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Arbitrary-oriented tunnel lining defects detection from GPR images using deep CNN

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ABSTRACT

Tunnel lining internal defect detection is essential for the safe operation of tunnels. This paper presents an automatic scheme based on rotational region deformable convolutional neural network (R²DCNN) and Ground Penetrating Radar (GPR) images for the accurate detection of defects and rebars with arbitrary orientations. The R²DCNN comprises inter-related modules, specifically, deformable convolution, feature fusion, and rotated region detection modules. In this study, synthetic GPR images, including rebars and various structural defects with different permittivities, as well as real GPR images obtained by model experiments, were constructed for the R²DCNN. Improved results were obtained while testing the R²DCNN on GPR images in comparative experiments. The mean average precision of the R²DCNN was enhanced by 8.21% compared to the R²CNN on synthetic GPR images. The R²DCNN showed satisfactory results in on-site experiments, which demonstrated the applicability of the R²DCNN to practical tunnels.

ARTICLE INFO

Keywords: Ground Penetrating Radar; Arbitrary-oriented defect detection; Automation; Deep learning; Tunnel inspection

1 Introduction

Tunnels progressively deteriorate due to ageing, environmental factors, man-made and natural influences, inadequate or poor maintenance, and deferred repairs [1-2]. Consequently, structural defects, including cracks, voids, and separations, occur in the tunnel lining, which can even cause partial collapses in tunnels and significantly affects the long-term and safe operation of tunnels. For instance, the collapse of the Sasago Tunnel in Tokyo killed nine people in 2012 [3]. Therefore, routine inspections and evaluations of tunnels are essential to ensure their safe operation.

Ground Penetrating Radar (GPR), a non-destructive detection tool that can obtain subsurface images, has high efficiency, high anti-interference level, and strong penetrating ability; it has been widely used in detecting subsurface abnormal objects [4]. The electromagnetic waves transmitted by GPR are reflected to form the B-Scan profile after hitting media with different electromagnetic properties. Therefore, the detection of subsurface abnormal objects can be considered as the detection of abnormal GPR signals, such as the reflected signals from subsurface abnormal objects of the B-Scan. In tunnel lining detection, the diagnostic interpretation of GPR images carried out by an experienced analyst is time-consuming and error-prone, which tends to result in poor quality inspections. An automated, cost-effective, and exhaustive inspection of tunnels would improve short and long-term security, and increase productivity [1, 5]. Therefore, automated inspection would become an important means of infrastructure inspection and would gradually become the trend for development in the future. Furthermore, automatic detection methods are a key part of automated inspection. It is necessary to explore a faster, efficient, practical, and automatic detection method to improve automated infrastructure inspections.

18 In the past few years, certain signal and image processing technologies, such as edge detection, Hough transform, and
 19 migration technologies, have been utilized for the automatic detection of abnormal GPR signals [6-9]. Thereafter, machine
 20 learning techniques, such as neural networks, support vector machines, grouping techniques, and genetic algorithms, have been
 21 utilized to detect subsurface abnormal objects using GPR images [10-13], resulting in effective detection performance. However,
 22 the afore-mentioned methods have been commonly observed to lack the ability to recognize multiple waves induced by
 23 water-bearing defects in complex GPR images and rely on parameter settings and handcrafted features. Deep learning has been
 24 effectively applied to recognize abnormal objects in GPR images and has attracted considerable research interest in various
 25 scientific disciplines. For road inspection, Xu et al. [14] integrated a feature cascade, an adversarial spatial dropout network, and
 26 the Soft-NMS algorithm into Faster R-CNN to improve the effectiveness of railway subgrade defect detection. Tong et al. [15]
 27 utilized the deep learning model of network in networks and GPR data to identify pavement distress types and measure the
 28 distress locations and sizes, which produced reasonable stability with different transmitting frequencies, numbers of samples per
 29 trace, and pavement structures. For rebar inspection, Xiang et al. [16] automatically detected the rebars of concrete structures
 30 using AlexNet and GPR images. The authors also evaluated the effects of different rebar arrangements and window sizes on the
 31 results. Similarly, Dinh et al. [17] combined conventional image processing techniques and a deep Convolutional Neural
 32 Network (CNN) for rebar recognition. These image processing techniques were used to localize pixels containing potential rebar
 33 peaks, and the CNN was employed to classify window images that were extracted from GPR images surrounding the potential
 34 pixels. For pipeline inspection, Alvarez et al. [18] used a deep learning framework to convert GPR images into subsurface
 35 permittivity maps to realize the intuitive display of subsurface images of sewer crowns. Furthermore, Ko et al. [19] used Faster
 36 R-CNN to detect buried pipelines in GPR images and adopted a data augmentation strategy for GPR images.

37 The recognition of GPR images has been successfully accomplished using deep learning, and it has been widely applied in
 38 various fields. To detect abnormal objects within a tunnel lining, Yang et al. [20] employed GPR data and a CNN to conduct
 39 defect segmentation for tunnel lining internal defects, thereby achieving visual display of the tunnel lining internal structure.
 40 Their method requests pixel-level labels to perform data annotation. However, owing to the uncertainty of the tunnel lining
 41 internal structure in practical situations, it is difficult to obtain a corresponding structural model from real GPR data collected
 42 from tunnels, thereby making it challenging to use pixel-level labels. Thus, the application of this method to practical situations
 43 is limited owing to the difference between synthetic and real GPR data. CNNs used for object detection can identify events or
 44 implications of GPR images that are difficult to annotate using pixel-level labels. For example, Xu et al. [21] constructed a
 45 convolutional neural network (GA-RCNN) which integrated the mechanism of guiding anchoring based on the two-stage object
 46 detection algorithm to accurately recognize the locations of the voids using GPR images in tunnels. However, certain challenges
 47 related to the internal abnormal object detection of tunnel linings still exist, such as:

48 (1) Unlike object detection in natural images, wherein the objects have clear boundaries, abnormal objects in GPR images
 49 commonly exhibit complex reflected signals with diffraction signatures. Even worse, complex irregular tunnel lining defects,
 50 particularly crack defects, may have arbitrary distributions (Fig. 1). Therefore, it is crucial to accurately delineate the locations of
 51 defects with arbitrary orientations from GPR images with relatively blurred boundaries.

52 (2) Owing to the diversity of tunnel lining defects, as well as multiple waves and scattering induced by water-bearing
 53 defects, the recorded GPR images can be rather complicated, with various reflected signals from tunnel lining defects. Defects in
 54 the same category may produce quite different GPR images, as shown in Fig. 1. Thus, it is essential for deep learning networks to
 55 have powerful feature representation and feature fusion abilities to extract rich features from various GPR images.

56 (3) Owing to unpredictable interference in the real world, real GPR images are inevitably accompanied by considerable
 57 noise and are more complicated than synthetic GPR images, as shown in Fig. 1. Furthermore, the availability of real GPR images
 58 for training deep learning networks is rather limited. Therefore, it is preferable for deep learning networks to learn the geometric
 59 transformations of reflected signals from tunnel lining defects adaptively and generalize the trained models for application to real
 60 GPR images.

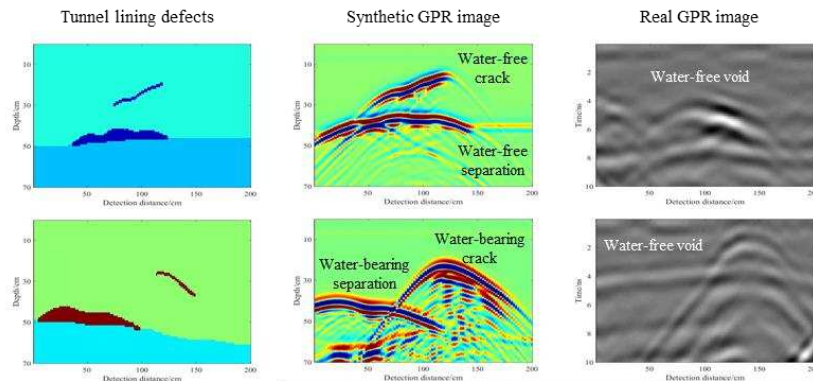


Fig. 1. The permittivity model and its corresponding synthetic GPR image as well as the real GPR image.

