Proceedings of the 8th IFAC International Conference on
Manoeuvring and Control of Marine Craft
September 16-18, 2009, Guarujá (SP), Brazil

Adaptive Neural Network based Sliding Mode Control for Fin Roll Stabilization of Vessels

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Abstract: The paper describes an adaptive neural network based sliding mode control for fin roll stabilization of ocean motoryachts. Radial basis function neural networks are used to adaptively learn system uncertainty bounds and network outputs are used to adjust the gain of the sliding mode control. The analysis of the control stability is based on the Lyapunov theory. The proposed controller is tested by a simulation study based on a nonlinear model, describing the dynamics of a vessel in four degrees of freedom. On this manoeuvring model output sea state disturbances are simulated as multisine time series.

Keywords: Sliding mode control, Neural networks, Adaptive control, Ship control, Lyapunov methods, Marine systems

1. INTRODUCTION

A significant aspect of the security and comfort in a motoryacht is the reduction of roll oscillations. These vessels are characterized by reduced sizes and high speeds and the wave conditions in which motoryachts become inoperable occur more frequently than those for larger ships. For the above reasons the issue of controlling such class of vessels to reduce the roll, while traveling at a nonzero forward speed and in spite of environmental disturbances has a great practical significance.

The problem of stabilizing ship roll oscillations has been deeply investigated in literature and different approaches have been developed such as bilge keels, anti-rolling tanks, active fin stabilizers and rudder roll stabilization. In particular the active fin stabilizer is widely used for roll stabilization (Perez, 2005, and references therein). This system consists in a hull stability equipment which controls the generated lift of the fins on both sides of a vessel.

In this paper a control system that uses fins for ship roll stabilisation is considered. The design of this control system has to take into account that the ship motion dynamics are multivariable and inherently non linear and the hydrodynamic coefficients are uncertain and depend on many factors as for example the vessel speed, actuators and wave encounter frequencies. Also sea state disturbances cannot be modelled precisely. For the above reasons strong model uncertainties and nonlinear control techniques have to be consider in the regulator design.

Several recent results on reducing roll motion of surface vessels using various nonlinear control techniques are available in Koshkouei et al. (2007); Cavalletti et al. (2007a); Yang and Jiang (2004). Also in this paper a nonlinear technique is investigated. In particular an adaptive neural network based Variable Structure Controller (VSC) has been considered, (Zhihong et al., 1998). This control scheme uses Neural Networks (NNs) to adaptively learn system uncertainty bounds and the output of these nets is used to adjust the gain of the VSC to eliminate the effects of dynamical uncertainties and guarantee asymptotic control error convergence.

Radial Basis Function Networks (RBFNs), recently proposed in Unar and Murray-Smith (1999); Zirilli et al. (2000) for marine control systems, have been used to develop this control scheme. These networks have been widely used for nonlinear system identification (Cavalletti et al., 2007b; Chen et al., 1991) because of their ability both to approximate complex nonlinear mappings directly from input-output data with a simple topological structure that avoid lengthy calculations and to reveal how learning proceeds in an explicit manner (Chen et al., 1991).

The analysis of the control performance has been done by numerical simulations with different environment conditions. A nonlinear model, describing the dynamics of the vessel in four Degrees Of Freedom (DOF) has been used. The ship motion due to the waves is simulated as multisine time series.

The paper is organized as follows. The considered models for the roll stabilization problem are introduced in Section 2. In Section 3 some preliminaries are given and details on the considered control are discussed. Results on numerical simulations are reported in Section 4. The paper ends with comments on the performance of the proposed controller.

2. SYSTEM MODELS

The equations describing motoryacht dynamics are based on the 4-DOF mathematical model presented in Perez

(2005) that has been adapted in this paper to the considered vessel developed by ISA (Italy) (ISA, 2007). The mathematical model presented in Perez (2005) consists of a manoeuvring model combined with a seakeeping model to describe the motion due to the waves. The rigid-body equations of motions in 4-DOF (surge, sway, roll and yaw) are formulated at the origin of the body-fixed frame and the vector of forces are separated into the hydrodynamic and hydrostatic forces, control device forces, propulsion forces (Perez, 2005). This model has been implemented by the Marine System Simulator (MSS) developed by the Norwegian University of Science and Technology (NTNU) (MSS, 2007). The platform adopted for the development of MSS is Matlab-Simulink®.

