Design and Application of an Adaptive Neural Network to Dynamic Positioning Control of Ship

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Abstract

This paper presents an adaptive neural network based controller and its application to Dynamic Positioning (DP) control system of ship. The proposed neural network based controller is developed for station-keeping and low-speed maneuvering control of ship. At first, the DP system configuration is described. And then, to validate the proposed DP system, computer simulations of station-keeping and low-speed maneuvering performance of a multi-purpose supply ship are presented under the influence of measurement noise, external disturbances such as sea current, wave, and wind. The simulations have shown the feasibility of the DP system in various maneuvering situations.

Keywords: Adaptive Neural Network, Dynamic Positioning, Station-keeping, Low-speed Maneuvering.

1. Introduction

Dynamic Positioning (DP) systems for marine vessels are commonly the systems that have station-keeping and low-speed maneuvering functions by means of the ship propulsion system [1]. Since the 1960s, DP systems have been developed using conventional PID controllers in cascade with low pass and/or notch filters; model-based control utilizing stochastic optimal control theory and Kalman filtering techniques etc… These studies of conventional control methods and their later extensions and modifications proposed by numerous authors for DP systems are briefly mentioned in Fossen [1].

More lately DP systems utilizing modified Linear Quadratic Gaussian (LQG) feedback controller and a model reference feedforward controller [2]; nonlinear output feedback [3]; passive nonlinear observer based control [4] and [5]; nonlinear control based on robust observer [6]; nonlinear passive weather optimal positioning control (WOPC) system [7] have been developed. Recently, intelligent control techniques have been also applied to DP systems, such as [8] and [9].

In this paper, a hybrid neural adaptive control scheme which can perform station-keeping and low-speed maneuvering of ships is developed. A conventional PD-controller for nonlinear DP model (see [1], page 430) is modified and combined with the adaptive neural networks by adaptive interaction (ANNAI). This ANNAI controller is based on the work in [10] and [11], and developed for ship control by the authors in [12] and [13]. In the proposed hybrid neural adaptive control scheme, PD-controller provides an approximate control, and ANNAI controllers with on-line training ability are introduced to adaptively compensate for unknown bias term representing slowly-varying environmental disturbances and minimize positioning error (in station-keeping) or tracking error (in low-speed maneuvering).

At first, the DP system configuration is described. And then, to validate the proposed DP system, computer simulations of station-keeping and low-speed maneuvering performance of a multi-purpose supply ship [4] are presented under the influence of measurement noise, external disturbances such as sea current, wave, and wind.

2. Mathematical Model of Ships

This section presents a brief mathematical model for dynamic positioning of ships based on [1] and [4].

2.1 Equations of Motion

The earth-fixed position (x, y) and heading ψ of the vessel relative to an earth-fixed coordinate $X_E Y_E Z_E$ are expressed in vector form by $\eta = [x, y, \psi]^T$, and the vessel-fixed linear velocity vector is expressed by $\nu = [u, v, r]^T$. These three modes are referred to as the *surge*, *sway* and *yaw* modes of a ship. The origin of the vessel-fixed coordinate *XYZ* is located at the vessel center line in a distance x_G from the center of gravity. The low frequency motion of DP ships in surge, sway and yaw can be described as follow:

$$M\dot{\nu} + D\nu = \tau + J^T(\eta)b \quad (1)$$

$$\dot{\eta} = J(\eta)\nu \quad (2)$$

Here, $\tau = [\tau_1, \tau_2, \tau_3]^T$ is a control vector of forces and moment provided by the propulsion system. $M \in \Re^{3x3}$ is the inertia matrix including hydrodynamic added inertia, and $D \in \Re^{3x3}$ is the damping matrix. Unmodeled external forces and moment due to wind, currents and waves are lumped together into an earth-fixed constant (or slowly-varying) bias term $b \in \Re^3$, $J(\eta)$ is the transformation matrix between the earth-fixed coordinate and the vessel-fixed coordinate. The transformation matrix has the following form

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

where $J(\psi)$ is nonsingular for all ψ and $J^{-1}(\psi) = J^T(\psi)$. For further details of the equations of motion, see [1].

