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Performance Comparison of Fuzzy Logic and Neural Networks Controllers for Ship

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Abstract: This paper explores the potential of fuzzy logic and neural networks controllers for heading motions of ship and analyses the performance of both controllers. For this purpose two separate; neural network and fuzzy logic controllers are developed. For neural network Multi-Layer Perceptron (MLP) network is used. The training of network is carried out by using back-propagation algorithm. For fuzzy logic controller Mamdani type Fuzzy Inference System (FIS) is used. The fuzzification of variables is based on triangular functions and the defuzzification is carried out by using centroid method. The processing of Inference system is carried out by developing 49 rules. For comparative analysis of both controllers during developing of controllers the parameters of controllers are kept same.

Keywords: Control, Ship, Fuzzy logic, Neural networks.

1. INTRODUCTION

The motion control of ship has been great challenge for controller design community because the dynamics of ship is nonlinear and coupled with hydrodynamics. The ship dynamics is determined by ship speed, water depth, wind and waves.

Hence, it is not easy to develop the exact model of ship. Traditional control techniques require exact model of ship. Practically it is very difficult to obtain the required model of ship; therefore, many assumptions are made for development of traditional controllers. Neural network and Fuzzy logic, normally termed as soft computing techniques, do not rely on model of ship. They are behavior based techniques used to map the input and output to obtain specific functional relation between input and output of system.

Fuzzy logic is a rule based technique to solve problems of fuzzy nature. Fuzzy logic uses Fuzzy Inference System (FIS) method to develop the map of specific inputs to specific outputs. This mapping provides the basis for making decisions.

The functionality of Artificial Neural Network (ANN) is based on simulation of human brain processing. For getting optimized output parameters, the training of network is carried out. This not only provides the best properties of a constant parameters controller but also the properties of an adaptive controller (Unar, 1999). Many authors (Unar, 1999; Contreras, 2011; Fraga and Liu, 2011; Pathan, *et al.*, 2012 (a); Pathan, *et al.*, 2012 (b); Shi-Lu *et al.*, 2011. Meng and Chen, 2011) explored the potential of fuzzy logic and neural networks techniques for ocean vehicles. However, Yan *et al.* (2010) and Zhao and Zhang (2010) worked on both techniques but they used the combination of neural and fuzzy techniques and developed hybrid type controller. Literature review reveals that no author presented the comparative analysis of both techniques for a particular application.

This paper aims to investigate the potential of Artificial Neural Network (ANN) and Fuzzy Logic control systems for heading motion of a tanker and presents a comparative analysis of both controllers, considering the performance of controllers in ideal conditions and varying depth. The range of heading maneuvers is considered from 3 degrees to 45 degrees in both directions aft and starboard. It is presumed that heading error should cross the limit of $\pm 3^{o}$ and control effort (i.e. rudder angle) should not exceed the $\pm 35^{o}$.

Marine vehicles exhibit six degree of freedom motion. The coordinates used to represent this motion are surge (u), sway (v), heave (w), roll (u), pitch (q) and yaw (r). However surface maneuvering of ship heading is represented by surge, sway and yaw only. The Esso 190,000 dwt is a tanker 304.8m long. The maneuverability of the tanker in terms of mathematical model given by Eq. 1 is well described by Berlekom and Fossen (1972) and Fossen (1994).

$$\dot{x} = Ax + Bu \qquad (1)$$

Where, A represents system matrix, B represents input matrix, x represents the vector of states

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(u, v, r and ψ) of the ship and u represents rudder deflection δr.

2. MATERIALS AND METHODS

2.1 Neural Network Controller

An Artificial Neural Network is developed for mapping the desired output to specific inputs. For this purpose a learning process is used which continuously changes the values of weights and biases. Once the learning process is completed; the networks hold on the optimized values of weights and biases. The resulting network acquires more predictable and self-adaptive characteristics.

