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An improved particle swarm optimization algorithm applied to long short-term memory neural network for ship motion attitude prediction

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Abstract

This paper proposes a prediction method of ship motion attitude with high accuracy based on the long short-term memory neural network. The model parameters should be initialized randomly, resulting in critical decreases of the nonlinear learning ability of current parameter optimization methods. Therefore, a multilayer heterogeneous particle swarm optimization is proposed to optimize the parameters of long short-term memory neural network and applied to the prediction of ship motion. In multilayer heterogeneous particle swarm optimization, this paper proposes the concept of attractors, transforms the speed update equation, enhances the information interaction ability between particles, improves the optimization performance of the particle swarm optimization algorithm, and improves its optimization effect on the parameters of the long short-term memory networks. In the simulations, the measured data were used as input to predict the results of the ship motion. The results showed that the proposed method offers higher learning accuracy, faster convergence speed, and better prediction performance for accurate estimation of ship motion attitude than existing methods.

Keywords

Ship motion attitude prediction, long short-term memory neural network, multilayer heterogeneous particle swarm optimization, attractor, prediction accuracy

Introduction

Ship sailing affected by wind, sea waves, and ocean current encompasses random and complex movements, such as roll, pitch, heave, yaw, sway, and surge motions. These six degrees of freedom – especially roll, pitch, and heave – largely determine the seaworthiness of a ship. For instance, if the ship sails at high speed during heavy wind, severe heaving, and pitching motions likely cause serious slamming, which poses a major threat to critical marine operations of the ship. The prediction of ship motion plays an invaluable role in reducing the occurrence of such accidents. If ship motion is predicted in advance, it could allow the operator to avoid major accidents and thus bring great benefits to the carrier aircraft take-off and landing, shipborne missile launch, and submersible movement. Therefore, short-term estimation of ship motion is essential for marine safety.

The commonly used prediction methods for ship motion include time series method (Guo et al., 2017), gray prediction method (Zeng and Liu, 2017) and neural network method (Yang et al., 2017). The time series method is generally applicable to short-term prediction, and when there is external interference, the prediction bias could be large. Although the traditional gray prediction method requires less information and has a simple operation, it offers poor accuracy for prediction of stable sequences, making it unsuitable for studying large samples. The neural network has self-learning and self-adaptation capabilities; thus, it is widely used in the study of nonlinear systems by training the adjusted weights and structures. Song et al. (2018) proposed an autoregressive model to predict ship motion attitude. Duan et al. (2015) applied the ARMA model to predict ship motion attitude and discussed in detail the influence of each parameter in the model on the prediction results. The input delay neural network was proposed by Wang, Soltani et al. (2017) to analyze and predict the characteristics of ship motion attitude. In the simulation, the method has higher accuracy and less prediction error. However, due to its weak generalization ability, the prediction accuracy still fails to meet the needs of practical applications.

As a deep learning model, long short-term memory (LSTM) neural network (Hochreiter and Schmidhuber, 1997) could accurately learn the influence and relationship between time series by learning past data and deeply investigate the inherent laws of time series by using the selective memory ability of machine learning; thus, further implementing short-term time series prediction. However, the LSTM network

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parameters should be randomly initialized before training the network model, making the network biased toward local extreme points that affect the nonlinear learning ability of the model. The existing methods for optimizing the LSTM network aimed to improve related parameters, such as the error function and the excitation function (Kim et al., 2018; Liu et al., 2018), or they used the intelligent algorithm to optimize the initial parameters of the network (Elsaid, et al., 2017; Gu et al., 2017; Moalla et al., 2017; Troiano et al., 2018). But in the PSO algorithm, the particles tend to concentrate near the global best and gradually lose speed in the late search. However, when the speed is zero, the particles fail to continuously search for excellence, leading to the group falling into local optimum. Various approaches have been proposed to solve this problem (Esmaeil et al., 2019; Tian et al., 2018; Zhou et al., 2019). Mohan and Albert (2017) proposed an improved particle swarm optimization (PSO) algorithm that prevents premature convergence by allowing particles to move closer to particles with better fitness values, rather than just moving toward particles at the optimal position. Nicholas et al. (2017) proposed two improved methods for standard PSO by introducing a new parameter. Wang, Cui et al. (2017) proposed a hybrid PSO algorithm named DNSPSO. The algorithm mainly used diversified enhancement mechanisms and neighborhood search strategies to avoid falling into local optimum. Based on self-organizing layered PSO with time-varying acceleration coefficient (HPSO-TVAC), Ghasemi et al. (2017) proposed a new type of optimization approach in which the algorithm is easy to converge to the local optimal solution. The simulation results showed that the algorithm resulted in better optimization solutions. Nobile et al. (2017) proposed an adaptive adjustment PSO (FST-PSO). This algorithm mainly used fuzzy logic (FL) for calculating the initial parameters of each particle in the particle swarm to achieve the adaptive adjustment of PSO. The novelty of the algorithm is that it does not require any empirical knowledge, and the behavior of each particle in the particle swarm is automatically and dynamically adjusted during the optimization process. This paper introduces a new group structure and speed update strategy to solve the problem of premature convergence and improve the performance of the PSO algorithm.

The accurate prediction of ship motion attitude is very important for the safe navigation of ships. To improve the prediction accuracy, an improved PSO algorithm (MHPSO) and a prediction model (MHPSO-LSTM) that combines with LSTM are proposed. Here, we present a multilayer heterogeneous particle swarm optimization (MHPSO) algorithm with hierarchical ring topology to improve the performance of PSO for a more accurate prediction of ship motion attitude. Firstly, the particle swarm population structure was set as a hierarchical ring topology, and the concept of attracting particles was proposed. By using the attracting particles to transform the speed update equation of the attractive ability of the particles, the ability of information interaction between the particles as well as the global optimization ability and convergence speed of PSO were enhanced. Then, by combining it with the LSTM neural network, a new model of the MHPSO-LSTM was constructed. Different from the traditional fully connected neural network, the LSTM network avoids gradient disappearance and has the ability to remember past information. Because the LSTM network has the problem of imprecise selection of initial weight and threshold parameters, the MHPSO was used to improve the optimization of these parameters. Finally, the measured data of a ship under three-level and five-level sea conditions were used to predict the ship motion attitude.

