Design of a neuro-autopilot maneuvering controller for under actuated ships

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This paper addresses the trajectory-tracking problem of a 3-Degrees Of Freedom (3 DOF) under actuated mariner class vessel. Feed-forward artificial neural networks were designed to enable the ship to track parabolic and S-shaped trajectories. A closed-feedback control system was developed using additional feed-forward neural gain compensators to minimize the path deviation and to obtain the required control input rudder angle. The results show that the path deviation is 6% when the main neural network is used without the gain compensator. The path deviation is limited to a maximum of 3% when the gain compensator is used alongside the main network.

تتناول هذه الورقة مشكلة اتباع المسارات الملاحية لسفينة بحرية ناقصة المشغلات ذات ثلاث درجات من الحرية، ومن أجل ذلك تم تصميم شبكات خلايا عصبية اصطناعية أمامية التغذية لكي يتسنى للسفينة اتباع المسارات المتعرجة والمسارات ذات شكل حرف S. كما تم تصميم نظام تحكم مغلق ذي تغذية راجعة وذلك باستخدام معوضات كسب ذات شبكات عصبية لتقليل الانحراف عن المسار إلى أقل نسبة ممكنة، وهذه المعوضات تعمل جنباً إلى جنب مع الشبكات العصبية الأساسية حتى يتم الحصول على متجه زاوية الدفة المطلوب ادخاله إلى نظام التحكم، وتوضح النتائج أن الانحراف عن المسار بلغ ٦% في حالة استخدام الشبكات العصبية الأساسية بدون معوضات الكسب، بينما ينحصر الانحراف عند ٣% عندما يستخدم معوض الكسب إلى جانب الشبكة العصبية الأساسية.

Keywords: Under actuated ships, Artificial neural networks, Neural gain compensation

1. Introduction

The last decade has witnessed an increased research effort in the area of trajectory tracking control for underactuated marine vessels. The study of these systems is motivated by the fact that it is usually costly and often impractical (due to weight, reliability, complexity and efficiency considerations) to fully actuate autonomous vehicles [1]. The tracking problem for underactuated vehicles is especially challenging because most of these systems are not fully feedback linearizable and exhibit nonholonomic constraints.

The path following problem of 3 DOF (degrees of freedom) vessel, as defined by Skjetne et al. [2], involves two tasks. The first task, which is the geometric assignment, is to force the ship to track a set of way-points which define the path. The second task, which is the speed assignment, is to satisfy a desired speed along the path. For an underactuated ship to accomplish these two tasks, a single rudder and a propeller are at least required for the geometric and speed assignments, respectively. Previous techniques for solving the trajectory tracking problem of underactuated marine vessels are based upon nonlinear Lyapunov designs, and applying averaging and backstepping techniques [1-9].

An Artificial Neural Network (ANN) is an information processing paradigm that is inspired by the way biological nervous systems process information. Very few attempts have been made to solve the trajectory tracking problem by utilizing artificial neural networks. Im and Hasegawa [10] addressed the problem of automatic ship berthing using a parallel neural controller, which proved to be of good control ability. This controller has a separate hidden layer, each control an engine, and a rudder respectively. The authors of this paper previously dealt with the underactuated ship trajectory tracking problem using artificial neural networks for circular and zigzag maneuvers [11]. The results obtained, from the several two-layer feed-forward neural networks, that were designed to fulfill the proposed objectives, were sufficiently accurate. The circular and zigzag trajectories are standard sea-trial test maneuvers. Since ship navigation involves direction change and avoidance of sea obstacles such as coral reefs, shallow waters, icebergs, etc., therefore tracking parabolic and S-shaped trajectories is very important. The work of [11] is extended in this paper to include two types of arbitrary trajectories: parabolic and S-shaped. The trajectory tracking problem in this paper is dealt with the geometric assignment point of view. The mariner class vessel model considered in this paper is a 3 DOF model with only one control input, which is the rudder angle vector.

