



Artificial neural network for tsunami forecasting

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ABSTRACT

This paper presents a data-driven approach for effective and efficient forecasting of tsunami generated by underwater earthquakes. Based on pre-computed tsunami scenarios as training data sets the Artificial Neural Network (ANN) is used for the construction of data-driven forecasting models. The training data comprised spatial values of maximum tsunami heights and tsunami arrival times (snapshots), computed with process-based TUNAMI-N2-NUS model for the most probable ocean floor rupture scenarios. Validation tests demonstrated that with a given earthquake size and location, the ANN method provides accurate and near instantaneous forecasting of the maximum tsunami heights and arrival times for the entire computational domain.

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1. Introduction

Over the past few decades, accurate process-based tsunami propagation models have been developed and thoroughly tested. Most advanced models require significant computational resources at fine grid resolutions; hence, they cannot be used for operational tsunami forecasts due to relatively long computational time required. Accurate and computationally fast data-driven methods are found to be able to mimic pattern of training data sets, which make them ideal for real-time operations. The use of data-driven methods can be extended to replace accurate but computationally demanding process-based tsunami propagation models by means of training data-driven models with a large number of pre-computed tsunami scenarios.

The simplest data-driven tsunami forecast system consists of a database of pre-computed scenarios and a case selection routine with a conventional interpolation algorithm such as those proposed in Whitmore and Sokolowski (1996). In this method, the closest matching event from the database is identified by comparing the pre-computed scenarios with measured wave characteristics near the earthquake epicenter. Other researchers have proposed different approaches such as inversion methods by Wei et al. (2003) and Lee et al. (2005). These methods were constrained by the assumption of the tsunami wave propagation being linear to perform linear superposition of pre-computed data. Barman et al. (2006) used the ANN method in the prediction of the tsunami arrival time in the Indian Ocean. Srivichai et al. (2006) used the general

regression neural network (GRNN) method to forecast tsunami heights. This method allows the application of nonlinear process-based tsunami models to build a database of scenarios, but the application was limited to only a few predefined discrete observation points.

Recently, the Center for Tsunami Research/National Oceanic and Atmospheric Administration (NOAA) has reported exploratory work to use EOF as a tool for tsunami model data analysis Burwell and Weiss (2006), Weiss (2007) and a related application of empirical orthogonal function processing which allows for short-term tidal predictions at tsunami buoy locations with the precision of more advanced methods and with minimal a priori knowledge about tidal dynamics is given by Tolкова (2008).

Wei et al. (2008) outlines NOAA forecasting methodology applying to the August 15, 2007 Peru tsunami. In this method, real-time tsunami data from a deep-ocean tsunami detection buoy were used to produce initial experimental forecasts within two hours of tsunami generation and comparison with real-time tide gage data showed accurate forecasts.

Dao et al. (2008) have developed a POD-based data-driven model for the quick and accurate prediction of maximum wave heights and arrival times of an earthquake-generated tsunami at all grid nodes in the entire domain of interest, provided that the initial location and magnitude of tsunami are given.

In this paper, we present the applications of the ANN technique for a rapid and accurate prediction of maximum wave heights and arrival times for any location in the computation domain without the need to solve the underlying governing partial differential equations (PDE). The well-trained ANN models are able to closely mimic the performance of the nonlinear model TUNAMI-N2-NUS within seconds.

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2. Tsunami propagation model

The tsunami propagation model used in this paper is originated from TUNAMI-N2 which was developed at the Disaster Control Re-

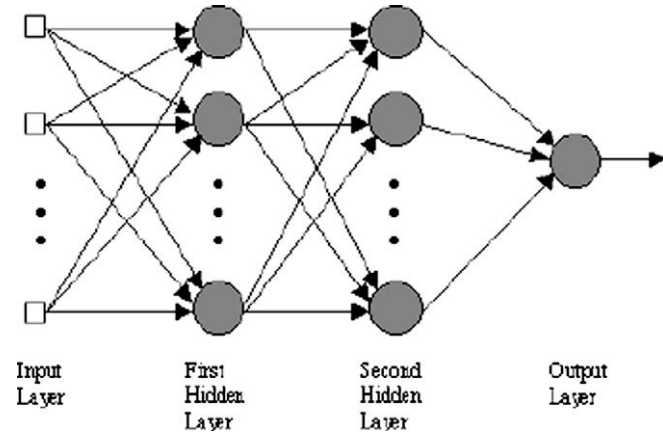


Fig. 1. Schematic diagram of a 2-hidden layer perceptron.

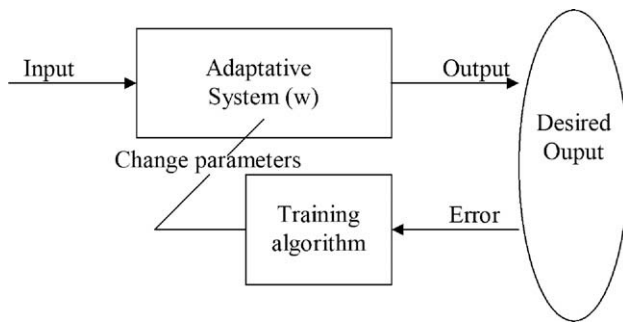


Fig. 2. Schematic diagram of back-propagation ANN.

