Research on GPR image recognition based on deep learning

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Abstract. It is difficult for traditional image recognition methods to accurately identify ground penetrating radar (GPR) images. This paper proposes a deep-learning based Faster R-CNN algorithm for the automatic classification and recognition of GPR images. Firstly, GPR images with different features were obtained by using gprMax, a professional GPR simulation software. Then, the feature of the target in the image was taken as the recognition object and the data set was made. Finally, Faster R-CNN's recognition ability of GPR images was analyzed from various accuracy, average accuracy and other indicators. The results showed that Faster R-CNN could successfully identify GPR images and accurately classify them, with an average accuracy rate of 93.9%.

1 Introduction

Ground penetrating radar (GPR) enables efficient and non-destructive detection of underground targets based on the reflection and scattering of electromagnetic waves in different media [1]. GPR has been widely used in geological survey, tunnel structure layer inspection, archeology, glacier exploration and other fields [2,4]. There are differences in the relative permittivity and conductivity of different dielectric materials, and various dielectric structures will show different waveform characteristics on GPR images [5]. The interpretation of GPR images is the key to analyze underground structures. However, due to the difference in cognition, manual recognition of GPR images is highly subjective and has the problem of low efficiency. Therefore, it is of great significance to realize automatic recognition of GPR images.

At present, common GPR image recognition methods include hough transform, shallow neural network, support vector machine (SVM), and compressed sensing (CS) related algorithms. Hough transform is not easy to be affected by noise and curve discontinuity, but it is not ideal for the recognition of complex curves and diverse signals [6]. The shallow neural network analyzes the GPR image features and then realizes the classification and recognition of GPR images according to the size of the feature values, but the recognition

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rate is not high [7]. SVM maps GPR images to high-dimensional feature space, which solves the over-learning and local minimum problems encountered by shallow neural network, but requires a large amount of data for image feature selection and model parameter optimization [8]. Compressed sensing, with its sparseness and compressibility, can use small amounts of data to reproduce GPR signals, but it cannot classify targets [9]. The above algorithm has a large artificial workload in the early stage, the recognition accuracy is not high, and the efficiency is low, which is difficult to meet the GPR image recognition requirements.

In recent years, deep learning has achieved rapid development and very significant achievements, providing many methods and ideas for image recognition. Among them, convolutional neural network (CNN) can directly learn features from images in a supervised learning mode. Compared with traditional recognition methods, CNN reduces complex image processing steps and a lot of parameter setting work, and is widely used in the field of image recognition. For example, the DeepID project of the Chinese University of Hong Kong (CUHK) uses deep learning and transfer learning to recognize faces [10]; Oberweger [11] applied CNN to gesture recognition; Lameri [12] used CNN for GPR image recognition and got better results compared with other traditional methods. Faster R-CNN is an end-to-end target detection algorithm based on candidate regions. A region proposal network (RPN) is proposed and the RPN is extracted on the GPU through a convolutional neural network. Therefore, this paper will use Faster R-CNN for automatic classification and recognition of GPR images.

2 Faster R-CNN

Faster R-CNN is a target detection algorithm proposed by Ross Girshick's team [13] based on RCNN and Fast R-CNN. It unifies the four basic steps of target detection (candidate region generation, feature extraction, classification, location refinement) into a deep network framework, which avoids repeated calculations and significantly improves the operating speed. The candidate region generation network RPN proposed by Faster R-CNN replaces the traditional selective search, and achieves end-to-end target detection.

Firstly, Faster R-CNN uses traditional CNN (convolution, pooling) for image feature extraction, then uses RPN to generate multiple candidate frames to locate candidate targets. Afterwards, Faster R-CNN uses softmax to determine whether the candidate target is foreground or background, that is, whether it is a desired target. And the bounding box regression is used to correct the position of the candidate box to obtain a more accurate position. Finally, the classification and recognition of the target are completed by the classification and regression of the candidate regions and feature maps. Faster R-CNN structure is shown in Figure 1.

Fig. 1. Faster R-CNN structure.