2. Ship model

The mathematical modeling of the ship is based upon that formulated by Fossen [12]. The modeling considers both the 3 DOF kinematics and dynamics. Kinematics require the definition of two main coordinate frames fig. 1, the first is an inertial Earth-fixed coordinate system (North-East Down), and the second is body-fixed. The dynamic equation of motion for the mariner class vessel is given by:

$$M\dot{\upsilon}+C(\upsilon)\upsilon=\tau\,, \tag{1}$$

where

$$\upsilon=[u,\upsilon,r]^T. \tag{2}$$

$$M=\begin{bmatrix} m_{11} & 0 & 0 \\ 0 & m_{22} & m_{23} \\ 0 & m_{32} & m_{33} \end{bmatrix}. \tag{3}$$

$$M=\begin{bmatrix} 0 & 0 & -(m_{22}\upsilon\ m_{23}r) \\ 0 & 0 & m_{11}u \\ (m_{22}\upsilon\ m_{23}r) & -m_{11}u & 0 \end{bmatrix}, \tag{4}$$

$$\tau=[X,Y,N]^T\,. \tag{5}$$

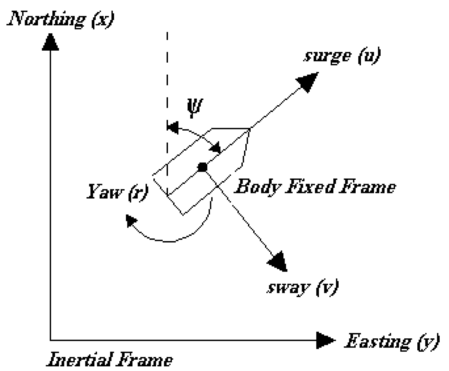

Fig. 1. Inertial and body-fixed frames.

The parameters defined in eqs. (3-5) can be found in [13]. The mariner class vessel has an overall length of 160.93 meters and its nominal speed is 15 knots. The maximum rudder angle is 30^0, and the maximum rudder turning rate is 5 deg/s [13].

3. Parabolic and S-shaped trajectories

In order to avoid sea obstacles, the ship should track parabolic or S-shaped trajectories. The duration of these types of maneuvers are usually around 180 to 600 seconds. Parabolic trajectories are generated by either applying a half-sinusoidal rudder angle input or by applying a ramp input starting from zero till a peak value δ_c, followed by a step input, followed by a ramp input to bring back the rudder angle value to zero. On the other hand, S-shaped trajectories are generated by a sinusoidal input rudder angle vector over a time domain ranging from 400 to 500 seconds.

4. Artificial neural networks design

For both types of maneuvers, the ANN will be trained using a series of trajectories as input, and specifying the associated rudder angle vector as target output, which will enable the ship to track these trajectories. Trajectory data, which is an implicit function of time, includes the position coordinates (x,y) and the ship's heading angle ψ. All ANNs are feed-forward networks, and were trained using the conjugate gradient method ('traincgp'). This method achieves the least mean square error in the least number of epochs.

After the ANN has been trained, it must be tested by a trajectory that was not included in the training process, in order to evaluate its capabilities. An input vector of the rudder angle is fed to the mathematical model of the mariner type vessel to generate a specified trajectory. The trained ANN is used to obtain the output vector representing the rudder angle for the trajectory not included in the training process, which is then compared with the original rudder angle vector. For a properly trained ANN, the error between the original rudder angle values and those simulated by the ANN should be a minimum. The output rudder angle vector of the ANN is fed to the mathematical model to yield a trajectory, which is compared to that originally specified to calculate the path deviation. If the two trajectories coincide, the ANN is perfectly trained.

The deviation of the path generated by the rudder angle vector output of the ANN from the original trajectory is calculated as a percentage using the following equation:

$$Pdev = \frac{\sqrt{(x_{sim} - x)^2 + (y_{sim} - y)^2}}{\sqrt{x^2 + y^2}} * 100 , \qquad (6)$$

where P_{dev} is the percentage path deviation, (x,y) and (x_{sim}, y_{sim}) are the Northing and Easting Coordinates of the original and ANN generated path, respectively.

