Neural Network Prediction of the Roll Motion of a Ship for Intelligent Course Control

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Abstract. For conventional ships, the mono-variable autopilot controls the heading of the ship in the presence of disturbances. During the heading control, there are many moments of time when the rudder command to control the yaw angle has a negative influence on roll oscillations. The prediction of the wave influence on the roll motion can be used to implement an intelligent heading control system, which is added to the mono-variable autopilot, generating only rudder commands with damping or non-increasing effects over roll movements. In this paper, aspects of roll angle and roll rate prediction using feed-forward neural networks are discussed. A neural network predictor of the roll rate, based on measured values of the roll angle, is proposed. The neural architecture is analyzed using different training data sets and noise conditions. The predictor has on-line adaptive characteristics and is working well even if both training and testing sets are affected by measurement noise.

Keywords: neural networks, time series prediction, neural predictor, intelligent course control.

1 Introduction

The conventional ships, like supply vessels, have one main aft thruster, which produces surge forces to control the ship forward motion, and a rudder actuated by the steering machine (SM), which generates yaw moments to control the yaw angle. The autopilot generates the rudder commands to control the heading of the ship in the presence of disturbances, during course-keeping or course-changing maneuvers [1].

A ship in open sea is a very complex dynamic system, affected by many types of perturbations. The waves are the most important disturbances, and they have a double effect on the ship: a zero-mean oscillatory movement induced by the first order waves, and a low frequency drift effect caused by the second order waves. The cumulated drift effect can be compensated by the control law of the autopilot system. Hence, in this paper only first order waves are considered as external perturbations.

The model parameters depend on the ship loading conditions and ship's forward speed, while the wave characteristics change frequently. In addition, the wave

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influence on the ship motions depends on the relative frequency between the wave and the ship, which is modified by the incidence angle and the ship's speed [2]. Therefore, the prediction of the wave influence is important for intelligent control systems and it can be achieved by nonparametric approaches, like neural networks (NN).

The commands of the rudder affect simultaneously the yaw and roll movements of the ship. The double control problem of using the rudder for simultaneous heading control and roll reduction have been analyzed by many authors [3], [4]. This is an under-actuated control problem, as there is only one actuator to achieve two objectives, which can be separated in the frequency domain [5], [6]. The main drawback is that the control systems take into account only one motion of the ship. There are many moments of time when the rudder command to control the yaw angle has negative influence on roll oscillations [7].

It is important for the autopilot to generate only rudder commands with damping or non-increasing effects over roll movements. For this, an intelligent control system can be added to conventional SISO autopilot, modifying the rudder command so that, roll damping effects to be obtained [8]. It takes into account the noisy measurements of roll angle and the estimation of roll rate. A more complex control law can be used, if the wave influence on roll motion can be predicted several steps ahead.

Neural networks, including feed-forward neural networks (FFNN) [11], [12], are widely applied for prediction problems [9], [10] due to their universal approximation and generalization capabilities. In particular, there are many applications reported in the literature of using NNs for time series prediction [13], [14], [15].

In this paper, aspects of roll angle and roll rate prediction using feed-forward neural networks are discussed. A neural network predictor of the roll rate is proposed, based on noisy measured values of the roll angle. The neural architecture is analyzed using different prediction steps, input dimensions, training data sets and noise conditions. The predictor has on-line adaptive characteristics and it is working well even if both training and testing sets are affected by measurement noise.

The paper is organized as follows. Section 2 provides mathematical models of the ship, steering machine and wave disturbances. In Section 3, the intelligent heading control problem is introduced. In Section 4, aspects of neural prediction techniques of roll motion are discussed. Section 5 describes the prediction results based on noisy measured values of the roll angle. Conclusions are presented in Section 6.

2 Preliminaries and Mathematical Models

The underactuated ship control problem is inherently nonlinear due to the uncontrollability of linear models. Moreover, the underactuated ships cannot be asymptotically stabilized by a linear time-invariant feedback control law [16]. Therefore, adaptive nonlinear control law must be considered.