An algorithm is developed for training of network. The algorithm is based on a primary and a secondary loop. By using the sliding mode controller, model of ship and reference model; from the primary loop a set of input and target data is produced for secondary loop. By taking input and target data set the training of network is carried out in secondary loop to get desired goal. For analyzing the performance for a wide range of commands; the training is carried out for a range of inputs from -45 degrees to +45 degrees. A tangent-sigmoidal function is selected for hidden layer however a purlin function is opted for output layer. The input and target for network training are selected as:

$x_error = [\, r_error, \psi_error \,]$ (input)

$u = [\delta r]$ (output)

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

On the basis trial and error, the number of neurons in hidden layer was increased from three to seven. Eventually, the ANN with two inputs, seven hidden neurons and one output neuron (given by Eq. 2) provided satisfactory performance.

$$u_1 = f_2\left(\sum f_1 \sum x_2 . w_{(2\times 7)} + b_7\right) \times w_{(7\times 1)} + b_1 \qquad (2)$$

Where,

$$f_1 = \frac{1}{(1+\exp(-(w.x+b))}$$

$f_2 = w.x + b$

w=weights

b=bias

u=output of network

2.2 Fuzzy Logic Controller

Fuzzy logic is a technique used to map the input space to an output space. Development of a fuzzy controller uses Fuzzy Inference System (FIS). A Fuzzy Inference System has three (input, processing and output) stages. The input stage assigns truth value to a crisp input by using appropriate membership function.

For fuzzy controller, certain rules are developed. The processing stage activates predefined rules and produces results for those rules. Finally, the outcomes of applied rules are combined to get aggregated output of processing stage. Output stage defuzzifies the aggregated output and convert it into crisp output. The stages of fuzzy controller are presented in following sections (Pathan, *et al.*, 2012 (a)).

2.3 Selection of Inputs and Outputs

During heading maneuvers, the states which significantly change are: sway velocity (v), heading_angle (ψ) and heading rate (r). The performance of controller is based to maintain these states as desired. This can be achieved by minimization of errors. By using second order differential equation the desired states are generated. The heading_error (ψ_error) and heading_rate_error (r_error) are selected as inputs and rudder deflection (δr) as the output of controller.

2.4 Ranges for Input and Output

By hit and trial, ranges for inputs and output selected as:

heading error (ψ_error)	0.4	to -0.4	deg
heading rate error (r_error)	0.01	to -0.01	deg/sec
rudder_deflection (δr)	0.8	to -0.8	deg

2.5 Fuzzification of Inputs and Output

The ranges for inputs and outputs (given in section 4.2) are further divided into seven subsets and labeled linguistically defined variables: large negative (LN), average negative (AN), minute negative (MN), Zero (ZE), minute positive (MP), average positive (AP) and large positive (LP). The ranges of subsets selected in such a manner that the overlap each other. Due to this overlapping the particular value of the subset can be member of more the one fuzzy subset therefore at same more than one rules are fired for that particular value.

Each of subset is fuzzified by using triangular membership function by using Eq. (3).

$$\mu(x_error, a, b, c) = \begin{cases} 0 & x_error \langle a, x_error \rangle c \\ \dfrac{x_error - a}{b - a} & a \le x_error \ge b \\ 1 & x_error = b \\ \dfrac{c - x_error}{c - b} & b \le x_error \ge c \end{cases} \qquad (3)$$

where a, b and c are limits of function, each of subset has its own limits.

2.6 Development and Processing of Rules.

The rules are written in *IF THEN* statements. In case of more than one input or output, statements of rules are combined by logical operators.

