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Identification-based controller design using cloud model for course-keeping of ships in waves

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ABSTRACT

Course-keeping plays an important role in ensuring navigation safety of ships. This contribution proposed new approaches about system identification and controller design to facilitate the main goal which is to design a controller for course-keeping of ships based on the identified ship plant and the cloud model. The investigated plant as the control model was the first order linear Nomoto model. In order to estimate the parameters of this model, the support vector machines (SVM) optimized by artificial bee colony algorithm (ABC) was applied in combination with simulated data including the rudder and heading angles generated by the dynamic model of a Mariner class cargo ship. Based on the identified linear Nomoto model of Mariner class cargo ship, the cloud model was then applied to design the controller for course-keeping. To well demonstrate the feasibility and effectiveness of the proposed controller, a fuzzy logic PID controller, and a PID controller were also considered as comparison mechanisms. Aiming at validating the robustness of the proposed cloud model-based controller, it was used to compensate for the critical environmental disturbances induced by waves. Finally, simulation results indicate the desirable performance of ABC on optimizing parameters in SVM. Comparison with PID and fuzzy logic PID controllers demonstrates that the cloud model-based controller presents slightly preferable performance on course-keeping. This is due to that the flexible and intuitive modification of the digital characteristics of the cloud model and the structure of cloud inference engines makes the cloud model efficient to satisfy the required mapping between inputs and outputs for a controller.

1. Introduction

Modern ship navigation systems are equipped with autopilot facilities to guide ships follow a desired course under constant speed conditions (Perera and Soares, 2012). However, a ship is able to be subjected to environmental disturbances of the wave, current, wind, and passing ships. These environmental disturbances push the ship away from the desired course. Therefore, it is important to apply a course-keeping controller which can automatically operate rudder to counteract the environmental effects and maintain the ship as closely as possible for a desired course (Azzeri et al., 2015).

Since (Minorsky, 1922) undertook the initial work on the PID controller for automatic ship steering systems, many researchers made their efforts to develop ship course-keeping controller which for instance are optimal control methods (e.g., linear quadratic control (LQG), model predictive control (MPC)), adaptive control methods (e.g., adaptive control based on backstepping control design, adaptive control based on gain scheduling, adaptive neural network control), intelligent control (e.g., intelligent control based on genetic algorithms, intelligent control based on neural networks, intelligent control based on fuzzy logic), and robust control (e.g., sliding mode control) (Gao et al., 2016). Whereas, more than half of the applications of controller in the maritime industries are the conventional or modified PID controller (Perera and Soares, 2012).

The main factors attracting industries to choose the PID controller can be summarized as the low cost, the simplicity of operation and maintenance, and the simple structure. However, the PID controller with fixed or improper gains is not suitable for the ship subject to the external disturbances due to its slow recovery and poor robustness. To overcome this drawback, gains tuning is a desirable solution as many methods have been studied. The commonly-used gains tuning methods are Ziegler–Nichols method (Ziegler and Nichols, 1993), neural network algorithm (Hernández-Alvarado et al., 2016), fuzzy logic (Yunsheng et al., 2015), genetic algorithm (Larrazabal and Peñas, 2016).

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Among these tuned PID controllers, the fuzzy logic self-adaptive PID controller is suggested as an alternative controller for complex systems with uncertainties and nonlinearities (Azzeri et al., 2015). Similarly, the cloud model firstly proposed by Li et al., (1998) is a mathematical representation of linguistic concepts involved with uncertainties including fuzziness and randomness. It can deal with the transformation between the qualitative concept and the quantitative value using natural language (Zhu et al., 2014). This characteristic makes the cloud model applicable in many fields, such as data mining, target recognition, pervasive computing improvement of the intelligent algorithm, and controller design. From the research on the cloud model-based controller design, for instance, synchro-control of twin rudders (Liu and Chang, 2012), energy management strategy for parallel hybrid vehicles (Wu et al., 2015), and flexible-link manipulator control system (Zhang et al., 2006), the cloud model-based controllers show good performance and application in systems with nonlinearities and uncertainties. However, only one-dimensional or two-dimensional cloud has been discussed, and the process of designing the cloud model-based controller is not easy to be repeated. Therefore, this study makes efforts to investigate characteristics of the cloud model-based controller, apply hybrid dimensional cloud to design the course-keeping controller for ships.

Due to the lack of experimental data, the control plant model of ships is employed for generating maneuvers data which have the similar feature as experimental maneuvers. The performance of the cloud model-based controller mainly depends on the precision of the control plant model and the accuracy of the model parameters. A precise mathematical model of the ship especially the 6 degrees of freedom (DOF) model can well satisfy the requirement of accuracy, but it, in turn, increases the complexity for designing the controller. To select a model describing ship steering dynamics, the ship response model also named the Nomoto model can be a desirable option because this model has been widely used to design the course-keeping controller (Ren and Zhang, 2013; Luo and Cong, 2016; Li and Sun, 2012; Du et al., 2014). Therefore, the Nomoto model is chosen as the control model in this study.

Parameter estimation of the control model as a preliminary step of the controller design procedure can be conducted through four ways, i.e., towing tank experiments, captive model experiments, computational fluid dynamics, and parameter identification methods (Skjetne et al., 2004). Comparatively, the parameter identification method combined with the full-scale or free-running model tests is a popular and highly cost-effective one. Some classic parameter identification methods such as least squares method (LS), extended Kalman filter (EKF) (Alessandri et al., 1998), maximum likelihood algorithm (ML) (Åström and Källström, 1976), recursive least square estimation (RLS) (Holzhüter, 2014), recursive prediction error method (RPE) (Zhou and Blanke, 1986), and model reference method (MR) (Van Amerongen, 1984) have been successfully used in maritime domain. Besides, some intelligent techniques of parameter identification are also developed for identifying ship dynamic models recently, e.g., estimation before modeling technique (Yoon and Rhee, 2003), genetic algorithm (Witkowska and Śmierzchalski, 2008), simulated annealing technique (Ferri et al., 2013), artificial neural network (Rajesh and Bhattacharyya, 2008), SVM (Luo et al., 2016; Zhu et al., 2017b), etc. Based on these parameter identification techniques, some studies focused on simultaneously cooperating two approaches to identify ship dynamic models (Araki et al., 2012).

