MITC-2

Aurora recognition procedure from all-sky image data by using deep learning technique

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Abstract

Since 2018, auroral image data in visible wavelength have been collected at Jang Bogo Station (JBS), Antarctica, using the All-Sky camera with a 1-minute temporal resolution. These data have been used to calculate auroral occurrence rates to investigate the characteristics of the auroral occurrences at JBS. Accurate auroral recognition is essential for the estimation of reliable occurrence rate. In the previous method, auroras were identified by subtracting two consecutive images with 1-minute interval to effectively eliminate background light. However, this approach often failed to detect stationary auroras that persist with consistent position and brightness across consecutive images. Recognizing auroras from background image remains challenging due to their ambiguous boundaries and irregular brightness variations. Furthermore, the large volume of image data requires efficient image processing methods. To overcome these limitations, we employ a Fully Convolutional Network (FCN) with a ResNet-50 backbone pre-trained on a subset of the Microsoft Common Objects in Context (MS COCO) dataset. This deep learning approach significantly improves recognition accuracy, particularly for stationary auroras, resulting in more reliable auroral occurrence rates.

Previous Method

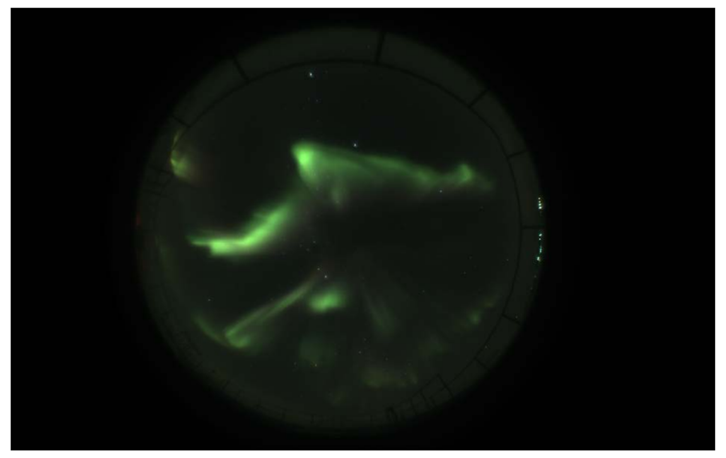

Figure 1. Aurora image captured at JBS on April 19, 2021, 10:53:30 UT (exposure time: 10 seconds).

- Jee et al. (2021) detected aurora by subtracting two consecutive images to remove the background light, such as artificial light from station, stars, or the Milky way, remains constant within one-minute period, in contrast to the dynamic nature of auroral activity.
- While effective in eliminating background light, auroras with similar intensity occurring at the same location within the one-minute interval were occasionally not recognized.

Data preparation

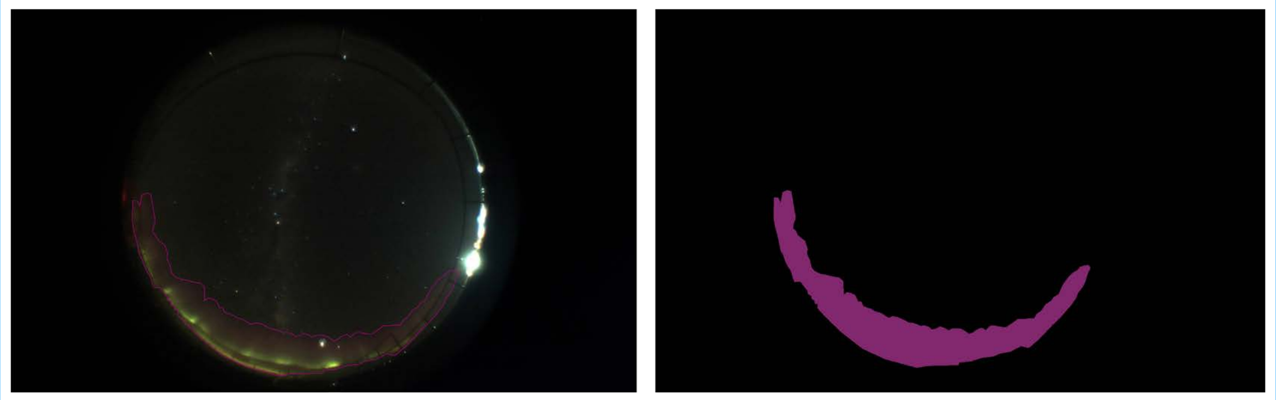

Figure 2. Contrast-stretched aurora image observed at JBS on July 2,2020, 07:02:00 UT, with manually labeled aurora (left) and the corresponding dataset label (right).

