Automatic Extraction of the Basal Channel Based on Neural Network

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Abstract—The basal channel is a morphological feature that widely exists at the bottom of ice shelves, which is mainly formed by the incision of warm water at the base of ice shelves. The study of the basal channel can contribute to further understanding the impact of global warming on polar ice shelves. In this article, the depression caused by the basal channel on the surface of an ice shelf is used to confirm and extract the channel’s position. The automatic acquisition of the channel is realized by machine learning. To extract the basal channel more efficiently and minimize the subjectivity caused by visual interpretation, a neural network was applied for the first time, which effectively improved the accuracy of basal channel extraction. We took the manual extraction results of basal channels as the training set input from the model. The improved U-NET network model was used to classify the 79NG ice shelf area, and the extraction accuracy was 73.58%. Then, the trained model was extended to the Peterman ice shelf and Ryder ice shelf located in Greenland. The extraction accuracies were 75.54% and 72.70%, respectively.

Index Terms—Basal channel, ice shelf, neural network, remote sensing.

I. INTRODUCTION

The stability of polar ice shelves plays a vital role in global sea-level rise, sea ice, and ocean circulation. Recently, several numerical simulations have emphasized the importance of ice shelves in regulating ice flux through grounding lines [1], [2]. Therefore, it is crucial to study ice shelf changes at depth. Relevant scholars have found that when excessive ice shelf thinning reduces the support for upstream glaciers, leading to faster ice floes into the sea and causing global sea-level rise, reducing the shelf support, there is almost an instantaneous change [3]. This indicates that the process may result in land ice flux changing quickly in response to ocean circulation.

The mass loss of ice shelves is mainly caused by ocean-driven melting, which is caused by the thermodynamic circulation of the ocean in the cavities beneath the ice shelves [4], [5]. The melting phenomenon at the bottom of the ice shelf is widespread, especially at the position of the grounding line [6]–[9]. The above phenomenon also results in apparent melting at the bottom of the ice shelf near the grounding line, and the slope of the ice shelf becomes gentler as it approaches the calving front. Many ice shelves are experiencing continuous thinning caused by the melting of the bottom [10]–[14]. The Greenland ice sheet has been a significant source of sea-level rise since the early 21st century. The loss of ice mass from the melting of the base of the shelf is up to 21.4 ± 4 Gt yr⁻¹. Researchers predict that as the Arctic warms, melting at the bottom will continue to increase [15]–[17]. The annual mass loss of the Antarctic ice shelf due to the melting of the bottom is approximately 1516 ± 106 Gt yr⁻¹ [18]. The thinning of the ice shelf reduces the supporting effect upstream of the glacier, which affects the stability of the ice sheet [19].

At present, the basal melting of the ice shelf on a large scale has made certain research progress [10], [18], [20]–[23]. These results will provide a good foundation for the future analysis of ice shelf stability. To further understand the influence of basal melting on a small scale, we focused our attention on studying the basal channel of the ice shelf [24]–[28]. Basal channels are features that are carved on the undersides of ice shelves, mostly due to the rising plume of melting water at the bottom of the ice shelf because of buoyancy. Vaughan et al. [19] found that the basal channel causes local static imbalance and increases tensile stress, and ice cracks then form and destroy the structural integrity of the ice shelf. In extreme cases, the calving front will disintegrate along the basal channel. Ice shelf disintegration can change the location of the calving front, leading to rapid ice shelf flow, changing the ocean circulation around the ice shelf, and having a feedback effect on the basal melting and basal channel of the ice shelf. Therefore, monitoring and analyzing the temporal and spatial changes in the basal channel in an ice shelf can provide important reference values for subsequent ice shelf stability studies. This study found that the basal channel is widely distributed at the bottom of the polar ice shelves, with a wide range and a complex structure. The particular geographic location poses a significant challenge to the field survey. At present, the measured data for the basal channel are mainly divided into two categories: the under-ice morphology based on ice-detecting