The models for the ship dynamics, steering machine and disturbances had to be generated for simulation purposes. By connecting the models, a nonlinear extended model for the underactuated ship is obtained, as shown in Fig. 1.

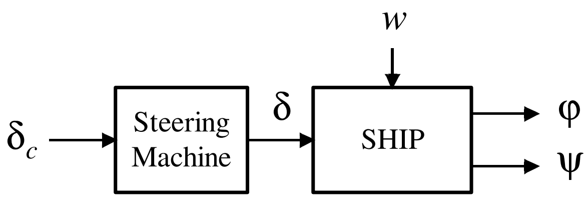

Fig. 1. Nonlinear model of an underactuated ship

The ship model is linear with parametric uncertainties. The model inputs are the rudder angle *(δ)* and wave disturbances *(w)*, and the outputs are the yaw angle *(ψ)* and roll angle (φ). The rudder command *(δ_C)* is generated by the autopilot.

By using the Newton's laws and expressing the conservation of hydrodynamic forces and moments, the equations describing the horizontal motion of the ship can be derived. A two degree-of-freedom linear model with parametric uncertainties can be identified [17]. Considering the wave disturbances (w), the Laplace equations of the ship's linear model are:

$$\begin{cases} \psi(s) = \psi_\delta(s) + \psi_w(s) = H_{\delta\psi}(s)\cdot\delta(s) + H_{w\psi}(s)\cdot w(s) & (1) \\ \varphi(s) = \varphi_\delta(s) + \varphi_w(s) = H_{\delta\varphi}(s)\cdot\delta(s) + H_{w\varphi}(s)\cdot w(s) & (2) \end{cases}$$

The transfer functions $H_{\delta\psi}$ and $H_{\delta\varphi}$ describe the transfer from the rudder angle (δ), to the yaw angle (ψ) and roll angle (φ), respectively. The transfer functions $H_{w\psi}$ and $H_{w\varphi}$ represent the wave influence, being in general unknown. Hence, the wave influence on ship motions must be predicted. The function parameters depend on the ship load conditions, speed of the ship (u) and incidence angle (γ). The roll angle represents a damping oscillatory movement, with natural frequency $\omega_n = 0.64$ (rad/s).

The steering machine model is nonlinear and it is based on a two-loop electro-hydraulic steering subsystem, common on many ships, as illustrated in Fig. 2. The model of the SM includes also a rudder angle limiter which is not represented in the figure, because the rudder angle is small enough and it is not limited, for all simulations. A common low performance SM is used in simulations, with maximum rudder deflection of ±35 (deg) and a maximum rudder rate of ±2.5 (deg/s).

Considering only the yaw angle and mono-variable autopilots, the first loop of SM can be disregarded, but for roll movements, the first loop increases the phase lag and decreases the rudder force moment on roll angle [18]. Therefore, the first loop can not be disregarded and the nonlinear steering machine model is considered.

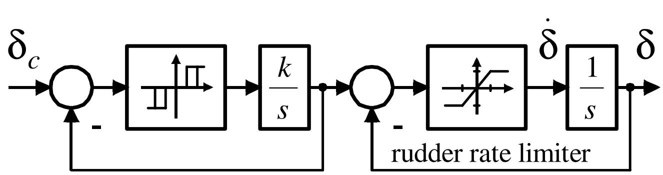

Fig. 2. Nonlinear model of the steering machine

In general, the wave disturbance can be regarded as an ergodic random process with elevation $\zeta(t)$ and zero mean. The wave can be modeled as the sum of a limited number of sinusoidal waves, based on the wave spectrum $\phi_{\zeta\zeta}(\omega)$:

$$w(t) = \sum_{i=1}^{N} A_i \cdot \sin(\omega_i \cdot t + \varphi_i), \quad A_i = \sqrt{2 \cdot \phi_{\zeta\zeta}(\omega_i) \cdot \Delta\omega}\ , \tag{3}$$

where A_i and ω_i are the amplitude and angular frequency of the i-th component, and φ_i is the phase angle drawn randomly from a uniform density distribution. The relative frequency between the wave and the ship modifies the wave spectrum $\phi_{\zeta\zeta}(\omega)$ and this transformation must be taken into account for the wave model generation [2].

