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Neural-network-based modelling and analysis for time series prediction of ship motion

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ABSTRACT

This paper presents a data-driven model for time series prediction of ship motion. Prediction based on past time series of data is a powerful function in modern ship support systems. For a large amount of ship sensor data, neural network (NN) is considered as a proper tool in modelling the prediction system. Efforts are made to compact the NN structure through sensitivity analysis, in which the importance of each input to the output is quantified and lower ranked inputs are eliminated. Further analysis about the impact of three different learning strategies, i.e. offline, online and hybrid learning on the NN, is conducted. The hybrid learning combining the advantages of both the offline learning and the online learning exhibits superior prediction performance. According to the long-term prediction ability of recurrent NN, multi-step-ahead prediction under the hybrid learning strategy is realised in a multi-stage prediction form. Experiments are carried out using collected ship sensor data on a vessel. The results show the feasibility of generating a data-driven model through modelling and analysis of the NN for ship motion prediction.

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Ship motion prediction; neural networks; sensitivity analysis; learning strategy; multi-step-ahead prediction

1. Introduction

The scale of the maritime industry in Norway has experienced a noticeable increase in recent years. Ships, as the backbone of most of the maritime business, are of great concern to both ship owners and companies, especially for economically and safety beneficial reasons (Baldauf et al. 2013). Usually, there are various sensors installed on the ship, some of which are used in real time for manoeuvring and related actions, and some of which are placed in sensitive areas like propeller blade to collect the data for future purpose such as system diagnosis (Lynch and Loh 2006). The sensor data are stored for years in huge size. One of the goals is to improve the control of ship motion from a prediction perspective (Fossen 2002). However, how to effectively dig into the data set and find out valid ship motion models is still challenging. This is because, on the one hand, ship dynamics varies with navigational status such as the load and the speed; on the other hand, environmental perturbations such as wave, wind and current are too complex to predict (Sørensen 2011).

Nowadays, prediction is applied in various domains, from weather forecast to product marketing. de los Campos et al. (2013) applied linear regression (LR) methods to approximate the true unknown genetic values which can be a complex function involving the genotype of the individual. Min and Lee (2005) proposed a grid-search technique to find out the optimal parameters for kernel function of support vector machine (SVM) to build a bankruptcy prediction model. Petrich et al. (2013) presented a long-term prediction model by using an extended Kalman filter (KF) to select a representative set of reasonable trajectories for a vehicle from a digital map. Carman (2008) investigated the relationship between tyre working parameters and soil compaction characteristics and applied the fuzzy logic (FL) method to predict the changes. Besides the above-mentioned techniques, some other popular predictive modelling techniques, such as decision tree (DT), model predictive control (MPC) and NN, are also considered to be efficient for predictive purposes (Mackay 1995; Qin and Badgwell 2003; Myles et al. 2004; Shen and Xie 2005). A simple comparison of these prediction methods is stated in Section 2.1.

For ship manoeuvring, health, safety, environment, security and cost are given high priority during maritime operations. Ship motion prediction is therefore essential for the emergence of new demands in offshore operations (Perera and Soares 2010; Li and Sun 2012; Qu et al. 2014). In the literature, attempts especially for developing NN-based models have been made to predict ship motion in terms of thruster forces, pitch and roll angles, heading, speed and position. For example, Lee et al. (2001) developed an online training functional-link NN to estimate the ship position during dynamic positioning. Yin et al. (2013) presented an online prediction model of ship roll motion by using

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a variable structure radial base function NN. Simoes et al. (2002) introduced a structured NN for modelling and prediction of the mooring cable forces. Zhang and Liu (2014) designed a wavelet NN with time delay to address the feasibility issues in ship heading prediction and control in the presence of disturbance.

Despite the fact that different types of NN models are applied for ship motion prediction, most of the aforementioned prediction models are tailor-made for certain specific prediction of ship motion. Furthermore, the learning strategies are seldom discussed in terms of prediction steps in this domain. In general, online, offline and hybrid learning procedures are the most often used strategies in conjunction with NN structures (Müller et al. 1995). Different strategies affect the ability of generalisation, as well as prediction accuracy. It is therefore of great significance to make efforts to develop a more general prediction model to investigate the effects of different strategies for short-/long-term ship motion prediction. The research of this paper builds upon the work by Li et al. (2016), but focuses on modelling and analysis of NN construction and learning strategies. The main contribution of this study lies in a complete procedure from raw data analysis to NN modelling to short-/long-term prediction of different aspects of ship motion.