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radar and under-ice detection using underwater robots, both of which have certain limitations [20], [23], [29]–[31]. The most widely used ice detection radar data are IceBridge provided by NASA, which is an aviation dataset. Due to the uncertainty of the annual flight mission and time, the data on the same route are limited, and it is not easy to achieve repeated trajectory observations. Underwater robot technology is still developing. The main difficulty lies in the coordination between underwater navigation and endurance. Although there are many shortcomings in the measured data about the basal channel, the extensive use of multisource remote sensing observation methods can still make up for this shortcoming help us understand the development process of the basal channel and fully grasp the local melting situation at the bottom of the ice shelf [24]. It is of great significance to explore the sensitivity of ice shelf changes to global warming.

At present, the extraction of the basal channel is based on professional visual interpretation combined with measured data, such as the Petermann glacier in Greenland and the Pine Island glacier in the Antarctic [27], [32], [33]. Considering that an ice shelf is an elastic fluid, if a basal channel exists under the ice shelf, there will be changes in the morphological characteristics of the ice shelf surface, which we call surface depression (see Fig. 1). This has a good correspondence with the position of the basal channel [24], [34]–[36]. Wang et al. [56] presented evidence from satellite and airborne remote sensing for the basal channel beneath the floating 79NG ice shelf. Temporal and spatial changes in the basal channels from 2000 to 2018 were obtained annually. They used ANSYS finite element software to simulate the creep process of the ice shelf and found that an ice shelf underlain by a basal channel exhibited a strong rate of subsidence. For an ice shelf without a basal channel, the surface depression where the surface of the ice shelf changes most with time is significantly less than that under the former condition. This provides strong theoretical support for visual interpretation and extraction of basal channels through surface depression. This article proposes an improved neural network to extract the surface depression automatically, and IceBridge data were used to confirm the bottom morphology of the ice shelf corresponding to the surface depression so as to obtain the distribution of the basal channel, which can reduce the influence of human subjectivity. The neural network recognizes the learning and extraction of data by simulating the connection between human brain neurons. According to the study of the basal channel, the extraction of the channel is mainly based on the morphological characteristics of the ice shelf surface. It is similar to roads or blood vessels, which have been extensively studied in the field of machine learning to extract automatically. The depression formed by the basal channel on the surface of the ice shelf has the primary conditions for automatic extraction of the neural network. We attempt to use the neural network to automatically extract the depression on the surface of the ice shelf. This article used the U-Net network model, which is commonly used in medical image extraction work [37]–[41]. For example, the extraction of human eyeball nerves, in which the eye nerves resemble a river in a stripe shape, is very similar in morphology to the basal channel studied in this article. Therefore, we attempt to extract the depression on the surface of the ice shelf through U-Net. This model is developed based on the fully convolutional network architecture [42]–[46]. The outstanding feature is the skip connection, which makes the pixel positioning of the U-Net more accurate, and the segmentation accuracy is higher, especially for samples with a small number and a single image background.

II. EXPERIMENTS

A. Study Area

The Nioghalvfjerdsfjorden ice shelf (79NG ice shelf) located in northeastern Greenland is one of the three ocean-terminating glaciers in the region and the most important overflow glacier in northeastern Greenland (see Fig. 2) [47]–[53]. The mass of the ice shelf loss is mainly from the ice-sea interface. 79 NG is 80 km long, 20 km wide, and 30 km wide on the calving front. The grounding line is 600 m below sea level. The glacier has a fast flow velocity and extends to 700 km inside the ice sheet. The 79NG ice shelf and the adjacent Zachariæ Isstrøm ice shelf...
together form the main ice flow overflowing glaciers in northeastern Greenland, and the potential for global sea-level rise is 1.1 m. Among them, the ice velocity of the 79NG glacier at the grounding line can reach a maximum of 1.4 km/yr, and the speed at the calving front decreases, mainly due to the limitations of some islands and ice layers. Relevant data show that the ice shelf lost 30% of the ice shelf thickness at the grounding zone between 1999 and 2014 [54]. Mayer et al. combined the surface feature observations of the ice shelf, ice thickness, and comprehensive analysis of bedrock data and found that the ice shelf has been out of balance for a long time since 2001 [55]. The above changes cannot be caused by ice flow or surface melting alone. However, is there a channel at the bottom of the ice shelf? What kind of environmental factors affect the formation of the basal channel, and how can basal channels be extracted more conveniently? All of the above-mentioned content deserves further study and discussion. This article further proposes an automatic extraction method for the basal channel to improve the extraction efficiency based on the research of Wang et al. [56].

