An Intelligent Model Free Control Approach for Vessel Autopilot

Yongqiang Zhuo[1] Yaseen Adnan Ahmed and Kazuhiko Hasegawa [2]
[1]Guangdong Ocean University, Zhanjiang, China
[2]Osaka University, Osaka, Japan
zhuoyq@gdou.edu.cn

Key words: vessel autopilot; non-linear system; intelligent model free control; neurofuzzy algorithm

ABSTRACT

To deal with the complex of vessel autopilot system due to its non-linear nature and the difficulty to describe precisely the vessel behaviour in the seaway using mathematical models, this paper proposes a vessel autopilot intelligent model free control. After collecting the input and output data sample of vessel motion in real-time, the dynamic output feedback control strategy is adopted in which the system error is instead of network error. An intelligent controller is established with neurofuzzy algorithm. The controller has the ability of on-line learning without model though studying the data of each time period and train system parameters repetitively. Finally, the model free control approach is verified by applied on an experimental boat.

1. Introduction

Nowadays the intelligent steering of vessels has been a goal of seafarers to reduce manning levels and increase vessel safety. At early time vessel autopilot manoeuvring had evolved mainly from the classical course-keeping task [1]. Course-keeping autopilot means to steer a vessel on a predetermined course by use of directional information taken from a gyrocompass. In many researches, such as the work of Sheng, course-keeping autopilot are based on conventional Proportional plus Integral plus Derivative (PID) control laws with fixed gain values [2]. Although each gain is adjustable by the user, it requires considerable experience and expertise to achieve the better settings. Therefore some researchers, such as Zhang, have applied intelligent methods to improve performance levels on this aspect of autopilot [3]. In recent 20 years, the track-keeping autopilot is getting popular. Track-keeping manoeuvre is performed between way-points which made up the straight lines as track. The developed tracking controller mainly designed using modern control design techniques such as Lyapunov's direct method [4], cascaded control theory [5] and backstepping control [6].

A common characteristic of all these analytical autopilot control strategies is their dependence on a reliable model of the vessel dynamic responses. That is, hydrodynamics plays a key point in vessel pilot systems. However, the vessel mathematical models have not been developed to the state so well that they model all vessels under all possible sea going states and environmental disturbance. The vessel dynamics has intrinsic nonlinearities that cannot be neglected in vessel motion for vessels are nonlinear time variant systems. A change in speed, mass loading and variations in the environmental disturbances will alter the dynamic characteristics of the vessel and so a corresponding modification of the control strategy of the autopilot would be required to compensate. Here a vessel intelligent model free control strategy is developed. It uses a repetitive learning neurofuzzy algorithm to update the controller parameters. The controller is independent of mathematical ship models and the learning is performed on-line.

2. The Description of Vessel Autopilot System

The underpinning principle of a vessel manoeuvre is the need to guide the vessel between two points whilst maintaining an adequate safety margin from known or presented possible dangers through steering and engine revolution adjustment [7]. A vessel autopilot system is one of the basic needs of the vessel manoeuvring control system. To achieve this it is necessary to have an up-to-date database of information concerning vessel location and environmental conditions. A vessel autopilot system is complex due to the many different influences present and the associated nonlinear, non-stationary and stochastic character of these influences. Based on seagoing experience it is found useful to view the vessel autopilot system as presented in Figure 1:

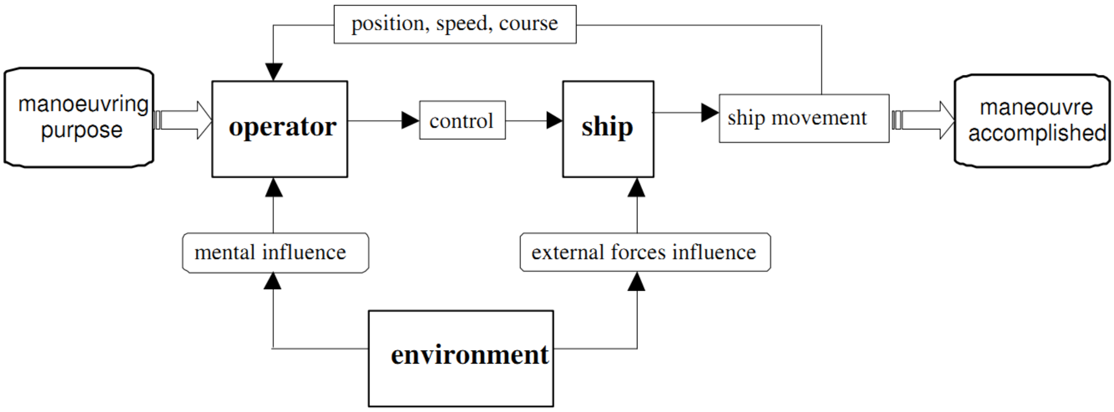

Fig.1 The structure of a vessel autopilot system

The controlled vessel manoeuvring motion is therefore modelled to consider the surge, sway and yaw responses of the vessel to rudder action. Only the horizontal vessel motions are considered.