Comparatively, SVM is a novel intelligent technique due to its good generalization and global optimal ability (Luo and Cong, 2016). Therefore, SVM is selected to estimate parameters of the control model. In order to improve the accuracy of identification results, ABC instead of cross-validation method and particle swarm optimization algorithm (Luo et al., 2016) is used to confirm the parameters in SVM due to ABC's superior optimization performance (Sulaiman et al., 2012). The SVM optimized by ABC is the first time to be used for parameter estimation of the ship response model in maritime domain.

The main contributions of this study can be described as: (1) The optimized SVM using ABC is developed to identify the control model by applying simulated data generated by the complex dynamic model with predetermined values of parameters of a Marine class ship. ABC-SVM has superior performance on parameter estimation due to its advantages, i.e., the strong optimization ability of ABC can ensure particular setting of parameters in SVM to guarantee global optimum of SVM, and the simultaneous achievement of structural risk minimization and empirical risk minimization makes ABC-SVM not so sensitive to the outlier. (2) A cloud model-based controller is proposed to automatically manipulate the rudder to decrease the errors between the desirable and actual courses of the ship. Compared with conventional PID controller and fuzzy logic PID controller, the cloud model-based controller has a slightly outstanding performance. Besides, the cloud model is efficient to satisfy the required mapping between inputs and outputs for a controller due to the flexible and intuitive modification of the digital characteristics of cloud models and the structure of cloud inference engines.

The paper is organized as follows. Section 2 introduces the control model, and describes the formulations of SVM and ABC and the procedure about applying ABC-SVM method to identify the control model. In Section 3, ship course-keeping controllers including cloud model-based controller, PID controller, and fuzzy logic PID controller are designed. Case studies for verifying the controllers are conducted in Section 4. Finally, concluding remarks are summarized in Section 5.

2. Problem formulation

2.1. Control model

Generally, the dynamic model of ships with six DOF can be described as Fossen (2011)

$$\boldsymbol{M}\dot{\boldsymbol{\nu}} + \mathbf{C}(\boldsymbol{\nu})\boldsymbol{\nu} + \mathbf{D}(\boldsymbol{\nu})\boldsymbol{\nu} + \mathbf{g}(\boldsymbol{\eta}) = \boldsymbol{\tau}_{ext} + \boldsymbol{\tau}, \tag{1}$$

where $\boldsymbol{\nu} = [u, v, w, p, q, r]^T$ is the spatial velocity state vector, $\boldsymbol{\eta} = [x, y, z, \phi, \theta, \varphi]^T$ presents the position and orientation states, $\mathbf{M}$ is the mass matrix, $\mathbf{C}(\boldsymbol{\nu})$ is the Coriolis and centripetal matrix, $\mathbf{D}(\boldsymbol{\nu})$ is the damping matrix, $\boldsymbol{g}(\boldsymbol{\eta})$ manifests the effects of buoyancy interaction with gravity, $\boldsymbol{\tau} = [X, Y, Z, K, M, N]^T$ denotes the actuator forces and moments generated by a set of propellers with revolutions per second $\mathbf{n} = [n_1, n_2, \ldots, n_{p1}]^T$ and a set of control surfaces with angles $\boldsymbol{\delta} = [\delta_1, \delta_2, \ldots, \delta_{p2}]^T$, $\boldsymbol{\tau}_{ext}$ is the external disturbances induced by currents, waves, etc.

Assuming that the mean ship forward speed is constant, the linear steering model without external disturbances items can be written as Fossen (1994)

$$\boldsymbol{M}\dot{\boldsymbol{\nu}} + \mathbf{N}(u_0)\boldsymbol{\nu} = \boldsymbol{b}\delta, \tag{2}$$

where $\boldsymbol{\nu} = [v, r]^T$, and $\mathbf{M} = \begin{bmatrix} m_{11} & m_{12} \\ m_{21} & m_{22} \end{bmatrix} = \begin{bmatrix} m - Y_{\dot{v}} & mx_g - Y_{\dot{r}} \\ mx_g - N_{\dot{v}} & I_z - N_{\dot{r}} \end{bmatrix}$, $\mathbf{N}(u_0) = \begin{bmatrix} n_{11} & n_{12} \\ n_{21} & n_{22} \end{bmatrix} = \begin{bmatrix} -Y_v & mu_0 - Y_r \\ -N_v & mx_g u_0 - N_r \end{bmatrix}$, $\mathbf{b} = \begin{bmatrix} b_1 \\ b_2 \end{bmatrix} = \begin{bmatrix} Y_\delta \\ N_\delta \end{bmatrix}$. where m is the mass of the ship, x_g is the x coordinate of the center of gravity with respect to the center of origin, u_0 means the constant forward speed, $Y_{\dot{v}}, \ldots, N_\delta$ are hydrodynamic coefficients.

Subsequently, a 1DOF model so-called Nomoto model is obtained by eliminating the sway speed from (2). This model is widely applied to design ship autopilot because of its compromise between simplicity and accuracy. The transfer function of this model is

$$\frac{r}{\delta}(s) = \frac{K(1 + T_3 s)}{(1 + T_1 s)(1 + T_2 s)}, \tag{3}$$