B. Data

The data used in this article are Landsat 8 satellite remote sensing images provided by the US Geological Survey. The satellite was launched in February 2013. The payload includes the Operational Land Imager and the Thermal Infrared Sensor. These two sensors execute the global observation (visible, near-infrared, and shortwave infrared) with a resolution of 30 m (thermal) and 100 m, respectively. In addition to the eighth band (15 m) with the highest spatial resolution, this article used the panchromatic band (B and 8) to segment the image.

| Date       | Path/Row | Series    | Cloud cover |
|------------|----------|-----------|-------------|
| 20130820   | 014002   | Landsat8  | 0.02%       |
| 20140721   | 007003   | Landsat8  | 0.07%       |
| 20150720   | 011002   | Landsat8  | 0.92%       |
| 20160720   | 013002   | Landsat8  | 1.48%       |
| 20170720   | 008003   | Landsat8  | 0.52%       |
| 20180719   | 044242   | Landsat8  | 0.28%       |

After data enhancement, 10,032 training data were obtained. Since the research object of this article was a slender form, the number of pixels in the image was only 4 to 7. To improve data utilization, we used 128 × 128 pixel images as network input and zero padding to ensure the integrity of the cropped image boundary. Considering that deep learning is supported by data, we used data augmentation methods to expand the dataset [57]. First, the data were augmented by multi-angle rotation (90°, 180°, 270°) and mirror mapping (horizontal and vertical images). Second, to improve the class imbalance, we calculated the proportion of positive and negative samples according to the ground truth of the training samples. If the ratio gap was too large, we used the oversampling method to balance the positive and negative sample proportions. After dataset expansion, the amount of training data was expanded at least six times. The image size after zero padding was 2816 × 2432 pixels; 418 training images could be obtained from each image after cropping, and 1672 pieces of training data were obtained. After data enhancement, 10,032 training data were obtained.

To ensure the authenticity of the basal channel, this article used IceBridge data to detect the morphological characteristics of the surface and bottom of the ice shelf. The IceBridge data acquired by NASA's IceBridge program combine a variety of airborne equipment to obtain ice sheet surface topography, bedrock topography, grounding line location, ice thickness, sea ice distribution, and other Arctic and Antarctic data. [48], [49]. A variety of Arctic and Antarctic data included terrain, grounding line, ice and snow thickness, sea ice distribution, etc. The data are based on the WGS-84 ellipsoid as the elevation reference. The data from the laser altimeter and radar echo sounder were combined with the magnetometer and the surveying camera, which can realize the dynamic, high-precision, and repeated observation of rapidly changing sea ice. According to the data requirements of this article, we used the Multichannel Coherent Radar Depth Sounder in the IceBridge ice radar dataset as the basis for the monitoring of glacier surface and bottom characteristics.

III. METHODOLOGY

Fig. 3 shows the architecture of the U-Net neural network, where arrows with different colors represent different convolution and sampling processes. The numbers represent the size and channel number of feature maps in each layer. The encoder of the U-Net network architecture was divided into five layers, and the input image size was 128 × 128 × 1. A 16 × 16 × 1024 feature map was obtained after five sets of convolutions and four max-poolings. To keep the image size unchanged after processing, the edge of the image was used with zero padding. This can help preserve features that exist at the edges of the original matrix.
and control the size of the output feature map. The decoder of the U-Net model contained four sets of convolutions and four upsamplings. The edge of the feature map was also filled with zeros before convolution to make the size of the final output of the classification result map unchanged. Subsequently, U-Net connected the feature maps obtained by the encoder and decoder of the same layer through the skip connection. The purpose of this study was to make full use of the feature maps at different levels and avoid using only high-level features and ignoring low-level features during classification. Finally, it realized the fusion of feature maps at different levels, ensuring the robustness and accuracy of the model.

