A Self Learning Fuzzy Logic Controller for Ship Steering System

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Abstract— A self learning fuzzy logic controller for ship steering systems is proposed in this paper. Due to the high nonlinearity of ship steering system, the performances of traditional control algorithms are not satisfactory in fact. An intelligent control system is designed for controlling the direction heading of ships to improve the high efficiency of transportation, the convenience of manoeuvring ships, and the safety of navigation. The design of fuzzy controllers is usually performed in an ad hoc manner where it is hard to justify the choice of some fuzzy control parameters such as the parameters of membership function. In this paper, self tuning algorithm is used to adjust the parameters of fuzzy controller. Simulation results show that the efficiency of proposed algorithm to design a fuzzy controller for ship steering system.

Keywords: Self Learning, Fuzzy controller, Ship Steering.

تصميم منظومة تحكم من نوع المنطق المضبب ذاتية التعليم للسيطرة على دفة السفينة

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الخلاصة: بسبب الخصائص اللاخطية لمنظومة دفة السفينة فأن تصميم منظومة تحكم تقليدية للسيطرة عليها يعد امرا غير فعال. لذا لابد من اقتراح منظومة تحكم ذكية لتحسين السيطرة على اتجاه ابحار السفينة وكفائة المناورة . تم اقتراح تصميم منظومة تحكم من نوع المنطق المضبب ذاتية التعليم لتغير استجابة المتحكم مع تغير الضروف الخارجية المسلطة على السفينة. ولقد اثبتت النتائج المستحصلة كفائة وفعالية منظومة التحكم المقترحة للسيطرة على دفة السقينة.

1. Introduction

Microprocessor and sensor technology have been applied to build automated ships to offer diverse information for safe navigation to reduce the occurrence of human error in ship operation and achieve labour cost reduction. Due to the complexity of ship motion and the randomizing of unpredictable environmental influences, the performances of traditional control algorithms are not satisfactory.

Some works are carried out to design a robust control system for ship steering autopilot. Layne and Passino used the fuzzy model reference learning control for ship steering system [1]. In reference [2], an ontology-based fuzzy support agent for ship steering control and desires to testify the validity of the proposal by applying the fuzzy control model to the steering control system based on linguistic instruction. A neural network based model reference adaptive control approach for controlling the direction heading of ships [3]. In reference [4], the authors proposed an intelligent voice instruction-based learning method and discuss the building of a ship's steering control system based on this method. Yang et al. presented a novel model reference adaptive robust fuzzy control algorithm for ship steering autopilot [5].

The fuzzy control system is successfully applied in some application area. The design of fuzzy controllers is usually performed in an ad hoc manner where it is hard to justify the choice of some fuzzy control parameters such as the parameters of membership function. In this case, a self-learning fuzzy system is effective to overcome these difficulties, as it possesses the capability of self-improvement of its performance over time. Many authors proposed a learning algorithm to make the fuzzy control system self tuning and adaptive. Some of them used learning ability of the neural networks to tune parameters of the membership function of the fuzzy inference systems [6, 7]. The learning mechanism of fuzzy model reference learning model employs a reference model to provide a closed-loop performance feedback for synthesizing and tuning the controller's knowledge base [8, 9]. Some

authors used the genetic algorithm to tune the parameters of the fuzzy logic system [10, 11].

In this paper, the self learning fuzzy controller that utilizes a sensitivity model and second-order reference model is proposed as a control system for controlling the direction heading of ships. In order to determine a sensitivity function, the function describing the dependence of two variables (or variables and parameters) must be differentiable. There is a class of fuzzy controllers widely used in practical applications, usually called the Takagi–Sugeno zero-order (or singleton) fuzzy controllers, which can be organized to assume an analytical and differentiable form. Some authors used this method to design a control system for different application [12-15].

The paper is organized as follows: Section 2 presents the nonlinear dynamic model of ship steering system. In section 3, the structure of the self learning fuzzy control based on sensitive functions is described. In section 4, numerical simulation is made to demonstrate the learning phase of the fuzzy controller for ship steering system. Finally, the conclusion is summarized in section 5.

