Real-time prediction of ship motion using artificial neural networks

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Abstract

Due to the random nature of ship motion in open water environments, ship-based deployment and recovery of aircraft can often be difficult and even dangerous. This paper presents an investigation into the application of artificial neural network methods for the prediction of ship motion relying only on measured ship data. It is shown that the artificial neural network produces excellent ship motion predictions and is able to predict the ship motion satisfactorily in real time for up to 10 seconds.

Keywords: Ship motion; Artificial neural networks; Ship roll angle

1. Introduction

The motion of a ship in an open water environment is the result of the complex interaction between hydrodynamic forces, wave patterns, wind and turbulence [1]. This paper presents an artificial neural network algorithm capable of predicting ship motion based only on past history data for successful and safe deployment of aircraft, missiles and decoys currently used on ships that operate in sea state conditions up to category 6. The launch of a decoy involves a delay between the moment the decision is made to deploy and the moment of actual launch. A key requirement for the proposed algorithm is to predict up to 10 seconds in advance and determine if ship roll angles are likely to exceed the 'launch lock-out angle' which is the condition where predefined operational limits are exceeded. If a lock-out is predicted the launch could be delayed or an alternative decoy be chosen.

2. Artificial neural networks

Artificial neural networks (ANNs) form a class of systems that are inspired by biological neural networks [2]. A three-layered feed forward ANN consisting of an input layer, a hidden layer and an output layer was utilized in this investigation.

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A single neuron has n inputs including a bias term, which has been set to 1 for this investigation. The inputs are each multiplied by their corresponding weight value, which are summed together and subsequently entered into an activation function. The output of the activation function will correspond to the output of the neuron. Mathematically, the output of a neuron is given as:

$$out = f(net) = f\left(\sum_{i=0}^{n-1} I_i w_i + w_n\right) \tag{1}$$

where the inputs are $\{I_i,\ i = 0, \ldots, n-1\}$. In this investigation the activation function shown below was used:

$$f(net) = \tanh(net)$$

The entire ANN process is depicted in Fig. 1.

2.1. Training the network

The training of the network can be viewed as a minimization process where the weights in the ANN are systematically adjusted in a manner that reduces the error between the output of the ANN and the desired output. The algorithm used to determine the minimum must ensure that global minimum is achieved and has not discovered a local minimum.

2.1.1. Conjugate-gradient algorithm

The conjugate-gradient (CG) algorithm created for

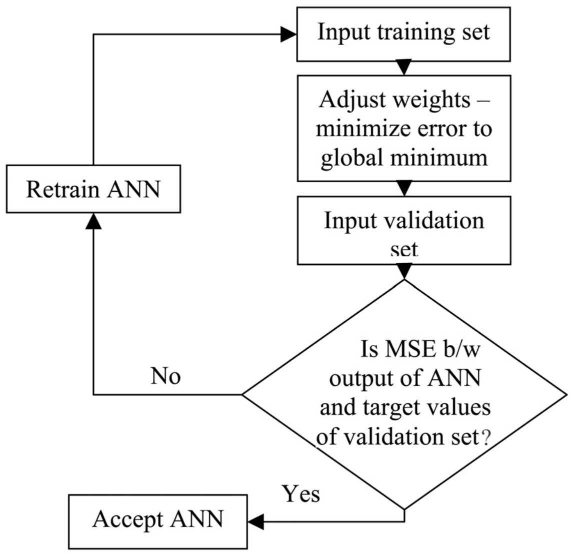

Fig.1. The artificial neural network process.

the ANN in this investigation was based on the Polak–Ribiere algorithm. The mathematical justifications for the algorithm are beyond the scope of this paper but a detailed description can be found in Polak [3]. In a general sense, the algorithm generates a sequence of vectors and search directions. It can be shown that the exact minimum will be obtained if the multi-dimensional function can be expressed as a quadratic. The ANN error function is quadratic close to the minimum so it is expected that, once close to a minimum, convergence to the local minimum will be very rapid [4].

