Automatic Extraction of Internal Solitary Wave Signatures in Himawari-8 Images Based On Deep Convolutional Neural Networks

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Abstract

In this study, we developed a deep convolutional neural networks (DCNN) based automatic internal solitary wave (ISW) signatures extraction method. This method is based on a tailored U-Net network and has been applied to extract the internal solitary wave signatures in the Himawari-8 geostationary satellite images. The preliminary results correspond well to the manually annotated ground truth images, implying this method is promising for the extraction of internal solitary wave signatures in satellites images even under complex imaging conditions.

Study Area

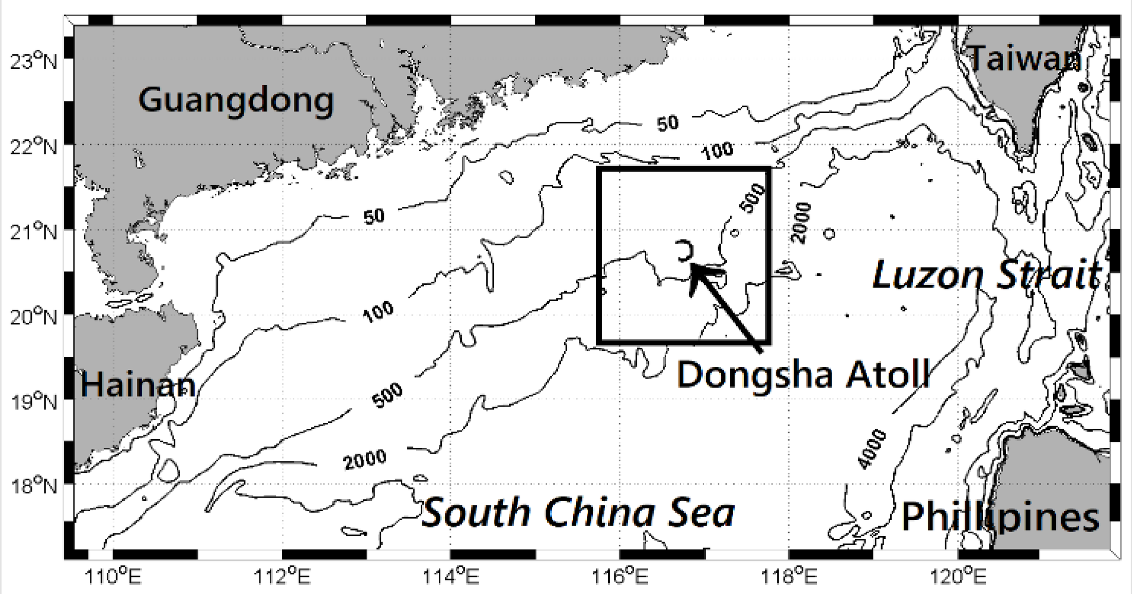

Figure 1. Bathymetric map (data from the GEBCO) of the northern South China Sea. The black box is the study area.

Data

ISWs in the SCS are frequently presented in these images under the clear sky conditions. In this study, the red (1 km resolution) band data from the HimawariCast service at Hohai University, which provides a subset of Himawari-8 image data, are used to train and test the U-Net network to investigate the extraction method.

Table 1. Himawari-8 images information.

Imaging date	Number of images	Resolution (km)
May 17, 2018	17	1
May 20, 2018	25	1
May 21, 2018	25	1
May 22, 2018	25	1
May 26, 2018	17	1
May 30, 2018	26	1
Jun. 26, 2018	27	1

Methodology

The U-Net [1] is a modified fully convolutional network [2], originally developed for biomedical image segmentation. Its architecture was designed to work with fewer training images but able to yield more precise segmentations.