2.2 Bias Modeling

A common model for the bias forces in surge, sway and yaw moment for marine vehicle control application is

$$\dot{b} = -T^{-1}b + \Psi n\ , \quad (4)$$

where $b \in \Re^3$ is a vector of bias forces and moment, n is a vector of zero-mean Gaussian white noise, T is a diagonal matrix of positive bias time constants and $\Psi \in \Re^{3x3}$ is a diagonal matrix scaling the amplitude of n. This model can be used to describe slowly-varying environmental forces and moments due to 2nd order wave loads, ocean currents, wind and unmodeled dynamics.

2.3 Wave Force Modeling

Wave forces can be divided into 1st-order wave disturbances and 2nd-order wave drift forces. For the practical application to control system design, the 1st-order wave disturbances can be described by three harmonic oscillators with some damping. Linear 2nd order wave forces are generally expressed as

$$\begin{aligned} \dot{\xi} &= A\xi + Ew \\ \eta_w &= C\xi \end{aligned} \quad (5)$$

where $\eta_w = [x_w, y_w, \psi_w]^T$, $\xi \in \Re^6$, and $w \in \Re^3$ is a zero means bounded disturbance vector and

$$A = \begin{bmatrix} 0 & I \\ \Omega_{21} & \Omega_{22} \end{bmatrix},\ E = \begin{bmatrix} 0 \\ \Sigma_2 \end{bmatrix},\ C = \begin{bmatrix} 0 & I \end{bmatrix} \quad (6)$$

where

$$\begin{aligned} \Omega_{21} &= -diag\{\omega_{01}^2, \omega_{02}^2, \omega_{03}^2\} \\ \Omega_{22} &= -diag\{2\zeta_1\omega_{01}, 2\zeta_2\omega_{02}, 2\zeta_3\omega_{03}\} \\ \Sigma_2 &= diag\{\sigma_1, \sigma_2, \sigma_3\}. \end{aligned}$$

Here ω_{oi} , ζ_i , and σ_i (i = 1, …, 3) are wave frequency, relative damping ratio and parameters related to wave intensity, respectively. For further details of the wave force modeling, see [1].

2.4 Measurement Systems

For conventional ships, positions and yaw angles are usually measured by global positioning system (GPS) or hydroacoustic positioning reference (HPR) systems, and gyro compasses. However, for ship positioning systems the *differential* GPS is usually applied to reduce positioning errors. The measurement can be written as

$$y = \eta + \eta_w + v \quad (7)$$

where $v \in \Re^3$ is the zero mean Gaussian white measurement noise. It is assumed that the total position of the ship can be obtained by superposition of the position and direction of the ship and the wave displacements.

3. The Design of Dynamic Positioning System

This section presents a new DP system based on the ANNAI controller (see [12] and [13]) with two functions: position-keeping and low-speed maneuvering. The proposed DP system does not require the necessity of estimating the bias term so the estimation error can be removed. Employing the on-line training ability of the ANNAI, unknown bias term representing slowly-varying environmental disturbances can be compensated for and positioning error (in station-keeping) or tracking error (in low-speed maneuvering) can be minimized.

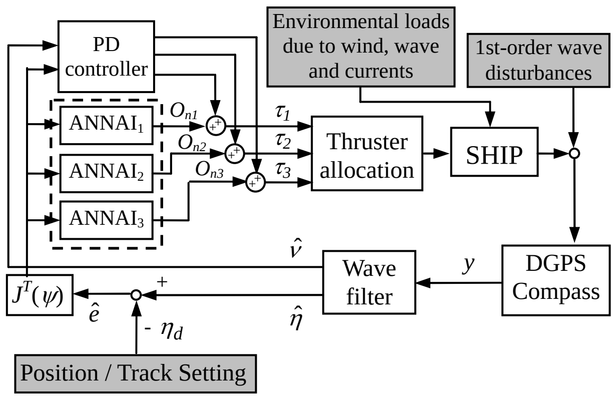

Figure 1. Configuration of the proposed hybrid neural adaptive DP system.

