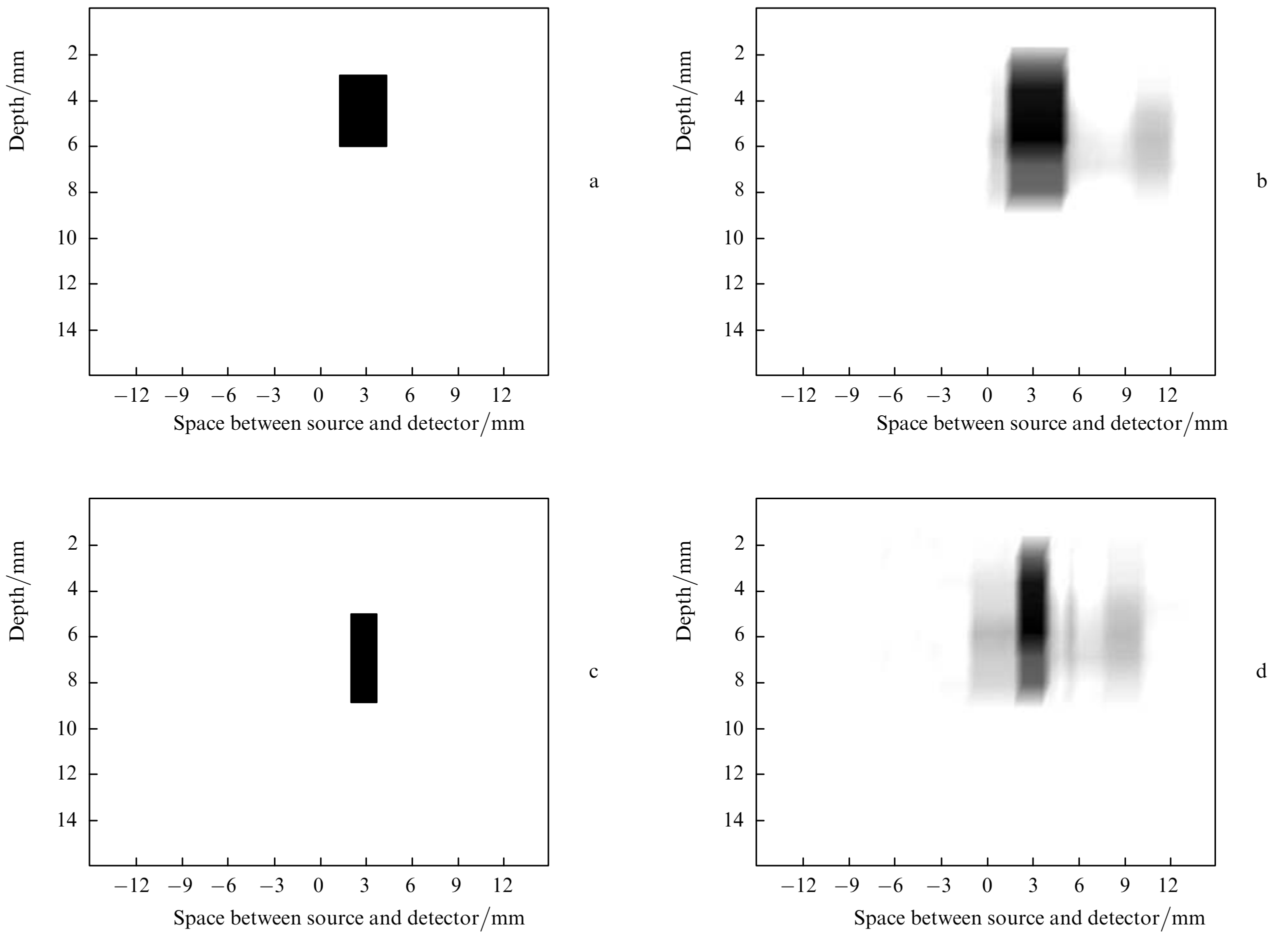

Figure 6. The actual and ANN reconstructed images of absorbing inhomogeneities with dimensions 3 × 3 mm localised at a depth 3 mm (a), (b), and 2 × 4 mm at a depth 5 mm (c), (d).

ANN with 20 neurons in the input layer, 5 in the hidden and 16 in the output layer to restore the image of the absorbing inhomogeneity. The differences in the structure between this network and the one we have previously used are determined by changes in the amount of inputs and outputs. The image of the inhomogeneity has been reconstructed by using 16 localisation points of the detector on the surface, which suggests the use of 16 neurons in the output layer. We have used 30 training sets for rectangular inhomogeneities.

The results of image reconstruction of the absorbing inhomogeneity located at different depths within the model medium are presented in Fig. 6. The tints of grey show the probability of the inhomogeneity localisation in the current position. The uniform colour of the background is the consequence of the ANN error. The network restores adequately the image of the inhomogeneity located near the surface with the upper boundary at the depth of 3 mm (Figs 6a, b), the regression coefficient R being 0.8. The output error becomes higher with increasing the depth of the inhomogeneity position down to 5 mm (Fig. 6c). The restored image becomes blurry (see Fig. 6d) and the regression coefficient R is 0.65.

4. Conclusions

The potential possibilities of using the ANN as a standard Matlab tool for the image reconstruction of absorbing inhomogeneities by the model of random scattering medium have been considered. It has been shown that the employment of the method of backscattering together with the ANN makes it possible to solve adequately the inverse problems such as the determination of the average size of scattering particles and the reconstruction of images of the structural inhomogeneities within the medium.

The potential application of the presented technique is non-invasive image reconstruction of the structural elements in healthy and abnormal biotissues and monitoring the extraneous inclusions localised within subsurface layers of biotissues. In addition, the current problem is especially urgent because of application of nanoparticles for neoplasm labelling in diagnostics/treatment of oncological diseases in order to enhance the contrast of the area of neoplasm localisation. Further development of the proposed technique will include implementation of polarisation effects of probe radiation.

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