WaveNet: learning to predict wave height and period from accelerometer data using convolutional neural network

Tong Liu¹, Yongle Zhang¹, Lin Qi*, Junyu Dong¹, Mingdong Lv², and Qi Wen²

1 Ocean University of China, Qingdao, China
2 Haiyan Electronics Co Ltd, Qingdao, China
E-mail: qilin@ouc.edu.cn

Abstract. Inertial sensors carried by buoys, such as accelerometers, are widely used in wave characteristics measurement. Traditional methods usually employ numerical integration on the accelerate data for wave height, where the “drifting” errors are intractable. In this paper we propose a novel method to predict wave height and period using machine learning approach, specially a convolutional neural network. The end-to-end 1D convolutional neural network named WaveNet predicts wave height and period from the raw acceleration data directly. We designed a simple device to simulate the motion of the buoy in the wave, and used it to collect data for training and testing our model. The results of the proposed method were compared with traditional numerical integration method and found that the proposed model outperforms existing method in outputting more accurate wave height and period.

1. Introduction

Wave characteristics are important in oceanography and coastal engineering research, such as wave energy exploitation, sediment movement measurements, port design and soil erosion. Traditionally, there are two kinds of method in wave prediction. One is based on the numerical model of wave generation and dissipation physical process. The development and research are carried out on the basis of wave theory, such as SWAN [1], [2], WAM [3], [4], Wave Watch III [5]. Recently, researchers have shown an increased interest in data-driven method for wave prediction, which is based on previous empirical models of real-time or quasi-real-time data for meteorological, wave data or online buoy[6], [7]. These methods include neural networks[8], [9], [10], [11], time series models, genetic algorithms[12], [13], [14], support vector machines[15], Decision tree [16] and model combining numerical model with neural network[17], [18], etc. The former kind of method is often used in regional prediction [19] while the later one is mainly used for point forecasting. Atmospheric modes and wave numerical models need to solve complex physical equations, and the computational cost is large. The data-driven model uses the buoy online monitoring data for real-time updating. It is based on the analysis and research of different state parameters, which can be used to solve the nonlinear function problem of numerical prediction. Recently, with the construction of online buoy monitoring networks, researchers have shown an increased interest in data-driven model predictions.

However, in a series of models for wave prediction based on data-driven patterns, most of the research data focus on past meteorological and wave data. These wave data used in experimental research is usually needed to calculate from the complex numerical model. For example, a wave height prediction model based on a data-driven pattern uses wave height values from previous period of time to predict the wave height values for the next period of time.
In the numerical model, the majority of surface deployed wave buoys use three dimensional acceleration signals processed using a double integration method to derive wave statistics. Such marine instruments are highly accurate but can be prohibitively expensive in terms of the initial purchasing, deployment/retrieval costs and servicing. Field measurements of wave parameters are typically derived using either pressure sensors, wave radar, acoustic sensors or motion sensing wave buoys. Wave buoys derive wave statistics by tracking the surface of the water using accelerometers.

Recently, deep learning methods have received amazing success in pattern recognition and machine learning application domains due to their outstanding capability to learn complex and robust representations. Convolutional networks, also known as CNNs, are a specialized kind of network for processing data that has a known grid-like topology. Examples include time-series data, which can be thought of as 1D grid taking samples at regular time intervals, and image data, which can be thought of a 2D grid of pixels. They have been shown to produce state-of-the-art results in image processing, computer vision [23] and speech recognition [24]. In recent years, CNNs have been successfully applied to NLP and document classification problems[25][26]. The input to CNNs is a feature map which corresponds to the pixels in an image or words in a sentence or document, or characters in words. This feature map is scanned in CNNs one area at a time by filters, assuming that filters slide, or convolve, around the feature map. The way CNNs adjust their filter weights is through back propagation, which means that after the forward pass, the network is able to look at the loss function and make a backward pass to update the weights. The CNN layer is followed by a pooling layer that compresses or generalizes over the CNN representations. It reduces the dimensionality of the CNN layer by down sampling the output and taking the maximum value as the feature corresponding to each filter. The pooling layer is typically followed by a feed-forward fully connected layer that takes the features from the pooling layer and makes new combinations for further learning or final predictions.

