Water Body Detection using Deep Learning with Sentinel-1 SAR satellite data and Land Cover Maps

Hyungyun Jeon[1], Duk-jin Kim[2] and Junwoo Kim[3]

[1]Combined MS/PhD Student, School of Earth and Environmental Sciences, Seoul National University

[2]Professor, School of Earth and Environmental Sciences, Seoul National University

djkim@snu.ac.kr

[3]Senior Researcher, School of Earth and Environmental Sciences, Seoul National University

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ABSTRACT

This paper suggests a novel and reliable method to detect water body from Sentinel-1 SAR satellite data using deep learning technique. There have been a lot of studies to extract water body from SAR images with deep learning. Although they achieved good performance, most of them used training data without guaranteeing good quality. In this study, land cover map generated by an official government agency were used for labelling ground truth data. After identifying the acquisition date of aerial photo used for generating the land cover map, vector polygons for river or reservoir were extracted and used as label data. This new method reduced producing time and cost to generate reliable training data. After training our deep learning model, it showed 0.874 of f1score. We also tested our deep learning model to the heavy rain season in Korea (August 2020) and successfully detected river flooding.

Index Terms— SAR, deep learning, land cover maps, water body detection, Sentinel-1

1. INTRODUCTION

Water body detection is important for flood monitoring, draught prediction and coastline change. Spaceborne remote sensing technology, which provides repetitive data of wide region has high possibility for water body detection.

SAR satellite has all-weather and all-day imaging capabilities because it is active sensor and uses microwave which can penetrate through Atmosphere. Therefore, SAR satellite has high availability for stable detection of water body.

In recent five years, many studies are aiming to combination of the SAR imagery and Deep Learning. Kang et al.[1] applied fully convolutional networks to detect flood in Gaofen-3 SAR satellite images. Multi-resolution dense encoder and decoder network was applied to automatic extraction of water and shadow in SAR images [2]. Nemni et al.[3] also performed study for rapid flood segmentation with fully convolutional neural network. With cascaded fully convolutional network and variable focal loss, water body was detected in high-resolution SAR images [4]. These researches showed high model performance and good result in evaluation data.

Nevertheless, most of Deep Learning based studies used manually labeled ground truth data for training data. Producing reliable training data manually for research requires a lot of time, cost and manpower. Furthermore, there is no guaranteeing of quality for manually made training data.

In this study, land cover map generated by the Korean Ministry of Environment were utilized to produce ground truth label. Sentinel-1 SAR satellite imageries that correspond to the date of land cover base map were selected and applied to deep learning-based water body detection.

2. MATERIAL

The official land cover map used in this study has been generated by following guidelines for 1:5000 cartography.

A procedure for generating detailed land cover map has 7 steps. First is preparing data such as remote sensing data and a digital map (1:5000). Second is decoding and classifying land cover boundary and property based on mainly remote sensing data. Third is field survey for ambiguous area and applying results. Fourth is inspecting quality between classified land cover and remote sensing data. Fifth is evaluating classifying accuracy. Sixth and seventh are generating metadata and making PDF files, respectively. Final land cover map has seven big classes; urbanization area, agricultural zone, forest area, grassland region, bare land and water area [1]. Especially, water area is composed by river, lake, reservoir and coastal marine water.

Sixty Sentinel-1 IW GRDH (Ground Range Detected in High resolution) data cover four major rivers with double polarization (VH and VV) were used in this study. For preprocessing, Sentinel-1 SAR satellite data were first removed GRD-border noise, then radiometric calibrated and speckle filtered, finally Range-Doppler Terrain Corrected using SRTM 1sec DEM. In conclusion, raw satellite data were transformed into 20m of pixel resolution, projection of WGS84 lat/lon (EPSG: 4326), channels with sigma0_VH, sigma0_VV and incidence angle.

3. METHOD

Forty land cover maps including four major rivers of Korea were analyzed; Han River, Nakdong River, Geum River and Yeongsan River. Then, finding the aerial image that has highest probability to generate land cover maps, shooting date of the land cover map were recorded.

After generating shooting date of land cover maps, Sentinel-1 SAR satellite data within 3 days of land cover base map were acquired. Then, water body extracted from land cover maps, which type are vector, were transformed into binary raster files. Next, preprocessed Sentinel-1 SAR satellite data were cropped by land cover maps. Finally, 3078 pairs of Sentinel-1 SAR satellite imagery and binary raster label of water body were generated.

However, dataset of 3078 pairs have 5.1% of water pixel ratio. Deep learning with imbalance dataset can face into overfitting for major class. To prevent effect of class imbalance, 3078 pairs were randomly resampled into four groups. First group has water ratio between 0%~10% and it has 90 pairs. Second group has water ratio between 10%~20% and it has 112 pairs. Third group has water ratio between 20%~30% and it has 112 pairs. Fourth group has water ratio more than 30% and it has 90 pairs. Then, water ratio of dataset changed into 21.22% from 5.1%.

Next, 404 pairs of balanced datasets were filtered by visual inspection. As there can be error and mismatch in datasets, VH and VV images were compared with water binary labels. After visual inspection, 348 pairs of data remained. Finally, 300 pairs of data are randomly selected for training data of deep learning and 48 pairs of data were applied for evaluation data.

In this study, U-Net, which shows robust performance for semantic segmentation were used as deep learning architecture [5]. Original U-Net uses cross entropy as loss function. Nevertheless, cross entropy suffers from imbalance dataset, focal loss was used as alternative. In addition, common data augmentation method was applied; rotation, horizontal flip and vertical flip [6].