The proposed fuzzy controller has two inputs and one output and seven membership functions. Keeping in view the structural symmetry of the system a square based $(7)^2 = 49$ rules system is developed. Some of the rules are given below:

Rule 1: IF *r_error* is *large positive* AND *ψ_ error* is *large positive* THEN *δr* is *large positive*

Rule 2: IF *r_error* is *average positive* AND *ψ_ error* is *large positive* THEN *δr* is *large positive*

Rule 3: IF *r_error* is *minute positive* AND *ψ_ error* is *large positive* THEN *δr* is *average positive*

Rule 4: IF *r_error* is *zero* AND *ψ_ error* is *large positive* THEN *δr* is *average positive*

Rule 5: IF *r_error* is *minute negative* AND *ψ_ error* is *large positive* THEN *δr* is *minute positive*

Rule 6: IF *r_error* is *average negative* AND *ψ_error* is *large positive* THEN *δr* is *minute positive.*

…… and so on

2.7 Defuzzification

A centroidal method is used for defuzzification process, where the aggregated output of the rules is converted into a single crisp value.

3. RESULTS

For simulations purpose a closed loop system is developed. The loop consist of model of ship, desired and Neural Network controller/Fuzzy logic controllers (shown in **Fig. 1**). The errors are generated at comparison element by comparing of desired and actual states form desired model and feedback path. On the basis of these errors, the controller regulates the taker for desired direction.

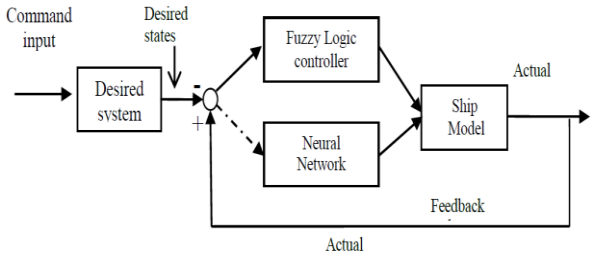


Fig. 1 Complete System Model

Controllers are developed by considering the ideal operating conditions. To prove the adaptively and effectiveness of Fuzzy Logic and Neural Networks controllers the simulation tests are carried out in different operating conditions i.e. in ideal conditions at under varying depths.

3.1 Results for Neural networks and Fuzzy Logic Controllers in Ideal Conditions

By using closed loop system the simulations are carried out. The depth of water is assumed to be constant (i.e. 24 m). Results are presented in figures 2-4. (**Fig. 2)** exhibits the performance of controllers for 30^o command heading angle. In given figure, solid line represents the desired heading, dotted line exhibits the performance of neural network and dashed line show the behavior of fuzzy logic controller. (**Fig. 3)** represents the errors. The dotted line shows the error caused by neural networks and the dashed line represents the error of fuzzy controller. (**Fig. 4)** exhibits the rudder deflection. The dotted line shows rudder deflection for neural network and dashed line represents rudder deflection for fuzzy controller.

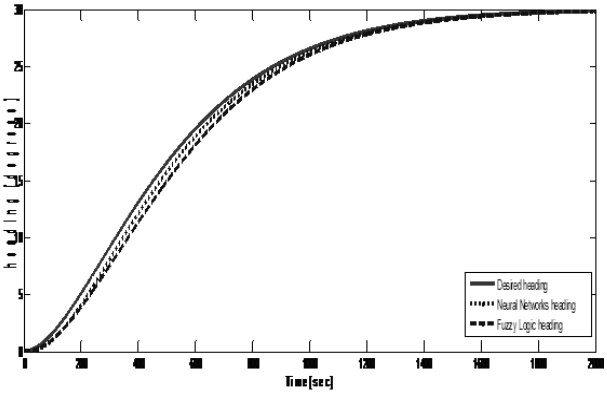


Fig. 2 Desired and actual heading (for neural networks and fuzzy logic controllers) at 30^o command heading angle (at constant depth 24m)