2. Nonlinear Dynamic Model of Ship Steering System

Ship steering dynamic model is obtained by applying Newton's Laws of motion. The coordinate system that is fixed to the ship is describing the motion of the ship as shown in Figure 1.
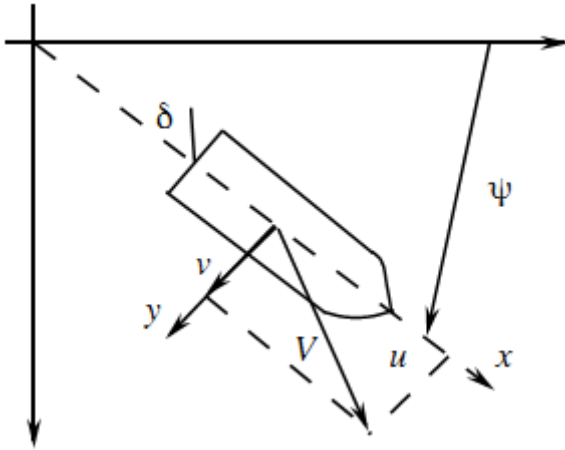
Figure 1 the coordinate system for the ship

A simple model of the ship's motion is governed by the following equation [1]:

$$\ddot{\psi}(t) + \left(\frac{1}{\tau_1} + \frac{1}{\tau_2}\right)\ddot{\psi}(t) + \left(\frac{1}{\tau_1\tau_2}\right)\dot{\psi}(t)$$
$$= \frac{K}{\tau_1\tau_2}\left(\tau_3\dot{\delta}(t) + \delta(t)\right) \quad (1)$$

where ψ is the heading of the ship and δ is the rudder angle. The Laplace transformation function for Eq. 1 at zero conditions is given as

$$\frac{\psi(s)}{\delta(s)} = \frac{K(s\tau_3 + 1)}{s(s\tau_1 + 1)(s\tau_2 + 1)} \quad (2)$$

where K, τ_1, τ_2 and τ_3 are parameters that are a function of the ship' constant forward velocity u and its length l.

Equation 1 is obtained by linearization the equations of the motion around the zero rudder angle. As result, the rudder angle should not exceed approximately 5° , otherwise the model will be inaccurate. Therefore, a model suited for rudder angles that are larger than 5° should be derived. The nonlinear model that is presented in [1] is used in this study. This extended model is given by:

$$\ddot{\psi}(t) + \left(\frac{1}{\tau_1} + \frac{1}{\tau_2}\right)\ddot{\psi}(t) + \left(\frac{1}{\tau_1\tau_2}\right)H\left(\dot{\psi}(t)\right)$$
$$= \frac{K}{\tau_1\tau_2}\left(\tau_3\dot{\delta}(t)\right.$$
$$\left. + \delta(t)\right) \quad (3)$$

where $H\left(\dot{\psi}(t)\right)$ is nonlinear function of $\dot{\psi}(t)$. An experiment known as the "spiral test" has shown that $H\left(\dot{\psi}(t)\right)$ can be approximated by

$$H\left(\dot{\psi}(t)\right) = a\dot{\psi}^3(t) + b\dot{\psi}(t) \quad (4)$$

where a and b are real valued constants such that a is always positive.

3. Self Learning Fuzzy Control Based on Sensitivity Functions

Figure 2 shows the structure of the proposed controller (self learning fuzzy control). The concept of the SLFLC block allows control of unknown inherently stable static and astatic nonlinear systems providing that desired closed-loop system behaviour can be represented with a linear second-order reference model. The fuzzy controller has two inputs $e(k)$ and $dy(k)$ and one output $u_{FC}(k)$. The Takagi-Sugeno type of fuzzy controller is used in this structure. The fuzzy rules which map the antecedent fuzzy relations R_i with the consequence parts containing an explicitly determined control input u_{FC}:

