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Research Note

Adaptive critic-based neuro-fuzzy controller for dynamic position of ships

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Ship control.

Abstract. In this paper, three adaptive critic-based neuro-fuzzy controllers are presented for improving attitude and position control of ships. The controllers include vessel position and heading errors and their derivatives as inputs. Three critic based reinforcement learning methods evaluate the situations of the ship in terms of satisfactory achievements of the control goals. The critic agent output, namely the reinforcement signal, is a measure of the controlled system stress. The controller modifies its characteristics in a way that the critic stress is decreased. The proposed controller has a simple structure and shows satisfactory transient responses and robustness to model uncertainty.

1. Introduction

Dynamic Positioning (DP) system is a computer controlled system to automatically maintain a vessel's position and heading by using its own propeller and thrusters. This is obtained either by installing tunnel thrusters in addition to the main screw(s), or by using azimuthing thrusters, which can produce thrust in different directions. Previously DP systems were designed using conventional PID controllers to suppress the wave-induced motion components. Balchen et al. [1] introduced advanced control techniques based on optimal control and Kalman-filter theory. This work has later been modified and extended by several research groups [2-4]. Several control methodologies have been applied to the DP controller design including fuzzy logic controller [5], H_∞ robust controller [6], nonlinear feedback linearization [7], backstepping controller [8], and nonlinear sliding mode controller [9]. These papers mostly use model based controller, so encourage one to use non model-based control methods, such as intelligent techniques, which neither relies on an accurate description of the plant, nor on the precise measurements. To find possible alternatives to the classical model-based controllers, great attention has been recently paid to the topic of intelligent control of complex systems.

Fuzzy control systems use the experience, knowledge, and decision-making process of expert human and engineer. An expert human expresses intuitively the behavior of a fuzzy controller by means of linguistic rules. In addition appropriate fuzzy logic controller can overcome the environmental variation during operation process [10].

Neuro-controllers have also been widely used in recent years. Motivated by the fact that human control actions are regulated by the brain, artificial neural networks have been designed as simplified models of human neural structures. The ability to act as universal approximators is a significant characteristic of these nets which has made them useful for modeling nonlinear systems. A neuro controller in general, performs as a specific form of adaptive control where

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the controller is in the form of multilayer neural network and the adaptable parameters are in the form of adjustable weights [11].

Some modern intelligent techniques have used neuro-fuzzy structures to combine the generalization capabilities of neural networks and decision making capabilities of fuzzy systems [12].

There are three learning methods characterized by the information source used for learning and classification. These learning methods are supervised learning, unsupervised learning, and reinforcement learning [13]. Adaptive critic is a special case of reinforcement learning [14] in which the condition of the controlled system is not interpreted by failure or success binary signal, instead a continuous reinforcement signal produced by the critic agent shows the degree of failure or success of control action or in other words, it shows the stress of the system under control. The controller adapts itself to reduce this stress [15-16].

In the present work, the idea of using adaptive critic-based neuro-fuzzy controller is applied to the dynamic position control of ships. Simulation results are provided to show the effectiveness of the proposed methodology.

The remaining part of this paper is organized as follows. Section 2 presents mathematical model of the ship. Section 3 describes the adaptive critic-based neuro-fuzzy controller structure and some mathematical fundamentals. Section 4 presents architecture of the ship controller. In Section 5, The case study and simulation results are presented. And finally in section 6, the conclusion remarks will be given.

2. Modeling of ships

2.1. Kinematics equation of motion

In order to explain ship motion, it is convenient to introduce two frames. The first one is earth-fixed frame that represents position and orientation of the vessel with respect to an earth-fixed frame $X_0Y_0Z_0$ which is expressed in the form of $\eta = [x, y, z, \varphi, \theta, \psi]$, and the second one is body-fixed frame that is fixed to the vessel. The vessel velocities are measured relative to this frame XYZ, by $v = [u, v, w, p, q, r]$ (see Figure 1).

