A deep learning network to improve tunnel lining defect identification using ground penetrating radar

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Abstract. Ground penetrating radar (GPR) is one of the most recommended tools for routine inspection of tunnel linings. However, the rebar in reinforced concrete has strong shielding effect on electromagnetic waves, which makes the defects beneath the rebar hard to be distinguished in GPR images. To suppress the reflection waves of the rebar network and reconstruct the defect echoes, we proposed a deep learning network based on generative adversarial networks (GAN). Taking the GPR images with rebar reflection waves as input, the network generated GPR images without rebar reflection waves. The GPR images processed by our networks are easier for manual interpretation and the existing object detection networks performs better on the images processed by proposed networks.

1. Introduction

Void is a common defect in tunnel lining due to environmental factors or improper construction. The inspection of tunnel lining is a critical issue since defects may have adverse effects on the safety and durability of tunnels. Compared with traditional methods such as core sampling and impact-echo, the ground penetrating radar (GPR) technique is non-destructive and efficient and has gained widespread use in tunnel engineering. However, the interpretation of GPR data mainly relies on manual work at present. The efficiency and accuracy of data explanation depend highly on technicians’ expertise. Therefore, developing automatic recognition algorithms is regarded as an essential way of improving the GPR data interpretation.

With the advent of convolutional neural networks (CNN), the deep learning method have made promising advances in the field of image recognition [1]. Many researchers have applied deep learning methods to recognize GPR images. Lamiri et al. designed a landmine detection algorithm based on CNN. By using the dataset that purely consists of finite-difference time-domain (FDTD) simulated GPR data, the networks can detect the landmine objects in GPR images[2]. Lei et al. used the Faster R-CNN to identify hyperbolic signatures from GPR images [3]. Pham et al. pre-trained the Faster R-CNN networks on the grayscale Cifar-10 dataset and fine-tuned the networks on both real and simulated GPR data. The detection results show that the pre-training method is quite promising when there are few training samples [4].
The existing deep learning methods have made a lot of progress in GPR data recognition tasks. However, the steel rebar built in concrete has strong shielding effect on electromagnetic waves, which blurs the reflection waves of defects and hence affects the interpretation of the GPR images. Kien et al. used the migration method to make the pixels containing rebar peaks have intensity values and can be picked after thresholding the GPR images [5]. However, they did not discuss the objects beneath the rebar. Wu et al. applied the hyper-curvelet transform to suppress the rebar echoes in GPR data. The strong rebar echoes in ground-penetrating radar images can be successfully suppressed using this method [6]. However, they did not verify their method on real GPR data.

Generating adversarial networks (GAN) have been widely used in image generation and translation tasks. Ian et al. proposed GAN networks that allow computers to generate images [7]. Flickr et al. introduced conditional variables in both the generator and the discriminator of the GAN networks and obtain conditional generative adversarial nets (cGAN), which can generate images according to human needs [8]. Phillip et al. proposed an image translation algorithm based on the idea of cGAN, which makes the image–to-image translation possible [9].

In our work, we proposed a GAN based deep learning network which can suppress or eliminate the rebar interference in GPR images. In the proposed method, the residual blocks were added to increase the depth of the networks. At the same time, the dilation convolution part was also used to extract information on multiple scales and realise accurate construction of reflection waves of different defects. We first introduce the overall structure and configuration of our networks. Then we applied the existing object detection networks to the GPR images processed by our networks to evaluate the performance of our method. After that, we present the test result, followed by a summary of the main work.

2. Method
In this section, we introduce the architecture and configuration of the deep learning networks which are used to eliminate the interference of rebar reflection waves. We first present the main building blocks of the networks, then describe the dataset used to train the networks. After that, the training process and the criteria for evaluating the effectiveness of our method are given.