5. Neural gain compensators

The need to design gain compensators arises from the fact that the mariner class vessel must track arbitrary paths to a sufficiently-accurate extent, especially when there exists increasingly external disturbances such as high winds, rough seas and strong sea currents. The compensator can also be used to adapt the output of the main ANN to accurately track trajectories not considered in the original training of the network. The neural gain compensator is fed with the error values of the Northing and Easting coordinates, in addition to the error values of the ship's heading angle. The output of the compensator is a gain vector which is added to the simulation output rudder angle output of the main ANN, to yield the final input rudder angle vector required to steer the ship to the desired path. Hence, a closed-loop feedback control process is applied. This process is illustrated in fig. 2.

6. Results

6.1. Parabolic trajectories

Two feed-forward ANNs were designed, the first for positive (port) rudder angle values, and the second for negative (starboard) rudder angle values.

Network #1 was designed for positive rudder angle values. Training was done using 13 different trajectories fig. 3, on a time domain of 400 seconds with a time increment of 10 seconds. The neural network #1 has 1066 tan-sigmoid neurons in the input layer, 533 tan-sigmoid neurons in the hidden layer, and a single pure-linear neuron in the output layer. The mean square error reached a final value of 0.3826 after 10,600 seconds (2.94 hours). A neural net gain compensator for network #1 was designed in order to minimize the path deviation. The gain compensator was trained twice, first by using the error values of the Northing coordinates, Easting coordinates, and the heading angle of the trajectories used in training network #1, and the second time by the error values of 13 other trajectories.

The neural net gain compensator has 1066 tan-sigmoid neurons in the input layer, 533 tan-sigmoid in the hidden layer, and a single pure-linear neuron in the output layer.

At the first time of training, the mean square error reached a minimum value of 0.1266 after 256 epochs in a time of 4300 seconds. As for training for the second time, the process elapsed 5270 seconds, and the mean square error reached a minimum value of 0.083 after 319 epochs. The results obtained when simulating both networks #1

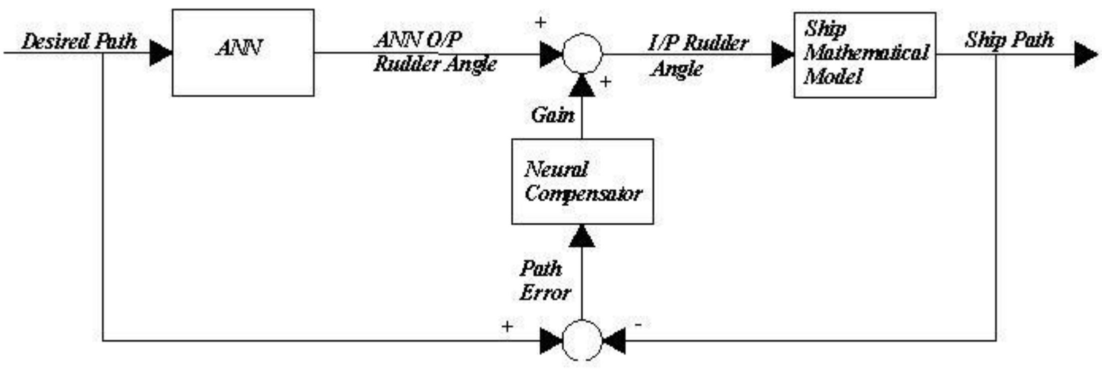

Fig. 2. Closed-loop feedback control using neural gain compensation.

