Improving deterministic pitch motions estimation using bivariate sequential wave input

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Abstract. As the ship navigates through waves, it will sway continuously with six degrees of freedom, which will adversely affect the offshore operations. Accurate real-time estimation of deterministic ship motions under wave excitation is a key to ship motion prediction and assistance decision-making. In the actual marine environment, ocean waves and ship motions are often nonlinear. Therefore, an effective nonlinear estimation model to accurately estimate the real-time response of the wave-induced ship motions is of great concern. Due to its unique advantages in dealing with nonlinear time series, Long Short-Term Memory network can provide a powerful method for the estimation of nonlinear wave-induced ship motions. Pitch motions as an oscillating motion put forward higher requirements for model input. Based on the Long Short-Term Memory network model using the wave time history information as input to estimate the ship pitch motion, this paper proposes a pitch estimation model received a bivariate sequential wave time series as input. With the use of the nonlinear wave generated by numerical simulation and the corresponding ship motion time history data, the feasibility of the new model is verified and compared with the corresponding single-point sequential wave input model, determined its superiority.

1. Introduction
In the actual marine environment, considering the influence of environmental factors such as ocean wind, wave and flow, the ship will continuously produce movements with six degrees of freedom. These ship motions pose serious threats to offshore operations such as aircraft take-off and landing, ship motion control, etc., especially in high sea conditions. Rapid and accurate estimation of the deterministic wave-induced ship motions, and prediction of ship motion state in a future wave (very short-term forecast), thus assisting the ship to make corresponding control decisions, will greatly improve the ship's navigation and offshore operation.

In order to improve the safety of operations and reduce the accident rate, many countries are vigorously carrying out research on ship motion prediction method. The ship motion prediction problem can be divided into long-term forecast (several years), shorter forecast (hours) and extremely short-term forecast (several seconds) according to the length of the prediction. For the actual operational requirements of the offshore operation in the waves, it is often necessary to estimate the ship motion state in a few seconds or tens of seconds in real time. Therefore, the ship motion estimation usually needs to be real-time and accurate in a short period of time.

The ship motion extremely short-term prediction models usually require real-time access to the ship motion posture, forecasting future motions and uses the results for the operation guidance and
compensation control of special offshore operations. Therefore, real-time fast estimation of ship motion is an important prerequisite.

At present, the real-time estimation method of ship motions is mostly based on the response amplitude-frequency operator (RAO) of ship motions and input wave spectrum. This method is called Hydrodynamic Transfer Function (HTF) model. However, the traditional RAO algorithm cannot deal with the nonlinear motion response, which makes it difficult to obtain accurate estimations of ship motion in medium and high sea conditions. Correspondingly, as a typical nonlinear method, neural networks have unique advantages in dealing with nonlinear problems.

Along with the rapid development of deep learning technology in recent years, many people have introduced this technology into different fields to solve problems that cannot be solved by traditional methods. Since the Recurrent Neural Network (RNN) introduced the concept of time memory into deep learning technology, more and more people have been using RNN and its various variants to deal with serialization problems, including nature language processing\textsuperscript{[1]} and the forecasting of financial stock price\textsuperscript{[2]}. And in the field of engineering applications, the typical problems solved by RNN model are traffic flow forecasting\textsuperscript{[3][4][5]} and wind forecasting\textsuperscript{[6]}. The Recurrent Neural Network method has gradually gained more and more attention and achieved good results in dealing with all kinds of problems. As one of the most commonly used variants of the RNN model, the LSTM model avoids the exploding gradient and vanishing gradient that often occur in traditional RNNs by introducing gate structures\textsuperscript{[7][8]}. In terms of real-time estimation of deterministic wave-induced ship motions, Duan et al. proposed a deterministic wave-induced ship motions estimation model based on Long Short-Term Memory networks. The model accepts the wave time history at the centre of gravity of the ship as input and maps it to the current motion state of the ship. The model achieves good results in estimating heave, but poor results in estimating pitch.

In response to this problem, this paper innovatively proposes a bivariate sequential wave inputs model that accepts the wave time series of two points symmetric to the centre of gravity of the ship as input. The model uses the two features wave time series as input with a single LSTM layer. In this paper, the ship pitch estimations of the model are compared with the results of the single-point wave input LSTM model, and the superiority of the method is verified.

2. Methodology for LSTM deep learning network

RNN is a type of deep learning network specifically for sequence analysis, which has significant advantages over traditional neural networks in nonlinear time series prediction. In the RNN network training, the hidden layer needs to be expended to a multi-layer feedforward neural network with parameter sharing on the timeline, and the time-steps of the input time series information correspond to the number of layers to be expanded. Too many layers of memory could affect the speed of training to a certain extent, and cause exploding gradient and vanishing gradient problems. This may cause the RNN model to fail to remember long-term input time series information. In response to this problem, some scholars have proposed a Long Short-Term Memory network architecture. This is a new network architecture based on RNN. LSTM establishes a time lag between input and feedback by setting input gates, forgetting gates and output gates. These gates can avoid exploding gradient and vanishing gradient problems and effectively improve the memory of deep learning networks.

For a given time-series $x$, based on standard RNN neuron structure (as shown in Figure 1), the iterative formula is used to get the neuronal status sequence $h$ and output sequence $y$. As equation (1) and equation (2) show:

$$h_n = \sigma(W_{sk}x_n + W_{sh}h_{n-1} + b_s) \tag{1}$$

$$y_n = W_{ly}h_n + b_y \tag{2}$$

$W$ is the weight coefficient matrix, $b$ is the offset vector, $\sigma$ is the activation function.
The LSTM model replaces the RNN neurons in hidden layer with LSTM neurons, empowering the model for long-term memory. The most widely used LSTM model structure is shown in Figure 2.