$$IF\ R_i THEN\ u_{FC} = a_i \quad (5)$$

where a_i is constant.
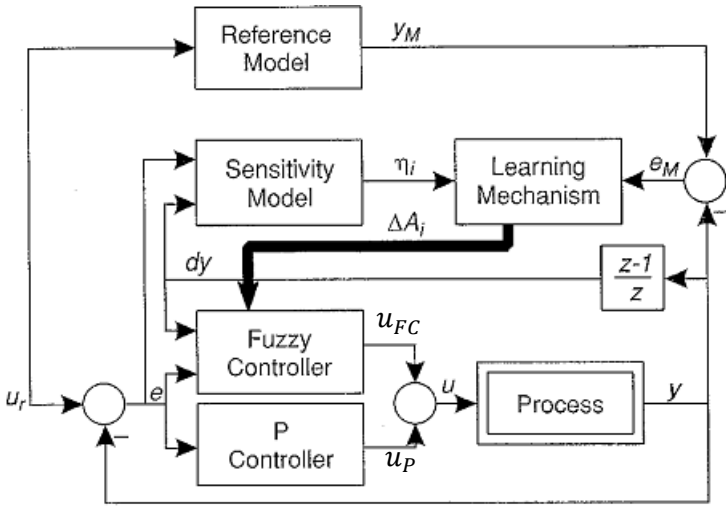The output of the fuzzy controller can be given as

Figure 2 the structure of the self learning

fuzzy control scheme

$$u_{FC}(k) = \sum_{i=1}^{r} A_i * \phi_i[e(k), dy(k)]$$

$$= \sum_{i=1}^{r} A_i * \frac{\mu_i[e(k), dy(k)]}{\sum_{i=1}^{r} \mu_i[e(k), dy(k)]} \quad (6)$$

where A_i is the centroid of the fuzzy controller output subset activated by the ith fuzzy rule; $e(k) = u_r(k) - y(k)$; $dy(k) = y(k) - y(k-1)$; r is the number of fuzzy rule; and μ_i is the member function of a fuzzy implication.

The input control signal to the process can be given as:

$$u(k) = u_{FC}(k) + K_P * e(k) \quad (7)$$

where K_P is proportional gain.

The second order reference model is used to determine the desired closed loop system. The transfer function of the reference model is given as:

$$\frac{Y_m(s)}{U_r(s)} = \frac{\omega_n^2}{s^2 + 2\eta\omega_n s + \omega_n^2} \quad (8)$$

where $y_m(k)$ is the desired output; $u_r(k)$ is the reference input; η is damping ratio; and ω_n natural oscillation frequency.

Sensitivity functions can be very useful to express how much influence some variables or parameters have on the focused variable. In this sense, sensitivity functions represent information about interactions between causes and consequences which may be very useful for planning interventions in the system. Having this concept in mind, a total differential of the system output $y(k)$ with respect to small variations of controller parameters is determined by

$$\Delta y(k) = \sum_{i=1}^{N} \frac{\partial y(k)}{\partial \lambda_i} * \Delta \lambda_i$$

$$= \sum_{i=1}^{N} \xi_{\lambda i}(k) * \Delta \lambda_i \quad (9)$$

where λ_i is i^{th} fuzzy controller parameter; $\xi_{\lambda i}(k)$ is the sensitive function related to parameter of the fuzzy controller.

By using the chain rule, the sensitive function can be written as

$$\xi_{\lambda i}(k) = \frac{\partial y(k)}{\partial \lambda_i} = \frac{\partial y(k)}{\partial u(k)} * \frac{\partial u(k)}{\partial \lambda_i}$$

$$= G_P * \frac{\partial u(k)}{\partial \lambda_i} \quad (10)$$

A sensitivity function of the controller output with respect to controller parameter variations has the form

$$\frac{\partial u(k)}{\partial \lambda_i} = \frac{\partial}{\partial \lambda_i} \left\{ \sum_{i=1}^{r} A_i * \phi_i[e(k), dy(k)] \right\} \quad (11)$$

In the proposed concept, system parameter variations will be compensated for only by modifying the centroid of the fuzzy output sets Ai (input membership functions remain predefined). Therefore

$$\frac{\partial u(k)}{\partial \lambda_i} = \frac{\partial u(k)}{\partial A_i} = \frac{\partial}{\partial A_i}\left\{\sum_{i=1}^{r} A_i * \phi_i[e(k), dy(k)]\right\}$$

$$= \frac{\partial}{\partial A_i}\left\{\sum_{i=1}^{r} A_i * \frac{\mu_i[e(k), dy(k)]}{\sum_{i=1}^{r} \mu_i[e(k), dy(k)]}\right\}$$

$$= \frac{\mu_i[e(k), dy(k)]}{\sum_{i=1}^{r} \mu_i[e(k), dy(k)]} \qquad (12)$$

Therefore, the update equation of the centroid of the fuzzy controller output is given as

$$A_i^{\theta+1} = A_i^{\theta} + \frac{\partial u(k)}{\partial A_i}$$

$$= A_i^{\theta} + \frac{\mu_i[e(k), dy(k)]}{\sum_{i=1}^{r} \mu_i[e(k), dy(k)]} \qquad (13)$$

