IEEE Second International Conference on Data Stream Mining & Processing
August 21-25, 2018, Lviv, Ukraine

Subsurface Object Identification by Artificial Neural Networks and Impulse Radiolocation

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***Abstract*—The problem of identification of objects under ground surface is solved by the application of irradiation of the surface by short impulse electromagnetic waves and the use of artificial neural networks (ANN) for the analysis of reflected field characteristics. As input data for ANN the normalized amplitudes of electrical component of the field in determined points of observation in equidistant moments of time are used. As an example of the object for the identification, the metal tube under surface of a ground is considered. The plane electromagnetic wave having Gaussian time dependence is used as an incident field. The influence of a number of hidden layers of ANN on precision of the recognition is investigated.**

Keywords—artificial neural network, impulse electromagnetic wave, subsurface radar, object recognition.

I. Introduction

The detection and recognition of objects localized in the complicated media as soils of different kinds are the actual subjects for a number of applications [1]. Another stage of the development of the area is the usage of the ultrawideband radars [2]. Owing to the very wide range of frequencies of a sensing electromagnetic wave spectrum [3], the radars provide significantly higher precision of a resolution and a depth of penetration in lossy media [4] in comparison with traditional ground penetrating radar (GPR) [5]. The idea of a GPR that radiates the electromagnetic wave without definite carrier frequency was proposed by Cook [6] 60 years ago, but the impetuous development of theory and technique of all components of the radar permits to obtain the predicted characteristics [7] of the impulse GPR in current time only [8].

Except the simplest formulation of the problem for a uniform medium of propagation with known parameters there are a number of tasks concerning the investigation of objects by limited set of sources of a reflected field [9] or the reconstruction of a dielectric profile of inhomogeneous media [10]. The problems require the application of complicated techniques especially for cases of mathematically incorrect statements. As for the pursuit of hidden objects of complex shapes there was proposed the approach based on concept of a presence of individual resonant frequencies for the object response on electromagnetic wave irradiation that can be used as their own footprints [11]. These frequencies were called “Natural Frequencies”. It was suggested that the objects form a response containing the natural frequencies under irradiation by an electromagnetic wave.

The investigation of reflected wave for the object recognition needs the application of complicated mathematical methods [12] to compensate the lack of input data. It is interesting to use more convenient and quick methods of recognition, for example, the approach built upon principles of information processing realized in cortexes of animals [13]. The understanding of the mechanism of brain unit action [14] permitted to construct artificial neural networks [15] that possess multidimensional function approximation properties of ultimate power [16]. Namely the ANN characteristics are used to solve the problem of dielectric object parameter finding from analysis of reflected electromagnetic fields [17]. The application of ANN significantly simplifies the solving of dielectric parameter recognition task by multifrequency multidimensional backscattering problem solution [18]. As it was mentioned above, the utilization of impulse electromagnetic wave for irradiation must provide researches by a bigger size of information about objects under investigation physically [19]. Moreover, the application of electromagnetic fields with ultra-wideband spectrum expands the possibilities to receive in reflected wave components that corresponds to the natural frequencies of hidden objects [11]. So, the approach based on ANN was used for analysis of dielectric parameters of a layered medium that is a model of human body surface [20-23]. There were studied and compared ANN of different structures. It was shown the stability of the parameter recognition in presence of noise of substantial level and measuring errors. The key hypothesis of the ANN actions was established on the prediction of self-invention of recognition method during training directly from time-dependent signals instead of its Fourier Transform or other preprocessing techniques [24]. As for tasks of the parameter recognition, the works [20-24] are more close to the practical problem of remote road quality surveying, but the results obtained cannot satisfy the parameter precision needed and reached by analytical method based on Hilbert transform [25]. The purpose of the work is to apply the same approach of direct time-domain signal processing for a subsurface object recognition, for example, described in [8] the problem of land mine finding.

