Application of Convolutional Neural Networks to the Evolution of Hydrodynamic Characteristics of Tsunami Waves around Islands and Reefs

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Abstract

Rapid prediction and assessment of tsunamis constitute a critical component of marine disaster prevention efforts, bearing significant implications for marine engineering and the safety of lives and property. This paper develops a hydrodynamic characteristic evolution model for tsunami-like waves over island-reef topography based on a one-dimensional convolutional neural network (1-Dimensional Convolutional Neural Network, CONV1D). By inputting observed values of tsunami-like wave height time-history curves, water level inundation time-history curves at designated locations on the island reef are obtained, thereby achieving time-series-to-time-series prediction for the purpose of marine disaster prevention. The results indicate that the average error in predicting the arrival time of tsunami-like waves is 0.71%, while the average error in predicting the maximum water level height is 6.99%. The hydrodynamic characteristics of tsunami-like waves over island-reef topography obtained by CONV1D exhibit good agreement with numerical results.

Full Text

Application of Convolutional Neural Network Methods in the Evolution of Hydrodynamic Characteristics of Tsunami-like Waves over Fringing Reefs

Abstract

Rapid and accurate tsunami prediction is a critical component of marine disaster prevention, with significant implications for marine engineering and the safety of lives and property. This paper constructs a tsunami-like hydrodynamic characteristic evolution model for reef topography based on a 1-Dimensional Convolutional Neural Network (CONV1D). By inputting observed wave height time series of tsunami-like waves, the model generates water inundation time series curves at specified locations on islands and reefs, achieving time-series-to-time-series prediction for marine disaster prevention. Results show that the average error in predicting the arrival time of tsunami-like waves is 0.71%, while the average error in predicting maximum water level is 6.99%. The hydrodynamic characteristics of island and reef terrains under tsunami-like waves obtained through CONV1D exhibit strong agreement with numerical simulation results.

Keywords: Deep learning, Convolutional neural network, Tsunami prediction, Hydrodynamic characteristics, Time series

The South China Sea represents a crucial element of China's "maritime power" strategic objective, holding paramount significance for national security and economic development. Since 2013, China's development of coral reefs in the region has accelerated, with increasing land reclamation activities at Meiji Reef, Zhubi Reef, and Yongshu Reef (Li et al., 2014; Yao et al., 2019). Situated at the intersection of the Eurasian, Pacific, and Indo-Australian plates, this sea area contains potential tsunami sources including the Manila Trench, Sulu Trench, and Sulawesi Trench. Extreme wave events caused by marine disasters such as storm surges and tsunamis constitute critical factors that engineering construction must consider (Bao, 2005). Early prediction and assessment of natural disasters like tsunamis are essential measures for protecting lives and property.

The China Sea Tsunami Warning Center primarily employs the German SeisComP3 and US Antelope seismic monitoring and processing systems. Traditional tsunami warning methods suffer from technical limitations; the 2011 Tohoku tsunami in Japan resulted in enormous economic losses and casualties due to inadequate disaster assessment (Liu et al., 2015; Xu et al., 2022). This has intensified focus on faster and more accurate tsunami warning methods. Neural networks had previously demonstrated preliminary warning capabilities, and more sophisticated architectures have since been developed. However, traditional neural networks incur prohibitive computational costs when simulating tsunamis due to massive datasets and complex nonlinear processes, making real-time tsunami warning a formidable challenge (Dong et al., 2021; Han et al., 2021).

Rapid advances in computing power have provided the necessary conditions for deep learning development. In 2012, Hinton's team's deep convolutional neural network (CNN) AlexNet (Krizhevsky et al., 2012) first achieved success in image processing, subsequently sparking widespread deep learning research across various fields. For time series problems, Recurrent Neural Networks (RNN) and Long Short-Term Memory networks (LSTM) have been widely applied (Graves, 2012). In 2015, Kiranyaz et al. designed a 1D CNN that classified ECG signals in minimal time, creating a state-of-the-art signal processing application (Kiranyaz et al., 2015). CNN-LSTM hybrid models can address discontinuous data problems (Lu et al., 2019). Makinoshima et al. (2021) distinguished this approach from traditional time prediction methods that infer next-moment data from previous moments (Weng et al., 2023), achieving observation-to-tsunami-inundation time-series-to-time-series prediction that enables immediate and accurate prediction of tsunami inundation time series at specified locations when tsunamis occur.

