ISSN:2790-1688 DOI: 10.56028/aetr.4.1.279.2023

Automatic Detection of Basal Units beneath Antarctic Ice Sheet in Radargram Based on Deep Learning

Na Wang [1, a], Wen Xu [2, b], Shinan Lang[3, c]and Xiangbin Cui* [4, d]

[1]School of Information and Electronic Engineering, Zhejiang University, Hangzhou, China;

[2] Ocean College, Zhejiang University, Zhoushan, China.

[3] Faculty of Information Technology, Beijing University of Technology

Beijing, China

[4] Polar Research Institute of Chin, Shanghai, China

Technology and Equipment Engineering Centre for Polar Observations,

Zhejiang University, Zhoushan, China

[a] 2240006893@qq.com, [b] wxu@zju.edu.cn, [c] langshinan@gmail.com

[d] cuixiangbin@pric.org.cn

Abstract. Sea level rise, caused by accelerated melting of glaciers in Greenland and Antarctica in recent decades, has become a major concern in scientific, environmental, and political arenas. A comprehensive study of subglacial conditions and processes is particularly important for reliable analysis about their future evolution. Basal units – visibly distinct englacial structures near ice-bedrock interface, could provide substantial insight into subglacial processes, ice-sheet dynamic history and dramatically influence the flow of surrounding ice. In order to enable improved characterization of these features, we develop and apply an algorithm that allows for automatic detection of basal units, therefore, an algorithm based on deep learning is proposed. Compared with traditional method based on manual feature extraction, proposed algorithm can achieve completely automatic recognition of basal units in radargram. The network is mainly composed of ResNet and ASPP module, which can achieve high accuracy in very small dataset. We use radar data collected by Polar Geophysics Group (PGG) of The Earth Institute at Columbia University in Antarctica in 2008-2009 and 2009-2010 for experiments, results confirm the effectiveness and robustness of proposed algorithm. At the same time, a more rapid deep learning method is tried, which uses the lightweight network MobileNet V3 as backbone, obtaining a network structure that can save 81.8 percent of training time and 92.2 percent of processing time with high accuracy. It provides a possibility for rapid network training, application on mobile devices and real-time processing of radargram.

Keywords: deep learning; automatic detection; basal units; radargram; Antarctic Ice Sheet.

1. Introduction

The Antarctic Ice Sheet (AIS) is an important part of global climate system. Human activities have increased the temperature of atmosphere and oceans and the melting of west Antarctica Ice Sheet has been accelerating since 2000s. With the research on evolution history of AIS and interaction between ice sheet, solid earth, atmosphere and ocean system by scientist, estimation of the influence of AIS on sea level rise has been changing [1].

The previous sub-ice research used the method of collecting ice core samples, which can obtain direct measurements of deep ice properties, but it is invasive and expensive [2][3]. In order to solve this problem, researchers have explored a new advanced tool - Radio Echo Sounding (RES), also called as ice penetrating radar [4][5]. RES is a geophysical technique that emits electromagnetic waves (frequency is usually lower than 1 GHz) to the ice sheet directly below, distinguishing characteristics of ice sheet in vertical direction under the condition of sufficient bandwidth. The electromagnetic wave propagates in ice, and the signal is reflected back to receiving antenna at positions with discontinuous permittivity. In the past few decades, RES has contributed most

ISSN:2790-1688 DOI: 10.56028/aetr.4.1.279.2023
measurements of ice thickness, bedrock elevation, internal structure of polar ice sheets [6][7]. Radar data obtained through RES measurements are crucial for better understanding structure and formation process of ice sheets in context of climate changes [7].

Identifying internal ice layers, ice-bedrock interface and even subglacial lakes from radargram has extensively studied. In recent years, scientists have found that distorted ice structures at the bottom of polar ice sheets, referred as basal units, are abound [9]. In 2012, the Chinese National Antarctic Research Expedition used a new ground-based RES system to map the ice sheet along the inland traverse from Zhongshan to Kunlun Station, and a typical ice freezing structure appeared in radargram. This structure appeared at the bottom of the ice sheet, which was formed by the melting of ice at ice-bedrock interface and then refreeze onto the ice again [10]. In 2018, Leysinger Vieli et al. observed huge feathery ice sheet structures in radargram in polar ice sheets. These basal units have ice layers bend upward and fold downward, and bulge upward from the bottom of the ice sheet [8]. In some places, the thickness of basal units can reach half of the thickness of the ice sheet [11]. Basal units not only affect ice sheet stratigraphy, but also affect ice flow. Isolated and accreted basal units will significantly change stratigraphic structure of the surrounding ice column, making it difficult to interpret ice core data. At the same time, during melting and refreezing, accumulated basal units will also affect ice flow through basal ice deformation and softening.