The paper is organised as follows. Section 2 introduces the related work about prediction techniques and the recurrent NN. In Section 3, the overall structure of the prediction system is described. Section 4 shows the modelling and analysis of NN structure, learning strategies and long-term prediction, followed by the corresponding experiments in Section 5. Conclusion and future work are shown in Section 6.

2. Related work

2.1. Comparison of prediction methods

To date, there have been various methods applicable to prediction purpose, as mentioned in Section 1. In order to find out which method is preferable to ship motion prediction, we summarise their pros and cons in Table 1.

Considering the high nonlinearity of ship dynamics and the stochastic external excitations exerted by waves and wind, using LR or KF will lead to loss of the multi-dimensional generalisation ability in the ship motion prediction case. SVM and MPC are good choices for generalisation, except for computationally expensive as complexity increases in uncertain systems. DT is simple to use, but it also suffers from being computationally complex. In addition, DT is not good at online learning, which is one of the strategies that we will use for comparison purposes. FL is a potential alternative for ship motion prediction. However, fuzzy rules are mainly obtained by trial and error from experiences,

Table 1. Comparison of predictive modelling techniques.

Prediction method	Advantages	Disadvantages
LR	• Assume linear approximation (Desai and Bharati 1998; Chambers and Dinsmore 2014) • Simple, easy to use and interpretability • Good results for small data sets	• No generalisation ability (Desai and Bharati 1998) • Not suitable for complex and nonlinear problems
SVM	• Less over fitting and robust to noise (Min and Lee 2005; Msiza et al. 2007) • No local minimal • Good in generalisation	• Computationally expensive (Auria and Moro 2008; Msiza et al. 2007) • Lack of transparency of results • Selection of kernel function
DT	• Simple to understand and interpret (Myles et al. 2004) • Fast construction	• Not suitable for online learning (Myles et al. 2004) • High computational complexity for uncertainty
KF	• Intuitive, engineering way of constructing approximations (Perera and Soares 2010; Welch and Bishop c1997–2016) • Computationally efficient • Theoretical stability available	• Does not work in considerable nonlinearities (Welch and Bishop c1997–2016) • Works only for Gaussian noise process
MPC	• Systematic design approach (Qin and Badgwell 2003; Li and Sun 2012) • Explicit use of a model • Stability guarantee	• Limited model choices (Qin and Badgwell 2003) • Large computation for nonlinear and uncertain systems
FL	• Flexible, intuitive knowledge base design (Albertos and Sala 1998; Carman 2008) • Natural way of expressing uncertainty	• Nontrivial and time consuming to obtain rules (Albertos and Sala 1998) • Difficult for performance-robustness tradeoff
NN	• Strong in generalisation ability (Mackay 1995; Müller et al. 1995) • Suitable for problems which are difficult to specify mathematically • Efficient for online learning	• Limited ability to explicitly identify possible causal relationships (Müller et al. 1995) • Prone to over fitting

which is nontrivial and time consuming in practice. In contrast, NN as a model-free method capable of approximation and adaptation does not have these problems. It is therefore considered in this paper that NN is the suitable method for ship motion prediction.

2.2. Nonlinear autoregressive exogenous network

A nonlinear autoregressive exogenous (NARX) network is a complex discrete-time nonlinear system with feedback connections (Menezes and Barreto 2008). For time series modelling, NARX utilises current and past values together with nonlinear input–output mapping for dynamical prediction. Figure 1 shows an example of a two-hidden-layer NARX network. It can be generally expressed in the following form:

$$y(n+1) = f(\boldsymbol{u}, \boldsymbol{y}) \tag{1}$$

where $\boldsymbol{u} \in \mathbb{R}^{p+1}$ and $\boldsymbol{y} \in \mathbb{R}^{q+1}$ are the inputs of NARX at the time step n; p and q denote the memory order of time history information of inputs and outputs, respectively; f is the nonlinear mapping for function approximation, implemented, in most cases, by a multilayer perceptron (MLP) NN (Gardner and Dorling 1998).

A NARX network with the closed loop is able to make long-term time series prediction. As pointed out by Lin et al. (1996), if the NARX network is unfolded in time, its output memories appear as jump-ahead connections in the unfolded network. Learning algorithms, such as the backpropagation through time (BPTT), can be used to find gradients along the unfolded path. As long as the jump-ahead connections with shorter paths provide a greater total gradient than the gradient through the layer-to-layer pathways, the output delays of NARX can help reducing the sensitivity of the network to long-term dependencies. Therefore, in this paper the NARX network is considered and applied to both short-/long-term prediction of nonlinear ship motion.