61 To solve the aforementioned issues, a rotational region deformable CNN (R²DCNN) was developed in this study for the

62 accurate detection of defects and rebars with arbitrary orientations from complex GPR images of tunnel linings. The R²DCNN
63 comprises inter-related modules, specifically, deformable convolution (DC) [22-23], feature fusion [24-25], and rotated region
64 detection modules [26]. DC enhances the ability to detect abnormal objects with geometric deformations, such as various
65 reflected signals from tunnel lining defects of different sizes and shapes, and enables the adaptive learning ability for diverse real
66 GPR images. Feature fusion for fine-grained feature extraction provides accurate location and shape information for abnormal
67 objects to improve the final detection accuracy of GPR images with blurred boundaries between the object and background.
68 Rotated region detection enables the accurate detection of abnormal objects with arbitrary orientations in GPR images. In this
69 study, synthetic GPR images, including rebars and various structural defects with different permittivities, as well as real GPR
70 images obtained by model experiments, were constructed for the R²DCNN. A comprehensive comparative experiment was
71 performed to confirm the effectiveness of the R²DCNN, and a model experiment was subsequently performed to demonstrate the
72 necessity of the R²DCNN on real GPR images. Furthermore, on-site experiments were employed to describe the implementation
73 process of the R²DCNN in detail. The defect detection method was verified in engineering and was applicable in practical tunnels,
74 laying a solid foundation for automated inspection of tunnels in the future.

75 The remainder of this paper is organized as follows: Section 2 describes the dataset, Section 3 introduces the R²DCNN
76 automatic detection method, Section 4 presents and provides an analysis of the experimental results, Section 5 conducts on-site
77 experiments and applications of the method, and lastly, Section 6 summarizes the contributions and draws certain conclusions.

78 2. Dataset construction

79 Considering that GPR images with reflected signals collected from practical tunnels are quite limited, which is not enough
80 for the training of the R²DCNN to realize the accurate detection of tunnel lining defects with arbitrary orientations, lots of GPR
81 images are constructed to improve the adaptability of the proposed method in engineering. This section describes the datasets
82 consisting of synthetic and real GPR images that are built to train, validate, and test the object detection network. Furthermore, it
83 elaborates the process of the GPR image annotation.

84 2.1. Synthetic GPR data

85 Tunnel linings containing rebars as well as various structural defects, including voids, cracks, and separations, were
86 modelled. These defects were further divided into water-bearing and water-free defects according to their permittivities and were
87 referred to as tunnel lining abnormal objects in the following sections.

88 Various objects with irregular borders of different shapes, categories, and permittivities were deployed at various positions.
89 In this study, the permittivities of water-free defects, water-bearing defects, and rebars were 1, 81, and 300, respectively. The
90 permittivities of the lining and surrounding rock were random, i.e., 6–7 and 8–10, respectively [27]. In addition, the interface
91 between the lining and surrounding rock was considered as a rough and irregular surface. The two-dimensional basic permittivity
92 models of the tunnel lining internal structure were established based on the above principles, as illustrated in Fig. 2, which
93 showed that there are various distributions of objects in the permittivity model, including single defects, different combinations
94 of multiple defects and rebars, and water-bearing and water-free defects distinguished by different permittivities as represented
95 by different colors. GPR equipment with dominant frequencies of 400 MHz or 600 MHz was relatively common in tunnel lining
96 detection. Therefore, to increase the diversity of the data and enhance the adaptability of the network, two Ricker wavelets with
97 dominant frequencies of 400 MHz and 600 MHz were used to forward modelling permittivity models based on the
98 finite-difference time-domain method. Finally, synthetic GPR data with 800 sampling steps and 99 traces was obtained. In this
99 work, a total of 1974 synthetic GPR data with different frequencies and conductivities were generated, and it took approximately
100 three days to generate these datasets. Among them, only the conductivity of 59 synthetic GPR data (0.5) with water-bearing
101 defects is different from other data (0.0005) to verify the generalization of the network. The specific defect categories and
102 numbers of the rest of the 1915 synthetic GPR data, including 900 GPR data with a dominant frequency of 600 MHz and 1015
103 GPR data with a dominant frequency of 400 MHz, are presented in Table 1. The dimensions of the model were 90×220 with a
104 mesh size of 0.01 m. Owing to the absorption boundary conditions of the convolutional perfectly matched layer, the actual model
105 was reduced by 10 meshes on each side. Therefore, the depth and distance of the tunnel lining covered in the synthetic GPR data
106 were 0.7 m and 2 m, respectively. It was difficult to annotate the synthetic GPR data containing direct waves covering some
107 portions of the target areas. Therefore, the direct waves were removed by subtracting the baseline GPR data generated by the
108 model without any abnormal objects. Fig. 2 depicts the permittivity models and their corresponding synthetic GPR data before
109 and after removing the direct waves. Moreover, owing to the diffraction signals appearing on the edges of the reflected signals
110 and the multiple waves and scattering induced by water-bearing defects, GPR images have characteristics that differ from those
111 of natural images. Hence, GPR images were chosen (instead of ImageNet) to pre-train the feature extraction network for
112 classification, thereby making it more adaptive to GPR images. Additional 28,600 synthetic GPR data with 800 sampling steps
113 and 99 traces were generated to pre-train the feature extraction network of the R²DCNN for classification. In total, it took
114 approximately a month to generate all the 30,574 synthetic GPR data, including 1974 GPR data for training and fine-tuning the
115 R²DCNN and 28,600 GPR data for pre-training the feature extraction network of the R²DCNN.

116

Table 1
Data distribution in dataset.

Dataset	Crack	Void	Separation	Crack_void	Void_separation	Crack_separation	Rebar
Water-free defects	132	150	150	133	150	150	150
Water-bearing defects	150	150	150	150	150	150	

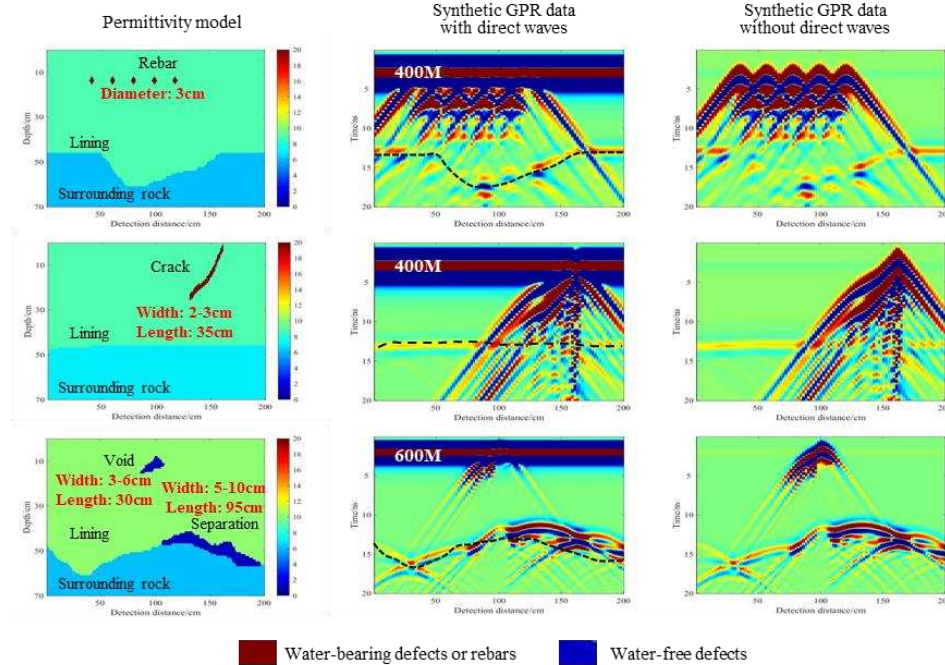


Fig. 2. The permittivity model of tunnel lining internal structure and its corresponding synthetic GPR data before and after removing direct waves. The water-bearing defects or rebars and water-free defects are represented by different colors.

117 2.2. Real GPR data

118 To verify the applicability of the proposed method in practical situations, model experiments were performed to obtain real
 119 GPR data using a 600 MHz Impulse Radar as the GPR, as shown in Fig. 3. A sandbox was exploited to simulate the tunnel lining
 120 internal structure, while acrylic boxes and waterproof boxes were used for simulating cracks and voids within the tunnel lining,
 121 respectively. Furthermore, acrylic boxes and waterproof boxes with different rotated angles were deployed at various positions
 122 and depths in the model of different depths to increase the diversity of real GPR data. The number of samples per trace and the
 123 trace-interval distance of this GPR device were 512 and 0.01 m, respectively.



