Underground Multi-Target Recognition of Ground Penetrating Radar Based on Multi-Feature Information Fusion

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Abstract
A multi-parameter feature and recognition method is established for GPR underground targets based on multi-feature information fusion ideas specific to complexity and diversity of detecting environment and underground media as well as non-stationarity and aperiodicity of GPR echo signals. This method carries out multi-parameter feature fusion by selecting power spectrum, wavelet packet energy spectrum and higher-order spectrum, and on this basis, executes recognition and classification with the wavelet neural network. The experimental results show that compared with single–parameter feature recognition methods, this method can effectively realize recognition of the tubular bodies, spheroids as well as geologic bodies made of metal, plastic, cement and other materials.
Key words: GROUND PENETRATING RADAR, TARGET RECOGNITION, WAVELET PACKET ENERGY SPECTRUM, HIGHER-ORDER SPECTRUM, WAVELET NEURAL NETWORK

1. Introduction

As a shallow-earth non-destructive detection technology, the Ground Penetrating Radar (GPR) is widely applied in detection and recognition of underground targets. It is difficult to determine target feature invariants and detect targets due to non-uniformity and chromatic dispersion of underground media, interference and clutter noise in the regional electromagnetic environment, as well as variety of underground targets. How to select and extract the target area data from massive data and correctly judge the extracted target data is a difficult problem in GPR data processing and application.

The core of target detection and recognition is firstly the extraction of target features, i.e. how to set up a feature attribute model of underground targets and non-target images, and on this basis, extract useful information and distinguish effectively underground targets; secondly it is feature selection, i.e. solve the cooperative degree between pattern classifier and feature set to improve the recognition and classification capacity of the classifier.

At present, the features of underground target recognition mainly include time domain instantaneous parameters feature, geometric feature, transform domain feature, polarization feature, etc. The time domain instantaneous parameters mainly include Instantaneous amplitude, Instantaneous phase position and Instantaneous frequency. With these three kinds of instantaneous information, the target bodies will be recognized more correctly.

The geometric feature mainly refers to hyperbola feature of underground targets. In the two-dimensional echo image (B-Scan image) formed by GPR multi-channel scanning data, the target echo wave mostly takes on the geometry form of a hyperbola or an approximate hyperbola. The transform domain feature means there are a number of clutter waves existing in the complex environment, which are of similar attribute to the targets to be recognized; in most cases, it is impossible to correctly classify and recognize them in such a complex environment. As a result, it is required to carry out concrete analysis on composition of echo signals. The common transform methods include Fourier transform, wavelet transform, principal component analysis, singular value decomposition, Wigner time-frequency distribution, etc. The polarization mode of transmitting and receiving antennas exerts an impact on waveform of echo signals, so different targets have different signal features under different polarization modes. The selection of features has a close relationship with actual environment, thus further analysis shall be carried out. In addition, full consideration is not given to the orientation information of underground targets during extraction of some features, so it is necessary to link together detection, imaging and recognition in order to improve the comprehensive analysis capability of targets.

The recognition methods of underground targets are summarized into the following types on the whole: time-frequency analysis method [1-3]; support vector machine method [4,5]; neural network method [6-10]; statistical method [11-14]; fuzzy clustering method[15,16]; wavelet transform method[17], etc. All these methods obtain good results, but none of them discuss GRP conditions at different noise ratios; moreover, most of features are recognized with single-parameter features, so in this case, the correct recognition rate is limited to a certain extent.

The key of underground target recognition is to extract the most distinguishable feature of GPR target's reflected echo signals. Due to diversity and complexity of detecting environment and non- stationarity of GPR echo signals, it is unlikely to completely distinguish underground target properties with the single feature, no matter which is obtained from time domain, frequency domain, wavelet domain or spectrum estimation. Also, there is no way to solve extraction and recognition problems of invariant feature of underground targets in different geological environments and interference effects. The extraction and recognition of underground targets is still a difficult problem.

The studies show that the power spectrum estimation method is relatively effective to distinguish and locate targets; the distribution of wavelet energy spectrum has a close relationship with the size, form and type of target and reflects the changes of target features. Compared with power spectrum, the higher-order spectrum can restrain Gaussian noise, has high resolution and could obtain signal phase position, energy, nonlinearity and other useful information. Therefore, this paper selects time domain parameter, Welch power spectrum, wavelet packet energy spectrum and higher-order spectrum to carry out multi-parameter feature fusion, and then uses a wavelet neural network classifier for classification.