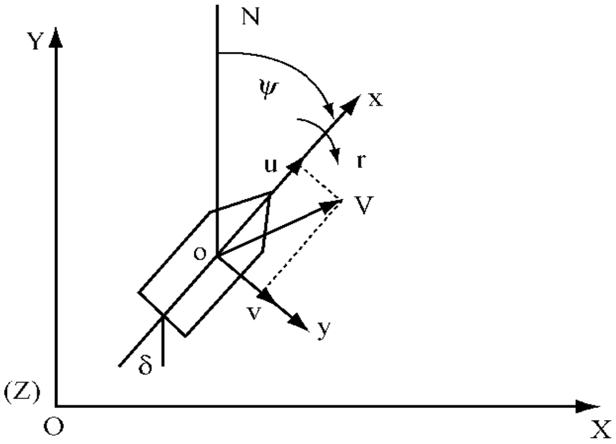

Fig.2 The diagram of vessel manoeuvring horizontal motion

Here, X, Y & N are the fore-aft force, the lateral force and the yawing moment about z axis respectively. u, v & r are forward speed, lateral speed and vessel heading rate respectively, δ is rudder angle.
The vessel nonlinear dynamic model is provided in (1), that is

$$\begin{cases} \dot{u} = [X_H + X_P + X_R + X_A + (m + m_y)vr]/(m + m_x) \\ \dot{v} = [Y_H + Y_P + Y_R + Y_A - (m + m_x)ur]/(m + m_y) \\ \dot{r} = (N_H + N_P + N_R + N_A)/(I_{zz} + J_{zz}) \\ \dot{x} = (u + u_c)\cos\psi - (v - v_c)\sin\psi \\ \dot{y} = (u + u_c)\sin\psi + (v + v_c)\cos\psi \\ \dot{\psi} = r \end{cases} \tag{1}$$

Here, m, m_x & m_y, I_{zz} & J_{zz} are the mass of vessel, the added masses of the vessel, the moment of inertia of vessel and the added inertia of the vessel respectively. Subscripts denote the source of forces and moments included and relate to bare hull (H), propeller (P), rudder (R) and wind (A). u_c & v_c are current speeds in the axial and transverse directions. ψ is the vessel heading. Vessel motion control is a highly nonlinear process. It involves various levels of uncertainty, primarily, due to the unpredictability of the characteristics of the environment and an in sufficient knowledge of the vessel dynamics.

3. The Strategy of Vessel Intelligent Model free control

Intelligent control in the context of vessel autopilot is the development and application to a vessel of appropriate forces and moments for operating course keeping and track control using intelligent methods. The intelligent controller should be based on an abundance of information, such as the information of sea environment and that of surrounding targets. Because of the complexity of the controller, the solution to the problem requires advanced technology, appropriate mathematical methods and advanced navigating equipment. Due to the development of low-cost satellite navigation systems, new and improved sensors, communications and computer technology, digital charts and electronically available weather forecasts, quite precise information is available for the necessary manoeuvre and it is now possible to design and implement an intelligent manoeuvring control system aboard a vessel to meet the requirement of marine safety, crew reduction and vessel automation. In parallel with the developing of model free control has become a hot research topic in the control field for this technology only need the input and output system data to design the controller. Model Free controller is put forward by Professor Han initially which is a new design method combining identification on-line and real-time control without the need for modeling, that is, during the controller design process, the modeling and controlling follow the identification of the observed data. Gradually the performance of the control law is improved [8]. This method can be used in the design of the control system to skip the process of building a mathematical model.

In a vessel autopilot model free control system the plant block gives the vessel state $X(t)$ through appropriate equipment. The controller block is usually a static function denoted by $u(\cdot)$; it maps the vessel state $X(t)$ into a continuous control action $\delta(t)$ that should achieve a given control objective, so that the vessel expect state output can reach a given control goal $X^{d}(t+T)$ at the moment $t+T$, T is the repetitive time period.

