R010-P08
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FMCW イオノグラム画像 E/Es 層エコー検出に関する一般物体検出モデルの高有効性

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High available of general object detection models for detection of E/Es layer echo on FM-CW Ionograms

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Since the sudden changes in the Ionospheric environment can cause some radio disturbance, it is important in space weather forecast to make continual observation of Ionospheric environment in quasi-real time. The purpose of this paper is to propose a highly accurate and robust method for detecting E-layer echoes and sporadic E-layer echoes from Ionogram images. We adopt some existing general object detection methods based on conventional neural network (CNN), and create a deep learning model trained on our own created training data, for our approach to detect E-layer echoes and sporadic E-layer echoes as object instances in an Ionogram image. The main objective of this paper is to reveal the usefulness of the general object detection methods, Faster-RCNN, YOLO and SSD detect E-layer echoes and sporadic E-layer echoes.

In this study, we prepare 1178 Ionogram images (January-December 2019, Sasaguri in Japan, using FMCW Rader) and split them randomly into the training data (942 images) and the validation data (236 images) in the ratio of 8:2 for our experiments. We apply two preprocessing, noise reduction using the bilateral filter which is one of the smoothing filters and smoothing in the horizontal direction, into each Ionogram image. We also perform the annotation process for the training data and give the position information of bounding boxes as the object regions and their class label. Here, the class labels for the E-layers and Es-layers are considered identical.

The results show that the Faster-RCNN and YOLO methods can detect E-layer echoes and sporadic E-layer echoes with high accuracy of 98.96% AP and98.68% AP, respectively, compared to 88.67% AP for SSD (AP is Average Precision: the most commonly used metric is AP for the accuracy of object detection network, derived from precision and recall). The average automatic scaling error of critical frequency foE and foEs was 0.1495, 0.2615, and 0.4373 MHz for Faster-RCNN, YOLO, and SSD, respectively. In addition, using the Faster-RCNN, YOLO and SSD models optimized for E-layer and Es-layer detection from Ionogram images in this study, we confirm that the occurrence distribution of foEs and foEs is consistent with the seasonal and regional occurrence distribution characteristics reported in previous studies.

This study reveals that three general object detection methods used in the experiments are useful for echo region search in Ionogram images. On the other hand, there is still room to reduce the computational complexity of the candidate region search by changing the machine learning network architecture to match the characteristics of each echo, including not only the E-layer echoes but also the normal F-layer echoes or the spread-F echoes during ionospheric disturbances. In the future, we aim to extend the object detection model optimized by Ionogram images as a multi-class classification and regression problem.