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Neural Network Steering Controller For A Ship

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Abstract: This paper presents the implementation of Multi-layer Preceptron (MLP) Feed-forward Neural Networks for direction control of an oil tanker, whose parameters vary with depth of water and randomly varying waves. The development of Artificial Neural Networks (ANN) controller is based on learning of networks, for this purpose back-propagation algorithm is used. For training, a nonlinear sliding mode controller is used as a supervisor. A network having one input, one hidden and one output layer has provided the satisfactory performance. The input layer has four neurons, the hidden layer has seven neurons and output layer has one neurons. The controller is developed for ideal conditions, to assure the robustness of controller the performance of controller is tested in different operating conditions; varying depth of water and in presence of wind generated waves. It has been demonstrated that the performance of controller remained satisfactory in all operating conditions.

Keywords: Heading Control, Ship, Multi-Layer Preceptron, Sliding Mode, Varying depth, Waves

1. INTRODUCTION

Since centuries sea transportation has remained a major source of communication, trade and transport. For a safe, secure and reliable transportation, the ship steering autopilot system has remained a great concern and interest for control design community. Various numerical methods have been devised for ship autopilot (Koyama, 1967; Norrbin, 1970; Fossen, 1994; Fang, *et al.,* 2004; McGookin, *et al.,* 1997; Zhang, *et al.,* 2000; Fang and Luo, 2005). The use of Neural Networks has some advantages over conventional control system. The conventional control system is not only sensitive to high frequency interference but also is not able to adapt to the dynamic characteristics of the ship in changeable sea conditions. Moreover, conventional control approaches require an exact knowledge of plant dynamics to be controlled. However, the ship dynamics is highly nonlinear and is influenced by external environmental disturbances like depth of water, waves, sea currents and winds.

Hence, it is very difficult to obtain a precise dynamic model of ship. Neural Network is an innovative control technique, which do not rely on precise mathematical control model of system. Compared with traditional autopilots its response is faster, it has capable to adapt in changing environmental conditions, it is robust and has a certain level of intelligence.

The feasibility of Neural Networks to steer a ship was studied by Endo *et al.,* (1989). Burns and Richter (1996) developed a neural network controller; they trained the network by using conventional PID controller as supervisor. (Unar 1999) worked on a multi-layer preceptron and radial basis function neural networks for ship steering control by using PID controller for training of the network. (Zirilli *et al.,* 2000) worked on radial basis function neural network for course changing of a containership in waves. This neural network controller was based on a linear adaptive controller. (Yang *et al.,* 2002) proposed a Hybrid intelligent control for ship steering control system for ship steering by integrating fuzzy logic, neural network and genetic algorithm. (Zhipeng *et al.* 2004) developed a General Fuzzified Cerebellar Model Articulation Controller (GFCMAC) for ship steering control by using neural network plus fuzzy logic. Santos *et al.* (2006) developed a neuro-fuzzy controller for fast ferry to reduce its vertical motion modeling. (Hess *et al.* 2005) developed a recursive neural network controller for motion control of a ship. Alarcin and Gulez (2007) adopted the neural network approach for roll stabilization of fishing vessel. The literature review reveals that linear controllers (e.g PID controllers) for the training of neural networks have been proposed by some researchers (Burns and Richter 1996; Unar 1999; Zirilli *et al.,* 2000). Some researchers have used the neural network by integrating it with other techniques like fuzzy logic, neural network and genetic algorithm (Yang *et al.,* 2002; Zhipeng *et al.,* 2004; Santos *et al.,* 2006). In this research, a sliding mode controller was used for training of a neural network for heading control of ship. Sliding mode controller is a nonlinear and robust controller. A properly trained neural network will automatically capture robustness properties of the supervisor (sliding mode).

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2. Dynamics Of Surface Ship

The motion of marine vehicles is regarded as six degree of freedom motion because six independent co-ordinates are used to describe the maneuverability of vehicle.

These coordinates are referred as:

surge (u): linear velocity along x-axis
sway (v): linear velocity along y-axis
heave (w) linear velocity along z-axis

Integration of (u, v, w) corresponds to linear positions (x, y, z) along X, Y and Z axes.

roll (p): angular velocity about x-axis
pitch (q): angular velocity about y-axis
yaw (r): angular velocity about z-axis

Integration of (p, q, r) corresponds to angular positions (ϕ,θ ψ) about X, Y and Z axes.