To have a reliable modeling we introduce $J(\eta)$ transformation matrix that represents the transformation between the body-fixed and the earth-fixed velocities vectors:

$$\dot{\eta} = J(\eta)v. \tag{1}$$

It should be mentioned that the transformation matrix depends on the Euler angles. We can derive $J(\eta)$ with some mathematic operations in transformation of frames [17]:

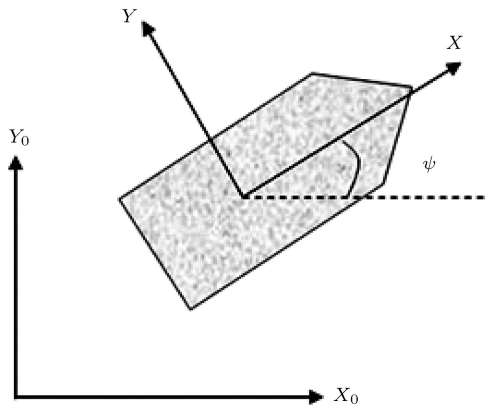

Figure 1. Definition of the earth-fixed $X_0Y_0Z_0$ and the vessel-fixed XYZ reference frames.

$$J(\eta)=\begin{bmatrix} c\psi c\theta & -s\psi c\phi & s\psi s\phi + c\psi c\phi s\theta \\ s\psi c\theta & c\psi c\phi + s\phi s\theta s\psi & -c\psi s\phi + s\theta s\psi c\phi \\ -s\theta & c\theta s\phi & c\theta c\phi \end{bmatrix}, \tag{2}$$

where $s.$ stands for $\sin(.)$ and $c.$ stands for $\cos(.)$. ϕ, θ and ψ are Euler angles that are about X, Y and Z coordinates, respectively. Conventional ships are not equipped with actuators in roll and pitch which suggest that the roll and pitch modes should be omitted in automatic control design procedure. In fact, this is an appropriate assumption since both the rolling and pitching motions of a ship are oscillatory with zero mean and limited amplitude. Moreover, a conventional ship is metacentric stable which implies that there exist restoring moments in roll and pitch. In this paper, it is assumed that the ship is sufficiently metacentric stable, such that only the rotation matrix in yaw can be used to describe the kinematic equations of motion [18]. For 3 DOF, the vessel position in earth-fixed frame and its velocities in body-fixed frame can be represented by $\eta = [x, y, \psi]$ and $v = [u, v, r]$, respectively. As a result of vessel motion in horizontal plane ($\phi = 0$ and $\theta = 0$), the transformation matrix depends on only yaw angle and we have:

$$J(\eta) = J(\psi) = \begin{bmatrix} \cos\psi & -\sin\psi & 0 \\ \sin\psi & \cos\psi & 0 \\ 0 & 0 & 1 \end{bmatrix}, \tag{3}$$

where $J(\psi)$ is nonsingular for all ψ. It should be noted that $J^{-1}(\psi) = J^T(\psi)$ [19].

2.2. Low Frequency (LF) ship model

We can model a surface ship motion in horizontal plane by the model:

$$M\dot{v} + Dv = u + J^T(\psi)b, \tag{4}$$

where u is a vector of control forces and moment that ship propulsion system provides it. M is the inertia matrix including hydrodynamic added inertia and $D > 0$

is a strictly positive definite matrix representing linear hydrodynamic damping. With considering starboard-port symmetry of ships, M and D matrixes can be written as:

$$M = \begin{bmatrix} m_{11} & 0 & 0 \\ 0 & m_{22} & m_{23} \\ 0 & m_{32} & m_{33} \end{bmatrix},$$

$$D = \begin{bmatrix} d_{11} & 0 & 0 \\ 0 & d_{22} & d_{23} \\ 0 & d_{32} & d_{33} \end{bmatrix}, \tag{5}$$

which states that there is no coupling between the surge and the sway-yaw subsystems. In general, M will be non-symmetrical, that is $m_{23} \neq m_{32}$ due to the properties of hydrodynamic added inertia. In fact, hydrodynamic added mass will depend on the speed of the ship and the wave frequency of encounter. However, for low-speed and zero speed applications, the inertia matrix $M = M^T$ is positive definite and constant. In general the damping matrix D will be nonlinear. However for DP and cruising at constant speed, linear damping is a good assumption [17].

For describing environmental forces and moments in the ship low-frequency model due to wind, ocean currents, and unmodeled dynamics we introduce a bias term $b \in R^3$ as [19]:

$$\dot{b} = -T^{-1}b + \Psi n, \tag{6}$$

where T is a diagonal matrix representing time constant, Ψ is the excitation gain and n is a vector of Gaussian white noise.

2.3. Wave Frequency (WF) model

The WF motions are mainly due to 1st-order wave loads. Assuming small amplitudes, a linear Wave Frequency (WF) model of order p can in general be expressed as:

$$\dot{\xi} = \Omega\xi + \sum w, \tag{7}$$

$$\eta_w = \Gamma\xi, \tag{8}$$

where $\xi \in R^p$ and $\eta_w = [x_w, y_w, \psi_w]^T$ is the WF earth-fixed position and heading vector, w is a vector of Gaussian white noise and Ω, $\sum$ and Γ are constant matrices of appropriate dimensions [18].