After train deep neural network, 48 evaluation data were analyzed with trained model. Then, mean overall accuracy, mean precision, mean recall, mean IOU and mean f1score were calculated with comparing to binary water raster label files.

4. RESULTS

In this study, training data based on land cover map and Sentinel-1 SAR satellite data were applied to deep learning approach of water body detection. Furthermore, not only performance indexes from training model, but also performance indexes from randomly selected dataset were evaluated. In addition, Han River and area includes 2020 Nakdong River flood were analyzed.

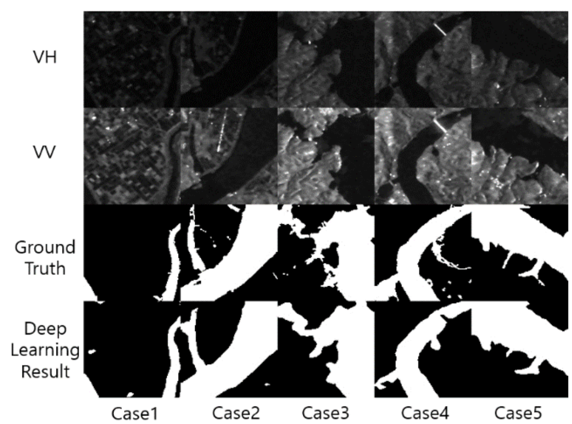

Figure 1. Five cases among 48 evaluation data.

Figure 1 shows five cases among 48 result of randomly selected evaluation data. First row is VH image, second row is VV image, third row is Ground Truth and fourth row is result of deep learning.

Table 1. Model performance of deep neural network

Overall accuracy	Precision	Recall	IOU	f1 score
0.946	0.873	0.877	0.778	0.874

Table 2. Performance of evaluation data analyzed by trained deep learning model

Overall accuracy	Precision	Recall	IOU	f1 score
0.936	0.851	0.892	0.771	0.871

Table 1 shows model performance of deep neural network while training. Table 2 shows performance indexes of evaluation data analyzed by trained deep learning model. Figure 2 shows a deep learning result and raw data of 2020.08.08 Nakdong River flood.

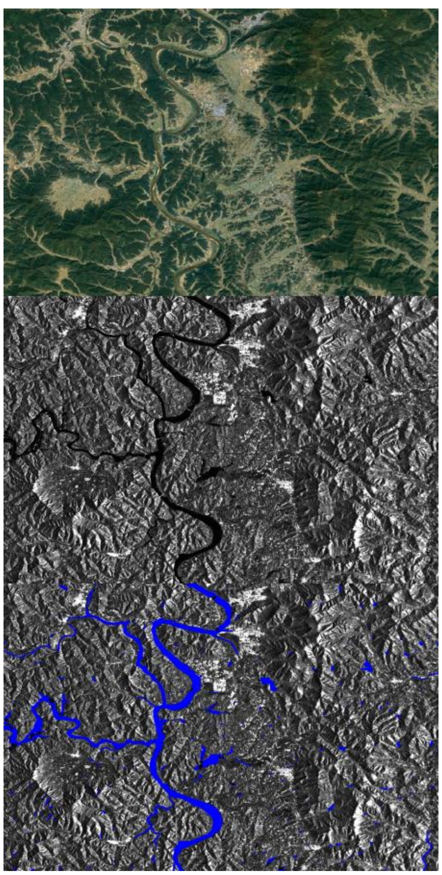

Figure 2. Analyzed result of 2020.08.08 Nakdong River flood. First row is a Google Satellite image (no flood), second row is a Sentinel-1 SAR satellite VV image (after flood), third row is a result of trained deep learning model (blue area).

5. DISCUSSION

In Figure 1, there are areas with water-filled rice paddy that looks like chessboard in case1 and case 2. Beside surface of water-filled rice paddy is water, A deep learning trained model by the new method didn't segmented water-filled rice paddy as water body. In case 3,4,5, shadow areas due to side-looking characteristic of SAR exist. However, results in case 3,4,5 shows almost same shape comparing to ground truth label. These results suggest the new method has tolerance to rice paddy and shadow effect.

In Table 2, the new method achieved high performance in model training. Furthermore, in Table 3, approximately same performance was achieved in evaluation data. These results suggest data made with the new method is reliable and homogeneous.

There was a flood event in Nakdong River region at 2020.08.08. Analysis between no flood event and after flood event war performed. In Figure 2, there are a Google Satellite image with no flood event, a Sentinel- SAR satellite VV image after flood and a deep learning result of the new method with the Sentinel-1 SAR satellite data. As there are no ground truth label data of flood, only qualitative evaluation was executed. There are a lot of inundation of the ROI comparing the Google Satellite image and the Sentinel-1 SAR VV image. The deep learning result shows approximately same shape to the Sentinel-1 SAR VV image. Furthermore, as there are many shadows due to SAR characteristic and slope, new model didn't classify them in to water body. This result suggests the new method has potential to monitor flood event.

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6. CONCLUSION

In this paper, the novel and reliable method to detect water body with Sentinel-1 SAR satellite data and land cover maps using deep learning. The new method reduced producing time and cost to generate training data with guaranteeing of quality. Moreover, the new method shows high performance in both model training and evaluation data. Especially, the new method didn't classify water-filled rice paddy into water body. In addition, analysis to flood event area was performed. The result suggests the deep learning model with the new method has tolerance to shadow effect

In a future work, there need additional method to increase performance. Acquiring more reliable data, using GIS data or POLSAR data can be alternative.

7. ACKNOWLEDGMENT

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