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Real-time forecasting of near-field tsunami waveforms at coastal areas using a regularized extreme learning machine

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ABSTRACT

This study applied an extreme learning machine to produce rapid forecasts of tsunami waveforms in coastal areas using tsunami signals recorded at specified locations. The remarkable training speed of the algorithm means that it can run in real-time, and therefore it is suitable for early warning systems in near-field tsunami events. Additionally, as a universal function approximator, the proposed method can capture nonlinearities exhibited by the tsunami. Therefore, it provides advantages over the standard inversion analysis used in many existing studies, which is typically developed under a linear assumption. We applied the proposed method to the 2011 Tohoku earthquake tsunami. Our results demonstrate that the proposed method is more accurate and does not significantly increase the computing time, when compared with the standard method. Furthermore, our model uncertainty analysis proves that the method is robust and reliable, despite its dependency on the random input weights and biases (the forecasts from several consecutive runs showed insignificant variability).

1. Introduction

It is difficult to provide a reliable forecast of a tsunami generated by a submarine earthquake. This is particularly true for near-field events, where there is limited time to execute a tsunami warning system and dissemination. Even though the current global network of sensors can be used to immediately retrieve information on the earthquake parameters, they do not always explain the exact characteristics of the resultant tsunami (Geist, 2002; Tsushima et al., 2009). Therefore, a tsunami early warning system (TEWS) solely based on seismic data produces a relatively large number of false-positive warnings (Behrens et al., 2010). The best way to identify a tsunami is from its incident waves detected by water level gauges. Subsequently, we can assimilate the truncated data to forecast the tsunami waveforms at other locations. However, we must consider the trade-off between forecasting accuracy and speed. Additionally, the spatial coverage of the deployed gauges has an important impact on the effectiveness of the forecast.

The standard tsunami forecasting method based on recorded waveforms uses tsunami waveform inversion (TWI). In general, this method can be independent of seismic information, and very accurately estimates the possibility of a tsunami. It can also produce a complete series of waveforms rather than only extracting certain wave features such as maximum amplitudes and arrival times. Many authors have proposed different TWI methods using various designs and settings, to develop both far-field and near-field TEWSs (e.g., Koike et al., 2003; Tsushima et al., 2009; Yasuda and Mase, 2013). A more advanced TEWS can even provide site-specific inundation forecasts within a reasonable time (Gusman et al., 2014), but this requires intensive computational efforts to construct a high-resolution inundation database, which is beyond the scope of this study. Aside from their effectiveness in detecting tsunamis, most TWI methods are not applicable to nonlinear processes because they impose a linear assumption. We believe that a method that captures the nonlinearities in tsunamis must be integrated into a TEWS.

Recent developments in computing technologies have resulted in a new paradigm of modeling and techniques for handling data and revealing underlying dynamics, which are sometimes not accessible by conventional approaches. Neural networks are part of the growing artificial intelligence branch, and are known for their ability in approximating most practical nonlinear functions. Neural networks have been applied to TEWS in previous publications (e.g., Hadihardaja et al., 2010; Mase et al., 2011; Romano et al., 2009). However, the triggering mechanisms for those TEWS rely on estimates of the earthquake parameters. Namekar et al. (2009) proposed a better solution by incorporating tsunami waveforms (as in the TWI) to forecast coastal waveforms and the run-up. Their method requires no (or minimal) earthquake information. The only drawback is that the back propagation algorithm requires iterative training, which results in considerable computation time. Consequently, it may not be appropriate for near-field tsunami events.

Here, we propose using a recent neural network algorithm called an extreme learning machine (ELM). The ELM can be trained up to 170 times faster than gradient-based methods such as back propagation,

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and produces better generalizations (Huang et al., 2006). Therefore, it is a promising alternative tool for future TEWS. We applied this method to near-field tsunami predictions of the 2011 Tohoku event, which was recorded at various measurement devices (offshore and onshore) covering the Tohoku and Hokkaido areas. To assess the performance of the proposed method, we compared our results to the standard TWI results and performed rigorous statistical evaluations. Additionally, we also conducted a model uncertainty analysis to ensure the consistency of the method, by determining confidence intervals and observing the variability of several test runs. This last assessment is necessary because, as with any typical neural network methods, the resulting forecasts are subject to uncertainties caused by the random network parameters.