II. Statement of the Problem

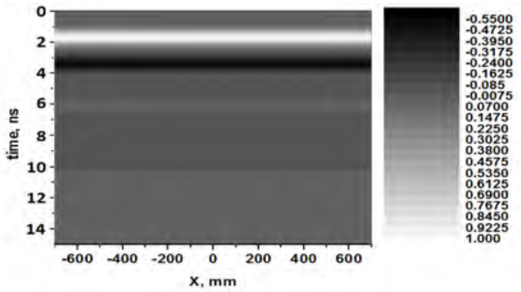
The source of input signals is the amplitudes of the electrical component of electromagnetic field reflected from ground surface and underground objects. The normally incident plane electromagnetic wave having the Gaussian time dependence with duration 0.6 ns. The reflected field is measured at the height 250 mm under the ground surface that is the convenient height to arrange real receiving antenna system. The number of the points for the measurement is 15 with spatial step along the ground surface 100 mm. There are three models of dielectric characteristics of the ground material: homogeneous substance with permittivity ε =9 and conductance σ =0.005 S/m; the same surrounding substance with trench of depth and width 600 mm filled with another matter having permittivity ε =12 or ε =6 and the same losses. Totally, it is considered six cases where the ground materials have no inclusions and have the inclusion in form of perfectly conducted tube with radius 100 mm buried into the depth 300 mm and oriented perpendicularly to the line of field probes and in parallel to the trench walls.

Each field probe transmit the signal to ANN in form of 500 values of amplitudes of the electrical field obtained with time step 30 ps that is not very dense in comparison with used in [25]. So, input layer of ANN must contain 7500 elements. The output layer consists of one neuron that shows the presence or the absence of tube. All neurons have the sigmoidal excitation function. One should solve the problem of diffraction of the impulse electromagnetic wave on the metal-dielectric structure in time domain, train the ANNs to recognize the presence of the tube for different number of hidden layers and different number of neurons in them.

III. The solution of the Problem

The problem of impulse electromagnetic wave scattering is solved directly in time domain by numerical FDTD method [26]. The results of the simulation are presented in Fig. 1-3, where the normalized amplitudes of electrical field are shown for different points in space along *OX* axis (from -700 mm to 700 mm) and for different moments of time (from 0 to 15 ns). The downward orientation of the time axis is chosen for better representation of underground object influence on amplitudes of reflected field and the object location in space without taking into account electromagnetic field slowdown in dielectric media. Fig. 1 describes the case of homogeneous substance with permittivity ε =9 and conductance σ =0.005 S/m, Fig. 2 and Fig. 3 conform to the same substance with the trench filled with other matter of permittivity ε =6 and ε =12 correspondingly. The pictures marked by the letter “a” shows the cases without any scatterer under a ground, whereas the letter “b” designates the cases with presence of the metal tube.

All figures contain the lightest area of incident pulse appearing and the darkest region of field reflected from the ground surface and changed their polarity. Other domains include significantly weaker changes of field amplitudes caused by influences of metal surface and permittivity changes supplementary diminished by losses in the media. The reflection of the wave from metal tube generates typical hyperboloid-like shape caused by time delay in reaching the observation point shifted from normal to the surface [2].



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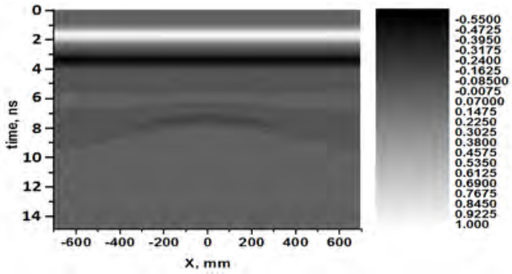

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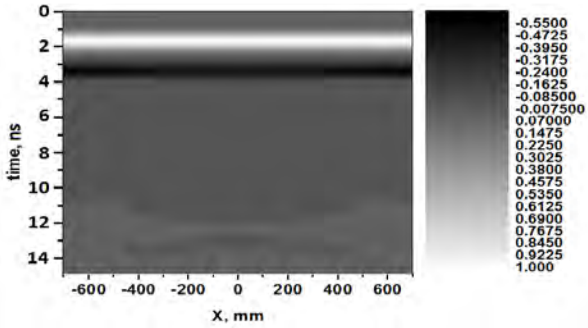
Fig. 1. Time dependence of the normalized amplitudes of electrical field in different points along *OX* axis calculated for the case of homogeneous substance with permittivity ε =9 and conductance σ =0.005 S/m (a) and the same substance with the metal tube buried at the depth 300 mm (b).

It is interesting to note that the case of trench filled with matter with smaller permittivity (Fig. 2) reminds the impulse field behavior in rectangular waveguide [27] whereas the field distribution for the case of bigger permittivity inside trench (Fig. 3) looks like the pattern for homogeneous ground (Fig. 1). Each of the six time-spatial distributions depicted in Fig. 1-3 forms the training set for our ANN. The purpose of the training is to get the zero level of the ANN output signal for sets presented in Fig. 1-3a and the unit level for sets pictured in Fig. 1-3b. The final result of the learning is checked on verification sets presented in Fig. 4, where the time-spatial distribution of the amplitude of electrical field of reflected wave is depicted for the cases of tube hidden under ground surface for shifted positions relatively to the case pictured in Fig. 1a in 20 mm downward (Fig. 4a), left-hand (Fig. 4b), and right-hand (Fig. 4c). Last two cases are equivalent of 20% error in positioning along *OX* axis, the first case corresponds to 66 ps error in time, i.e. more than two time steps.

The structures of ANN and results their check on the data corresponded the cases depicted in Fig. 4 are presented in Table 1. It is seen that the case #2 of ANN with two hidden layers governs the worst result for all verification tests whereas the biggest deflection is observed for the case #1. The best fit is supervised in case #4 that can be explained by the biggest informational capacity of the ANN that helps to successfully recognize the presence of the tube.



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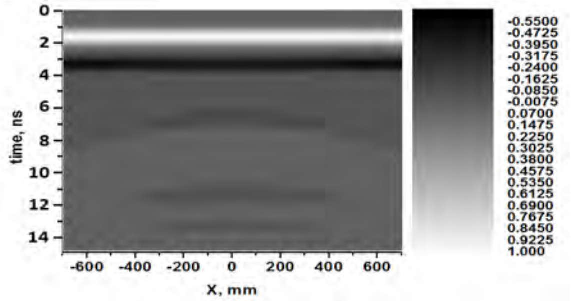

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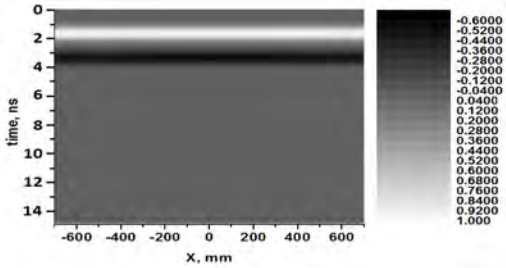
Fig. 2. Time dependence of the normalized amplitudes of electrical field in different points along OX axis calculated for the case of homogeneous substance with permittivity ε=9 and conductance σ=0.005 S/m with trench filled with the matter with permittivity ε=6 and the same σ=0.005 S/m (a) and for the same substances and geometry but with the metal tube buried at the depth 300 mm (b).

It is interesting to illustrate the values of weight coefficients between layers for the best case #4 presented in Table I. The data are depicted in Fig. 5, where the numbers of interconnected neurons are shown on axes, and the brightness of the corresponding dots reflects the values of the weight coefficients



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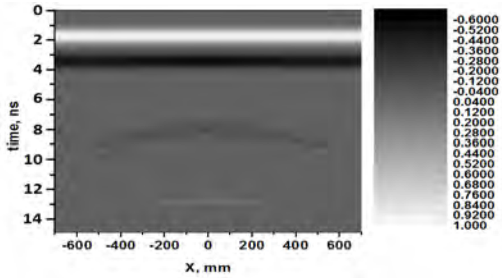

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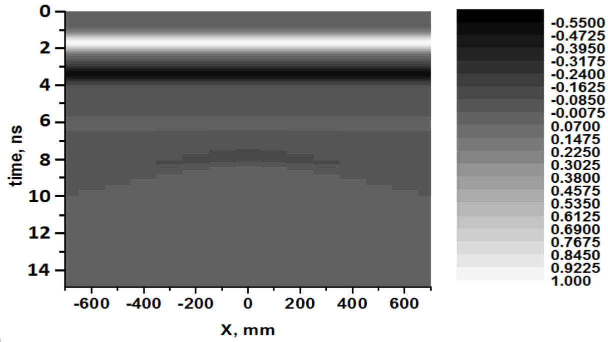
Fig. 3. Time dependence of the normalized amplitudes of electrical field in different points along OX axis calculated for the case of homogeneous substance with permittivity ε=9 and conductance σ=0.005 S/m with trench filled with the matter with permittivity ε=12 and the same σ=0.005 S/m (a) and for the same substances and geometry but with the metal tube buried at the depth 300 mm (b).

Its magnitudes for third and fourth layers are displayed in Fig. 5a, for second and third layers are represented in Fig. 5b, for first and second layers are imaged in Fig. 5c. It is seen that the values have chaotic character in Fig. 5a and Fig. 5b, but the picture in Fig. 5c shows definite periodicity that corresponds to similar algorithm of processing data from each of 15 probes found by ANN during training.



