Ice Crevasse Detection with Ground Penetrating Radar using Faster R-CNN

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***Abstract*—To further enhance the security capability of polar scientific research, ground penetrating radar (GPR) has been used for ice crevasse detection. In this paper, we proposed a crevasse detection method based on Faster Region Convolutional Neural Network (Faster R-CNN), which can detect crevasses and continuous snow layers automatically in a short time. First, feature maps of GPR images extracted by convolutional layers of Faster R-CNN and region proposals generated by Region Proposal Networks (RPN) are input into regions of interest (ROI) pooling layers. Then the proposal feature maps can be obtained and used to identify crevasses and continuous snow layers. Finally, classification results are obtained according to analyzing confusion matrix. Experimental results show that our method can detect crevasses with high accuracy rate, F1 score and Kappa coefficient while low false positive rate, false alarm rate and missing report rate. The proposed method will be useful for automatic ice crevasse detection in real-time.**

Keywords—Ground Penetrating Radar, Crevasse Detection, Deep Learning, Faster R-CNN

I. INTRODUCTION

During Antarctic Scientific research, polar exploration is always in danger due to hidden ice crevasse under the ice sheet. As shown in Figure 1, there are three features in ice crevasses: snow bridge, diffractions, and void. It is dangerous for over-snow vehicle traverses because there are snow bridges over the void and ice crevasses cannot be found by vehicle drivers. Ground Penetrating Radar (GPR) is a useful polar exploration equipment, which provides lots of images for human operators to interpret crevasses in ice sheets. In recent years, an autonomous robot Yeti was developed to conduct GPR surveys, which is a battery-powered GPR device with 200 MHz or 400 MHz antenna and is mounted in a sled [2]. But, for the large amount of GPR data, the determination of ice crevasse by manual interpretation, i.e. the operator's experience and subjectivity , can't meet the requirements of accuracy and real time performance. In order to solve these problems, there are many machine learning related methods have been proposed[1][2], such as some feature-based machine learning methods, Histogram of Oriented Gradient (HOG), Hidden Markov Model (HMM), Support Vector Machine (SVM).

But as we know, deep learning is still rarely used in this field. There are some object detection algorithms based on deep learning, such as YOLO [3], Single Shot MultiBox Detector (SSD) [4], Region Convolutional Neural Network (R-CNN) [5], Fast R-CNN [6], Faster R-CNN [7]. Among them, YOLO and SSD belong to one-stage detection methods, which are characterized by reducing the spatial resolution and are suitable for detecting large objects rather than small ones.

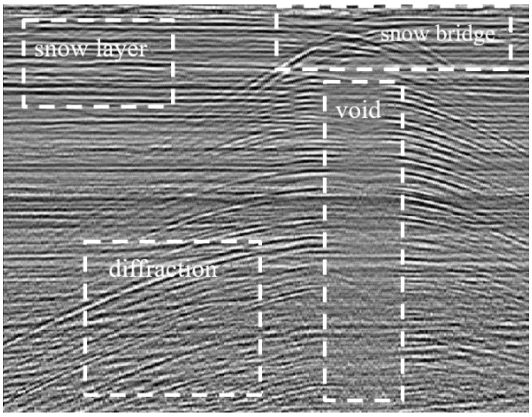

Fig. 1 Experimental GPR data with a crevasse

R-CNN, Fast R-CNN and Faster R-CNN are two-stage object detection algorithms based on region proposal method. R-CNN method uses region proposal method to avoid repeated calculation and to improve detection speed. Fast R-CNN method extracts the feature of the whole image only once compared to R-CNN, which further improves the detection speed. Besides, Fast R-CNN can train end-to-end through multi task loss function, which improves the accuracy of the model. Faster R-CNN replaces region proposal method with the internal deep network, which greatly improves the speed and efficiency of detection, and is more suitable for detecting small targets, such as ice crevasses in our work, than YOLO and SSD. The accuracy and real time performance of Faster R-CNN is exactly what we need to detect ice crevasses. In this paper, considering the efficiency of Faster R-CNN used for the detection of small targets, Faster R-CNN is used on GPR data to improve the identification accuracy and processing speed to obtain better detection results with real time performance. Three experiments were performed to validate the effectiveness of the proposed method based on the GPR dataset from the United States Antarctic Program Data Center (USAP-DC).

