An interpretation model of GPR point data in tunnel geological prediction

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ABSTRACT

GPR (Ground Penetrating Radar) point data plays an absolutely necessary role in the tunnel geological prediction. However, the research work on the GPR point data is very little and the results does not meet the actual requirements of the project. In this paper, a GPR point data interpretation model which is based on WD (Wigner distribution) and deep CNN (convolutional neural network) is proposed. Firstly, the GPR point data is transformed by WD to get the map of time-frequency joint distribution; Secondly, the joint distribution maps are classified by deep CNN. The approximate location of geological target is determined by observing the time frequency map in parallel; Finally, the GPR point data is interpreted according to the classification results and position information from the map. The simulation results show that classification accuracy of the test dataset (include 1200 GPR point data) is 91.83% at the 200 iteration. Our model has the advantages of high accuracy and fast training speed, and can provide a scientific basis for the development of tunnel construction and excavation plan.

Keywords: Tunnel geological prediction, deep learning, GPR, Wigner distribution, time frequency map, convolution neural network.

1 INTRODUCTION

GPR, which is the main method of tunnel geological prediction, has the advantages of fast detection speed, small damage to the tunnel environment and convenient operation [1,2]. GPR sends the fixed frequency electromagnetic wave into the tunnel face. Then, the electromagnetic wave will be reflected and refracted in the surface of geological anomalous body. The anomalous behind the tunnel face was located and explained according to the change of the receiving wave. There are two working style of GPR: line and point. In line style, the GPR scans the tunnel face and gets the GPR line data which can reflect the continuous change of the tunnel geological; In point style, the GPR observes the key point of the tunnel face and gets the GPR point data which can accurately reflect the geological features of that point. The GPR line data and GPR point data all play important role in the process of tunnel geological prediction [2].

It is difficult to accurately distinguish GPR data only depending by expert experience or shallow machine learning methods [3], because of the complexed and changed geological environment of the tunnel. In related field, Lance [4] distinguished the BEHs (Buried explosive hazards) GPR line data by an autoencoder model and achieved a classification accuracy of 91%. However, the disadvantage of autoencoder model is that the computation quantity becomes very large with the increase of image dimension. Sakaguchi [5] discriminated the subsurface target GPR line data about 420 different underground regions by a CNN model [6]. The CNN model has the advantages of anti-target displacement, zoom and distortion. As the GPR line data, the GPR point data plays an absolutely necessary role in the tunnel geological prediction too. The GPR point data is usually analyzed by FFT which is embed in the GPR instrument. FFT is usually used to deal with the stationary signals, but GPR point data is the non-stationary signal and very complex. So, it is difficult to identify the GPR point data by FFT and experience.

Different from the GPR line data of literature [4] and [5], in this paper, the GPR point data is researched. Inspired by literature [6], a GPR point data interpretation model based on WD [7] and CNN is proposed. It is aimed to provide a high accuracy and short training time interpretation model for the process of tunnel geological prediction.

Eighth International Conference on Graphic and Image Processing (ICGIP 2016), edited by Tuan D. Pham, Vit Vozenilek, Zhu Zeng, Proc. of SPIE Vol. 10225, 102252J · © 2017 SPIE · CCC code: 0277-786X/17/$18 · doi: 10.1117/12.2266226

2 THE TIME-FREQUENCY ANALYSIS OF GPR POINT DATA

The effective detection depth of the GPR is generally 20~35m, which belongs to the short range predict mode. GPR point data is a typical non-stationary signal that the signal spectrum changed over depth. The typical GPR point data shows in Fig.1. The raw GPR point data consists of the useful target location information. However, it can't be distinguished only depending by expert experience or shallow machine learning methods.