For some sequence processing problems, one-dimensional convolutional neural networks has excellent performance and the computational cost is usually much smaller. Recently, one-dimensional convolutional neural networks have achieved great success in the fields of audio generation and machine translation. In addition to these specific achievements, one-dimensional convolutional neural networks can apply to these tasks such as text classification and time series prediction with fast speed. One-dimensional convolution can extract local one-dimensional sequence segments from the sequence and identify local patterns in the sequence. Since the same input transformation is performed for each sequence segment, the patterns learned at a certain position in the sentence can be identified at other locations, which makes the one-dimensional convolutional neural network have translation invariance. Moreover, the sequence data can be subjected to a one-dimensional pooling operation, extracting a sequence segment from the input, and then outputting its maximum value or average value. Like the two-dimensional convolutional neural network, this operation is also used to reduce the length of a one-dimensional input.

This paper explore the use of machine learning method to predict wave characteristics from sensor data. Since we are not sure whether the accelerometer is accurate in real sea conditions, it is likely that the data collected will not be accurate when the equipment is directly applied to the real sea conditions. In order to measure and correct the accuracy of sensor equipment, we have designed a specific device to simulate the buoy in the wave. We therefore can judge and correct the accuracy of accelerometers and can access more accurate and realistic data to carry out a series of research in the real experimental environment. Based on these data, we propose an end-to-end convolutional neural network named WaveNet to process the obtained sensor data and predict wave height and period. The study found that the WaveNet model outperforms numerical integration method in our experiment.

2. Data acquisition and preprocessing

2.1. Data acquisition
According to the stochastic wave spectrum theory[20][21], waves are random because of the random changes in wind speed and pressure relative to position and time. Waves have random properties which are composed of many waves with different amplitude, frequency and phase, so we can use waveform curves to simulate the motion process of the buoy.

As shown in the Figure 1, the device simulates the movement of a buoy on the sea surface. the wave height equals twice of the distance R. After the device rotating, the acceleration sensor in the outputs a periodic acceleration signal moving, and a series of discrete vertical acceleration signals are collected through a certain sampling frequency to estimate the motion trajectory. By adjusting the distance between accelerator and the center of the rod and setting different periodic values, we can get multiple sets of data with different height values and period values. We use the data for research in the next experiment.

2.2. Data preprocessing

Data preprocessing are needed before feeding the data into the convolutional neural network for training or testing. Given the raw three-axis accelerometer data, we first calculate the projected components on the vertical direction to the sea surface in the geographic coordinate system using the deflection angles.

We calculated the displacement by twice integrating the acceleration data. Then we used the cross-zero point to calculate the wave period and height. By comparing them with the ground truth, we can test the accuracy of methods. We also use these acceleration data to train the model and predict wave characteristics.

In the training data processing stage, we sampled the acceleration sequence data to compose training data. Each group of training data is 2048 continuous acceleration values, which belongs to one piece of an entire acceleration sequence data. After that we can form the final training data combined the sampled acceleration series data with the corresponding wave height value and periodic value.

3. Methodology

3.1 Numerical integration

Numerical integration was used to estimate the vertical movement of the buoy[22]. The zero-crossing point was used to locate the peak and trough. The average value of wave height and period can then be calculated.
3.2 Proposed Convolutional networks-WaveNet

As shown in Figure 2, Convolutional neural networks are selected here due to their capability to learning hierarchical representations. Especially, the input dimension of the samples is 2048 and output are height and period. We implemented WaveNet model using Keras based on Google Tensorflow. All experiments are conducted on a computer equipped with a NVIDIA GPU 8G.

3.3 Training methodology

After the data processing stage, we obtained the training data suitable for the model. In general, in order to evaluate the network while adjusting network parameters, we can divide the data into training sets and verification sets, but since the data points are few data points, the verification set is very small. Therefore, the verification score may fluctuate greatly depending on the verification set and test set selected. That is to say, the way the verification set is divided may result in a large variance in the verification score, so that the model cannot be reliably evaluated. Therefore, we can use the K-fold cross-validation to evaluate the model. In addition, after we divide the training data into a training set and a test set, the test set must not be used. Instead, the test set is used to test the performance of the model after adjusting various network parameters. As the neural network performs better on the training data, the model maybe overfitting and gets worse results on previously unseen data. Therefore an effective overfitting strategy is necessary. Deep learning model does not process the entire data set at the same time, but splits the data into small batches. We use these import strategies in our proposed model.

