Supervised Model for Gravity Wave Detection on Antarctic Ice Shelves

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1. Abstract

Antarctic ice shelves play a pivotal role in restraining, buttressing, and modulating the flow of grounded ice into the Southern Ocean. Recent collapses of these barriers have shown the vital role they play in regulating sea level rise. Hypotheses explaining rapid Antarctic ice shelf disintegration (RAISD) implicate low-frequency gravity wave events (LFGWEs) as potential triggers.

Although there are many types of LFGWEs, this study focuses specifically on detecting infragravity waves and swells. These events were chosen because they occur commonly and produce clearly visible features in spectrograms as seen in Fig. 1(b).

In an effort to catalog these events for further study, we present the U-Net for Panoptic Seismic Spectrogram Segmentation (UP3S). UP3S is a supervised machine learning approach to detecting, classifying, and cataloging LFGWEs using panoptic spectrogram segmentation. The data used during training were collected by a broadband seismic array deployed on the RIS from November 2014 to 2016.

We achieved a Dice similarity coefficient (DSC) of over 0.73 during event detection and an accuracy of 94.4% during classification, outperforming alternative rule-based techniques. This study serves as a proof-of-concept for using deep-learning algorithms to predict the long-term stability of cryogenic structures.

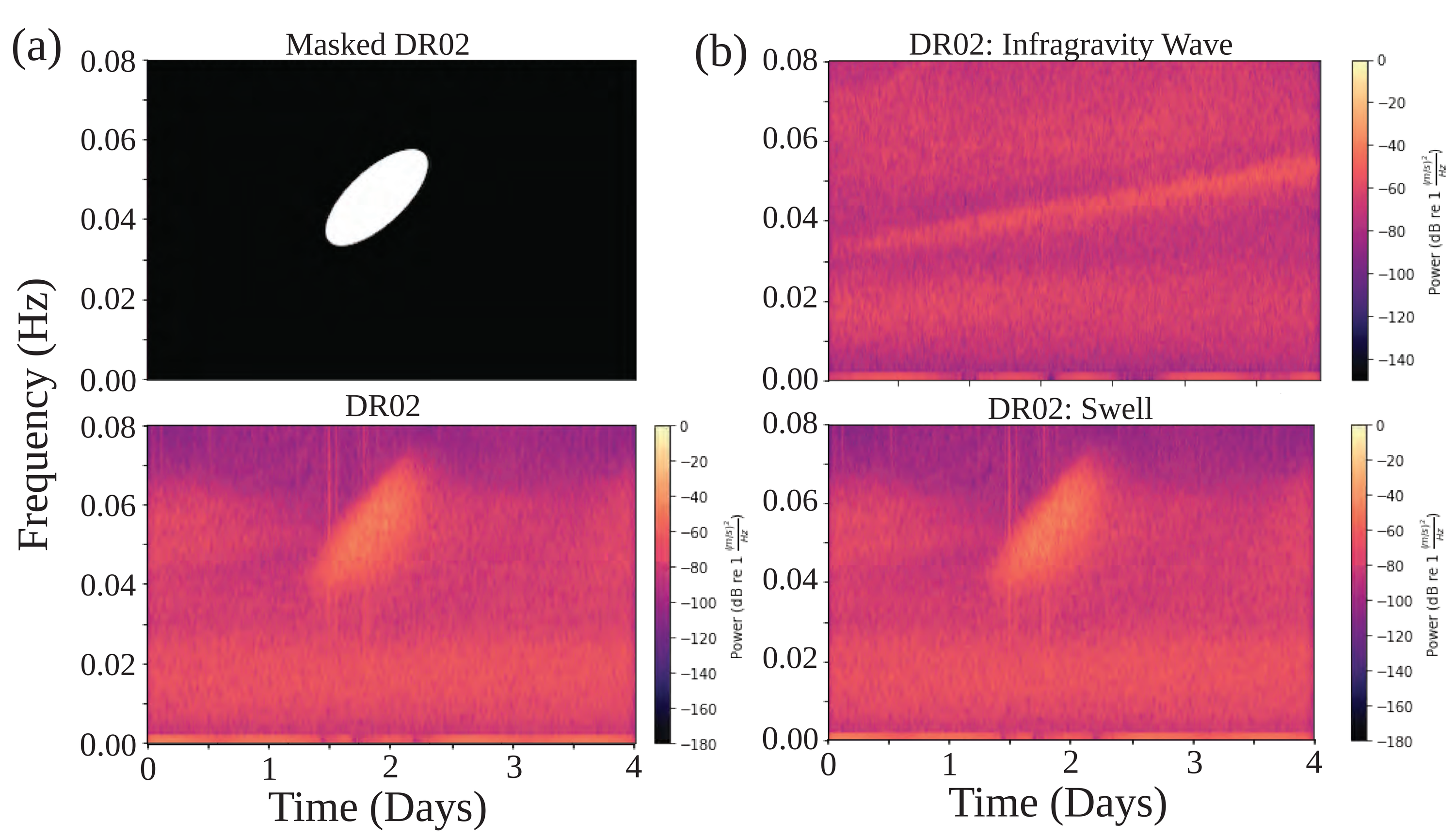

Figure 1: The left column (a) illustrates a swell and its corresponding binary mask. The right column (b) shows the features of an infragravity wave (top) and swell (bottom).

2. Introduction

Ice shelves are large floating platforms of ice anchored on at least one side to a landmass. They serve as instrumental mediators of the boundary between ocean and glacier—restricting, buttressing, and controlling the flow of grounded ice into the ocean. As such, the collapse of Antarctic ice shelves accelerates ice flow from upstream glaciers, causing an increase in sea level rise projections.[3]

Various processes including hydrofracture, warming atmospheric rivers, and infragravity-wave (IG) induced rifting have been proposed to explain RAISD[6,4,1].

This study focuses on the last of these hypotheses, exploring LFGWEs as triggers for RAISD. Their long periods can induce flexure in large sections of the shelf simultaneously, allowing for long, rapidly forming fractures to catalyze or trigger rapid shelf-wide disintegration.

More evidence in the form of LFGWE catalogs is necessary to verify this theory. A database of such events could be used to correlate real-time satellite imagery with seismic data, allowing for a better undertanding of the stability of these shelves and consequent projections about future sea level rise.