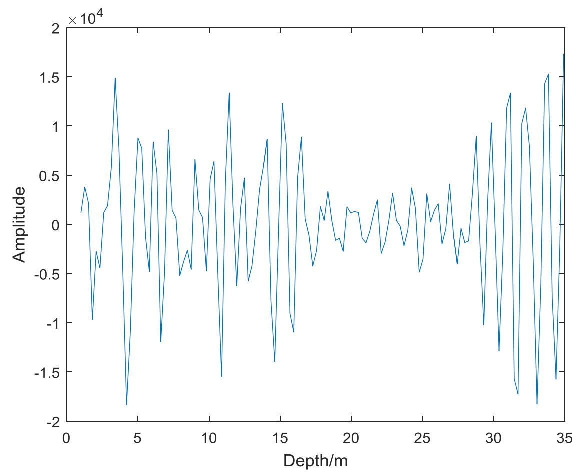

Figure 1. The raw GPR point data

Cohen presents a unified theory, generalized bilinear frequency distribution, to get a different energy time frequency distribution by designing a suitable integral kernel. The generalized bilinear time frequency distribution of the $s(t)$ signal is given by

$$P_s(t, f) = \iiint r_s(u,\tau)k(\xi,\tau)\,\mathrm{e}^{-j2p(\xi t+f\tau-\xi u)}\,d\xi du d\tau \tag{1}$$

$$r_s(u,\tau) = s(u-\frac{\tau}{2})s^*(u-\frac{\tau}{2}) \tag{2}$$

Where $r_s(u,\tau)$ is instantaneous correlation function of $s(t)$. $k(\xi,\tau)$ is the kernel function, which determines the form and character of the time-frequency distribution. When $k(\xi,\tau)=1$, it's a Wigner distribution; when $k(\xi,\tau)=\exp(\mathrm{j}\xi\tau)$,it's a Kirkwood distribution; when $k(\xi,\tau)=\exp(\mathrm{j}\xi|\tau|)$, it's a Page distribution; when $k(\xi,\tau)=\cos(\xi\tau/2)$,it's a Margenau-Hill distribution; when $k(\xi,\tau)=\exp(-\xi^2\tau^2/\delta^2)$, it's an exponential distribution. In this paper, the Wigner distribution is used to deal with the raw GPR point data for the simple form and easy calculation.

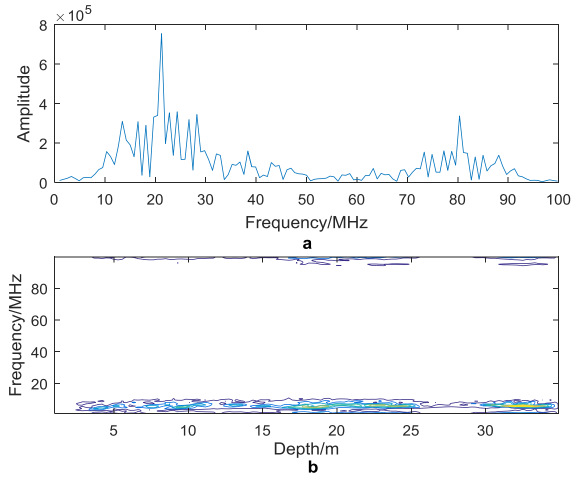

Figure 2. Frequency domain and time-frequency distribution of typical GPR point data

The frequency domain of the GPR point data transformed by FFT show in Fig.2(a), which describes the spectrum distribution of GPR point data in the entire time. It has the information which can identify the target geology, but it lacks the position information; The time frequency joint distribution of GPR point data transformed by WD show in Fig.2(b), which describes the signal spectrum changed over depth. Although the time-frequency map contains the information about the location of the geological anomaly target, but the content of the maps is abstract and not easy to identify. Firstly, the content of time-frequency map of GPR point data has no clearly physical meaning. Secondly, time frequency maps of different types of GPR point data have the differences in the frequency domain, while the differences are not significant for direct identification. Finally, time frequency maps of same type GPR point data from different regions have the inevitable shift 、distortion and zoom in frequency (horizontal).

