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A Ground-penetrating Radar Object Detection Method Based on Deep Learning

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Abstract

The Ground-penetrating radar (GPR) is widely applied in the detection tasks. This paper proposes a new detection method of the GPR objects, which is based on the Cascade Regional Convolutional Neural Network (Cascade R-CNN). The proposed method effectively addresses the problems caused by the existing methods with the high time cost, low detection accuracy and poor adaptability. Additionally, an adaptive clutter filter algorithm is also proposed to realize the operation of data preprocessing when constructing the data set, so as to increase the signal-to-noise ratio(SNR). The experiment results on the collected and simulation data show that the great performance of the proposed method, achieving the average precision more than 85%. It accurately detects the buried objects in different environments, demonstrating the good generalization and robustness of the proposed method.

Introduction

The Ground-penetrating radar (GPR) utilizes the electromagnetic waves to detect the distributions and structures of the underground medium and objects. As a result of the characteristics of high efficiency, non-destructiveness and anti-interference, the GPR is widely applied in the field of detection tasks.

During the process of collecting GPR data, the received signal is under the condition with strong interference, which greatly affects the quality of data. Therefore, the preprocessing operations, such as cluttering filtering and signal amplification, are necessary to improve the signal-to-noise ratio (SNR). However, the recently filtering methods could not achieve the adaptively update of the background signal. And there have been many different detection algorithms to detect buried objects after preprocessing, such as utilizing the reflecting phase change and the energy of different signals. However, they exist high time cost, poor generalization and relying on human analysis. With the rapid development of deep learning, the technologies to detect buried objects are promoted to combine with Convolutional Neural Networks (CNNs) to ease these problems.

This paper proposes a new algorithm for accurately and automatically detecting buried objects based on the Cascade Regional Convolutional Neural Network (Cascade R-CNN), where an adaptive clutter filtering method as data preprocessing is also proposed. The proposed detection algorithm could not only effectively filter out the clutter and facilitate the extraction of features, but also achieve the detection of buried objects according to the fine-grained features automatically, which addresses the problems of the existing methods.

The Proposed Method

This paper proposes a new detection algorithm of GPR data based on the deep learning, which consists of three steps, that is as follows: (1) building the data set; (2) constructing the network model; (3) training the network; (4) detecting the GPR buried objects.

A. Building the data set

In order to meet the requirement of data of the CNNs, the collected GPR data and simulation data are both used as the training data.

1) The collected data

The background clutter in the collected GPR data has the horizontal characteristics on the radar images, presenting the periodicity and stability. We propose the adaptive clutter filtering algorithm. The appropriate filtering parameter α is selected to construct the sliding window *W*. The α is selected according to the four conditions:

a) Fewer changes of the surface undulations: the α is chosen from [1, 20];
b) Larger changes of the surface undulations: the α is chosen from [10, 100];
c) Slower changes of object signals: the α is chosen from [1, 20];
d) Faster changes of object signals: the α is chosen from [10, 100].

And then the sliding window *W* can be written as $W = \lfloor N/\alpha \rfloor$, where *N* denotes the columns of the image matrix **B**(M×N) and *M* denotes the sampling points of each trace. The average values of the sampling points in each *W* is calculated while sliding the window. For the first *N*-*W*+1 trace data, the operation can be described as

$$X_i' = X_i - \frac{1}{W}\sum_{j=i}^{j+W} X_j, 1 \le i \le N - W + 1$$

And the operation for the marginal data can be described as

$$X_i' = X_i - \frac{1}{N-1}\sum_{j=i}^{N} X_j, N - W + 2 \le i \le N$$

The original GPR data and the data filtered by the different chosen α are shown in Figure. 1. The signal amplification is also performed on the data to enhance the features.

2) The simulation data

The gprMax is used to generate the B-Scan images of various GPR data, through adjusting the size, shape and depth of the underground objects, as well as the center frequency of the antennas. After the preprocessing, the GPR data are mapped to [0, 255] and then the pixel resolutions are adjusted to 375×500. Meanwhile, the data augmentation, such as transformation, translation and rotation, are took to further augment the data set to prevent non-converge and over-fitting of the model.

B. Constructing the network model

We utilize the Cascade R-CNN to extract the multiple features, where the cascade method is proposed to gradually increase the thresholds to generate further refined proposals. The proposals at each stage are adjusted in the same way according to the IOU threshold, and then the positive samples with higher IOUs are selected for the next stage to train the network. The architecture of the Cascade R-CNN is shown in Figure. 2.

C. Training the network

The distinguishable features of the training data are automatically learned by the network. Meanwhile, the network is optimized by the back propagation. During the training, the network minimizes the cascaded loss function to obtain the model parameters with the better performance for detecting the GPR buried objects. The loss function can be written as

$$L(x^s, g) = L_{cls}(h_s(x^s), y^s) + \lambda L_{reg}(f_s(x^s, b^s), g)$$

where $L_{cls}()$ and $L_{reg}()$ denote the classification and the regression loss function respectively. $h_s()$ and $f_s()$ represent the classification and regression function respectively. x^s is the input of the s-th stage, y^s is the label of the x^s at s-th stage, b^s is the corresponding bounding boxes and *g* is the GT of the xs. The Smooth *L1* and cross entropy are adopted as the regression and classification loss function respectively in this paper.

