Roadbed defect detection from ground penetrating radar B-scan data using Faster RCNN

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Abstract. Ground penetrating radar (GPR) is the main technical method to detect roadbed subgrade defect. The recognition of subgrade defect is still mainly based on manual interpretation, which requires high professional knowledge of interpreters, resulting in the demand for automatic detection technology. In this paper, a solution for automatic detection of roadbed defect by implementing Faster RCNN with GPR system is presented. We simulated 30000 roadbed defect GPR B-scan data by simulation software gprMax, labeled them appropriately and automatically. Specifically, Faster RCNN was chosen, as a compromise between accuracy and ease of comparison. Preliminary detection results show that the AP (Average Precision) is 0.8067, proving that our simulation for defect is reasonable and reliable. And the Faster RCNN trained on the simulation dataset without any actual data also has excellent performance on the actual GPR data. Our method of detecting defects automatically with CNN can be easily generalized to other GPR tasks, e.g., detecting pipe, horizon extraction. It’s the biggest open-source GPR B-scan dataset as far as we know. Our simulation dataset and trained model will be made available.

1. Introduction
Defect detection of subgrade structure is an important subject in the field of near-surface geophysical prospecting. If the defeat can not be found and treated in time, it will seriously affect the traffic/car safety. At present, the detection of road subgrade diseases mainly adopts the method of Ground Penetrating Radar (GPR) [1][2]. The Ground Penetrating Radar (GPR) [3] is a remote sensing modality that has been used to collect underground data for the defect of roadbed substructure. The returns of the GPR can be organized as images in which the characteristic visual patterns of defeat can be leveraged using visual descriptors.

But the amount of detection data from GPR is huge. The recognition of subgrade diseases is still mainly based on manual interpretation, which requires high professional knowledge of interpreters, and the speed of data analysis is very low and human errors cannot be avoided. Therefore, how to improve the efficiency of disease identification of road subgrade detection data and achieve it automatically are big problems that need to be solved [4]. There are some automatic detection methods based on single trace detection for disease [5]. But all the methods based on single trace cannot make use of the correlation between different traces. Compared with the image-based method, the effect of this method will be greatly reduced.

Recently, convolutional neural networks (CNNs) have been applied to this problem, inspired by their state-of-the-art-performance on object detection tasks in natural images. The network in object detection can be divided into 3 categories: one-stage, two-stage and multi-stage. One-stage network gives category and location information directly through the backbone network. It’s faster than two-stage network, but
a little less accurate. Typical network is yolov3 (You only look once v3) [6], SSD (Single Shot MultiBox Detector) [7]. Two-stage network uses RPN(Region Proposal Network) network to generate series proposal region, then make further classification by network. Typical network is Faster RCNN (Faster Region Convolutional Neural Network) [8], R-FCN (Region-based fully convolutional network) [9]. Multi-stage network uses cascade RPN network and different IOU (Intersection over Union), to get a more accurate boundary. Typical network is Cascade RCNN (Cascade Region Convolutional Neural Network) [10].

One well known limitation of CNNs is that they require large amounts of data for training (i.e., parameter inference) to avoid overfitting (i.e., poor generalization). This presents a major challenge for target detection in GPR because of the few labeled examples of targets and non-target GPR data.

The most popular way to get labeled data as training set is to mark manually. But the disadvantages of this method are obvious. First, manually labeling can be highly subjective. Different interpreters may provide much different interpretation result. The incomplete or inaccurate labeling in the training set may mislead the training of CNN and the trained CNN cannot make reliable predictions. Second, only a few institutions have enough actual data. So, we use simulation data generated by simulation software gprMax [11]. We simulated 30000 data to meet CNN's demand for big data. In addition, label is also an important aspect, just as import as data. The traditional labeling method is manual labeling. Otherwise, in the field of Geophysics, using convolution model to label is also a common method [12]. But in many cases, the GPR data do not satisfy the conditions of convolution model [13]. So according to the actual situation of our simulation data, we use simple geometric calculation to get the appropriate label.

In the following paragraphs, I will introduce the simulation dataset, how to label it automatically, the principle of Faster RCNN, give our test result and draw the conclusion.

2. Methodology

In this part, we will detail the three components of this work: simulation dataset, label automatically, and Faster RCNN.

2.1. Simulation dataset

Road structure is mainly composed of three layers: surface layer (concrete, asphalt), base layer (mixture such as lime soil) and subgrade layer (soil, gravel). GPR mainly detects the diseases in the subgrade layer, because the diseases of the surface layer and the base layer are usually visible to the naked eye. Therefore, the disease is set in the subgrade layer (the third layer). The subgrade structure and electrical parameters are set as follows as Figure 1: surface layer is 30cm thick, relative permittivity $\varepsilon_r=4$, electric conductivity $\sigma=0.005$. Base layer is 30cm thick, relative permittivity $\varepsilon_r=9$, electric conductivity $\sigma=0.05$. Subgrade layer is 3.4m, relative permittivity $\varepsilon_r=12$, electric conductivity $\sigma=0.005$. The width of simulation is 8m. So the whole simulation oversize is 8m×4m. According to the common diseases of subgrade, we have designed the following five types of diseases as Figure 2.

![Figure 1. Simulated Road Structure and electrical parameters](image)

There are two types of disease media: air and containing water. Three antenna frequencies are simulated: 300MHz, 900MHz and 2GHz. For each defect, with different disease media types and antenna frequencies, we have carried out 100 simulations. Here are 3000 simulation data. And then we did 10 times data augmentation using different AGC, different scale, and different crop and add different noise. So we finally get 30000 simulation data.