With the wide application of RES, the amount of RES data we have obtained and collected, and radargram from radar data have increased dramatically. While providing more opportunity to study basal units, these progresses also propose much challenge for identifying and extracting distorted ice structure. Although visual observation can support the representation of several targets, it is subject to many restrictions. The first reason is visual observation can only detect radargram one by one through human eyes, which consumes huge time and is not suitable for processing massive radargram. Secondly, visual observation is relatively subjective. Different researchers have different perceptions of one image, and there are also deviations due to concentration and energy. Therefore, automatic methods to detect and process polar data continue to emerge [11][13][14], which not only help researchers improve work efficiency and reduce work pressure, but also provide more possibilities for faster and wider exploration of polar regions.

In the literature, the methods for automatic analysis of subglacial structures in RES data are mainly divided into three categories. The first is numerical simulation of ice sheet geological process and local inference of subglacial structure. The numerical models [15] and [16] take data and analysis from different sensors as input, and only extract the ice sheet thickness and the terrain of bedrock topography. The second strategy is to automatically analyze subglacial structure of radargram without considering bedrock and interface of ice sheet with line detection algorithm, while modeling the interference using line slope [17] [18]. However, these techniques focus on the analysis of ice rupture and do not map ice sheet. The third method is to extract the main geological targets by machine learning. The research in literature [19] divides the radargram into three targets: ice layer, bedrock and echo free zone (EFZ). However, this method is based on manually extracted prior features of spatial and statistical characteristics, using support vector machine (SVM) to perform pixel classification. The features extracted manually depend on human design and are only applicable to model specific features. With the increase of categories of features, the performance of this method will be reduced. Recently, deep learning provides a powerful means for radargram segmentation in various applications [20][21][22]. In addition, the method based on deep learning can automatically extract features, providing a basis for subsequent applications in other areas.

There have been some achievements in applying deep learning method to polar exploration. Literature [23] proposed a U-Net architecture based on contraction path to capture context and added attention gate (AG) modules in network. These modules force network to pay more attention to relevant feature areas of input data. Literature [24] further improved the model by adding an Atrous Spatial Pyramid Pooling (ASPP) module to main network structure to control feature resolution. The research in [25] uses ResNet network to segment ice layer, thermal noise, echo free area and bedrock in radargram, getting overall accuracy similar to SVM based traditional machine

ISSN:2790-1688 DOI: 10.56028/aetr.4.1.279.2023

learning method. Literature [26] used U-Net network and ASPP module to detect ice layer structure, classifying radargram into bedrock, echo free area, ice layer and basal ice, which is somewhat similar to basal units. Recently, deep learning has been applied to radar image recognition and achieved good results, mainly for: 1) ice detection [26][27]; 2) Simulate RS image using generative countermeasure network (GAN) [28]; 3) Target detection [29]; And 4) Radargram segmentation [24] [30][31].

In this paper, a new method based on deep learning for automatic detection of basal units is proposed, at the same time, pixel level segmentation of radargram is realized to better understand ice sheet and its composition. Radargram are divided into different categories, including ice layer, base (including bedrock and the part below bedrock) and basal units. Basal units are ice blocks growing from the bottom of ice sheet, which have different formation mechanism, temperature system and shape from normal isochronous ice layer. Their distribution is shown in Fig. 1. Ice layer, base and basal units are characterized by specific spatial distribution in distance and azimuth, but have significant differences in size and scale. Therefore, the paper selects ResNet network with ASPP module to identify features. ASPP module can realize multi-scale feature extraction to improve recognition of characteristics in different sizes. Compared with conventional convolution, ASPP module includes a wider range of backgrounds by expanding receptive field, while saving the number of network parameters, so as to segment image robustly at multiple scales. ResNet network can not only deepen network depth, but also prevent parameter over fitting, improving convergence speed and accuracy of network training. In order to verify effectiveness of the algorithm, radar data collected by AGAP(Gambertsev Project in Antarctica) and GAMBIT(Gambertsev Aerial Geophysical Mapping Project for Bedrock and Ice Cap) in 2008-2009 and 2009-1010 were used as the training set, which obtained a good result, proving that the algorithm can achieve favorable detection of basal units.