The motion of ship is regarded as surface motion and its motion is confined in course of earth fixed X_E-Y_E plane instead of three dimensional space, hence the heading motion of ship is considered to be three degree of freedom motion because only three independent co-ordinates (surge, sway and yaw) are required to specify the heading motion of vehicle as shown in **(Fig. 1).**

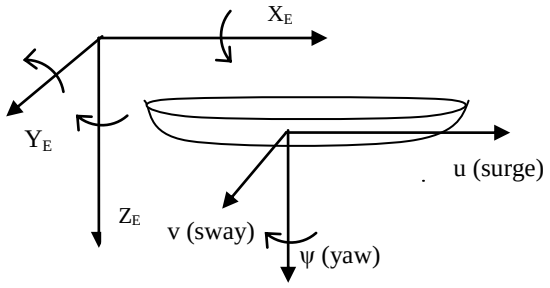


Fig. 1. Ship fixed and earth fixed axes

2.1 The ESSO 190000 dwt tanker

The ESSO is a large size tanker of length of 304.8 m. The Mathematical model describing the maneuverability of this tanker is given by Van Berlekom and Goddard (1972). The parameters of ESSO are described by Fossen (1994).

Length between perpendiculars = 304.8 m
Beam = 47.17 m
Draft to design waterline = 18.46 m
Displacement = 220000 m^3
Block co-efficient = 0.83
Design speed = 16 knots
Nominal Propeller = 80 rpm

The model of the tanker is represented as:

$$\dot{\underline{x}} = A\underline{x} + B\underline{u} \quad (1)$$

where $\underline{x}=[u\ v\ r\ \psi]$, $\underline{x}$ represents the states of the ship, A is the system matrix, B is the input matrix and $\underline{u} = [\delta r]$, δr represents rudder deflection. The purpose of this investigation is to develop a Artificial Neural Network (ANN) control system which provides satisfactory performance for any reference direction in terms of heading angles ranging from $\pm 3^o$ to $\pm 45^o$ in variety of environments like ideal conditions, varying depth and in presence of randomly varying waves. The plus minus sign indicate the controller is able to turn on both port and starboard sides. For all these conditions the performance index was set that the heading error should not exceed $\pm 3^o$ and control effort (i.e rudder angle) should not exceed the $\pm 35^o$.

3. Artificial Neural Networks

ANN is a branch of artificial intelligence. The development of ANN is based on functional principle of biological neural networks. ANN facilitates to develop a computational model of a human brain processing by taking consideration of the structural and functional features of brain.

3.1 Mathematical model of Artificial Neural Networks

An artificial neural network consists of neurons connected in parallel forming a layer. The output of each neuron of a layer is connected to every neuron of next layer and multiplied different weights. An artificial neural network can have input, output and hidden layers.

Mathematically artificial neural networks can be represented by Eq.2 given below.

$$u_k = f_l\,(\ldots . \Sigma f_2(\Sigma f_1(\Sigma x_i . w_{ij} + b_j) \times w_{jk} + b_k \quad (2)$$

where i is number of inputs, j is the number on neurons in hidden layer, k in number of neurons in output layer, l is number of layers of network, w is weight matrix, b is bias vector, x is input vector, $f_l(.)$ activation function of correspondence layer and u is output of network.

The objective of developing a network is to get the desired output from network by providing specific input. This can be achieved by continuously changing the values of weights and biases of network by a learning process. Once the training phase is completed the network retains the final values of weights and biases and the configuration of network remains fixed. The resulting network acquires more predictable and self-adaptive characteristics.

4. MATERIAL AND METHODS

Methodology For Development Of Neural Network Controller.

For training of network an algorithm based on primary and secondary loop is developed **(Fig. 2).** The

primary loop consists of a reference model, model of ship and sliding mode controller. The secondary loop consists of sliding mode controller neural network. For training of network a pair of input and target data set is generated by a primary loop. On the basis of this

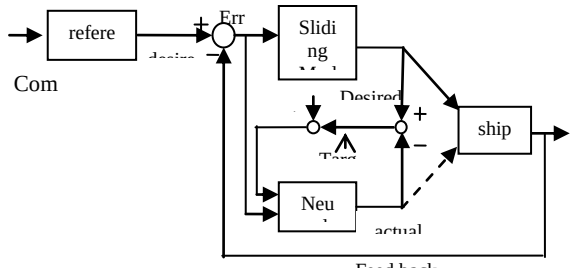


Fig. 2. Diagrammatic View for Training Network

data the network is trained to achieve desired goal. For network tangent-sigmoidal function for hidden layer and purlin function for output layer is selected.