2. Extraction of multi-feature parameters of underground target

Since the actual underground target bodies are different in the form and material, the time domain parameter feature, Welch power spectrum feature and wavelet energy spectrum feature are hereby used to carry out multi-parameter composite feature fusion and the target recognition will be realized with a wavelet neural network classifier. The whole process is shown in Figure 1.

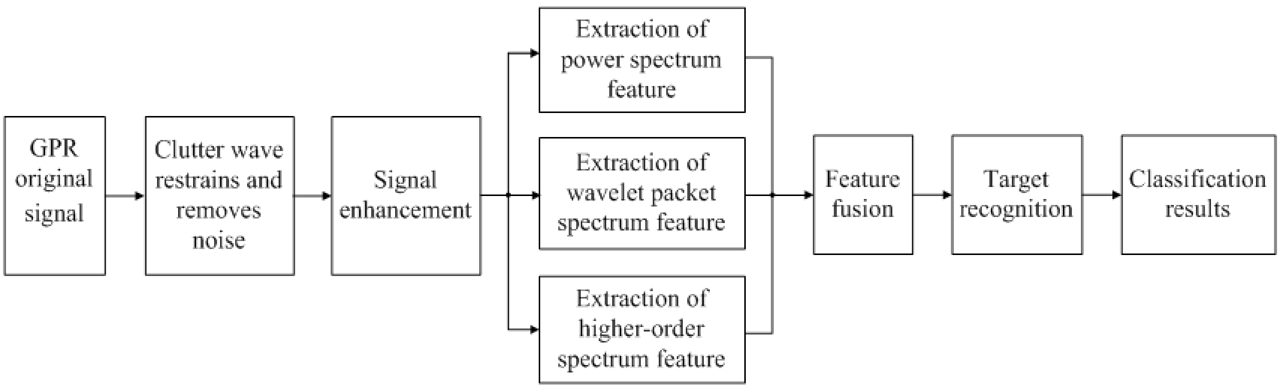

Figure 1. Block diagram of extraction and recognition principles of GPR underground target feature

2.1 Pre-processing of GPR data

The GPR echo signal is composed of direct-coupled wave, ground reflected wave, back scattering wave produced by discontinuity of underground media, random disturbance, etc. The direct wave that is constituted by direct-coupled wave and ground reflected wave has a direct impact on target echo signals. As a result, a series of preprocessing must be carried out on original data in order to extract the useful signals from target signals, including filtering, time-delay calibration, etc. As for original B-scan data extracted, this paper firstly restrains ground clutters and direct current with the mean value method, and then removes wideband clutters and periodic random waves through Wiener filtering.

2.2 Welch power spectrum estimation of GPR echo signal

Because GPR echo signal is non-stable or aperiodic, the traditional Fourier transform spectrum estimation method cannot be used, especially for ultra-wideband transient electromagnetic scattering signals. The studies show that, among many spectrum estimation methods, the partially-scanned Welch averaging overlap and periodic spectral estimation is effective to distinguish and locate targets [18]. This paper conducts computation by selecting Welch power spectrum as one of composite features of under -ground targets.

The basic principle of Welch power spectrum method is to divide data into K sections to ensure each section has some overlap; smooth each section of data with a proper window function, and finally average each spectrum. Different commonly-used window functions have different impacts on results of estimation. The main lobe of rectangular window is narrow with high resolution ratio, but it has big variance and high noise level; the main lobes of Blackman and Hamming windows are wide with low resolution ratio, but they have small variance and low noise level. The window function can be selected according to specific signal conditions and occasions.

Welch spectrum estimation and calculation method: divide sampled data into L sections to ensure each section has some overlap; smooth each section of data with a proper window function, and finally average each spectrum. According to probability and statistics theory, if the data with original length of N is divided into L sections without any overlap and the length of each section is $M = N / L$, the estimated variance will be only $1 / L$ of the original data without division, thus realizing the purpose of consistence. In the premise of keeping the amount of data unchanged, if L increases but M decreases, the resolution ratio will be reduced. By contrast, if L decreases but M increases, although the deviation is reduced, the estimated variance is increased. Thus, the values of L and M shall be properly selected on the condition of paying attention to requirements of resolution ratio and variance. When dividing, ensure each section of data has some overlap in order to reduce influences of the number of sections on resolution ratio.