II. BACKGROUND

R-CNN uses region proposal method and CNN to locate and classify objects, which is different from traditional object detection methods. It uses Selective Search to create about 2000 regions of interest (ROI), which are warped and inputted into CNN classifier. The output of CNN classifier is inputted into SVM and Bounding Box Regressors (BBox), which output the classification and location of images respectively. R-CNN needs lots of ROIs to improve accuracy. But many

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ROIs overlap with each other, which makes R-CNN's training and testing speed slow. Fast R-CNN uses the feature extractor (i.e. CNN) to extract the features of the whole image instead of extracting each image block multiple times, which can significantly reduce processing time. However, Fast R-CNN relies on external region proposal method, such as selective search, which makes these algorithms run slowly on CPU.

Compared with Fast R-CNN, Faster R-CNN is composed of two modules: Region Proposal Network (RPN) and Fast R-CNN detector. It uses RPN instead of Selective Search to create ROIs, which greatly improves the speed of training and testing. Fast R-CNN detector's testing speed can reach 0.2 seconds per image while R-CNN's testing speed is 50 seconds per image, which makes it can meet the requirements of real-time detection. As shown in Figure.2, the testing sample is standardized and inputted to CNN to get feature maps. RPN is used to extract feature information of these feature maps and generate proposals. ROI pooling layer changes proposals to ROI proposals, which are inputted to classifier and regressor to get the results of classification and location.

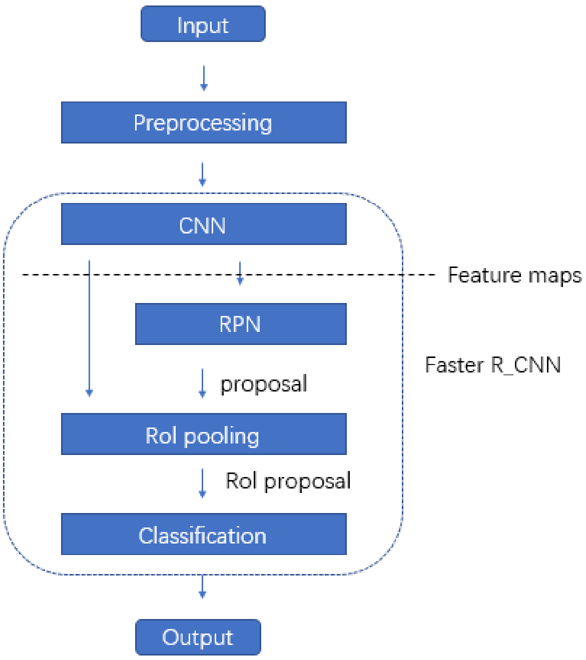

Fig.2 A general flowchart of the proposed method

III. Proposed Method

In this paper, we proposed an ice crevasse detection method with Ground Penetrating Radar by using Faster R-CNN. First, GPR data is preprocessed into an appropriate format. Second, the preprocessed GPR data is inputted into Faster R-CNN for training to get the trained Faster R-CNN. Third, the testing samples are inputted into the trained Faster R-CNN, and output the classification results (crevasse or continuous snow layer) and samples' location contained in GPR data. Finally, the confusion matrix is used to evaluate the experimental results. More detailed procedures are presented as follows.

First, GPR data is standardized in gray scale and cropped to the same size. VOC dataset is one dataset used in object detection task, in which VOC annotation method is often used to create annotations. Considering the VOC annotation information exists in the XML file, we use VOC annotation method to label GPR data to create xml files and generate its index.

Second, the preprocessed GPR data is inputted into Faster R-CNN for training to get the trained Faster R-CNN network. The training procedure includes alternate training between RPN and Fast R-CNN, which can be described as the following four steps.

Step.1 RPN's First Training

For the preprocessed GPR data with size $M \times N$, its corresponding feature maps with size $M/16 \times N/16$ are extracted by CNN of Faster R-CNN. Anchors with different size are applied on these extracted feature maps. The VGG model provided by Faster R-CNN is used to train RPN based on the preprocessed GPR data.