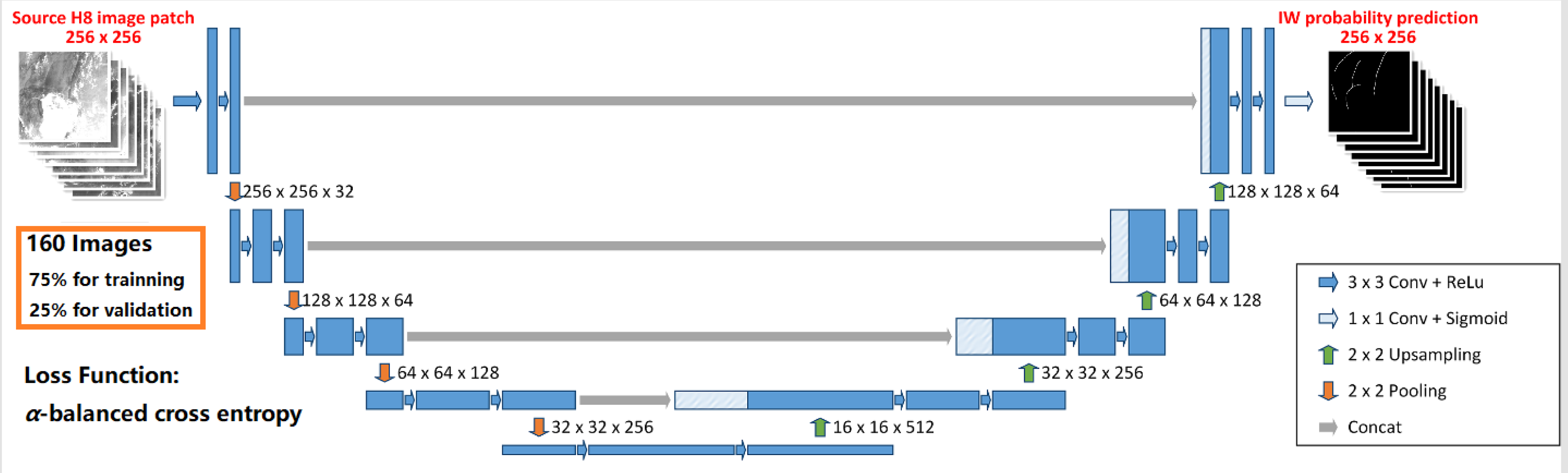

Figure 2. The U-Net architecture specially tailored for this study.

In this case, the samples are highly unbalanced, i.e., the numbers of the background samples are much higher than those of ISW samples. Motivated by [3], in this study, we use the α-balanced cross entropy as follows

$$L_{\alpha BCE} = \begin{cases} -\alpha \log \hat{y}, \text{ if } y = 1 \\ -(1-\alpha)\log(1-\hat{y}), \text{ if } y = 0 \end{cases} \quad (1)$$

where αBCE stands for α-balanced cross entropy, $\alpha \in (0,1)$ is the hyperparameter to balance the influence of samples in the loss function, y is the true label, and ŷ is the predicted result. If we want to put more weight on the ISW samples in the loss function, we just have to set α to a higher value.

Results

We used Keras default Adam optimizer, the α-balanced cross entropy as the loss function (α is set to 0.99), and the classification accuracy as performance metric. The overall extraction accuracy of the testing set is 99.03% and the IoU (Intersection over Union) is 68.3%.

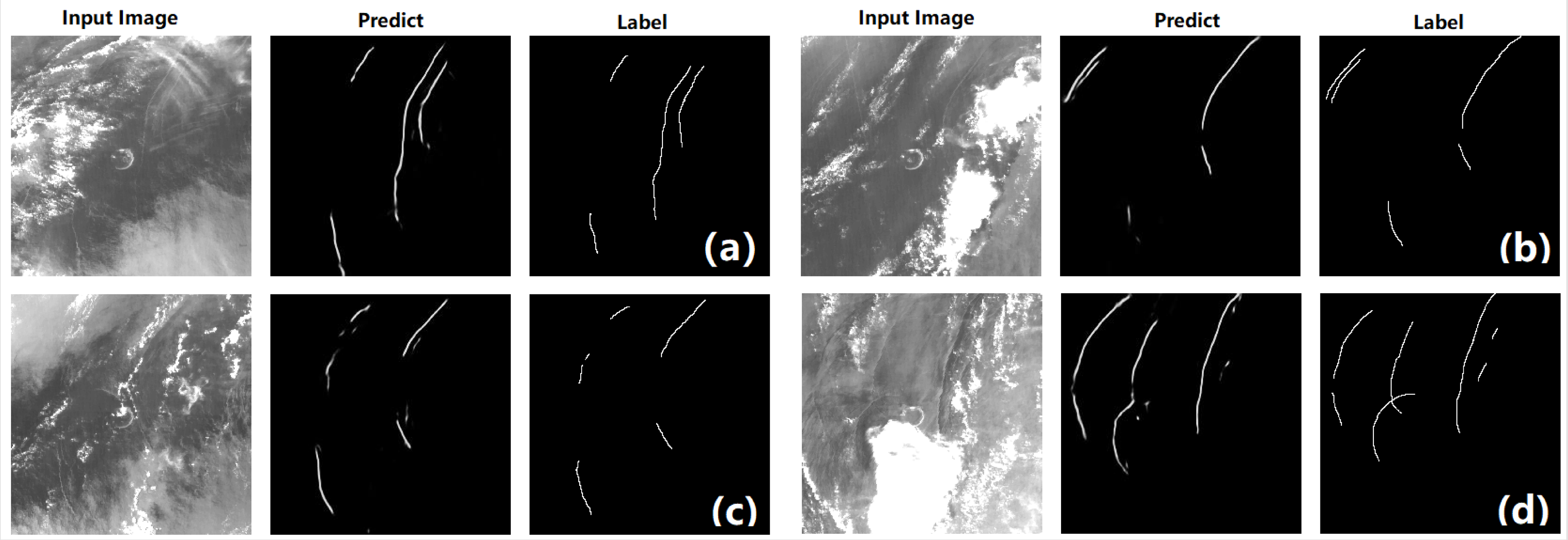

Figure 3. Four examples of the 40 testing results. The three columns are the input Himawari-8 images (see Figure 1 for geographic location), the trained model extraction results, and the manually annotated ground truth images, respectively. (a), (b), (c) and (d) were taken at 06:40 on May 17, 04:40 and 07:40 on May 30, and 05:10 on June 26, 2018 (UTC), respectively.