Fig. 3. The sketch of model experimental environment. (a) Simulated underground structure defects; (b) Acrylic box for the simulating crack; (c) Waterproof box for the simulating void; (d) GPR system utilized in the experiment; (e) Experiment after increasing the height of the model.

124 Unlike synthetic GPR data, real GPR data is inevitably accompanied by noise signals because of the heterogeneity of the
 125 subsurface medium, mutual wave interactions, and the influence of external conditions during data collection. Therefore, these
 126 data should be subjected to visualization enhancement using pre-processing techniques, such as time-zero correction, clutter
 127 removal, and noise reduction. After a series of pre-processing techniques, the real GPR data with 10 ns of depth in a two-way
 128 time domain and 2 m of spacing in the horizontal direction was obtained due to the limitation of sandbox depth. Their
 129 morphology patterns varied in terms of abnormal objects and complex geological structures. In total, 118 real GPR data
 130 comprising diverse reflected signals representing rebars as well as various structural defects, including voids, cracks, and
 131 separations, were obtained.

132 2.3. GPR image annotation

133 In this study, additional 28,600 synthetic GPR data with 800 sampling steps and 99 traces, mentioned in Section 2.1, were
 134 converted into images with resolutions of 224×224 pixels to pre-train the feature extraction network of the R²DCNN for
 135 classification. They need not be annotated by inclined rectangular boxes using the LabelImg software. Therefore, a total of 2092
 136 GPR datasets were used for annotation, including 1974 synthetic GPR datasets and 118 real GPR datasets, to train the R²DCNN.
 137 For subsequent image annotation, 2,092 GPR datasets (800 sampling steps and 99 traces) were converted into images with
 138 resolutions of 533×533 pixels. The reflected signal features of each GPR image could be related to specific types of tunnel
 139 lining internal objects. In particular, the reflected signals generated by the abnormal objects may have phases that are reversed
 140 compared with that of the direct waves when the permittivity of the abnormal objects is higher than that of the tunnel lining [11].
 141 Therefore, different objects can be distinguished and discriminated based on the reflected signal features of their GPR images.
 142 The object determination of real GPR images primarily depends on the position and type of the object buried in the sand,
 143 whereas the abnormal objects of synthetic GPR images were annotated according to the established permittivity model and the
 144 GPR image corresponding to the model. Finally, GPR image annotation was manually performed using the open-source software
 145 LabelImg in which dissimilar objects were framed using inclined rectangular boxes in various categories in GPR images with
 146 resolutions of 533×533 pixels. These GPR images were randomly divided into a training set including 1,300 synthetic GPR
 147 images and 38 real GPR images, a validation set of 290 synthetic GPR images, and a test set including 384 synthetic GPR images
 148 and 80 real GPR images according to the types of images to ensure equal distribution in each type for training and fine-tuning the
 149 R²DCNN.

150 3. Methodology

151 Although object detection networks based on horizontal rectangular boxes can detect abnormal objects in GPR images
 152 [28-29], they cannot accurately delineate the locations of the distributed reflected signals with arbitrary orientations in GPR
 153 images. For example, for crack defects shown in Fig. 1, object detection networks based on horizontal rectangular boxes may
 154 produce relatively large regions, which cannot locate the objects very precisely. Thus far, various object detection networks based
 155 on inclined rectangular boxes have been used for detecting objects with arbitrary orientations [26,30-31]. However, such
 156 networks cannot achieve ideal detection for GPR images of the tunnel lining for several reasons described in Section 1. Therefore,
 157 it is essential for deep learning networks to have powerful feature representation and feature fusion abilities to learn various
 158 abnormal objects adaptively and generalize the trained models for application to real GPR images with limited data.

159 In view of the characteristics and challenges related to the GPR images of tunnel linings, we developed an improved
 160 R²DCNN method based on the R²CNN architecture for automatic detection of abnormal objects with arbitrary orientations in
 161 complex GPR images. The R²DCNN can improve the rapidity and intelligence of detection methods, laying a solid foundation
 162 for the automated inspection of tunnels in the future. The R²DCNN comprises inter-related modules, specifically, DC, feature
 163 fusion, and rotated region detection modules. The flowchart of the R²DCNN is shown in Fig. 4. Firstly, a DC based feature
 164 extraction network is employed to extract powerful features from original GPR images with the irregular convolution kernels that
 165 change their shape according to the shape of the object. Secondly, the feature fusion module that concatenates the shallow and
 166 deep feature maps in the feature extraction network provides a rich feature map with both detailed and semantic information for
 167 the following detection. Finally, rotated region detection is used to perform image classification and regression on a series of
 168 candidate boxes obtained through region proposal network (RPN) using multi-scale ROI Align, so as to obtain the final detection
 169 results. The specific structure of each module is illustrated in Fig. 5. The following sections will describe each of the
 170 corresponding modules in detail.

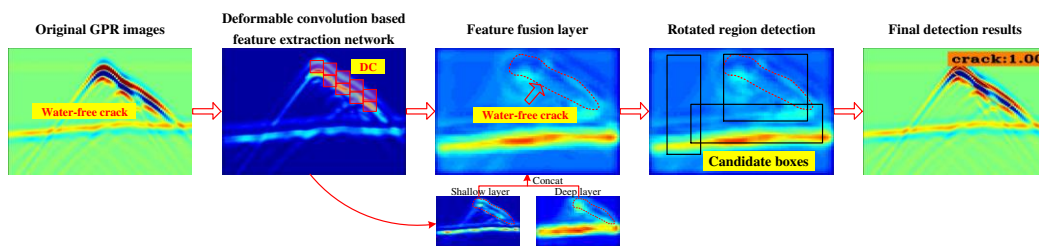


Fig. 4. The flowchart of the R²DCNN.

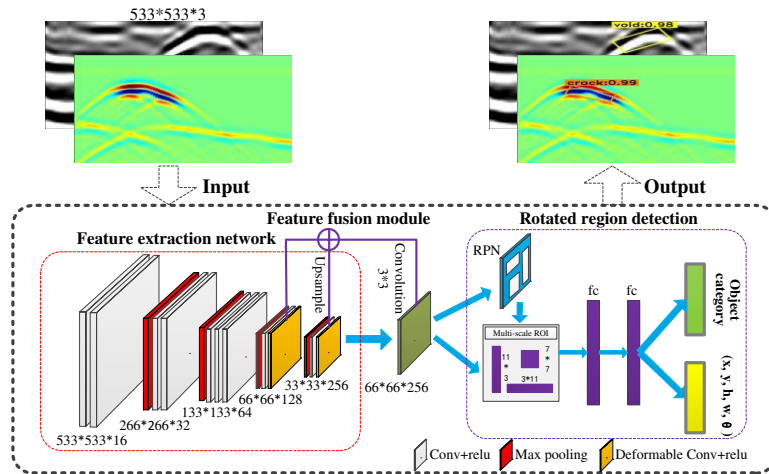


Fig. 5. The network structure of the R²DCNN.

171 3.1. Deformable convolution based feature extraction network

172 The reflected signals of the GPR images show considerable diversity and irregularity due to the various geometric shapes
 173 and filling materials of the complex tunnel lining defects. In addition, unpredictable interference in the real world may induce
 174 significant noise in the real GPR images, thereby diversifying and complicating the GPR images under the influence of noise.
 175 However, real GPR images obtained by model experiments are limited. Thus, it is preferable for deep learning networks to learn
 176 the geometric transformations of reflected signal morphologies adaptively and generalize the trained models for application to
 177 real GPR images with limited data. CNNs with fixed sampling locations are inherently limited for modelling geometric
 178 transformations [32]. DC realizes anisotropic sampling by learning the offsets of the sampling points, as shown in Fig. 6 (a).
 179 Therefore, a DC module that can adapt to various reflected signals with different sizes and shapes was introduced into the feature
 180 extraction network, as shown in Fig. 5.