Compared with Kalman filter (Li et al., 2008), BP neural network (Yang et al., 2017), LSTM neural network (Gu et al., 2017) and PSO-LSTM network model (Moalla et al., 2017), the results show that MHPSO-LSTM model can achieve higher learning accuracy and faster convergence speed and has better prediction performance in the prediction of ship motion attitude. The proposed model can be potentially used to predict the ship motion attitude in practice.

This paper is organized as follows. In Section 2, the LSTM neural network is introduced. Section 3 presented the PSO algorithm. Based on the PSO, the MHPSO algorithm is proposed in Section 4. Section 5 described the MHPSO algorithm for optimizing the weight of the LSTM neural network. The proposed MHPSO-LSTM architecture and its applicability in the prediction of ship motion attitude are discussed in Section 6. In Section 7, numerical simulation is implemented and analyzed to investigate the effectiveness of the MHPSO algorithm. Finally, a few conclusions are drawn in Section 8.

LSTM neural network

The LSTM network is a special recurrent neural network (RNN). The model can learn long-term dependency information while avoiding the problem of gradient disappearance. It adds a structure called a memory cell to remember past information in the hidden layer of RNN. And three (Input, Forget, Output) structures are added to control the use of historical information.

LSTM (as shown in Figure 1) can be described below as

$$i_t = sigmoid(W_{hi}h_{t-1} + W_{xi}x_t) \tag{1}$$

$$f_t = sigmoid(W_{hf}h_{t-1} + W_{hf}x_t) \tag{2}$$

$$c_t = f_t \odot c_{t-1} + i_c \odot \tanh(W_{xc}x_t + W_{hc}h_{t-1}) \tag{3}$$

$$o_t = sigmoid(W_{hx}x_t + W_{ho}h_{t-1} + W_{co}c_t) \tag{4}$$

$$h_t = o_t \odot \tanh(c_t) \tag{5}$$

where i_t, f_t, and o_t are the input gate, forget gate, and output gate of LSTM, respectively. h_t is the output from the LSTM. *sigmoid* and tanh are the activation functions. c_t is the cell unit of the neural network. W_h and W_x denote the weight of the neural network. W_{hi}, W_{xi}, W_{hf}, W_{xc}, and W_{hc} are the connection weights of different connections in the LSTM neural network structure. $\odot$ is the element-wise product. The bias terms are omitted in equations (1–5), but they are applied by default.

PSO and relevant variants

PSO is an intelligent optimization algorithm for simulating the foraging of birds proposed by Eberhart and Jamne (1995). Each particle in the search space adjusts its speed and position

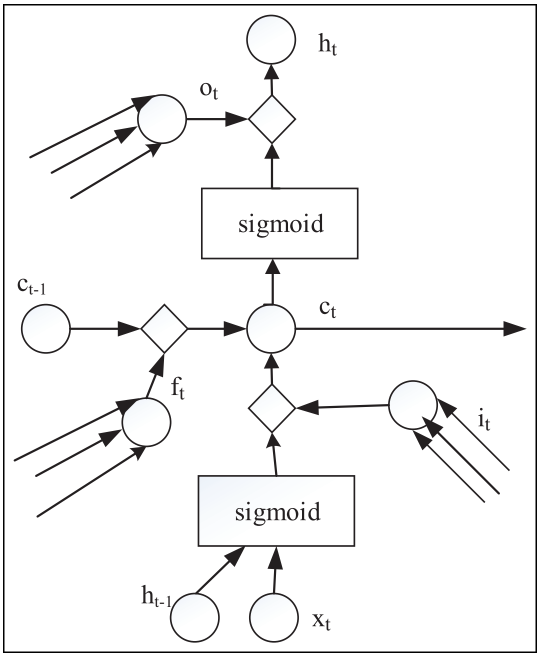

Figure 1. The unit structure of the LSTM network.

to optimize the simulation based on equations (6) and (7) until the termination of conditions converge

$$V_{i,j}^{t+1} = \omega V_{i,j}^{t} + c_1 r_{1,i,j}^{t}(\hat{y}_i^t - x_{i,j}^t) + c_2 r_{2,i,j}^{t}(y_{i,j}^t - x_{i,j}^t) \quad (6)$$

$$x_{i,j}^{t+1} = x_{i,j}^{t} + V_{i,j}^{t+1} \quad (7)$$

where $V_{i,j}^t$ is the velocity of particle i in dimension j at time t, $x_{i,j}^t$ is the position of the particle i at time t, ω is the inertia weight that represents the effect of memory of particles on the new position, c_1 and c_2 are constant acceleration coefficients, $y_{i,j}^t$ is the personal optimal solution of particle i at time t, $\hat{y}_i^t$ is the global optimal solution known at time t, $r_{1,i,j}^t$, and $r_{2,i,j}^t$ are random numbers, and $V_{i,j}^t \in [-V_{\max}, V_{\max}]$, where $V_{\max}$ is a constant.

Improved PSO

As the particles in the PSO gather to their local optimal position and global optimal location of aggregation, thereby forming the rapid convergence effect of the particle population, they are prone to falling into the local extreme, that is, premature convergence or stop phenomenon. A dynamic PSO algorithm with hierarchical ring topology, that is, the MHPSO algorithm was proposed. This algorithm focuses on establishing the vertical interaction between multiple layers. The particle population structure is shown in Figure 2, where each layer contains the same number of particles.

In this algorithm, every five particles in a population are randomly assigned to a ring, and all rings form a rule tree. The advantages and disadvantages of each ring are determined by the sum of the fitness values of all the particles in the ring. The advantages and disadvantages of the ring determine the position of the ring in the tree, and the better ring is at a higher level in the tree. During the running of the algorithm, the level at which the ring is located is dynamically adjusted according to the advantages and disadvantages of the ring. In the population structure, the particles in the father node of each particle are used as their attractors, which are also the attractors of the particles in their child nodes. For the particles in the uppermost layer, their attracting particles are other particles in the same layer since they all have relatively good fitness values in the population. In addition to moving to their local optimal position and global optimal position, the particles move to the position where their attractors are located. As Figure 2 shows, the attractors of Particle A include five particles (B, C, D, E, and F). The neighbors of the particles (such as X) in the ring at the root node are only the other four particles in the same ring.