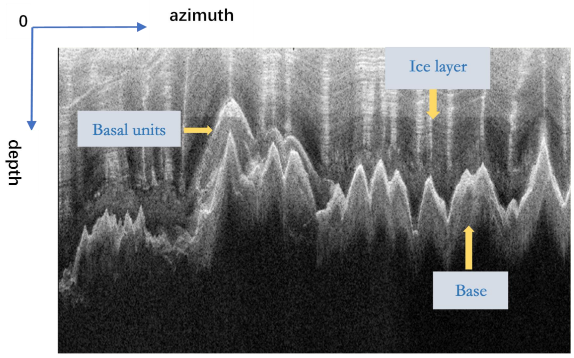


Fig. 1 Example of ice sheet with basal units

The paper is mainly composed of four parts. The first part introduces the target of research and background. The second describes the method of feature extraction using deep learning method, dataset and experimental process. And then we show training results and analyzing the results after algorithm processing; The last part is a conclusion.

2. Methodology

2.1 Network

When network structure is as shown in Fig.2, we get the highest accuracy in very small dataset. Backbone adopts ResNet 101 network, which is mainly composed of 5 serial blocks. The first four blocks have 3, 4, 23 and 3 bottlelayers respectively. Each bottlelayer consists of convolution, pooling, batch normalization and relu operation, as shown in the bottom right of Fig.2. Output stripe represents the ratio of spatial resolution of input image to final output image resolution. From 1 to 4 blocks, output stripe is 2, 4, 8 and 8 respectively. In order to avoid further reduction of the spatial resolution, parallel dilated convolution is adopted, which is embodied in ASPP structure. Then

ISSN:2790-1688 DOI: 10.56028/aetr.4.1.279.2023
concat operation is used to fuse the features of different dilated convolution outputs, and then classification results are output through 1 * 1 convolution.

2.1.1 ResNet

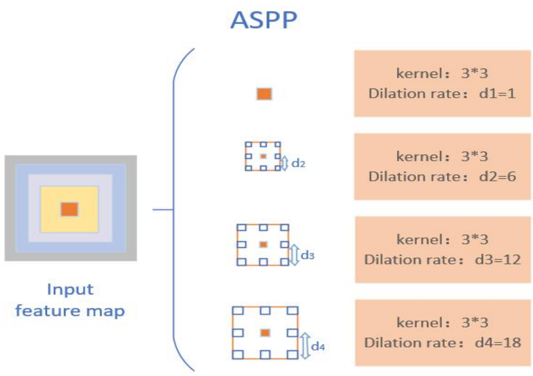
ResNet makes network training more efficient by adding a residual unit to deep neural network. This structure can speed up the training of neural network very quickly, and also can greatly improve accuracy of the model. In network training of this paper, because data set is very small, it is necessary to increase network depth and training times to improve detection accuracy. ResNet 101 can avoid the problem of degradation and ensure that the network training is stable at a certain highest accuracy rate.

2.1.2 Atrous Spatial Pyramid Pooling

Atrous Spatial Pyramid Pooling (ASPP) applies four dilation convolutions with different dilation rate to the top of feature map in parallel to change the receptive field of network filter, which helps network integrate global view and pay attention to the details of radar image. It is an effective measure to extract and accurately classify features of different scales within any range, meeting the needs of extracting features in different scales from images of different sizes in this paper.

Dilation convolution is an operation that expands receptive field of convolution filter by changing dilation rate d. As shown in Fig.2, d corresponds to the sampling step of input signal, and standard convolution is a special case of d = 1. Dilation rate d means that the size of convolution kernel is increased by adding d-1 zeros in the middle of convolution filter, and filter resolution is changed at the same time. The size of convolution kernel is determined by $k_x * k_y$ becomes $k_x^{'} * k_y^{'}$:

$$k_x^{'} = k_x + (k_x - 1)(d - 1)$$



$$k_y^{'} = k_y + \left(k_y - 1\right)(d - 1)$$

Fig. 2 Dilation convolution.

ASPP with different expansion coefficients can effectively capture multi-scale information, however, in practice, the larger the sampling rate, the less the number of effective filter weights[32]. In order to overcome this problem and integrate global semantic information into algorithm model, this paper uses image level features, with the structure shown in Fig. 3. The specific representation is to use the global average pooling model on the last feature map of the model, and inputting the resulting image level features into 1*1 convolution filter with 256 layers, then use bilinear interpolation to upsample features to required spatial dimensions. Compared with conventional convolution, ASPP module can steadily segment images on multiple scales by expanding receptive field to include a wider range of backgrounds, while saving the number of network parameters.