- We used manually labeled visible all-sky camera (ASC) images observed at JBS, along with their corresponding raw images, as a dataset for aurora image segmentation.
- The selected images were contrast-adjusted using a uniform ratio, and then manually labeled by aurora experts, producing a dataset of 1502 images (Figure 2).
- These images were divided into training, validation, and test datasets, consisting of 1201, 150, and 151 images, respectively.

Method

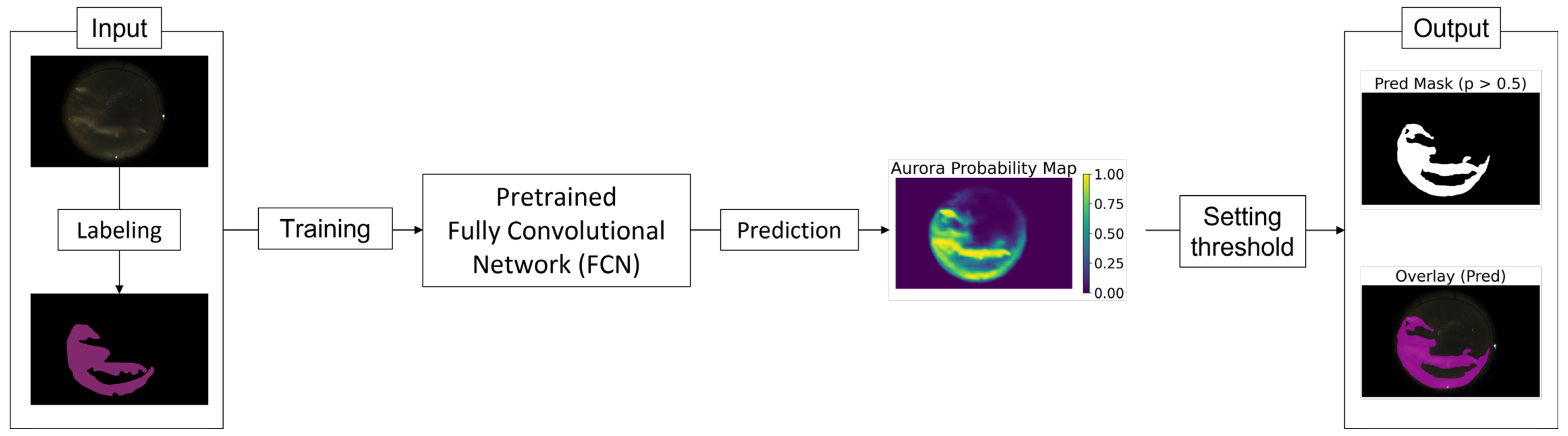

Figure 3. Procedure of aurora recognition based on FCN

- We employed a Fully Convolutional Network (FCN) for image segmentation. (Long et al., 2015).
- The model operates in the following steps (Figure 3):
  1. It is trained using the manually labeled images along with their corresponding raw images.
  2. The backbone model (ResNet-50, in this study) extracts features from each input image, and the fully convolutional layers compute aurora probability for each pixel, classifying them as either aurora or background.
  3. A threshold (0.5, in this study) is applied to the aurora probability map to generate a binary (black-and-white) 2D array that indicates the presence of aurora at each pixel.

Summary

- The previous method, based on subtracting the two consecutive images to remove background light, occasionally failed to detect stationary auroras.
- To overcome this limitation, we applied a pretrained FCN using manually labeled visible ASC images captured at JBS.
- Compared to the previous method, the deep learning-based approach effectively detected the aurora, especially near the equatorward horizon, where stationary auroras frequently occur.
- The deep learning-based method enables a more reliable calculation of auroral occurrence, which is useful for studying auroral characteristics.