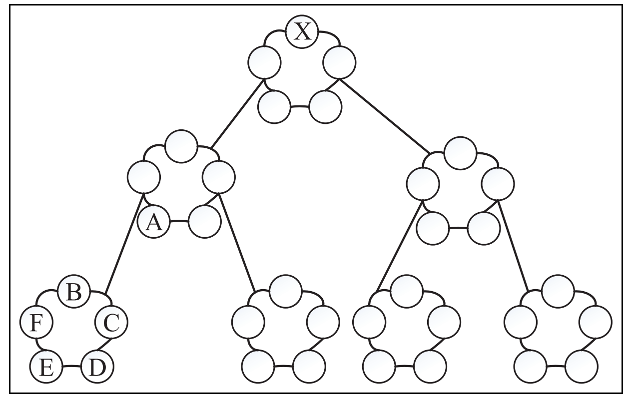

Figure 2. The structure chart of the particle population.

In the new algorithm, the speed update equation (8) includes an additional term from the attracting particles

$$\begin{aligned} V_{i,j}^{t+1} = {} & \omega V_{i,j}^{t} + c_1 r_{1,i,j}^{t}(\hat{y}_i^t - x_{i,j}^t) + c_2 r_{2,i,j}^{t}(y_{i,j}^t - x_{i,j}^t) \\ & + \sum\nolimits_{a=1}^{A_j^i} c_3 r(i)_{a,j}^t (x(i)_{a,j}^t - x_{i,j}^t)/A_j^i \end{aligned} \quad (8)$$

where $x(i)_{a,j}^t$ is the position of the attractor a of i, A_j^i is the total number of attractive particles of particle i, c_3 is the constant acceleration coefficient, $r(i)_{a,j}^t$ is the attracting coefficient corresponding to the attracting particle a of particle i.

To improve the robustness of the algorithm, the calculation method of particle attracting coefficient $r(i)_{a,j}^t$ is different under the following two circumstances, and thus ensuring that the influences of attractors on each particle are balanced

1) When $S(i)_{a,j}^t \leqslant \bar{S}(i)_j^t$,

$$r(i)_{a,j}^t = r_{\min}^t + \frac{(r_{\max}^t - r_{\min}^t)(S(i)_{a,j}^t - S(i)_{\min,j}^t)}{\bar{S}(i)_j^t - S(i)_{\min,j}^t} \quad (9)$$

2) When $S(i)_{a,j}^t > \bar{S}(i)_j^t$,

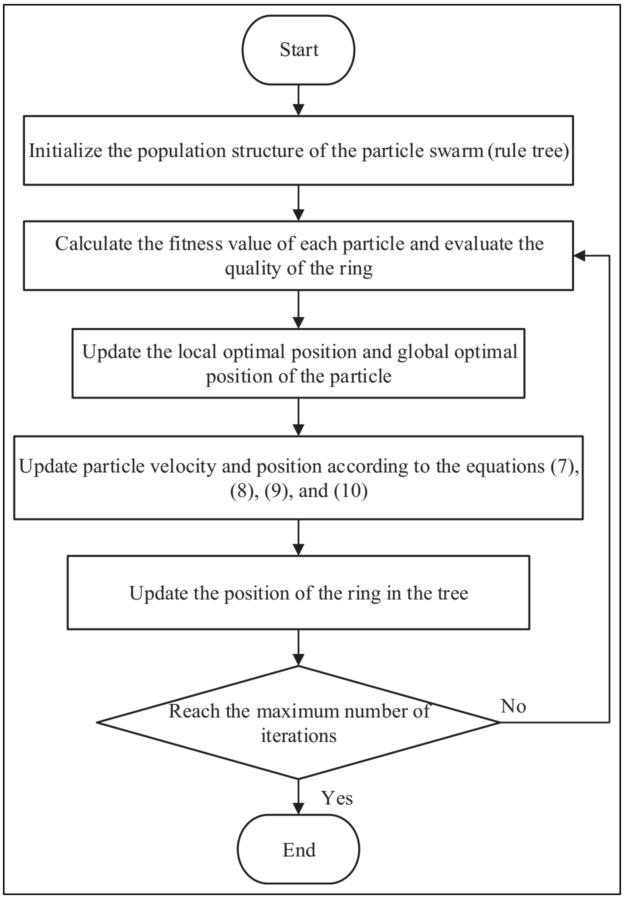

Figure 3. The flowchart of MHPSO.

$$r(i)_{a,j}^{t} = r_{\min}^{t} + \frac{(r_{\max}^{t} - r_{\min}^{t})(S(i)_{\max,j}^{t} - S(i)_{a,j}^{t})}{S(i)_{\max,j}^{t} - \bar{S}(i)_{j}^{t}} \tag{10}$$

where $r_{\min}^{t}$ and $r_{\max}^{t}$ are respectively the minimum and maximum values of the attracting coefficient. $S(i)_{\min,j}^{t}$ and $S(i)_{\max,j}^{t}$ are respectively the minimum and maximum values of the particle position of particle i. $S(i)_{a,j}^{t}$ is the distance from the attractor a of particle i to particle i, and $\bar{S}(i)_{j}^{t}$ is the average of all the attractive particles positions of particle i. When $S(i)_{a,j}^{t} \leq \bar{S}(i)_{j}^{t}$, the attractor a would correspond to a larger attraction factor; when $S(i)_{a,j}^{t} > \bar{S}(i)_{j}^{t}$, the attractor a would correspond to a smaller attraction factor.

The flowchart of the MHPSO algorithm is shown in Figure 3.