Experiments and Analysis

The experiment is implemented on the deep learning toolbox using the training data and the Cascade CNN model. The number of the total GPR data is 6800 images, consists of 4800 simulation data and 2000 collected data. They are divided into training, validation and test data on the basis of the ratio of 8:1:1. The training epoch is set to 60 with the 0.0025 initial learning rate, where the learning rate decreases 0.1 at the 45 epoch and 57 epoch respectively. And the model is also trained with 80 epochs as the comparative experimen.

The experiment results are shown in Table 1. The recall and average precision with IOU threshold 0.5 (AP0.5) are both high, where the AP0.5 remains above 85%, indicating the effectiveness of the proposed method for the detection of buried objects. Because of the better convergence, the precision is 1.5% higher with the increase of the training epoch.

We use the data which are not trained as the prediction GPR images. The partial detection results are shown in Figure. 3. It can be seen that the GPR objects in different environments could be detected accurately, whether it is the single object or the multiple objects. The detection results demonstrate the great robustness of the proposed detection method. Meanwhile, the prediction time of the model is in the order of milliseconds, which could achieve the efficient detection.

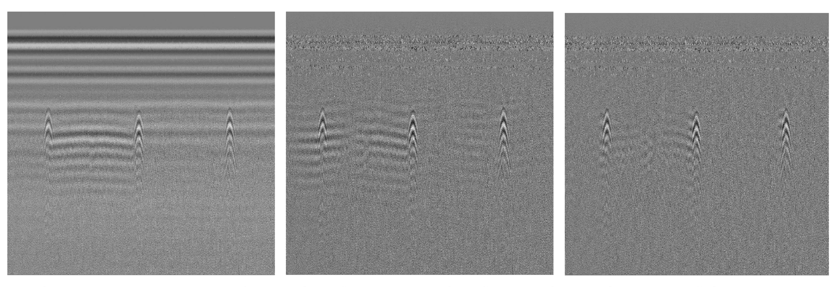

Figure. 1. GPR data before and after the clutter filtering: (a) original GPR data; (b) GPR data filtered with small α; (c) GPR data filtered with large α.

Table 1. EXPERIMENT RESULTS.

	Epoch	Recall	AP0.5
The proposed method	60	95.4%	86.7%
The proposed method	80	96.7%	88.2%

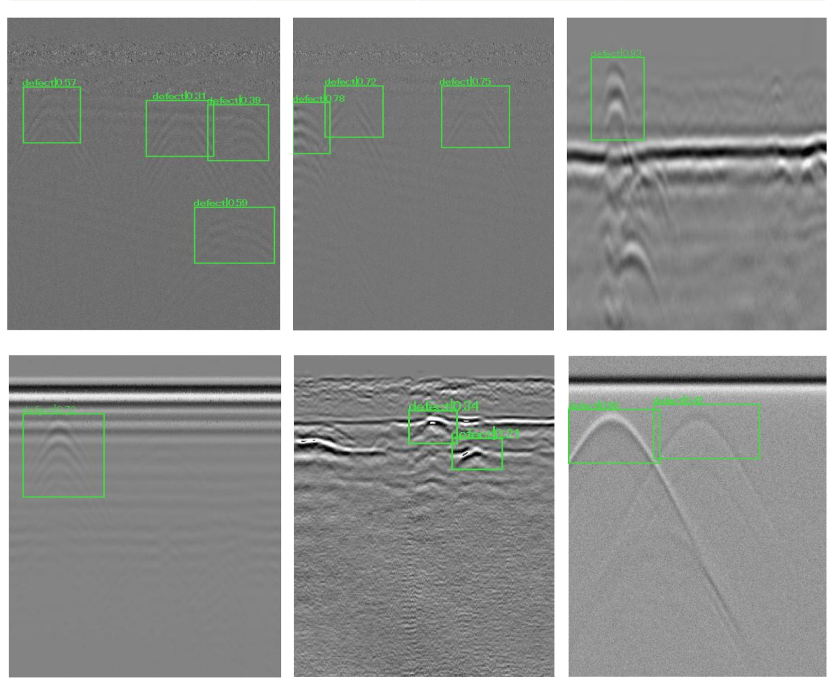

Figure 3. Examples of the partial detection results.