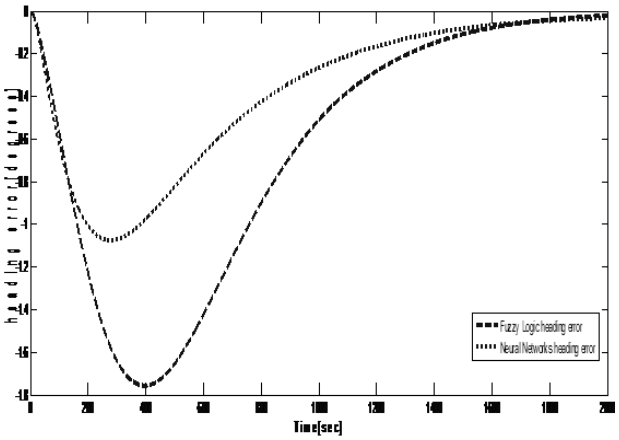


Fig.3 Heading errors for neural networks and fuzzy logic controllers (at constant depth 24m)

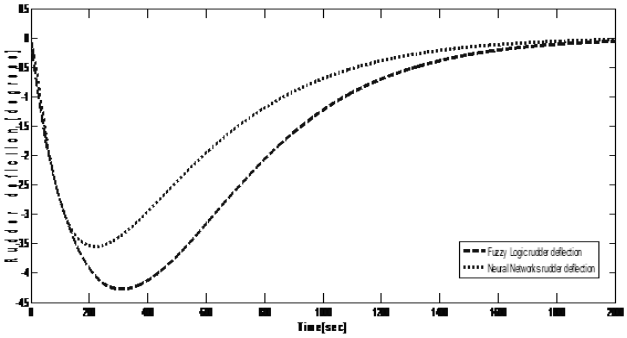


Fig. 4 Performance of control component (rudder deflection) for neural networks and fuzzy logic controllers (at constant depth 24m)

3.2 Results for Neural Networks and Fuzzy Logic Controllers under Varying Depth of Water.

Considering the of dynamics of tanker, two depth regions (i.e. greater and less then 100m) are demonstrated for maneuvering of the tanker. Mathematically these deep and confined waters are described by *depth ratio* (ζ), given by Eq.4. (Fossen, 1994).

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

where h is water depth and T is draft to design waterline. Eq. 4 demonstrates a transition point where hydrodynamic coefficient $Y_{uv\zeta}$ changes and obeys the condition:

if $\zeta < 0.8$, then $Y_{uv\zeta} = 0$
if $\zeta \geq 0.8$, then $Y_{uv\zeta} = -0.85(1-0.8/\zeta)$
(Fossen, 1994; Zhou *et al.*, 2010; Wu *et al.*, 2010)

Simulations are carried out for a range of water depths continuously changing from shallow waters (24 m) to deep waters (150 m), by considering above said condition. Figures 5-8 represent the performance comparisons of both controllers, in these figures the solid lines represent the desired behaviour, the dashed lines exhibit the neural networks performances and dashed lines represents fuzzy logic controller. **(Fig.5)** shows the headings, **(Fig.6)** demonstrates the errors, **(Fig.7)** shows the performance of control components (rudder deflections) and **(Fig. 8)** shows varying depth.

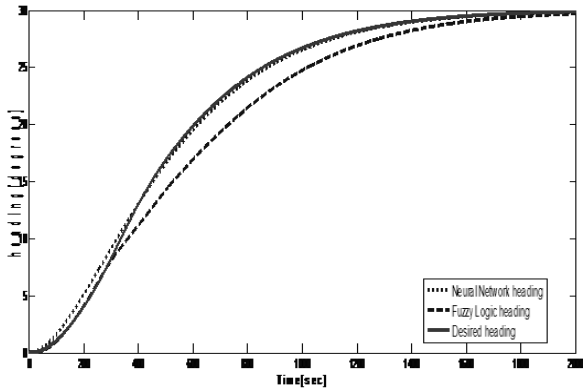


Fig. 5 Desired and actual heading (for neural networks and fuzzy logic controllers) at 30° command heading angle (at varying depth)