ISSN:2790-1688 DOI: 10.56028/aetr.4.1.279.2023

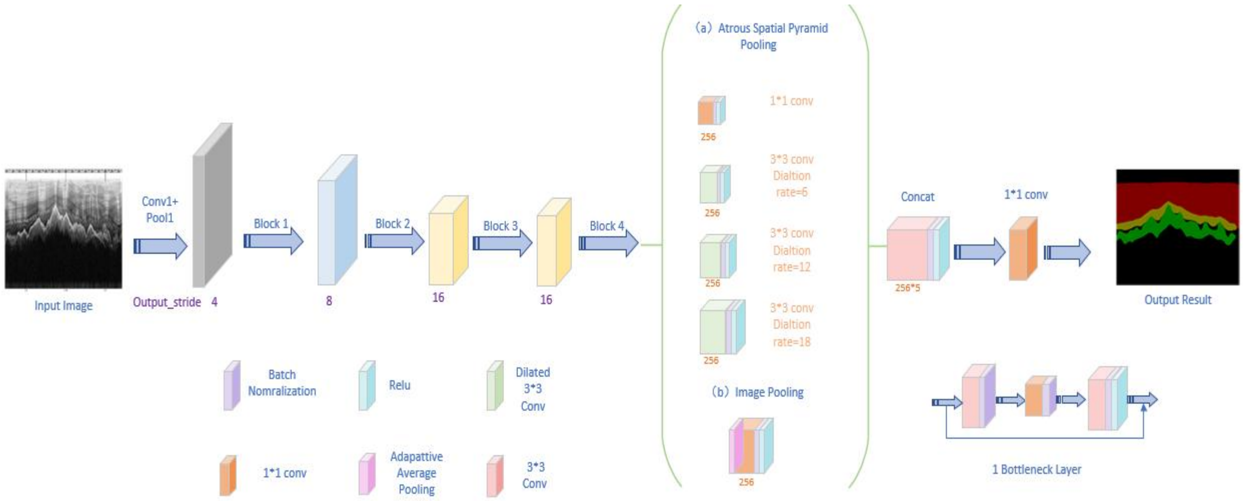


Fig. 3 Diagram of network structure

2.2 Network Training

2.2.1 Dataset

The experimental data comes from radar data collected by Polar Geophysical Research Group (PGG) of Institute of Earth Research in Columbia University during 2008-2009 and 2009-2010 from Gambertsev Project in Antarctica (AGAP) and Gambertsev Aerial Geophysical Mapping Project for Bedrock and Ice Cap (GAMBIT). The data are all processed by 1D-SAR (synthetic aperture radar) algorithm and displayed as radargram. The collection routes include north-south route (50 in total), east-west route (16 in total), the specific collection routes in Fujiding (6 in total) and Vostok Lake (6 in total)). The north-south interval is 5km, and east-west interval is 33km. Searching basal units samples in radargram as original dataset and we found 110 in total, dividing the data set into training set and test set with a ratio of 9:1, all images are labelled by software Labelme for supervised training.

2.2.2 Learning rate

This paper uses poly strategy to adjust learning rate [33]. The specific formula is as follows:

$$\mathrm{lr} = \mathrm{base\_lr} \times \left(1 - \frac{\mathrm{epoch}}{\mathrm{num\_epoch}}\right)^{\mathrm{power}}$$

Where lr is updated learning rate, base_lr is benchmark learning rate, "epoch" is the number of iterations, "num_epoch" is maximum number of iterations, and power determines the shape of curve. In training of the algorithm, power is set to 0.9. Poly policy will dynamically adjust the value of learning rate with the number of training iterations epoch. Benchmark learning rate is set to 0.0001. At the initial training stage, the convergence speed is fast. With the increase of number of iterations epoch, learning rate gradually decreases, slowly approaches an optimal value, and finally tends to be stable, indicating that network training has reached convergence at this time.

2.2.3 Data augmentation

The number of samples of basal units is very small in polar database and so available training set is very small, too. Therefore, data augmentation is used to increase the number of samples to improve network robustness. In this paper, we use rotation, symmetry and zoom methods to process original image and annotation data at the same time. Rotating the original picture at a probability of 0.8 within the scope$[-\theta_{max}, +\theta_{max}]$, where $\theta_{max}$is the maximum allowable rotation angle, which is 10 degrees. Mirror the original image symmetrically with a probability of 0.5. If the pixel size of original image is $\mathrm{m} * \mathrm{n}$, transform the pixel size to $0.85 * \mathrm{m} * \mathrm{n}$ with a probability of 0.8. While not changing the authenticity of original polar structure, increase the number of training set to 5 times the original samples.

