NEURAL NETWORK ALGORITHMS FOR ACOUSTICAL IMAGE RECONSTRUCTION AND ANALYSIS *

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Abstract - The results of application of the neural network approach for acoustical image reconstruction and analysis are presented.

1. Introduction

The steady interest in investigation of possibilities for application of the neural network algorithms to the solution of various types of inverse problems in mathematical physics, including reconstruction and imaging problems, is shown only for the latest time [1-3]. One can note three basic directions in information acoustics, on which such investigations are carried out nowadays: (a) using multilayer pereptron for solving data interpretation problems; (b) using Hopfield networks for solving linearized tomographic and holographic problems and (c) design neural networks with special architecture. In this work the Hopfield nets have been used for reconstruction of binary inhomogeneities in layered medium using data of acoustical remote sensing.

2. Geometry of the problem

Let us consider the medium formed by two homogeneous half-spaces D_1 and D_2 separated by a horizontal planar interface γ_{12}. An examined homogeneous z-oriented cylindrical object of arbitrary cross-section Ω in the plane (x, y) is placed in D_2 (Fig. 1). To formulate a mathematical model of the remote sensing, we will assume that the immersion media as well as object under the investigation to be stationary, linear and isotropic materials in which dispersion in the working frequency range can be neglected. The initial field U_0 is generated by the array S located in the half-space D_1 as a plane monochromatic wave of angular frequency ω. Let us assume that the wave propagates in positive direction of the x axis perpendicularly to the interface γ_{12} , and temporary dependence is characterized by the function $\exp(-j\omega t)$. The density ρ is considered to be known and constant in the entire space and any losses are absent. Then, the problem corresponds exactly to the case of two-dimensional scalar inverse scattering problem of refraction type in aspect-limited data configuration [4-5]. The rigorous mathematical approach to solving such problem is finding solution of Fredholm integral of first kind

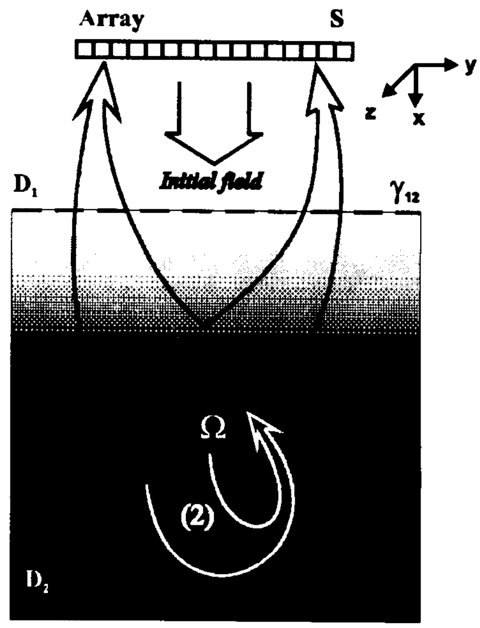

Figure 1: The geometry of the inverse scattering problem.

$$u(\mathbf{r}) = \int_{\Omega} G_{12}(\mathbf{r}, \mathbf{r}')\ U(\mathbf{r}')\ \epsilon(\mathbf{r}')\ d\mathbf{r}' , \qquad (1)$$

where $\mathbf{r} \in S$, $\mathbf{r}' \in D_2$. Eq. (1) is an observation equation. This equation puts in conformity to a scattered field $u(\mathbf{r})$ registered on S the field of sources of secondary radiation $U(\mathbf{r}')\epsilon(\mathbf{r}')$ formed as a result of interaction of the total field $U(\mathbf{r}')$ on Ω with medium inhomogeneities given by function $\epsilon = k^2(\mathbf{r}') - k_2^2$ which is determined in D_2 and is equal to zero outside of Ω. In turn it is necessary to use the integral Fredholm equation of the second kind to find the total field $U(\mathbf{r}')$ in Eq. (1) :

$$U(\mathbf{r}) = U_0(\mathbf{r}) \int_{\Omega} G_{22}(\mathbf{r}, \mathbf{r}')\ U(\mathbf{r}')\ \epsilon(\mathbf{r}')\ d\mathbf{r}' , \qquad (2)$$

where $\mathbf{r}$, $\mathbf{r}' \in \Omega$. Eq. (2) is a coupling or state equation (multiple scattering equation). The development of the methods for joint solving (1) - (2) concerns to the objectives of nonlinear computerized diagnostics. The main dif-

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ficulty in development of methods for solving such problems is, that conditions of regularity (such as convertibility of derivative in the solution vicinity) [6], which is the standard in the nonlinear analysis, are not fulfilled, that in turn causes an expediency of new ideas in development and analysis of approximate methods for solving similar problems.