Step.2 Fast R-CNN's First Training

Based on the trained RPN, the ROI proposals can be obtained for Fast R-CNN training. Then the anchor is detected whether it's positive or negative by SoftMax and generate region proposals by Bounding Box regression. The loss function is defined in [7].

Step.3 RPN's Second Training

Then, the adjusted parameters of Fast R-CNN are used to train RPN and fix the convolution layer which is obtained in the second step. The Loss of RPN and Classification to loss functions are used for updating anchors (i.e. the number of iterations determines the times of the anchors' updating). And the learning rate, i.e. super parameter which guides us how to use the gradient of loss function to adjust the network weight in gradient descent method, is used to train RPN. Based on the trained RPN, the convolution layer is shared by Fast R-CNN and RPN.

Step.4 Fast R-CNN's Second Training

Fix the shared convolution layer and use the adjusted RPN proposals to fine-tune the remaining parameters of Fast R-CNN. In this way, RPN and Fast R-CNN share the same convolution layer. And the trained Faster R-CNN can be obtained.

Third, based on the previously trained Faster R-CNN, the testing samples are inputted into the trained Faster R-CNN to obtain the classification results. The testing GPR data is inputted into the trained CNN to get the feature maps. Then, the feature maps are inputted into the trained RPN to get the proposals. After that, the ROI pooling layer obtains proposals from RPN and feature maps from CNN, and outputs ROI proposals to the classifier. And the classifier outputs a set of rectangular crevasse or continuous snow layer proposals, in which every proposal has an abjectness score (i.e. the score is used to determine whether the data is crevasse or continuous snow layer). The confusion matrix is used to evaluate the experimental results, as shown in Table I. In this study, TP, TN, FP and FN respectively indicates that true positive (i.e. the number of positive samples correctly classified as crevasses), true negative (i.e. the number of negative samples correctly classified as continuous snow layers), false positive (i.e. the number of negative samples incorrectly classified as crevasses), and false negative (i.e. the number of positive samples incorrectly classified as continuous snow layers).

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TABLE I. Confusion Matrix

		Predicted Value	
		Crevasse	Continuous snow layers
Actual Value	Crevasse	TP	FN
	Continuous snow layers	FP	TN

IV. EXPERIMENTAL RESULTS

In this work, experimental GPR data is obtained from the United States Antarctic Program Data Center (USAP-DC). The radar system was mounted on a sled and towed by a robot, which comprises a GSSI SIR-30 32-bit two-channel control unit and model 5103 "400 MHz" antenna units [1][2]. Some parameters of GPR device are listed in Table II.

TABLE II. The Parameters of GPR Device

Parameter name	**Values & Units**	
	Values	***Units***
radar style	impulse	-
RF center frequency	400	**MHz**
signal bandwidth	600	**MHz**
ADC resolution	16	**Bits**
samples per scan	4096	-
samples per nanosecond	4	-
scans per second	20	-
antenna beamwidth (along track)	60	**deg**
antenna beamwidth (cross track)	45	**deg**

For the obtained GPR data, all crevasses used in the following experiments are hand-labeled by the experienced GPR operators. We selected 264 crevasse images as Crevasse Set and randomly selected 215 continuous snow layer images from the ice sheet data as Continuous Snow Layer Set. Before the experiments, all GPR data are preprocessed to be uniform size with the normalized gray level from -1 to 1. Considering the actual depth of crevasse, we mainly focused on 70 to 600 samples in depth for each GPR trace, which corresponding to 1.5m to 13.5m in depth. Based on the average width of the hand-labeled crevasse, the trace samples in distance is set as 50. To meet Faster R-CNN's requirements for input images, the normalized GPR data is divided into many images using the sliding window with uniform size 400*50 and sliding distance 10, as shown in Fig.3. Two measurements, i.e. Dataset1 with 60 crevasse samples and Dataset2 with 36 crevasse samples, are selected as testing samples while remain crevasses are used as training samples. Data enhancement was performed on the training crevasse samples of these two measurements with horizontal flipping and adding noise. In this way, the training datasets for two measurements can be obtained as follows: 608 crevasse images and 510 continuous snow layer images for Dataset1, and 616 crevasses images and 510 continuous layer images for Dataset2.