181 The backbone network is based on VGG16 [33], consisting of five convolution blocks (Conv1, Conv2, Conv3, Conv4, and
 182 Conv5), a max pooling layer following each convolution block, and the activation function, ReLU, which is used after each
 183 convolution layer. The max pooling layers are mostly utilized to reduce the size of the feature map, making it focus on important
 184 areas. The activation function is employed to ensure that the values in the feature map are within a reasonable range. Moreover,
 185 to reduce the computational burden on the feature extraction network, the number of channels of the feature maps in the five
 186 convolution blocks was modified and varied block-wise, as shown in Fig. 5. In this study, DC with learned offsets and a
 187 modulation mechanism derived from Deformable ConvNets v2 [22] were employed because of the blurred boundaries between
 188 the object and background in the GPR images of the tunnel lining. To better utilize the DC to produce superior detection results,
 189 two DCs were added to the relatively backward convolution layers, containing Conv4_2 and Conv5_2 of the feature extraction
 190 network, which are more sensitive to the position information of the GPR images [32], and the numbers of convolutional layers
 191 in the latter two convolution blocks were reduced accordingly. Meanwhile, atrous convolution with a dilation of 2 was used in
 192 the DC module to increase the receptive fields of the offsets and modulation learning with the same complexity as common
 193 convolution in terms of the parameters and computation. The offsets of the sampling points, which are learned from the
 194 preceding feature maps in the standard convolution, and the modulation mechanism, which adjusts the scope of deformation
 195 modelling, enable better adaptation to the sizes and shapes of the reflected signals without the influence of irrelevant content,
 196 such as noise, diffraction signals, and multiple waves in the GPR images, thereby preventing the spread of samples beyond the
 197 area of interest.

198 Owing to the different characteristics of the GPR images and natural images, GPR images were chosen (instead of
 199 ImageNet) to pre-train the feature extraction network for classification. To achieve pre-training of the feature extraction network,
 200 two fully connected layers followed by dropout and the softmax layer were added. The dropout layers following fully connected
 201 layers were applied to combat the overfitting problem. The obtained pre-trained model parameters were exploited to initialize the
 202 CNN model of the R²DCNN.

203 3.2. Feature Fusion Layer

204 Conventional CNNs, such as R²CNN, only use the feature learned from the last convolutional layer of the network to
 205 perform image classification and regression by multi-scale ROI Align, which provides more semantic information but less details.
 206 This method may compromise the accuracy of the location information that is crucial for abnormal object detection in GPR
 207 images because the sizes and shapes of the abnormal objects are changeable. In particular, cracks with large aspect ratios can be
 208 regarded as small objects [34], the boundaries between the objects and background are blurred in GPR images of tunnel linings,
 209 and multiple waves and scattering are produced by water-bearing defects. The features of the lower layer contain more detailed

210 information, such as information regarding the underlying texture and color, but the semantic information is less abundant.
 211 Therefore, the feature fusion layer is employed for detection instead of using the last feature map to improve the detection effect
 212 for multi-scale objects in complex GPR images.

213 In terms of the sizes of abnormal objects in GPR images and the receptive field of the feature extraction network, rich
 214 multi-scale features of the low-level layer Conv4_2 and high-level layer Conv5_2 are fused, as shown in Fig. 6 (b). The sizes and
 215 numbers of feature maps vary for different layers, which implies that the fusion layers are not directly stacked together. Thus, the
 216 feature map of the same size as Conv4_2 is generated by upsampling Conv5_2 using nearest neighbor interpolation.
 217 Subsequently, the layers of Conv5_2 and Conv4_2 are concatenated along their channel axis to perform fusion. Thereafter, 3×3
 218 convolution is utilized to generate the final fusion feature maps for detection to eliminate the aliasing effect of the upsampling
 219 and adjust the number of channels of the feature map.

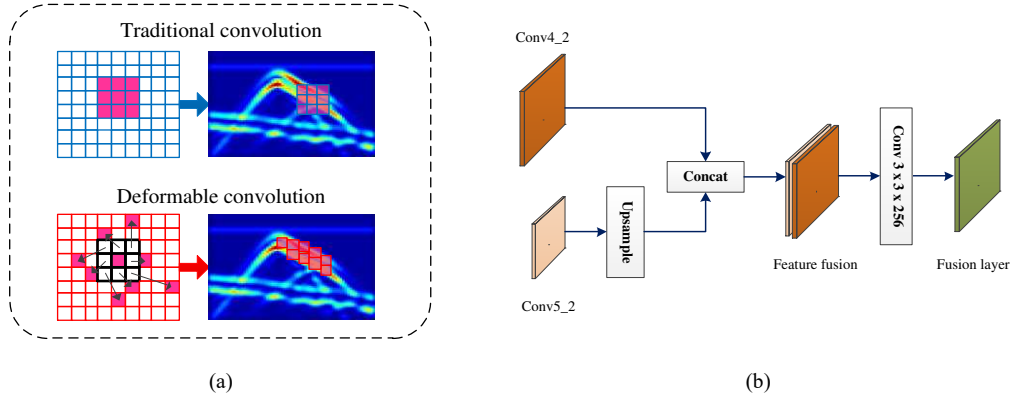


Fig. 6. (a) Different calculation positions under traditional convolution or deformable convolution; (b) Architecture of feature fusion module.

220 3.3. Rotated region detection

221 For the detection of tunnel lining abnormal objects using GPR images, horizontal region detection with a relatively large
 222 redundant region is not feasible because of the arbitrary orientations of the reflected signals in GPR images. Rotated region
 223 detection based on R²CNN was introduced into the proposed network to enable accurate detection of abnormal objects with
 224 arbitrary orientations.

225 As shown in Fig. 5, the rotated region detection also involves a RPN and Fast R-CNN, which share a common feature
 226 extraction network. The RPN is employed to generate a set of horizontal proposals that may enclose the reflected signals of the
 227 input GPR images. Thereafter, each horizontal proposal obtains feature maps of different sizes (7×7 , 11×3 , 3×11) through the
 228 multi-scale ROI Align layer to preserve the complete feature information. The Fast R-CNN stage only predicts inclined
 229 rectangular boxes (x , y , h , w , and α), which are represented using the coordinates of the center points, the height, width, and
 230 rotated angle of the rectangular box [34]. The classification is conducted using concatenated multi-scale features, and the final
 231 inclined rectangular boxes are obtained by inclined non-maximum suppression.

232 4. Experimental results and discussion

233 This section is divided into four parts. Section 4.1 describes the experimental details and introduces the evaluation indicators.
 234 Section 4.2 presents the comprehensive comparative experiments and results on synthetic GPR images. Section 4.3 conducts
 235 model verification experiments to discuss the results of the R²DCNN on real GPR images. Finally, Section 4.4 presents
 236 discussion.

237 4.1. Experimental details and evaluation indicators

238 The training of the R²DCNN consists of two main stages. The first stage was used to obtain pre-training model parameters
 239 by pre-training the feature extraction network for classification using 28,600 synthetic GPR images. The second stage was
 240 utilized to obtain a detection model of defects and rebars within the tunnel lining by training and fine-tuning the R²DCNN using
 241 the pre-trained model parameters and 2092 synthetic and real GPR images with different frequencies described in Section 2.
 242 Before training the network, the intensity values of the GPR images were standardized to enhance their contrast.

243 Our method was implemented on the TensorFlow framework, and an Intel Xeon (R) Gold 5118 CPU with a GTX 1080 Ti
 244 GPU was employed for training. In the pre-training phase of the feature extraction network, the input GPR image was resized to
 245 224×224 . The Adam [35] optimization algorithm was employed during 50 epochs of training. The weight decay and batch size
 246 were 0.0005 and 50, respectively. The initial learning rate remained $5e-5$ for the first 25 epochs and decayed to $5e-6$ at epoch 25.
 247 For the R²DCNN, the GPR image remained the original size of 533×533 . The training step was 50,000 epochs with an initial
 248 learning rate of $5e-5$, and the learning rate decay strategy was stepped at the 20,000th and 40,000th epochs with a coefficient of
 249 0.1. The weight decay and batch size were 0.0005 and 1, respectively. The multi-task loss containing cross-entropy loss for
 250 classification and smooth L1 loss for regression was utilized to optimize the R²DCNN through the Adam optimization algorithm.

251 Although the training of the R²DCNN may take a relatively long time, the detection time for a GPR image would be significantly
 252 short.

253 In our experiment, recall, precision, F-measure, and average precision (AP) were used as evaluation indicators for the
 254 detection of internal defects and rebars in the tunnel lining. Recall and precision are the basic indicators to measure the
 255 performance of an algorithm under a specific Intersection over Union (IoU) between the predicted boxes and ground truth. The
 256 F-measure is the weighted average of recall and precision. The AP, average precision under different recalls, is a comprehensive
 257 evaluation indicator that is not affected by the selected thresholds. The mean average precision (MAP) is the average of the AP
 258 across all the different defect types.