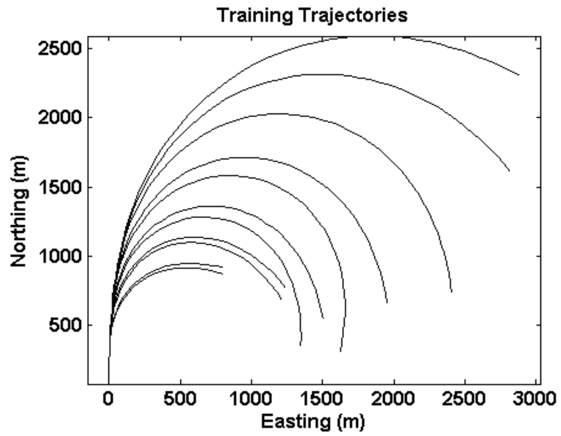

Fig. 3. Trajectories used in training network #1.

and its gain compensator with trajectories that were not used in the training processes are very good as can be seen in fig. 4. It can be clearly seen that the neural-net gain compensator is very effective and the maximum path deviation is limited to about 3%. Therefore, it is recommended to use the gain compensator along with the main neural network #1 when the ship is tracking parabolic trajectories for positive rudder angles.

In a similar fashion, another artificial neural network (network #2) and a neural gain compensator were designed to enable the ship to track parabolic trajectories for negative rudder angle values. Both networks comprise 1000 tan-sigmoid neurons in the input layer, 500 tan-sigmoid neurons in the hidden layer, and a single pure-linear neuron in the output layer.

Network #2 was trained using 17 different trajectories fig. 5. The training process elapsed 12,670 seconds (3.52 hours), and the mean square error reached a minimum value of 0.3689 after 500 epochs.

The neural gain compensator was trained twice, the first time using the error values of the 17 trajectories that were used in training network #2, and the second time using the error values of 11 other trajectories. The first training time elapsed 3860 seconds, where the mean square error reached a minimum value of 0.132 after 198 epochs. As for the second training process, the mean square error reached a minimum value of 0.1078 after 410 epochs, during a time of 5234 seconds.

The results obtained from networks #2 and its gain compensator are very good as can be clearly seen in fig. 6. The maximum path deviation is limited to about 3 %. Therefore, it is recommended to use the neural gain compensator alongside with the main network #2, when the mariner class vessel is following a parabolic path, for negative rudder angle values.