search Center (Tohoku University, Japan) through the Tsunami Inundation Modeling Exchange (TIME) Program, Goto et al. (1997). TUNAMI-N2 code has been improved by the authors Dao and Tkalich (2007) to capture the effects of Earth's curvature, Coriolis force, and wave dispersion to simulate transoceanic tsunami propagation. The original nonlinear shallow water equation model (NSWE) is reformulated as:

$$\frac{\partial \eta}{\partial t} + \frac{1}{R \cos \phi} \left[\frac{\partial M}{\partial \lambda} + \frac{\partial (N \cos \phi)}{\partial \phi} \right] = 0 \quad (1)$$

$$\begin{aligned} \frac{\partial M}{\partial t} + \frac{1}{R \cos \phi} \frac{\partial}{\partial \lambda} \left(\frac{M^2}{D} \right) + \frac{1}{R} \frac{\partial}{\partial \phi} \left(\frac{MN}{D} \right) + \frac{gD}{R \cos \phi} \frac{\partial \eta}{\partial \lambda} + \frac{\tau_x}{\rho} \\ = (2\omega \sin \phi)N + \frac{gD}{R \cos \phi} \frac{\partial h}{\partial \lambda} + \frac{1}{R \cos \phi} \frac{\partial D\psi}{\partial \lambda} \end{aligned} \quad (2)$$

$$\begin{aligned} \frac{\partial N}{\partial t} + \frac{1}{R \cos \phi} \frac{\partial}{\partial \lambda} \left(\frac{MN}{D} \right) + \frac{1}{R} \frac{\partial}{\partial \phi} \left(\frac{N^2}{D} \right) + \frac{gD}{R} \frac{\partial \eta}{\partial \phi} + \frac{\tau_y}{\rho} \\ = -(2\omega \sin \phi)M + \frac{gD}{R} \frac{\partial h}{\partial \phi} + \frac{1}{R} \frac{\partial D\psi}{\partial \phi} \end{aligned} \quad (3)$$

Here, λ is the longitude and ϕ is the latitude; the radius and the angular velocity of the Earth are given by $R = 6378.137$ km and $\omega = 7.27 \times 10^{-5}$ rad/s, respectively; the total water depth is $D = h + \eta$, where h is the still water depth and η is the sea surface elevation; M and N are the water velocity fluxes in the x- and y-directions; the terms τ_x and τ_y (related to Manning's roughness) represent the bottom friction in the x- and y-directions; ψ is the linear dispersion potential.

The initial condition of a tsunami is prescribed as a static instantaneous elevation of sea level identical to the vertical coseismic displacement of the sea floor, as given by [Mansinha and Smylie \(1971\)](#) for inclined strike-slip and dip-slip faults. Initial sea surface deformation due to multiple and non-simultaneous ruptures is calculated by repeating the fault model of [Mansinha and Smylie \(1971\)](#) for each individual rupture, and the resulting surface deformation is linearly added to the current sea surface. A moving boundary condition is applied for land boundaries to al-

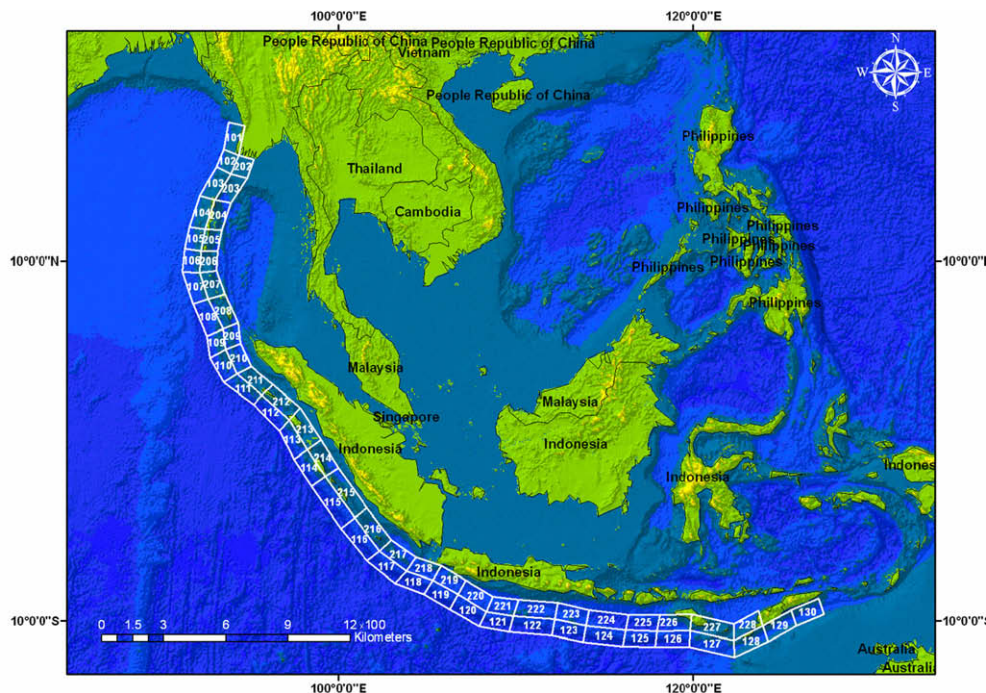


Fig. 3. Segmentation of the Sunda Arc. The entire trench is divided into 30 pairs of boxes.

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