2. Materials and methods

2.1. Tsunami data and bathymetry

This study used tsunami waveforms recorded by four types of measurement devices: ocean bottom pressure (OBP) gauges, global positioning system (GPS) buoys, wave gauges, and tidal gauges. We used data from four OBP gauges: two are deployed off the coast of Iwate (TM1 and TM2) and operated by The University of Tokyo and Tohoku University, and the other two are located off the coast of Tokachi (PG1 and PG2) and are operated by the Japan Agency for Marine-Earth Science and Technology. The other gauges used were six GPS buoys (G801, G802, G803, G804, G806, and G807), six wave gauges (W202, W203, W205, W219, W602, and W613), and three tide gauges (T618, T624, and T625), which are operated by the Ministry of Land, Infrastructure, Transport, and Tourism. The locations of all the gauges are shown in Fig. 1. All the data were pre-processed to remove signals from other sources (i.e., tides and wind waves), and resampled into 15-s intervals.

To generate the synthetic waves used in the forecast algorithm, this study used a numerical simulation with nested grid systems that covers an area between 140–148°E and 35–44°N. The grid size of the model for the offshore stations was 30 arc sec, and 10 arc sec for the coastal gauges. For the larger grid size, we obtained the bathymetry data from the General Bathymetric Chart of the Oceans (GEBCO_08 Grid) provided by the British Oceanographic Data Center. The bathymetry for the smaller grid (10 arc sec) was resampled from the J-EGG500, which is a 500-m gridded bathymetric data set provided by the Japan Oceanographic Data Center. The bathymetry profile for the study area is shown in Fig. 1.

2.2. Tsunami waveform inversion

TWI is based on the principle of linear superposition of unit sources distributed inside the source-influenced area. These unit sources can be represented by either a fault model or an auxiliary basis function. The main goal of conventional TWI is to determine the magnitude of the slip on a fault plane or to infer the initial displacements that excite the tsunami. However, it can also be extended to estimate waveforms outside the inversion time range. Our study used a two-dimensional Gaussian shape (Mulia and Asano, 2015) instead of a fault model to represent the initial water surface deformation. This is more practical for TEWS, because we do not need information about the fault geometry that initiated the earthquake. We distributed equidistant unit sources at 20-km intervals throughout the study area (Fig. 2). Then, for each unit source, the tsunami propagations were computed using the COMCOT model based on the linear shallow water equation (Wang, 2009). The resulting synthetic waveforms were stored for all the

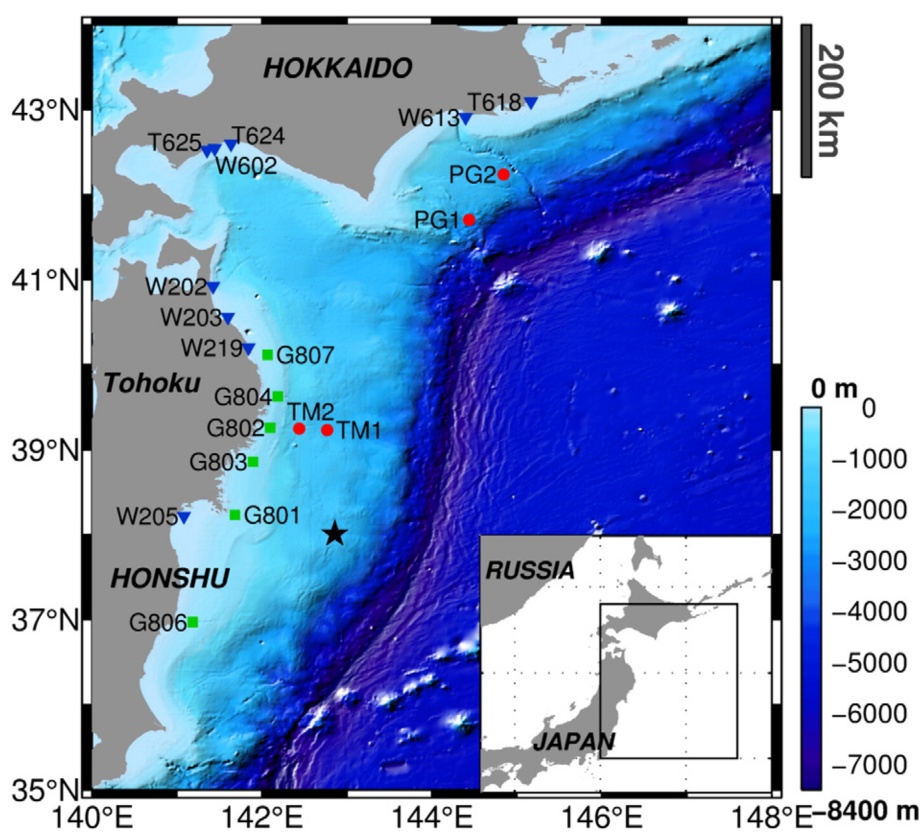

Fig. 1. Bathymetry profile of the study area and gauge locations. The red dots are the OBP gauges, the green squares are the GPS buoys, and the blue triangles are the coastal gauges (T: tide gauges and W: wave gauges). The black star is the epicenter of the 2011 Tohoku earthquake.