3. Methodology

Waveform data were drawn from a broadband seismic array deployed on the RIS from November 2014 to November 2016. These data were lowpass filtered at 80 mHz and converted into spectrograms with dimensions of 432 pixels by 224 pixels as seen in Fig .1(b). Corresponding binary masks were created for each of these spectrograms, with event pixels labeled white and noise labeled black as seen in Fig. 1(a).

UP3S consists of a baseline U-Net[5] model with batch normalization[2] layers added between down and up-convolutional layers. This modification helped avoid overfitting on the relatively small dataset of spectrograms used. UP3S was trained on 189 spectrogram-mask pairs for 100 epochs using binary cross entropy loss.

Model output post-processing involveed four steps—(1) denoising, (2) event separation, (3) classification, (4) cataloging. Most outputted masks contained noise artifacts that were removed as seen in Fig. 2(a). Following denoising, days with multiple event detections were separated and proceesed indivdually.

A logistic regression classifier was trained to distinguish infragravity waves and swells. The outputs of this classification are color coded as seen in Fig. 3(d). Columnar iteration is then used to timestamp each event. Aggregate results were used to create an event catalog.

4. Results

UP3S was trained on 189 hand labeled spectrograms, a relatively small dataset considering the high SNR (signal-to-noise ratio) present in the data. The addition of batch normalization layers[2] allowed the model to avoid overfitting. Furthermore, delegating classification as a step in post-processing allowed the model to learning more generalizable features without accounting for event type. The model was evaluated using Dice similarity coefficients (DSCs) and raw pixel accuracies. After 100 epochs of training using an Adam optimizer with a learning rate of 0.0001, UP3S achieved a peak DSC of 0.73 and raw pixel accuracy of 97.4%. Qualitative assesment of its performance on feature extraction can be seen in Fig. 2(b). UP3S accurately extracts general areas of high power in the correct low frequency bands, ignoring features at unlikely frequencies and in unlikely shapes. Post-processing logistic regression classification achieved an accuracy of 94.4% while differentiating infragravity waves and swells. Classifier accuracy can be judged qualitatively from Fig. 3(d). Performance of UP3S's batch inference can be seen in Fig. 2(b) and the end-to-end process—from feature masking to event classification—can be seen in Fig. 3.