4. Simulation and Results

The nonlinear model of the ship steering, which is given in Eq. 3, is used to demonstrate the effectiveness of the self learning fuzzy control algorithm. For our simulations, the values of both a and b, which are shown in Eq. 4, are chosen to be 1. The reference model is defined as: $\omega_n = 0.05$ and $\eta = 1$.

The type of the fuzzy controller that had been used in this simulation is Takagi-Sugeno type. To design the fuzzy controller, the triangular membership functions are used for the input variables as shown in Figure 3. While the singleton membership functions are used for the output variable with random centroid values.

Eighty one rules are used to describe the fuzzy rules based as shown in Table 1, where the values

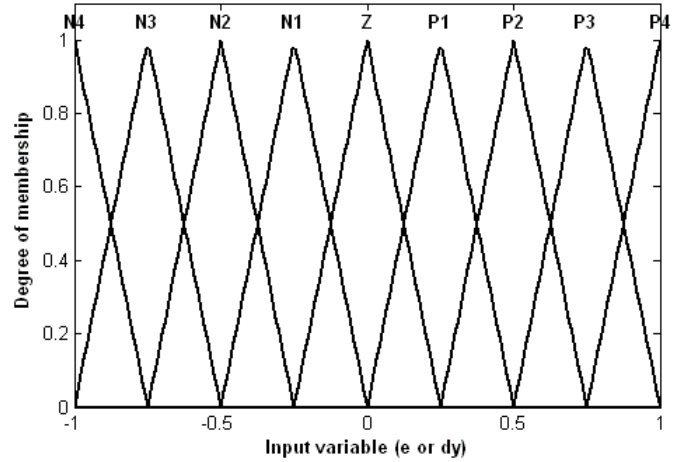of the variable a_i for $i \in \{1, 81\}$ are arbitrary value.

Figure 3 Triangular membership functions for the input variable

		dy								
		N4	N3	N2	N1	Z	P1	P2	P3	P4
	N4	a_1	a_2	a_3	a_4	a_5	a_6	a_7	a_8	a_9
	N3	a_{10}	a_{11}	a_{12}	a_{13}	a_{14}	a_{15}	a_{16}	a_{17}	a_{18}
	N2	a_{19}	a_{20}	a_{21}	a_{22}	a_{23}	a_{24}	a_{25}	a_{26}	a_{27}
e	N1	a_{28}	a_{29}	a_{30}	a_{31}	a_{32}	a_{33}	a_{34}	a_{35}	a_{36}
	Z	a_{37}	a_{38}	a_{39}	a_{40}	a_{41}	a_{42}	a_{43}	a_{44}	a_{45}
	P1	a_{46}	a_{47}	a_{48}	a_{49}	a_{50}	a_{51}	a_{52}	a_{53}	a_{54}
	P2	a_{55}	a_{56}	a_{57}	a_{58}	a_{59}	a_{60}	a_{61}	a_{62}	a_{63}
	P3	a_{64}	a_{65}	a_{66}	a_{67}	a_{68}	a_{69}	a_{70}	a_{71}	a_{72}
	P4	a_{73}	a_{74}	a_{75}	a_{76}	a_{77}	a_{78}	a_{79}	a_{80}	a_{81}