2.1.2. Genetic algorithm

The genetic algorithm (GA) is part of a rapidly growing field of artificial intelligence called evolutionary computing and can be used to find the global minimum. It uses the principle of survival of the fittest where the 'fittest' (best) 'survivor' (solution) evolves to create the next population [5]. The entire GA process is depicted in Fig. 2. To ensure maximum efficiency, the GA is used to establish an approximate location of the global minimum and then the conjugate gradient method is used to rapidly ascertain the exact values of the weights.

2.1.3. Singular value decomposition

The aim of this investigation is to develop a methodology to predict ship motion in real time. The application of the singular value decomposition (SVD)

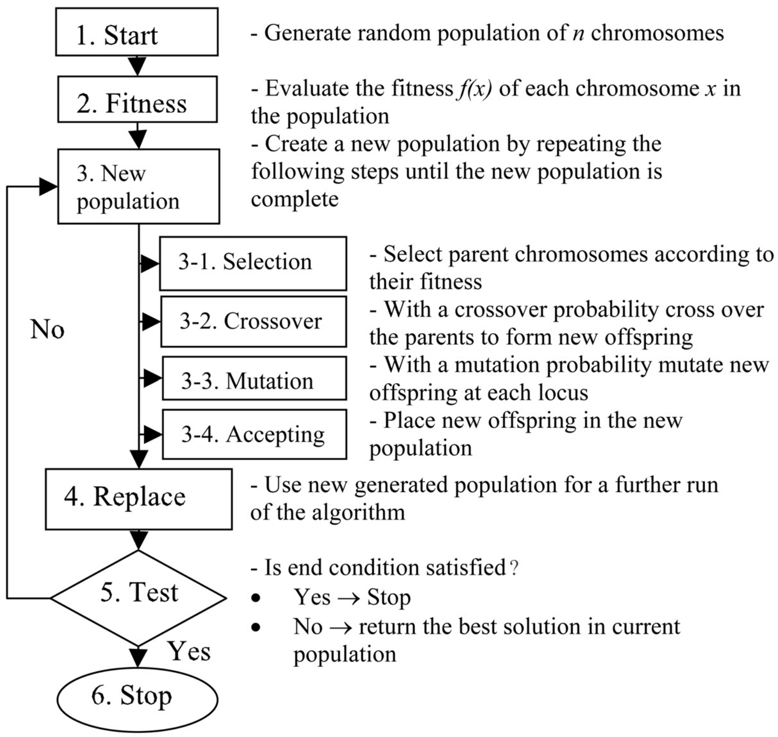

Fig.2. Flow chart of genetic algorithm process.

method showed a significant increase in the speed at which the weights for the ANN are calculated. A detailed description of the SVD technique is beyond the scope of this paper but essentially the matrix $\boldsymbol{X}$ which satisfies the function:

$$A.X = B \tag{3}$$

when A and B are known can be calculated efficiently using SVD. When applying it to the ANN process the weights between the input layer and the hidden layer are initially randomly generated. The training samples are then inserted into the ANN and the hidden layer activation functions are calculated creating a matrix equivalent to $\boldsymbol{A}$. Also, the values for the inverse transfer function of the output are also calculated creating a matrix equivalent to $\boldsymbol{B}$. Applying SVD and solving Eq. (3), the approximate optimal weights $\boldsymbol{X}$ are found.

2.2. Validation of ANN model

To ensure that the weights in the ANN have been correctly set and that the output of the ANN is sufficiently reliable, a validation process is applied after training has been completed. Essentially the data used to test and evaluate the ANN model is divided into a training set and a validation set. The training set is exclusively used for training the ANN while the validation set is used to test the accuracy of the ANN model.

3. Application of ANN to ship motion prediction

The algorithms developed were applied to measured ship roll angle data taken from Frigate class vessels operating in sea states 5–6. The ANN algorithms were applied to nine separate data sets which were each between 300–600 seconds in length. The training data was set to two thirds of the data sets and the validation set was designated as the final third of the data sets. All results shown are the predictions made using the validation set only.