259 *4.2. Experimental results*

260 This section conducts a comprehensive comparative experiment using synthetic GPR images to confirm the superior
 261 performance of the R²DCNN. The ablation experiments were initially performed on synthetic GPR images. Comparisons with
 262 the existing optimal methods were subsequently conducted. Finally, we present comparisons of evaluation indicators for various
 263 methods.

264 *4.2.1. Ablation experimental results*

265 We benchmarked the R²DCNN along with variant architectures using our synthetic and real GPR images of the tunnel lining
 266 to evaluate the contribution of each module in our model, such as the feature fusion and DC modules. Notably, the feature
 267 extraction network of the R²DCNN without DC is VGG16.

268 Fig. 7 presents the results of the R²DCNN along with those of variant methods for synthetic GPR images with different
 269 frequencies. The detection result is a GPR image with inclined rectangular boxes used to locate the object, a defect type of each
 270 box, and a confidence of each box in the upper right corner that indicates the probability that the object is of this type. In Fig. 7,
 271 the first column presents the permittivity model corresponding to the GPR image, the second column presents GPR images with
 272 different frequencies, and the third, fourth, and fifth columns provide the detection results of the R²DCNN without DC, R²DCNN
 273 without fusion, and R²DCNN, respectively. It can be seen from Fig. 7 that the R²DCNN can accurately locate various reflected
 274 signals of GPR images with precise inclined rectangular boxes, whereas there are missing detected objects and imprecise
 275 detection boxes in the results of the other variants. These observations indicate that the feature fusion module, which provides
 276 accurate location and shape information, together with the DC module, which achieves anisotropic sampling, can jointly improve
 277 the ability to detect various abnormal objects with irregular shapes of GPR images with different frequencies in tunnel linings.

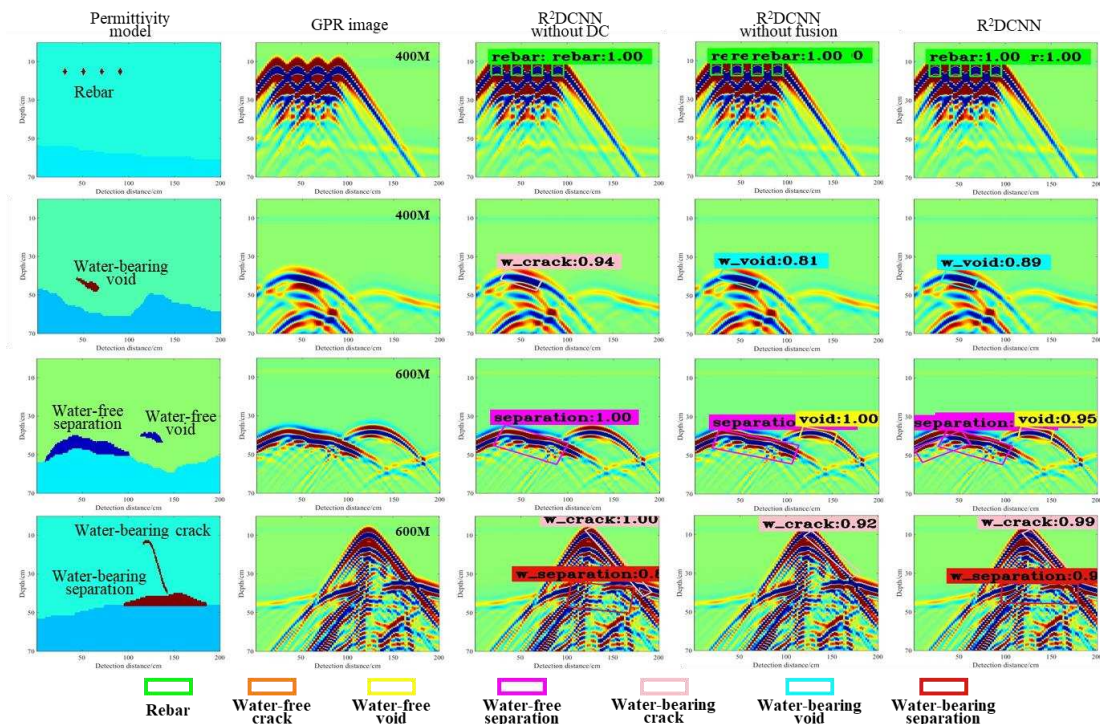


Fig. 7. Object detection results of the R²DCNN along with variant methods when applied to synthetic GPR images with different frequencies. Different types of abnormal objects are indicated by boxes of different colors, as shown in the last row.

278 *4.2.2. Comparative study and results*

279 We selected two well-known methods, the Faster R-CNN for buried object detection using B-scan GPR images [36] and the
 280 R²CNN for scene text detection [26], for comparison to verify the effectiveness and superiority of the R²DCNN in tunnel lining
 281 defect detection.

282 Fig. 8 shows the object detection results obtained by applying different methods to synthetic GPR images, including GPR
 283 images of single and combined defects as well as synthetic GPR images with defects of different types and conductivities
 284 compared to those in the training set. The first column depicts the permittivity model corresponding to the GPR image; the
 285 second column shows the GPR images with different frequencies; and the third, fourth, and fifth columns present the detection
 286 results of the Faster R-CNN, R²CNN, and R²DCNN, respectively. As shown in Fig. 8, the R²DCNN can accurately locate all
 287 abnormal objects in the GPR images, whereas the other two methods produce relatively poor detection results. The Faster
 288 R-CNN is designed to generate horizontal rectangular detection boxes including more background with relatively large redundant
 289 regions. Moreover, certain detection results cannot be accurately marked or are overlooked. The R²CNN is used for the detection
 290 of inclined rectangular boxes, which can address the problem of the detection of abnormal objects with arbitrary orientations in
 291 GPR images. But as a result of inaccurate prediction of the direction information of inclined rectangular boxes, this method
 292 cannot conduct accurate detection of abnormal objects in GPR images. Additionally, for certain abnormal objects with large
 293 changes in shape and unknown forms, the other two methods may yield missing, redundant, or false object detection boxes.
 294 These observations indicate that the adaptability and transferability of the two methods are weak. The R²DCNN performs well in
 295 a variety of situations and is more adaptive to the detection of various reflected signals with arbitrary orientations of GPR images
 296 with different frequencies in tunnel linings.

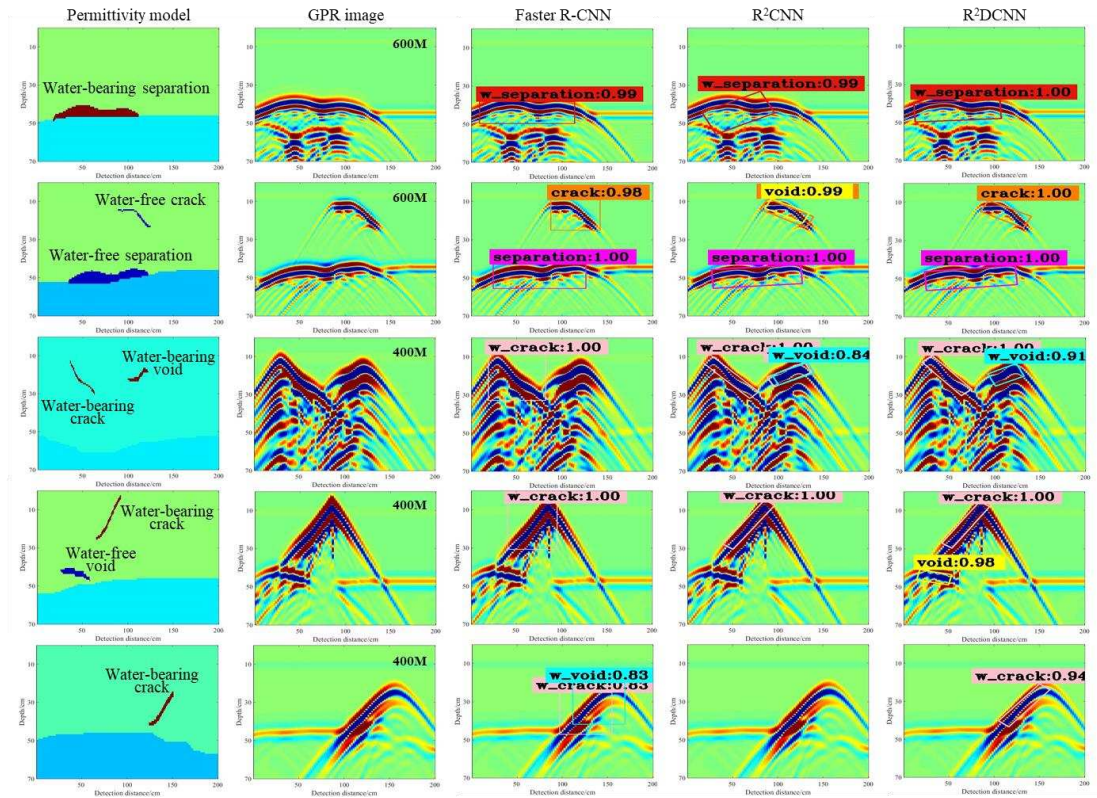


Fig. 8. Object detection results of different methods when applied to synthetic GPR images with different frequencies, containing GPR images of single (the first row) and combined (the middle two rows) defects along with GPR images with defects of different types and conductivities compared to those in the training set (the last two rows).