LSTM network optimization based on MHPSO

The main purpose of this algorithm is to optimize the weight of the LSTM network by the MHPSO algorithm to improve its prediction performance. The concrete steps are as follows:

Step 1: Initialize the particle swarm parameter and the structure of the LSTM network. Particle swarm consists of population size, population stratum, number of iterations, learning factor, and particle position and velocity, where the initial values of particle position and velocity are random. The initialization of the LSTM network structure mainly refers to determining the number of neurons and the number of hidden layers.
Step 2: Determine the evaluation functions of the particle. The fitness function of the particles in the population is defined as

$$fit_i = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{Y_i - y_i}{y_i}\right| \tag{11}$$

where n denotes the population size, Y_i denotes the sample output value, and y_i denotes the actual output value.

Step 3: Calculate the fitness value of each particle and construct the hierarchical population structure. The fitness values of each particle are calculated and sorted based on equation (11).
Step 4: Update the local optimal position and the global optimal position of the particle.
Step 5: Update the speed and position of the particle itself according to equations (7), (8), (9), and (10).
Step 6: If the end condition of the iteration (good enough position or a maximum number of iterations) is reached, then turn to Step 3 and continue to iterate.
Step 7: The obtained optimal particle is assigned to the connection weight of the LSTM network. Output time series predict the optimal solution after training the LSTM network prediction model.

Ship motion prediction based on MHPSO-LSTM

In this section, the proposed MHPSO-LSTM architecture and its applicability in ship motion prediction are analyzed and discussed. The LSTM architecture comprises two steps: network optimization and ship motion prediction. The complete architecture framework of our proposed model is shown in Figure 4. The model receives data as input; then the MHPSO algorithm is used to optimize the neural network architecture. As this is supervised learning, the network is trained with input, and output data proved to the model. This information is then used to dynamically reconfigure the neural network architecture for predicting the next-step next ship motion data.

Simulation analysis

Comparison of simulation results

The PSO and QPSO were selected for comparison of the simulation results, and *Quadric* and *Rosenbrock* were selected as reference functions to evaluate the performance of the MHPSO model. The values of parameters used in the three algorithms are listed in Table 1.

Figures 5 and 6 show the optimized and compared results of the three algorithms for *Quadric* and *Rosenbrock*. It can be

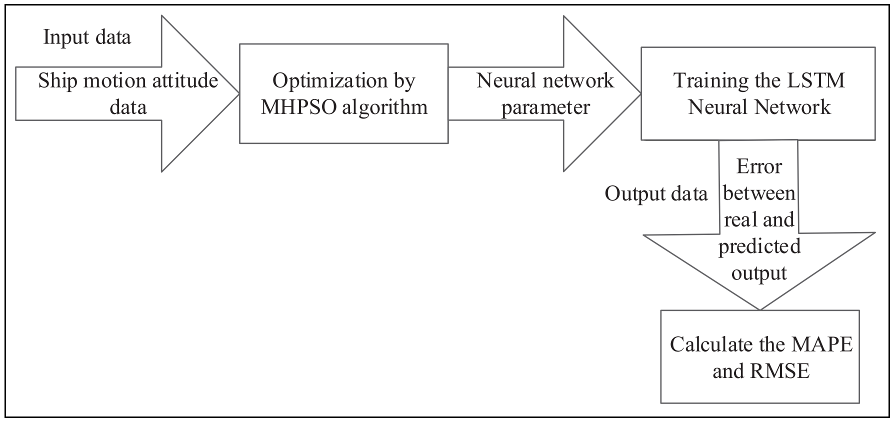

Figure 4. The architecture of MHPSO-LSTM model.

Table 1. The setting of parameters.

Parameter	PSO	QPSO	MHPSO
ω	linearly decreasing from 0.7 to 0.2	linearly decreasing from 0.7 to 0.2	linearly decreasing from 0.7 to 0.2
c_1	linearly decreasing from 2.5 to 0.5	linearly decreasing from 2.5 to 0.5	linearly decreasing from 2.5 to 0.5
c_2	linearly increasing from 0.5 to 2.5	linearly increasing from 0.5 to 2.5	linearly increasing from 0.5 to 2.5
c_3	null	null	the number of attractors divided by 2.5
r_1	obey uniform distribution$U(0, 1)$	obey uniform distribution$U(0, 1)$	obey uniform distribution$U(0, 1)$
r_2	obey uniform distribution$U(0, 1)$	obey uniform distribution$U(0, 1)$	obey uniform distribution$U(0, 1)$
r^t_{min}	null	null	0.3
r^t_{max}	null	null	1.2

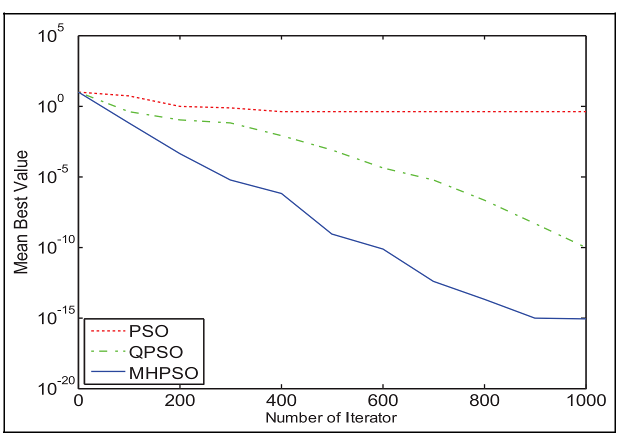

Figure 5. The optimization results of *Quadric* function.

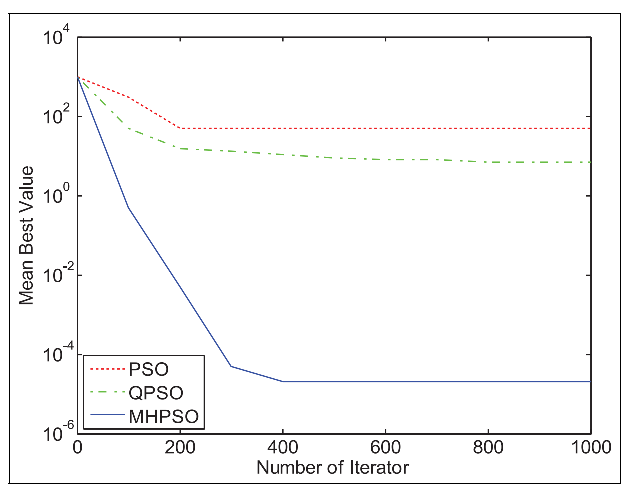

Figure 6. The optimization results of *Rosenbrock* function.

seen that the MHPSO demonstrated excellent search capabilities from the beginning of the initial stage. When the multi-peak function was tested, it achieved the required accuracy in a very short time. On the other hand, when the unimodal function was tested, the optimal value of the MHPSO showed a linear decrease with powerful exploration ability.