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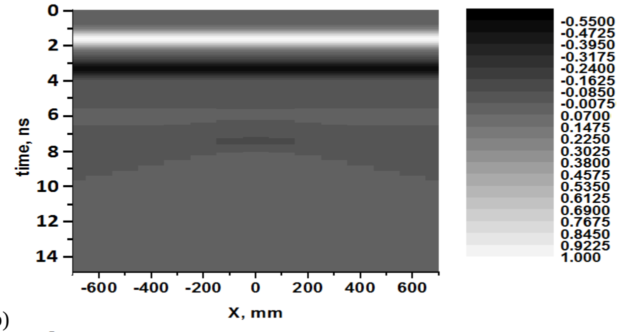

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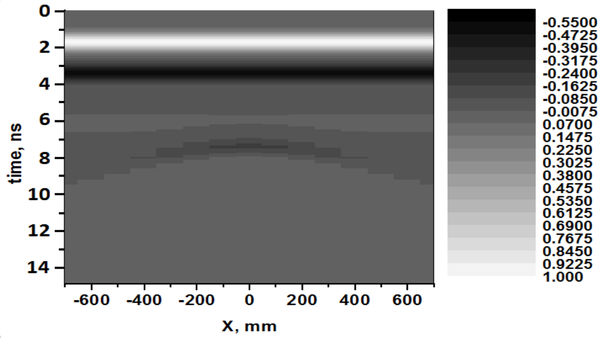
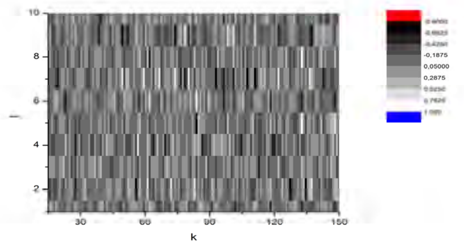


c)

Fig. 4. Time dependence of the normalized amplitudes of electrical field in different points along *OX* axis calculated for the case of homogeneous substance with permittivity ε =9 and conductance σ =0.005 S/m with the buried metal tube as well as presented in Fig. 1b but for shifted position of tube in 20 mm downward (a), left-hand (b), and right-hand (c).

IV. Conclusion

It is shown that ANN can effectively find objects whose presence have a distributed influence on data acquired by the impulse electromagnetic field irradiation of a ground. It is seen that a bigger number of hidden layers of ANN permits to improve the object recognition quality. The occurrence of errors and a low contrast of significant part of the training input data do not hamper the creation of successful methods of object recognition by ANN. The process of ANN training has created a necessary algorithm of signal processing and recognized the samples of the data from different probes blindly preferring the usage of similar manipulation with input data of different probes.



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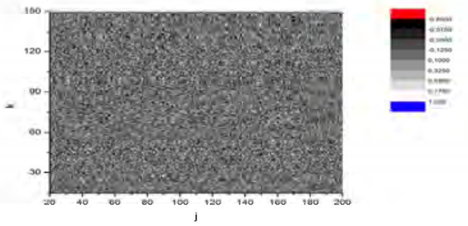

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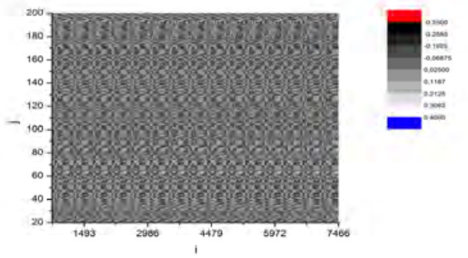

c)

Fig. 4. The values of weight coefficients between k and l neurons of third and fourth layers (a), j and k neurons of second and third layers (b), i and j neurons of first and second layers (c).

TABLE I. ANN STRUCTURES AND RESULTS OF THEIR VERIFICATIONS

ANN number	**ANN characteristics**			
	Structure, number of neurons in layers	***Output signal for case in Fig. 4a***	***Output signal for case in Fig. 4b***	***Output signal for case in Fig. 4c***
1	7500-100-50-25-1	0.9943	1.2001	1.3316
2.	7500-100-50-1	0.9809	0.9569	0.9493
3.	7500-200-100-50-1	1.0085	1.0227	0.9471
4.	7500-200-150-10-1	1.0065	1.0068	1.0099

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