Result

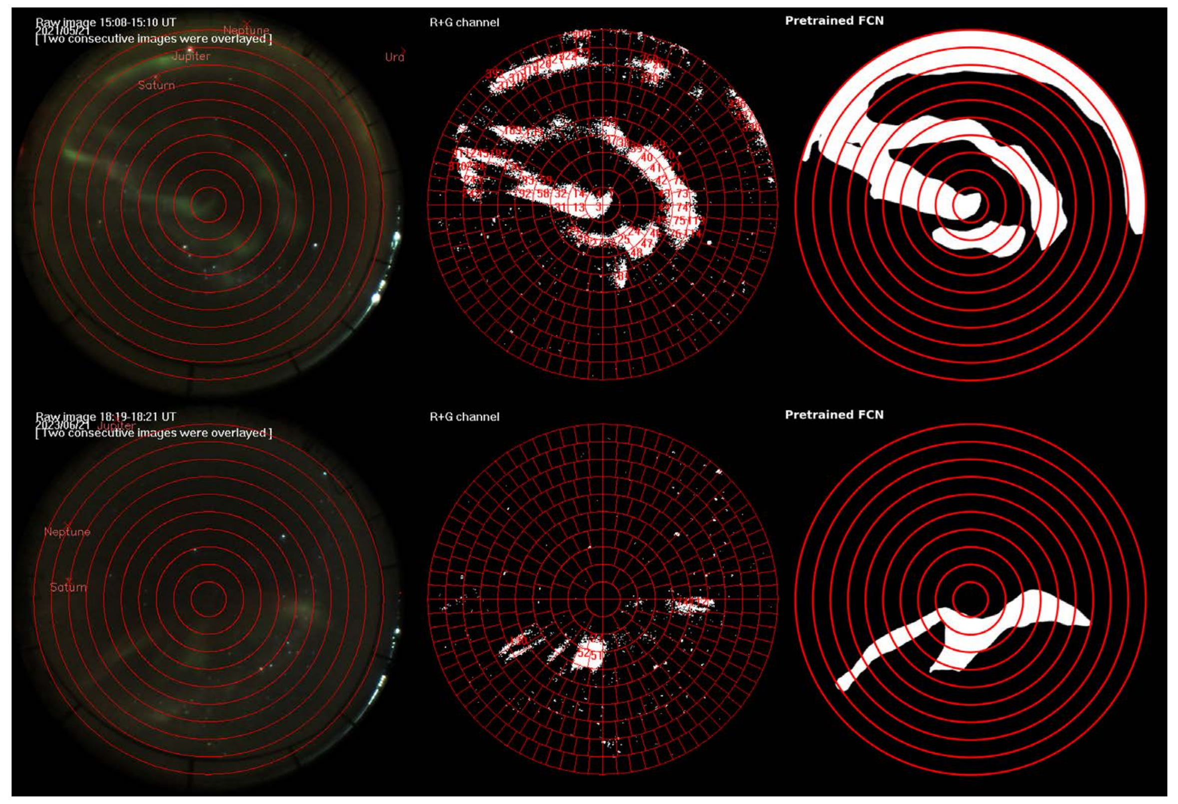

Figure 4. Comparison of aurora detection results using the previous method (Jee et al. 2021) and a deep learning-based approach (FCN). Each row shows overlays of all-sky images captured at a 2-minute interval (left), aurora detection by the previous method (center), and detection by the pretrained FCN (right). All images are shown in geomagnetic coordinates. Concentric circles denote elevation angles at 10° intervals, centered at the zenith. The previous method identifies auroral cells by evaluating pixel differences in R and G channels across 400 equal-area sky cells, while the FCN directly segments auroral region from images.

- We compared the previous method, which subtracts images taken at 2-minute intervals, with the deep learning-based approach
- The previous method may have missed parts of the auroral structure, especially in equatorward horizon. It is possibly due to structures with similar brightness appeared at the same location in both images taken at a two-minute interval (Figure 4).
- Conversely, the pretrained FCN model successfully detected auroral features that were missed by previous method.