The plant and the feedback controller are denoted by the following equation:

$$\begin{cases} \delta(t) = u(X(t), X^{d}(t+T)) \\ X(t+T) = g(X(t), \delta(t), \omega(t)) \end{cases} \tag{2}$$

Data $X(t+T)$ are collected after the time of vessel navigation which do not dependent on the mathematical model of the vessel movement, that is, $g(\cdot)$ is an actual ship motion process, $\omega(t)$ is the external disturbance which is uncertain. The basic structure of intelligent model free control to a vessel autopilot system is demonstrated in Fig.3:

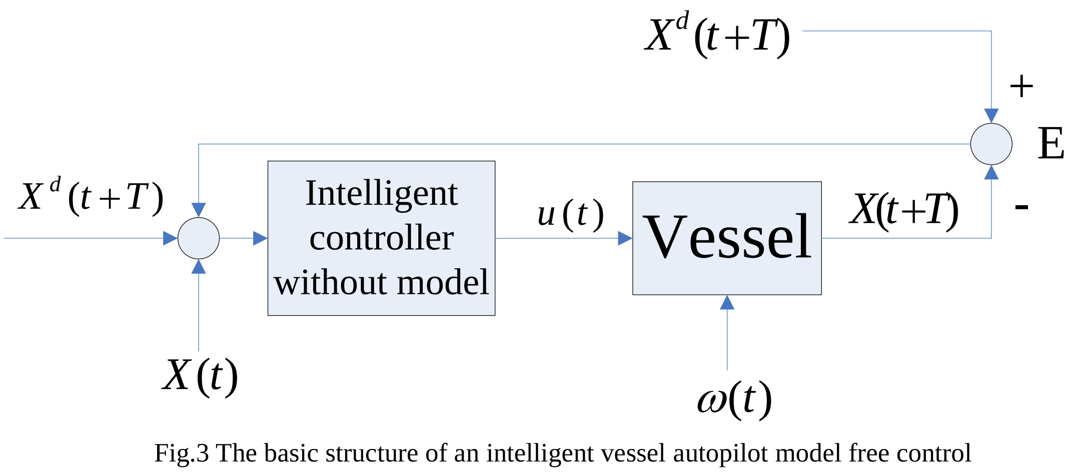

Fig.3 The basic structure of an intelligent vessel autopilot model free control

$X^{d}(t+T)$ is the expected output of the vessel at the moment, E is the error between actual output of the ship and the desired output. Here the specialized learning approach is adopted. The network error $\left\| u^{d}(t) - u(t) \right\|$ is minimized instead of the overall system error $\left\| X^{d}(t+T) - X(t+T) \right\|$. This procedure requires knowledge of the Jacobian of the plant.

4. Neurofuzzy Learning Algorithms

4.1 Fuzzy Inference System

Fuzzy inference is the process of formulating the mapping from a given input to an output using fuzzy logic. The mapping then provides a basis from which decisions can be made, or patterns discerned. The process of fuzzy inference involves selection of membership functions, fuzzy logic operators and if-then rules. The human expertise can guide the learning process to an initial point in the parameter space that is not too far from the optimal one, whereas the learning can fine-tune the domain knowledge to achieve a better performance. By using domain knowledge for structure determination, the initial membership functions for heading error $\Delta\psi$, track error $\Delta\varepsilon$ and yaw rate error Δr are set first.

The form of the if-then rule base is generalized as follows:

Rule k If $\Delta\psi$ is A_1^k , $\Delta\varepsilon$ is A_2^k and Δr is A_3^k ,

Then $\delta = f_k(\Delta\psi, \Delta\varepsilon, \Delta r) : k = 1,2,\cdots,27$,

where A_1^k , A_2^k and A_3^k are linguistic constants. That is, they assume the nominal signs of *NB* (negative big), *PB* (positive big) and *ZR* (zero). With the ship operators' domain knowledge, the initial assigned values of $f_k(\cdot)$ are set in accordance with Table 1. Here the values of [*+B +M +S ZR -S -M -B*] are linguistic constants corresponding to the rudder angle of [35^{o} 20^{o} 10^{o} 0^{o} -10^{o} -20^{o} -35^{o}].