Figure 1 shows the configuration of the proposed DP system, where hybrid neural adaptive controller consists of a PD controller (which has gains K_p and K_d) and three adaptive neural networks ANNAI_1, ANNAI_2, ANNAI_3. Principally, the difference between the proposed DP system in this study with that of previous studies is: the ANNAI controller is introduced to obtain adaptability in controlling nonlinear ships with unmodeled dynamics and external disturbances.

3.1 Position-keeping Control

Consider the nonlinear DP model

$$\dot{\eta} = J(\eta)\nu \quad (8)$$

$$M\dot{\nu} + D\nu = \tau + J^T(\eta)b \quad (9)$$

$$y = \eta + \eta_w \quad (10)$$

Instead of using integral action to compensate for b, in [1] a PD-controller

$$\tau = -J^T(\psi)K_p e - K_d \nu - J^T(\psi)b\ , \quad (11)$$

$$e = \eta - \eta_d \tag{12}$$

was used under the assumption that b is known (perfect compensation) and η_d is the desired states, $\dot{\eta}_d = 0$. However, it is impossible to measure b, so in their study, a state observer which can generate estimates of η, ν and b and at the same time provide wave filtering was needed. The controller using the estimates states $\hat{\eta}$, $\hat{\nu}$, and $\hat{b}$ is

$$\tau = -J^T(\psi)K_p\hat{e} - K_d\hat{\nu} - J^T(\psi)\hat{b}\,, \tag{13}$$

$$\hat{e} = \hat{\eta} - \eta_d \tag{14}$$

In this paper we propose a hybrid neural adaptive control scheme based on (13) and (14) as follow

$$\tau = -J^T(\psi)K_p\hat{e} - K_d\hat{\nu} - O_n\,, \tag{15}$$

$$\hat{e} = \hat{\eta} - \eta_d \tag{16}$$

where $O_n = F[J^T(\psi)\hat{e}]$, $O_n \in \Re^3$ is outputs of three ANNAI controllers which are combined with the PD-controller. The estimates states $\hat{\eta}$ and $\hat{\nu}$ are obtained with proper wave filters. The selected ANNAI controllers are multi-layer feedforward neural networks with one hidden layer. Let $X = J^T(\psi)\hat{e}$ be the input vector of ANNAI controllers, the cost functions for the ANNAI controllers have the following form

$$E_i = \frac{1}{2}[\rho_i X_i^2 + \lambda_i O_{ni}^2 + \kappa_i \dot{\hat{\nu}}_i^2] \tag{17}$$

where ρ_i, λ_i, κ_i (i = 1, …,3) are positive constants.

The adaptation law for the hidden layer of the ANNAI as in [12] can be written as

$$\dot{w}_i^{hid} = X_i\phi_i\sigma(-I_i^{hid}) \tag{18}$$

where $\sigma(\cdot)$ is a sigmoidal activation function and

$$\phi_i = w_i^{out}.\dot{w}_i^{out} \tag{19}$$

$$I_i^{hid} = \sum w_i^{hid} X_i + \theta_i^{hid} \tag{20}$$

where θ_i^{hid} is the threshold values of the hidden layers. For the output layer, the adaptation law has the following form

$$\dot{w}_i^{out} = \gamma_i\sigma(I_i^{hid})(\rho_i X_i + \lambda_i O_{ni} + \kappa_i\dot{\hat{\nu}}_i) \tag{21}$$

Here, γ_i are learning rates of the ANNAI. In this study, output neurons have tangent sigmoidal activation function, so that

$$O_{ni} = \tan sig(I_i^{out}) \tag{22}$$

$$I_i^{out} = \sum w_i^{out}\sigma(I_i^{hid}) + \theta_i^{out} \tag{23}$$

where θ_i^{out} is the threshold values of the output layers.

To summarize, the ANNAI controllers can minimize the cost function (17) using adaptation laws (18) and (21). Once the outputs O_n of the ANNAI controllers are determined, the control input of the DP system is determined by (15). Using the control scheme described in (15) and (16), unknown bias term representing slowly-varying environmental disturbances can be compensated for and positioning error can be minimized. Further details of the ANNAI adaptation laws can be found in [12] and [13].