The simulation results showed that the MHPSO algorithm provided better search efficiency than the other two algorithms, and the optimization results for the benchmark function were more apparent compared to those obtained by the other two algorithms. Interaction between particles in the MHPSO algorithm was more effective, thereby reducing the possibility of the population falling into local extremum as well as improving the local development capability of the population in the feasible domain space and the convergence speed of the algorithm.

Prediction of ship motion attitude

The prediction of ship motion attitude is to predict the future motion data based on the known motion data. To validate the effectiveness of the MHPSO-LSTM, we used the Kalman filter (Li et al., 2008), BP neural network (Yang et al., 2017), LSTM neural network (Gu et al., 2017) and PSO-LSTM network (Moalla et al., 2017) model for comparative simulations.

Equation (12) was used to normalize data to [0, 1] to enhance the training speed

$$M_i = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \tag{12}$$

where x_i denotes the input fault data($i = 1, 2, \ldots, n$), $x_{\max}$ denotes the maximum value in the fault data, $x_{\min}$ denotes the minimum value in the fault data, and M_i denotes the normalized data.

Many evaluation indicators can be used for prediction error. In this paper, we mainly used Mean Absolute Percentage Errors (MAPE) and Root Mean Square Error (RMSE) as the evaluation indicators of the prediction results. The calculation formula is provided as follows

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{\hat{x}_t - x_t}{x_t}\right| \times 100\% \tag{13}$$

$$RMSE = \sqrt{\frac{\sum_{j=1}^{n}(\hat{x}_t - x_t)^2}{x_t}} \tag{14}$$

where $\hat{x}_t$ is the forecast results of ship motions, and x_t is the measured value of ship motion.

In the course of the simulation, the input measured data in this paper were the data of the heave displacement, roll angle, and pitch angle of a ship moving at a speed of 24 knots under third-level and fifth-level sea conditions. The sampling frequency of 0.2 seconds was used. The number of each type of data was 200, and the number of training samples and predicted samples were set respectively as 150 and 50. The parameters of the PSO and MHPSO models are shown in Table 1. The ship heave displacement, pitch angle, and roll angle were predicted separately.

Prediction of ship motion attitude. The above five models were used to predict the ship heave displacement, pitch angle, and roll angle under three-level and five-level sea conditions. Figure 7 shows the comparison of the prediction results of five models under five-level sea conditions. Figure 8 shows the output error of the five models under five-level sea conditions. Table 2 shows the MAPE and RMSE values for the predictions of the five models under five-level sea conditions. As shown in Figures 7 and 8 and Table 2, the MHPSO-LSTM network model provided smaller errors with better prediction results than other models.

Figure 9 shows the comparison of the prediction results of the real data, Kalman, BP, LSTM, PSO-LSTM, and MHPSO-LSTM models under three-level sea conditions.

Figure 10 shows the output error of the five models under three-level sea conditions.

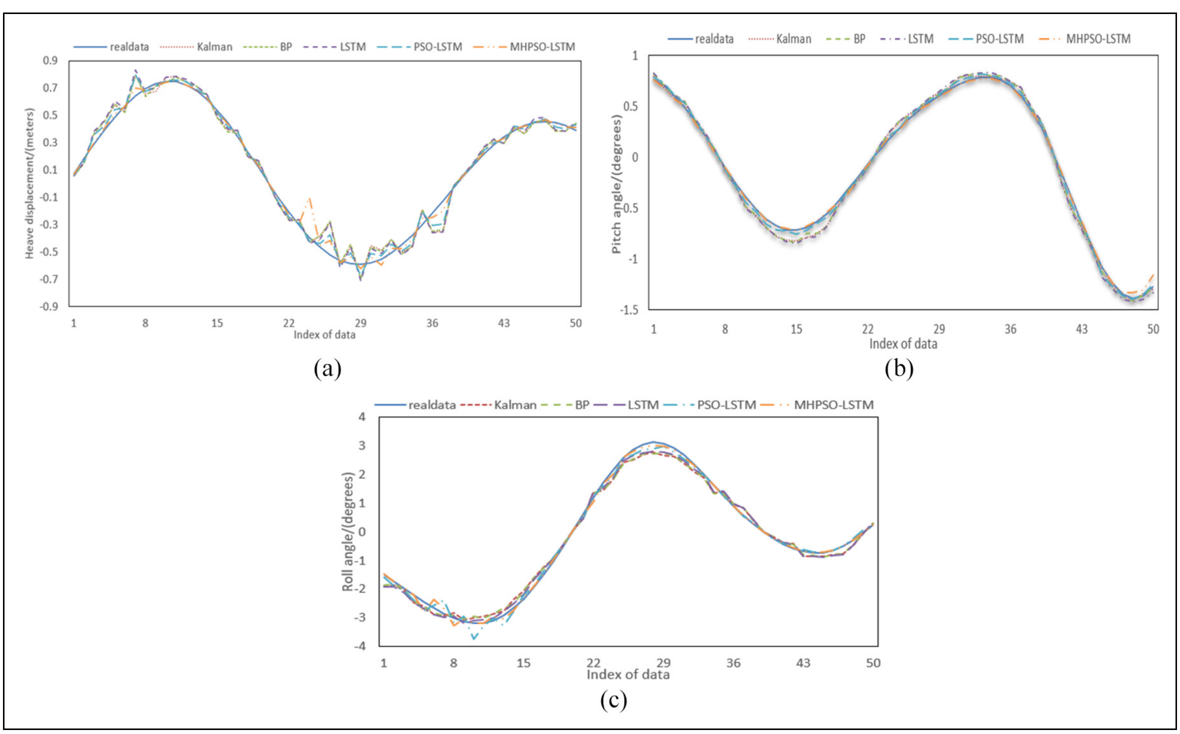

Figure 7. Prediction results of the five models under five-level sea conditions.
(a) Prediction results of the heave displacement.
(b) Prediction results of the pitch angle.
(c) Prediction results of the roll angle.