To make U-Net more suitable for the extraction of depressions on the surface of the ice shelf, we made specific optimizations based on the traditional U-Net network architecture. The traditional U-Net network uses the $3 \times 3$ kernel when performing convolution calculations on the input image. This structure has been widely used in many neural networks. However, for the research object of this article, the surface of the ice shelf was recessed as a stripe. This required that the neural network used in the extraction work was susceptible to the linear features in the image. Therefore, we added two convolution processes, $1 \times 3$ and $3 \times 1$, based on the original $3 \times 3$ kernel.

Fig. 4 shows the processing of the input image in the convolution process of the traditional U-Net model. It was assumed that the size of the original image was $5 \times 5$. To avoid the loss of image edge information, we performed zero padding before the convolution operation. The position shown by the gray dotted line in Fig. 4 refers to zero padding. At this time, the size of the input image became $7 \times 7$, and the feature map obtained after the convolution was still of the same size as the original input image, which preserved more image information and facilitated subsequent analysis and processing. The above is a comparison of the traditional U-Net neural network. In the image convolution process, the kernel used was a regular square. In this article, some improvements were made based on the original convolution kernel to obtain a network that was more suitable for the extraction of the surface depression. The kernel used in traditional U-Net is more sensitive to the planar features in the input image, but the research object of this article was mainly linear features. Taking the 79NG ice shelf in northeastern Greenland as an example, the surface depression width is 50–100 m. The 8th band with the highest resolution of Landsat 8 is displayed approximately 4–7 pixels in the image. For this, we modified the kernel of U-Net, enhancing its sensitivity to linear features to achieve a more accurate extraction effect.

Fig. 5 shows the added kernel of the improved U-Net neural network. As mentioned above, the characteristics of the ice shelf surface depressions are narrow and linear; as the number of network layers $n$ increases, the features of surface depressions will be reduced by $2^n$. Therefore, using the traditional $3 \times 3$ convolution kernel alone is not conducive to the expression of depressions. In view of this, we added $3 \times 1$ and $1 \times 3$ convolution kernels to the first two modules of the network to strengthen the learning of linear features. In particular, a $3 \times 1$ kernel was used to perform the convolution operation to obtain Feature Map A. At this time, the vertical linear features of the original input image were mainly extracted from the feature map. Then, the $1 \times 3$ kernel was used for the convolution operation on Feature Map A to obtain Feature Map B. At this time, Feature Map B already contained the horizontal and vertical directional linear features. To combine the advantages of the traditional U-Net in planar feature extraction, tensor summation was performed on Feature Map B and the feature map was processed by the traditional U-Net kernel. The tensor sum was the feature map we needed. To keep the feature dimension unchanged after each convolution, a zero padding operation was used. This convolution operation can be applied to ice shelves with obvious surface depressions.
IV. EXPERIMENTS RESULTS AND DISCUSSION

In total, the dataset comprises 76 scene images, of which the pixel resolution is 15 m. These images were obtained from Landsat 8 images and fixed at 400 × 400 pixels. Some example images from the improved U-Net dataset are shown in Fig. 6.

A. Parameter

Table II shows the main parameter settings of the three neural networks. The original intention of SegNet was to process street scene images using an encoder–decoder structure to achieve an end-to-end training mode. U-Net was initially applied in the field of medical image segmentation. Because the structure of surface depression is similar to the information in medical images, we used it for the target extraction of remote sensing images. The U-Net neural network achieves the purpose of fusing more information in the image by performing skip connections on different levels of semantic information. Table III shows the performance of various network models in the four semantic segmentation evaluation criteria, where precision represents the proportion of correct prediction results of the model to all prediction results. The recall represents the proportion of accurate prediction results of the model to all right results, and F1 represents the overall accuracy of the model. Intersection over union (IOU) represents the ratio of the intersection and union of the model’s prediction result of the surface depression and the actual result. In the comparative experiments of the three neural networks, the precision is above 75%, indicating that the accuracy of the extracted surface depression is relatively high.