The calculation process of Welch power spectrum estimation of GPR echo signals is as follows: provided $s_N(n)$ length of A-scan signal is 512, now divide it into $L = 7$ sections and the length of each section is $N = 128$, 50% overlapped. Besides, add a Hanming window $w(n)(n = 128)$ to each subset[19].

Firstly calculate Welch power spectrum of each section

$$\hat{P}^i(\omega) = \frac{1}{MU}\left|\sum_{n=0}^{M-1} s_N^i(n)\cdot w(n)e^{-j\omega n}\right|^2 \tag{1}$$

where,

$$U = \frac{1}{M}\sum_{n=0}^{M-1} w^2(n) \tag{2}$$

is a normalization factor, in order to obtain an evolutionary spectrum without offset estimation; $w(n)$ is a window function. Average L-section periodogram, and the power spectrum estimation of the whole signal $s_N(n)$ is gained:

$$\tilde{P}(\omega) = \frac{1}{L}\sum_{i=1}^{L} P^i(\omega) = \frac{1}{MUL}\sum_{i=1}^{L}\left|\sum_{n=0}^{M-1} s_N^i(n)\cdot w(n)e^{-j\omega n}\right|^2 \tag{3}$$

2.3 Extraction of wavelet packet energy spectrum feature of GPR echo signal

The GPR echo signal has a characteristic of non-stationarity, the traditional analysis method based on stationary signals cannot realize scientific processing and analysis while the wavelet transform with the time-frequency localization function is an ideal tool for non-stationary signal processing. While reserving the time domain feature of target echo signals at each scale, the wavelet packet analysis can also provide signal feature information within different frequency ranges and reflect subtle variation of target features, thus improving the time-frequency resolution ratio of signals. The studies show that, the target reflection echo signal of GPR is composed of a variety of frequency components, and different frequency components have different features in the scale space of wavelet; in other words, the wavelet spectrum structural feature of signals at each scale space has obvious difference. As a result, the wavelet spectral features with different distribution can be used to study detail features and recognition problems of GPR signals in the multi-scale space. The ideas are as below: based on finding the wavelet spectrum of signals at different scales, set up a wavelet energy spectrum function about decomposition scale and build a feature sample model according to the corresponding spectrum feature vectors formed by various target bodies, thus analyzing the signal of target bodies. In such case, carry out wavelet packet decomposition for GPR target signals extracted, in order to extract target feature information.

Carry out wavelet packet decomposition for GPR signals $x(n)$ to obtain the energy distribution characteristic within different frequency ranges. Provided that the wavelet packet coefficient at k time on decomposition scale of the jth layer is $C_j(k)$, the wavelet energy of signals at the jth layer is defined as:

$$E_j = \sum_{k=1}^{N} | C_j(k) |^2, \quad j = 1, 2, \cdots, J \tag{4}$$

When the signal energy is large, the value of wavelet energy E_j gets high; in order to highlight the signal structural feature of sample models and facilitate data analysis, normalize processing results of wavelet energy spectrum feature vectors to eliminate energy difference caused by the same targets with different burial depths. The normalized energy of signals at the jth layer is as below:

$$E'_j = \frac{E_j}{\sum_{j=1}^{J} E_j} \tag{5}$$

The wavelet energy spectrum feature vector of signal $x(n)$ at each sampling point is as below:

$$\mathbf{E} = [E'_1, E'_2, \cdots, E'_J] \tag{6}$$

2.4 Higher-order estimation of GPR echo signal

The further research shows that it is impossible to reach high recognition ratio by distinguishing with the wavelet energy spectrum method when the energy distribution is approximate. For this reason, by analysis on high-order statistic features of the signal, this paper extracts the high-order spectrum feature vectors for recognition. The higher order statistics generally refers to higher-order moment, higher-order cumulant and their spectrum—high-order moment spectrum and high-order cumulant spectrum, which are all called higher order spectrum. Compared with higher-order moment, the higher -order cumulant can effectively restrain Gaussian background noise with high resolution ratio and can obtain phase position, energy, non-linearity and other useful information of the signal. Therefore, the higher-order cumulant is usually used as a tool of analyzing time series during actual application. The higher-order spectrum used in this paper refers to the higher-order cumulant spectrum.