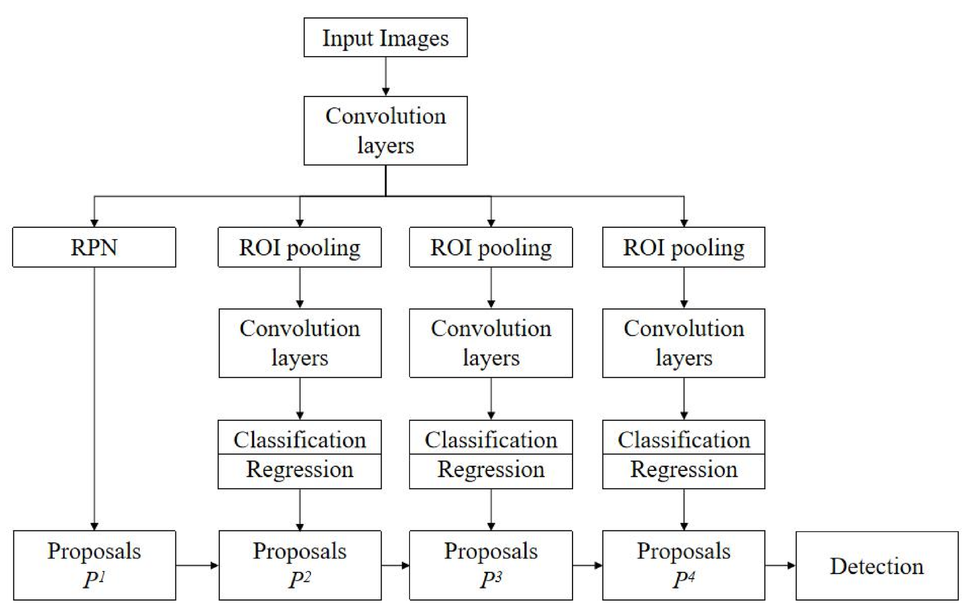

Figure. 2. Architecture of the Cascade R-CNN.

Conclusions

Addressing the problems of the time-consuming, low feature representation and poor adaptability of the existing detection methods, a new detection algorithm based on the Cascade R-CNN is proposed in this paper, and the adaptive clutter filtering method is also proposed as the data preprocessing. The experimental results demonstrate that the proposed method has the better abilities to extract the relatively complete and distinguishable features of the single object and multiple objects, and could realize the accurate and efficient detection of the GPR buried objects.

References

[1] W. Zhao, E. Forte, R. R. Colucci and M. Pipan, "High-resolution glacier imaging and characterization by means of GPR attribute analysis," Geophysical Journal International, vol. 206, no. 2, pp. 1366-1374, March 2016.
[2] L. Liu, Y. Han, J. Li, H. Xu and B. Wang, "GPR detection of underground void based on low-rank and sparse representation," 2018 17th International Conference on Ground Penetrating Radar (GPR), Rapperswil, Switzerland, pp. 1-4, June 2018.
[3] H. Brunzell, "Detection of shallowly buried objects using impulse radar," IEEE Transactions on Geoscience and Remote Sensing, vol. 37, no. 2, pp. 875-886, March 1999.
[4] Yang Q. F. and Shi X. X. "Removing for the direct wave noise in ground penetrating radar." Journal of China Coal Society, vol. 33, pp. 770-774, July 2018.
[5] Dmitry Kalika, Mary T. Knox, Leslie M. Collins, Peter A. Torrione and Kenneth D. Morton, "Leveraging robust principal component analysis to detect buried explosive threats in handheld ground-penetrating radar data".Defense + Security Symposium.Ed.. SPIE, United States, vol. 9454, pp. 94541D-94541D-10, May 2015.
[6] Mohapatra, S. and G. A. Mcmechan. "Prediction and subtraction of coherent noise using a data driven time shift: A case study using field 2D and 3D GPR data." Journal of Applied Geophysics, vol. 111, pp. 312-319, October 2014.
[7] W. P. J. van der Meer and Y. Inoue, "Using interference to determine the phase change of a reflected GPR pulse," Proceedings of the Tenth International Conference on Grounds Penetrating Radar, 2004. GPR 2004., Delft, Netherlands, vol. 1, pp. 299-302, June 2004.
[8] Mesut Dogan and Gonul Turhan-Sayan, "Preprocessing of A-scan GPR data based on energy features," SPIE Defense + Security.Ed.. SPIE, United States, vol. 9823, pp. 98231E-98231E-8, May 2016.
[9] J. Wang and Y. Su, "Underground object detection based on cross correlation and Hough transform," 2011 MICROWAVES, RADAR AND REMOTE SENSING SYMPOSIUM, Kiev, Ukraine, pp. 363-366, August 2011.
[10] Krizhevsky A, Sutskever I, Hinton G E, "Imagenet classification with deep convolutional neural networks," Proceedings of the Advances in Neural Information Processing Systems, pp. 1097-1105, 2012.
[11] Z. Cai and N. Vasconcelos, "Cascade R-CNN: Delving Into High Quality Object Detection," 2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition, pp. 6154-6162, June 2018.
[12] Cragig Warren, Antonios Giannopoulos and Iraklis Giannakis, "gprMax: Open source software to simulate electromagnetic wave propagation for Ground Penetrating Radar," Computer Physics Communications, vol. 209, pp. 163-170, 2016.
[13] S. Ren, K. He, R. Girshick and J. Sun, "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 39, no. 6, pp. 1137-1149, June 2017.