Reconstructing signal from fiber-optic measuring system with non-linear perceptron

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Abstract

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. The Gaussian distributions of some physical quantity are selected as learning patterns. Neural network is learned by error back-propagation using the conjugate gradient and coordinate descent 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

1 Introduction

The fiber-optic distributed measuring systems were being actively developed during the past few years. Particularly these systems can be used for acoustic field investigating, for monitoring of stresses in industry, in geophysical researches, etc. The reconstruction of information obtained by measuring system needs solving of tomographic problem. But frequently such solution is complex, needs large computer consumption and cannot be performed in real time. Therefore previously learned neural network can be utilized for solving of tomographic problem.

An optical perceptron, which was implemented using a collection of amplitude holograms recorded on a disk-shaped holographic carrier and processing the output data from a fiber-optic measuring system, is reported in Ref. Another computer linear neural network was developed by authors of Refs. We present the similar computer non-linear feed-forward neural network in this paper.

2 Description of the neural network

Consider two-dimensional fiber-optic distributed measuring system being set of measuring lines. The fiber-optic phase sensors form square \( n \times n \) lattice also having \( 2n - 1 \) diagonal lines (Fig. 1). The phase shift \( \theta \) in this linear sensor is proportional to physical action value integrated over the line while the intensity of the transmitted light \( \propto \cos^2 \theta \). The phase shift in fiber-optic line have to be along one cosine half-period. Signal from such measuring system is simulated on input of neural network which is intended to reconstruct the value of physical action at intersection points.

For solving of tomographic problem we choose perceptron with the non-linear hidden layer since this network has universal approximation capability.

The neurons of the first layer serve as network inputs and feed data from the measuring system to the next layer. The second (hidden) layer proceeds following transformation:

\[
s_j = f \left( \sum_k w_{jk} \sigma_k \right),
\]

where \( \sigma_k \) are states of neuron inputs being signals from mea-
suring sensors, \( s_j \) are states of outputs and \( w_{jk} \) are synapses. We used tanh as activation function \( f \). The hidden layer of neurons has \( 4n - 1 \) inputs and \( n \times n \) outputs.

The output layer of the neurons takes the linear transformation:
\[
S_j = \sum_j w_{ij} s_j, \tag{2}
\]
where \( S_j \) are states of third layer neuron outputs, \( w_{ij} \) are synapses of third layer.

We selected Gaussian distributions of the some physical quantity with one or two peaks as learning patterns. The following expression was used as objective function:
\[
D = \frac{1}{2} \sum_{\mu,i} (S^\mu_i - \zeta^\mu_i)^2, \tag{3}
\]
where \( \mu \) is superscript indicating number of learning pattern, \( \zeta_i \) are output states of the neural network for some learning pattern. For the training pattern \( \sigma_k \) are formed as squared cosines of the sum of \( \zeta_i \) along the corresponding measuring line. We used error back-propagation for the network training, so we had to minimize \( D \) with respect to \( w_{jk}, w_{ij} \).

We combined conjugate gradient and coordinate descent minimization methods for neural network learning. When conjugate gradient method failed we switched to the coordinate descent and after some iterations tried to start conjugate gradient minimization again. Also we applied the “thermal jumps” technique. The minimization procedure finished after certain iteration count or on given accuracy reaching.

3 Results

On the first step we learned the neural networks to reconstruct the signal having, as well as training patterns, one Gaussian peak. Examples of initially unknown reconstructed distributions with different variances and \( n = 5 \) are shown in Tables 1, 2. The neural networks was learned independently in all the cases with the similar randomly generated patterns.

On the next step we trained neural networks reconstructing distributions with two Gaussian peaks. Examples are shown in the Tables 3, 4. In the case of the smooth distribution the reconstructed signal is close to the original. For the \( \delta \)-like distributions the locations of the peaks are recovered correctly but their magnitude differs from the original.

One can see from Tables that neural network sufficiently accurately reconstructs unknown pattern and can be used in practice.

Presented neural network unlike Refs. [6, 7] can work not only with signal from fiber-optic measuring line being within the interval of linear dependence of light intensity on phase shift.

| Table 1: The initial (a) and reconstructed by the neural network (b) \( \delta \)-like distribution of physical quantity with one peak. Each cell corresponds to intersection point within measuring system (see Fig. 1) and represents certain \( \zeta_i \). |
| --- |
| \( \begin{array}{cccccc} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0.00005 & 0.00327 & 0.00005 & 0 & 0 \\ 0 & 0.00327 & 0.20712 & 0.00327 & 0 & 0 \\ 0 & 0.00005 & 0.00327 & 0.00005 & 0 & 0 \\ \end{array} \) |
| \( \begin{array}{cccccc} 0.00001 & 0.00063 & 0.00027 & -0.00003 & 0.00003 & 0 \\ 0.0019 & 0.0080 & -0.00022 & 0.00044 & 0.00052 & 0 \\ -0.00021 & 0.00044 & 0.00397 & -0.00242 & 0.00077 & 0 \\ 0.00071 & 0.00117 & 0.21311 & 0.00188 & 0.00113 & 0 \\ -0.00097 & -0.00081 & 0.00274 & -0.00012 & 0.00063 & 0 \\ \end{array} \) |

| Table 2: The initial (a) and reconstructed by the neural network (b) smooth distribution of physical quantity with one peak. |
| --- |
| \( \begin{array}{cccccc} 0.00186 & 0.00283 & 0.00186 & 0.00052 & 0.00006 & 0.00006 \\ 0.01534 & 0.02341 & 0.01534 & 0.00432 & 0.00052 & 0.00006 \\ 0.0544 & 0.08312 & 0.0544 & 0.01534 & 0.00186 & 0.00052 \\ 0.08312 & 0.12681 & 0.08312 & 0.02341 & 0.00283 & 0.00052 \\ 0.0544 & 0.08312 & 0.0544 & 0.01534 & 0.00186 & 0.00052 \\ \end{array} \) |
| \( \begin{array}{cccccc} 0.00199 & 0.00240 & 0.00034 & 0.00064 & -0.00028 & 0.00006 \\ 0.01396 & 0.02222 & 0.01447 & 0.00485 & 0.00030 & 0.00030 \\ 0.05322 & 0.07995 & 0.05383 & 0.01536 & 0.00183 & 0.00030 \\ 0.0834 & 0.12471 & 0.08357 & 0.02404 & 0.00435 & 0.00030 \\ 0.05421 & 0.08396 & 0.05473 & 0.01380 & 0.00243 & 0.00030 \\ \end{array} \) |
4 Conclusions

The computer model of the neural network solving tomographic problem is proposed. This network can be used in conjunction with the distributed fiber-optic measuring system and partly may be made as electronic or optical hardware.

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