3.2 Low-speed Maneuvering Control

This subsection presents low-speed maneuvering control function of the DP control system. To maneuver the ship the *Reference Point* method is used. At every control cycle, the ship is stabilized on a moving *Reference Point* R(x_d, y_d) (Figure 2) at a desired heading ψ_d. In this case the desired states vector is $\eta_d = [x_d, y_d, \psi_d]^T$. Suppose that we want to make a certain point H(x_H, y_H) of the ship (as shown in Figure 2) follow the desired track (be stabilized at R). If $\eta_H = [x_H, y_H, \psi]^T$ is the ship states at H, the error vector is now expressed as

$$e = \eta_H - \eta_d \tag{24}$$

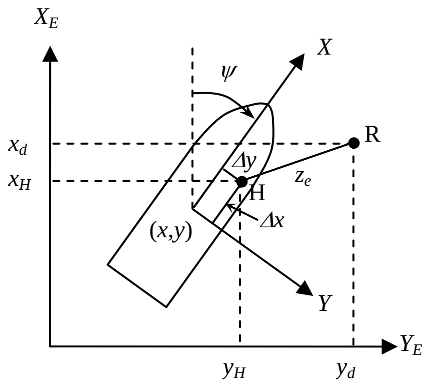

Figure 2. General framework of low-speed maneuvering.

In Figure 2, position of H in the vessel-fixed reference coordinate is determined by Δx and Δy. The position of H in the earth-fixed reference coordinate can be easily obtained as

$$\eta_H = \hat{\eta} + J(\psi)\begin{bmatrix}\Delta x\\ \Delta y\\ 0\end{bmatrix} = \hat{\eta} + J(\psi)d_H \tag{25}$$

where $d_H = [\Delta_x, \Delta_y, 0]^T$. From (15), (24), and (25) the hybrid neural adaptive control scheme to stabilize H at the reference point R is proposed as

$$\tau = -J^T(\psi)K_p\hat{e} - K_d\hat{\nu} - O_n\,, \tag{26}$$

$$O_n = F[J^T(\psi)\hat{e}] \tag{27}$$

$$\hat{e} = \hat{\eta} + J(\psi)d_H - \eta_d \tag{28}$$

Here, the adaptation laws of the ANNAI controllers are similarly determined as in subsection 3.1. Using the control scheme expressed in (26), (27), and (28), unknown bias term representing slowly-varying environmental disturbances can be compensated for and tracking error can be minimized.

In order to make the ship follow the desired track, we propose an algorithm to move the reference point R along the desired track. Let z_e be the distance HR, one can have

$$z_e = \sqrt{(x_H - x_d)^2 + (y_H - y_d)^2} \tag{29}$$

Based on the work of Do, Jiang and Pan in [14], the speed u of R is chosen as

$$u(t, z_e, \Delta\psi) = u^*(1 - \chi_1 e^{-\chi_2(t-t_0)})e^{-\chi_3 z_e} e^{-\chi_4|\Delta\psi|} \tag{30}$$

where additional term $e^{-\chi_4|\Delta\psi|}$ is added, and $u^* \neq 0$, $\chi_i > 0$, $i = 1, \ldots 4$, $\chi_1 < 1$, and $\Delta\psi = \psi - \psi_d$.

The choice of $u(t,z_e)$ in (30) has the following desired features: when the tracking error z_e and/or heading error $\Delta\psi$ are large, the reference point R will wait for the ship position and her heading to reach to the set point η_d; when z_e and $\Delta\psi$ are small, the reference point R will move along the desired track at the speed closed to u^* and the ship follows it within the specified look ahead distance while maintaining the desired heading [14].