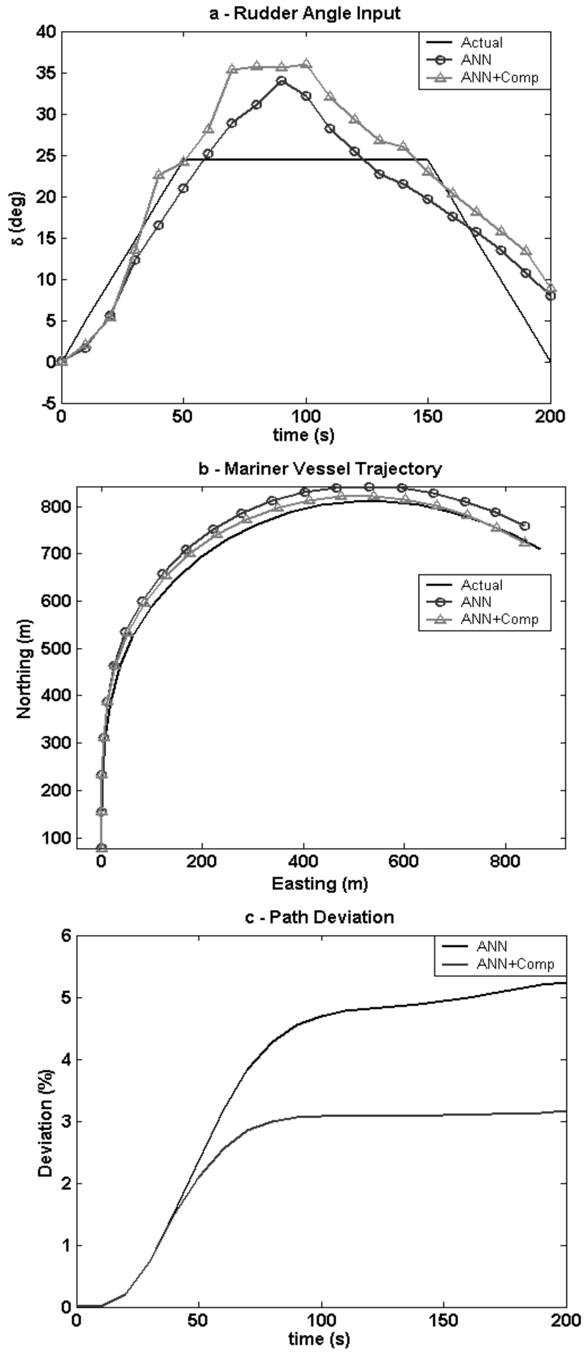

Fig. 4. Positive trapezoidal rudder angle input and corresponding ship trajectory, and path deviation (network #1 and its gain compensator).

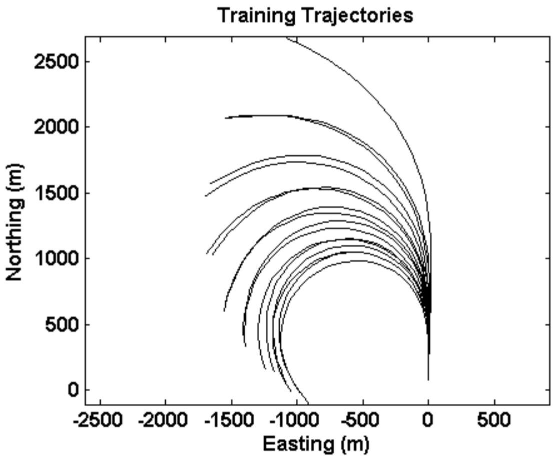

Fig. 5. Trajectories used in training network #2 for negative rudder angle.

6.2. S-shaped trajectories

In order for the ship to follow S-shaped paths, two artificial neural networks were designed, the first for positive rudder angle values, and the second for negative values. In addition, two neural gain compensators were designed for each of the two main networks previously mentioned.

Network #3 was designed in order for the vessel to track S-shaped trajectories for positive rudder angle values. The neural network comprises 1000 tan-sigmoid neurons, 500 tan-sigmoid neurons, a single pure-linear neuron, in the input, hidden, and output layers, respectively. Sixteen different trajectories, illustrated in fig. 7 were used in the training process. The mean square error reached a minimum value of 0.07184 after 500 epochs in duration of 12,755 seconds (3.54 hours).

The neural gain compensator has 1000 tan-sigmoid neurons in the input layer, 500 tan-sigmoid neurons in the hidden layer, and a single pure-linear neuron in the output layer. The training process was carried out twice, the first time by using the error values of the trajectories used to train network #3, and the second time by using the error values of 14 other trajectories. The first training process elapsed 25,870 seconds (7.2 hours), where the mean square error reached a minimum value of 0.0302 after 1117 epochs. The second training process elapsed 5530 seconds, where the mean square error reached a minimum value of 0.091 after 320 epochs.