The fins are moved by means of hydraulic machineries implemented using the model of van Amerongen (van Amerongen, 1982). Magnitude constraints for the mechanical angle of $35deg$ and maximum rate of $25deg/s$ are considered.

The seakeeping model is simulated as multisine time series using the motion frequency response functions of the vessel in combination with the wave spectrum (Perez, 2005). The ITTC spectrum has been considered in this paper and has been particularized for a slight and a rough sea state. A vessel cruise speed of $8m/s$ in beam, bow and quartering seas has been considered.

3. CONTROL DESIGN

An adaptive NN-based variable structure controller (VSC) is developed for the roll stabilization problem of the considered ocean motoryacht. Technical aspects of the proposed solution are stated in the following: same preliminaries are first considered and details on the design of the control strategy and on its implementation by neural networks are given in Subsection 3.2.

3.1 Preliminaries

Consider the class of single-input single-output nonlinear dynamical systems expressed in the following companion form (Zhihong et al., 1998; Slotine and Li, 1991):

$$x^{(n)}(t) = f(\boldsymbol{x}(t)) + g(\boldsymbol{x}(t))u(t), \tag{1}$$

where t is the time, $u(t) \in \mathbb{R}$ is the control input, $x(t) \in \mathbb{R}$ is the output of interest, $\boldsymbol{x}(t) = [x^{(0)}(t), x^{(1)}(t), \cdots, x^{(n-1)}(t)]^T \in \mathbb{R}^n$ is the state vector with $x^{(i)}(t),\ i = 0, 1, \cdots, n$ the i-th derivative of $\boldsymbol{x}(t)$, $f(\boldsymbol{x}(t))$ and $g(\boldsymbol{x}(t))$ are unknown nonlinear functions of the state. It is assumed that all $x^{(i)}(t)$ are available for measurement. Equation (1) can be expressed in the following state-space representation:

$$\dot{\boldsymbol{x}}(t) = \boldsymbol{A}\boldsymbol{x}(t) + \boldsymbol{B}(f(\boldsymbol{x}(t)) + g(\boldsymbol{x}(t))u(t)), \tag{2}$$

where the matrices $\boldsymbol{A}$ and $\boldsymbol{B}$ have the controllability canonical form (Slotine and Li, 1991).

For further analysis, let assume (Zhihong et al., 1998):

A1) The nonlinear function $g(\boldsymbol{x}(t))$ is lower bounded by $g_L(\boldsymbol{x}(t))$:

$$0 < g_L(\boldsymbol{x}(t)) < g(\boldsymbol{x}(t)) \tag{3}$$

for $\boldsymbol{x}(t) \in \Omega$ with $\Omega \subset \mathbb{R}^n$.

A2) The nonlinear function $f(\boldsymbol{x}(t))$ is upper bounded by $f_U(\boldsymbol{x}(t))$:

$$|f(\boldsymbol{x}(t))| < f_U(\boldsymbol{x}(t)) \tag{4}$$

for $\boldsymbol{x}(t) \in \Omega$ with $\Omega \subset \mathbb{R}^n$.

Let the error vector be defined as:

$$\boldsymbol{e}(t) := \left[e^{(0)}(t), e^{(1)}(t), \cdots, e^{(n-1)}(t)\right]^T \tag{5}$$

with $e^{(i)}(t) := x^{(i)}(t) - x_r^{(i)}(t)$ where $x_r^{(i)}(t)$, $i = 0, 1, \cdots, n-1$, are the bounded reference signals.

If $g_L(\boldsymbol{x}(t))$ and $f_U(\boldsymbol{x}(t))$ are known, the standard VSC can be used to design the control law.