Table 2. The MAPE and RMSE of the five models' prediction results under five-level sea conditions.

Model		Kalman	BP	LSTM	PSO-LSTM	MHPSO-LSTM
Heave displacement	MAPE (%)	14.25	14.72	13.45	8.63	4.53
	RMSE	0.0419	0.0479	0.0342	0.0254	0.0199
Pitch angle	MAPE (%)	16.55	16.74	15.65	10.37	5.58
	RMSE	0.1796	0.1827	0.1685	0.1302	0.0842
Roll angle	MAPE (%)	18.72	18.81	18.52	11.95	6.35
	RMSE	0.1968	0.1975	0.1827	0.1595	0.0954

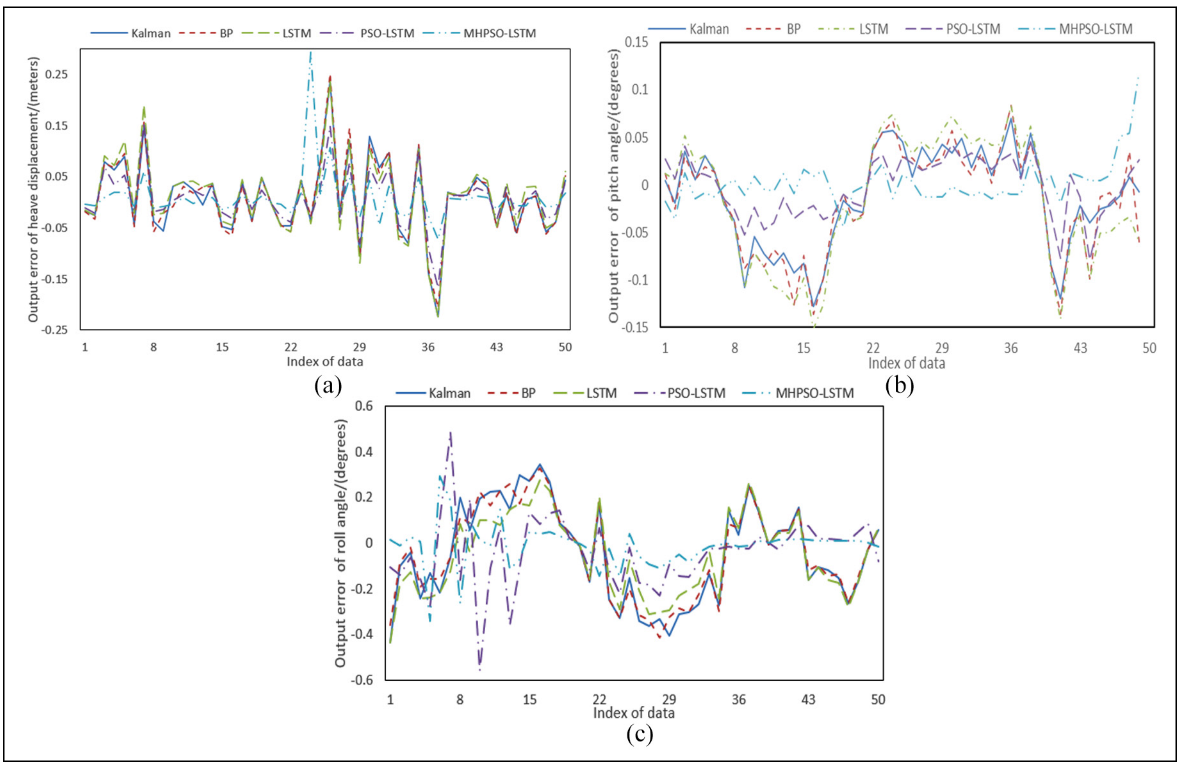

Figure 8. Output errors of the five models under five-level sea conditions.
(a) Prediction errors of the heave displacement.
(b) Prediction errors of the pitch angle.
(c) Prediction errors of the roll angle.

Table 3 shows the MAPE and RMSE values for the predictions of the five models under three-level sea conditions.

It can be seen from the prediction results of the above five models that the MHPSO algorithm enhanced the global search capability of the PSO algorithm by enhancing the information interaction between particles. In the parameter optimization process of the LSTM neural network model, higher precision parameters were generated, manifesting the MHPSO-LSTM network model as a more suitable algorithm for highly accurate ship motion prediction. Thus, the proposed model can be used to predict the ship motion in practice.

Conclusion

The LSTM neural network with memory function was applied to improve the accuracy of ship motion prediction, which helps to reduce marine navigation accidents.

We have developed the MHPSO algorithm, which enhanced the global optimization ability and convergence speed of PSO by improving the PSO population structure and speed update equation. Meanwhile, MHPSO and LSTM were combined to propose a prediction model of ship motion based on the optimization of MHPSO, which optimized the initial weight and threshold of LSTM, overcame the imprecise parameter selection, realized the global high-precision optimization of network parameters, and further improved the