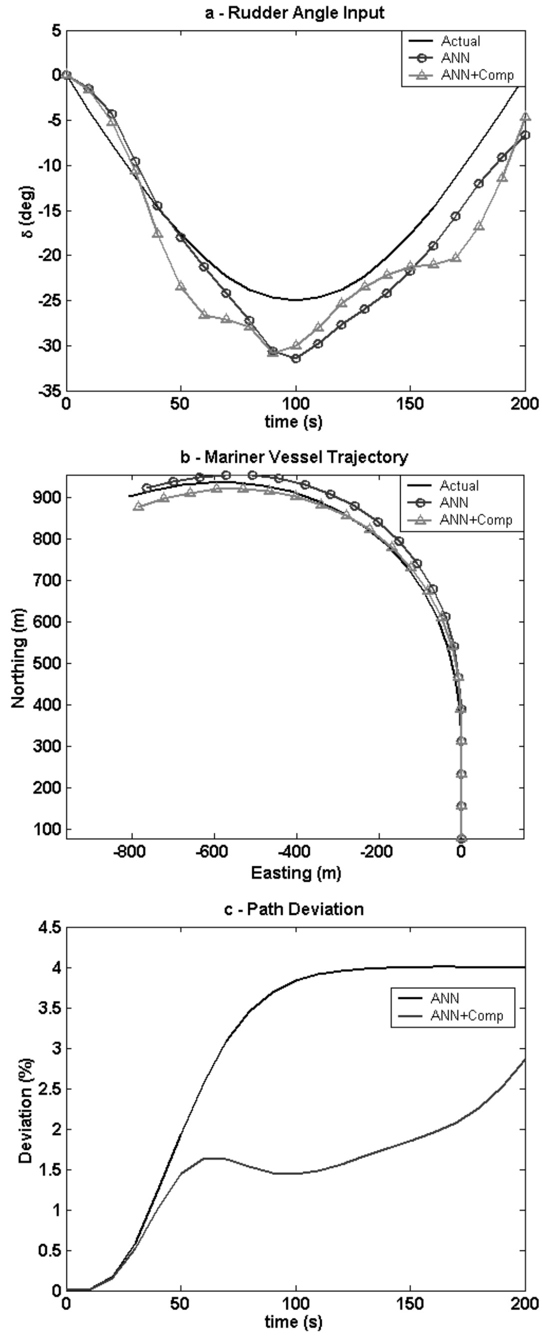

Fig. 6. Negative half-sinusoidal rudder angle input and corresponding ship trajectory, and path deviation (networks #2 and its gain compensator).

It can be seen in fig. 8 that by using the network #3, along with its neural gain compensator, very good results are obtained since the maximum path deviations are limited to 1%. Hence, it is recommended to use the gain compensator along with the main

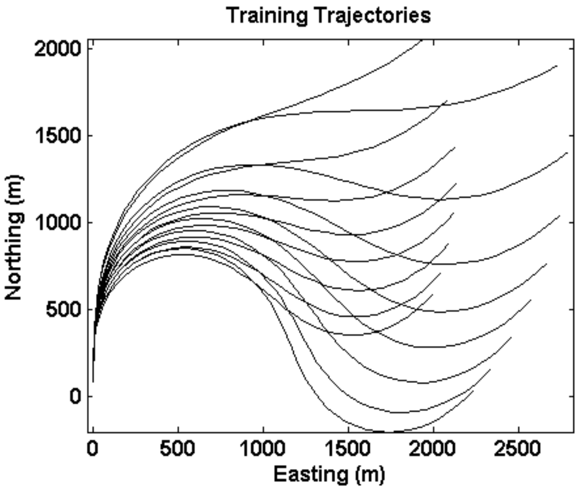

Fig. 7. Trajectories used in training network #3 (S-shaped trajectories).

neural network #3 when the mariner class vessel is tracking S-shaped trajectories, for positive rudder angle input values.

Similarly, another neural network #4 was constructed in addition to a neural gain compensator in order for the ship to track S-shaped trajectories, for negative rudder angle input values. Both the main network and the gain compensator have 1000 tan-sigmoid neurons in the input layer, 500 tan-sigmoid neurons in the hidden layer, and a single pure-linear neuron in the output layer.

The main network #4 was trained using 16 different paths fig. 9. The training process elapsed 13,370 seconds (3.71 hours), and the mean square error reached a minimum value of 0.0916 after 500 epochs.

The neural gain compensator was trained twice; the first time using the error values of the trajectories used in training the main network #4, and the second time using the error values of 14 other trajectories. The first training stage elapsed 6,500 seconds, and the mean square error reached a minimum value of 0.0532 after 292 epochs.

On the other hand, the second training stage took 13,272 seconds (3.69 hours) in which the mean square error reached a minimum value of 0.0685 after 755 epochs. The performance test of network #4 together with the neural gain compensator is illustrated in fig. 10. It can be clearly observed that the maximum path deviation is limited, especially when using the neural gain compensator along with the main neural network. Hence, it is recommended to use the neural gain compensator along with the main network #4 when the ship is following S-shaped trajectories.

