DIELECTRIC CYLINDER DISCRIMINATION WITH ANN USING PHASE INFORMATION OF SYNTHESIZED TIME-DOMAIN RESPONSE

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The application of the three-component stacked artificial neural network (ANN) for discrimination of dielectric cylinders of different diameters using phase information of synthesized time-domain response is considered. The network consists of two sparse autoencoders and the softmax unit. Neural networks are not tied to the frequency range, unlike many well-known methods based on the resonant properties of objects, and they are a powerful tool for object recognition. In contrast to well-known results, information about the phase of the time-domain signal, which is synthesized from multi-frequency data, is used for discrimination. For ANN training, phase images for cylinders with the radius of 15 to 35 mm are obtained using the method of auxiliary sources (MAS) The possibility of successful recognition was confirmed for the case of the diameter deviation of 1 mm and the presence of additive Gaussian noise with SNR of up to 0 dB.

Keywords: artificial neural networks, autoencoder, softmax, targets discrimination, dielectric cylinders, method of auxiliary sources (MAS), phase images.

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1. Introduction

The dielectric cylinder is considered as one of the basic objects in subsurface sounding investigation [1]. Some experimental results in mm-range have been presented in [2]. A key problem is discrimination with size estimation. Neural networks are a powerful tool for object recognition [3–5]. The problem is to obtain a reflected signal for a set of objects with various diameters with small step in a comparatively simple way for network training. The method of auxiliary sources (MAS), based on the shifting of the sources from the real surface to auxiliary surfaces, allows for high-precision calculations and obtaining reliable results, which is confirmed by good agreement with experimental data [6].

The application of the three-component stacked neural network to classify radio images of dielectric cylinders of different radii based on numerical experiment data was introduced in [7], where each image was considered as the array of reflectivity absolute values, and the influence of the noise level and the deviation of the diameter value on the probability of correct classification was investigated.

Purpose of this article is to include phase distribution of the complex reflection coefficient into consideration and to evaluate the efficiency of cylinder classification by a neural network using phase images.

2. Amplitude and phase images

The scattered electromagnetic field at the waveguide was expressed by MAS [6], where a horn antenna was used both as the electromagnetic wave radiator and receiver. Using this approach, complex reflectivity distribution for five dielectric cylinders ($\varepsilon = 2.56$) with radii in the range between 15 and 35 mm with a 5 mm step were obtained t a grid of frequencies. The signals in time-domain were calculated by means of DFT. The time-domain dependences were recalculated in dependence against longitudinal axis x. Scanning along transversal y-coordinate was done. The example of dependences of the reflection coefficient modulus against the x- and y-axis is shown in Fig. 1. Dash line corresponds to the reflection from rear part of the cylinder.

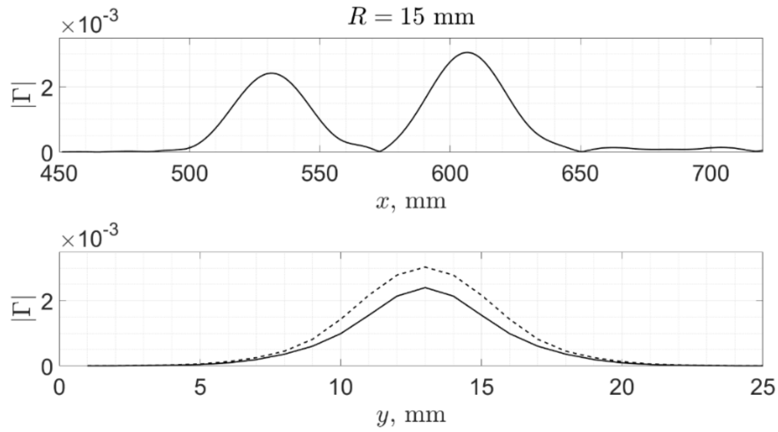

Fig. 1. Dependences of the reflection coefficient modulus against longitudinal (x) and transversal (y)axes

According to the results obtained in [7], classification accuracy for some radio image sets dropped to 50%when SNR in the presence of white Gaussian noise was equal to 5 dB (Fig. 2).This problem was solved by increasing the size of the hidden layers of the network components, which led to an increase in network training time from 2 to 8 minutes.

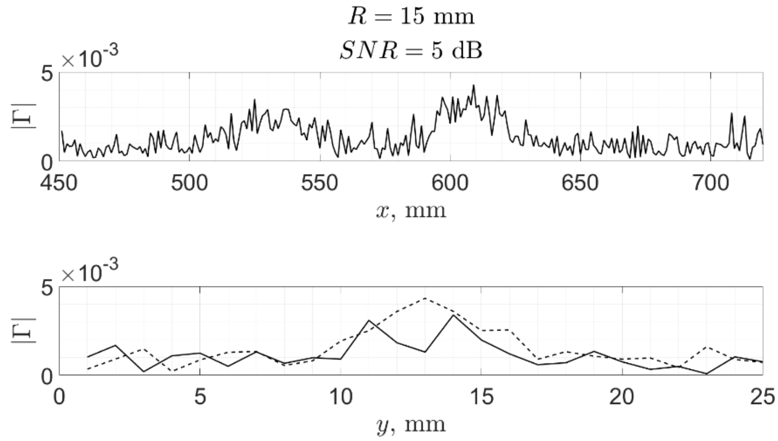

Fig. 2. Dependences of the reflection coefficient modulus against longitudinal (x) and transversal (y) axes in the presence of white Gaussian noise

When considering reflectivity phase distribution of time-domain signal, it is possible to create a network training dataset from reflectivity phase images. It is important to note that the phase values are calculated by applying a mask with an amplitude threshold for the reflectance values, which allows for isolating the reflections from the front and back parts of the cylinder (Fig. 3, 4). In Fig. 4 the data with noise are presented.

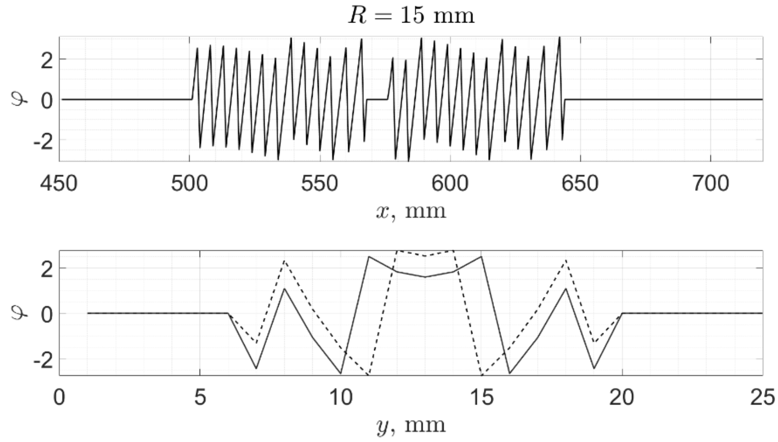

Fig. 3. Dependences of the time-domain signal phase against longitudinal (x) and transversal (y) axes

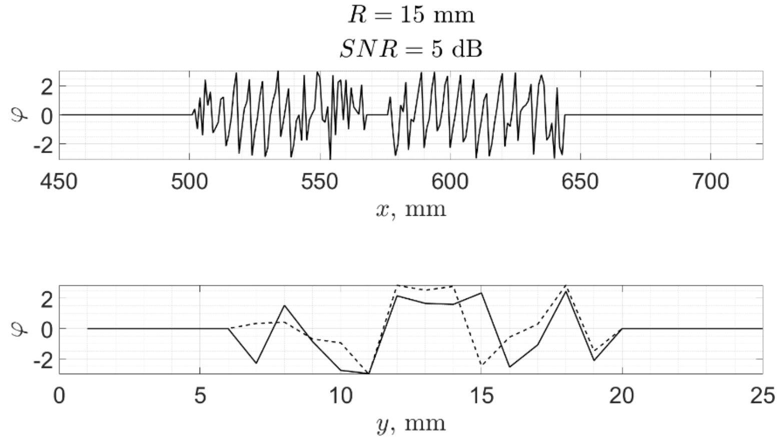

Fig. 4. Dependences of the time-domain signal phase against longitudinal (x) and transversal (y)axes in the presence of white Gaussian noise

3. Network training and testing

As per previous section, the classification task can be formulated as determining whether a considered cylinder belongs to one of the five classes of radii via the analysis of its reflectivity phase image. Each image was a 270-by-25 array of phase values. Consideration of such frames is sufficient to accommodate both reflections.

The stacked neural network for classification contains two encoders from sparse autoencoders as hidden layers, and the softmax unit as output layer (Fig. 5).