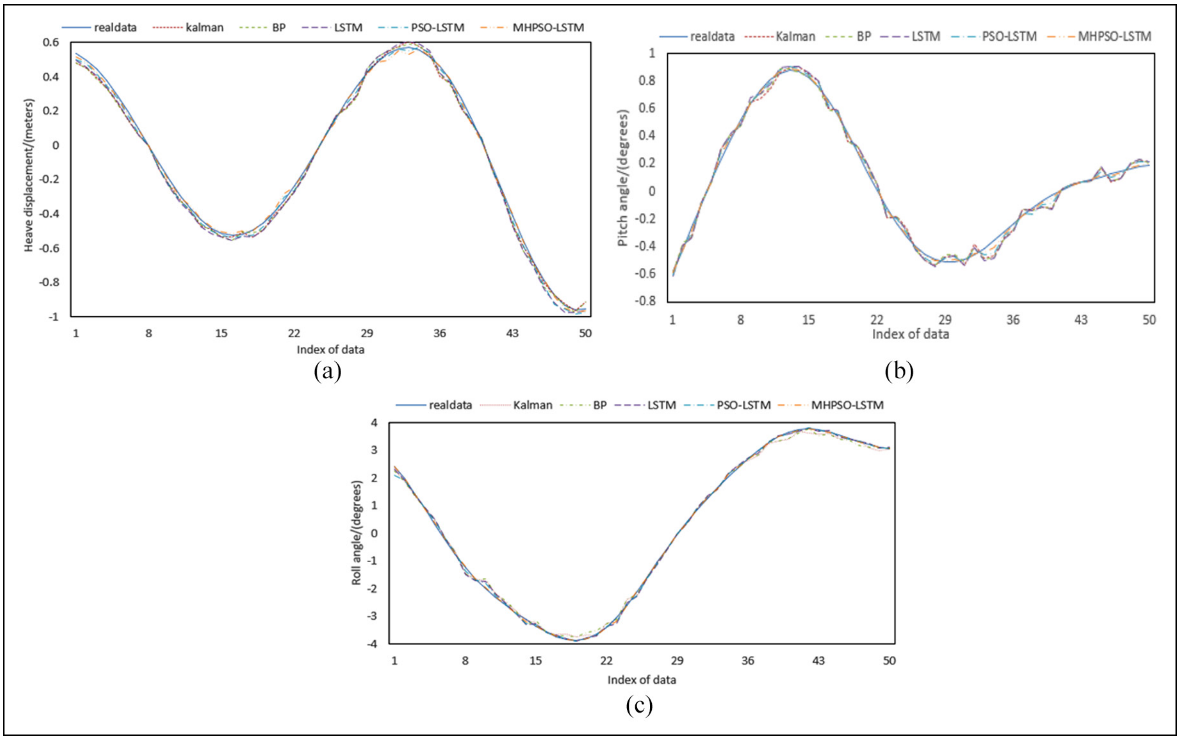

Figure 9. Prediction results of the five models under three-level sea conditions.
(a) Prediction results of the heave displacement
(b) Prediction results of the pitch angle
(c) Prediction results of the roll angle

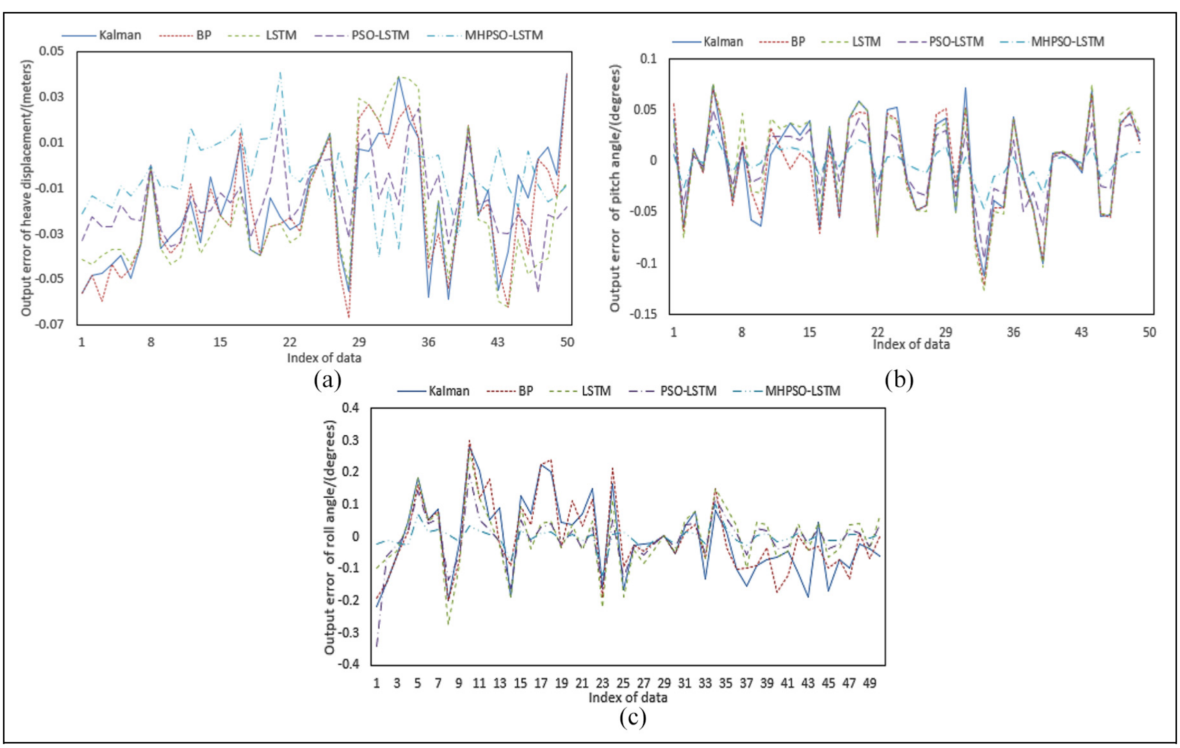

Figure 10. Output errors of the five models under three-level sea conditions.
(a) Prediction errors of the heave displacement.
(b) Prediction errors of the pitch angle.
(c) Prediction errors of the roll angle.

Table 3. The MAPE and RMSE of the five models' prediction results under three-level sea conditions.

Model		Kalman	BP	LSTM	PSO-LSTM	MHPSO-LSTM
Heave displacement	MAPE (%)	20.13	20.25	19.80	15.73	8.74
	RMSE	0.0135	0.0136	0.0124	0.0082	0.0031
Pitch angle	MAPE (%)	15.72	15.28	13.57	9.48	5.01
	RMSE	0.0384	0.03782	0.0314	0.0271	0.0153
Roll angle	MAPE (%)	13.14	12.96	12.57	7.48	3.01
	RMSE	0.0476	0.04681	0.0426	0.0358	0.0311

prediction accuracy of LSTM for accurate prediction of ship motion.