Table 1 The rules of the fuzzy controller

For any fuzzy logic controller design, it is necessary to check the surfaces between the proposed membership function and the control action in order to make sure of the rounding process inside the fuzzy system. Figure 4 shows the control surface (before tuning the parameters of output membership function) between inputs/output variables using the proposed membership functions.
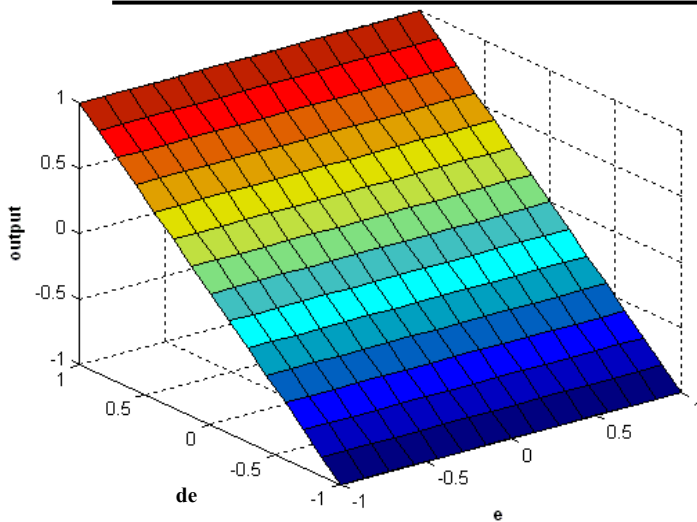
Figure 4 Control surface between inputs and
output variables (before tuning)

The self learning Fuzzy Control Based on
Sensitivity Functions is used to tune the parameters
of the output membership functions of the fuzzy
controller. Figure 5 depicts the structure of the self
learning fuzzy controller with ship steering model
during the training phase. It can be seen that the

self learning fuzzy controller is acting in parallel
with compensator controller. This means that the
fuzzy controller acts like an adaptation mechanism,
having a goal to improve the overall system
performance. The internal model control algorithm
is used to select the optimal parameters of the
compensator block. The structure of the
compensator block that is used in this simulation
can be obtained from Control System Toolbox in
MATLAB and it is given as:

$$\frac{U(s)}{E(s)} = \frac{-3.43s - 0.12}{2230s^3 + 194.48s^2 + s} \qquad (14)$$

The update equation 13 is used to tune the
parameters of the fuzzy controller. After 21
iterations the optimal values of the centroid of the
fuzzy controller output can be obtained. Table 2
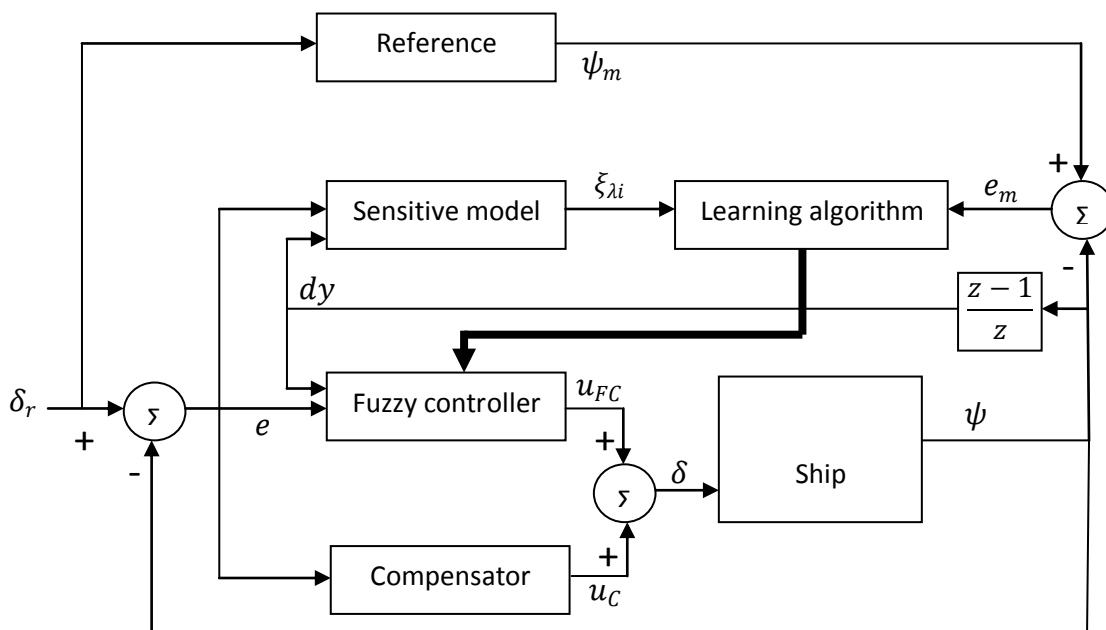shows the tuned centroid parameters.