B. Comparative Studies Using Different Networks and Evaluation Metrics

Based on the linear feature structure of the surface depression, we attempted to use SegNet [58]–[61], U-Net, and an improved U-Net neural network as extraction methods. To describe the extraction result of the surface depression by each network model more accurately, we used semantic segmentation evaluation criteria to discuss different networks, including precision, recall, F1, and IOU. The calculation method is as follows:

\[
\text{Precision} = \frac{TP}{TP + FP} \quad (1)
\]

\[
\text{Recall} = \frac{TP}{TP + FN} \quad (2)
\]

\[
F1 = \frac{2 \times TP}{2 \times TP + FN + FP} \quad (3)
\]

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

where true positive (TP) denotes the surface depression extracted correctly, true negative (TN) denotes the no surface depression extracted correctly, false positive (FP) denotes the surface depression extracted incorrectly, and false negative (FN) denotes the surface depression that is missed.

As shown in Table III, SegNet performed poorly in all four parameters, especially recall, which was only 12.21%. This was mainly because the width of the ice shelf surface depression was narrow. This feature was easily ignored after pooling. Based on the above reasons, many targets were undetected, resulting in poor final accuracy. Compared with SegNet, the accuracy of the U-Net network was significantly improved. Among them, precision was 88.17%, recall reached 62.51%, and F1 was 73.16%. The above data fully show that U-Net was more suitable for extracting target features in this article. This was mainly due to the advantages of the network architecture. The skip connection in
the U-Net network combined the image with low-resolution and high-resolution information, namely, the high-level information added to the semantic information of images, and refined the outline of the split in the bottom information. Therefore, the classification results had higher precision.

Comparing the traditional U-Net with the method in this article named improved U-Net, it was found that the precision values both exceeded 80%. From the recall value of the extraction result, the improved U-Net was 4.53% higher than the traditional method. Since the precision and recall values cannot independently represent the pros and cons of the network architecture, it is more reasonable to use the reconciled average value F1 of the two for evaluation. The F1 of the improved U-Net was 0.42% higher than that of the traditional U-Net. The value of IOU was also 0.53 percentage points higher, which shows that the improved U-Net network was more suitable for extracting the surface depression. This also indicates that more target features can be extracted through this network.

The reason for the above-mentioned results was that the improved U-Net proposed in this article increased the number of kernels to improve the sensitivity of the network to linear features. Compared with the traditional U-Net, the extraction of the surface depression effect was better. An additional explanation was that the precision value of this method was 6.65 percentage points lower than that of the traditional U-Net. This was because the method is more sensitive to linear features such as depressions, and more ice shelf surface features were extracted. The precision value represents the proportion of the correct prediction results of the network to the total prediction results. As the number of predictions increases, the corresponding precision value decreases.

Fig. 7 can more intuitively express the meaning of each parameter. The white pixels in the figure represent the correctly extracted surface depression. Red represents the missing surface depression, and blue represents the incorrectly extracted surface depression. From top to bottom in Fig. 7, there is the Landsat image of the experimental area, the classification results of SegNet, the results of the traditional U-Net, and the improved U-Net. When we examine the SegNet results in the second line in Fig. 7, red is the main color, and blue pixels are rarely found. This shows that SegNet was not sensitive enough to the detailed features when extracting ice shelf surface depressions. The extraction probability was small; therefore, there are very few blue pixel blocks representing the incorrect extraction results in the window. Compared with the results of SegNet, U-Net was more sensitive to linear features, and the extraction accuracy was significantly improved. It can also be seen from the figure that the proportion of white pixels (the correctly extracted ice shelf surface depressions) increased dramatically. Following the results obtained after improving U-Net in this article, there are more blue pixel blocks in the improved U-Net extraction results. The above phenomena are sufficient to show that the additional introduction of $1 \times 3$ and $3 \times 1$ kernels improved the extraction effect of image details, predominantly linear features.