2.1. Network configuration
We build our deep learning networks on the basis of cGAN, which is used to generate data conditioned on the given information, such as class labels. The architecture of the rebar interference elimination network is depicted in Fig. 1. Unlike cGAN using random noise as the input of the generator, our networks taking the GPR images with rebar reflection waves as the input and generate GPR images in which the rebar reflection waves are eliminated. Then the output of generator is taken into the discriminator. The discriminator judges whether the images generated by networks are real enough. The details of the networks are described in the following subsections.
2.1.1. **Objective function.** Our rebar elimination network is modified from cGAN. The network learns a mapping from observed image \( x \) and random noise vector \( z \), to \( y \). The objective function of the cGAN can be expressed as

\[
L_{GAN}(G, D) = \log D(x, y) + \log(1 - D(G(x, z), x))
\]

where \( G \) tries to minimize this objective against an adversarial \( D \) that tries to maximize it. Some researchers have found it beneficial to mix the GAN objective with more traditional loss [10]. We use the L1-distance loss to make the generated images near the ground truth in an L1 sense. L1-distance loss can be expressed as

\[
L_{L1}(G) = \| y - G(x, z) \|
\]

Then, our final objective function is

\[
G^* = \arg\min_G \max_D L_{GAN}(G, D) + \lambda L_{L1}(G)
\]

where \( \lambda \) is the weighting factors of L1-distance loss.

2.1.2. **U-net based generator.** The generator of our network is modified and improved from U-net. There is a great deal of low-level information shared between the input and output. We add skip connections, following the general shape of a “U-net”. We use 20-layer residual neural networks as the encoder. The architecture of the decoder of the networks is quite the same as the original U-net.

Considering the complexity, connectivity and difference of the scale of reflection waves in GPR images, it is important to increase the receptive field of feature points and keep the detailed information. As shown by some state-of-art deep learning models [11], dilated convolution layers can be a desirable alternative of the pooling layer. Our network uses several dilated convolution layers.
with skip connections in the centre part. The centre part can be unrolled as paralleled mode as shown in Fig. 1. The receptive field of each path is different, from top to bottom the receptive fields are 31, 15, 7, 3, and 1, respectively. So the network can combine features from different scales.

2.1.3. Patch GAN discriminator. The L1 loss can accurately capture the low-frequency features and produce blurry results. The discriminator should focus on model high frequency structure. So the discriminator do not have to take the whole image as input. We adopt the Patch GAN discriminator which only penalizes structure at the scale of patches. This discriminator first divides the whole GPR image into $N \times N$ patches and then tries to classify if each $N \times N$ patch in an image is real or fake. The discriminator runs across the image convolutionally and averaging all responses to provide the ultimate output of D. The $N$ in the patch GAN structure can be much smaller than the size of images and smaller patch has fewer parameters, run faster as well as produce high-quality result.

2.2. Acquisition of training data

We create a series of synthetic models to simulate the GPR detection of tunnel lining using gprMax program [12], a Python-based FDTD solver of Maxwell’s equation. The geometry of the synthetic model is depicted in Fig. 2(a), where there is a row of equally spaced steel bars. Beneath the steel bars, there are targets to be detected, that is, voids filled with water or air and the voids distribute in concrete randomly. The spaces between the steel bars range from 10 to 40 cm, while the steel bars are 5 to 10 cm away from the surface and the horizontal location is randomly chosen. We use built-in material free space for air and voids and pec for steel ribs. We also define the tunnel lining concrete with $\varepsilon_r = 9$, $\sigma = 1 \times 10^{-5}$ s/m and water for voids with $\varepsilon_r = 81$, $\sigma = 0.01$ s/m. The FDTD simulation setup is listed in Table 1. To get the GPR images without rebar waves, we can simply delete the rebar in models as shown in Fig. 2(c) and simulate the model again. Then we get a series of paired GPR images to train our rebar interference elimination networks.

| Parameter                  | Value       | Unit       |
|----------------------------|-------------|------------|
| Dimension                  | 2.0 × 1.0   | m²         |
| Grid size                  | 0.002 × 0.002 | m        |
| Source wavelet             | Ricker      |            |
| Central frequency          | 800         | MHz        |
| Antenna separation         | 0.02        | m          |
| Trace interval             | 0.01        | m          |
| Time window                | 20          | ns         |
2.3. Network training

There are over 60 million parameters that need to be trained in our deep learning networks, yet the amount of simulated GPR data is far from enough since the FDTD simulation is computing-power-demanding. Transfer learning is proved to be an effective method to improve network performance in most situations, especially when the training data is limited. Instead of training the network with a set of randomly initialized parameters, we applied the pre-trained weights getting from label to photo task, train on Cityscape dataset.