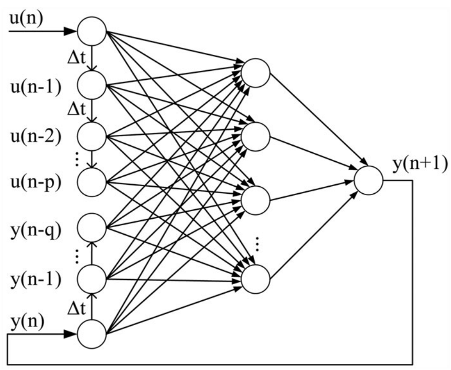

Figure 1. NARX model with delayed inputs and outputs.

3. Ship motion prediction model based on the NARX network

3.1. System structure for ship motion prediction

A framework for ship motion prediction is proposed based on collected ship sensor data. The system features flexible and versatile data since for different ships their collected sensor data can be easily imported into the system to obtain the predictive motion model. Figure 2 illustrates the overall structure. It consists of three components:

- *Purification*: Considering the raw sensor data may contain noisy, discontinuous and redundant information, it is necessary to purify it so that its effect on further analysis and modelling can be minimised. We resample the data that have different frequencies and delete discontinuous data in advance.
- *Prediction*: Prediction is the core of the scheme. It bridges the gap between the user and the generated database for better understanding and modelling the data set. Two ways that potentially improve prediction performance are used. On the one hand, it provides the user with the ability to optimise the data set. For instance, to generate a predictive model for fine manoeuvring one can filter the velocity and the position of the ship to form a subset of the database before NN learning. On the other hand, the NARX network with different NN learning strategies is used to analyse and model the data, aiming to realise short-/long -term time series prediction of ship motion.
- *Verification*: To verify the model, the subset is divided into a training set and a testing set in the proportion of 3:1. The result is visualised by both plotting and animation. The prediction performance is straightforward. From the practical point of view, the procedure from purification to verification can repeat until reaching the expected prediction error.

Note that in the verification component, the trained predictive model is not applicable for other ships, as the model inherits certain physical characteristics like inertial dynamics from the specific vessel. In other words, the training and the testing sets must originate from the same vessel. Violating this principle will result in invalid prediction results.

3.2. Ship sensor data collection

To generate a reliable prediction model, on-board ship sensor data have been collected by our partner – 'Rolls-Royce Marine AS' for a long time. Four types of data modules with a sampling frequency from 1 up to 4000 Hz have been collected and imported into the database. The high sampling frequency data modules are mostly used for propulsion system analysis, e.g.

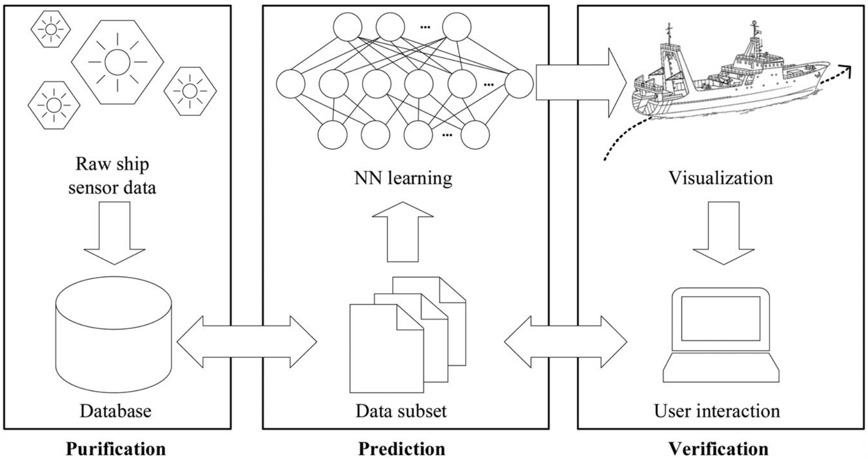

Figure 2. System diagram of ship motion prediction.

the thruster vibration, the shaft torque and the bending moment, whereas the low sampling frequency data modules are the collection of ship status, as shown in Table 2. Note that M1 is the ship's extrinsic representation caused by the intrinsic control parameters like thruster forces from M2. We used both the low sampling frequency data modules M1 and M2 for ship motion prediction.

3.3. Ship motion modelling and visualisation

NN modelling is designed to be as flexible as possible. Regarding generating the NN structure, users are able to model from the number of layers and nodes, the type of activation function, to the concrete NN inputs and output parameters. In addition, the learning rate and terminate conditions are also optional for modelling.

To better understand the resultant predictive model, the model visualisation is responsible for animating the ship motion, as well as the predictive curves over time. In the framework, model visualisation involves two parts. First, users are provided with an interface for model interaction. One can filter the training and testing data set as necessary, for example, to filter the constraints of the speed and the position for fine manoeuvring modelling. Second, there is a flexible overview of the results. One can select a time line of interest to display, and to zoom in/out to compare the results. In this way, users can easily figure out whether the NN modelling and learning procedure are good enough for certain type of ship motion prediction.

