Applied Ocean Research 30 (2008) 256–263

Contents lists available at ScienceDirect

Applied Ocean Research

journal homepage: www.elsevier.com/locate/apor

System identification for nonlinear maneuvering of large tankers using artificial neural network

G. Rajesh, S.K. Bhattacharyya *

Department of Ocean Engineering, Indian Institute of Technology Madras, Chennai-600036, India

ARTICLE INFO

Article history:
Received 8 July 2008
Received in revised form
20 October 2008
Accepted 23 October 2008
Available online 1 January 2009

Keywords:
Hydrodynamic derivatives
Maneuvering
Neural network
Neurons
Nonlinear
Ship
Simulation
System identification
Tanker

ABSTRACT

This paper deals with the application of nonparametric system identification to a nonlinear maneuvering model for large tankers using artificial neural network method. The three coupled maneuvering equations in this model for large tankers contain linear and nonlinear terms and instead of attempting to determine the parameters (i.e. hydrodynamic derivatives) associated with nonlinear terms, all nonlinear terms are clubbed together to form one unknown time function per equation which are sought to be represented by the neural network coefficients. The time series used in training the network are obtained from simulated data of zigzag maneuvers and the proposed method has been applied to these data. The neural network scheme adopted in this work has one middle or hidden layer of neurons and it employs the Levenberg–Marquardt algorithm. Using the best choices for the number of hidden layer neurons, length of training data, convergence tolerance etc., the performance of the proposed neural network model has been investigated and conclusions drawn.

1. Introduction

System identification can be defined as a systematic approach to find a model of an unknown system from the given input–output data. For system identification to be successful, three items should be properly selected or designed; mathematical model of the system, input–output data and parameter estimation scheme. The area of ship maneuvering has seen extensive application of a variety of system identification methods. Some of the established system identification methods in this area are indirect model reference adaptive systems [1], continuous least square estimation [2], recursive least square estimation [3,4], recursive maximum likelihood estimation [5], recursive prediction error technique [6], extended Kalman filter approach [7]. In recent times, various approaches and techniques of system identification that have been used in the area of ship hydrodynamics are Markov process theories, statistical linearization techniques [8] and reverse multiple input-single output methods [9,10]. Recently, the neural network based identification has drawn attention in ship maneuvering [11–13]. The mathematical model of the neural network is so called because it mimics the learning process of the human brain and does not use a physical model. Because of this, it should be more robust than the classical physical model based identification techniques, especially when the physical models are complex and semi-empirical in nature. Neural network based system identification models, developed in this paper, are shown to provide an attractive alternative to the identification methods relying upon physics based mathematical models of ship maneuvering. The input–output data required for this neural network based identification method can be directly obtained either from free running model tests or full-scale maneuvering trials so that the method is accurate enough for all practical simulation work.

Whereas neural network based identification in ship maneuvering has been treated in the literature in a preliminary way [11–13], all the studies consider the classical Abkowitz model [7] of nonlinear maneuvering and its variants. This class of maneuvering models hold good for cargo ships but are quite inadequate for large tankers. The well proven mathematical models of maneuvering of large tankers [14–16] are quite different from that of cargo ships [7, 15] in several respects. The principal among them are (i) strong coupling between propulsion hydrodynamics involving propeller thrust, rpm and thrust deduction factors etc. with maneuvering hydrodynamics, (ii) coupling between rudder hydrodynamics and propulsion hydrodynamics such that propeller rpm affects the flow speed past the rudder and this in turn modifies the hydrodynamic

* Corresponding author. Tel.: +91 44 22574803; fax: +91 44 22574802.
E-mail address: skbh@iitm.ac.in (S.K. Bhattacharyya).

0141-1187/$ – see front matter © 2008 Elsevier Ltd. All rights reserved.
doi:10.1016/j.apor.2008.10.003

forces and moments acting on the tanker that appear in its maneuvering equations, (iii) shallow water effect on maneuvering. To date, neural network based identification has not been studied in the context of the maneuvering of large tankers. The present paper makes an attempt to do so for the first time.