Table1 Initial fuzzy rules for selecting rudder angle

δ		$\Delta\varepsilon = NB$, $\Delta\psi$			$\Delta\varepsilon = ZR$, $\Delta\psi$			$\Delta\varepsilon = PB$, $\Delta\psi$		
		NB	*ZR*	*PB*	*NB*	*ZR*	*PB*	*NB*	*ZR*	*PB*
Δr	*NB*	*+B*	*+M*	*+S*	*+M*	*+S*	*ZR*	*+S*	*ZR*	*-S*
	ZR	*+M*	*+S*	*ZR*	*+S*	*ZR*	*-S*	*ZR*	*-S*	*-M*
	PB	*+S*	*ZR*	*-S*	*ZR*	*-S*	*-M*	*-S*	*-M*	*-B*

4.2 Proposed Neurofuzzy Network Architecture

The fuzzy inference system is designed in an iterative open-loop fashion. Fuzzy inference systems developed so far are static. Therefore, fuzzy logic system with its interpretative linguistic rules cannot learn. Both the performance measures and adaptation strategies are subjective. It means that it is the designer who specifies a fuzzy rule base, and then enters an assessment design loop. Hence the neural networks are utilized as the learning algorithms to create fuzzy logic inference from training data sets. The neurofuzzy constructs an input-output mapping based on both senior pilots and captain's vessel operation experience, as well as stipulated input-output data sets. The controller architecture of neurofuzzy network used to identify the parameters of FIS is demonstrated in Fig. 4. The neurofuzzy network is designed 5 layers. The subscripts i , j , k and l define the number of neural units in each layer respectively. The first layer is actually the member function. The fifth layer is the single output layer that calculates the total output. It equals the vessel rudder angle.

The bell-shaped member functions are defined to have the form:

$$\mu_{A_i}(x) = \frac{1}{1 + \left({x - c_i}/{a_i} \right)^{2b_i}} \tag{3}$$

The control law of δ_k is defined in the last layer as follows:

$$\delta = O_m^5 = \sum_l \overline{w}_l f_l = \sum_l \overline{w}_l (u_l \Delta\psi + q_l \varepsilon + s_l \Delta r + t_l) : l = 1,2,\cdots,27 \tag{4}$$

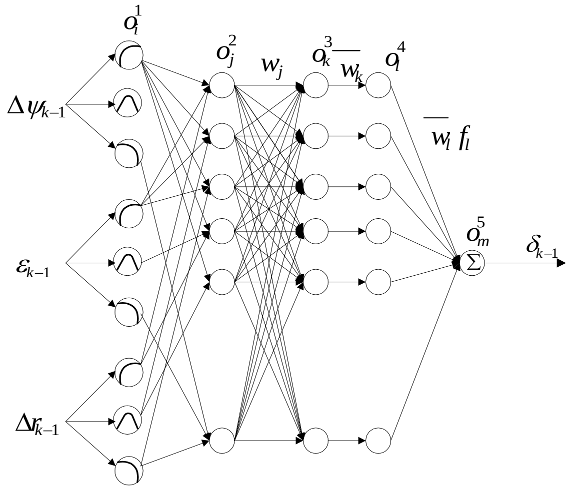

Fig.4 The proposed neurofuzzy controller

4.3 Neurofuzzy learning algorithm

On-line learning is concerned with identification of parameters from learning data as the system operates even though that data might exist only for a short time. Here neurofuzzy implies that the back-propagation gradient descent method for updating consequent parameters V (u_l, q_l, s_l and t_l) of Sugeno-type fuzzy inference systems and member function parameters w (a_i, b_i and c_i) to emulate a given training data set. The parameters are undated after each data presentation due to the on-line repetitive learning paradigm.
The error function is defined as

$$E_k = \frac{1}{2}\varepsilon_k{}^2 \tag{5}$$

The notations are defined as follows:

$f_k = f(v_{k,l}\xi_k)$, $F_k = F(V_k\xi_k) = \sum_l f(v_{k,l}\xi_k)$, $u_k = u(w_k F_k) = u(w_k F(V_k\xi_k))$,

$g_k = g(u_k) = g(u(w_k F_k)) = g(u(w_k F(V_k\xi_k)))$, so

$$E_k = g(\delta_k) = g(u_k) = g(u(w_k F(V_k\xi_k))) \tag{6}$$

The learning law of the parameter is calculated by back-propagation algorithm, represented by

$$w_{k+1} = w_k - \eta\frac{\partial E_k}{\partial w} + \alpha\Delta w_{k-1} \tag{7}$$

$$v_{k+1,l} = v_{k,l} - \eta\frac{\partial E_k}{\partial v_l} + \alpha\Delta v_{k-1,l} \tag{8}$$

Equation (9, 10) is used to train the neurofuzzy network in order to minimize the error E_k. α is the momentum term that can increase the convergence rate. η is the learning-rate.

$$\frac{\partial E_k}{\partial w} = g'(u(w_k F(V_k\xi_k)))u'(w_k F(V_k\xi_k))F(V_k\xi_k) \tag{9}$$

$$\frac{\partial E_k}{\partial v_l} = g'(u(w_k F(V_k\xi_k)))u'(w_k F(V_k\xi_k))w_k f'(v_{k,l}\xi_k))\xi_k \tag{10}$$

5. Applications

To demonstrate the intelligent model free control system for autopilot, in this paper an experimental boat named 'Esso Osaka' 3-m model is chosen which belongs to Naval Architecture and Ocean Engineering Department, Osaka University. It is scaled as 1:108.33 for a Tanker. Its details are given in Table 2. Fig.5 shows the experimental boat used for the experiment purpose of autopilot control.