Table 2. Specification of ship sensor data in low sampling frequency.

Module	Frequency	Parameter	Unit
M1	1 Hz	Speed	(m/s)
		Position	(m, m)
		Heading	(deg)
		Roll	(deg)
		Pitch	(deg)
		Yaw rate	(deg/s)
		Roll rate	(deg/s)
		Pitch rate	(deg/s)
M2	1.65 Hz	Rotational speed	(RPM)
		Drive of motor	(W)
		Propeller force	(N)
		Propeller pitch	(deg)

4. Network structure and learning strategies analysis

4.1. Sensitivity analysis

Since ship motion prediction refers to various information as shown in Table 2, it is better to construct different predictive models against the specific motion prediction. The reasons lie in two aspects. Regarding the complexity of the model, a single predictive goal will simplify the network structure and hence improve the generalisation ability. Furthermore, for different predictive tasks, the output would have a different degree of reliance on input information. It is much appropriate to select proper information as inputs to restrict the network dimension in an acceptable scope.

Sensitivity analysis plays a role in evaluating the importance of individual input for the output in the NARX network (Dimopoulos et al. 1995). For a three-layer NARX network, suppose the input vector $\boldsymbol{x}$, the hidden vector $\boldsymbol{h}$ and the output y, the input–output derivatives can be described as follows:

$$\begin{aligned} s_i &= \frac{\partial y}{\partial x_i} \\ &= f'(y)\sum_j w_{ho} f'(h_j) w_{ih} \end{aligned} \tag{2}$$

where $f(\cdot)$ is the activation function; w_{ih} and w_{ho} are the weights between the input-hidden layer and hidden-output layer, respectively. This type of derivatives reflects how much contribution the input to the output provides in a moment. To estimate the overall contribution with respect to time series, we followed the definition of sum of square derivatives (SSD) by Dimopoulos et al. (1995):

$$\mathrm{SSD}_i = \sum_t (s_i)^2 \quad (3)$$

which indicates the influence degree of the input to the output. In accordance with the SSD values, selection of inputs can be achieved by deleting these inputs that have smaller SSD values than the threshold. As a result, it will compact the network structure, but retain the ability of representing the input–output mapping of the system.

4.2. Learning strategies

Three learning strategies are applied on the NARX network to compare the impact of prediction precision, as shown in Figure 3. For offline prediction, the inputs and the desired output are extracted from the training set of ship sensor data in advance. The learning cycle is single in the offline process, which means weights and biases are only updated for the NARX network after the entire time series of the inputs and the corresponding desired outputs are presented. It is a kind of batch learning. The prediction results depend on the training set and the number of epochs.

For online prediction, the learning strategy is required to deal with sensor data in a real-time manner. In general, both the inputs and the desired output in this strategy are presented in the form of a sequential order. The inputs thus can be considered as the latest ship sensor data from the interaction that had just happened between the ship and the environment. The output is represented as the prediction of ship motion in the near future. Figure 4 illustrates a single-step ahead prediction procedure using the online learning strategy. Note that different from offline prediction, the weights are updated per time step. The benefit is to make the trained network be adapted to environmental changes.

The hybrid prediction is a combination of the above two strategies. It contains two stages. First, it follows the offline learning procedure. The weights containing prior knowledge of pasted ship motion is obtained as the initial weights of the NARX network. Second, it starts the online learning strategy by further adjusting the weights while the ship is moving. The weights are updated through BPTT by using the error between the measured and the desired outputs. In theory, the hybrid strategy is more efficient since the knowledge from offline learning decreases the prediction errors and converges to acceptable range once online learning is started.

4.3. Multi-step-ahead prediction

In real applications, the single-step-ahead prediction of ship motion is insufficient, as the navigator may be lacking a full picture of ship motion in mind and cannot foresee the operational consequence promptly. From ship's safety point of view, it is critical to use multi-step-ahead prediction methods to promote the navigator's awareness of decision-making.