297 4.2.3. Comparisons of evaluation indicators

298 To quantitatively evaluate the performance of various methods and the effect of each module on the model performance, the
 299 evaluation indicators detailed in Section 4.1 are utilized to assess the comprehensive performance of the R²DCNN along with
 300 other methods when applied to GPR images. Table 2 compares the overall performances of the different methods on synthetic
 301 GPR images. The R²DCNN achieves competitive results with a recall of 81.11%, a precision of 87.46%, an F-measure of 84.07%,
 302 and a MAP of 73.91% when applied to synthetic GPR images.

303 For synthetic GPR images, the R²DCNN is slightly worse than the Faster R-CNN, but considerably better than the R²CNN
 304 for all indicators. The R²DCNN can locate various abnormal objects more accurately with inclined rectangular boxes, which have
 305 the smallest enclosing areas. And few objects were repeatedly detected, as evidenced by the visual outputs. Therefore, for

306 abnormal objects with larger aspect ratios, if the box size and location are not sufficiently precise, the recall and precision
 307 decrease easily, making the indicators have lower values than when the Faster R-CNN is applied. According to the results from
 308 Table 2, R²DCNN without fusion achieves 2.97% and 4.21% performance gains in F-measure and MAP, respectively, compared
 309 to the R²CNN. Adding the feature fusion module to the R²CNN also improves the F-measure by 2.28% and MAP by 3.09%. This
 310 confirms that powerful feature representation and feature fusion abilities both contribute towards improved detection in
 311 complicated GPR images. The R²DCNN provides greater improvements compared to other variant methods. The F-measure and
 312 MAP are improved by 5.62% and 8.21%, respectively. Meanwhile, our method only consumes a little time (0.0877s) for
 313 detecting a GPR image using the configuration described in Section 4.1 (Table 3). And it also increases little time cost compared
 314 to the R²CNN baseline. This means that the R²DCNN can detect GPR images with higher accuracy and little time cost. Therefore,
 315 our proposed method can provide a more accurate suggestion for a less experienced analyst with very little time cost, which can
 316 save a considerable amount of time for tunnel lining defect detection. In summary, the R²DCNN is superior to the other methods
 317 when applied to GPR images with different frequencies in tunnel linings.

318 As can be seen from the object detection results and evaluation indicators of the R²DCNN along with other methods on
 319 GPR images, only using the DC or feature fusion module could not produce good experimental results. The two modules need to
 320 be introduced simultaneously to enhance the stability and generalization of the network. The R²DCNN is more sensitive to
 321 abnormal objects in complex GPR images than the other methods, thereby exhibiting appropriate stability and robustness when
 322 applied to GPR images with different frequencies in tunnel linings.

Table 2

Comparison of experimentally obtained indicators for synthetic GPR images.

Methods	Recall	Precision	F-measure	MAP
Faster R-CNN	0.8166	0.9113	0.8601	0.7668
R ² CNN	0.7473	0.8285	0.7845	0.6570
R ² DCNN without DC	0.7731	0.8474	0.8073	0.6879
R ² DCNN without fusion	0.7799	0.8553	0.8142	0.6991
R ² DCNN	0.8111	0.8746	0.8407	0.7391

Table 3

Detection time of the R²DCNN and R²CNN.

Methods	R ² CNN	R ² DCNN
Time	0.0842s	0.0877s

323 4.3. Results on real GPR images

324 Because we aim to apply the R²DCNN to practical situations, it is vital to demonstrate the applicability and effectiveness of
 325 the R²DCNN using real GPR images. Compared to the synthetic GPR images, real GPR images produce reflected signals with
 326 more prominent irregularity and complexity under the influence of considerable noise due to the unpredictable interference in the
 327 real world. Moreover, real GPR images are limited. Hence, three real GPR images with rebars and water-free voids of different
 328 rotation angles, depths, and positions were used to evaluate our scheme; different depth sandbox models were also used. Fig. 9
 329 compares the results of the R²DCNN with those of some existing algorithms on real GPR images. The first column depicts the
 330 sandbox model corresponding to the GPR image; the second column shows the real GPR images obtained by sandbox model
 331 experiments; and the third, fourth, and fifth columns present the detection results of the Faster R-CNN, R²CNN, and R²DCNN,
 332 respectively. Because the depth of the sandbox models presented in Fig. 9 is different, the position of the interface of the GPR
 333 image corresponding to the sandbox model is also inconsistent. Moreover, the signal below the interface of the GPR image is
 334 generated by the medium under the sandbox, which is not related to the medium inside the sandbox. For rebars and defects under
 335 rebars of the third row in Fig. 9, these three methods fail to recognize the right defect under rebars due to the weaker signal
 336 caused by the interference of reflected signals from rebars. Except for defects under rebars, the R²DCNN can accurately locate
 337 abnormal objects with arbitrary orientations on real GPR images, while the Faster R-CNN produces missing and imprecise object
 338 detection boxes with relatively large redundant regions, and the R²CNN produces missing object detection boxes that face
 339 difficulty in detecting the real GPR image. In summary, the R²DCNN obtains convincing detection results, far superior to other
 340 methods. The comparative results indicate that the R²DCNN can be applied to complicated datasets effectively, thereby providing
 341 a good basis for the recognition of real GPR images.

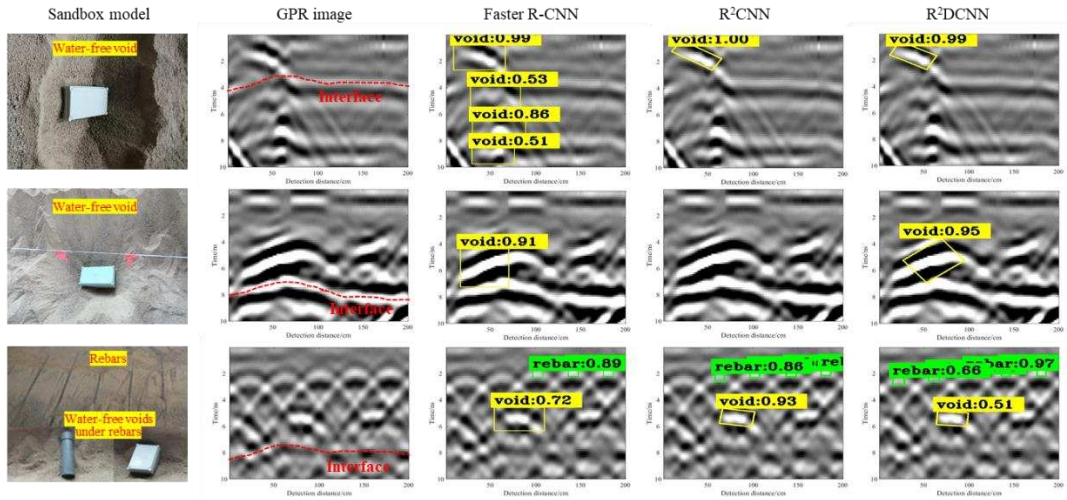


Fig. 9. Object detection results of different methods when applied to real GPR images.

342 4.4. Discussion

343 An ablation and comprehensive comparative experiment with the existing optical methods, as well as model verification
 344 experiments, are performed as described in Section 4.2 and 4.3. The results confirm that the R²DCNN overcomes the negative
 345 effects of complicated real GPR images with limited data in the tunnel lining and exhibits good stability and generalization when
 346 applied to GPR images with different frequencies. For further verification of the feasibility of the R²DCNN, the intermediate
 347 processes of the network are visualized.