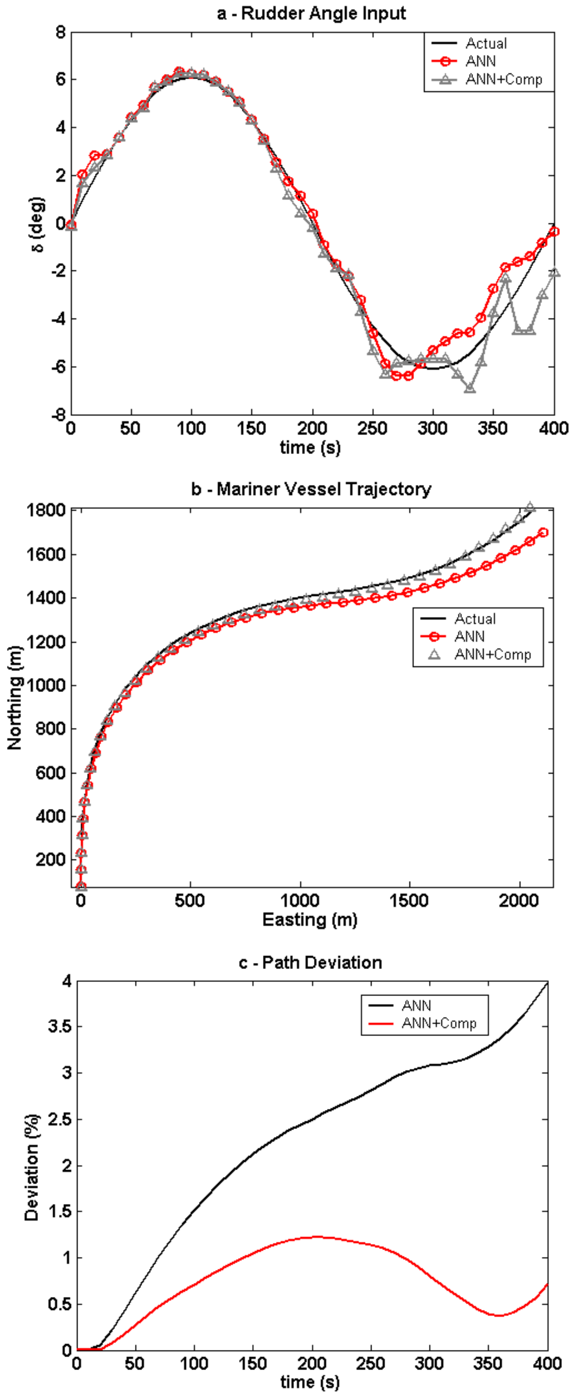

Fig. 8. Positive sinusoidal rudder angle input and corresponding ship trajectory, and path deviation (networks #3 and its gain compensator).

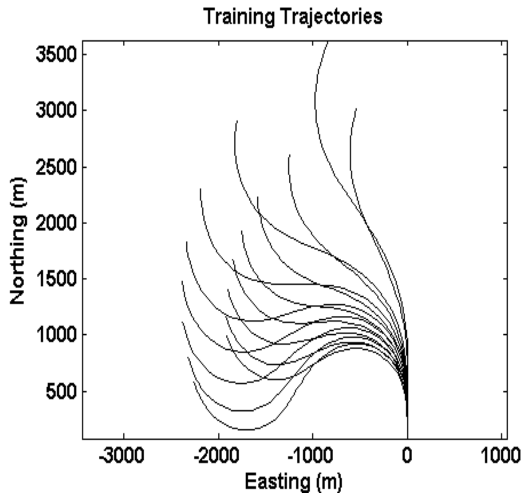

Fig. 9. Trajectories used in training network #4.