As introduced in Section 2.2, the NARX network is able to make multi-step-ahead prediction because of the feedback loop from the output. On the one hand,

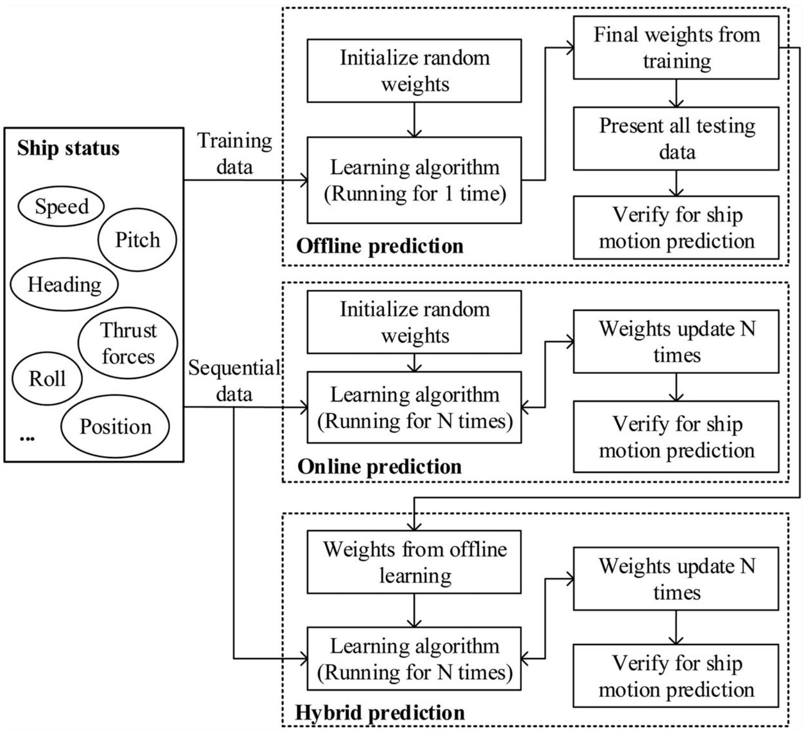

Figure 3. Three learning procedures for ship motion prediction.

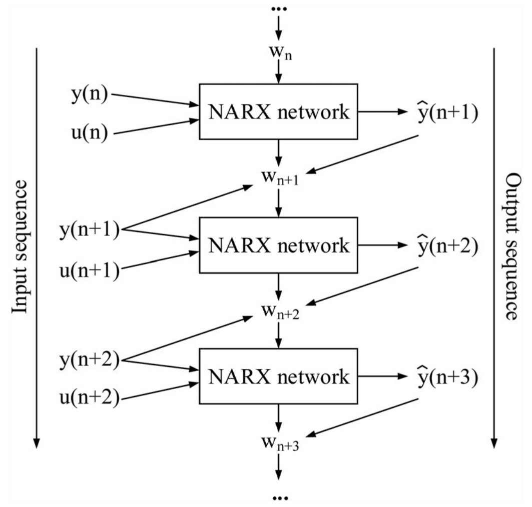

Figure 4. Online learning strategy for single-step-ahead prediction.

the inputs supply medium to long-term information about the dynamical property of the ship status. The output with feedback loop, on the other hand, supplies short-term information about the same time series. Because there are no new external inputs being added during the long-term prediction process, training the NARX network to converge to small output errors is challenging.

To realise multi-step-ahead prediction of ship motion, attempts have been made by applying the hybrid prediction strategy with small modifications. First, through offline learning, the weights and bias are obtained for single-step-ahead prediction. Then, in the online learning process, instead of performing single-step-prediction, multi-step-ahead prediction is executed in a multi-stage form before weight update, as shown in Figure 5. It is worth noting that the estimated output is fed back and included as the only updated input. Therefore, the confidence level for

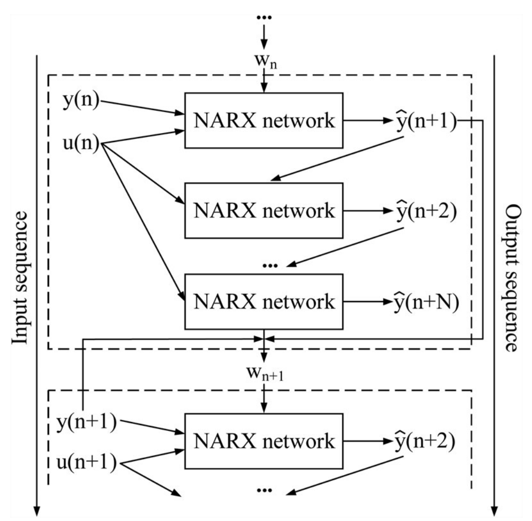

Figure 5. Multi-step-ahead prediction based on the NARX network.