348 The reflected signals of GPR images yielded by abnormal objects of different sizes and shapes within the tunnel lining show
 349 diversity and irregularity, and the real GPR images are limited and accompanied by considerable noise. It is difficult to detect
 350 abnormal objects of various shapes and sizes on more complex GPR images using traditional convolution because of the fixed
 351 sampling location. Hence, a DC module, composed of offset learning of sampling points and a modulation mechanism, was
 352 introduced, making the sampling points more suitable for the shapes and sizes of the abnormal objects in GPR images than if a
 353 fixed rectangular form had been used.

354 For improved understanding of the behavior of the DC module, we visualized the spatial support of the network nodes using
 355 their effective sampling locations and compared those of DC with traditional convolution methods using synthetic GPR images.
 356 The standard operations in DC were neglected because they did not affect the offsets of the sampling points. Fig. 10 shows the
 357 relative contributions of these sampling locations to the network nodes. The two different types of GPR images with different
 358 frequencies are shown in the first two and last two rows of Fig. 10. The receptive field and sampling locations in the standard
 359 convolution were fixed, whereas the DC module adaptively adjusted them according to the sizes and shapes of the abnormal
 360 objects. Although GPR images are different from natural images because of the existence of considerable clutter interference and
 361 abnormal objects with relatively large aspect ratios in GPR images, the spatial support of DC can approximately cover the entire
 362 object and enable better adaptation to various objects when the nodes are on the abnormal objects in GPR images. In the first
 363 column of Fig. 10, all sampling points in the DC are more widely distributed when the nodes are in the background of the GPR
 364 images. Therefore, DC enables better detection of different types of abnormal objects within the tunnel lining according to the
 365 shapes and sizes of the reflected signals from abnormal objects in GPR images.

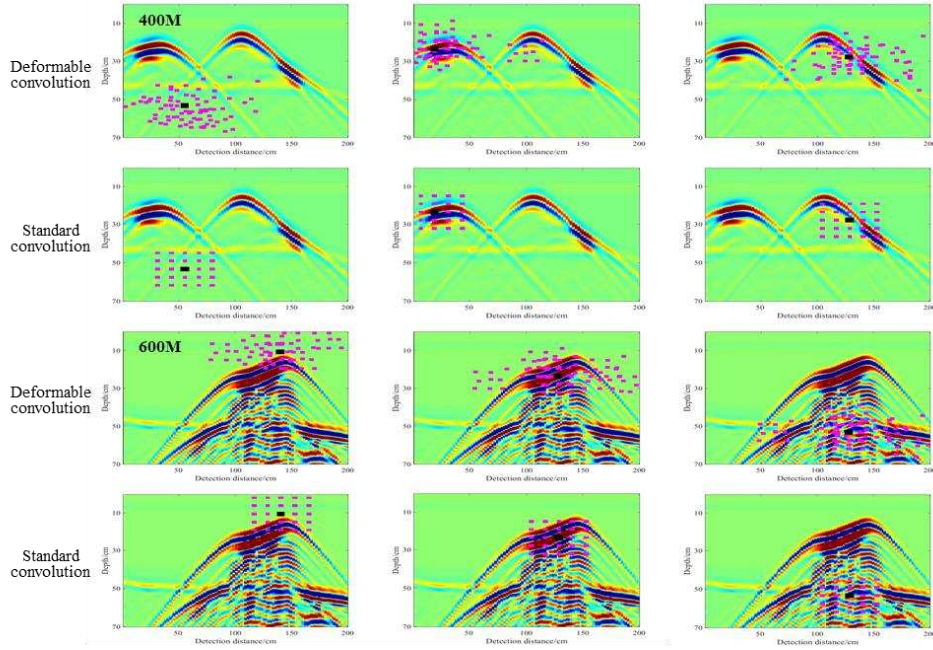


Fig. 10. Spatial support of network nodes in deformable and standard convolution networks. The visualized nodes (center points in black for synthetic GPR images with different frequencies) are in the background (left) and on abnormal objects in the GPR images (middle and right).

366 The boundaries between the object and background are blurred in the GPR images of the tunnel lining due to diffraction
 367 signals, and multiple waves and scattering are induced by water-bearing defects. The feature fusion module was exploited to
 368 reuse the feature information. The module combines the advantages of shallow features (Conv4_2) that provide accurate location
 369 and shape information and deep features (Conv5_2) that contain more semantic information. The shallow, deep, and fused feature
 370 maps were visualized on synthetic and real GPR images, as shown in Fig. 11, to demonstrate the role of the feature fusion
 371 module more clearly. The first and second rows present the visualizations of the synthetic and real GPR images, respectively. For
 372 the shallow feature maps in the second column, multiple objects in the GPR images represented different specific types of defects.
 373 Subsequently, the areas of interest were circled using dashed lines of different colors. In Fig. 11, all defects of shallow features in
 374 the second column contain more detailed information than deep features in the third column, such as those related to the
 375 underlying texture, shape, and location; the deep features produce large swaths of highlighted information, which is semantic
 376 information about the defects, and there is no clear information about the location or shape; the feature maps fusing the shallow
 377 and deep features in the fourth column contain the detailed information, wherein the defects that are circled using dashed lines of
 378 different colors have dark and bright colors that are extremely similar to the shallow features, and semantic information, wherein
 379 the outsides of the defects surrounded by dashed lines of different colors have large swaths of highlighted information that are
 380 similar to those of the deep features. This observation further confirms the effectiveness of the feature fusion module when
 381 applied to GPR images.

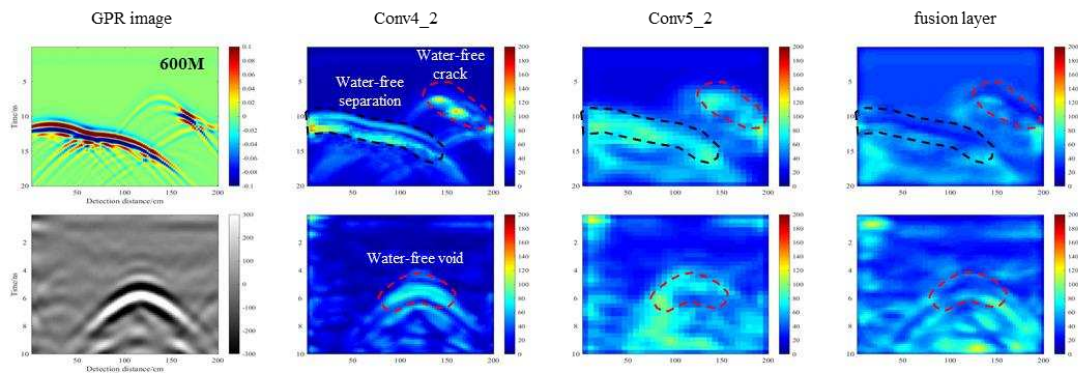


Fig. 11. Visualization of feature fusion module effects using synthetic and real GPR images.

382 5. On-site experiments

383 The R²DCNN produced convincing results upon application in real GPR images obtained by model experiments, which
 384 reflects its excellent adaptability, and it can be used in engineering due to the greater similarity between real GPR images

385 collected from the model experiments and practical tunnels. To further verify the applicability of the proposed method in
 386 engineering, it was implemented to automatically detect reflected signals in GPR images obtained from the surveys of multiple
 387 tunnels, such as the Nanshibi Tunnel in Jiangxi Province and the Shuiquanwan Tunnel in Shanxi Province. The implementation
 388 process of the proposed method in practical tunnels is summarized in Fig. 12.
 389

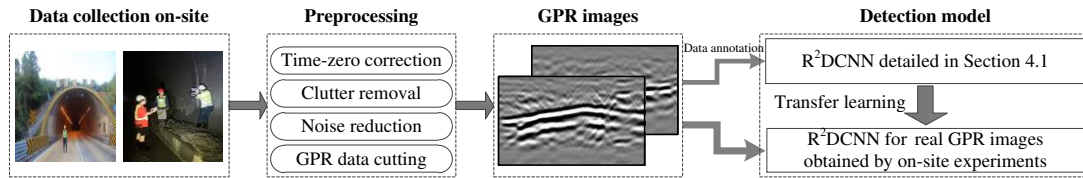


Fig. 12. The implementation process of the proposed method in practical tunnels.