4. Simulation Results

In order to validate the proposed DP control system, we carry out computer simulations using the nonlinear model of a off-shore supply ship *Northern Clipper* which was presented in [4]. The length of *Northern Clipper* is L = 72.6 (m) and the mass is m = $4.591 \cdot 10^6$ (kg). The coordinate system is located in the center of gravity. The bias time constants were chosen as $T = diag\{1000, 1000, 1000\}$. The wave model parameters were also chosen as in [4] with ζ_i = 0.1 and ω_{oi} = 0.8976 (rad/s) corresponding to a wave period of 7.0 (s) in surge, sway and yaw.

The ANNAI controllers are feedforward neural networks with four input neurons, six hidden neurons and one output neuron. The input vector of each neural network consists of X_i and their three delayed signals. Number of training iterations in one control cycle of each neural network is fixed at 50. The other parameters are

$$[\rho_1, \rho_2, \rho_3] = [0.125, 0.175, 0.25] \tag{31}$$

$$[\lambda_1, \lambda_2, \lambda_3] = [1, 0.025, 0.2] \tag{32}$$

$$[\kappa_1, \kappa_2, \kappa_3] = [1.5, 0.02, 0.2] \tag{33}$$

$$[\gamma_1, \gamma_2, \gamma_3] = [0.3, 0.5, 0.5] \tag{34}$$

The gains of PD-controller are chosen as:

$$K_p = diag\{50e3, 50e3, 200e3\} \tag{35}$$

$$K_d = diag\{10e3, 10e3, 40e3\} \tag{36}$$

4.1 Station-keeping Simulation

In this simulation, the center of gravity is stationed at the point (0,0). Initial ship heading is 90^0, after 300s the heading is changed to 160^0 and after 1700s it is changed to 135^0 (Figure 3).

The simulation result has shown the ability of the DP system in station-keeping. The ship was stably kept at desired position and direction was correctly changed under the effect of external disturbances represented by bias term.

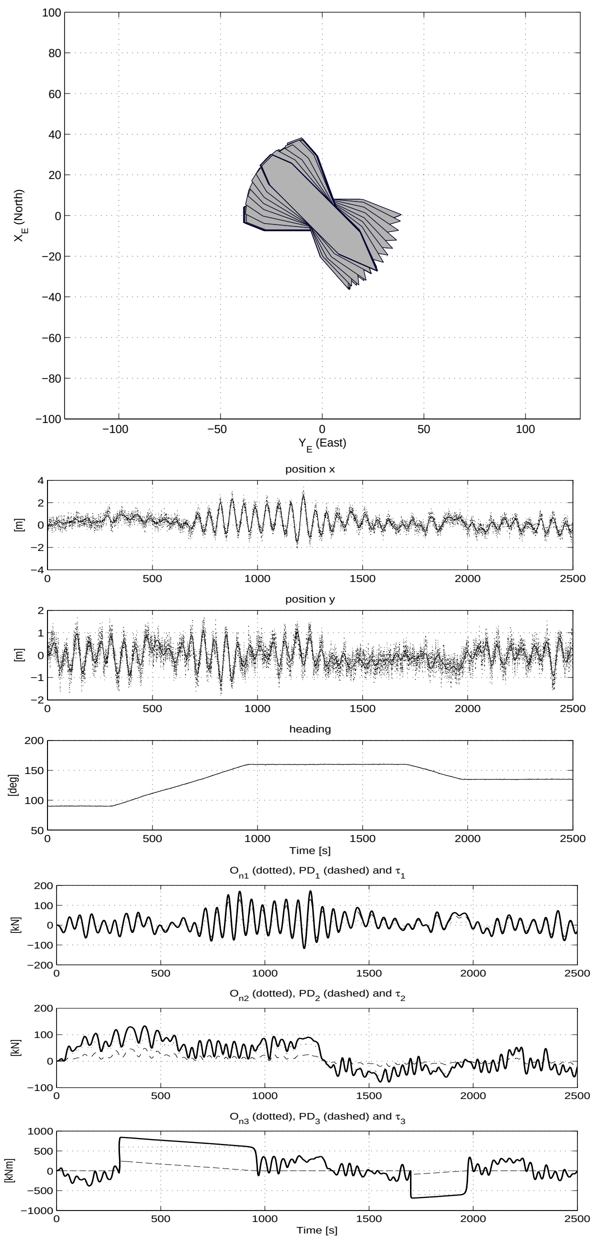

Figure 3. xy plot (top); measured (dotted), filtered position and heading; and control forces and moment.