This paper constructs a time-series-to-time-series 1D CNN tsunami warning model. Using numerical simulation data of tsunami-like wave propagation over reef topography for training, the model accurately predicts time series changes at specific reef flat locations when tsunamis arrive. CONV1D's low computational complexity makes it suitable for real-time, low-cost prediction, providing new approaches for marine environment and engineering research, expanding deep learning applications in marine science, and promoting interdisciplinary development between machine learning and oceanography.

2 Model Validation

Regarding tsunami numerical simulation methods, previous studies have provided many reliable approaches. This paper employs the non-hydrostatic single-phase flow model NHWAVE, using the parameterized tsunami-like waveform proposed by Qu et al. (2017; 2021) to establish a high-precision numerical wave flume for simulating hydrodynamic processes of tsunami-like waves over reef topography. Numerical validation follows Liu et al. (2021). Experimental data originates from the physical wave flume experiments conducted by Roeber et al. (2012) in a tsunami basin. Our 2D numerical wave flume model's computational domain layout is substantially similar to Roeber's physical experimental setup, as shown in [Figure 1: see original paper]. The left computational domain inlet serves as the wave generation boundary, the right outlet as a solid wall boundary, with total length of 50 m, reef front slope of 1:5, reef flat length of 28 m, and 11 water level measurement points (WG01-WG11). The x-direction is the tsunami wave propagation direction with grid size dx=0.05 m; the z-direction is water depth direction with 20 grid layers. The non-hydrostatic model validates impermeable reef physical experiments from Roeber et al. with incident wave height of 0.5 m, water depth of 1 m, reef flat water depth of 0 m, and offshore water depth of 1 m across 14 measurement points.

Validation results are shown in [Figure 2: see original paper]. Comparison demonstrates good agreement between simulation and experimental results.

[Figure 1: see original paper] Computational layout for fringing reef
[Figure 2: see original paper] Time series of water elevation at different wave gauges (H=1.0m)

3 Dataset

[Figure 3: see original paper] shows the schematic diagram of the tsunami-like wave neural network model based on CONV1D. First, NHWAVE performed 117 numerical simulations of tsunami-like wave propagation over reef topography as the CONV1D dataset, including 106 training sets and 11 test sets. Training data serves as learning samples, enabling the model to learn patterns, relationships, and rules from input features for generalization on unseen data. Test sets evaluate machine learning model performance and generalization capability on unseen data. Numerical simulations set different initial tsunami-like wave heights, with minimum wave height 0.20 m and maximum 0.78 m. Test set wave heights were selected at equal intervals: 0.25 m, 0.30 m, 0.35 m, 0.40 m, 0.45 m, 0.50 m, 0.55 m, 0.60 m, 0.65 m, 0.70 m, and 0.75 m, ensuring independence, representativeness, target outputs, and sufficient quantity.

The tsunami-like wave sampling frequency is 0.02 Hz, collecting 16 seconds of hydrodynamic characteristic propagation processes over reef topography. Water level measurements from 10 locations (WG01-WG10) serve as multi-time-series inputs for CONV1D, predicting hydrodynamic characteristic evolution at specified reef location (WG11). Tsunami wave observation durations are divided into five categories: 5 s, 6 s, 7 s, 8 s, and 9 s.

[Figure 3: see original paper] Schematic diagram of the convolutional neural network architecture

4 Network Configuration

CONV1D primarily consists of twelve neural network layers: six 1D convolutional layers, three pooling layers, and three fully connected layers. Each 1D convolutional layer is followed by a Leaky ReLU activation function layer (Maas et al., 2013) with negative slope parameter of 0.01. A random dropout layer before the final fully connected layer uses a dropout rate of 0.5, meaning 50% of features are used for fully connected output during each training iteration to prevent overfitting (Nitish et al., 2014). The convolutional layers use three kernel sizes: 7, 5, and 3, with stride of 1 and padding to maintain sequence length after convolution. After every three convolutional layers, a max pooling layer optimizes feature quantity. For the five observation durations (5 s, 6 s, 7 s, 8 s, and 9 s), only the number of features after convolution differs, with longer observation periods yielding more learning parameters (see).