Figure 5 the structure of the self learning fuzzy controller with ship

Table 2 The parameters of the centroid of the fuzzy controller output after tuned

9.271	3.269	1.034	0379	-0.591	0	0	0.911	-0.106
-1.717	-1.548	0.221	-0.611	-1.702	0	0	0.663	-1.339
2.405	0.148	0.012	-0.519	1.766	0	0	4.522	2.174
2.259	0.639	0.82	2.058	-1.403	0	-0.004	-1.153	-1.287
-4.629	0.430	1.255	-2.267	-4.25	0	0.139	-1.920	-3.075
0	0	0	0	0	0	0	0	0
0.153	1.298	0.066	0	-0.159	0	0	0	-0.159
-1.783	-2.573	-0.539	0	5.214	0	0	4.716	4.398
-1.508	-1.61	-3.27	0	-8.461	0	0	-6.91	-6.637

Figure 6 and Figure 7 show the reference input, ship steering system output, and reference model responses for the first six iterations and for the last four iterations, respectively. It can be seen that after completion of learning process the direction heading of the ship follows the reference model response. The output of ship steering system with a compensator controller has high overshoot and reaches the steady state after eight seconds, while the hybrid self-learning fuzzy controller enforces system to reach the steady state in less than two seconds without overshoot. This proves that addition of the SLFLC in parallel to the compensator block has contributed to a much better quality of the system response.
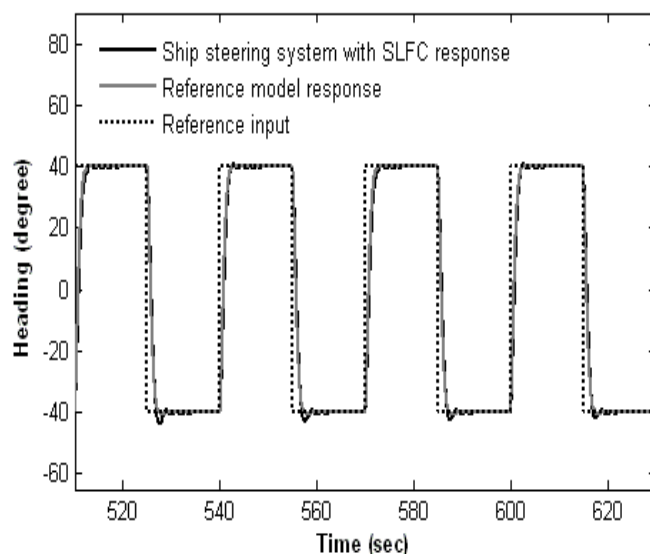

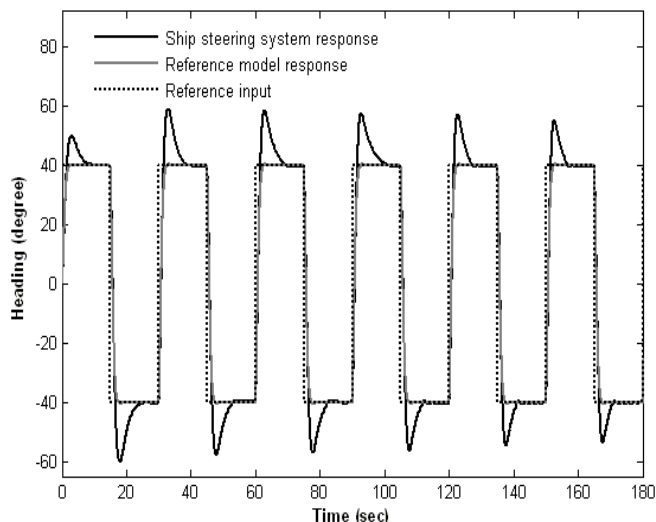Figure 7 the responses for the last four iterations

