Detection of Landslide Candidate Interference Fringes in DInSAR Imagery Using Deep Learning

Joko KAMIYAMA[1*], Tomoyuki NORO[1], Masayuki SAKAGAMI[1], Yamato SUZUKI[1]
Kazuo YOSHIKAWA[2], Shuhei HIKOSAKA[2] and Ikushi HIRATA[2]

[1] National Institute for Land and Infrastructure Management, MLIT, Japan
[2] PASCO Corporation, Japan
[*]Corresponding author. E-mail: kamiyama-j253@mlit.go.jp

INTRODUCTION

Since Differential Interferometric SAR (DInSAR) using the synthetic aperture radar mounted on a satellite can regularly observe slight landslide movements in wide area, it is considered an effective monitoring technology in Japan, where there are many and wide areas with high risk of sediment disaster. In DInSAR imagery, ground surface movements appear as interference fringes but there are also various factors that produce interference fringes, such as satellite orbit differences or delay of radio waves due to water vapor. Therefore, interference fringes that may be landslide movement are interpreted by expert. On the other hand, there have been developed some models (e.g., Krizhevsky, 2012) in recent years that perform image recognition with high accuracy using Convolutional Neural Networks (CNNs), one of the deep learning approaches. Then, we studied whether CNNs can similarly identify the interference fringes detected by expert to have a possibility of landslide movement.

METHOD

For learning of the CNNs, as teacher data, imagery were cut into small areas (150 x 150 pixels for each), consisting of two types: One is "landslide candidate" that was detected by expert to have a possibility of landslide movement and the other is "others" sampled at random from other areas of interference imagery. In order to evaluate the classification performance of the learned CNNs model, we used cross-validation that can maximize the use of limited data and evaluate the generalization of the model. Dividing the teacher data into 5 groups, 4 of which are for learning and the remaining group is for validation, we conducted learning and validation 5 times in total by changing the combination of groups each time. In addition, using the learned CNNs model, we classified InSAR imagery into "landslide candidate" and "others" by small area (10 x 10 pixels) and evaluated the interpretation performance.

The data of "landslide candidate" and "others" used for learning and validation each time were 45,000 images for learning and 11 images and 1500 images for validation. Generally, the performance of CNNs will improve as the amount of learned data increases, but the amount of "landslide candidate" data used in this study was limited. Therefore, considering the rate at which the number of images can be increased by turning, reversing, or moving in parallel the images, 42 to 44 images were increased to 45,000 images for learning each time. In order to enhance the generalization of the model, images were turned or reversed, but it is difficult to confirm whether such interference fringes appear on unknown images. As data for learning, we used the DInSAR imagery of the ALOS/PALSAR data observed in an areas of Yamagata, Niigata, Ishikawa, Nagano, Shizuoka, Nara, Wakayama and Kochi from 2008 to 2011.

As indices for evaluating the classification performance of CNNs, we used Recall, Precision, and Break Even Point (BEP). Recall is the ratio of data forecasted by CNNs as "landside candidate" to the data that is actually "landside candidate." Precision is the ratio of the data that is actually "landside candidate" to the data forecasted by CNNs as "landside candidate." Further, we used BEP to evaluate the classification performance when Recall and Precision are balanced. BEP is the value at which the recall equals the precision when the threshold to the probability value of the landside candidates class is raised or lowered.

RESULTS

The average of validation made 5 times with cross-validations was 90.9% in Recall, 99.5% in Precision, and 99.4% in BEP, each of which shows accurate evaluation of "landslide candidates" detected by expert (**Table 1** "Classification"). In addition, interpretation of DInSAR imagery by CNNs resulted in 94.5% in Recall and 1.5% in Precision (**Table 1** "Detection"). Since many images with similar characteristics to "others" were included in the learned data of "landslide candidate," CNNs is considered to have detected many "landslide candidates." In addition, "landslide candidates" detected by CNNs includes much data in which area is smaller than that interpreted by expert. For interference fringe with a small area, it is difficult even for experts to determine whether it is "landslide candidate" or "others." Therefore, we applied size filtering to remove images less than 10 x 10 pixels from the result of interpretation by CNNs, and Precision slightly improved to 2.1%.

Table 1 Evaluation result of detection performance of CNN model

Evaluation index	Classification (%)	Detection (%)	
		Size filtering	
		Not applied	Applied
Recall	90.9	94.5	94.5
Precision	99.5	1.5	2.1
BEP	99.4	—	—

CONCLUSIONS

It was found that CNNs can detect, like experts, interference fringes with a possibility of landslide movement. On the other hand, since this study did not have enough teacher data on "landslide candidate," it is difficult to say that CNNs with high generalization has been established. Therefore, the future challenge is to improve the accuracy of models by increasing teacher data, trying methods that enable efficient learning even with small teacher data, etc.

REFERENCES

Krizhevsky, A., Sutskerver, I., Hinton, G.E. (2012) ImageNet Classification with Deep Convolutional Neural Networks, Advances in Neural Information Processing Systems 25, pp.1106-1114.

Keywords: Landslide detection, DInSAR, Deep Learning, CNNs