For stationary random process $\{x(n)\}$ with a zero mean value, the k-order cumulant expression [20]is as below:

$$c_{kx}(\tau_1, \tau_2, \cdots, \tau_{k-1}) = cum\{x(n), x(n+\tau_1), \cdots, x(n+\tau_{k-1})\} \quad k \geq 3 \tag{7}$$

The 2-order to 4-order cumulant expression is as below

$$c_{2x}(\tau) = cum\{x(n), x(n+\tau)\} = E\{x(n)x(n+\tau)\} = R_x(\tau) \tag{8}$$

$$\begin{aligned} & c_{3x}(\tau_1, \tau_2) = cum\{x(n), x(n+\tau_1), x(n+\tau_2)\} \\ & = E\{x(n)x(n+\tau_1)x(n+\tau_2)\} \end{aligned} \tag{9}$$

$$\begin{aligned} & c_{4x}(\tau_1, \tau_2, \tau_3) = cum\{x(n), x(n+\tau_1), x(n+\tau_2), x(n+\tau_3)\} \\ & = E\{x(n)x(n+\tau_1)x(n+\tau_2)x(n+\tau_3)\} \\ & \cdot R_x(\tau_1)R_x(\tau_3-\tau_2) - R_x(\tau_2)R_x(\tau_3-\tau_1) \\ & - R_x(\tau_3)R_x(\tau_2-\tau_1) \end{aligned} \tag{10}$$

where, $R_x(\tau) = E\{x(n)x(n+\tau)\}$ stands for self-correlation function of signal $x(n)$.

Based on Wiener-Khintchine theorem, the self-correlation function and power spectrum density of any stationary random process $\{x(n)\}$ are a pair of Fourier transform, so the higher-order cumulant and higher-order cumulant spectrum are a pair of Fourier transform.

Provided that the higher-order cumulant $c_{kx}(\tau_1, \tau_2, \cdots, \tau_{k-1})$ is absolutely summable as below

$$\sum_{\tau_1=-\infty}^{\infty} \cdots \sum_{\tau_{k-1}=-\infty}^{\infty} | c_{kx}(\tau_1, \tau_2, \cdots, \tau_{k-1}) | < \infty \tag{11}$$

The k-order cumulant spectrum $C_{kx}(\omega_1, \omega_2, \cdots, \omega_{k-1})$ of $\{x(n)\}$ exists and is continuous, and can be defined as $(k-1)$ Fourier transform of k-order cumulant as below

$$C_{kx}(\omega_1, \omega_2, \cdots, \omega_{k-1}) = \sum_{\tau_1=-\infty}^{\infty} \cdots \sum_{\tau_{k-1}=-\infty}^{\infty} c_{kx}(\tau_1, \tau_2, \cdots, \tau_{k-1}) \exp[-j \sum_{i=1}^{k-1} \omega_i \tau_i] \tag{12}$$

Where, $|\omega_i| \leq \pi, i = 1, \cdots, k-1$

When $k = 3$, it is the three-order spectrum, also called Bispectrum, the Fourier transform corresponding to three–order cumulant is:

$$C_{3x}(\omega_1,\omega_2)=\sum_{\tau_1=-\infty}^{\infty}\sum_{\tau_2=-\infty}^{\infty}c_{3x}(\tau_1,\tau_2)\exp[-j(\omega_1\tau_1+\omega_2\tau_2)] \tag{13}$$

When $k=4$, it is the four-order spectrum, the Fourier transform corresponding to four–order cumulant is:

$$C_{4x}(\omega_1,\omega_2,\omega_3)=\sum_{\tau_1=-\infty}^{\infty}\sum_{\tau_2=-\infty}^{\infty}\sum_{\tau_3=-\infty}^{\infty}c_{4x}(\tau_1,\tau_2,\tau_3)\exp[-j(\omega_1\tau_1+\omega_2\tau_2+\omega_3\tau_3)] \tag{14}$$

The higher-order spectrum is featured with:

(1) The higher-order spectrum is mostly a multi-dimensional compound function; in other words, it has amplitude and phase position. The higher-order spectrum contains phase position information while the power spectrum does not contain such information.