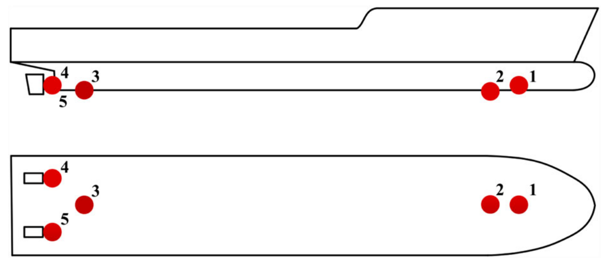

Figure 6. Thruster configuration of the ship.

multi-step-ahead prediction decreases with the growth of prediction horizon. The prediction process repeats until reaching the predefined prediction horizon. Last, the weight of the NARX network is updated in the new round of prediction according to the difference between the measured and the desired outputs. As a result, the modified learning strategy enables the NARX network to estimate ship motion in the sense of long-term prediction.

5. Experiments

Experiments have been carried out to validate the prediction capability of the proposed model based on the NARX network. We used Matlab neural network toolbox to implement the NARX network. The collected data are from a supply vessel. It has a mass of 5417 tons and a length of 68.2 m. Figure 6 illustrates the thruster configuration. There are five thrusters on the vessel: thrusters 1 and 2 are lateral bow thrusters; thruster 3 is an azimuth thruster in the midway between the bow and the stern and thrusters 4 and 5 are main propellers with rudders at the stern.

5.1. Sensitivity analysis result

From the ship status information listed in Table 2, there are 29 attributes in total available in the database. For simplicity, we only show three of the attributes, i.e. heading, roll and pitch as the prediction targets. In addition, the time series of raw data is purified and cut down for minimising the affection on further modelling and analysis.

Three NARX networks with full of 29 attributes as inputs were independently generated for the three prediction targets. The memory for past inputs and outputs are set p=3 and q=3 (see definition in Figure 1). Through BPTT, the weights of the networks were updated and the SSD values in (3) that represent the contribution of each input to the output were then obtained. Figure 7 shows part of the attributes that contain relatively high SSD values. Note that besides the high values of self-correlation of heading, roll and pitch, the three prediction targets are also closely related to the forces from thruster 1, 4 and 5. The result, to some extent, reveals that the forces from the

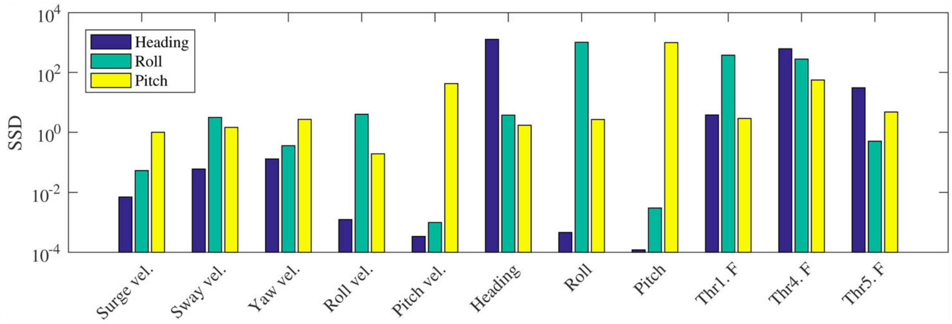

Figure 7. SSD values of heading, roll and pitch in the time series of training data.

three thrusters are dominant for propelling in the time series of data.

To compact the NN structure and hence improve the generalisation ability of the network, the inputs having SSD values lower than a thresholds of 0.01, 0.1 and 1 for heading, roll and pitch, respectively, were deleted from the networks. The prediction performance of the trimmed NN is verified in the same order of magnitude as that of the untrimmed NN. Therefore, the following experiments were performed using the trimmed NN.

5.2. Learning strategies comparison

We have tested the three learning strategies, i.e. offline, online and hybrid learning, in one-step-ahead predicting different aspects of ship motion, including trajectory, heading, roll, pitch, surge, sway and yaw velocity. For concise reasons, only the pitch angle prediction is illustrated in Figure 8 for comparison. In general, there is no regular pattern in the time series of the pitch angle. Through sensitivity analysis, 18 of 29 attributes were selected as the inputs of the NARX network for pitch angle prediction.