3 Aspects of Intelligent Heading Control

The two objectives of using the rudder for simultaneous heading control and roll reduction can be separated in the frequency domain, based on the frequency characteristics of the rudder influence on yaw and roll motions, as shown in Fig. 3. Low frequencies are used for heading control, and high frequencies for roll reduction. Thus, the problem is divided into two mono-variable control systems,

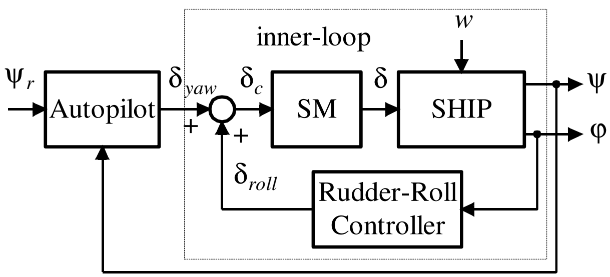

Fig. 3. Separated closed loops for rudder-yaw and rudder-roll controls

The main drawback of the frequency separation principle is that the mono-variable autopilot and the rudder-roll controller take into account only one motion of the ship and ignore the other one. There are many moments of time when the command of the rudder to control the yaw angle (δ_{yaw}) has negative influence on roll oscillations [9].

It is important for the autopilot to generate only the rudder commands with damping or non-increasing effects over roll movements, with acceptable small errors of the yaw angle. For this, a fuzzy rudder-roll damping (FRRD) system can be added to conventional SISO autopilot, which modifies the autopilot commands based on the noisy measurements of the roll angle and the estimation of the roll rate [10].

In addition, if the wave influence on the roll motion can be predicted several steps ahead, a more complex intelligent control law can be implemented. In this paper, some aspects of the roll angle and roll rate prediction using feed-forward neural networks are discussed, based on measured values of the roll angle, as illustrated in Fig. 4.

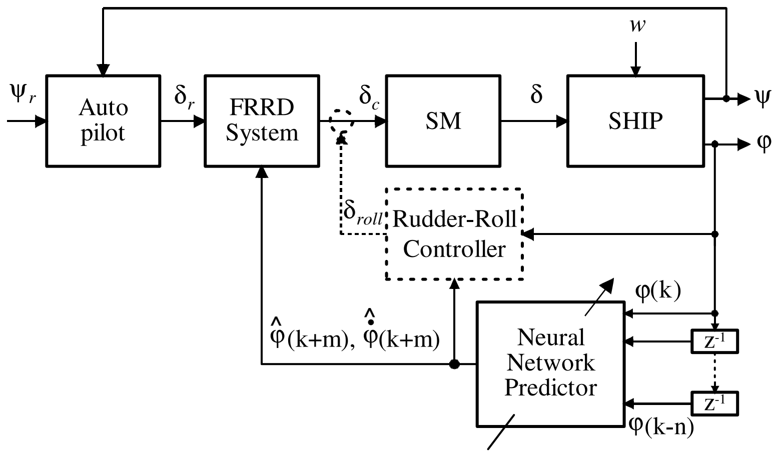

Fig. 4. Neural Network Predictor and FRRD System for Intelligent Heading Control

4 Neural Prediction of the Roll Motion

For the intelligent heading control, the roll angle and roll rate are of interest. Eq. 2 describes the influences of the rudder angle and the additive wave perturbations on the roll motion of the ship. The influence of the rudder can be identified at the beginning of the ship voyage, but the wave influence changes frequently and must be predicted on-line, based on the measured values of the roll angle.