ISSN:2790-1688 DOI: 10.56028/aetr.4.1.279.2023

2.2.4 Transfer learning

It is complex to train a neural network completely, accelerating training speed and finally making the network converge not only requires a large enough data set, but also consumes a lot of training time and computing resources. Based on this, for the automatic detection of basal units, transfer learning is introduced in training process, which is to use pre-trained weights to replace the randomly initialized weights in network, so as to speed up the convergence and reduce training time [34].

Transfer learning has been widely used in the field of computer vision and has achieved certain success. Research in recent years shows that mobility of features increases with the decrease of difference between target data and training data of transfer training method, which proves that the effect is better than before even if there are obvious field differences between the two. Therefore, this paper conducts transfer learning on MS-COCO (Common Objects in Context, please refer to [35] for details) training set and radar image basal units dataset through pre training method to accelerate convergence and shorten training time.

3. Experimental Result

3.1 Classification Accuracy

The experiment uses ResNet 101 network as backbone, combined with ASPP module as transition. When batch size is 8, the highest detection accuracy is obtained. The global pixel detection accuracy in very small data set can reach 93.1%. Global accuracy is expressed as:

$$\text{global accuracy} = \frac{\sum_i n_{ii}}{\sum_i t_i}$$

$$\text{Classification accuracy} = \frac{n_{ii}}{t_i}, i = 1,2,3$$

Where n_{ii} represents number of pixels of category i predicted as category i and $t_i = \sum_i n_{ii}$ represents total number of pixels of target category i (real tags). Global accuracy indicates the accuracy of pixel detection and classification accuracy indicates the accuracy of each category, as shown in Table I. Compared with U-Net based network structure shown in[26], the method proposed in this paper improves the global accuracy by 9.5% without data augmentation, at the same time, the detection accuracy of basal units has reached 84.7% with very small dataset, indicating that the algorithm is still feasible and has high accuracy on small datasets. Because of the few samples, some rare features in polar ice sheet cannot obtain satisfactory detection results using most of the deep learning networks, however, this algorithm still has a high detection accuracy on small datasets, so it can be applied to the automatic detection of some rare features in ice sheet in future polar research.

Table 1. Classification accuracy

Method	Experimental result			
	Global accuracy	Ice layer	Base	Basal units
U-Net +ASPP	83.6%	85.2%	82.2%	/
Method of the paper	93.1%	96.1%	88.9%	84.7%

ISSN:2790-1688 DOI: 10.56028/aetr.4.1.279.2023

3.2 A More Rapid Method

To save training time, try lightweight network MobileNet V3 as backbone. Lightweight network is characterized by fewer parameters, less computation, and fast training speed. The structure is shown in Fig. 4:

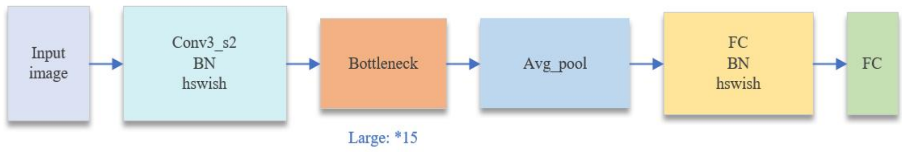


Fig. 4 MobileNet V3 structure

Where conv3 represents conventional convolution with kernel size of 3 * 3, *s* represents stride of convolution kernel, BN is batch normalization and h-swish indicates optimized activation function, which is expressed as:

$$\mathrm{h-swish}[x] = x\frac{\mathrm{ReLU\ 6}(x+3)}{6}$$

$$\mathrm{ReLU\ 6} = \min(\max(\mathrm{features}, 0), 6)$$

The activation function can reduce the computation cost and training time in the case of high-dimensional features. When features less than 0, the results of ReLU6 is 0 and when features is greater than 6, results will be set to 6. Bottleneck is the basic network structure. MobileNet V3 Large has 15 bottlenecks, Avg_ Pool is the average pooling operation and FC is full connection layer.

Intel Core i7-7700 @ 3.6GHZ computer and Tesla V100-PCIE32G GPU are adopted in the experiment. When batch size=8, the results are shown in Table 2.