We get 200 paired simulated GPR data and these data are subjected to data processing such as gain, background removal, etc. to make the reflection waves of objects more visible.

Our network uses Adam solver as the optimiser [13]. The learning rate and beta1 are set as 0.0002 and 0.5, respectively. We keep the same learning rate for the first 100 epochs and linearly decay the rate to zero over the next 100 epochs. The batch size is set as 1 during the training. We train our networks for 300 epochs on a system equipped with NVIDIA RTX 2080ti GPU and the training process took 14.5 h to complete. Fig. 3 shows the images synthesized in 1, 100, 200, 300 epoch. The training process is stable and after training for 100 epochs the networks can generate GPR images similar to the ground truth.
Figure 3. The output of networks after 1, 100, 200, 300 epochs. The left column is the input of the networks, the middle column is the GPR images without rebar, and the right column is synthesized images with our networks.

2.4. Criteria for evaluating the effectiveness of networks
We use the object detection network to detect the original GPR images and the GPR images process by our rebar interference elimination networks separately. We take the improvement of detection performance on the processed GPR images as criteria of evaluating the effectiveness of proposed networks. We use the state-of-art object detection network YOLOv4 to do the test [14]. We have already trained this network beforehand. Four metrics are used to evaluate the detection performance, which are recall, precision, F1 score and mAP value.

\[
    \text{Precision} = \frac{TP}{TP + FP} \quad (4)
\]

\[
    \text{Recall} = \frac{TP}{TP + FN} \quad (5)
\]

\[
    F1 \text{ score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (6)
\]

where TP is true positive, TN is true negative, FP is false positive, and FN is false negative.

3. Result
We gather 400 simulated GPR images with rebar built in the model as the test set. Then these images are put into the YOLO networks to detect void objects. We get four metrics aforementioned and summarized them in the first column of Table 2. Then we processed these GPR images with our rebar interference elimination networks. As shown in Fig. 4, we can see that the rebar reflection waves had already been suppressed largely or eliminated after processing. We put these processed images into the YOLO network and got four metrics summarized in Table 2.
Figure 4. Two sample GPR images processed by our networks and the detection result, the left column is detection result of original images and the right column is detection result of processed images.

From Table 2 we can see that the recall value is greatly increased, which means that more objects were detected after the GPR images were processed by our rebar interference elimination networks. F1 score is 0.95 when the object detection networks are used to detect the object in the processed GPR images, for original GPR images are 0.84. Relatively high F1 score means the detection networks achieve high recall and precision value simultaneously. The mean average precision value increases by 12.4% after applying our networks.

We can conclude that, after using our rebar interference elimination networks, the reflection waves of rebar in original GPR images are suppressed largely or eliminated. The reflection waves of defects beneath the rebar networks are more visible, which means the processed GPR images are easier to interpret for on-site technicians. Taking the improvement of the detection performance on the images processed by our networks as criteria, our method is effective.

Table 2. Four metrics of the detection networks.

| metrics  | Original images | Processed images |
|----------|----------------|-----------------|
| recall   | 73.92%         | 95.80%          |
| precision| 95.43%         | 94.67%          |
| F1 score | 0.84           | 0.95            |
| mAP value| 84.04%         | 96.44%          |

4. Conclusion
In this paper, we proposed a GAN-based network to eliminate the rebar interference in GPR images. The rebar reflection waves are suppressed or eliminated by our networks. The GPR images processed by our networks are easier for technicians to interpret and also beneficial to the existing object detection networks.

This work is preliminary research for improving the identification of tunnel lining defects using the deep learning method. However, in this work, we have only validated the effectiveness of our networks on the model has void defects. Due to the scarcity of precisely labelled GPR images, it is difficult to do the investigation on other defects such as cracks, untight and other types of tunnel lining defects. In our future work, more classes of tunnel lining defects should be in consideration.

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