2. Nonlinear equations of motion

The nondimensional surge, sway and yaw equations of large tankers [15,16] are considered in this paper. These are:

$$\dot{u} - vr = gX \tag{1}$$

$$\dot{v} + ur = gY \tag{2}$$

$$(Lk_z)^2\dot{r} + Lx_G ur = gLN \tag{3}$$

where

$$\begin{aligned} gX = {} & X_{\dot{u}}\dot{u} + L^{-1}X_{uu}u^2 + X_{vr}vr + L^{-1}X_{vv}v^2 + L^{-1}X_{c|c|\delta\delta}|c|c\delta^2 \\ & + L^{-1}X_{c|c|\beta\delta}c|c|\beta\delta + X_{\dot{u}\zeta}\dot{u}\zeta + L^{-1}X_{uu\zeta}u^2\zeta + X_{vr\zeta}vr\zeta \\ & + L^{-1}X_{vv\zeta\zeta}v^2\zeta^2 + gT(1-\hat{t}) \end{aligned} \tag{4}$$

$$\begin{aligned} gY = {} & Y_{\dot{v}}\dot{v} + L^{-1}Y_{uv}uv + L^{-1}Y_{v|v|}v|v| + L^{-1}Y_{|c|c\delta}|c|c\delta + Y_{ur}ur \\ & + L^{-1}Y_{|c|c|\beta|\beta|\delta|}|c|c|\beta|\beta\,|\delta| + Y_{ur\zeta}ur\zeta + L^{-1}Y_{uv\zeta}uv\zeta \\ & + L^{-1}Y_{|v|v\zeta}|v|v\zeta \\ & + L^{-1}Y_{|c|c|\beta|\beta|\delta|\zeta}|c|c|\beta|\beta\,|\delta|\,\zeta + Y_{\dot{v}\zeta}\dot{v}\zeta + Y_T gT \end{aligned} \tag{5}$$

$$\begin{aligned} gLN = {} & L^2(N_{\dot{r}}\dot{r} + N_{\dot{r}\zeta}\dot{r}\zeta) + N_{uv}uv + LN_{|v|r}|v|r + N_{|c|c\delta}|c|c\delta \\ & + LN_{ur}ur + N_{|c|c|\beta|\beta|\delta|}|c|c\,|\beta|\,\beta\,|\delta| \\ & + LN_{ur\zeta}ur\zeta + N_{uv\zeta}uv\zeta \\ & + LN_{|v|r\zeta}|v|r\zeta + N_{|c|c|\beta|\beta|\delta|\zeta}|c|c|\beta|\beta|\delta|\zeta + LN_T gT \end{aligned} \tag{6}$$

$$gT = L^{-1}T_{uu}u^2 + T_{un}un + LT_{|n|n}|n|n \tag{7}$$

$$k_z = L^{-1}\sqrt{I_z/m}, \qquad c^2 = c_{un}un + c_{nn}n^2,$$

$$\zeta = \frac{d}{h-d}, \qquad \beta = v/u. \tag{8}$$

In the above, u and v are the velocities along X (towards forward) and Y axis (towards starboard) respectively, r is the yaw rate ($= \dot{\psi}$, where ψ is the yaw angle in the horizontal plane), an overdot denotes time (t) derivative, L is length of the ship, d is the draft of the ship, k_z is the nondimensional radius of gyration of the ship in yaw, m is the mass of the ship, I_z is its mass moment of inertia about Z axis (vertically downward with axis origin at free surface), x_G is the nondimensional X coordinate of ship's centre of gravity (Y coordinate of ship's centre of gravity y_G is taken as zero), g is acceleration due to gravity, X, Y and N are the nondimensional surge force, sway force and yaw moment respectively, δ is the rudder angle, c is the flow velocity past rudder, ζ is the water depth parameter, c_{un} and c_{nn} are constants, T is the propeller thrust, h is the water depth, $\hat{t}$ is the thrust deduction factor and n is the rpm of the propeller shaft. All other quantities are constant hydrodynamic derivatives. All quantities in the above equations are nondimensional and may be related to their dimensional counterparts (denoted by an overbar) using BIS system given by [15] according to

$$\begin{aligned} &(u, v) = (\bar{u}, \bar{v})/\sqrt{Lg} \\ &r = \bar{r}/\sqrt{g/L} \\ &(\dot{u}, \dot{v}) = (\dot{\bar{u}}, \dot{\bar{v}})/g \\ &\dot{r} = \dot{\bar{r}}/(g/L) \\ &(x_G, y_G) = (\bar{x}_G, \bar{y}_G)/L \\ &\omega = \bar{\omega}/\sqrt{g/L} \\ &m = \bar{m}/(\rho\nabla); \qquad I_z = \bar{I}_z/(\rho\nabla L^2). \end{aligned} \tag{9}$$

In the above equations ω is the nondimensional circular frequency, ρ is the sea water density and ∇ is the volumetric displacement of the hull. The system of three equations, as represented by (1), contains 10 hydrodynamic derivatives in the X-equation (surge) and 12 in both Y-(sway) and N-(yaw) equations, a total of 34 hydrodynamic derivatives.