Figure 8 and Figure 9 show the hybrid self-learning fuzzy controller outputs at the beginning of learning (almost just the compensator controller is active) and at the end of learning (both controllers are active).
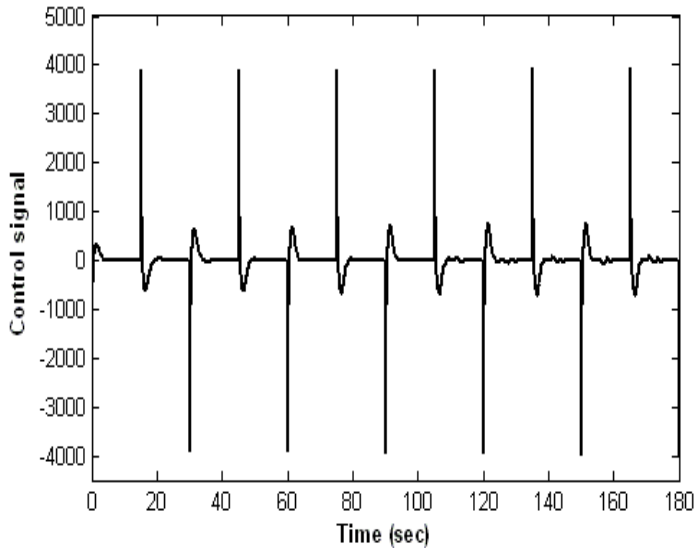

Figure 6 the responses for the first six iterations

Figure 8 the responses for the first six iterations

Figure 10 Control surface between inputs and output variables (after tuning)
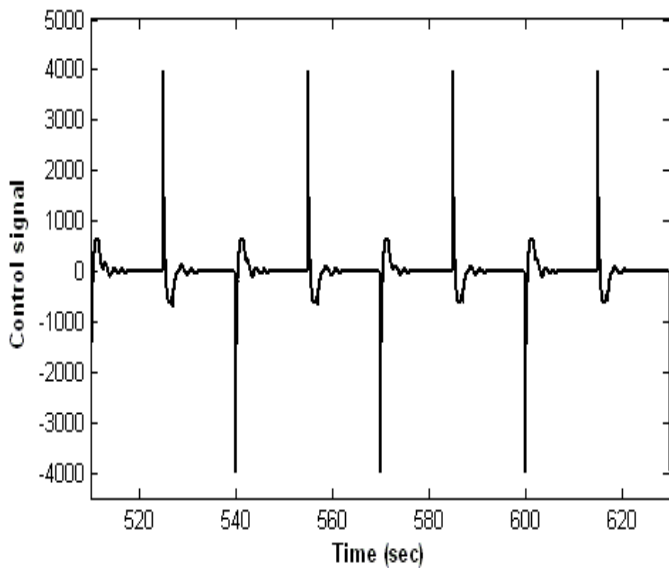

Figure 9 the responses for the last four iterations

Figure 10 shows the control surface (after the process of the training is completed) between inputs/output variables using the proposed membership functions
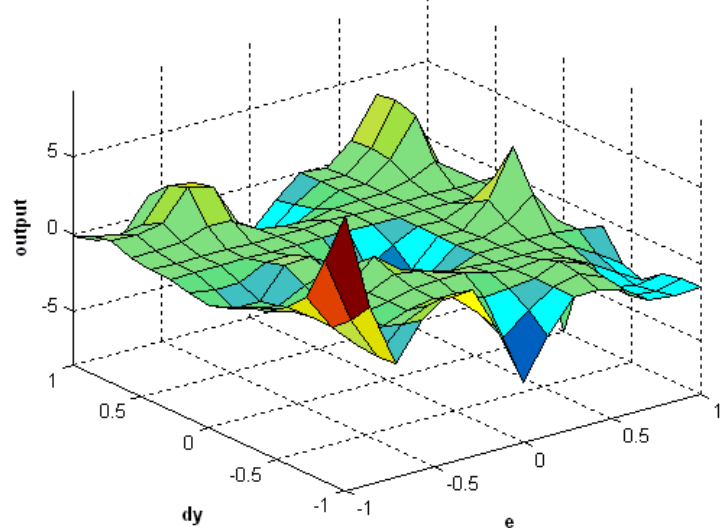
5. Conclusion

The self learning Fuzzy Control Based on Sensitivity Functions is effectively used to tune the parameters of the output membership functions of the fuzzy controller for controlling the direction heading of the ships. The simulation results show that after completion of learning process the direction heading of the ship follows the reference model response. The output of ship steering system with a compensator controller has high overshot and reaches the steady state after eight seconds. But when the hybrid self-learning fuzzy controller is acting in parallel with compensator controller, the overshoot of the output response of the ship steering system is omitted and the steady state enforces to be reached in less than two seconds.

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