2.4. Measurements

Only position and heading measurements are available. The measurement vector y is assumed to be a superposition of the LF and WF motions, in addition to the measurement noise v, that is:

$$y = \eta + \eta_w + v. \tag{9}$$

3. Adaptive critic-based neuro-fuzzy controller

3.1. Neuro-fuzzy networks

Fuzzy set is a simple extension of the definition of a classical set in which the characteristic function is permitted to have any number between 0 and 1. A fuzzy set A in X can be defined as a set of ordered pairs:

$$A = \{(x, \mu_A(x))|x \in X\}, \tag{10}$$

where $\mu_A(x)$ is called membership function for the fuzzy set A. It maps each x to a membership grade between 0 and 1. Also a fuzzy If-Then rule (fuzzy rule, fuzzy implication, or fuzzy conditional statement) is expressed as follow:

$$\text{If } (x \text{ is } A) \text{ then } (y \text{ is } B), \tag{11}$$

where A and B are linguistic values defined by fuzzy sets. (x is A) is called antecedent or premise, while (y is B) is called the consequence or conclusion. Fuzzy systems are made of a knowledge base and reasoning mechanism called fuzzy inference engine. A fuzzy inference engine turns fuzzy If-Then rules into a mapping from the inputs of the system into its outputs, using fuzzy reasoning methods. It means that fuzzy systems represent nonlinear mapping accompanied by fuzzy If-Then rules from the rule base. Each of these rules describes the local mappings. The rule base can be constructed either from human expert or automatic generation that is extraction of rules using numerical input-output data. There are two types of fuzzy inference system that are commonly used: Mamdani and Takagi-Sugeno-Kang (TSK). In neuro-fuzzy networks, TSK type fuzzy inference system is used. The output of each rule can be a linear combination of input variables plus a constant term or can be only a constant term. The final output is the weighted average of each rules' output. Basic neuro-fuzzy system architecture that has two inputs x and y and one output f is shown in Figure 2. The rule base contains two TSK If-Then rules as:

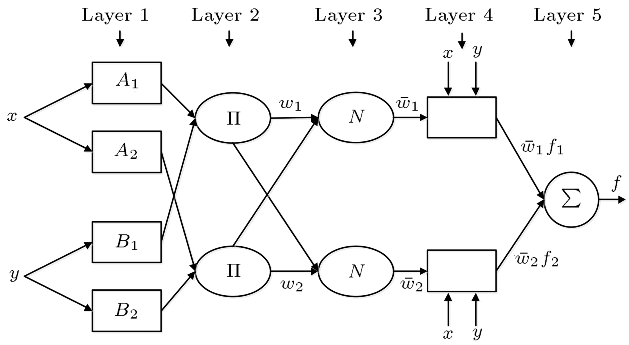

Figure 2. A neuro-fuzzy structure which is equivalent to a TSK fuzzy inference system.

Rule 1: If x is A_1 and y is B_1, then:

$$f_1 = a_1 x + b_1 y + c_1, \tag{12}$$

Rule 2: If x is A_2 and y is B_2, then:

$$f_2 = a_2 x + b_2 y + c_2. \tag{13}$$

The node functions in a layer are the same as described below:

- Layer 1: Every node i in this layer is a square node with a node function as:

$$o_{1,i} = \mu_{A_i}(x) \quad (i = 1, 2), \tag{14}$$

$$o_{1,i} = \mu_{B_{i-2}}(y) \quad (i = 3, 4), \tag{15}$$

  where x is the input to node i, and A_i (or B_{i-2}) is a linguistic label (such as small or large) associated with this node. In other words $o_{1,i}$ is the membership grade of a fuzzy set A_i and it specifies the degree to which the given input x satisfies the quantifier A_i. Parameters in this layer are referred to premise parameters.

- Layer 2: Every node in this layer is labeled by II whose output is the product of all incoming signals:

$$o_{2,i} = u_i = \mu_{A_i}(x)\mu_{B_i}(x) \quad (i = 1, 2). \tag{16}$$

  Each node output represents the firing strength of a fuzzy rule.

- Layer 3: Every node in this layer is labeled by N. The i-th node calculates the ratio of the rules firing strength to the summation of all rules firing strengths:

$$o_{3,i} = \bar{u}_i = \frac{u_i}{(u_1 + u_2)} \quad (i = 1, 2). \tag{17}$$

  Outputs of this layer are called normalized firing strengths.

- Layer 4: In this layer, every node is adaptive, due to its adjustable parameters, with a node function as:

$$o_{4,i} = \bar{u}_i f_i = \bar{u}_i(a_i x + b_i + c_i), \tag{18}$$

  where $\bar{u}_i$ is a normalized firing strength from layer 3 and $\{a_i, b_i, c_i\}$ is the parameter set of this node. Parameters in this layer are referred to consequent parameters.

- Layer 5: The single node in this layer is labeled by $\sum$ that computes the overall outputs as the summation of all incoming signals:

$$o_{5,i} = \sum_i \bar{u}_i f_i = \frac{\sum_i u_i f_i}{\sum_i u_i}. \tag{19}$$

  Thus a network which is functionally equivalent to the TSK fuzzy inference system has been constructed.

3.2. The controller structure

According to psychological theories, some of the main factors of human being learning are emotional signal such as satisfaction and stress. Emotion can be defined as states elicited by instrumental reinforcing stimuli, which their occurrence, termination or omission is made contingent upon the making of a response, and alter the course of future emission of that response [20]. Adaptive critic design is based on reinforcement learning concept. The critic agent assesses the behavior of the control system through evaluation of plant output and provides reinforcement signal namely r. In classical reinforcement learning, there exists a reinforcement signal, R, which usually accepts binary values. For example, if $R = 1$, the control system has failed and should modify itself so that a reinforcement signal of value zero is achieved, i.e. the critic is fully satisfied in subsequent trials [21]. However, in novel or non-classical reinforcement learning methods, the reinforcement signal (r) is always continuous and accepts any value between -1 and 1, with $r = 1$ (or -1) indicating the total failure of the control system. The closer the reinforcement signal gets to zero, the better the control action. Here the system does not wait for a total failure to occur before it starts learning. Instead, it continues its learning process at the same time as it applies its control action. Generally, in a multivariable system for each output a critic is assigned. Inputs of the critic are usually error between the system's output and its desired or reference value, and its derivative, and its output is the corresponding reinforcement signal. The reinforcement signals contribute collaboratively for updating parameters of each neuro-fuzzy controller. It should be noticed that the structure of controller is like a TSK fuzzy system whose parameters are updated using the reinforcement learning. The aim of the control system is minimization of the square value of reinforcement signals. Structure of adaptive critic-based neuro-fuzzy controller is shown in Figure 3.

Let define the error function for each controller as:

$$E_j = \frac{1}{2} r_j^2 \quad (j = 1, 2, ..., m), \tag{20}$$

where r_j is the output signal of critic j, and m

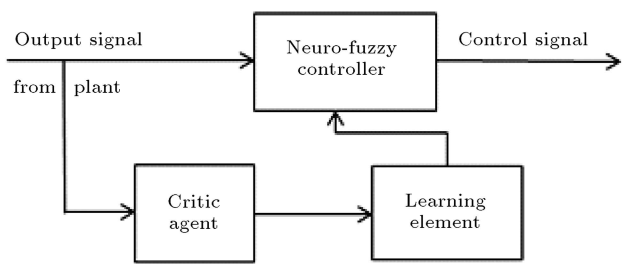

Figure 3. Structure of adaptive critic-based neuro-fuzzy controller.

is the total number of outputs. The goal of the learning procedure is to minimize error signal E_j for the adjustment of controller weights; so the steepest descent method is used as:

$$\Delta w_i = -\eta_i \frac{\partial E_j}{\partial w_i} \quad (i = 1, 2, ..., n) \; (j = 1, 2, ..., m), \tag{21}$$

where η_i is the learning rate of the corresponding controller, w_i's are the tunable weights of each controller, and n is the total number of controller parameters. In order to calculate the relative derivative of Eq. (21), the chain rule is used:

$$\frac{\partial E_j}{\partial w_i} = \frac{\partial E_j}{\partial r_j} \frac{\partial r_j}{\partial y_j} \frac{\partial y_j}{\partial u_i} \frac{\partial u_i}{\partial w_i}$$

$$(i = 1, 2, ..., n \text{ and } j = 1, 2, ..., m). \tag{22}$$

From Eq. (21) and also the dynamic equations of the system, we have:

$$\frac{\partial E}{\partial r_j} = r_j \quad (j = 1, 2, ..., m), \tag{23}$$

$$\frac{\partial y_j}{\partial u_i} = J_{ji} \quad (i = 1, 2, ..., n \text{ and } j = 1, 2, ..., m), \tag{24}$$

where J_{ji} is the element in the i-th column and j-th row of the Jacobin matrix of the system, and u_i is the i-th control input. If the direction of changes of the system output with respect to the input is known we can approximate J with its sign. Also we have:

$$e_j = y_{(\mathrm{ref})j} - y_j \quad (j = 1, 2, ..., m), \tag{25}$$

where e_j is the error produced in the tracking of the j-th output and y_{ref} is the desired output. Let us define the reinforcement signal of the j-th critic as a linear combination of error e_j, and derivative of error $\dot{e}_j$ as:

$$r_j = K_j e_j + L_j \dot{e}_j \quad (j = 1, 2, ..., m), \tag{26}$$

where K_j and L_j are positive constants of the j-th critic. By the chain rule and using Eq. (26), we can write:

$$\frac{\partial r_j}{\partial y_j} = \frac{\partial r_j}{\partial e_j} \frac{\partial e_j}{\partial y_j} = K_j(-1) = -K_j \quad (j = 1, 2, ..., m). \tag{27}$$

From Eqs. (21) to (27), Δw_i will be calculated as:

$$\Delta w_i = \eta_i K_j r_j J_{ji} \frac{\partial u_i}{\partial w_i}. \tag{28}$$

Eqs. (29) to (31) are used for updating the learning parameters, a_i, b_i and c_i, in Eq. (14):

$$a_{ij\mathrm{new}} = a_{ij\mathrm{old}} + \alpha_i r_j x \frac{u_i}{\sum_{i=1}^{n} u_i}, \tag{29}$$

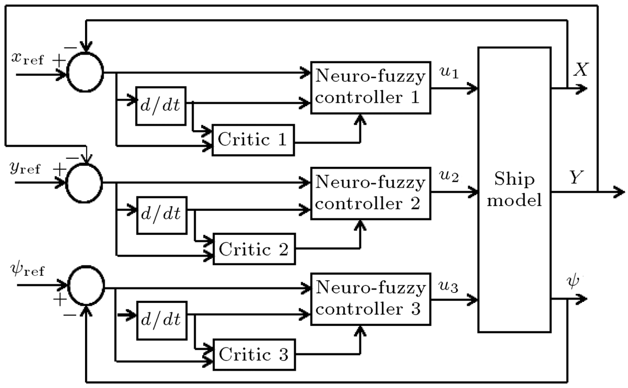

Figure 4. Structure of ACNFC for dynamic positioning of ships.

$$b_{ij\mathrm{new}} = b_{ij\mathrm{old}} + \beta_i r_j y \frac{u_i}{\sum_{i=1}^{n} u_i}, \tag{30}$$

$$c_{ij\mathrm{new}} = c_{ij\mathrm{old}} + \gamma_i r_j \frac{u_i}{\sum_{i=1}^{n} u_i}, \tag{31}$$

where α_i, β_i and γ_i are learning rates for each rule. Here it is assumed that $K_j = 1$ and $J_{ii} = 1$, $J_{ji} = 0$, $i \neq j$ (instead of the Jacobian matrix its sign is used).

4. Architecture of the ship controller

Figure 4 shows the structure of the designed Adaptive Critic based Neuro-Fuzzy Controller (ACNFC) for dynamic position control of ships. This structure is made of three neuro-fuzzy controllers with three critics for control of vessel position (x, y) and heading ψ. The inputs of each controller are the outputs$'$ error signal and its derivative, and three linguistic variables (negative (N), positive (P), and zero (Z)) are used in each input in order to tune the rules, and accordingly nine rules are formed for each controller. We have considered three membership functions for each of the inputs. The sigmoid functions for the variables N and P, and the Gaussian function for the variable Z are defined, respectively as:

$$\mu_{F_{ji}}(x_i) = \left[1 + \exp(-a_{ji}(x_i - c_{ji}))\right]^{-1}, \tag{32}$$

$$\mu_{F_{ji}}(x_i) = \exp\left[-(\frac{x_i - c_{ji}}{\delta_{ji}})^2\right], \tag{33}$$

where c_{ji} is the center of function, δ_{ji} is the function variance, and a_{ji} is the curve inflection parameter. The membership functions of the linguistic variables are shown in Figure 5.

The main section in ACNFC is the critic. Inputs of each critic are the output's error signal and its derivative, which are used to evaluate the system performance. For example, if the error signal is positive but its derivative is negative, then the performance is good. As another instance, if the error signal

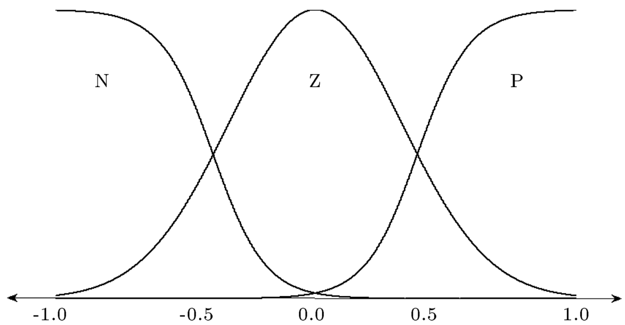

Figure 5. The membership functions of the corresponding linguistic variables of the proposed ACNFC.