In this structure, $i, f, o, c$ sequentially represents the input gate, the forgetting gate, the output gate and the cell state, where $tanh$ is the hyperbolic tangent activation function. The input gate, the forgetting gate, and the output gate are shown as equations (3)(4)(5):

$$ i_n = \sigma(W_i x_n + W_f h_{n-1} + b_i) $$  \hspace{1cm} (3)  

$$ f_n = \sigma(W_i x_n + W_f h_{n-1} + b_f) $$  \hspace{1cm} (4)  

$$ o_n = \sigma(W_o x_n + W_o h_{n-1} + b_o) $$  \hspace{1cm} (5)  

For LSTM neuron status $c$, it is shown in equation (6)

$$ c_n = f_n c_{n-1} + i_n \tanh(W_c x_n + W_c h_{n-1} + b_c) $$  \hspace{1cm} (6)  

For LSTM neuron output $h$ and $y$, they are shown in equations (7) and (8):

$$ h_n = o_n \tanh(c_n) $$  \hspace{1cm} (7)  

$$ y_n = \phi(W_o x_n + b_o) $$  \hspace{1cm} (8)  

$W$ is the weight coefficient matrix, $b$ is the offset vector, $\sigma$ is the activation function.

3. Results and discussion

3.1 Brief descriptions of the nonlinear ship motions

The models use the C11 ship's numerical simulation data at zero speed in the four-level, five-level and six-level sea states\textsuperscript{9}\textsuperscript{-10}. The data length is 9500s and the sampling interval is 0.5s, last 500s data is divided into test set. We used the root mean square error of the test sets to measure the prediction accuracy of the model. In Table 1, the main scale of C11 ship was given. Moreover, in Figure 3, the pitch motion curve of the ship under four-level sea condition was provided.

| Item     | Value       | Item     | Value      |
|----------|-------------|----------|------------|
| $L_{pp}$ | 262(m)      | $X_{CG}$ | 5.7681(m)  |
| Breadth  | 40(m)       | $K_G$    | 18.4358(m) |
| $C_{block}$ | 0.5657     | $K_{yy}$ | 0.24 $L_{pp}$ (m) |
| Draught  | 11.8(m)     | $K_{xx}$ | 0.38 Breadth (m) |
| Drainage | 69957.96(ton)| $GM$    | 1.9(m)     |

Table 1. Main scale of the C11
3.2 Estimation results under different sea conditions

We estimated the pitch motion of the ship by using a single-point sequential wave input model and a bivariate wave input model, compared the prediction results obtained by the two methods under different sea states. Both methods use LSTM models with the same network parameters. They all have a hidden layer which has sixteen LSTM neurons. LSTM neurons in the hidden layer use the hyperbolic tangent function as an activation function, and the activation function of the output layer is set as linear. We used Adam as the optimizer, and set its parameters to learning-rate = 0.1, beta_1 = 0.9, beta_2 = 0.999, and epsilon = 1×10-8.

For different sea conditions, we used time series with different input time-steps as input. In the LSTM model for ship pitch estimate under four-level sea state, five-level sea state and six-level sea state, the time-steps are 80, 65 and 60.

We used two methods to train the ship's pitch calculation model under four-level sea condition, five-level sea state and six-level sea state. These models were applied to the corresponding ship pitch estimate and compared with the true value of the numerical simulation.

In Table 2, the RMSE between all calculated values and the corresponding real values is given to measure the accuracy of the model.

In Figures 4-6, the pitch estimation results of two LSTM models with different input characteristics under different sea conditions are given. In these figures, the solid line represents the numerical simulation data, the dash line with circle and the dash line with triangle are the data solved by the Single-point sequential wave input model and bivariate sequential wave input model.

| Sea states | Single-point Input Model | Bivariate Input Model |
|------------|--------------------------|-----------------------|
| Level 4    | 0.0197                   | 0.0114                |
| Level 5    | 0.0409                   | 0.0250                |
| Level 6    | 0.0603                   | 0.0308                |

Figure 4. Estimation results of pitch under four-level sea condition.
There is little phase deviation among those curves in the picture, which means both models can grasp the trend of motion very well when calculating the ship’s pitch. However, in terms of the magnitude of the motion signal, we found that the bivariate sequential wave input model always performs better. Especially in the non-stationary part of the ship’s motion signal, the motion values calculated by the single-points wave input model tend to deviate from the actual values. And the calculation results in the Table 2 also show a clear difference. In all sea conditions, the RMSE between the results of the bivariate sequential wave input model and true value is significantly lower than it between the result of the single-point wave input model and true value, the former is almost half of the latter. It indicates that for the calculation of the amount of rotation, creating complete mapping directly using only the wave input at the axis of rotation is difficult. Therefore, it is necessary to have multiple inputs that are symmetrical about the axis of rotation.

4. Concluding Remarks
Deep learning neural networks have unique advantages in dealing with the nonlinear problem. The LSTM model provides a viable calculation method for deterministic wave-induced ship motions. As a highly sensitive statistical learning method, the correct design of the model structure of deep learning is crucial. At the same time, the method hopes to establish a mapping between input and output by learning the statistical characteristics of the data in the training sets. Therefore, using the right input is critical in building a useful model.

In the traditional linear method, the ship motion in each degree of freedom is usually calculated based on the wave at the centre of gravity. It seems reasonable that we use the wave at the centre of gravity as the input to the LSTM estimation model of ship pitch motion. However, it was found that using two points of the wave as input can significantly improve the ship pitch motion calculation results. Therefore, we have reasons to believe that non-barycentre wave information is also of great value to rotational motion.

In summary, this paper proposed a calculation model for the pitch of a ship based on bivariate sequential wave inputs and verified its accuracy. This new model provides a promising approach to the calculation of ship pitch motion.
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