In Table 1 the accuracy and the speed of the ANN can be seen. Criterion 1 is the percentage of predictions accurate within the 95% confidence interval. As stated in the introduction, the success criterion for this investigation is to develop an algorithm that can predict when a predefined angle is exceeded. The second criterion is percentage forecasts that correctly predicted that the roll angle would exceed a predefined lock-out angle of 7°.

Two ANN training regimes were used. The first used a combination of the GA and CG algorithms to calculate the weights for the ANN. The second used the SVD method to calculate the weights for the ANN. A range of different ANN structures were used in this investigation. The number of input nodes varied from 4 to 6 and the number of hidden layer nodes varied from 1 to 3. The results shown in Table 1 are the average results found by applying the ANN to the nine data sets. Ten trials were used for every ANN trained using the SVD node configuration and the best result chosen. The processing times for the SVD method shown in Table 1 represent the total time to complete the ten trials. Figure 3 shows an example of a prediction made using SVD-based algorithm to calculate the ANN weights.

4. Discussion of investigation results

Table 1 shows the effectiveness of ANN for the prediction of ship motion. Using the GA and CG combination for training the ANN produced slightly higher accuracy than that of the ANN trained using the SVD-based algorithm, however, the SVD algorithm was

Table 1
Results of ANN investigation

Prediction interval (sec)	Combined GA and CG method			SVD method		
	Criterion 1	Criterion 2	Processing time (sec)	Criterion 1	Criterion 2	Processing time (sec)
1	99.76	100	18.85	99.76	100	0.116
2	99.72	100	19.53	99.63	100	0.105
3	99.81	100	18.78	99.75	100	0.118
4	99.73	100	31.46	96.42	100	0.123
5	94.66	100	47.46	94.67	99.88	0.115
6	99.79	100	34.68	99.66	100	0.118
7	99.78	100	29.59	99.55	100	0.113
8	99.71	100	28.68	99.64	100	0.126
9	99.78	100	34.35	99.71	100	0.137
10	96.41	100	25.79	94.53	98.78	0.114

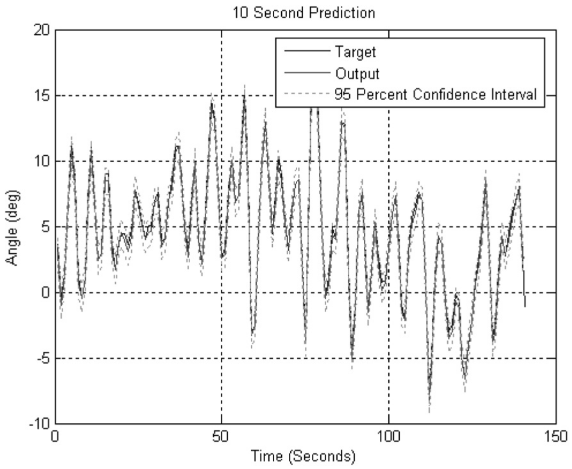

Fig.3. Ten second prediction using singular value decomposition weights (calculated in 0.01 sec on Pentium IV 2.8G-z PC).

much faster. The results in Table 1 show that the ANN algorithms were capable of producing predictions within the 95% confidence intervals that had an accuracy of greater than 94% for predictions of up to 10 seconds. The ability of the SVD-based algorithm to produce a set of weights that allows very accurate predictions in fractions of a second imply that this method has the real-time capability required in operational circumstances. The ANN architecture is therefore sufficiently capable of representing the motion of ship in an open sea environment subjected to complex hydrodynamic forces.

5. Conclusion

In this paper artificial neural network-based methods for the prediction of ship motion were presented. It was shown that the artificial neural networks are capable of learning ship motion behavior and produce highly accurate predictions of roll angles for intervals up to 10 seconds. It was shown that an artificial neural network which uses a combination of the genetic algorithm and conjugate gradient algorithms to calculate the appropriate weights was capable of producing excellent predictions up to 10 seconds but with the penalty of high computational time. However, it was also found that the artificial neural network using the singular value decomposition method gave slightly less accurate results but predictions could be produced in fractions of a second. It is concluded that an artificial neural network using singular value decomposition is capable of predicting ship motion with the required accuracy and in real time.

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