Automatic Approach to Low-Frequency Earthquakes Detection in Southwest Japan Based on Deep Learning Technique

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Slow earthquakes have been observed on both shallower and deeper sides of seismogenic zone of megathrust earthquakes and therefore been thought to potentially interact with disastrous megathrust ruptures. A class of slow earthquakes at a dominant frequency of 2–8 Hz, marked as deep low-frequency events (LFEs), are observed continuously along the Nankai Tough from the Southwest Shikoku to the Kii peninsula in Japan. The frequent occurrence of LFEs in this region may suggest an increased probability of impending megathrust earthquakes. Therefore, precise monitoring of the seismic activity of these LFEs may provide a key clue to the quantitative prediction of huge earthquakes and deepen our understanding of diverse earthquake processes. However, traditional approaches to earthquakes detection such as STA/LTA method fails to detect LFEs signal masked by background noise because of the lack of impulsive phase arrivals, which makes it challengeable to detect LFEs from raw seismograms automatically. The matched-filter method leverages the similarity of representative template waveform and continuous seismic waveform and has been used in the Japan Meteorological Agency (JMA) to distinguish and catalog LFEs automatically since July 2014, but it also makes detectability restricted by the limited prior knowledge that refers to available matching templates.

The recent advance in the field of deep learning has shown a robust capability of predictions or discriminations by using general features learned from fitting data, which can potentially be used in tackling LFEs detection. Deep-learning models are basically trained by scanning through large datasets and meanwhile tweaking their parameters gradually toward the direction in which the difference between fed data and the model's predictions descends.

To create training dataset in our study, we prepared a total of 4 years continuous three-component velocity seismograms data recorded by 75 stations of High-sensitivity Seismograph Network Japan (Hi-net) operated by the National Research Institute for Earth Science and Disaster Resilience (NIED) across Southwest Japan from January 2010 to December 2013. We first preprocessed raw data streams without applying bandpass filter and cut them into millions of single-station, 3-channel, 10-seconds event-waveform windows vectorized as 2D arrays at a sampling rate of 100 Hz. We then labeled 3,179,167 windows as noise, 161,930 windows as regular earthquakes, 29,090 windows as LFEs, and 262,209 windows as deep low-frequency tremors, which were considered to be a continuous LFEs signal, according to the JMA's seismic catalog and the World Tremor Database (WTD). Due to the fluctuation of the positions of seismic phases in the waveform windows, we choose to use the Convolution Neural Network (CNN); a deep-learning model that first extracts local features and then integrates them hierarchically so less disturbed by the inhomogeneity of data than the traditional model does. For each data window, the model outputs four probabilities corresponding to the likelihood of each respective class. Event detection is declared when one of four probabilities exceed the threshold we set (50% for general).

We trained the model preliminarily and evaluate the accuracy of the model on a brand-new test dataset generated by the same rules as those of creating training dataset using receiver operating characteristic

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(ROC) analysis. We were given the area under the ROC curve (AUC) score of 0.923, 0.991, 0.981, and 0.914 (naive baseline = 0.5) for noise, regular earthquake, LFEs, and deep low-frequency tremor respectively, which suggests that our model is capable of classifying waveform windows correctly with high confidence. We also noticed that there are a lot of LFEs that are incorrectly identified as tremors in spite of the low ratio of tremors that are incorrectly identified as LFEs. To find a rational explanation for this asymmetric structure and the classifying borderlines of our model, we will do more error analysis and unbox each layer of our model to visualize how they are activated in further research. And we will further tune our model and integrate the single-station classifiers to build local networks that can identify earthquake events coherently.

Keywords: slow earthquakes, LFEs, deep low-frequency tremors, earthquake detection, deep learning

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