3 CLASSIFICATION AND INTERPRETATION MODEL OF GPR POINT DATA BASED ON WD AND CNN

Deep learning model has turned out to be very good at discovering intricate structures in high-dimensional data and is therefore applicable to many domains of science, business and government [8-13]. In this paper, the deep learning model(CNN) is used to deal with the time frequency maps of the GPR point data which is not easy to identify. CNN is a typical deep learning model consisting of multiple forward feed neural network layer. The CNN model contains three parts, which is input layers, low-hidden layers and high-connected layers (see Fig.3).

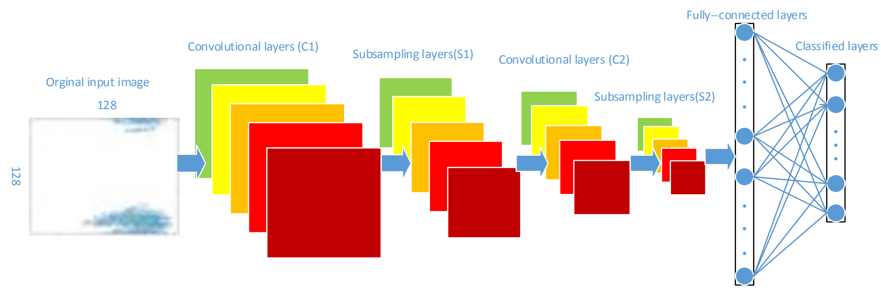

Figure 3. Typical structure of CNN model

Signal processing systems with CNN are composed of many layers of nonlinear processing stages, where each lower layer's outputs are fed to its immediate higher layer as the input. The raw image is input in the input layers. low hidden layers consist of convolutional and subsampling layer alternately. high-connected layers consist of fully-connected layer and classified layers [8]. The most important convolution formula is:

$$y_j = f(\sum k_{ij} \otimes x_i + b_j) \quad (3)$$

Where, k_{ij} is the convolutional kernel function, x_i is the parent feature map, y_i is the son feature map, b_j is the bias, $\otimes$ is the convolution operator, $f()$ is the activation function, such as sigmoid、tanh and ReLU. In subsampling stage, each feature map was independent operated by the average pooling or max pooling. Comparing with DBN (deep belief network) [11] model, the CNN model has been more widely used because it can directly input the raw image and has the advantages of anti-target displacement, zoom and distortion.

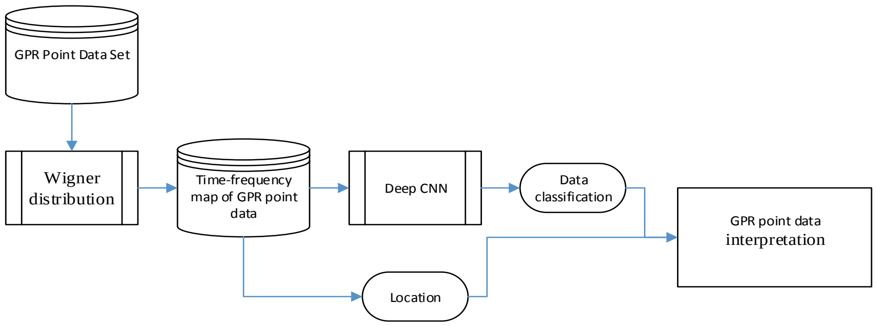

Fig.4 Interpretation model of GPR point data based on WD and CNN

According to the degree of fragmentation and water in rock, there are six kinds of types GPR point data, which is karst cave in cavity, karst cave filling with mud rock, partial broken country rock, broken country rock with Rich water, full broken country rock with low water, no significantly abnormal country rock. In this paper, a GPR point data interpretation model is proposed (see Fig 4). First of all, GPR point dataset were transformed by WD to obtain the time-frequency maps. Then, the maps were classified by CNN model and extracted approximate location information. Finally, GPR point date were interpreted according to the classification results and location information of time-frequency map.