390 Firstly, it is necessary to collect a large amount of raw GPR data at the tunnel site through GPR equipment to verify the
 391 proposed method. During this verification process, a 600 MHz Impulse Radar system was used to scan multiple tunnel walls to
 392 collect the GPR data on-site. The number of samples per trace and the trace-interval distance of this GPR device were 512 and
 393 0.01 m, respectively. Secondly, certain pre-processing techniques were employed to highlight the reflected signals from tunnel
 394 lining defects and obtain the GPR data of the corresponding size. A total of 219 GPR data were obtained, in which each GPR data
 395 covered a detection distance of 2m and a time window of 20ns in depth over the tunnel lining. The GPR data was then converted
 396 into images with resolutions of 533×533 pixels to fine-tune and test the R²DCNN. Unlike synthetic GPR data, real GPR data is
 397 inevitably accompanied by considerable noise. Therefore, it is difficult for the R²DCNN, trained through both synthetic and real
 398 GPR images obtained from the previously described sandbox experiments, to directly test the GPR images collected from
 399 practical tunnels. Thus, after a series of pre-processing techniques, only 99 GPR images were annotated to fine-tune the
 400 R²DCNN (based on R²DCNN weights in Section 4.1), and the number of iterations was 10000. The training time of the R²DCNN
 401 was approximately 3 hours. Finally, the detection model of defects and rebars was utilized to detect abnormal objects of the
 402 specific tunnel.

403 Fig. 13 depicts the results of the R²DCNN on the remaining 120 GPR images. The first row shows the real GPR image
 404 collected from practical tunnels, and the second row shows the detection results of the R²DCNN. It can be seen that the R²DCNN
 405 produces superior detection results. In particular, the R²DCNN could detect small abnormal objects in GPR images in the first
 406 column of Fig. 13. The practical tunnel we selected for on-site experiments has a large number of structural defects, which
 407 needed to be repaired by reinforcing the surrounding rock after the lining. Therefore, grouting pipes were hit in the tunnel to
 408 reinforce the surrounding rock. Considering that the defect inside the tunnel lining is concealed, the GPR images collected from a
 409 tunnel lining with grouting pipes are utilized to further demonstrate the adaptability of our proposed method. The detection
 410 results are shown in Fig. 14. The R²DCNN can accurately locate and recognize reflected signals from grouting pipes in the GPR
 411 image. The reflected signals are recognized as a water-bearing void because of the similar defect characteristics between the
 412 grouting pipe and the water-bearing void. The evaluation indicators detailed in Section 4.1 are utilized to analyze the
 413 comprehensive performance of the R²DCNN on practical tunnels, as presented in Table 4. The R²DCNN produces favorable
 414 performance with a recall of 60.13%, a precision of 72.45%, an F-measure of 60.43%, and a MAP of 47.45% when applied to
 415 real GPR images collected from practical tunnels. The indicators of real GPR images are slightly lower than those of synthetic
 416 GPR images. This gap may be because the real GPR images are limited and more complicated under the influence of noise,
 417 revealing various reflected signal morphologies. Thus, the R²DCNN enables the accurate detection of defects inside the tunnel
 418 lining, which proves it is applicable in engineering.

419 In case of other tunnels, the raw GPR data collected using the GPR equipment needs to be pre-processed (such as time-zero
 420 correction, clutter removal, or noise reduction, etc.) to obtain a large number of GPR images with appropriate sizes and clear
 421 reflected signals. Subsequently, only a small number of GPR images with reflected signals, manually annotated by inclined
 422 rectangular boxes using the Labelling software, are exploited to fine-tune the R²DCNN due to the different characteristics of the
 423 GPR data collected from different tunnels. As long as the GPR image between the training and test set has similar settings, there
 424 is no specific setting for data collection and the size of GPR images. Although it might take a relatively long time for data
 425 annotation and network training to obtain a defect detection model for tunnel linings (approximately 4 hours), the detection time
 426 for a GPR image would be significantly short (approximately 0.0877 s). Moreover, the model can detect different defect types
 427 and their locations. For example, detecting a continuous scan of a tunnel wall, including approximately 10,000 GPR images,
 428 might take nearly 16 min using our proposed method, which has a high detection efficiency. As an automatic detection system, it
 429 has the potential to analyze more GPR images than a trained analyst in a shorter period, and it can also serve as an aid to a less
 430 experienced analyst by suggesting interpretations that might not be obvious.

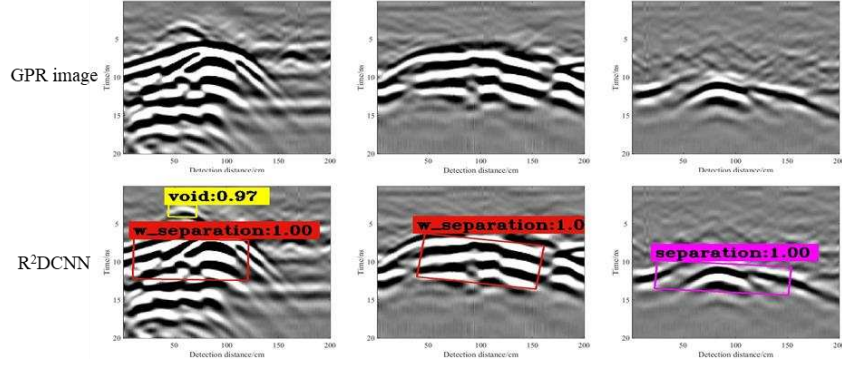


Fig. 13. Object detection results of the R²DCNN when applied to real GPR images collected from practical tunnels.

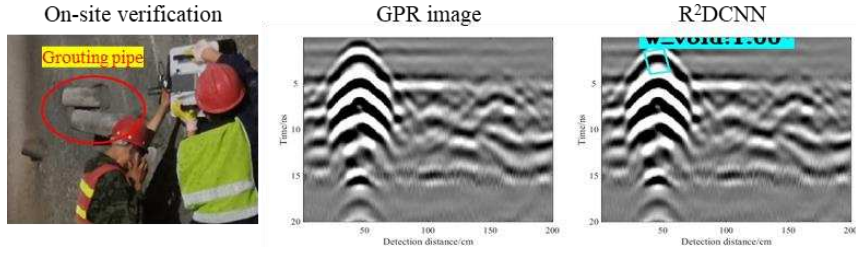


Fig. 14. On-site experiment results.

Table 4

Results of the R²DCNN on real GPR images collected from practical tunnels.

Method	Recall	Precision	F-measure	MAP
R ² DCNN	0.6013	0.7245	0.6043	0.4745

431 6. Conclusions

432 In this study, we propose the R²DCNN for the automatic detection of abnormal objects with arbitrary orientations in GPR
 433 images of tunnel lining, and the following conclusions are obtained.

434 (1) The R²DCNN is capable of fine-grained feature extraction and has a powerful modelling ability for abnormal objects of
 435 various shapes and sizes, using DC, feature fusion, and rotated region detection modules. This method enables accurate detection
 436 of defects and rebars of various shapes and sizes with arbitrary orientations in tunnel linings.

437 (2) A comprehensive comparative study shows that the F-measure and MAP of the R²DCNN are improved by 5.62% and
 438 8.21%, respectively, compared to the R²CNN when applied to synthetic GPR images. And the R²DCNN only increases little time
 439 cost for detecting a GPR image compared to the R²CNN baseline. Additionally, a model verification experiment confirms the
 440 effectiveness of the R²DCNN on real GPR images. The R²DCNN exhibits appropriate stability and generalization when applied
 441 to synthetic and real GPR images with different frequencies, as well as GPR images with defects of different types and
 442 conductivities compared to those of the training set in tunnel linings.

443 (3) On-site experiments are employed to describe the implementation process of the R²DCNN in detail and confirm its
 444 effectiveness in practical tunnels. The R²DCNN produces favorable performance with a recall of 60.13% and a precision of 72.45%
 445 when applied to real GPR images collected from practical tunnels. As an automatic detection system, it has the potential to
 446 analyze numerous more GPR images than a trained analyst in a shorter period. Furthermore, the R²DCNN could serve as an aid
 447 to a less experienced analyst by suggesting interpretations that might not be obvious. Therefore, the proposed method can
 448 improve the key technical links of automated tunnel inspections in the future and has practical prospects.

449 (4) Although the R²DCNN achieves suitable results when applied to both synthetic and real GPR images, it poses certain
 450 limitations on the diversity of real GPR images. Further experimentation on a larger and more diverse set of real GPR images is
 451 required in order to better verify the system performance for practical applications. In our future research, we also wish to
 452 compare and analyze the experimental results of the deep learning model using GPR images of different frequencies and sites to
 453 verify the stability and superiority of the network.

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