Figure 6. Moored tanker, $L = 200.6$ (m) [8].

and its derivative are both negative, the controller behavior will not satisfy the critic. Finally by applying the stress signal to each ACNFC, The controller parameters are tuned in order to optimize the system performance by minimizing the square of reinforcement signal.

5. Dynamic position control

Consider the moored tanker shown in Figure 6. Numerous simulations are performed to evaluate the performance of controllers using MATLAB software. The case studies are based on the following non-dimensional model of the moored tanker (Bis-system) [8,17]:

$$M = \begin{bmatrix} 1.0825 & 0 & 0 \\ 0 & 2.0575 & -0.4087 \\ 0 & -0.4087 & 0.2153 \end{bmatrix}, \tag{34}$$

$$D = \begin{bmatrix} 0.0865 & 0 & 0 \\ 0 & 0.0762 & 0.1510 \\ 0 & 0.0151 & 0.0031 \end{bmatrix}. \tag{35}$$

The Bis-system is based on the use of the time unit defined by $\sqrt{\frac{\text{Ship length}}{\text{Gravity const}}}$, the mass unit defined by $m = \mu\rho\nabla$, and the body mass ratio $m/\rho\nabla$ where ∇ is the hull contour displacement and ρ is the water density, as normalization variables. The method of non-dimensionalization is presented completely in [17]. The bias time constants were chosen as:

Table 1. Parameters of critic agents.

K_1	L_1	K_2	L_2	K_3	L_3
0.14	0.85	0.25	0.9	0.05	0.13

$$T = \begin{bmatrix} 56.7 & 0 & 0 \\ 0 & 12.9 & 0 \\ 0 & 0 & -213.5 \end{bmatrix}. \tag{36}$$

Performance of the ACNFC depends on the values of learning rate and coefficients of critic. The values of the coefficients of critic agents are given in Table 1, they have been chosen by trial and error mechanism. It should be emphasized that the critic role is to truly evaluate the situation but indeed not needed to be so accurate. The sample time of 0.1 sec is chosen and learning rates are constant and equal to $\eta_1 = \eta_2 = \eta_3 = 0.35$. Also the controllers initial weights are selected randomly between [-1 1]. In the simulations measurement noise is modeled as white noise and WF motions are modeled by a 2nd-order linear model. The initial value for the position x is chosen -10, and its desired value is 0. Also the initial position y is set to -10, and its desired value is 0. Finally the set point for the heading is chosen to be -10, which is applied at instance 10 as a step function from initial value of 0. The control systems have been implemented and simulated to investigate their performance. The results show that wave filtering, positioning and tracking are performed with no visible offsets, and satisfactory accuracy is obtained. The Simulation results are shown in Figures 7-9. In all of the following figures all the values represent the difference from the corresponding steady state values. It should be noted that all values of state variables and the system parameters are non-dimensionalized according to [17]. To obtain the real values of state variables, the non-dimensional position

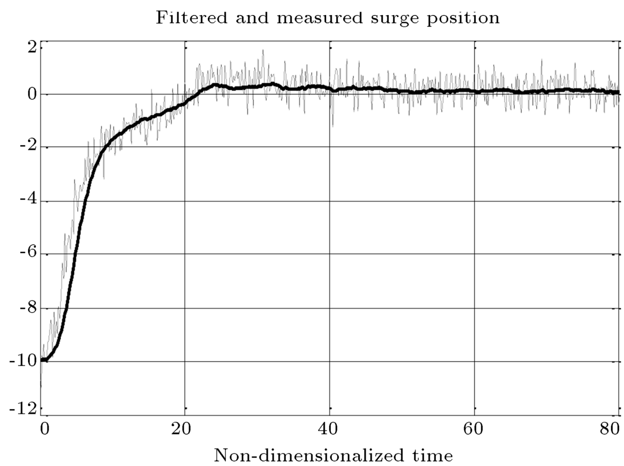

Figure 7. Performance of ACNFC, position x.