The top panel of Figure 8 is the result of offline learning. Two-thirds of the raw data are used for training, while the rest is used for testing. The network stopped training after 113 epochs until the mean-squared error (MSE) decreased to a magnitude of 10^{-6}. The prediction result is accurate and close to the raw data. The middle panel of Figure 8 shows the online learning result. The MSE for the whole sequence

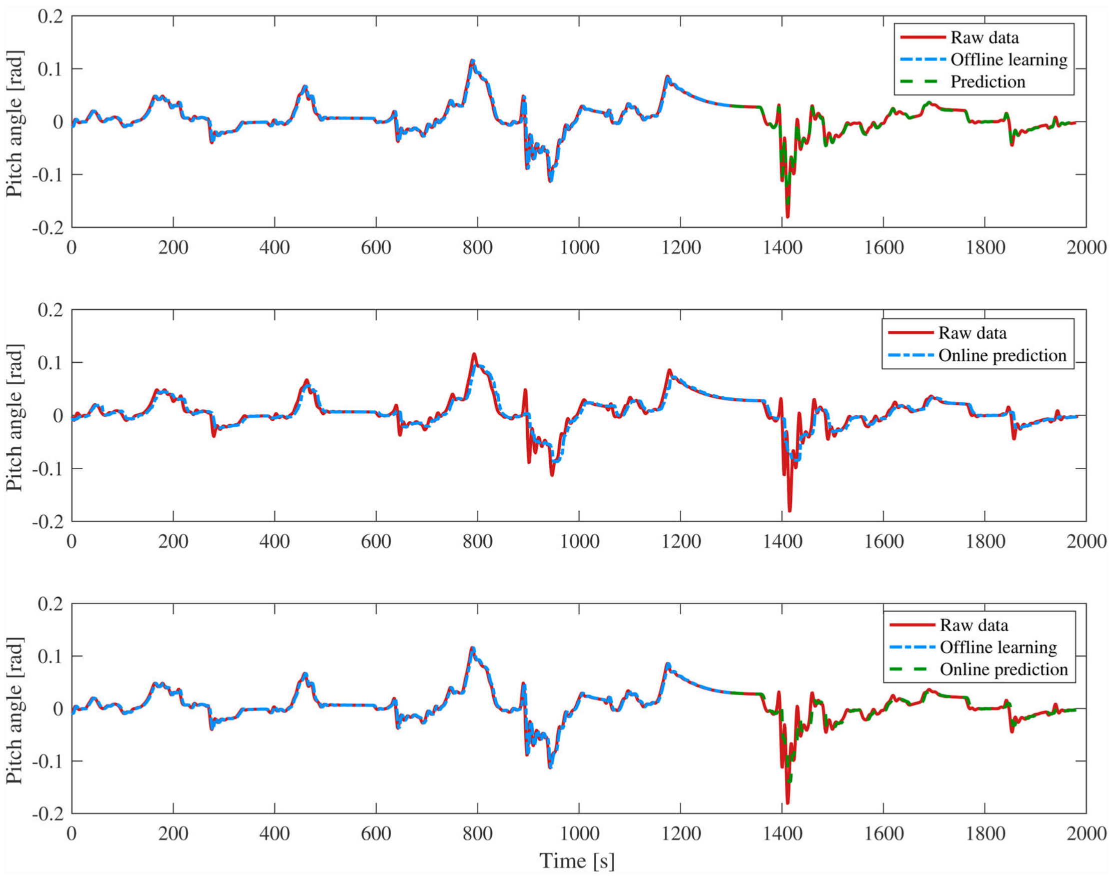

Figure 8. Comparison of pitch angle prediction using three different learning strategies.

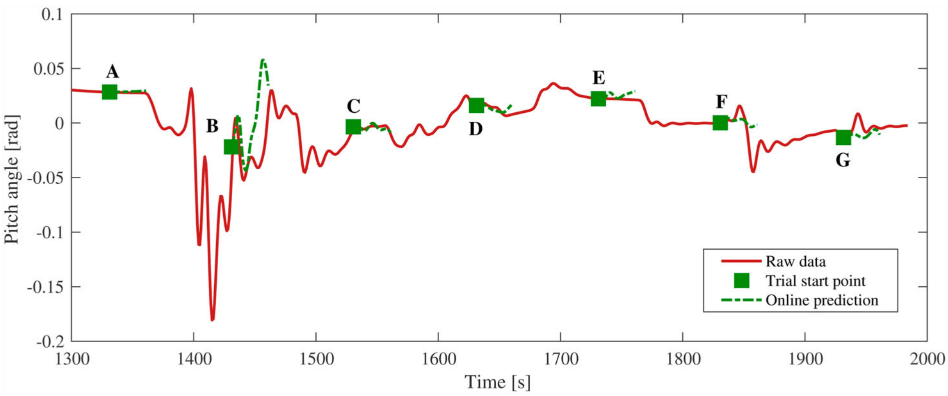

Figure 9. Trials of 30-step-ahead prediction after offline learning.

is about 9.33×10^{-5}, which indicates the prediction performance is relatively poor, especially when the spikes occur. It depends on how fast the NN weights are updated to respond to the rapid changes of pitch angle in the consecutive sequence. The hybrid learning result is at the bottom panel of Figure 8. Compared with online learning, the prediction performance is satisfactory, where the average MSE is significantly decreased to 9.04×10^{-8}. It is obvious that the hybrid learning strategy is superior for fast convergence of the prediction error in a real-time fashion.