Mean Squared Error (MSE) between simulated and predicted waveforms serves as the loss function throughout training, with the Adam optimizer (Kingma et al., 2014) minimizing loss by optimizing neural network weights. The learning rate is 0.0002, with other parameters at default values. Model construction uses the PyTorch framework on the Pycharm platform. Training for 8,000 iterations requires approximately 60 minutes using an i9-12900hx processor and RTX 4060 series GPU.

5 Training Results

After CONV1D training, we evaluated the model using 11 numerical simulation results from the test set. shows model parameters and required time for different observation durations, where T represents observation duration, N represents parameter quantity needed for model construction, and TP represents prediction time required. indicates that longer observation times require more parameters. A 1 s increase in observation data adds 25,600 parameters, primarily due to the large size of fully connected layers after convolutional layers, with corresponding increases in training time and prediction time trends, though actual time depends on computational power. Using CONV1D for tsunami assessment requires less than 0.1 s, significantly faster and requiring fewer computational resources than traditional tsunami warning mechanisms and numerical simulation methods. These data demonstrate that CONV1D efficiently generates water level time series curves for reef measurement points, rapidly obtaining tsunami-like wave hydrodynamic characteristic evolution processes for tsunami assessment and prediction. This approach enables real-time monitoring of extreme waves like tsunamis.

Number of parameters and prediction time used for different observation duration models

[Figure 4: see original paper] compares time series results for five observation durations, with initial tsunami-like wave heights of H=0.30 m in (a) and H=0.70 m in (b). Results show that CONV1D predictions under all five observation durations agree well with numerical simulation results. For H=0.30 m waves, WG11 measurement point water level time series curves show better agreement with increasing observation duration. For H=0.70 m waves, increasing observation duration leads to early arrival time and under-prediction of maximum water level, possibly due to overfitting from increased parameters. [Figure 5: see original paper] shows Sum of Squared Errors (SSE) for different observation durations. [Figure 4: see original paper] and [Figure 5: see original paper] indicate small SSE differences across observation duration models, with 5 s observation duration meeting tsunami-like wave hydrodynamic characteristic assessment requirements while demonstrating strong CONV1D stability and generalization capability.

[Figure 4: see original paper] Comparison of neural network prediction results for different observation durations
[Figure 5: see original paper] Sum of squared errors for different observation durations

[Figure 6: see original paper] compares prediction results for different wave heights under 6 s observation duration. As initial tsunami-like wave height increases, measurement point water level time series curves show more distinct features and feature values, yielding higher CONV1D calculation accuracy and better representation of tsunami-like wave hydrodynamic characteristic propagation evolution processes over reef topography.

[Figure 6: see original paper] Comparison of different wave height predictions under a 6-second observation duration

For further model performance evaluation, we analyze two metrics: tsunami-like wave arrival time at reef flat measurement points and maximum water level at those points. Analysis uses the T=6 s model with largest SSE, as shown in , where H represents initial tsunami-like wave height, represents observed time at wg11, represents observed water level at WG11, represents predicted time, represents predicted water level at WG11, and represents time error.

shows maximum water level errors ranging from 2.64% to 14.46%, with average error of 6.99%; arrival time errors range from 0% to 1.709%, with average error of 0.71%. [Figure 7: see original paper] shows scatter plots of maximum water level and arrival time errors for different initial wave heights. Maximum water level errors show larger fluctuations, while time errors show smaller fluctuations with minimal values, both exhibiting regular patterns. and [Figure 7: see original paper] indicate that precisely predicting tsunami-like wave hydrodynamic characteristics remains challenging, requiring more complex CONV1D models, though the model shows high reliability for tsunami arrival time assessment.

Maximum water level and arrival time for different wave heights under a 6-second observation duration
[Figure 7: see original paper] Error in maximum water level and arrival time for different wave heights under a 6-second observation duration

This paper constructs a CONV1D model to predict tsunami-like wave hydrodynamic characteristic evolution over reef topography. Model predictions agree well with numerical simulation results, with consistent performance across different observation durations. Under the largest SSE conditions, the model achieves average maximum water level error of 6.99% and average arrival time error of only 0.71% at specified reef locations. CONV1D requires minimal computational resources while achieving high efficiency, enabling early and accurate wave information acquisition for disaster prevention and protection of lives and property.

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Note: Figure translations are in progress. See original paper for figures.