Table 1. Comparison of different backbones

Backbone	Data aug	Global accracy	Training time	Processing time	Space occupied
ResNet 50	× √	92.1% 92.9%	3:21:16 10:43:18	\\ 2.679s	\\ 320M
ResNet 101	× √	93.1% 94.0%	2:15:16 8:43:26	\\ 4.370s	\\ 466M
MobileNet V3	× √	89.4% 91.3%	0.29.29 1:35:04	\\ 0.341s	\\ 84.3M

It can be seen that when backbone is ResNet 101 and dataset is augmented, the global accuracy is the highest and reaches 94.0%. MobileNet V3 can effectively shorten the training time, which is 81.8 percent shorter than ResNet 101, saving a lot of training time resources. At the same time, the data augmentation improves the accuracy of MobileNet V3 backbone by 1.9 percent. MobileNet V3 reduces the radargram processing time by 92.2 percent and the space occupied by 81.9 percent compared with ResNet 101, which is a huge improvement. In view of the relatively high accuracy of MobileNet V3 after data augmentation, as well as its excellent image processing speed and small space occupation, it is suitable for mobile devices, which can process the images obtained from radargram in real time and output the detection results immediately, so that polar researchers can obtain the internal feature information of ice sheet while obtaining data.

ISSN:2790-1688 DOI: 10.56028/aetr.4.1.279.2023

3.3 Visualization result

Labelme software is used to label radargrams, which are classified as basal units, ice layer and base, and the labeled images are used as ground truth. Original image is input, finally we use trained network model to classify the pixels of radargram, some classification results are visualized as follows:

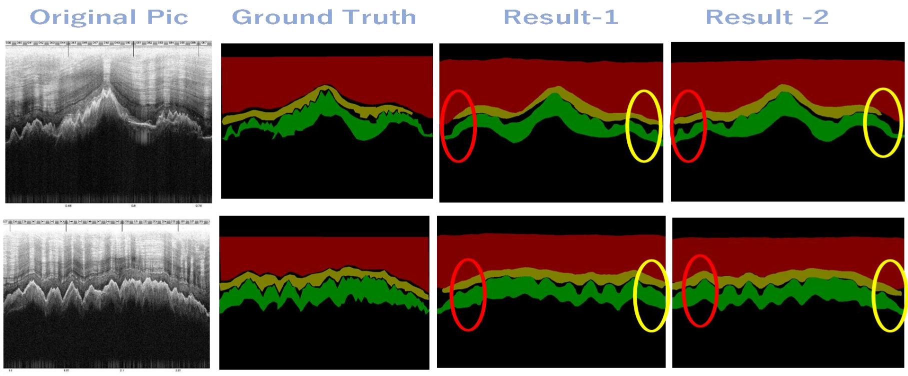


Fig.5 Visualization result

The red is ice layer, and yellow represents basal units, green is base. Result - 1 is the result of initial algorithm, using ResNet 50 backbone and without data augmentation. Result - 2 is the result after optimization, including data augmentation, setting optimal parameters, and changing backbone with Resnet 101. It can be seen that the optimized algorithm has more accurate pixel recognition and better handling of details, here, Result-2 corresponds to the algorithm with highest global accuracy.

4. Conclusion

This paper proposes a new automatic detection method of basal units, which can automatically divide radargram into various categories, as well as solving the problem of low efficiency and time-consuming in manual analysis of ice radargram. It mainly includes two aspects. For highest classification accuracy, the network is composed of ResNet 101 backbone and ASPP module. ResNet network can improve the accuracy while deepening the network depth, ASPP module extracts features with different receptive fields, enhances the detection and recognition of targets with different sizes. For improving training and processing speed, we replace lightweight network MobileNet V3 with ResNet 101 as bcckbone, which can save 81.8 percent of training time and 92.2 percent of processing time with high accuracy. It provides a possibility of rapid network training, real-time processing of radargram and application on mobile devices. The method has been tested on radargram dataset collected in Antarctica, and results confirm that algorithm can achieve pixel classification and high precision in distinguishing subglacial structure at the same time.

In the future, pre-processing will be added to the original radargram to reduce image noise and increase image definition, as well as improving the accuracy of the algorithm. At the same time, more exploration will be added to lightweight network, combining it with appropriate hardware devices to reduce training time and processing time, so as to achieve the goal of real-time image processing in polar data acquisition process.

5. Acknowledgment

This work was supported by the Shanghai Science and Technology Development Funds (21ZR1469700), the National Natural Science Foundation of China (41941005, 41941006, 41606219, 41776186), and the International Research Cooperation Seed Fund of Beijing University of Technology. We also thank all reviewers for their constructive comments.