The specific training details of WaveNet model are as follows:
- Use BatchNorm to speed up the network learning rate
- Each layer uses the ReLu activation function in addition to the final output layer
- Optimize network parameters using the MSE loss function
- We take the ADAM stochastic optimization algorithm as the training algorithm
- Learning rate can use the default learning rate
- The batch size of the network training is 128
- Two-layer fully connected network in the Dense layer uses l2 regularization
- The value used in the dropout layer is 0.5
- We use five-fold cross validation to test the accuracy of the algorithm
- The early stopping strategy is used
- The number of iterations for the entire network on the training set is 200

4. Result and discussion

4.1 Evaluation metrics

We evaluated the performance of WaveNet using the mean absolute error (MAE) and the mean square error (MSE), which have been widely used. The smaller value, better performance.
4.2. Result and discussion

As shown in Table 1, the experimental results show that the performance of WaveNet on the MAE is 0.1537, and the MSE is 0.1948. The MAE and MSE indicate the overall difference between the ground truth and the WaveNet prediction. It was suggested that the WaveNet model has better performance.

In the experiment, we use the correlation graph to compare the WaveNet prediction and the ground truth. As can be seen from Figure 3, the correlation coefficient between the true height and the height predicted by WaveNet is 0.97, the correlation coefficient between the true period and the period predicted by WaveNet is 0.99. The results show that prediction by WaveNet have a very strong correlation with the truth.

In the experiment, we set the height and period values using the device and collected corresponding experimental data. As shown in Figure 4, the velocity and displacement sequences are recovered by the numerical integration method using the acceleration. We chose ten groups of different data for comparison. Table 2 show several sets of comparison values, including the ground truth, numerical integration results and WaveNet predictions.

![Table 1. Evaluation metric of WaveNet](image)

|       | MAE  | MSE  |
|-------|------|------|
| WaveNet | 0.1537 | 0.1948 |

As shown in Table 1, the experimental results show that the performance of WaveNet on the MAE is 0.1537, and the the MSE is 0.1948. The MAE and MSE indicate the overall difference between the ground truth and the WaveNet prediction. It was suggested that the WaveNet model has better performance.

In the experiment, we use the correlation graph to compare the WaveNet prediction and the ground truth. As can be seen from Figure 3, the correlation coefficient between the true height and the height predicted by WaveNet is 0.97, the correlation coefficient between the true period and the period predicted by WaveNet is 0.99. The results show that prediction by WaveNet have a very strong correlation with the truth.

In the experiment, we set the height and period values using the device and collected corresponding experimental data. As shown in Figure 4, the velocity and displacement sequences are recovered by the numerical integration method using the acceleration. We chose ten groups of different data for comparison. Table 2 show several sets of comparison values, including the ground truth, numerical integration results and WaveNet predictions.

![Figure 3. The correlation between and the truth and the predicted results using WaveNet](image)
Figure 4. The velocity (2nd row) and the distance (1st row) recovered by numerical integration of the acceleration (3rd row). The ground truth wave height and the period is set to be 1.5m and 15s respectively on the device.

Table 2. Several sets of comparison results, including the ground truth, numerical integration results and WaveNet predictions.

| Test No. | Wave Height (H) and Period (T) | Ground Truth | Numerical Integration | WaveNet |
|----------|--------------------------------|--------------|-----------------------|---------|
| 01       | H(m) 1.5                         | 1.44         |                       | 1.458   |
|          | T(s) 15                          | 14.41        |                       | 15.27   |
| 02       | H(m) 1.2                         | 1.12         |                       | 1.2     |
|          | T(s) 15                          | 13.88        |                       | 14.55   |
| 03       | H(m) 1.0                         | 1.04         |                       | 0.96    |
|          | T(s) 15                          | 10.07        |                       | 14.68   |
| 04       | H(m) 1.2                         | 1.22         |                       | 1.15    |
|          | T(s) 14                          | 14.53        |                       | 13.88   |
| 05       | H(m) 1.1                         | 1.09         |                       | 1.11    |
|          | T(s) 12                          | 14.41        |                       | 12.01   |
| 06       | H(m) 1.5                         | 1.56         |                       | 1.39    |
|     |   T(s)   | H(m) |   T(s)   | H(m) |
|-----|----------|------|----------|------|
| 07  | 10       | 1.0  | 10.19    | 1.02 |
|     |          |      | 10.05    | 1.15 |
| 08  | 10       | 1.0  | 10.12    | 0.86 |
|     |          |      | 10.08    | 0.93 |
| 09  | 5        | 1.0  | 7.52     | 1.03 |
|     |          |      | 6.11     | 1.05 |
| 10  | 6        | 1.5  | 6.23     | 1.52 |
|     |          |      | 6.08     | 1.48 |
|     | 4        | 1.5  | 4.00     | 3.96 |

5. Conclusion
In this paper, an end-to-end 1D Convolutional network WaveNet was proposed to predict wave height and period from accelerometer data of a buoy. We designed a device to simulate the movement of a buoy on the sea surface and collected accelerometer data with different wave characteristics. Experiments show that the WaveNet successfully learns the wave pattern and outperforms traditional numerical integration method. Due to practical constraints, we didn’t test with data from real conditions, which would be the future work.