4 SIMULATION EXPERIMENT

4.1 Experimental Data

Experimental data was collected from the freeway tunnel in Guangxi. The experimental data was divided into two different data sets: training data set and test data set. The training data set contains 4800 GPR point data from different regions. The test data set contains 1200 GPR points from different regions (see table 1). The length of GPR point data is 128.

Table.1 Test data set

Type	Karst cave in cavity	Karst cave filling with mud rock	Partial broken country rock	Broken country rock with Rich water	Full broken country rock with low water	No significantly abnormal country rock
Quantity	210	198	203	191	192	196

4.2 Simulation experiment

4.2.1 Experiment one

SVM (Support vector machine) is often used to solve the problem of data classification. In this experiment, the classification accuracy rate of our model and SVM are compared. Our model is showed in Fig 4. The convolution kernel function size of low hidden layers is 3,6 and 10, Subsampling kernel function size is all 2. The training data set is 4800 samples, and the test data set is 1200 samples. Our model is trained 200 times, and the result is recorded.

Table.2 Performance comparison of our method with SVM

Method	SVM	Our model
Classification accuracy rate	67.29%	91.83%

From table 2, the classification accuracy rate of SVM is 67.29%, the classification accuracy rate of our model is 91.83%. Our model has a higher classification accuracy rate than that of SVM. Because of the complexity and uncertainty of the data, it is difficult to accuracy distinguish the GPR point date by using SVM. Our model is based WD and CNN. The time frequency maps, which is the GPR point data transformed by WD and can reveal the data nature, retain the feature information and the position information of the geological object at the same time. CNN model, one of deep learning model, has an advantage of anti-target displacement, zoom and distortion. So, our model can solve this problem with a high accuracy rate.

4.2.2 Experiment two

In order to further verify the performance of our model, a 16384-1024-512-6 DBN model is selected to replace the CNN in Fig 4 frame which is named model-REF. In this experiment, the classification accuracy rate of the model-REF and our model are compared in the same iterations. The iteration is from 20 to 200, and the step size is 20. The training data set is 4800 GPR point data, and the test data set is 1200 GPR point data.

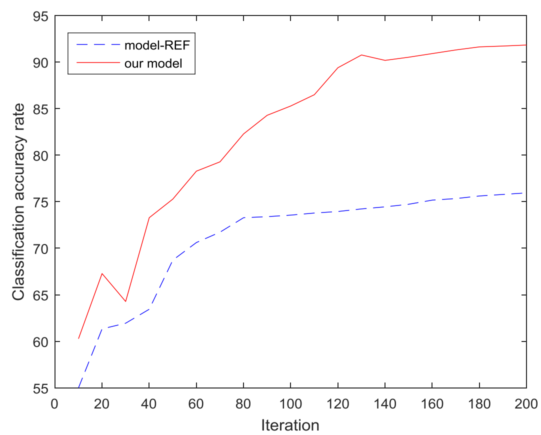

Fig5 Performance comparison between our model and model-REF

From the Fig5, the accuracy rates of two models are gradually increase with the increase of the iteration number of the model and tend to stable in the last stage. While the accuracy of our model is significantly better than the model-REF. At 200 iterations of the model, our accuracy rate is 91.83%s and the model-REF accuracy rate is 75.94%. At the same time, the computation time of our model is about half of the model-REF at the same iterations. Considering the classification accuracy rate and computation time, our model has better performance than that of the reference model-REF. It also implies that CNN is better than DBN in dealing with complex image problems.

5 CONCLUSION

1. In this paper, an advanced GPR point data interpretation model based on WD and CNN is proposed. Compared with SVM, our model has better performance in classification accuracy rate. Compared with model-REF, our model has better performance in classification accuracy rate and computation time at the same iteration. At 200 iterations of our model, our accuracy rate is 91.83%. It can be used to solve practical engineering problems.

2. In our model, WD is selected to get the time frequency maps. other forms of time frequency method can be used to replace WD to get better performance. Our model extends the application field of CNN model and can be used to solve same problems in other related fields.

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