Cloud Blocked ?

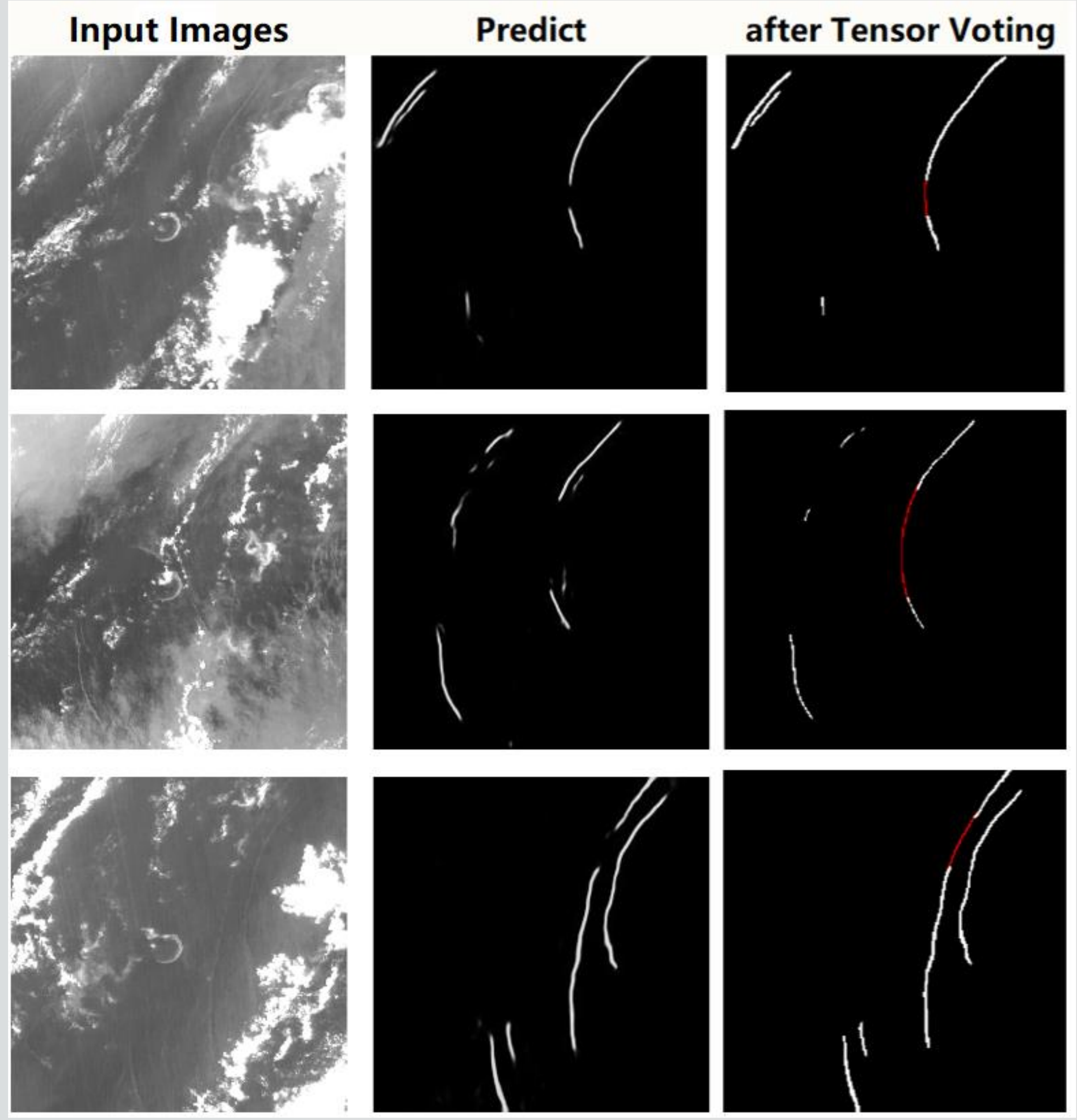

Figure 4. The Tensor Voting algorithm [4,5] was used to complement the internal wave signals that are sometimes blocked by the cloud (see the red parts).

Conclusions

In this study, an automatic ISW signatures extraction method based on the tailored U-Net is proposed and applied to Himawari-8 satellite images. The preliminary results show that the DCNN-based method is promising for the extraction of ISWs information in satellite images even under complex imaging conditions.

Future Work

In the future, with the extracted signals, we will statistically analyze the features of ISWs in the South China Sea by calculating relative parameters, such as phase velocity, mixed layer depth and so on.

Reference

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