5.3. Multi-step-ahead prediction result

Precise long-term prediction of ship motion is a tough task, since there are a lot of operational interactions and environmental disturbances. The goal in this experiment does not intend to improve the precision of long-term prediction. Instead, we aim to find out the feasibility of the proposed strategy in Section 4.3 and analyse why the potential consequences are generated.

The hybrid learning strategy for multi-step-ahead prediction was carried out. Again, we use the pitch angle prediction for illustration. Figure 9 shows 7 trials of 30-step-ahead prediction of the pitch angle (naming from A to G). Offline learning was done in advance to obtain prior knowledge of past pitch angle variation. Each trial was then performed after the online update of weights, ensuring that the NN is adapted to the recent changes of time series of data. Figure 10 illustrates the prediction errors of the corresponding trials. The prediction error is small if the change of the pitch angle is small (e.g. trials A, F and G). Whereas prediction performance decreases when there are dramatic fluctuations of the pitch angle (e.g. trial B). Another finding from Figures 9 and 10 reveals that the prediction is highly dependent on the pattern of recent changes of the pitch angle. Trials A and B are much in evidence among these trials. This is consistent with the modified hybrid learning strategy where the NN weights are updated in an online manner.

The performance of multi-step-ahead prediction is not as satisfactory as the one of single-step-ahead prediction. The main impact factor lies in the multi-stage prediction form. Because the inputs are fixed during prediction, the NARX network tends to suffer from error accumulation problems as it tries to capture the fluctuations of the finite past of both inputs and outputs in time series. The bias and variance from previous time steps are therefore accumulated and propagated into future predictions. The NARX network cannot eliminate this phenomenon. Nevertheless, it is possible to associate the prediction with a confidence interval, e.g. a higher fluctuation of inputs implying a lower confidence interval, and vice versa, to

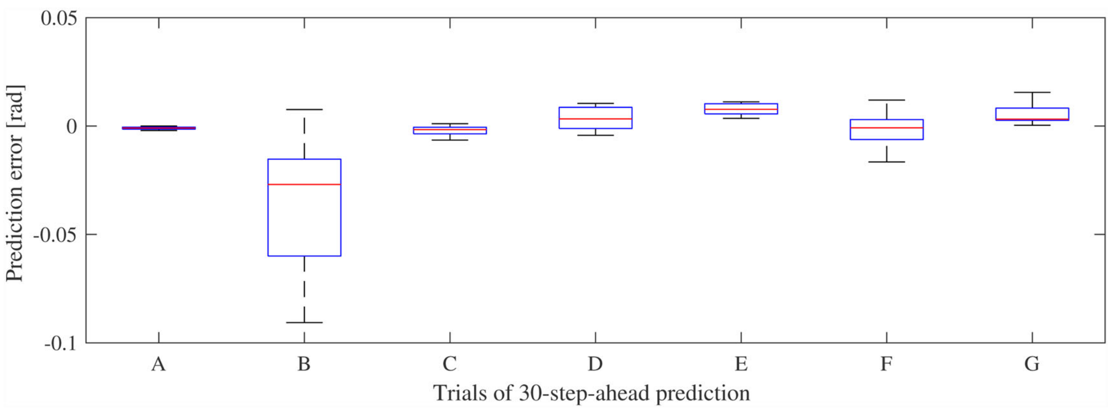

Figure 10. Prediction errors of trials in 30-step-ahead pitch angle prediction.

complement the multi-step-ahead prediction uncertainty.

6. Conclusion

In this paper, the modelling and analysis of a data-driven model for ship motion prediction is emphasised. By comparing with different prediction techniques, the NARX network is chosen as the core of our ship motion prediction framework. Ship sensor data are collected and purified in advance. In order to model a compact NN structure, sensitivity analysis is used for quantification of the significance from the inputs to the outputs. Three learning strategies, including offline, online and hybrid learning, are analysed. The hybrid learning shows better prediction performance as it combines the other two strategies together. Taking advantage of the long-term prediction ability of the NARX network, multi-step-ahead prediction is realised under the hybrid learning strategy. Experimental results show that modelling and analysing of the NARX network are helpful in generating the data-driven model for ship motion prediction.

Future work will focus on two aspects. First, more information about the environmental changes like wind speed and wave height should be involved in modelling the NARX network. Second, what is the appropriate memory in the NARX network will be investigated and optimised for long-term prediction of ship motion.

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