7. Conclusions

Four main artificial neural networks were designed in order for the mariner type vessel to follow parabolic and S-shaped trajectories. A neural net gain compensator was designed alongside each main neural network in order to minimize the path deviation. The results indicate that by using each main neural network along with its neural net gain compensator, the maximum path deviation from the original trajectory is limited to 3% and sometimes there is virtually no deviation at all. Therefore it is recommended to use each neural net gain compensator along with its main neural network when the ship is tracking parabolic and S-shaped trajectories.

Nomenclature

C is the coriolis damping matrix,
M is the mass matrix,
N is the yaw moment,
r is the yaw rate,
u is the surge velocity,
v is the sway velocity,
X is the surge force,
Y is the sway force,
ν is the velocity vector, and
τ is the force vector.

Abbreviations

ANN is the artificial neural network, and
DOF is the degrees of freedom.

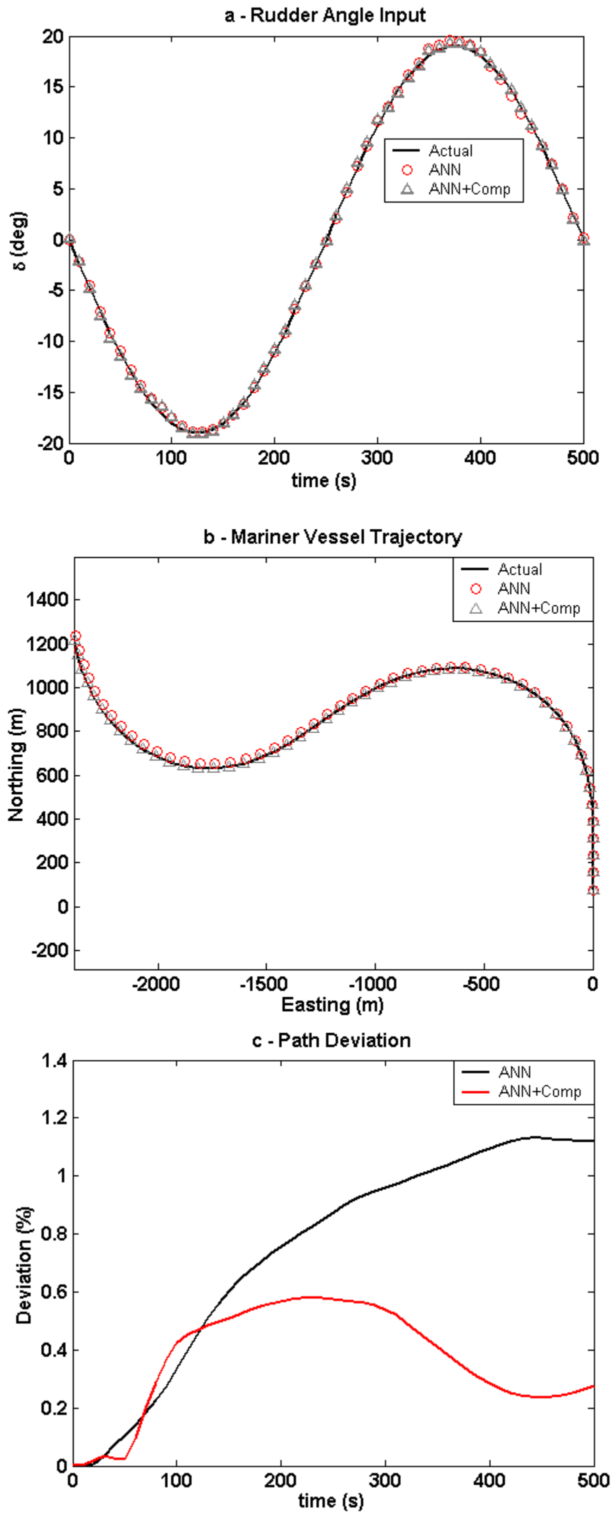

Fig. 10. Negative sinusoidal rudder angle input and corresponding ship trajectory, and path deviation (networks #4 and its gain compensator).

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