Theoretically, if the roll angle is not affected by measurement noise, the roll rate can be obtained by numerical computation from roll angle. The roll angle and roll rate without measurement noise are illustrated in the left side of Fig. 5. The wave was generated based on the ITTC spectrum with significant height $h_{1/3} = 4\ m$. The wave spectrum was corrected with the ship's speed $U = 7.2\ m/s$ (*14 knots*) and the incidence angle of the wave $\gamma = 135\ deg$, resulting the corrected wave, denoted *wc*.

Practically, the measured values of the roll angle (φ_m) are affected by additive measurement noise (φ_p), which is considered white noise with different power levels:

$$\varphi_m(s) = \varphi_\delta(s) + \varphi_w(s) + \varphi_p(s) \tag{4}$$

Using numerical computation based on the measured values of the roll angle, the resulted roll rate is useless and is overwhelmed by noise, as shown in the right side of Fig. 5. Hence, the roll rate must be estimated. The noise amplitude was considered *10%* from the maximum value of the theoretical roll angle. The sample period was chosen $T = 0.1\ s$.

The wave influence on the roll motion can be predicted, based on the measured values of roll angle, by placing the rudder angle to zero:

$$\varphi_m\big|_{\delta=0} = \varphi_w + \varphi_p \tag{5}$$

The roll angle samples represent a time series, $\varphi_m(1)$, $\varphi_m(2)$, ... $\varphi_m(k)$, illustrated on the second row in the right side of Fig. 5. Using the time series as noisy input data set, the roll angle and roll rate can be predicted several steps ahead using neural networks.

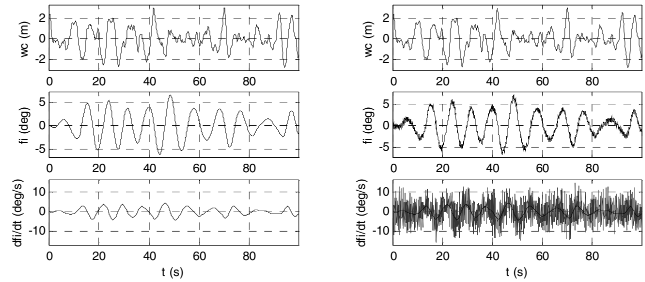

Fig. 5. Roll Angle and Roll Rate without and with measurement noise

In general, the simplest approach for learning the time series model by means of a NN is to provide its time-delayed samples to the input layer of the NN. The output represents the predicted value at $k+m$ time moment:

$$\hat{y}(k+m) = f\left(y(k), y(k-1), \dots, y(k-n)\right) \tag{6}$$

The more complex the series are, the more information about the past is needed, and the size of the input layer ($n+1$) is increased, depending also on the prediction step m. For every step $k+m$, the prediction error $e(k+m)$ is computed based on the measured and predicted values of the output, which is used in the neural network training:

$$e(k+m) = y_m(k+m) - \hat{y}(k+m) \tag{7}$$

5 Simulation Results

In this paper, the neural prediction of the noisy roll rate is discussed. The FFNN predictor receives ($n+1$) time-delayed samples of the measured roll angle, $\varphi_m(k-n), \dots \varphi_m(k)$, as shown in Fig. 4. The output is the m step predicted value of the roll rate, $\hat{\dot{\varphi}}_m(k+m)$.

The FFNN has one hidden layer with $Nhn = 10$ linear neurons and is trained using Levenberg-Marquardt back-propagation algorithm. The performance function is *mse*, the mean squared error of the predicted roll rate related to initial noisy roll rate. During the learning and testing of the NN, the same performance criterion is used, denoted *msel* and *mset*, respectively. To illustrate the filtering properties of the NN, *mset2* is used, based on the prediction error to real value of the roll rate. The prediction error on the testing data set and its normalized autocorrelation function are used for model validation.