References

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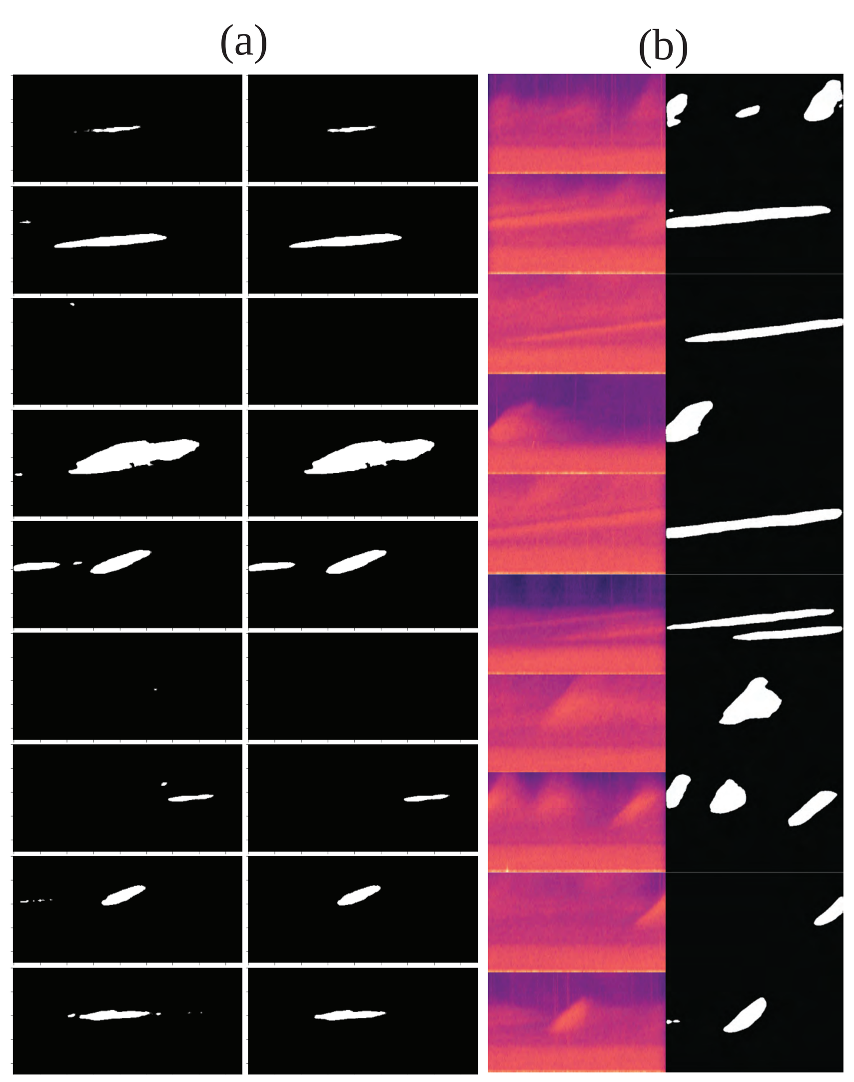

Figure 2:

The two leftmost columns (a) depict post processing denoising. Each horizontal pair of images represents a model output and corresponding denoised mask.

The two rightmost columns (b) show the model's predictions of events locations in the spectrograms. This inference step was performed with a batch size of 10.

Figure 3: Column (a) contains inputs to the model. Column (b) contains corresponding masked outputs. Column (c) contained denoised outputs. Column (d) contains event classifications with infragravity waves labeled in yellow and swells in green.