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Neural network for reconstruction of signal from distributed measuring system of optical amplitude sensors

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A computer model of the feed-forward neural network with the hidden layer is developed to reconstruct physical field investigated by the fiber-optic measuring system of amplitude sensors. Neural network is learned by error back-propagation using the conjugate gradient minimization of deviation. Learned neural network reconstructs the two-dimensional scalar physical field with distribution having one or two Gaussian peaks.

Keywords: *Neural networks, optical tomography, fiber-optic measuring systems*

INTRODUCTION

Problems of control of the solid body destruction frequently occur in industry, engineering, geophysics. The fiber-optic measuring networks can be utilized for data acquisition [1–3]. However the information obtained by such the network requires the reconstruction. This needs solution of the inverse Radon transformation by using of numerical methods (linear back-projection, filtered back-projection, algebraic reconstruction technique). But such the approaches suffer from drawbacks. One of them is complicated solid body surface shape which frequently occurred in practice cannot be described by using of simple models. Another demerit is impossibility of creation of the ideal measuring network because its sensors have various sensibilities, the distance between sensors can vary and so on. Moreover the classical methods usually require large computer consumption and cannot be executed in real time.

The complex constructions are widely used in industry and engineering. The buildings, levees, ships having the composite structure and shape require the state control since damage resulted by their destruction is large. Traditional methods of monitoring all the times are not suitable for solving of such the problems. So the neural network can be utilized for processing of the information from the measuring network. The neural network can be learned and adapted for specific conditions.

SIGNAL RECONSTRUCTION BY NEURAL NETWORK

The modeled measuring network consist of the optical amplitude sensors located along the fiber-optic line. The attenuation of the transmitted light intensity is proportional to the physical action value. Moreover the sensibility of each modeled sensor has randomly generated weight r_l in range 0.5–1. The sensors are located in the surface by triplets near line intersections forming the square $n \times n$ lattice (see Fig. 1). The fiber-optic lines are aligned with three directions. The detected and amplified signal feeds through analog-digital converter into the computer where the information is processed by neural network.

For solving of tomographic problem we choose perceptron with the non-linear hidden layer since this network has universal approximation capability [4,5] and can perform inverse Radon transformation.

The neurons of the first layer serve as network inputs and feed data from the measuring system to the next layer (see Fig. 2). Each neuron of input layer corresponds to the certain measuring line and output potential of this neuron x_k is proportional to intensity of detected light. The second (hidden) layer proceeds following transformation:

$$s_j = \tanh\left(\sum_k \overline{w}_{jk} x_k\right), \tag{1}$$

where x_k are states of neuron inputs being signals from measuring sensors, s_j are states of outputs and $\overline{w}_{jk}$ are synapses. The hidden layer of neurons has $4n-1$ inputs and $n \times n$ outputs.

The output layer of the neurons takes the linear transformation:

$$y_i = \sum_j w_{ij} s_j \ , \tag{2}$$

where y_i are states of third layer neuron outputs, w_{ij} are synapses of third layer.

The accuracy of the signal reconstruction is determined by the neural network training error (object func-

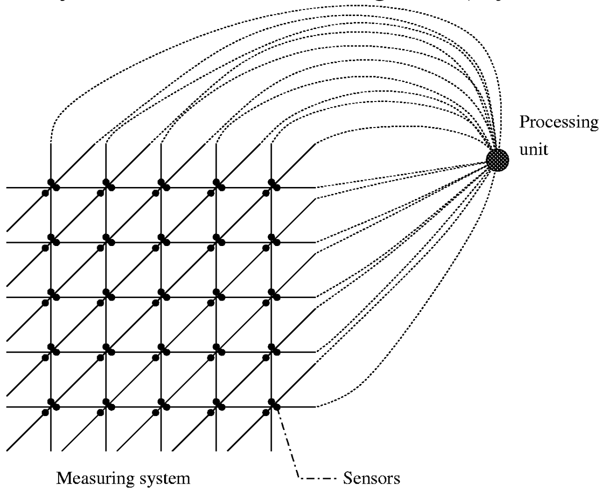

Fig. 1. The 5×5 fiber-optic distributed measuring system.

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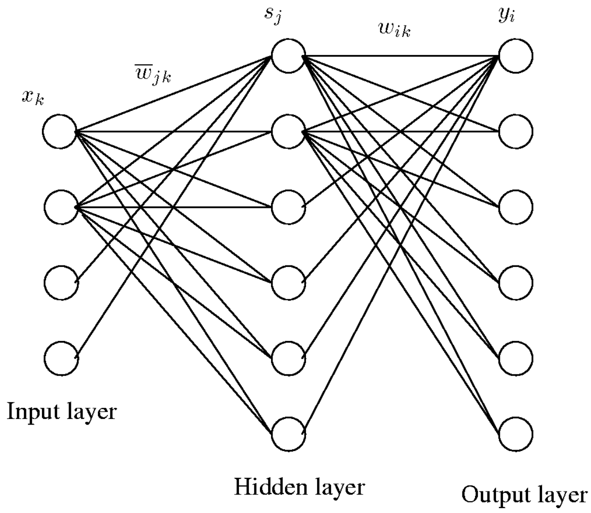


Fig. 2. Schematic diagram of three layered neural network.

tion). The following expression was used as object function:

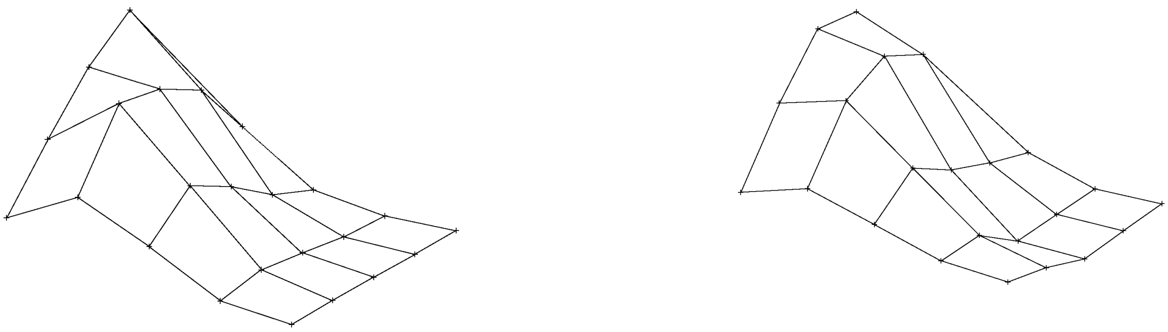
$$D = \frac{1}{2}\sum_{\mu,i}\left(y_i^{\mu} - \tilde{y}_i^{\mu}\right)^2 , \qquad (3)$$

where μ is superscript indicating number of learning pattern, $\tilde{y}_i$ are output states of the neural network for some learning pattern. We selected Gaussian distributions of the some physical quantity with one or two peaks as learning patterns, $\tilde{y}_i^{\mu}$ were calculated from these distributions. The number of training patterns was 1000. For each training pattern $\tilde{x}_i^{\mu}$ are formed as products of $\tilde{y}_i^{\mu}$ along the corresponding measuring line: $\tilde{x}_i^{\mu} = \prod_l r_l \tilde{y}_l^{\mu}$. In Eq. 3 y_i are calculated using expression:

$$y_i = \sum_j w_{ij} \tanh\left(\sum_k \overline{w}_{jk} \tilde{x}_k^{\mu}\right).$$

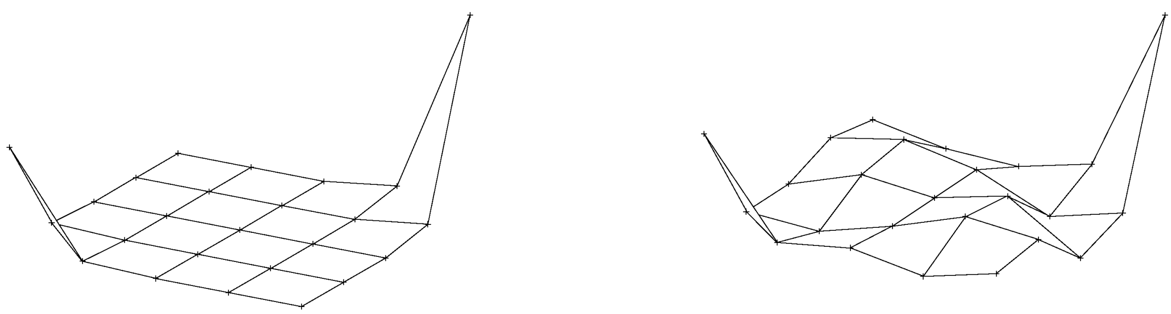
We used error back-propagation for the network training, so we had to minimize D with respect to $\overline{w}_{jk}$, w_{ij}. We utilized conjugate gradient method for minimization of the object function. Also we applied the annealing technique to avoid local minima of D. The minimization procedure finished after certain iteration count or on given accuracy reaching.

Examples of initially unknown reconstructed by the



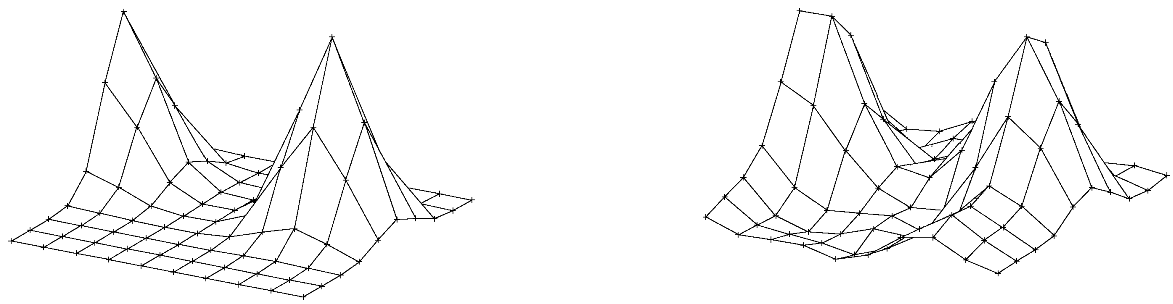
(a) (b)

Fig. 3. The original (a) and reconstructed by the neural network (b) smooth distributions of physical field with $n = 5$.



(a) (b)

Fig. 4. The original (a) and reconstructed by the neural network (b) δ-like distributions of physical field with $n = 5$.



(a) (b)

Fig. 5. The original (a) and reconstructed by the neural network (b) distributions of physical field with $n = 10$.

neural network distributions with different variances and n are shown in Figs. 3, 4 and 5. The neural networks was learned independently in all the cases with the similar randomly generated patterns. One can see from Figures that neural network sufficiently accurately reconstructs unknown pattern and can be used in practice.

CONCLUSIONS

The computer model of the neural network solving tomographic problem is proposed. The neural network can reconstruct information from the fiber-optic distributed measuring network of weighted amplitude sensors. This network can be used in conjunction with the distributed fiber-optic measuring system and is planned to be implemented as optoelectronic hardware.

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