As mentioned earlier, the blue pixel blocks appearing in the results are the incorrect extraction. The reasons for these misjudgment results are mainly divided into two points. First, the surface morphology of the ice shelf at these locations conformed to the characteristics of the depression. However, the bottom of the ice shelf did not correspond to the basal channel. This was because when we made the verification set, we already had certain prior knowledge; that is, according to the IceBridge data. We learned the spatial distribution and geometry of the basal channel in the area, although some ice shelf surfaces had similar features. However, the ice-penetrating radar did not find a similar morphology to the basal channel at the specified location. The neural network we used could not learn the linear data such as IceBridge and the optical images obtained by the Landsat series satellites at the same time. Therefore, the results obtained by the neural network could only be further screened in the later stage. Second, we extracted the basal channel through the surface depression of the ice shelf to obtain the distribution of the basal channel indirectly. The width of the surface depression in the image was approximately 4 to 5 pixels. From the improved U-Net extraction results, we can see that the width of some of the surface features extracted incorrectly was also in this range. From the perspective of the extraction of depressions on the surface of the ice shelf, the improved U-Net was more sensitive to the detailed features of the ice shelf, effectively improving the efficiency and accuracy of manual visual interpretation.

To verify whether there was a basal channel corresponding to the 79NG ice shelf surface depression in Fig. 7, we used IceBridge data, including elevation information on both the surface and bottom of the ice shelf. The results are shown in Fig. 8 (lower figure). The solid black line represents the morphology of the ice shelf surface, and the red line represents the bottom morphology of the ice shelf. Fig. 8 shows the shape of the basal channel (the area with yellow background). The channel has obvious “bulges,” and the morphological characteristics are the opposite of those at the surface (black line). The distribution of basal channels obtained after screening by IceBridge data is shown in Fig. 8. We can also prove that the white pixel block was indeed
Fig. 7. Comparison results of surface depression extraction. The image on the left corresponds to Landsat8 image of 79NG ice shelf surface and the extraction results of ice shelf surface depressions of the three neural networks. The image on the right corresponds to the amplification results in the yellow box of the image on the left (the meanings of each color pixel in the figure is as follows: White: correct extraction; Red: leakage extraction; Blue: wrong extraction).

the location of the basal channel because surface depressions correspond to basal channels according to IceBridge data.

V. MODEL OF GENERALIZATIONS

To prove that the method in this article is equally applicable to other ice shelves, we chose the Petermann ice shelf and the Ryder ice shelf in northern Greenland as the verification areas. The results are shown in Figs. 9 and 10. By comparing the surface depression results extracted by the neural network with the visual interpretation results, the final accuracy was obtained and is shown in Table IV. The surface depressions on the Petermann ice shelf could be extracted relatively completely. From the specific accuracy indicators, except precision, the other three indicators improved, especially F1, which represents the overall accuracy of the model. Compared with the 79NG ice
Fig. 8. Distribution of basal channels after screening by IceBridge data (upper figure) and the IceBridge in 79NG ice shelf. The location of this data is indicated by solid black line in lower figure (Granule ID: IRMCR2_20120514_02).

TABLE IV
ACCURACY OF SURFACE DEPRESSION EXTRACTION OF PETERMANN AND RYDER ICE SHELF

| Ice shelf | Precision (%) | Recall (%) | F1 (%) | IOU (%) |
|-----------|---------------|------------|--------|---------|
| Petermann | 76.10         | 74.99      | 75.54  | 60.69   |
| Ryder     | 70.82         | 74.69      | 72.70  | 57.11   |

The accuracy of surface depression extraction of the Petermann ice shelf, this parameter increased by 1.96%, which shows that the method in this article is also applicable to the surface depression extraction of the Petermann ice shelf. The extraction accuracy of the surface depression of the Ryder ice shelf was slightly lower than that of the Petermann ice shelf area, where the precision was 70.82%, which was 5.28% lower than the extraction accuracy of the Petermann ice shelf depression. The recall value was the same as that of the Petermann ice shelf. Finally, the extraction accuracy F1 of the improved U-Net on the Ryder ice shelf was 72.7%, which was 2.84% lower than that on the Petermann ice shelf.