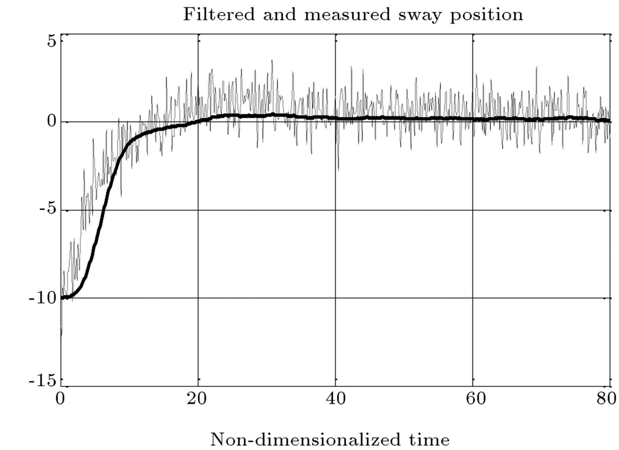

Figure 8. Performance of ACNFC, position y.

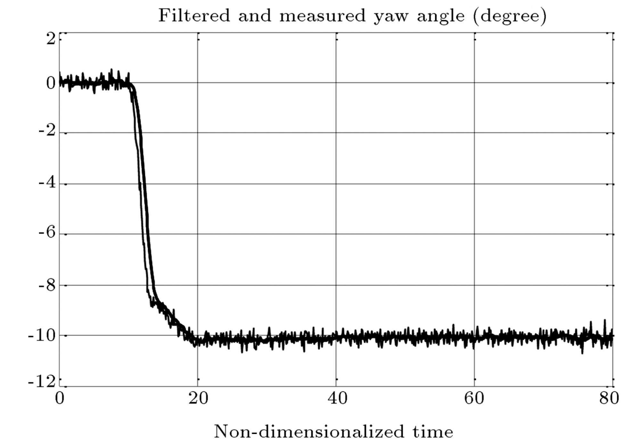

Figure 9. Performance of ACNFC, heading ψ.

and time should be multiplied by the ship length and time unit defined by $\sqrt{\frac{\text{Ship length}}{\text{Gravity const}}}$, respectively. The real values of forces can be obtained using the values of ship length, ship mass and the mentioned time unit.

To check the robustness of the controlled system to model uncertainty, the ACNFCs are implemented on the ship model whose matrices in Eqs. (34) to (36) are changed ±30% around their nominal values. We can see that the performance of the ACNFCs is not strongly affected and only slight deviations are visible in the control signals, position and heading response. The computer simulations are shown in Figures 10-12.

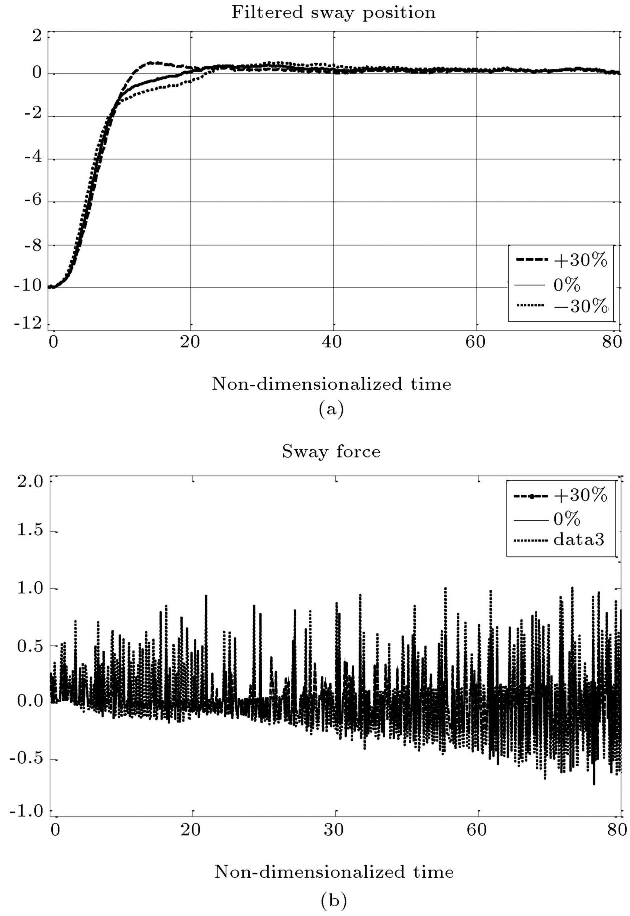

Figure 11. Performance of ACNFC wrt model uncertainties: (a) Position y; and (b) sway force.