We can see in Figure 3 that AGC amplifies the effective signal reasonably, so the appropriate AGC can improve the quality of simulation data. This is also more in line with the process of manual detection,
because when the GPR signal is detected manually, the appropriate magnification is constantly adjusted to make final judgment.

| defect         | Sketch Map |
|----------------|------------|
| empty          |            |
| void           |            |
| fault          |            |
| fault+void     |            |
| uncompacted    |            |

**Figure 2. Simulated subgrade defect**

(a) Origin data  
(b) after AGC  
(c) after AGC+scale+crop  
(d) empty  
(e) void  
(f) fault  
(g) fault+void  
(h) uncompacted

**Figure 3. Data augmentation**
2.2. Label automatically

The label of object detection only needs 4 coordinates: the maximum and minimum values in x direction and y direction. It is not necessary to use mask label [14] to accurately outline specific waveforms like image segmentation [15]. So when use convolution model to label 1,2,5 in Figure 2, we can simplify it by considering only the top and bottom surfaces and the left and right boundaries. And all wave velocities are given by

$$v = \frac{v_c}{\sqrt{\varepsilon_r}}$$  

(1)

where \(v_c\) is the speed of light, \(\varepsilon_r\) is the relative permittivity of medium. But we can't label 3,4 directly with convolution model, since 3,4 in Figure 2 do not satisfy the condition of convolution model. It has inclined plane, will lead to migration.

![Image](image1.png)

Figure 4. Migration

Fortunately, our model is designed very simple, and we can get the position of the reflection event from the reflection surface by simple geometric calculation.

![Image](image2.png)

Figure 5. Faster RCNN framework [16]

2.3. Faster RCNN

Although there are many other object detection networks, they may have better performance in speed or accuracy. But considering speed and accuracy, Faster RCNN is still a reliable choice, especially in our simulation dataset with unknown effects.

Faster RCNN is a typical two-stage object detection network. It can be separate into 2 parts: region proposal and classification. Conventional selective search is a slow and time-consuming process affecting the performance of the network. Instead of using selective search algorithm, a separate network (Region Proposal Network – RPN) is used to predict the region proposals. The RPN is a fully convolutional network that simultaneously predicts object bounds and object scores at each position.
The RPN is trained end-to-end to generate high-quality region proposals. The RPN and the Fast RCNN are merged into a single network, Faster RCNN, by sharing their convolutional features.

3. Result
In order to evaluate our simulated GPR dataset, we divided the data into 55% training sets, 25% validation set and 20% test set. Use our simulation data to train Faster RCNN with pre-trained model training on Imagenet. Some paper indicated that using pre-trained model trained on cifar-10 [17] or Aerial Images [18] can improve accuracy. But considering our main purpose is to verify the rationality of our simulation data, we use the same pre-trained model just as Faster RCNN (Ren et al., 2015). Hyperparameters are set as follows: we use stepped learning rate, the learning rate of first 50000 iterations is 0.001, the last 50000 iterations is 0.0001. The momentum is 0.9, weight decay is 0.0005.

| Dataset                      | AP   |
|------------------------------|------|
| Our Simulation dataset      | 0.8067 |
| VOC2007(Ren, S., et al, 2015) | 0.698 |

Table 1. Test result for simulation dataset

As shown in Table 1, the AP trained on our simulation dataset is a little better than other natural image dataset. It’s reasonable because there is a part of similarity inside in simulation dataset. The difference between same type of defect but different parameters set in simulation is much smaller than different person in natural image dataset. It can also prove that our automatic labeling method is fit for our 5 defect in Figure 2.

The model trained on our simulation dataset have some good performance in actual data, even though the model haven't seen any actual GPR data. As shown in Figure 6, the trained model successfully detected different types of diseases since we all label different diseases as one class 'defect'. Figure 6 (a), (b), (d) all have a typical void structure, and (b), (d) also have the characteristics of faults since the discontinuity of the horizon. (c) detects a deep potential hole, which may indicate the essential reason for the disorder of the upper layer.

The performance of Faster RCNN trained on our simulation dataset and tested on the actual data shows the rationality and effectiveness of our simulation and defect detection method.

4. Conclusions
We have applied the well-known Faster RCNN framework to the detection of roadbed defect from GPR B-scan data training on our own simulation dataset. We simulate 30000 roadbed defect GPR B-scan data by gprMax, and label them appropriately and automatically. Specifically, Faster RCNN was chosen, as a compromise between accuracy and ease of comparison. Preliminary detection results show that the AP (Average Precision) is 0.8067, proving that our simulation for defect is reasonable. The AP trained in our simulation dataset is a better than other natural image dataset. It's reasonable because there is a part of similarity inside in simulation dataset. And the performance of Faster RCNN that trained on simulation dataset and tested on actual data shows the rationality and effectiveness of our simulation. The way we simulate GPR data and label them can be easily generalized to other GPR tasks, e.g., detecting pipe, horizon extraction. It’s the biggest open-source GPR B-scan dataset as far as we know. Our simulation dataset will be made available.

In the following research, we will continue to add more different models in our dataset and try to make more refined labels as pixel level labels to meet the higher requirements of different and complex tasks.
Figure 6. Test results on actual data

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