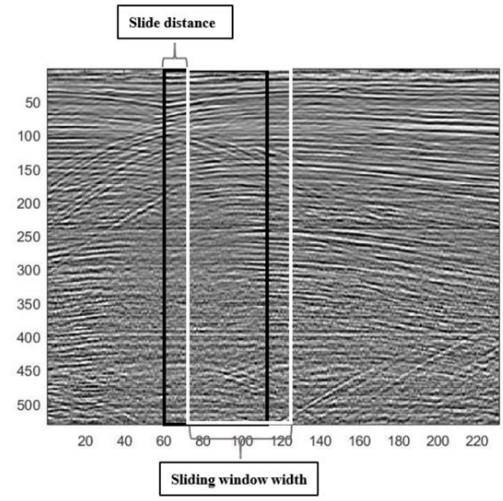

Fig.3 Experimental GPR data with a crevasse after preprocessing

In the following experiments, some parameters of Faster R-CNN are set as follows: learning rate is 0.0001, batch size (i.e. the number of samples per input network) is 16 and iteration (i.e. iterations determine the times of the anchors' updating) is 10000. All experiments were performed under Windows 10 and Python programing language on GeForce GTX 960M and 4GB of running memory. Based on the proposed method, we carried out three experiments as follows.

Firstly, Exp.1 and Exp.2 are carried out based on Dataset1 and Dataset2 separately, in which Faster R-CNN is trained with the parameters as described before. And the confusion matrix can be obtained after classification as shown in Table I. Six metrics are used to describe the performance: accuracy rate (AR), true positive rate (TPR), recall rate (RR), false alarm rate (FAR), missing report rate (MRR), false positive rate (FPR), F1-score (i.e. expressed in terms of RR and TPR), and Kappa (i.e. a consistency measure of a confusion matrix), which are presented as follows.

$$AR = \frac{TP+TN}{TP+FP+TN+FN} \qquad TPR = \frac{TP}{TP+FP}$$

$$RR = \frac{TP}{TP+FN} \qquad FAR = \frac{FP}{TP+FP}$$

$$MRR = \frac{FN}{TP+FN} \qquad FPR = \frac{FP}{TN+FP}$$

$$F1 = 2 \times \frac{TPR \times RR}{TPR+RR} \qquad Kappa = \frac{AR-p_e}{1-p_e}$$

$$p_e = \frac{(TN+FN)\times(TN+FP)+(FP+TN)\times(FN+TN)}{(TP+FP+FN+TN)^2}$$

As shown in Table III, both experiments obtained higher AR and TPR, which means the proposed model can detect crevasses effectively. FAR is higher than MRR with very small value, which means the proposed model seldom mistakenly judges the continuous snow layer as crevasse. Low FPR and high RR indicate that our model seldom make a mistake on detecting a true crevasse. High Kappa indicates high consistency of the classier. The average computing time is 67 minutes for training and 0.183 seconds for each test samples in Exp.1 and Exp.2. Test time is close to real time performance. Training time and test time can be further reduced by improving the hardware performance.

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TABLE III. Experimental Results for Exp.1 And Exp.2

Exp.	*AR*	*TPR*	*FPR*	*RR*	*MRR*	*FAR*	*F1-score*	*Kappa*
Exp.1	0.95	0.936	0.035	0.967	0.033	0.065	0.951	0.9
Exp.2	0.941	0.921	0.029	0.972	0.028	0.079	0.946	0.882

Secondly, Exp.3 is carried out, in which 4852 traces consecutive GPR data are tested using the proposed method, as shown in Fig. 4. In this experiment, 628 crevasse images and 510 continuous snow layer images are used as training samples. The selected traces are divided into 483 images with size 400*50, which are used as testing samples. Based on the Faster R-CNN with the previous setting parameters, we can obtain the detection results as shown in Fig. 4. From Fig. 4, we can see that all three hand-labeled crevasses are detected while one suspected crevasse with hyperbolic diffractions is detected as crevasse. It means that the proposed method can detect crevasses effectively and accurately. Some suspected crevasses with crevasse features can also be detected. In the future work, we can further improve algorithms to reduce FAR.