(2) The higher-order spectrum is a periodic function with the period of 2π.

(3) The higher-order spectrum is symmetrical.

Among all higher-order spectrums, the three-order spectrum is the one with the lowest order, easy to calculate, but it has all features of the higher-order spectrum. Therefore, this paper adopts the feature extraction method based on three-order spectrum (also called bispectrum). Similar to power spectrum estimation, the estimation of higher-order spectrum is divided into two categories: one is parametric estimation method and the other is non-parametric estimation method, including direct and indirect methods. Take bispectrum estimation as an example, the direct method firstly estimates the Fourier sequence and then carries out triple correlation calculation for the sequence, thus obtaining bispectrum estimation; the indirect method firstly estimates the three-order cumulant and then obtains bispectrum through the Fourier transform of cumulant sequence. In this paper, the bispectrum estimation is carried out with the indirect method, and the steps are as follows:

(1) Divide the experiment data $\{x(n)\}$ with the length of N into K sections, and each section has M data, i.e. $N=K*M$, and then de-mean.

(2)Provided that $\{x_i(n)\}$ $(n=1,2,\cdots,M, i=1,2,\cdots,K)$ is data at the i th section, its three-order cumulant estimation formula is as below:

$$\hat{c}_{3x,i}(l,m)=\frac{1}{M}\sum_{n=-k_1}^{k_2}x_i(n)x_i(n+l)x_i(n+m) \tag{15}$$

(3) Carry out statistics of $\hat{c}_{3x,i}(l,m)$ and calculate its mean value to get cumulant estimation of K-group data, i.e.:

$$\hat{c}_{3x}(l,m)=\frac{1}{K}\sum_{i=1}^{K}\hat{c}_{3x,i}(l,m) \tag{16}$$

(4) Carry out bispectrum estimation:

$$\hat{C}_{3x}(\omega_1,\omega_2)=\sum_{l=-L}^{L}\sum_{m=L}^{L}\hat{c}_{3x}(l,m)w(l,m)\exp(-j(\omega_1\tau_1+\omega_2\tau_2)) \tag{17}$$

Where, $L<M-1$, $w(l,m)$ is a 2-dimensional window function, and the commonly-used windows include optimal window, Parzen window and spectral domain uniform window. Similar to estimation of power spectrum, the purpose of using a window function is to get the approximately smooth estimation results.

3. Underground multi-target recognition based on multi-feature information fusion

3.1 Wavelet neural network classifier

The traditional classifier algorithm firstly obtains parameter estimation from training samples, and then calculates the matching degree of samples to be identified and various pattern samples. Since it is difficult to obtain a complete sample set due to complex underground environment and various forms of target bodies, the target recognition cannot reach the expected performance in the actual application. Wavelet neural network (WNN) is a network formed by widely-interconnected non-linear processing units, with the properties of large-scale parallel processing, distributed information storage, non- linear dynamics and global scope of network, etc. The sample parameters of wavelet neural network classifier are hidden in connection weight of network. It does not need to be known and the expected goal will be achieved by feedback and automatic adjustment of network output errors during repeated trainings. Therefore, this paper selects the wavelet neural network design classifier, whose structure is shown in Figure 2.

The number of nodes at input layer, hidden layer and output layer is respectively T,K,N. The weight value of hidden layer is the wavelet base function, and the transfer function of output layer is sigmoid function