Table 2 Principal particulars of experimental boat and full-scale vessel

Items		Experimental boat	Full-scale vessel
Scale	s	1/108.33	
Length between perpendicular	Lpp (m)	3.000	325.00
Breadth moulded	B (m)	0.48925	53.00
Draught moulded at midvessel	d_H (m)	0.20114	21.73
Displacement	Δa	244.4kg	319,040t
Propeller Diameter	D_p (m)	0.08400	9.100
Rudder Breadth	b (m)	0.08308	9.0
Rudder Height	h (m)	0.1279	13.85

Fig 5 Esso Osaka 3-m model of Osaka University

Here course-keeping autopilot control is tested to verify the intelligent model free control approach. The RPS of the ship is designed to 15. The experimental purpose is to change the boat course from 90 degree to 105 degree. Fig.6 shows the course-keeping performance under wind disturbances using intelligent controller. Due to the environmental disturbances the vessel, but the controller still fulfill its task well. The vessel course could be changed in one minute and kept on it.

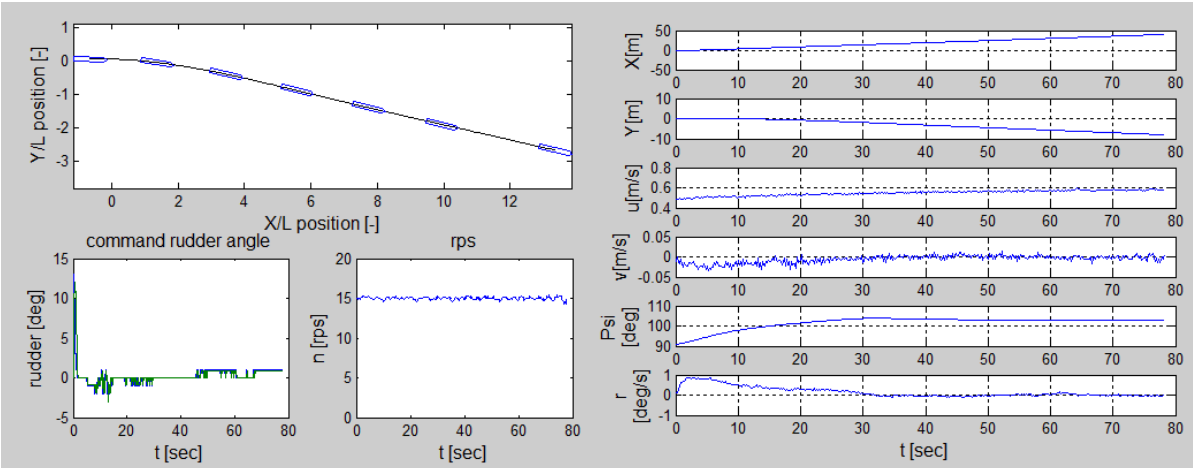

Fig.6 The course-keeping performance using autopilot intelligent model free control approach

6. Results and Discussions

It has been verified that the vessel can be controlled to perform autopilot well on a given task subject such as course-keeping using an intelligent free model controller. The proposed intelligent control strategy avoids the need for vessel mathematics model. Together with the self-learning ability of the neurofuzzy network, the controller works well, even suffering environmental disturbances.

The intelligent controller combines a fuzzy inference system that mimics human experiences and a neural network using back-propagation that fine-tunes the domain knowledge to achieve a better performance. Despite the wind disturbance and there being only one epoch during each period, the model free controller can sufficiently quickly to bring about early control. The experiment of track-keeping autopilot control will be implemented in the near future.

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Author's Biography

Zhuo Yongqiang, male, doctor of philosophy, born in October, 1969. He graduated from Navigation Institute, Jimei University, China in July, 1992 and became a deck officer in Hong Kong Worlder Vesselping Co., Ltd. He obtained his master degree in Dalian Maritime University in Aprial, 1999. He obtained his doctor degree in University of Southampton, UK in March, 2005. At present he is a professor in Guangdong Ocean University, His main research is about marine traffic system engineering and vessel intelligent control.