The input vector for training consists of set of errors given as:

$x_{error} = [r \ \psi \ r_{error}, \psi_{error}]$

The target of network is given as:

$\underline{u} = [\delta r]$

where

ψ_{error} is heading, r_{error} is yaw error and δr is rudder deflection.

For obtaining the optimal performance for a wide range of commands, the data is generated by series of control commands (ranging from -45^o to 45^o).

The development of network started with trial and error basis. Training started with three neurons for hidden layer and one neuron in the output layer. By gradually increasing the number of hidden neurons, finally the network represented by Equation 3, having 4 inputs, 7 hidden neurons and 1 output neuron provided satisfactory performance.

$$u_k = f_2(\Sigma f_1(\Sigma x_i . w_{ij} + b_j) \times w_{jk} + b_k \qquad (3)$$

For this particular application, the values are taken as:

number of input = $i = 4$

number of neurons in hidden layer = $j = 7$

number of neurons hidden output layer = $k = 1$

size of hidden layer weight matrix = $(i \times j) = (4 \times 7)$

size of output layer weight matrix = $(j \times k) = (7 \times 1)$

hidden layer activation function

$= f_1 = 1/(1+exp(-(w.x+b))$

output layer activation function = $f_2 = w.x+b$

After successful training the controller provided the exact mapping of output of the network to its trainer.

5. Simulation Of System

After getting a trained network, the controller is incorporated in a closed loop system consisting of desired system model, Neural Network controller and ship model **(Fig. 3).** From the desired state model the desired states are generated and by feedback path the actual states which influences the heading motion of submarine feed-back and error (i.e the difference between the actual state and the desired state) is generated The errors are fed to the controller and on the basis of deviation/ error the controller directs the ship to regulate it to the desired direction.

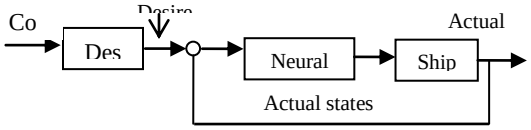


Fig 3. Complete System Model

6. SIMULATION RESULTS

The controller is developed by considering the ideal conditions, when no external environmental disturbances are present. To prove the adaptively and effectiveness of controller the tests are carried out in ideal conditions, under varying depths and in presence of randomly varying waves. Simulations are carries out using MATLAB version 7.

6.1 results in ideal conditions and under varying depth of water

For model of tanker, deep and confined waters are described by a parameter called *depth ratio* (ζ). This ratio is calculated by Fossen (1994) by using Eq. (4).

$$\zeta = \frac{T}{h - T} \qquad (4)$$

where h is water depth and T is draft to design waterline. The relation between ζ and h provides a transition point where hydrodynamic coefficient $Y_{uv\zeta}$ changes value and it obeys the following condition:

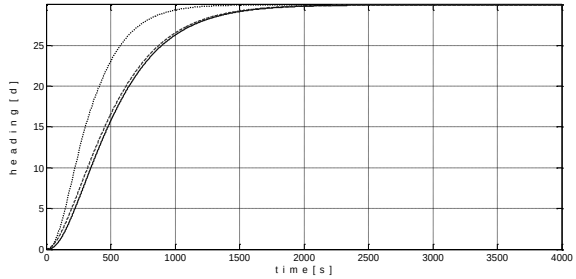
if ζ is less then 0.8, then $Y_{uv\zeta} = 0$