$$\sigma(u)=\frac{1}{1+e^{-u}} \tag{18}$$

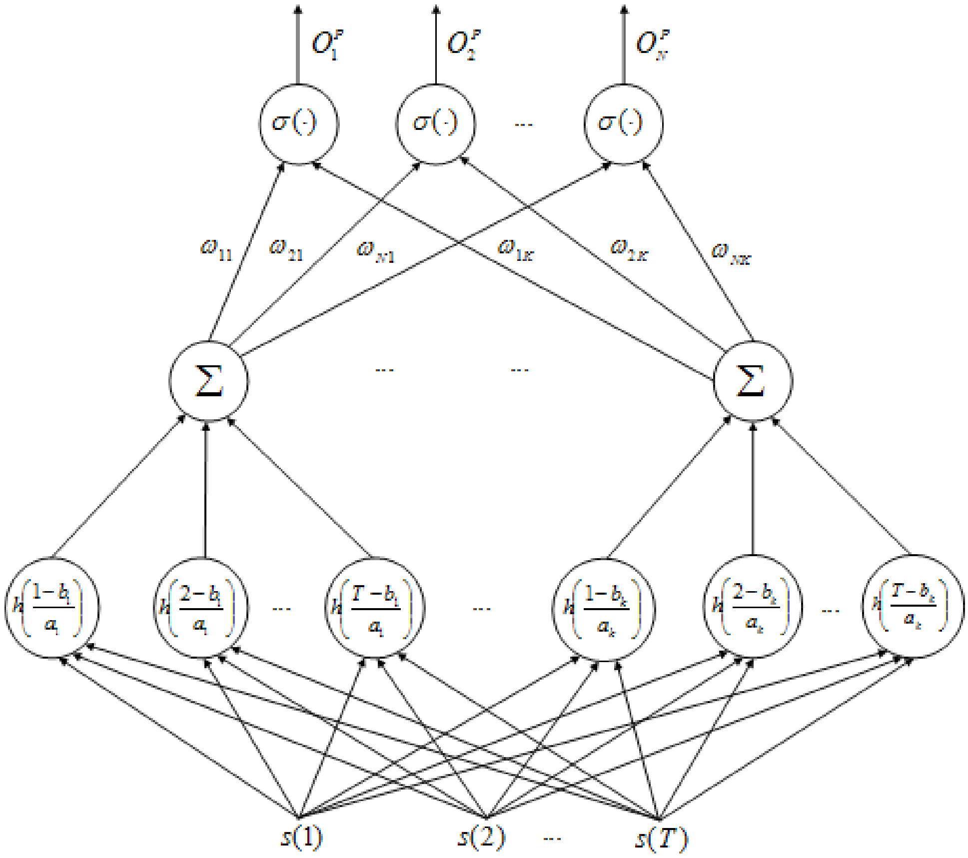

Figure 2. Wavelet neural network classifier

Provided the total number of input training samples is P , the output of the pth sample and the nth node can be expressed by the following formula

$$O_n^p = \sigma(u_n) = \sigma\left(\sum_{k=1}^{K} w_{n,k} \sum_{i=1}^{T} s^p(i) h\left(\frac{i-b_k}{a_k}\right)\right) \quad (19)$$

Here we choose Morlet wavelet, use conjugate gradient method to optimize the WNN and adopt one-dimensional variable-step searching method to solve the step size $\alpha_w^i, \alpha_b^i, \alpha_a^i$.

4. Comparative analysis of measured data processing

The test data is collected and supplied by a GPR system developed by Professor Yang Feng Team of China University of Mining and Technology (Beijing). For comparative analysis, the experiment is conducted in four aspects:

(1) Test the recognition of objects with different forms. Adopt the data respectively measured from spheroids, tubular bodies, squares, etc. The experiment method is firstly to preprocess the measured data, calculate parameters and extract features in order to recognize the form of target.

(2) Recognition of objects made of different materials. Adopt the data measured respectively from metal (iron) tubes, plastics, cement, soil, etc. Firstly preprocess the measured data to obtain typical-channel data and goalless multi-channel soil data. Carry out training and recognition through Welch power spectrum and higher-order spectrum estimation and by using wavelet neural network.

(3) For above measured data, carry out target recognition respectively by using the wavelet neural network (WNN), BP neural network (BP-NN) and RBF neural network (RBF-NN); Table 1-3 lists out the recognition results of four types of underground targets with three methods respectively.

(4) For above measured data (the number of training samples and samples to be recognized is the same), carry out recognition with wavelet packet neural network respectively by using the Welch power spectrum, wavelet packet spectrum, higher-order spectrum estimation and other single parameters, to verify the performance of multi-feature parameters proposed in this paper. Table 4 lists out recognition results of four types of underground targets under single-feature parameters.

Table 1-4 shows that, the average recognition rates of WNN, BP-NN and RBF-NN classifiers are respectively 96.17%, 77.57% and 83.70% for four types of targets.