Fig. 9. Petermann ice shelf surface morphology and surface depression extraction results. The lower figure is the verification of existing of basal channel by IceBridge data (Granule ID: IRMCR2_20140331_01).

Fig. 10. Ryder ice shelf surface morphology and surface depression extraction results. The lower figure A and figure B are the verification of existing of basal channel by IceBridge data (Granule ID A: IRMCR2_20140502_01; Granule ID_B: IRMCR2_20120330_01).
shelf, and the IOU value was reduced by 3.58%. On the whole, the extraction effect of the method in this article on the surface depression of the Petermann ice shelf was better than that of the Ryder ice shelf. The surface morphology of the Petermann ice shelf was clearly textured. There should be no error extraction or omission of a large number of surface depressions during the extraction process. Whether it was on the Petermann ice shelf or the Ryder ice shelf, the value of F1 was above 70%. The above data can fully illustrate that the improved U-Net proposed in this article has a strong generalization ability. The added kernel of the improved U-Net neural network is particularly effective for the linear feature extraction of ice shelf surface depressions. This convolution operation applies to ice shelves with obvious surface depressions except for the surface characteristics of some ice shelves, which are not obvious due to the influence of snow cover and other factors.

To confirm whether the above two ice shelf surface depressions correspond to the existence of the basal channel, we obtained the morphology of the ice shelf surface and bottom through IceBridge data, as shown in Fig. 9, which shows the Landsat image of the Petermann ice shelf area and its IceBridge results. According to ice-penetrating radar data, the area with yellow background corresponds to the yellow circles in the upper right figure. There were indeed five basal channels at the bottom of the Petermann ice shelf. There were apparent depressions on the upper surface of the corresponding position. Fig. 10 shows the surface texture of the Ryder ice shelf and the related IceBridge data. According to the ice radar data, the Ryder ice shelf had a basal channel extending from the grounding line to the calving front and a short basal channel near the calving front. The above contents can be confirmed from the corresponding relationship between the yellow background area in IceBridge data and yellow circles in the extraction of basal channel results by U-Net. All of these are shown in Fig. 10. It was confirmed by IceBridge data that the surface depressions located on the Petermann ice shelf and Ryder ice shelf corresponded to the existence of a basal channel; therefore, the positions corresponding to the white pixel block in Figs. 9 and 10 are the locations of the basal channels.

VI. CONCLUSION

Through the improved U-Net, it was successfully applied to the extraction of basal channels. The applicability of the network model was verified by analyzing the extraction results of the basal channel of the Greenland 79NG ice shelf. To further confirm whether this method has generalization ability, we also carried out a network of two ice shelves in northern Greenland, the Petermann ice shelf, and the Ryder ice shelf. The final accuracy was good, and the results are as follows.

1) Comparing the extraction results of the 79NG ice shelf basal channel by SegNet and traditional U-Net, it was found that compared with SegNet, the skip connection with the U-Net network architecture significantly improved the extraction accuracy because it combined the low-resolution information and high-resolution information in the image.

2) The improvement of the traditional U-Net by adding two kernels, $1 \times 3$ and $3 \times 1$, enhanced the sensitivity of the network to linear features. Therefore, the accuracy of the basal channel extraction result was improved, and the value of F1 was 0.42% higher than that of the traditional U-Net network.

3) The improved U-Net performed well in extracting the Petermann ice shelf and Ryder ice shelf in northern Greenland. The values of F1 were all above 70%. Because the surface morphology of the Petermann ice Shelf is clearly textured, its F1 reached 75.54%. The above results show that the improved U-Net has a strong generalization ability.

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