if ζ is greater than or equal to 0.8, then $Y_{uv\zeta} = -0.85 (1-0.8/\zeta)$

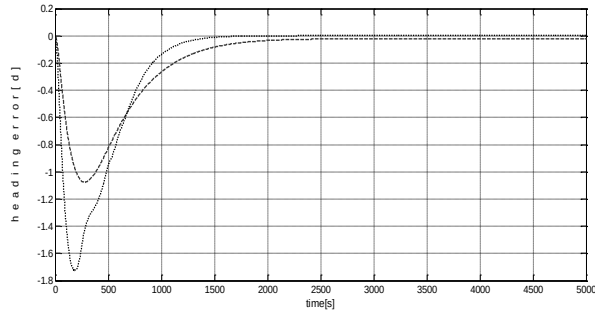
(Fossen 1994; Zhou, *et al.,* 2010 Wu, *et al.,* 2010) This relation demonstrates two depth regions (i.e greater and less then 100m) where the dynamics of the vehicle change. By incorporating the above condition, simulations are carried out in ideal conditions by assuming the depth of water constant and for a range of water depths continuously changing from shallow waters (24m) to deep waters (200m) as shown in Fig. 4(d). Fig. 4 (a,b,c) represents the performance of controller and comparison between ideal conditions and varying depths. In Fig. 4(a) the solid line shows the desired direction and dashed line represents the actual

heading at constant depth; however the dotted line exhibits the heading for varying depth. Fig. 4(b) represents errors; the dashed line shows the error for constant depth, while the dotted line represents the error for varying depth of water. Similarly the Fig. 4(c) represents the performance of rudder; the dashed line shows the rudder deflection for constant depth and the dotted line represents the rudder deflection for varying depths.

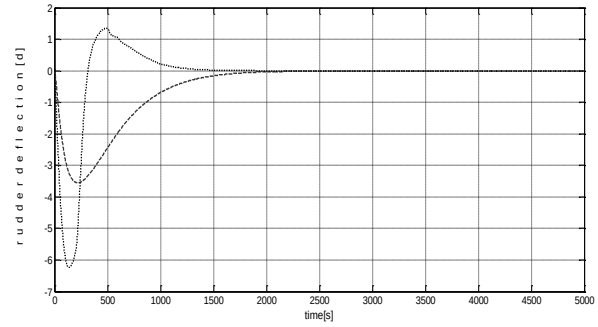
From figures the dashed lines (for ideal conditions) exhibits a smooth performance of controller. For varying depth, the controller observes some oscillations in error and in rudder. From figure it is clear these oscillations are observed in the region of shallow water (less then 100m). However in deep waters the performance of controller becomes smooth. This shows that the dynamics of ship is direly affected by the shallow water but because of robustness of neural networks the controller becomes able to overcome such effects.



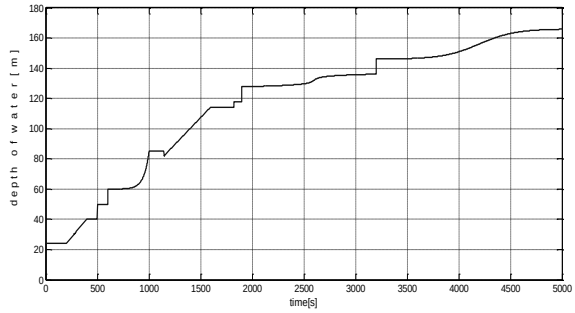
(a) Desired heading, actual heading for ideal conditions and actual heading for varying depth



(b) Comparison of errors for ideal conditions and varying depth



(c) Comparison of rudder deflections for ideal conditions and varying depth



(d) Continuous varying depth (from 24m to 200m)

Fig 4: Performance controller in ideal conditions and continuous varying depth

6.2 Simulation Results in presence of wind generated waves

Blowing of wind develops ripples on surface of ocean; these ripples ultimately generate waves and oscillations on the surface of the water in form of spectrum of frequencies. The forces and moment developed by waves are experienced in the X_B -Y_B plane. The *X*, *Y* forces will act along the 'x' and 'y' axis and *N* moment about z-axis and denoted by X_{wave} Y_{wave} and $N_{wave.}$ These are the function of various factors like wave slope, wave elevation, wave numbers, amplitude of wave and wave spectral density functions (Fossen, 1994). For this paper Pierson-Moskowitz (PM) Spectrum density function has been chosen. Simulations are carried out by incorporating the model of waves in Eq.1.

$$\dot{x} = Ax + f + Bu \qquad (5)$$

where

$f = [X_{wave}\ Y_{wave}\ N_{wave}\ 0]$

The results are obtained(see Figures 5 a,b,c,d,e,f). In figure 5(a) solid line shows the desired heading and dashed line represents actual heading. Figure 5(b) shows the error and Figure 5 (c) represents rudder deflection. Figure 5(d,e,f) shows the effects of randomly varying wave components X_{wave}, Y_{wave} forces and N_{wave} moment.