Table 1. The recognition results of four types of underground targets with BP-NN methods

Material of objects	The number of training samples	The number of recognition samples	BP-NN recognition rate
Metal	910	165	81.21%
Plastic	770	169	73.37%
Cement	850	173	79.77%
Soil	1030	220	75.91%
The average recognition rate	-	-	77.57%

Table 2. The recognition results of four types of underground targets with RBF-NN methods

Material of objects	The number of training samples	The number of recognition samples	RBF-NN recognition rate
Metal	910	165	87.27%
Plastic	770	169	85.21%
Cement	850	173	83.24%
Soil	1030	220	79.09%
The average recognition rate	-	-	83.70%

Table 3. The recognition results of four types of underground targets with WNN methods

Material of objects	The number of training samples	The number of recognition samples	WNN recognition rate
Metal	910	165	98.18%
Plastic	770	169	97.04%
Cement	850	173	95.38%
Soil	1030	220	94.09%
The average recognition rate	-	-	96.17%

Table 4. The recognition results of four types of underground targets under single-feature parameters

Material	Time domain parameter	Welch power spectrum	Wavelet packet energy spectrum	Higher-order spectrum
Metal	73.94%	83.03%	87.27%	95.19%
Plastic	65.09%	72.20%	78.11%	93.49%
Cement	69.36%	73.41%	76.88%	89.60%
Soil	70.45%	78.18%	79.09%	89.55%
The average recognition rate	69.71%	76.71%	80.34%	91.96

WNN has better classification and recognition performance than BP-NN and RBF-NN, and its convergence speed is also higher 17.79% than that of BP-NN. This indicates that: the time domain feature parameters can reflect the form and position information of signals to some extent; the power spectrum estimation is relatively effective to distinguish and locate targets, and the distribution of wavelet energy spectrum has a close relationship with the size, form and type of targets, reflecting changes of target features. The higher-order spectrum has advantages in restraining Gaussian noise, improving resolution ratio and describing phase position, energy, nonlinearity and other details of signals. The recognition ratio can be effectively improved by combining above four items.

5. Conclusions

It is impossible for the traditional stationary-signal-based analysis method and single parameters to extract target features specific to complexity and diversity of detecting environment and underground media as well as non-stationarity of GPR echo signals. The wavelet packet decomposition can improve the time domain resolution ratio of signals and the energy spectrum indicates the distribution interval of signal energy, but the single energy spectrum cannot correctly distinguish different signals; the higher- order spectral analysis can effectively restrain Gaussian background noise, with high resolution ratio, and can also obtain the phase position, energy, nonlinearity and other useful information of signals. As a result, this paper proposes an underground target extraction and recognition method based on multi- parameter feature fusion. In other words, adopt the power spectrum, wavelet energy spectrum and higher-order spectrum to carry out multi-parameter feature fusion, and recognize and classify with the wavelet neural network. Finally, verify by processing the measured data that such method can effectively recognition of the tubular bodies, spheroids as well as the geologic bodies made of metal, plastic, cement and other materials. However, due to insufficient samples, the generalization ability of this method still requires further verification and improvement.