ISSN:2790-1688 DOI: 10.56028/aetr.4.1.279.2023

References

[1] T. L. Noble, E. J. Rohling, A. R. A. Aitken, H. C. Bostock, Z. Chase, and N. Gomez et al. “The sensitivity of the Antarctic ice sheet to a changing climate: past, present, and future,” Reviews of Geophysics, 4th ed., vol. 58. 2020.

[2] O. Alemany, P. Talalay, P. Boissonneau, J.Chappellaz, J. F.Chemin and, R.Duphil, “The SUBGLACIOR drilling probe: hydraulic considerations,” Annals of Glaciology, 84th ed., vol. 62. 2020, pp.131-142.

[3] Q. Schiermeier, “Speedy Antarctic drills start hunt for Earth's oldest ice,” Nature, 2016, pp.18-19.

[4] F. Rodriguez, “Advanced multifrequency radar instrumentation for polar research,” IEEE Transactions on Geoscience & Remote Sensing, 2014, pp.2824-2842.

[5] Xiangbin Cui, Bo Sun, Xiangpei Zhang,Dong Zhang, Xin li, Xueyuan Tang， et al. “A review of ice radar's technical development in polar ice sheet investigation,” Chinese journal of polar research (in Chinese). 4th ed., vol. 21, 2009, pp.322 − 335.

[6] X. Cui, H. Jeofry, J. S. Greenbaum, J. Guo, L. Li, L. E. Lindzey, et.al. “Bed topography of Princess Elizabeth Land in East Antarctica," Earth Syst. Sci. Data, 12, 2765–2774, https://doi.org/10.5194/essd-12-2765-2020, 2020.

[7] A. C. Frémand, P. Fretwell, J. Bodart, H. D. Pritchard, A. Aitken and J. L. Bamber, et al. “Antarctic Bedmap data: FAIR sharing of 60 years of ice bed, surface and thickness data,” Earth Syst. Sci. Data Discuss, https://doi.org/10.5194/essd-2022-355, 2022.

[8] N. Ross, H. Corr and M. Siegert “Large-scale englacial folding and deep-ice stratigraphy within the West Antarctic Ice Sheet”. The Cryosphere, 6th ed., vol. 14, 2020, pp. 2103-2114.

[9] R. E. Bell, K. Tinto, I. Das, M. Wolovick, W. Chu and T. T. Creyts, et al. “Deformation, warming and softening of Greenland’s ice by refreezing meltwater”. Nature Geoscience, vol. 7, 2014, pp. 497-502.

[10] X. Tang, B. Sun, J. Guo, X. Liu, X. Cui and B. Zhao, “A freeze-on ice zone along the Zhongshan–Kunlun ice sheet profile, East Antarctica, by a new ground-based ice-penetrating radar,” Science bulletin, 5th ed., vol. 60, 2015, pp. 574–576.

[11] R. E. Bell, F. Ferraccioli, T. T. Creyts, D. Braaten, H. Corr and I. Das et al. “Widespread persistent thickening of the East Antarctic Ice Sheet by freezing from the base,” Science, 2011, 6024th ed., vol. 331, pp. 1592-1595.

[12] O. Tasar, Y. Tarabalka and P. Alliez, “Incremental learning for semantic segmentation of large-scale remote sensing data,” IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 2019, pp. 3524-3537.

[13] E. Donini, L. Carrer, C. Gerekos, L. Bruzzone and F. Bovolo, “An unsupervised fuzzy system for the automatic detection of Candidate Lava Tubes in radar sounder data,” IEEE Transactions on Geoscience and Remote Sensing, 2021, PP. 1-19.

[14] E. Donini, S. Thakur, F. Bovolo and L. Bruzzone, “An automatic approach to map refreezing ice in radar sounder data,”// Image and Signal Processing for Remote Sensing XXV, Vol. 11155, pp. 433-442, October 2019.

[15] M. Schäfer, T. Zwinger, P. Christoffersen, F. Gillet-Chaulet, K. Laakso and R. Pettersson et al. “Sensitivity of basal conditions in an inverse model: Vestfonna ice cap, Nordaustlandet/Svalbard,” The Cryosphere, 2012, pp. 771-783.

[16] K. Christianson, R. W. Jacobel, H. J. Horgan, R. B. Alley, S. Anandakrishnan and D. M. Holland et al. “Basal conditions at the grounding zone of Whillans Ice Stream, West Antarctica, from ice-penetrating radar,” Journal of Geophysical Research: Earth Surface, 11th ed., vol. 121, 2016, pp. 1954-1983.