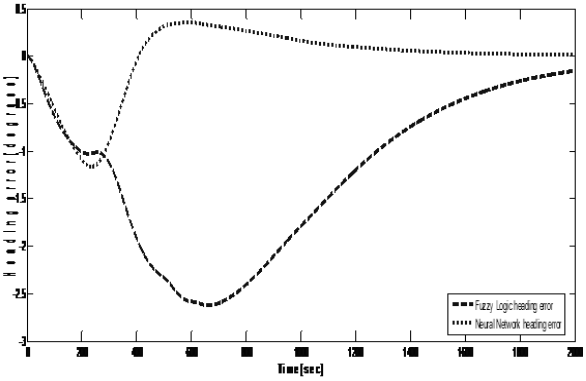


Fig. 6 Heading errors for neural networks and fuzzy logic controllers (at varying depth)

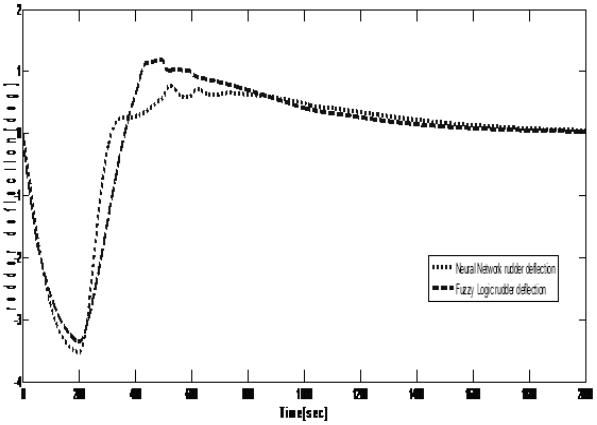


Fig. 7 Performance of control component (rudder deflection) for neural networks and fuzzy logic controllers (at varying depth)

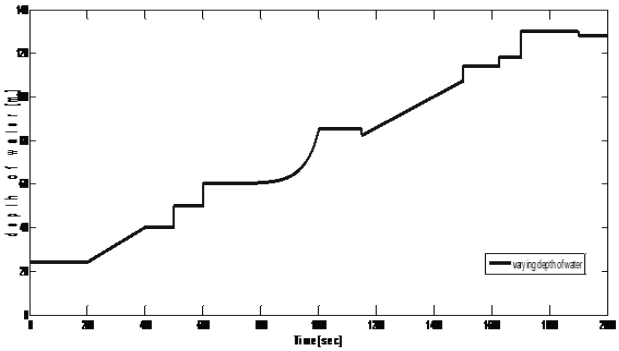


Fig. 8 Varying depth of water from 24m to 150 m depth

4. DISCUSSION

In case of constant depth it is observed that for both controllers the states smoothly converge to steady state and states are within the specified limit. However it is observed that fuzzy logic controller exhibits slightly greater error (-1.8^o) as compared to neural networks (-1^o), accordingly the rudder deflects more (-4.5^o) in case of fuzzy logic as compared to neural network controller (-3.5^o).

For varying depth both controllers observe some oscillations in their performances this is because of effects of continuously varying depths. However the actual heading motion for neural network controller seems to be best fit with desired heading motion. The heading motion obtained by fuzzy controller exhibits more deviation from desired heading motion. In case of neural network the maximum error is observed error -1^o, however in case of fuzzy the maximum error reaches to -2.7^o. Therefore more oscillations are observed in rudder deflection in case of fuzzy controller.

5. CONCLUSION

In this paper the potential of Fuzzy Logic and Neural Network have been investigated for heading control of ships. The objective of this work is to develop fuzzy logic and neural networks controllers for heading motion of a tanker and compare the performance of both controllers by keeping the same value of bandwidth. The observations obtained are gives as:

- Both controllers take same time to reach Steady State condition.
- The heading error and control effort remained within the prescribed limits, but the fuzzy controller exhibits slightly greater amount of error as compared to neural networks controller therefore more effort (deflection of rudder) is required to rectify the error. It is concluded that the Neural Networks controller is more appropriate for above application.

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