3. Neural network reconstruction

Inverse problem of the reconstruction we will consider from the point of view of optimization problem, which, in one's turn, will be solved by the utilization of the properties of Hopfield neural structure [7]. Let us characterize the state of the i-th neuron by a value of the inhomogeneity ϵ_i ($i = 1, \ldots, N_\epsilon^2$) where N_ϵ is dimensionality of sampling grid along one of the coordinate axes. As the initial magnitudes for neural network synthesis will be choosen the number of the elements of the receiving array N (n=1, ..., N); amount of the pixels N_ϵ^2; matrix G_{ni} corresponding to the Green function of the problem un-

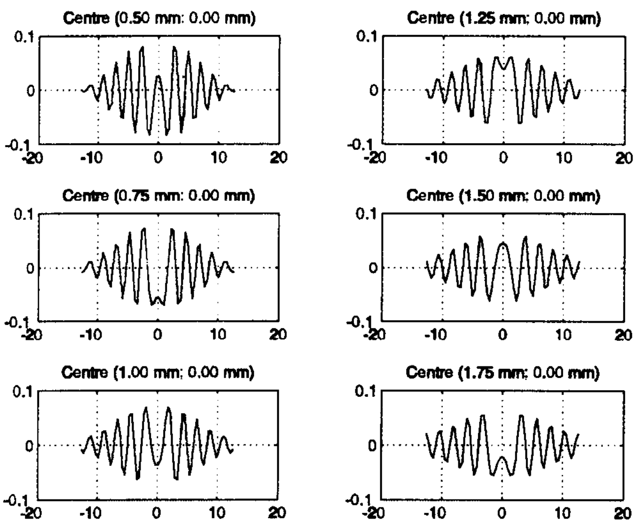

Figure 2: Real part of the scattered field in the case of plane wave irradiation of a rectangular medium-contrast object. The measuring aperture is plased at 1 mm above the interface between two fluid lossless media. The spacing between the receivers is 0.4 mm. The dimensionality of the inhomogeneity is 16 $\times$ 16 pixels. The discretisation interval is 0.1 mm.

der the consideration; measuring data or data of numerical experiment $\mathbf{u}^m$ (Fig.2). In functional representation, the linearized variant of the direct scattering problem in statement (1) takes the form:

$$Re\,\{\mathbf{u}^c\} = \hat{\mathbf{Q}}\epsilon, \qquad (3)$$

where $\hat{\mathbf{Q}} = Re\{\hat{\mathbf{G}}\hat{\mathbf{U}}_0\}$; $\hat{\mathbf{G}}$ is an integral Green's operator; $\hat{\mathbf{U}}_0$ is an multiplicative operator; $Re[\cdot]$ denotes real part. Defining matrix synaptic connections of the Hopfield net T_{ij} and the bias input vector B_j accordingly [8]:

$$T_{ij} = -\sum_{p=1}^{N} Q_{pi}Q_{pj}, \quad B_j = \sum_{n=1}^{N} Q_{nj}u_n^m \qquad (4)$$

and considering ϵ as the output vector of the Hopfield recurrent neural network we obtain the neural network

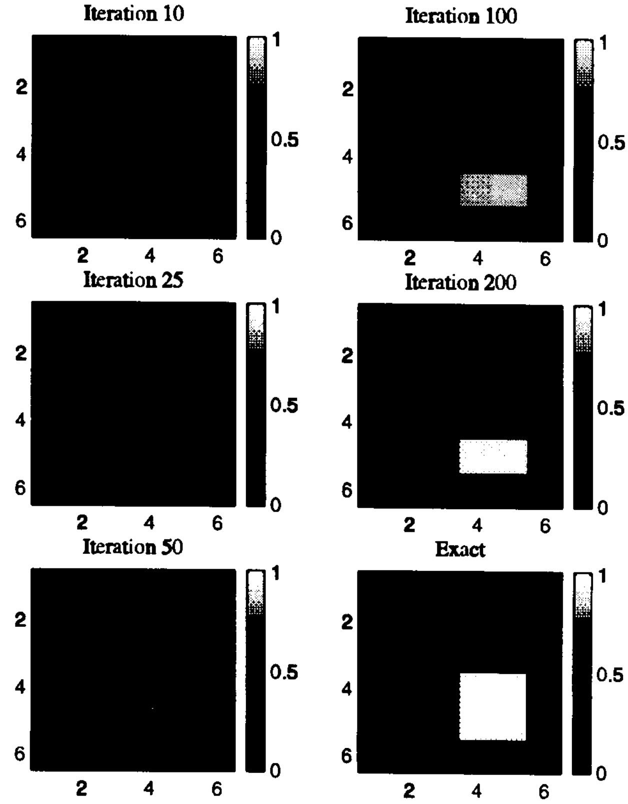

Figure 3: The gray-scale pictures of neural network reconstruction of the inhomogeneity by using the Hopfield recursive architecture.

analog of an iterative gradient method of minimization of the appropriate cost functional:

$$\epsilon_i^{(l+1)} = \epsilon_i^{(l)} + \eta_i \left\{ \sum_{j=1}^{N_\epsilon^2} T_{ij}\epsilon_j^{(l)} + B_i \right\} \delta t, \qquad (5)$$

where η_i is a gain for the i-th neuron; l is the number of iteration. The contrast retrived from the data corrupted by 2% noise are presented in Fig. 3.

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