Several neural architectures are tested, for different prediction steps ($m = 1, 5, 10$), input dimensions ($n+1 = 5, 10, 20$), training data sets and noise conditions. Training data sets are selected from the first time interval (*0-20 s*) of the noisy roll angle for input data and the roll rate for desired output, shown in the right side of Fig. 5.

Three training sets are used, with the number of learning vectors *Nlv*: *50, 100* and *200*. The testing set has *500* vectors selected from the rest of the time series (*50 s*).

During training, the performance goal is *msep = 25* and a maximum of *300* epochs are allowed.

The measurement noise of the roll angle generates an initial mean squared error of the computed roll rate related to the real roll rate value, denoted *msen*, which is the base for the performance analysis of the neural predictor. Three indices are computed: $I_1=msel/msen$, $I_2=mset/msen$, $I_3=mset2/msen$. If indices are close to 1, the output performance is close to the initial roll rate noise. The results are represented in Table 1.

Table 1. The network performance for different neural predictors

m	Nlv	n+1 = 5			n+1 = 10			n+1 = 20		
		I_1	I_2	I_3	I_1	I_2	I_3	I_1	I_2	I_3
1	50	0.972	1.004	0.149	0.883	1.303	0.113	0.712	1.652	0.645
	100	0.978	1.148	0.050	0.947	1.067	0.081	0.865	1.196	0.178
	200	1.023	1.072	0.041	0.980	1.066	0.026	0.962	1.112	0.045
5	50	0.946	0.965	0.104	0.859	1.507	0.252	0.739	1.652	0.472
	100	0.959	1.191	0.059	0.935	1.000	0.096	0.814	1.187	0.177
	200	1.007	1.083	0.044	0.987	1.076	0.028	0.930	1.183	0.080
10	50	0.905	1.404	0.153	0.859	1.392	0.279	0.647	1.432	0.596
	100	1.037	1.032	0.033	0.872	1.303	0.155	0.800	1.502	0.243
	200	1.018	1.089	0.026	0.989	1.087	0.032	0.883	1.260	0.129

The performance goal is reached very fast and the prediction is good for the entire testing set. The testing index I_2 has values close to 1, which means that the prediction error is within the noise range of initial computed roll rate. The prediction error, related to similar training index I_1, can be decreased by choosing a bigger training data set. Bigger values for prediction step *m* impose bigger values for *n* and *Nhn*. Also, the prediction error increases with *m* and it depends on the number *Nlv*.

An important feature is the filtering property of the NN, observed at index I_3, which is based on prediction error related to the real value of the roll rate. For the selected neural architecture (*m=5, n+1=10, Nlv=200*), the initial time series of the computed roll rate and the training and testing results are illustrated in Fig. 6. The time ranges of training and testing prediction results are marked distinctly.

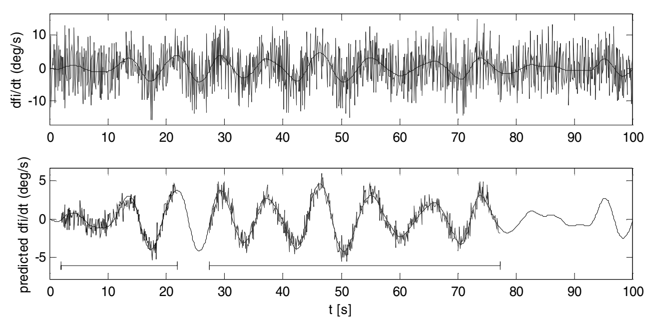

Fig. 6. Training and testing results for the selected neural predictor

6 Conclusions

The wave influence on the roll motion of a ship can be predicted, and a feed-forward neural network was chosen for this task. The predictor is working well even if the training is done on-line and the samples are affected by measurement noise. After training, the prediction remains good for a wide time horizon and the estimated error is within the noise range. Also, the neural predictor is robust, working well for different levels of the input noise.

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