4.2 Low-speed Maneuvering Simulations

In these simulations we select a desired track connecting four *marked points* (0,0), (100,-100), (200,0), (100,100), (0,0). In all simulations the ship positions are plotted every 60 seconds, off-track distance, filtered position in x, y and ship heading, control forces and moment are shown. In low-speed maneuvering following *marked points*, we use distance from R to current marked point Z_{ep} as in [14] to modify equation (30) as follow:

$$u(Z_{ep}, z_e, \Delta\psi) = u^*(1 - \chi_1 e^{-\chi_2 Z_{ep}}) e^{-\chi_3 z_e} e^{-\chi_4 |\Delta\psi|} \qquad (37)$$

where

$$[\chi_1, \chi_2, \chi_3, \chi_4] = [0.95, 0.2, 0.2, 15]. \qquad (38)$$

Equation (37) can reduce ship speed exponentially while approaching the marked point to prevent position overshoot. By selecting values of Δx , Δy to determine position of H, we can make a specific point of ship follow the desired track. The following three cases are simulated:

Case 1: The point H is located at the center of gravity of the ship and follows the desired track while ship heading on each segment is set to 0^0, 315^0, 225^0, 135^0. In this case, position of H in vessel-fixed reference coordinate is chosen as: $\Delta x = 0$, $\Delta y = 0$. The initial position and heading of ship is (0,0) and 0^0. The simulation result is shown in Figure 4.

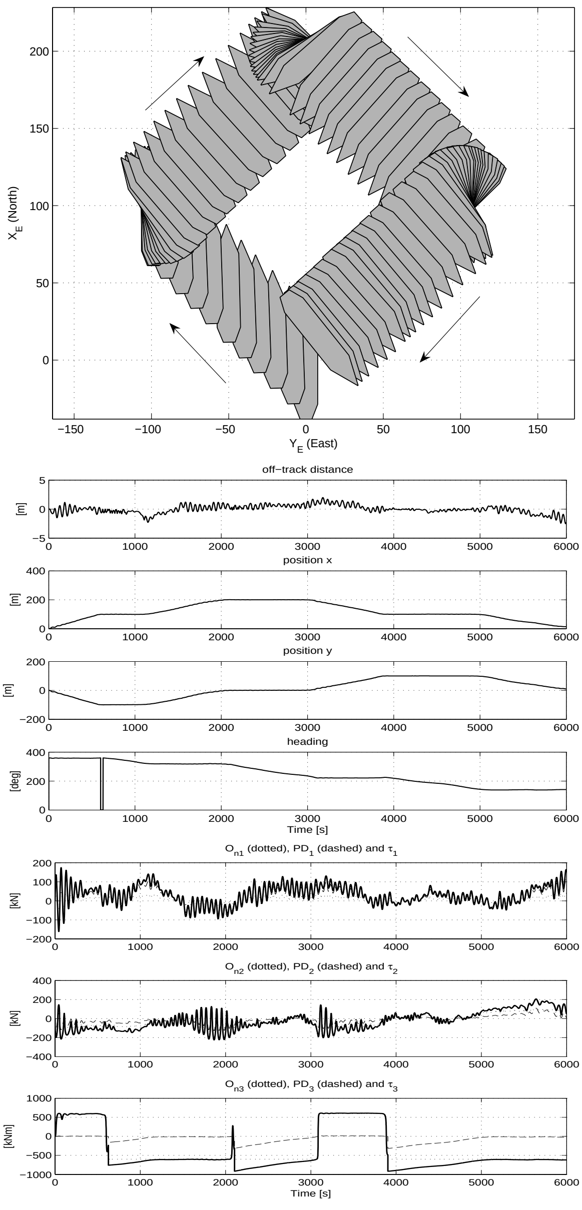

Figure 4. Ship track (top); off-track distance, position and heading; and control forces and moment (case 1).