In this paper, the positive nonlinear functions $g_L(\boldsymbol{x}(t))$ and $f_U(\boldsymbol{x}(t))$ have been considered unknown and under Assumptions A1 and A2 the universal approximation capability of RBF neural networks (Poggio and Girosi, 1990) is used to adaptively estimate the uncertain bounds $b_1(\boldsymbol{x}(t)) := g_L^{-1}(\boldsymbol{x}(t))$ and $b_2(\boldsymbol{x}(t)) := f_U(\boldsymbol{x}(t))$ defined on the compact set $\Omega \subset \mathbb{R}^n$. In particular the following two RBF nets have been used:

$$\hat{b}_1(\boldsymbol{x}, \hat{\boldsymbol{\theta}}_{b_1}) = \hat{\boldsymbol{\theta}}_{b_1}^T \boldsymbol{\phi}_{b_1}(\boldsymbol{x}) \tag{6}$$

$$\hat{b}_2(\boldsymbol{x}, \hat{\boldsymbol{\theta}}_{b_2}) = \hat{\boldsymbol{\theta}}_{b_2}^T \boldsymbol{\phi}_{b_2}(\boldsymbol{x}) \tag{7}$$

where $\hat{b}_1(\boldsymbol{x}, \hat{\boldsymbol{\theta}}_{b_1})$ and $\hat{b}_2(\boldsymbol{x}, \hat{\boldsymbol{\theta}}_{b_2})$ are NN-based estimates of $b_1(\boldsymbol{x}(t))$ and $b_2(\boldsymbol{x}(t))$, respectively, and $\hat{\boldsymbol{\theta}}_{b_1}^T$ and $\hat{\boldsymbol{\theta}}_{b_2}^T$ are the weight vectors of the RBF nets. The vectors $\boldsymbol{\phi}_{b_1}(\boldsymbol{x}) \in \mathbb{R}^{b_1}$ and $\boldsymbol{\phi}_{b_2}(\boldsymbol{x}) \in \mathbb{R}^{b_2}$ are Gaussian type basis functions (Zhihong et al., 1998).

Remark 1. The widths, centers and initial values of the weight vector of the Gaussian functions are chosen as shown in Subsection 4.1. Therefore, the adjustable weights $\hat{\boldsymbol{\theta}}_{b_1}$ and $\hat{\boldsymbol{\theta}}_{b_2}$ appear linearly with respect to the known nonlinear function $\boldsymbol{\phi}_{b_1}(\boldsymbol{x})$ and $\boldsymbol{\phi}_{b_2}(\boldsymbol{x})$, respectively (Chen et al., 1991).

For the further analysis, the following assumptions are made (Poggio and Girosi, 1990; Zhihong et al., 1998):

A3) Given two arbitrary small positive constants ω_1^* and ω_2^* and the continuous functions $b_1(\boldsymbol{x}(t))$ and $b_2(\boldsymbol{x}(t))$ defined on a compact set $\Omega \subset \mathbb{R}^n$, with Assumptions A1 and A2, there exist two optimal bounded weight vectors $\boldsymbol{\theta}_{b_1}^*$ and $\boldsymbol{\theta}_{b_2}^*$ such that the outputs $b_1^*(\boldsymbol{x}, \boldsymbol{\theta}_{b_1}^*)$ and $b_2^*(\boldsymbol{x}, \boldsymbol{\theta}_{b_2}^*)$ of the two optimal neural networks with enough centers and the same structure of (6) and (7) satisfy (Zhihong et al., 1998):

$$\left|b_1^*(\boldsymbol{x}, \boldsymbol{\theta}_{b_1}^*) - b_1(\boldsymbol{x}(t))\right| = |\varepsilon_1^*| < \omega_1^* \tag{8}$$

$$\left|b_2^*(\boldsymbol{x}, \boldsymbol{\theta}_{b_2}^*) - b_2(\boldsymbol{x}(t))\right| = |\varepsilon_2^*| < \omega_2^*. \tag{9}$$