[17] C. Panton, N. B. Karlsson, “Automated mapping of near bed radio-echo layer disruptions in the Greenland Ice Sheet,” Earth and Planetary Science Letters, 2015, pp. 323-331.

[18] L. C. Sime, R. C. Hindmarsh and H. Corr, “Automated processing to derive dip angles of englacial radar reflectors in ice sheets,”. Journal of Glaciology, 2011, pp. 260-266.

ISSN:2790-1688 DOI: 10.56028/aetr.4.1.279.2023
[19] A. M. Ilisei, L. Bruzzone, "A system for the automatic classification of ice sheet subsurface targets in radar sounder data," IEEE Transactions on Geoscience and Remote Sensing, 6th ed., vol. 53, 2015, pp. 3260-3277.

[20] J. Long, E. Shelhamer and T. Darrell, "Fully convolutional networks for semantic segmentation," Proceedings of the IEEE conference on computer vision and pattern recognition, 2015, pp. 3431-3440.

[21] O. Tasar, Y. Tarabalka and P. Alliez, "Incremental learning for semantic segmentation of large-scale remote sensing data," IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 12th ed., vol. 9, 2019, pp. 3524-3537.

[22] V. Badrinarayanan, A. Kendall and R. Cipolla, "Segnet: A deep convolutional encoder-decoder architecture for image segmentation,". IEEE transactions on pattern analysis and machine intelligence, 12th ed., vol. 39, 2017, pp. 2481-2495.

[23] O. Ronneberger, P. Fischer and T. Brox, "U-net: Convolutional networks for biomedical image segmentation," International Conference on Medical image computing and computer-assisted intervention. Springer, Cham, 2015, pp. 234-241.

[24] P. Guo, X. Su and H. Zhang, "A multi-scaled receptive field learning approach for medical image segmentation," ICASSP 2020-2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2020, pp. 1414-1418.

[25] Y. Cai, S. Hu and S. Lang, "End-to-end classification network for ice sheet subsurface targets in radar imagery," Applied Sciences, 10th ed., vol. 7, 2020, pp. 2501.

[26] E. Donini, F. Bovolo and L. Bruzzone, "A deep learning architecture for semantic segmentation of radar sounder data," IEEE Transactions on Geoscience and Remote Sensing, vol. 60 , 2022, pp.1-14.

[27] H. Kamangir, M. Rahnemoonfar and D. Dobbs, "Deep hybrid wavelet network for ice boundary detection in radra imagery," IGARSS 2018-2018 IEEE International Geoscience and Remote Sensing Symposium. IEEE, 2018, pp.3449-3452.

[28] M. Yari, M. Rahnemoonfar and J. Paden, "Smart tracking of internal layers of ice in radar data via multi-scale learning," 2019 IEEE International Conference on Big Data (Big Data). IEEE, 2019, pp.5462-5468.

[29] M. Rahnemoonfar, J. Johnson and J. Paden, "Ai radar sensor: Creating radar depth sounder images based on generative adversarial network," Sensors, 2019, pp. 5479.

[30] E. Donini, F. Bovolo and L. Bruzzone, "An unsupervised deep learning method for subsurface target detection in radar sounder data," 2021 IEEE International Geoscience and Remote Sensing Symposium IGARSS. IEEE, 2021, pp. 2955-2958.

[31] M. H. García, E. Donini and F. Bovolo, "Automatic segmentation of ice shelves with deep learning," 2021 IEEE International Geoscience and Remote Sensing Symposium IGARSS. IEEE, 2021, pp. 4833-4836.

[32] M. H. García, E. Donini and F. Bovolo, "Transfer learning for the semantic segmentation of cryoshpere radargrams," Image and Signal Processing for Remote Sensing XXVII. SPIE, vol. 11862, 2021, pp. 223-233.

[33] W. Liu, A. Rabinovich, A. C. Berg, "Parsenet: Looking wider to see better," Computer Science, 2015.

[34] M. Long, Y. Cao and J. Wang, "Learning transferable features with deep adaptation networks," Proceedings of the 32nd International Conference on Machine Learning, Lile, France, 2015, pp. 97–105.

[35] T-Y Lin, M. Maire, S. Belongie, J. Hays, P. Perona, Ramanan, D. and et al. "Microsoft COCO: Com-´mon objects in context," In ECCV, 2014.