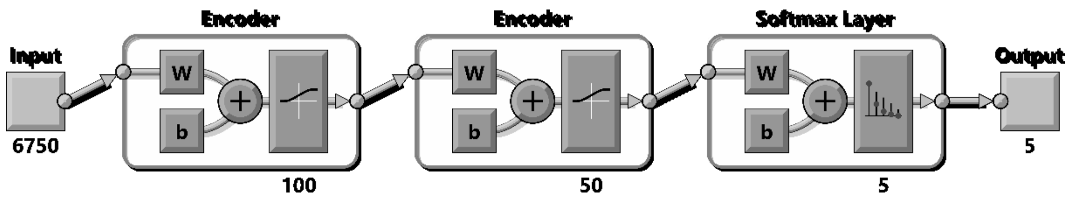

Fig. 5. Diagram of the created stacked neural network

Training dataset consisted of 100 phase image variations for each class when white Gaussian noise was added to the original radio images. Autoencoders learnt useful features of their input data in an unsupervised way by separating the factors of variation [8]. The first autoencoder hidden representation size was set to 100, which means that 100 features were selected for each image. The input of the second autoencoder was fed by the training set passed through the first one. In order to form an even smaller features set, the second autoencoder hidden layer size was reduced to 50. The maximum number of epochs was set to 400 for the first autoencoder, and then reduced to 100 for the second one. Both autoencoders were trained with the scaled conjugate gradient algorithm, when L_2 and sparse regularizers were added to the mean squared error cost function.

The softmax unit applied a softmax function to the 50-dimensional feature vectors from its input and represented the probability distribution over the specified cylinder classes. This unit was trained with a supervised learning, when the target set was a 5-by-500 matrix of associated class vectors (of zeros and ones) defining which of the five classes each input was assigned to. The training process was based on minimizing the cross-entropy between the empirical distribution defined by the training set and the softmax distribution obtained.

For the testing process, another 100 noisy image variations for each radius class were generated. Subsequent retraining by performing the back propagation was the final stage of network setup. The total network training time took approximately 2 minutes.

4. Results and discussion

The confusion matrix for network performance visualization for the cases of added noise with an SNR of 5 to 0 dB is presented in Fig. 6.The rows correspond to the predicted class, the columns correspond to the true class, the diagonal cells correspond to images that are correctly classified, the off-diagonal cells correspond to incorrectly classified images, the far-right column shows the percentages of all the images predicted to belong to each class that are correctly and incorrectly classified, and the bottom right cell represents the overall accuracy. As can be seen, the network was able to classify noisy images with almost 100 percent accuracy, which indicates that the reflectivity phase is robust to noise. When comparing figures 1, 2 and 3, 4 in pairs, it also can be noticed that the added noise has less effect on the phase of the reflection coefficient than on its amplitude. Thus, cylinder classification based on phase images is more accurate in conditions of significant noise.

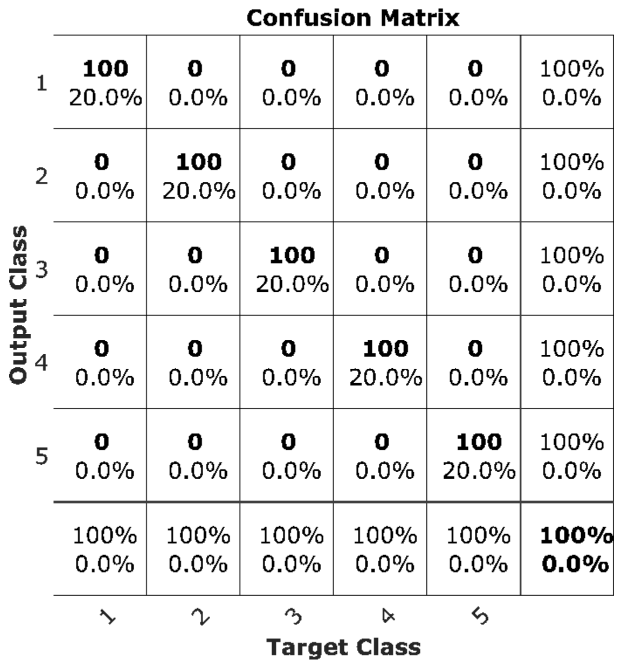

Fig. 6. Confusion matrix for the cases of added noise with an SNR of 5 to 0 dB

On the other hand, it was also found that the phase is unstable to cylinder size deviation. When a set of phase images of five dielectric cylinders with radii in the range between 16 and 36 mm with a 5 mm step was fed to the trained network input, the network was not able to classify images correctly. Thus, the approach based on phase images analysis is not suitable when considering objects with dimensions deviating from those underlying the classification.

5. Conclusions

The use of phase images for recognition of cylindrical objects using neural networks allows one to obtain an additional processing effect in the presence of a higher noise level compared to using only amplitude data. It seems appropriate to use a combined approach based on a combination of amplitude and phase information. It is also of interest to consider the distribution of real and imaginary parts of the complex reflection coefficient separately.

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