Now, substituting (4) in (1), we get

$$(1 - X_{\dot{u}} - X_{\dot{u}\zeta}\zeta)\dot{u} = g_1(u, v, r, T, \zeta, c, \delta). \tag{10}$$

Similarly, substituting (5) in (2) and (6) in (3), we get

$$(1 - Y_{\dot{v}} - Y_{\dot{v}\zeta}\zeta)\dot{v} = g_2(u, v, r, T, \zeta, c, \delta) \tag{11}$$

$$(k_z^2 - N_{\dot{r}} - N_{\dot{r}\zeta}\zeta)\dot{r} = g_3(u, v, r, T, \zeta, c, \delta) \tag{12}$$

where

$$\begin{aligned} g_1 = {} & L^{-1}(X_{uu} + X_{uu\zeta}\zeta)u^2 + (1 + X_{vr} + X_{vr\zeta}\zeta)vr \\ & + L^{-1}(X_{vv} + X_{vv\zeta\zeta}\zeta^2)v^2 + L^{-1}(X_{|c|c\delta\delta}|c|c\delta^2) \\ & + L^{-1}(X_{|c|c\beta\delta}|c|c\beta\delta) + gT(1-\hat{t}) \end{aligned} \tag{13}$$

$$\begin{aligned} g_2 = {} & L^{-1}Y_{uv}uv + L^{-1}Y_{|v|v}|v|v + L^{-1}Y_{|c|c\delta}|c|c\delta + (Y_{ur} - 1)ur \\ & + L^{-1}Y_{|c|c|\beta|\beta|\delta|}|c|c\,|\beta|\,\beta\,|\delta| + Y_{ur\zeta}ur\zeta + L^{-1}Y_{uv\zeta}uv\zeta \\ & + L^{-1}Y_{|v|v\zeta}|v|v\zeta + L^{-1}Y_{|c|c|\beta|\beta|\delta|\zeta}|c|c|\beta|\beta\,|\delta|\,\zeta + Y_T gT \end{aligned} \tag{14}$$

$$\begin{aligned} g_3 = {} & L^{-2}\{N_{uv}uv + LN_{|v|r}|v|r + N_{|c|c\delta}|c|c\delta + L(N_{ur} - x_G)ur \\ & + N_{|c|c|\beta|\beta|\delta|}|c|c\,|\beta|\,\beta\,|\delta| + LN_{ur\zeta}ur\zeta + N_{uv\zeta}uv\zeta \\ & + LN_{|v|r\zeta}|v|r\zeta + N_{|c|c|\beta|\beta|\delta|\zeta}|c|c|\beta|\beta|\delta|\zeta + LN_T gT\}. \end{aligned} \tag{15}$$

3. Model for neural network

From the maneuvering equations given by (10)–(15), it may be observed that the inertia terms contain linear hydrodynamic derivatives (one in each equation) and their corrections (one in each equation) and the functions g_1, g_2 and g_3 contain only nonlinear hydrodynamic derivatives. System identification requires knowledge of at least some of these derivatives and in the present model it is obviously acceleration derivatives (first order) which are relatively easy to estimate. Therefore in this work we have chosen a model for system identification where the three linear hydrodynamic derivatives and their water depth dependent corrections alone are assumed known as given in (10)–(12). Thus, this model requires knowledge of three acceleration derivatives $X_{\dot{u}}$, $Y_{\dot{v}}$ and $N_{\dot{r}}$ and their corrections due to water depth, i.e. $X_{\dot{u}\zeta}$, $Y_{\dot{v}}\zeta$ and $N_{\dot{r}\zeta}$, a total of six constants.

4. Neural network formulation

The unknown nonlinear functions g_1, g_2 and g_3 are simply the sum of all nonlinear terms in (13)–(15) and hence to be determined by a neural network model. A three layer neural network model is used in the present work to represent the unknown functions g_1, g_2 and g_3 as shown in Fig. 1. The input layer has time functions surge velocity $u(t)$, sway velocity $v(t)$, yaw velocity $r(t)$, rudder angle $\delta(t)$ and a bias with value of unity, i.e. a total of five neurons. The middle layer has m neurons where the value of m has to be found by numerical trials. The output layer consists of the functions g_1, g_2 and g_3. Denoting

$$x_1 = 1, \qquad x_2 = u(t), \qquad x_3 = v(t), \qquad x_4 = r(t) \quad \text{and} \quad x_5 = \delta(t) \tag{16}$$

we relate the input and middle layer neurons as

$$z_i = \sum_{j=1}^{5} w_{ij}x_j \quad (i = 1, \ldots, m-1) \tag{17}$$

and then transform them using a squashing function as

$$\sigma_i = \begin{cases} (1 + e^{-z_i})^{-1}, & i = 1, \ldots, m-1 \\ 1, & i = m. \end{cases} \tag{18}$$