

Machine learning of the real GNSS displacement time series for automated SSE detection

Yusuke Tanaka (1), Masayuki Kano (2), Keisuke Yano (3)

(1) Geospatial Information Authority of Japan, Kitasato 1, Tsukuba 305-0811, Japan

tanaka-y96e4@mlit.go.jp

(2) Disaster Prevention Research Institute, Kyoto University, Gokasho, Uji, Kyoto 611-0011, Japan

kano.masayuki.4m@kyoto-u.ac.jp

(3) The Institute of Statistical Mathematics, 10-3 Midori-cho, Tachikawa, Tokyo 190-8562, Japan,

yano@ism.ac.jp

Detection of slow slip events (SSE) is essential to precisely evaluate the frictional behavior of the plate interface and the potential of future large earthquake. To detect transient signal hidden in the displacement time series by Global Navigation Satellite System (GNSS) observation, various mathematical techniques have been utilized such as template matching, sparse estimation, and decomposition analysis. However, machine learning has still rarely been utilized. Especially, almost no previous studies have conducted the training of real GNSS time series.

On the other hand, Japan has accumulation of continuous GNSS observations of more than 1300 stations and 30 years from 1990s. Through the training of this rich dataset, we can efficiently capture the noise behavior and their background physics. According to this motivation, we are developing machine-learning-based SSE detection through the training of the real GNSS time series in southwest Japan, where the several SSE detection catalogs have been established as the true label of training.

We carried out single-site SSE detection using Convolutional Neural Network (CNN). The input of the model is displacement time series of horizontal two components (EW and NS) with the window length of 121 days. Then, the output is the signal probability. Based on the existing SSE detection catalog of short-term SSEs, we created approximately 26000 training data of noise and signal time series. As a result of training them, we obtained 75–76% of accuracy. The larger signals showed higher detectability. Then, almost all of the signals over 3.0 mm were successfully detected. Positive detections showed continuous spatial distribution and well coincided with the true slip area. Additionally, the estimated signal probabilities for continuous time series showed clear peak around the event date. We also tried to input time series of adjacent two stations based on Delaunay triangle. However, the obtained accuracy was 76–77%, which is only a little higher than the single-site case.

We need further expansion of training data and model architecture for higher detection accuracy. For example, combination of real noise time series and synthetic signals is effective option to increase the number of signal data. We can also consider ensemble learning which combines multiple training models based on different noise datasets. In the presentation, we show the details of our results and latest progress about the development of sophisticated training dataset.