6. References
[1]. Ou S-H, Liau J-M, Hsu T-W and Tzang S-Y 2002 Simulating Typhoon Waves by SWAN Wave Model in Coastal Waters of Taiwan Ocean Eng 29 947-971.
[2]. Rogers W E, Kailhatu J M, Hsu L, Jensen R E, Dykes J D and Holland K T 2007 Forecasting and Hindcasting Waves with the SWAN Model in the Southern California Bight Coastal Eng 54 1-15.
[3]. Hersbach H, Janssen P A E M 1999 Improvement of the short-fetch behavior in the Wave Ocean Model (WAM) Journal of Atmospheric and Oceanic Technology 16 884-892
[4]. Monbaliu J, Padilla-Hernández R, Hargreaves J C, Albiach J C C, Luo W, Sclavo M and Günther H 2000 The spectral wave model, WAM, adapted for applications with high spatial resolution Coastal Engineering 41 41–62
[5]. Mentaschi L, Besio G, Cassola F, and Mazzino A 2015 Performance evaluation of Wavewatch III in the Mediterranean Sea Ocean Modelling 90 82–94
[6]. Mahjoobi J, Etemad-Shahidi A and Kazeminezhad M H 2008 Hindcasting of wave parameters using different soft computing methods Ocean Res 30 28–36
[7]. Agrawal J D and Deo M C 2002 On-line wave prediction Marine Structures 15 57–74
[8]. Deo M C, Jha A, Chaphekar A S and Ravikant K 2001 Neural networks for wave forecasting Ocean Engineering 28 889–898
[9]. Gunaydın K 2008 The estimation of monthly mean significant wave heights by using artificial neural network and regression methods Ocean Engineering 35 1406–1415
[10]. Deo M C and Naidu C.S 1999 Real time wave forecasting using neural networks Ocean Eng 26 191–203.
[11]. Londhe S N and Panchang V 2006 One-day wave forecasts based on artificial neural networks Journal of Atmospheric and Oceanic Technology 23 1593–1603.
[12]. Zanaganeh M, Mousavi S J and Etemad-Shahidi A 2009 A hybrid genetic algorithm–adaptive network-based fuzzy inference system in prediction of wave parameters Engineering Applications of Artificial Intelligence 22 1194–1202
[13]. Canellas B, Balle S and Tintore J and Orfīla A 2010 Wave height prediction in the western mediterranean using genetic algorithms Ocean Engineering 37 742–748
[14]. Nitsure S P, Londhe S N and Khare K C 2012 Wave forecasts using wind information and genetic programming Ocean Eng 54 61–69.
[15]. Mahjoobi J, Mosabbeb E A 2009 Prediction of significant wave height using regressive support vector machines Ocean Engineering 36 339–347
[16]. Mahjoobi J and Etemad-Shahidi A 2008 An alternative approach for prediction of significant wave height based on classification and regression trees Applied Ocean Research 30 172-177
[17]. O'Donncha F, Zhang Y, Chen B and James S C 2018 An integrated framework that combines machine learning and numerical models to improve wave-condition forecasts Journal of Marine Systems 186 29–36
[18]. Berbić J, Ocvirk E, Carević D and Lončar G 2017 Application of neural networks and support vector machine for significant wave height prediction Oceanologia 59 331–349
[19]. kumar N K, Savitha R and Mamun A A 2017 Regional ocean wave height prediction using sequential learning neural networks Ocean Engineering 129 605–612
[20]. Massel S R 1996 Ocean surface waves: their physics and prediction Advanced Series on Ocean Engineering
[21]. Thomas T J and Dwarakish G S 2015 Numerical wave modelling – a review Aquatic Procedia 4 443–448.
[22]. Massel S R 2001 Wavelet analysis for processing of ocean surface wave records Ocean Engineering 28 957–987
[23]. Krizhevsky A, Sutskever I and Hinton G E 2017 ImageNet classification with deep convolutional neural networks Communications of the ACM 60 84-90
[24]. Graves A, Mohamed A and Hinton G 2013 Speech recognition with deep recurrent neural networks IEEE International Conference on Acoustics, Speech and Signal Processing
[25]. Kim Y 2014 Convolutional Neural Networks for Sentence Classification Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP)
[26]. Johnson R and Zhang T 2015 Effective Use of Word Order for Text Categorization with Convolutional Neural Networks Proceedings of the 2015 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies