# Recognition of Underground Target Material Based on Average Phase Difference and Radial Basis Function Neural Network

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***Abstract*—Recognition of the material of underground targets is always an important part of GPR (Ground Penetrating Radar) applications. According to target return time, truncating the data to remove the direct waves, and then select the typical data of the different materials target echoes. By comparing the phase of different targets with that of no target, the average phase difference is obtained. And the average phase difference is used as the input of the RBF (Radial Basis Function) neural network to realize the classification and recognition of underground target materials. Simulation result shows that this method can realize the identification and classification of common materials, such as metals, water and hole.**

***Keywords—Ground penetrating radar, average phase difference, RBF neural network, material recognition***

## I. INTRODUCTION

In the practical application of ground penetrating radar, it is greatly significant to classify and recognize the material properties of underground targets. For example, in landmine detection, only by accurately classifying the target can we determine whether there are mines and their types. At present, the main methods of material recognition include feature parameter recognition, which mainly uses the echo signal of ground penetrating radar to extract feature parameters, and uses classification and recognition methods to realize target material recognition. Common feature parameter extraction methods mainly include spectral analysis [1], continuous wavelet transform [2] and time-frequency analysis [3]. Common methods for classification and recognition based on feature variables include support vector machine [4], nearest neighbor method, Bayes method, fuzzy clustering [5] and neural network [6]. In recent years, because of their high degree of parallelism, high degree of non-linear global action, and strong self-adaptation and learning capabilities, neural networks have been widely used in various recognition and classification fields [7].

Underground target material identification in GPR requires feature extraction of the echo signal. According to the scattering characteristics of the target in the lossy medium, the spectrum and phase of the echo signal of different target materials have different features. Therefore, the characteristic parameters are obtained by comparing the phase spectrum of the received signal with the reference signal. The parameters are applicative to identification and classification. And the material recognition and classification system is required to be insensitive to noise and has good generalization ability. The neural network meets this demand. At present, among the commonly used neural network methods, the RBF neural network has extremely fast training speed, can approximate any non-linear function, can handle the difficult-to-analyze regularity in the system, and is more in line with the requirements of underground target recognition and classification. Thus, the RBF neural network is used for automatic target recognition in this paper.

This paper provides a method that combines phase spectrum and RBF neural network to realize the automatic recognition and classification of different materials of underground targets. Through the simulation of echo signals of several common materials, the feasibility of this method is confirmed.

## II. PHASE FEATURE EXTRACTION OF ECHO SIGNAL

Due to the difference in electromagnetic characteristics between the target and the background medium, the underground target scattering signal is formed. The signal is related to the target size, shape, buried depth, the electromagnetic characteristics difference between the target and the background medium. There will be a distinction between the underground target and the background medium. Therefore, the phase spectrum characteristics of the target are used to classify the material in this paper.

The phase spectrum of the target scattered echo signal generally consists of two parts, linear delayed component of the input signal $\varphi_L(\omega)$ and component of the target signal $\varphi_M(\omega)$. The phase spectrum can be expressed as

$$\begin{aligned}\varphi(\omega) &= \arg\left\{FFT\left[s(t)\right]\right\} = \arg\left[S(j\omega)\right] \\ &= \varphi_M(\omega) + \varphi_L(\omega)\end{aligned} \tag{1}$$

where, $s(t)$ represents the time domain signal of the target scattering echo, In the classification algorithm, the useful signal is $\varphi_M(\omega)$.

The phase difference between the reference signal and the target signal is

$$\Delta\varphi(\omega) = \varphi_M(\omega) - \varphi_M^{'}(\omega) \tag{2}$$

The average phase difference of the target signal relative to the reference signal is

$$\Delta\overline{\varphi} = \frac{1}{L}\sum_{i=1}^{L}\Delta\varphi(\omega_i) \tag{3}$$

where, $L$ represents the number of frequency points in the frequency band.

## III. RBF NEURAL NETWORK

In the RBF neural network, the radial basis function is used as the "base" of the hidden unit to form the hidden layer space so that the input vector can be directly mapped to the hidden space. The hidden layer can map the vector from the low dimension to the high dimension, which makes the linearly inseparable situation linearly separable.

The RBF neural network is composed of three parts, the input layer, the hidden layer and the output layer. For neural networks, the most important thing is to determine hidden layer neurons. In this paper, since the number of categories is certain, k-means clustering can be used to get the hidden layer of neurons. When the neurons of the hidden layer are determined, the output of the hidden layer neurons is known, and the connection weights of the neural network can be calculated by solving the linear equations.

The schematic diagram of the RBF neural network is shown in Fig. 1.

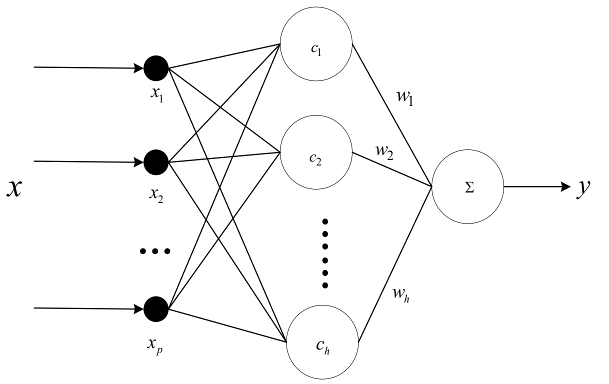


Fig. 1. The schematic diagram of the RBF neural network.

The main steps of the RBF neural network algorithm are as follows.

*1) Hidden layer:* Determine the number of hidden layer neurons, that is, the number of center points of the cluster. Directly select the first $h$ of the data as the initial center point.

*2) k-means clustering:* For each sample point, find the center point closest to it. The point closest to the same center point is a class, and then complete a clustering.

$$\min\left\{\left|x_i - c_j\right|\right\} \qquad i = 1,\ldots,p \quad j = 1,\ldots,h \tag{4}$$

where, $p$ represents the number of the input data, $h$ represents the number of the center point.

Calculate the center point of each cluster. If the center points of all classes are as same as that of the last time, the classification is completed. Otherwise, update the center points and repeat the k-means clustering step again. The clustering procedure is shown in Fig. 2.

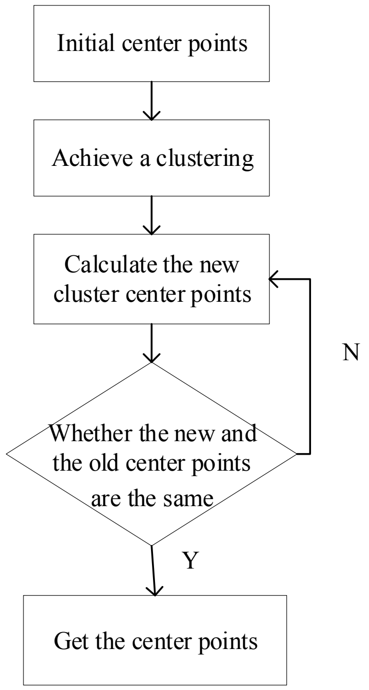


Fig. 2. The procedure of clustering.

*3) Activation function:* The activation function of the RBF neural network can be expressed as

$$r_{ij} = \exp\left(-\frac{1}{2\sigma^2}\left\|x_i - c_j\right\|^2\right) \tag{5}$$

where $r_{ij}$ can form the stimulated matrix $\Gamma$, and $\Gamma$ can be expressed as

$$\Gamma \in R^{p\times h} = [r_{ij}] \qquad \begin{matrix} i \in \{1,\ldots,p\} \\ j \in \{1,\ldots,h\} \end{matrix} \tag{6}$$

*4) Radial basis of Gaussian kernel:* For the radial basis of the Gaussian kernel function, the variance is solved by the following formula

$$\sigma = \frac{c_{\max}^2}{\sqrt{2h}} \qquad i = 1,2,\ldots,h \tag{7}$$

where $c_{\max}$ is the maximum distance between the selected center points.

The variance parameter determines the response range of hidden neurons to external input signals. The center point position and response width range of each hidden neuron can be different, and they are responsible for their respective local mapping actions.

When the input signal is close to the center of a certain neuron, the neuron is activated and produces a larger output. When the input signal is far away from the center, the output of the neuron tends to zero.

*5) Connection weight: D*etermine the weight of the RBF network connection based on the matrix pseudo-inverse idea. The calculation formula of the weight $W$ is

$$W = \Gamma^{+} Y^{T} \tag{8}$$

where, $\Gamma^{+}$ represents the pseudo-inverse matrix of the excitation matrix and $Y$ is the output vector of the training sample.

*6) Network output:* After getting the neuron and connection weight, the output of the entire network is

$$\hat{y}_{pj} = \sum_{i=1}^{h} \exp\left(-\frac{1}{2\sigma^2}\left\| x_p - c_i \right\|^2\right) w_{ij} \qquad j = 1,2,...,h \tag{9}$$

## IV. Recognition and Classification of Underground Target Material Based on RBF

### A. Typical Data Selection and Processing

Generally, the selection of typical data requires that the data must be invariant to translation, rotation and scale transformation. The formed feature data set has good consistency for the same type of target and a large difference for different types of targets, which is conducive to identification.

In this paper, the echo data is extracted in the center areas as typical data. In the echo signal, the useful signal is mingled with a large direct wave that should be removed for further analysis. For the simulated signal, there is no noise interference. So the echo signal can be truncated and removed directly based on the target arrival time. For the measured data, it is necessary to remove the direct wave by means such as mean filtering.

### B. Average phase difference

After obtaining the typical echo data, we can calculate phase spectrum of each target of different materials. The echo signal data when there is no target is selected as the reference signal. Calculate the phase difference of the echo data of metal, water and hollow with the reference signal. Then the average phase difference $\Delta\bar{\varphi}$ is obtained as the input of the RBF neural network.

### C. RBF Neural Network Training and Recognition

The ground penetrating radar feature data set $(x_1, x_2, ..., x_n)$ used for training is divided into three categories, the metal target data, the water target data and the hollow target data. The characteristic data are marked with corresponding labels $(y_1, y_2, ..., y_n)$. Here, the subscript 1, 2, 3 represent water target, metal target and hollow target respectively.

The input of the RBF network is an array corresponding to $n$ average phase difference data samples. The output of the RBF network is a $1\times 3$ array, from which the signal label is got and the training is completed. Then input the test data into the network, and calculate the error between the known classification results and the network classification results. Recognition successful rate can be obtained.

## V. Processing and Analysis of Simulation Results

GPRMAX2.0 is used to simulate the model that is shown in Fig. 3. The excitation signal is the Ricker wavelet. The center frequency is 100MHz, and the background medium is concrete with a relative dielectric constant of 5. The target in the model is a sphere with a radius of 2.5m and buried depth of 10m. The sphere is filled with water (dielectric constant of 81), metal and hollow respectively. In order to contrast, a no target signal is selected as the reference signal as shown in Fig. 4. And Fig. 5 shows the time domain echo waveforms in the three scenarios. It can be seen from the waveform that there is a significant difference in the phase for different targets.

The experiment uses 180 channels of echo data. First, calculate the average phase difference relative to the reference signal. Then divide these data into two groups. One group is used as the input of the neural network for training, and the other is used as test data.

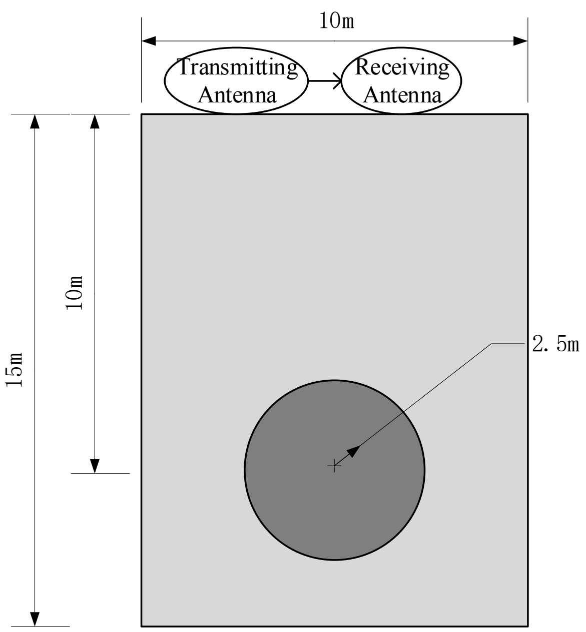


Fig. 3. Simulation model.

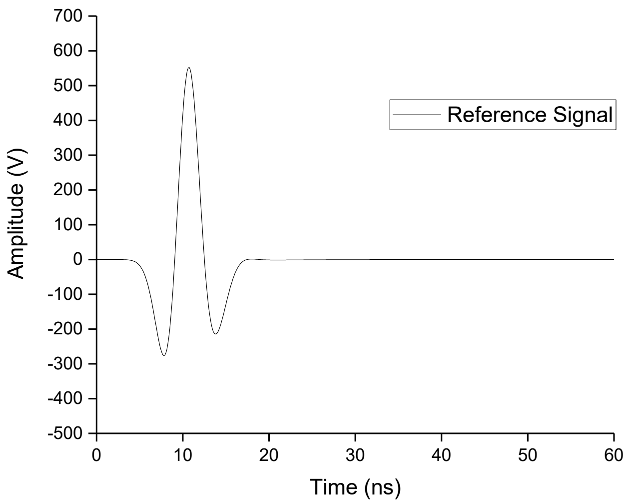


Fig. 4. Reference signal.

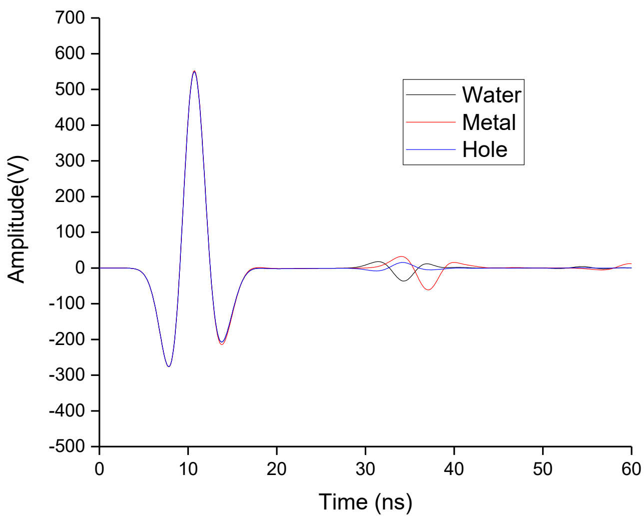


Fig. 5. Echo signals of different targets.

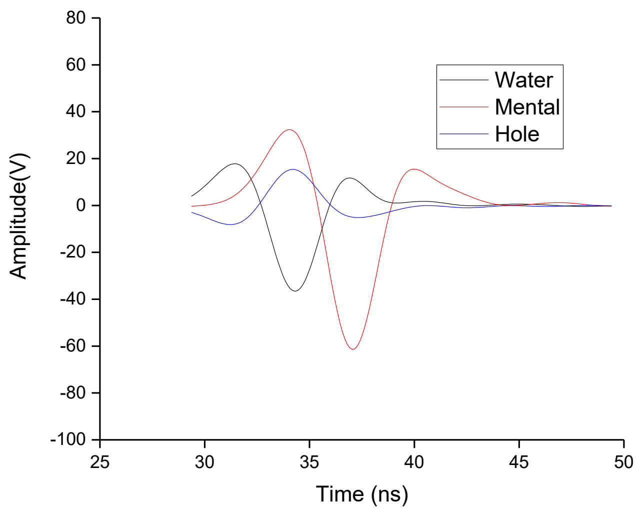


Fig. 6. The signals after the direct wave is removed.

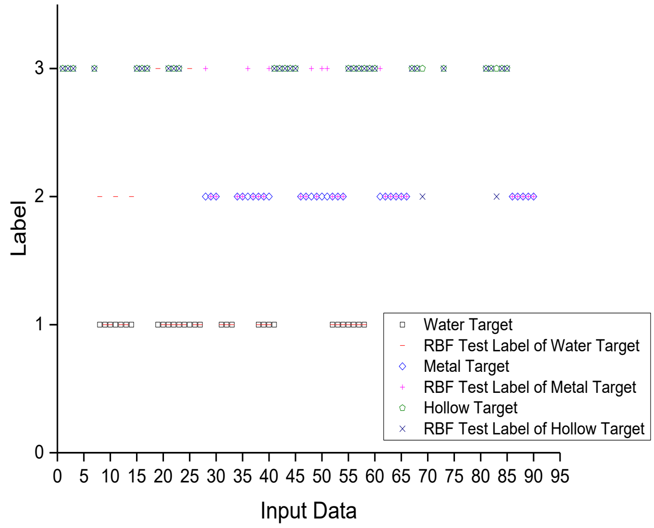


Fig. 7. RBF neural network test results.

TABLE I. RBF NETWORK RECOGNITION RESULTS

| **Training Data Number** | **Test Data Number** | | | **Recognition Successful Rate** |
|---|---|---|---|---|
| | ***Water target*** | ***Metal target*** | ***Hollow target*** | |
| 90 | 30 | 30 | 30 | 0.83333 |

The simulation results are shown in Fig. 7 and Table I. Here the label1, 2, 3 represent water target, metal target and hollow target respectively. Combining the average phase difference as a characteristic parameter, the RBF neural network can successfully recognize and classify different targets.

## VI. CONCLUSION

This paper proposes a method for GPR underground target material recognition based on the combination of RBF neural network and average phase difference. The radar echo signal is preprocessed to calculate the average phase difference between the target signal and the reference signal. By inputting these data into the RBF neural network for training to identify unknown target materials, classification and recognition are successfully realized for different material targets. This method greatly facilitates the application in practice.

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