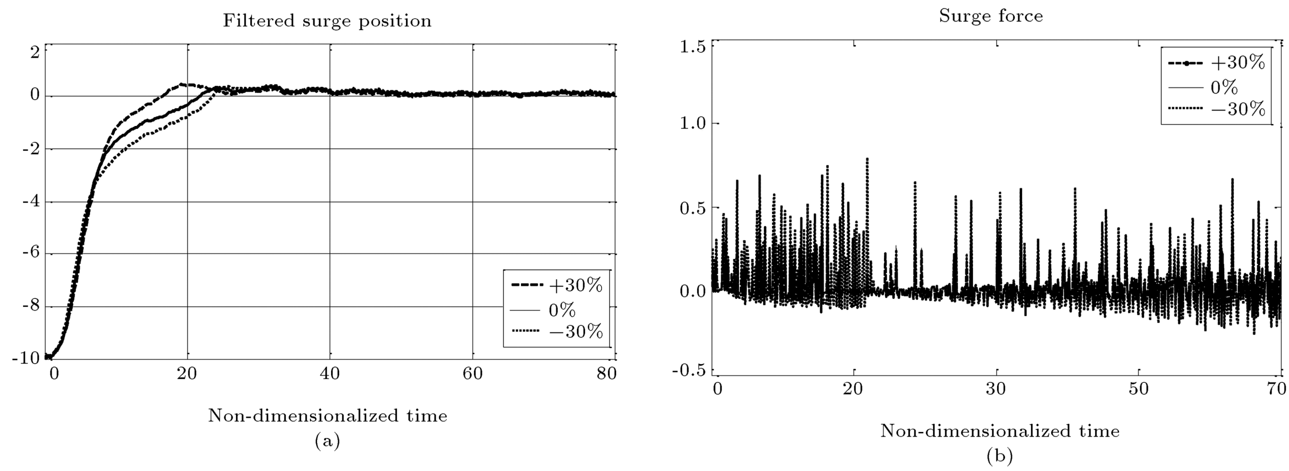

Figure 10. Performance of ACNFC wrt model uncertainties: (a) Position x; and (b) surge force.

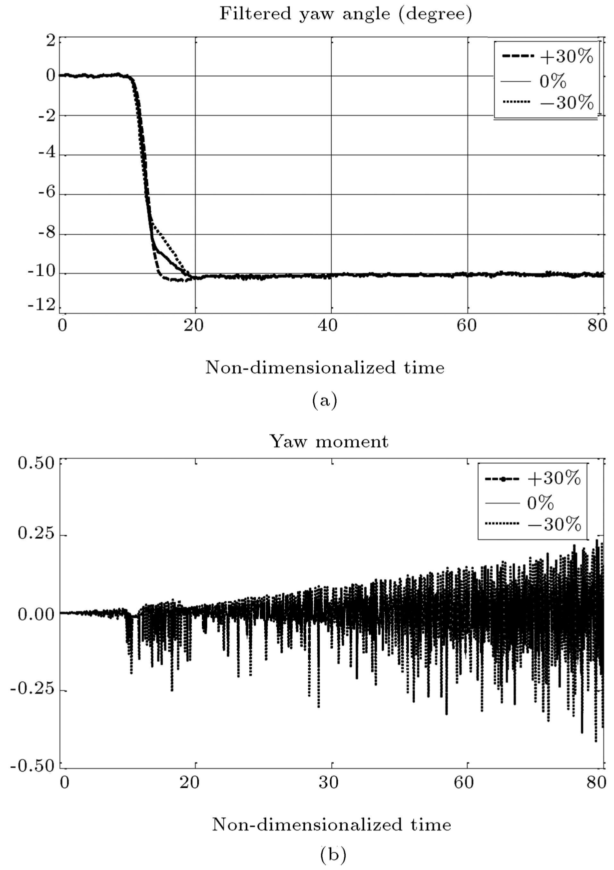

Figure 12. Performance of ACNFC wrt model uncertainties: (a) Heading ψ; and (b) yaw moment.

6. Conclusion

In this article three adaptive critic-based neuro-fuzzy controllers were proposed in order to control the dynamic positioning of ships. The unique aspect of this type of controller is that it uses the critic which simulates the expert operation in reality. Here we design the critic instead of designing the controller itself. This feature increases the degree of intelligence and robustness of the system and results in a self-tuning and adaptive controller. Learning rules are very simple and therefore the computational speed is high. Considering the simplicity of ACNFC and its independence from the model, this control method has advantage of online learning and control, and can be applied to a large variety of systems. The proposed controller was applied to control the position x, position y and heading angle of the moored tanker. Simulation results show that the controller has good convergence and robust performance which are concluded from the adaptive and intelligent structure of the proposed control.

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