6.3 RESULTS AND DISCUSSION

From Figures 4(a), 5(a), it is observed that the tanker takes approximately 2000 seconds to reach the steady state position. This is because of the large size of the vehicle.

Results show that in for 30^o command angle, for ideal condition the controller exhibits -1.1^o error, however the error slightly increases to -1.7^o for varying depth. Consequently the rudder also deflects

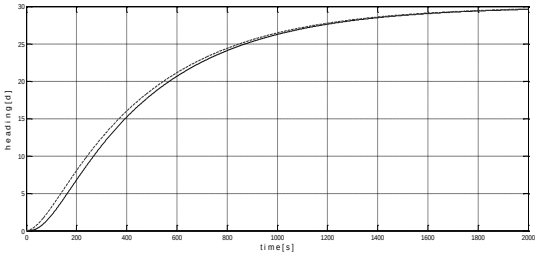
from -6^o to +1 ^{o} but finally it converges to steady state. This is because rapidly changing of dynamics of ship. In presence of waves the error remains -1.1^o and rudder deflects -4.7^o.

7. CONCLUSION

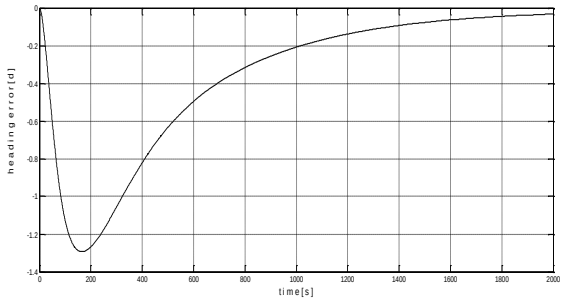
In this paper a Neural Network controller is designed for heading control of a tanker. The controller is designed in such a manner that the tanker can turn on both sides starboard and port of the vehicle. The controller is developed in ideal conditions but the performance of the controller is tested in ideal conditions, under varying depths and in presence of randomly varying waves. In all cases the error remained within the prescribed limits. In all cases the heading and rudder converge smoothly to steady state condition. From given simulations it is concluded that neural network robust enough and it is capable to adapt in changing environmental conditions.

8. ACKNOWLEDGEMENT

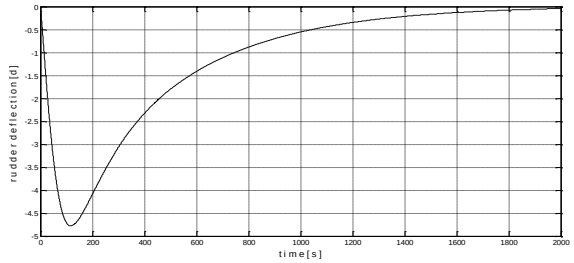
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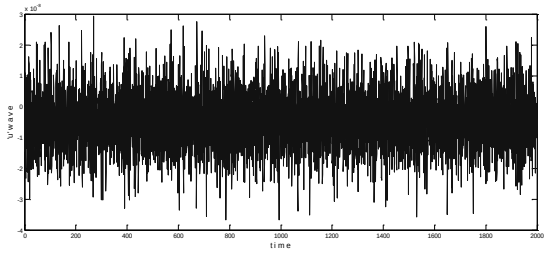
(a) Desired and actual heading angles in presence of waves



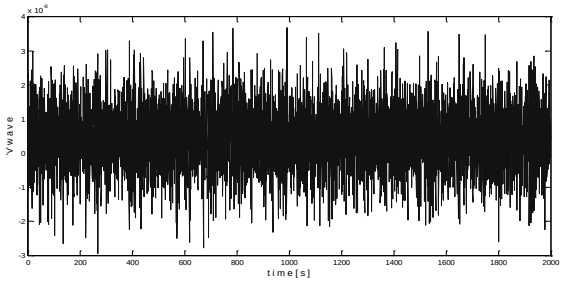
(b) Heading error in presence of waves



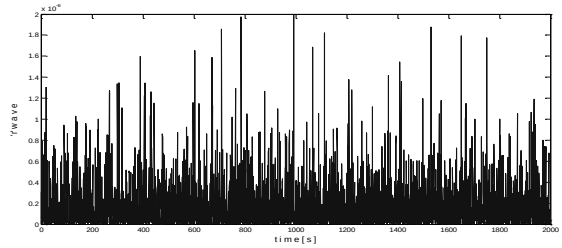
(c) Rudder deflection



(d) Effects of X_wave forces



(e) Effects of Y_wave forces



(f) Effects of N_wave moments

Fig 5. Performance of controller in presence of randomly varying waves

REFERENCES:

Alarcin, F., and K. Gule, (2007) Rudder Roll Stabilization for Fishing Vessel using Neural Network Approach. Ocean Engineering, (**34**): 1811-1817.