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References

1. Guillermo C.G, Hans C.S. (2001) Applications of (Wigner-Type) Time-Frequency Distributions to Sonar and Radar Signal Analysis. *7th International Wigner Symposium* ,College park, MD USA.
2. Guillermo C.G, Hans C.S. (1996) Signal analysis by means of time-frequency (Wigner-Type) distributions applications to sonar and radar echoes. *Proceedings of the IEEE,* 84(9), p.p.1231-1248.
3. Sun Y, Li J. (2003) Time-frequency analysis for plastic landmine detection via forward-looking ground penetrating radar. *IEEE Proceedings of Radar, Sonar and Navigation*, 150(4), p.p.253-261.
4. Zhang C.C, Zhou Z.O. (2005) Research on ground penetrating radar target identification based on support vector machines in shallow subsurface application. *Acta Electronica Sinica*, 33 (6), p.p.1019-1094.
5. Hu J.F, Zhou Z.O, Kong L.J. (2006) Reseacrh on GPR multi-object recognition. *Journal of Electronics & Information Technology*, 28 (1), p.p.26-30.
6. Savelyev T.G, Van Kempen L, Sahli H. (2003) GPR anti-personnel mine detection: improved deconvolution and time-frequency feature extraction. *Proceedings of SPIE*, vol.5046, p.p. 232-241.
7. Chang S.S, Ruane M.F. (2003) Feature extraction of ground-penetrating radar for mine detection. *Proceedings of SPIE*, vol.5089, p.p. 1201-1209.
8. Gamba P, Lossani S. (2000) Neural detection of pipe signatures in ground penetrating radar images. *IEEE Transactions on Geoscience and Remote Sensing,* 38(2), p.p. 790-797.
9. Yang C.C, Bose N.K. (2005)Landmine detection and classification with complex-valued hybrid neural network using scattering parameters dataset . *IEEE Transactions on Neural Networks*, 16(3), p.p. 743-753.
10. Caorsi S, Cevini G. (2005)An electromagnetic approach based on neural networks for the GPR investigation of buried cylinders. *IEEE Geoscience and Remote Sensing Letters*, 2(1), p.p. 3-7.
11. Gader P.D, Mystkowski M, Zhao Y.X. (2001) Landmine detection with ground penetrating radar using hidden Markov models. *IEEE Transactions on Geoscience and Remote Sensing*, 39(6) ,p.p. 1231-1244.
12. Gader P, Lee W.H, Wilson J.N. (2004) Detecting landmines with ground-penetrating radar using feature-based rules, order statistics, and adaptive whitening. *IEEE Transactions on Geoscience and Remote Sensing*, 42(11), p.p. 2522-2534.
13. Ho K.C, Gader P.D. (2002)A Linear prediction land mine detection algorithm for hand held ground penetrating radar . *IEEE Transactions on Geoscience and Remote Sensing,* 40(6), p.p. 1374-1384.
14. Torrione P.A, Throckmorton C.S, Collins L.M. (2006) Performance of an adaptive feature-based processor for a wideband ground penetrating radar system. *IEEE Transactions on Aerospace and Electronic Systems*, 42 (2), p.p. 644-658.
15. Delbo S, Gamba P, Roccato D. (2000) A fuzzy shell clustering approach to recognize hyperbolic signatures in subsurface radar images. *IEEE Transactions on Geoscience and Remote Sensing*, 38(3) , p.p.1447-1451.
16. Gader P, Keller J.M, Frigui H, Liu H.W. (1998) Landmine detection using fuzzy sets with GPR images. *Proceedings of the IEEE International Conference on Fuzzy Systems*, p.p.232-236.
17. Le-Tien T, Talhami H, Nguyen D.T. (1997) Target signature extraction based on the continuous wavelet transform in ultra-wideband radar. *IEEE*

Electronics Letters, 33(1) , p.p.89-91.
18. Wang Q, Ni H.W, Xu Y.G. (2003)A study on mine detection and identification through patter recognition with the help of multi-features. Journal of Applied Sciences, 21(1), p.p. 53-58.
19. Li J X, Zheng J T. (2005) Automatic target recognition for ultra-wideband ground penetrating radar . *Chinese Journal of Radio Science,* 20(4), p.p. 535-540
20. Zhang X.D.(1996) *Time series analysis-higher-order statistics method*. Beijing: Tsinghua University Press.

Information Extraction of Building Set of SAR Image Based on Genetic Algorithm

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Abstract
Due to the problem of low level of accuracy and practicability in the existing method, this paper puts forward geometric information extraction framework of buildings based on the matching degree of model and image. On one hand, this framework maps building model to image to determine the typical feature region of the image which contains the geometrical information of buildings, such as overlapping and shadow region, on the other hand, it makes use of building contour and other information obtained from the building detection stage to find the best model parameters through the matching degree of the two. The new framework is applied universally. Geometric model of building parameters, typical feature region and the extraction method could all be adjusted in accordance with practical application. Take the most commonly seen flat topped buildings as an example; it discussed a specific application of the framework: under the condition of different imaging parameters and model parameters, it analyzed in detail the method of mapping building model into of overlapping and shadow typical feature region of images; it designed the matching degree of overlapping boundary and shadow boundary to measure the matching degree between the model and the image; The optimization method based on genetic algorithm is presented. The model parameters which enable the maximum matching function are used as the geometric parameters