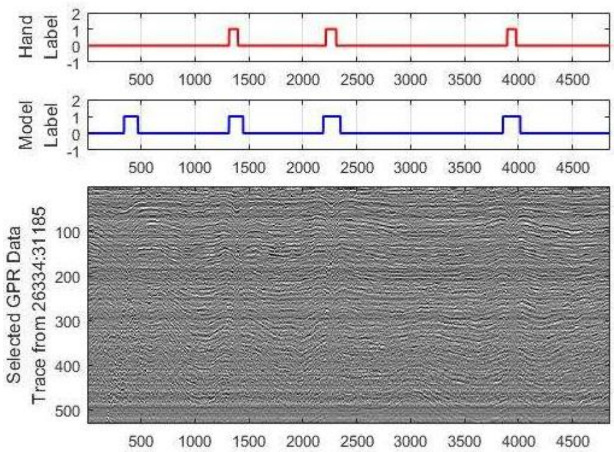

Fig.4 Classification results for Exp.3

The results for some experiments using a wavelet method to detect crevasses based on the same GPR data are shown in Table Ⅳ. We compare the proposed method with the Wavelet-based method [8]. Comparing the results in Table III to Table IV, we can see that the proposed method obtains higher accuracy, recall rate, true positive rate, and lower missing report rate, false positive rate, false alarm rate, which shows the efficiency of the proposed method in detecting ice crevasses.

TABLE Ⅳ. Results for Wavelet-based Method

Exp.	*AR*	*TPR*	*FPR*	*RR*	*MRR*	*FAR*
Exp.1	0.612	0.569	0.190	0.934	0.066	0.431
Exp.2	0.628	0.578	0.091	0.975	0.025	0.422

V. Conclusion

In this paper, based on GPR data, an automatic crevasse detection method using Faster R-CNN was proposed. The proposed method used Faster R-CNN to extract proposal feature maps of crevasses and continuous snow layers in a short time with amount of GPR data, which meets the crevasse detection accuracy and real-time requirements. Experimental results show that the proposed method got higher AR, RR and TPR while low FPR, FAR and MRR in detection between crevasses and continuous snow layers compared with wavelet-based method. And more effective methods for detecting suspected crevasses need further study in the future work.

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References

[1] B. Walker and L. Ray, "Multi-Class Crevasse Detection Using Ground Penetrating Radar and Feature-Based Machine Learning," IGARSS 2019 - 2019 IEEE International Geoscience and Remote Sensing Symposium, Yokohama, Japan, 2019, pp. 3578-3581

[2] R. M. Williams, L. E. Ray, J. H. Lever and A. M. Burzynski, "Crevasse Detection in Ice Sheets Using Ground Penetrating Radar and Machine Learning," in IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 7, no. 12, pp. 4836-4848, Dec. 2014

[3] Joseph Redmon, Santosh Divvala, Ross Girshick, and Ali Farhadi, "You Only Look Once: Unified, Real-Time Object Detection," in IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2015.

[4] Wei Liu, Dragomir Anguelov, Dumitru Erhan, Christian Szegedy, Scott Reed, Cheng-Yang Fu, and Alexander C. Berg, "SSD: Single Shot MultiBox Detector," in European Conferencen on Computer Vision (ECCV), 2016, pp. 21-37.

[5] Girshick, Ross, Jeff Donahue, Trevor Darrell, and Jitendra Malik. 2013. “Rich feature hierarchies for accurate object detection and semantic segmentation.”, in IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2014.

[6] Girshick, Ross, “Fast R-CNN,” in International Conference on Computer Vision (ICCV), 2015.

[7] Ren, Shaoqing, Kaiming He, Ross Girshick, and Jian Sun, “Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks,” in Conference and Workshop on Neural Information Processing Systems (NIPS), 2015.

[8] Yan Liu, Chao Fang, Xuanyuan Ji, Bo Zhao, and Deyuan Chen, “Gabor filter banks used for crevasse detection with Ground Penetrating Radar data”, in the 18th International Conference on Ground Penetrating Radar (GPR), 2020.

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