3 Data set and evaluation

3.1 GprMax

GprMax is a GPR professional simulation software based on the finite-different time-domain (FDTD) algorithm, which can simulate detection of complex environments and different media materials. Users can set model shape parameters, structural layer parameters, dielectric characteristics, select antenna type and detection step size according to the detection needs. GPR image and detection model can be obtained after simulation calculation [14].

This paper uses gprMax to build three different models, as shown in (a1), (a2), (a3). The targets are designed as rebar, roundness and rectangle which are filled with air. The filling material is clay, relative permittivity is 6 and conductivity is 1. It uses a ricker wavelet with a frequency of 900MHz and time window of 12ns. The GPR images obtained after the simulation calculation are shown in Figures (b1), (b2) and (b3). It can be seen that the forward modeling results of the circular cavity are similar to a smooth curve with the opening downward, and the change in the field strength at the top is most obvious. There is an acquaintance curve at the lower end of the curve, which is the reflected wave generated at the interface between the lower part of the roundness and the soil. The forward simulation results of a rectangle are similar to a smooth curve, with the opening facing down. The curvature at the top of the curve is very low, close to a straight line, and the farther to the ends, the higher the degree of curve bending. The simulation results of the rebar are similar to several arched curves connected side by side, with the openings facing downwards. The top of the curve responds clearly, and there are weaker reflected waves below.

Fig. 2. gprMax simulation model and GPR image.

3.2 Data set production

The data in this paper are all obtained through gprMax simulation. As mentioned in the previous section, three models are designed. By changing the size, position and related parameters of the target or combining the three targets with each other, about 40 different GPR images were obtained. Due to the small number of data samples, this article uses the DA method (including horizontal, vertical flipping, stretching, compression, image cropping and enhancement, etc.) to enhance the data. The expanded data contains 200 pictures. The data is made into VOC2007 format, and the training set and test set are divided at a ratio of 8: 2.

3.3 Evaluation criteria

In order to evaluate the recognition effect of Faster R-CNN on GPR images, this paper uses two indicators: average precision (AP) and Mean AP.

$$AP = \int_0^1 P(r) dr \quad (1)$$

$$MAP = \frac{\sum_{i=1}^n AP(i)}{n} \quad (2)$$

$P(r)$ is the P-R curve (precision-recall), where Recall on the abscissa represents the recall rate and Precision on the ordinate represents the accuracy rate. The formulas are as follows.

$$Precision = \frac{TP}{TP + FP} \quad (3)$$

$$Recall = \frac{TP}{TP + FN} \quad (4)$$

where TP is the number of correct identifications, FP is the number of incorrect identifications, and FN is the number of unrecognized ones. In GPR image recognition, correct recognition indicates that the target is successfully located and classified correctly. Incorrect identifications indicates that the target is located but classified incorrectly. Unrecognized is not located to the target.

4 Recognition results and analysis

The GPR images recognition results are shown in Figure 3. It can be seen that Faster R-CNN can accurately recognize GPR images of roundness, rectangle, and rebar. When two or three different targets exist simultaneously, they can also be successfully identified and classified.

Fig. 3. Faster R-CNN recognition results.

It can be seen from Figure 4 that the accuracy rate of rebar and roundness has reached 100%, which is related to the small data set in this paper and the overly simple simulation model of the forward modeling; Relatively speaking, the accuracy rate of rectangle is only 81.8%. Through calculation, the average accuracy rate is 93.9%, which fully shows that the ability of Faster R-CNN to recognize GPR images is excellent.

Fig. 4. Average precision and Mean AP.

5 Summary

In this paper, Faster R-CNN was used to realize the automatic classification and recognition of GPR images. GprMax, a professional simulation software for ground penetrating radar, was used to construct three detection models of roundness, rectangle and rebar. The GPR images were obtained through simulation calculation, using the DA method to expand the data, then the expanded image was made into a data set. The Faster R-CNN network was trained and tested and the results showed that Faster R-CNN could successfully recognize the three types of GPR images: roundness, rectangle and rebar, reaching the average accuracy

rate 93.9%. Subsequent work will increase the data set capacity and use real detection pictures to apply Faster R-CNN to actual engineering applications.

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