In this simulation, the center of gravity of the ship moved along the desired track with small off-track distance and heading is kept at desired value. At each marked point, ship heading was changed to new desired value before the ship continued to move along new segment. This action is resulted in by the effect of new item $e^{-\chi_4 |\Delta\psi|}$ in equation (30).

Case 2: The point H is located on the bow of the ship and follows the desired track while ship heading on each segment is set to 0^0, 90^0, 180^0, 270^0. In this case, position of H in vessel-fixed reference coordinate is chosen as: $\Delta x = L/2$, $\Delta y = 0$. The initial position and heading of ship is (-L/2,0) and 0^0. The plot of the ship positions is shown in Figure 5.

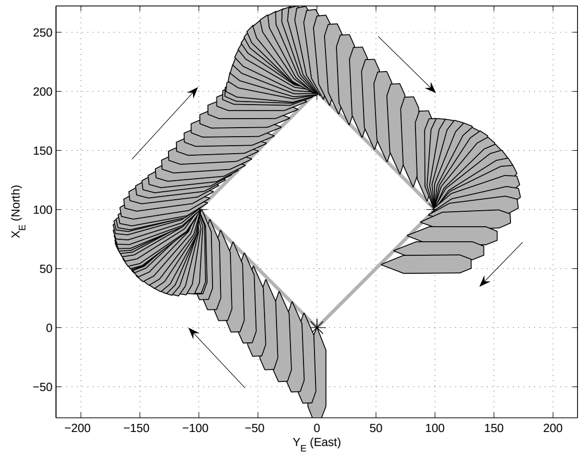

Figure 5. Plot of the ship track in case 2.

Case 3: Similar to the Case 2 but the ship heading on each segment is set to 315^0, 45^0, 135^0, 225^0. The plot of the ship positions is shown in Figure 6.

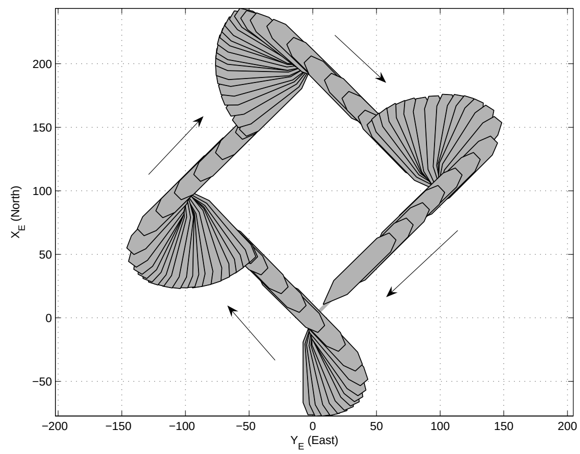

Figure 6. Plot of the ship track in case 3.

In the simulations of cases 2 and 3, ship's bow followed the desired track, and the desired heading was maintained. At each marked point, the ship's bow was stationed at the point so that ship heading changed to new value before moving along new segment. Clearly, this action is also resulted in by the effect of new item $e^{-\chi_4 |\Delta\psi|}$ in equation (30).

5. Conclusion

This paper presents a new hybrid neural adaptive DP system for ship using ANNAI controllers and conventional PD-controller. Principally, the difference between the proposed DP system in this study with that of other studies is that the ANNAI controller is introduced to adaptively compensate for unknown bias term representing slowly-varying environmental disturbances and minimize positioning and tracking error. Employing the advantages of the ANNAI controller, the DP system can also cope with unmodeled nonlinear dynamics of ships.

Additionally, a method of moving the reference point is modified and applied to low-speed maneuvering shows the effectiveness of stabilizing ship at reference point while maintaining the desired heading. This ability is useful for specialized tracking functions for supply ships, cable and pipe laying ships.

Finally, to validate the proposed DP system, computer simulations have been carried out and shown the feasibility of the DP system in position-keeping as well as various maneuvering situations. Next studies will consider the actuator allocation and saturation, extreme environmental situations.

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