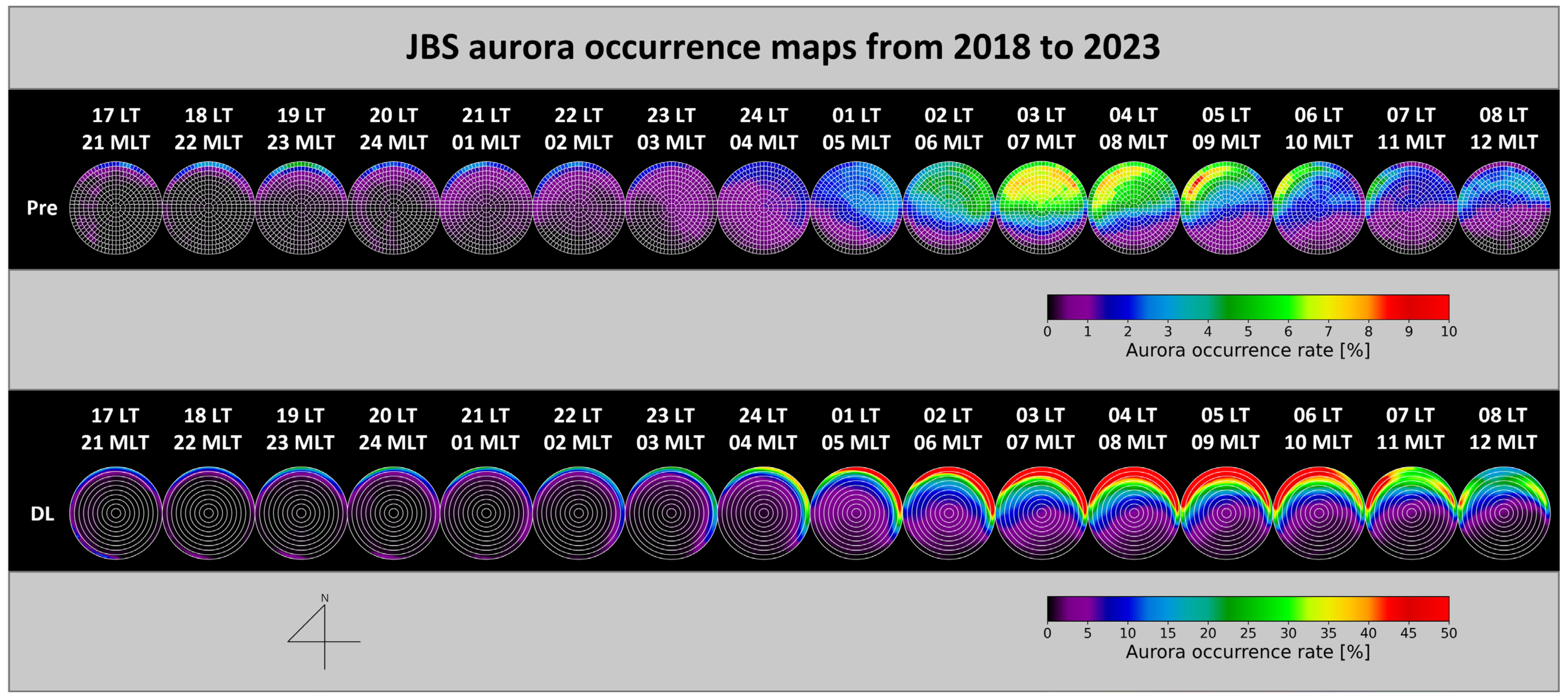

Figure 5. Aurora occurrence map from 2018 to 2023 are presented for each magnetic local time, based on auroral detections identified using two methods: the previous method, which subtracts two images taken at a two-minute interval (top) and the pretrained FCN model (bottom). Each map is oriented with magnetic north (equatorward) at the top and magnetic south (poleward) at the bottom.

- Figure 5 presents auroral occurrence maps over JBS, derived from both the previous method and the pretrained FCN model.
- The occurrence rate obtained using the pretrained model is approximately five times higher than that of the previous method.
- Furthermore, the occurrence rate near the equatorial horizon of JBS increased. This is likely because the equatorial region of JBS is close to the auroral oval, where persistent auroras were not effectively detected by the previous method.

References

- Jee, Geonhwa, et al. "Observations of the aurora by visible all-sky camera at Jang Bogo Station, Antarctica." Journal of Astronomy and Space Sciences 38.4 (2021): 203-215.
- Long, J., Shelhamer, E., & Darrell, T. (2015). Fully convolutional networks for semantic segmentation. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 3431-3440).