Burns, R., and R. Richter, (1996) A Neural Network Approach to the Control of Surface Ships. Control Engineering Practice, 4 (**3):** 411-416.

Endo, M., J. Van Amerongen and A.P. Bakkers, (1989) Applicability of Neural Networks to Ship Steering. Proceeding of the IFAC workshop on control applications in marine system, The Technical University of Lyngby, CAMS'89, 221-232.

Fang, M-C., and Luo J-H, (2005) The Nonlinear Hydrodynamic Model for Simulating a Ship Steering in Waves with Autopilot System. Ocean Engineering (**32**): 1486-1502.

Fang, Y., E. Zergeroglu, M. De Queiroz and D.M. Dawson, (2004) Global Output Feedback Control of Dynamically Positioned Surface Vessel: An Adaptive Control Approach. Mechatronics (**14**): 341-356.

Fossen, T. I., (1994) Guidance and Control of Ocean Vehicles, John Wiley & Sons, New York.

Hess D. E., E. Faller William, C. Fu Thomas and E. S. Ammeen, (2005) Development of an Advanced Ship Simulation and Control System Using Neural Network. Proceeding of 13th International Conference on Intelligent Systems Applications to Power Systems: 253-260.

Koyama, T., (1967) On the Optimum Automatic Steering System of Ships at Sea. Journal of Society of Naval Architecture, Japan (**122**): 18-35.

McGookin, E.W., D.J. Murray Smith, Y. Li, and T.I. Fossen, (1997) Parameter Optimisation of a Non-linear Tanker Control System using Genetic Algorithms. IEE Conference on Genetic Algorithms in Engineering Systems: Innovations and Applications, 2-4 September 1997, Conference Publication (**446**).

Norrbin, N.H., (1970) Theory and Observation on use of Mathematical Model for Ship Maneuvering in Deep and Confined waters. Proceedings of 8th Symposium on Naval Hydrodynamics, Pasadena, USA: 807-904.

Santos, M., R. Lopez, and J.M. Cruz De La, (2006) A Neuro-fuzzy Approach to Fast Ferry Vertical Motion Modeling. Artificial Intelligence, (**19**): 313-321.

Unar, M.A., (1999) Ship Steering Control using Feed-forward Neural Networks. Ph.D thesis, Department of Electronics and Electrical Engineering, University of Glasgow.

Van Berlekom, W.B., and T.A. Goddard, (1972) Maneuvering of Large Tankers. Transactions of the Society of Naval Architects and Marine Engineers, (**80**): 264-298.

Wu, Y., M. Xue, and P. Wu, (2010) Study on Fuzzy Neural Network-Based Ship Autopilot. Sixth International Conference on Natural Computation.

Yang, G., C. Guo, and X. Jia, (2002) Study on ship Steering Based on Hybrid Intelligent Control. Proceeding of the American Control Conference, Anchorage, AK.

Zhang, R., Y. Chen, Z. Sun, and F. Sun, and H. Xu, (2000) Path Control of Surface Ship in Restricted Waters using Sliding Mode. IEEE Transaction on Control System Technology 8(**4**):7 22-732.

Zhipeng, S., C. Guo, and J. Sun, (2004) Reinforcement Learning Control for Ship Steering Based on General Fuzzified CMAC. 5th Asian Control Conference: 1552-1556.

Zhou, Y., W. Pan and H. Xiao, (2010) Design of Ship Course Controller Based on Fuzzy Adaptive Active Disturbance Rejection Technique. Proceedings of the IEEE International Conference on Automation and Logistics, Hong Kong and Macau August 16-20.

Zirilli, A., G.N.Roberts, A. Tiano, and R. Sutton, (2000) Adaptive Steering of a Container Ship Based on Neural Network. International Journal of Adaptive Control and Signal Processing (**14**): 849-873.