In the simulation, on the one hand, the MHPSO, PSO, and QPSO were respectively used to optimize the benchmark function, and the results showed that the MHPSO had better optimization performance. On the other hand, the prediction models of the MHPSO-LSTM, Kalman filter, BP neural network, LSTM network, and PSO-LSTM network were respectively used to predict the motion data of two kinds of ships under three-level and the five-level sea conditions. The results showed that the MHPSO-LSTM model demonstrated better prediction capability and generalization performance to predict ship motion with high precision.

Because few studies have so far investigated the optimization of the LSTM neural network parameters, little is known on the simultaneous optimization of the LSTM neural network parameters and structures. In future research, we will focus on the simultaneous optimization of the LSTM neural network parameters and structures and apply the MHPSO-LSTM model to practical problems and combine other intelligent algorithms to optimize MHPSO to further improve the performance of the model.

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References

Duan WY, Huang LM, Han Y, et al. (2015) A hybrid AR-EMD-SVR model for the short-term prediction of nonlinear and non-stationary ship motion. *Journal of Zhejiang University-Science A*. 16(7): 562–576.

Eberhart RC and Jamne K (1995) A new optimizer using particle swarm theory. In: *Proceedings of the 1995 Sixth International Symposium on Micro Machine and Human Science*, Nagoya, Japan, 4–6 October 1995, pp. 39–43. Piscataway, NJ, USA: IEEE.

Elsaid A, El Jamiy F, Higgins J, et al. (2017) Optimizing long short-term memory recurrent neural networks using ant colony optimization to predict turbine engine vibration. *Applied Soft Computing* 73: 969–991.

Esmaeil S, Milad M, Francisco G, et al. (2019) Quantum neural network-based intelligent controller design for CSTR using modified particle swarm optimization algorithm. *Transactions of the Institute of Measurement and Control* 41(2): 392–404.

Ghasemi M, Aghaei J and Hadipour M (2017) New self-organising hierarchical PSO with jumping time-varying acceleration coefficients. *Electronics Letters* 53(20): 1360–1362.

Gu XJ, Zhao L, Jin M, et al (2017) Research on short-term prediction of typical trial sea environment in china based on LSTM neural network. *Ship building of China* 58(4): 100–107.

Guo S, Guo D, Chen L, et al (2017) A L1-regularized feature selection method for local dimension reduction on microarray data. *Computational Biology and Chemistry* 67: 92–101.

Hochreiter S and Schmidhuber J (1997) Long short-term memory. *Neural Computation* 9(8): 1735–1780.

Kim C, Li F and Rehg JM (2018) Multi-object tracking with neural gating using bilinear LSTM. In: *Proceedings of the European Conference on Computer Vision*, Munich, Germany, 8–14 September 2018, pp. 200–215. Springer Verlag Publishing.

Li XY, Zhong Z and Yang GH (2008) The study on the method of ship rolling prediction based on Kalman filter. In: *Proceedings of 2nd Joint Student Workshop on Mechatronics*, Harbin, China, 16-22 September 2008, pp. 85–90. Secr Office of JSPE Sci Comm on Intell. Mechatronics Fac of Eng, Kagawa Uni 2217–20: Hayashi-cho Publishing.

Liu J, Shahroudy A, Xu D, et al. (2018) Skeleton-based action recognition using spatio-temporal LSTMnetwork eith trust gates. *IEEE Transactions on Pattern Analysis and Machine Intelligence* 40(12): 3007–3021.

Moalla H, Elloumi W and Alimi AM (2017) H-PSO-LSTM: Hybrid LSTM trained by PSO for online handwriter identification. In: *Proceedings of the 24th International Conference on Neural Information Processing*, Guangzhou, China, 14–18 November 2017, pp. 41–50. Springer Verlag Publishing.

Mohan VJ and Albert TAD (2017) Optimal sizing and sitting of distributed generation using particle swarm optimization guided genetic algorithm. *Advances in Computational Sciences and Technology* 10(5): 709–720.

Nicholas F, Brian M and Samuel M (2017) A hybrid particle swarm optimization algorithm for maximum power point tracking of solar photovoltaic systems. In: *Proceedings of the 29th National Conference of Undergraduate Research*, Memphis, Tennessee, 6-8 April 2017, pp. 207–214. Available at: http://ncurproceedings.org/ojs/index.php/NCUR2017/article/view/2423

Nobile MS, Cazzaniga P, Besozzi D, et al (2017) Fuzzy self-tuning PSO: A settings-free algorithm for global optimization. *Swarm and Evolutionary Computation* 39: 70–85.

Song HH, Yu GX and Qu YB (2018) Monitoring and forecasting system for ship attitude motion based on extended kalman filtering algorithm. *Journal of Chinese Inertial Technology* 26(1): 6–12.

Tian ZD, Li SJ, Wang YH, et al. (2018) SVM predictive control for calcination zone temperature in lime rotary kiln with improved PSO algorithm. *Transactions of the Institute of Measurement and Control* 40(10): 3134–3146.

Troiano L, Villa EM and Loia V (2018) Replicating a trading strategy by means of LSTM for financial industry applications. *IEEE Transactions on Industrial Informatics* 14(7): 3226–3234.

Wang H, Cui ZH, Sun H, et al. (2017) Randomly attracted firefly algorithm with neighborhood search and dynamic parameter adjustment mechanism. *Soft Computing* 21(18): 5325–5339.

Wang YL, Soltani M and Hussain DMA (2017) Ship attitude prediction based on input delay neural network and measurements of gyroscopes. In: *Proceedings of the American Control Conference* Seattle, WA, United States, 24–26 May 2017, pp. 4901–4907. IEEE

Yang G, Jie QM and Tao NQ (2017) Prediction of ship motion attitude based on BP network. In: *Proceedings of the 29th Chinese Control and Decision Conference*, Chongqing, China, 28–30 May 2017, pp. 1596–1600. IEEE.

Zeng B and Liu S (2017) A self-adaptive intelligence gray prediction model with the optimal fractional order accumulating operator and its application. *Mathematical Methods in the Applied Sciences* 40(18): 7843–7857.

Zhou WD, Xing ZJ, Bai WB, et al. (2019) Route planning algorithm for autonomous underwater vehicles based on the hybrid of particle swarm optimization algorithm and radial basis function *Transactions of the Institute of Measurement and Control* 41(4): 942–953.