An Intelligent Guidance and Control System for Ship Obstacle Avoidance

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Abstract — An intelligent guidance and control system using a neurofuzzy network multistep ahead predictor model is introduced and applied to ship obstacle avoidance, which uses only observed input/output data generated by on board and external sensors, and a data fusion algorithm to generate the desired waypoints. A simple and effective waypoint guidance scheme based on line-of-sight is derived for a data based ship model. A neurofuzzy network predictor, based on using rudder deflection angle for the control of ship heading angle, is utilised on the simulation of ESSO 190000dwt tanker model to demonstrate the effectiveness of the system. The approach is generic and extendable to aircraft and missile control and guidance problems where the vehicle dynamics change significantly during flight in a manner dependent upon operational use, the only requirement for implementation being observed data to construct sensor and vehicle models.

Keywords — neurofuzzy networks, intelligent guidance, ship navigation, adaptive predictive control.

List of notation

$B_{k,m}(\overline{x}_i)$ – univariate B-spline basis function.
$D\delta_{max}$ – the maximum angle changing rate.
$e(t+d|t)$ – the model residual.
$\mathbf{f}(\bullet)$ – a vector valued function.
$g(\bullet)$ – nonlinear function.
I_z – the moments of inertia about the normal axis ship surface plane.
J – cost function.
L_i – the number of univariate B-spline basis function.
m – mass of ship.
$N_k^{(n_l)}(.)$ – multidimensional basis function.
n – the shaft velocity.
r – yaw angular velocity.
t – time index.

T_s – the sampling time of the system.
u – surge velocity.
$\mathbf{u} = [\delta_d, n_d]^T$ – input command signals.
v – sway velocity.
x_G – the Cartesian coordinate of the center of gravity along surge axis.
$\overline{x}_i$ – definition given in Eq.(6).
$\mathbf{x} = [u, v, r, \psi, x, y, \delta, n]^T$.
$[x_k^d, y_k^d]$ – the waypoint.
$X(\bullet)$, $Y(\bullet)$ and $N(\bullet)$ – external forces and moment.
δ – the rudder deflection angle.
δ_{max} – the maximum rudder angle.
ρ_0 – radius of the circle of acceptance.
ω_{p+k}'s – constant weights.
ψ – the ship heading angle.
$\psi_d(t)$ – desired heading angle command.
$\hat{\psi}(t+d|t)$ – model prediction.
$\tau = \{\tau_1, \tau_2, \cdots, \tau_{L+m+1}\}$ – knot vector.
λ – the constant weighting factor.

1 Introduction

With the rapid advances in computer signal processing technology, modern control theory, accurate positioning and navigation systems, there is a growing interest in the development of an intelligent ship guidance and control system which automates the procedure of determining the course, attitude and speed to be followed by the ship, and the associated control law for operating the ship to perform the task commanded by the guidance system. The design and implementation of an intelligent guidance and control system for ship collision avoidance with obstacles in congested water is a complex task due to many limitations and/or constraints from ship kinematics and mechanics, manoeuvrability, hydrodynamics, and ship environment (weather, sea state, collision avoidance regulations). For guidance, it is difficult to precisely determine an obstacle free trajectory in a distinct form as the ship positioning coordinates evolve as a function of time. Even if the guidance law has been established, it is not easy to find the corresponding control input due to the difficulty in solving the inverse of *a priori* known ship dynamics.

Ideally a practical intelligent guidance and control system should be designed in a simple and effective format whilst exploiting state-of-the-art technology. Based on a widely applied classical ship control principle that the steering is responsible for the ship heading, the system can be simplified and decoupled, with the ship heading angle as the system output and rudder deflection angle as input. The relationship between ship heading angle and rudder deflection angle is a highly complicated nonlinear function. It is well known that nonlinear models such as neural networks possess strong approximation ability for unknown nonlinear functions. A wide class of nonlinear models can be represented as a linear-in-the-parameters structure so that linear learning methods and control methods can be readily applied. Non-linear system dynamical modelling using neural networks including a B-spline neuro-fuzzy network has been widely studied in recent years[1]. Having desirable properties such as a compact support, a partition of unity, locality, logicality and transparency, the B-spline neuro-fuzzy network and algorithms have been extensively developed enabling the applicability of neurofuzzy controller and guidance system, such as the neuro-fuzzy multi-sensor data fusion algorithm with applications in helicopter guidance[2]. To overcome the curse of dimensionality, input selection and an analysis of variance (ANOVA) decomposition can be used while limiting the degree of interactions among input components[3].

In this paper, a new practical intelligent guidance and control system is introduced for ship obstacle avoidance. The methodology proposed here assumes no *a priori* knowledge of the ship dynamics via mechanic equations (such as Eqn's(1)-(3), which are used here purely to generate appropriate data), but rather access to a data base of observed ship's behaviour from which data based input/output models can be derived to synthetise guidance and control systems. However for the purpose of illustration a realistic ship model is used to generate such a data base, here a model of ESSO 190000dwt tanker given by[4] is used. A simple and effective waypoint guidance scheme by line-of-sight (LOS)(see eg [5]) is used, assuming that current ship state (not only heading angle) can be accurately observed and fedback for the adaptive computation of desired heading angle. If these states are unavailable database neurofuzzy state estimator algorithms[6] can be used to reconstruct representative states. The ship steering is modelled based on an input affine single-input-single-output (SISO) multi-step ahead predictor modelled using neurofuzzy network with the analysis of variance (ANOVA) decomposition. The model is identified using a recursive least squares method, followed by a simple adaptive neurofuzzy model predictive controller design. Based on the feedback of state variables for the adaptive computation of guidance law, the guidance, identification, and control are integratedly processed. It is shown that most of the difficulties of ship guidance and control can be overcome by this simple and effective system.

The paper is organised as follows. Section 2 describes the test ship dynamics, kinematics and the LOS guidance scheme. The neurofuzzy modelling and controller design based on an input affine neurofuzzy multi-step ahead predictor model structure is introduced in section 3. The proposed algorithm is then applied to a practical ESSO 190000dwt tanker model and the simulation results presented in Section 4. Section 5 is devoted to conclusions.

2 Ship modelling and waypoint guidance by line of sight

For the simulation and verification of the designed guidance and control strategy, a good mathematical model of the ship is required to generate typical input/output data. Without loss of generality, the dynamics of the ship under this study is described by a model based on the horizontal motion with the motion variables of surge, sway and yaw. The movement of a ship is determined by the hydrodynamic forces and moments, the input variables of which are shaft angular velocity (related to propeller thrust) and the rudder deflection angle. Note that these physical input variables subject to constraints. The ship motion can be defined over two coordinate frames using a body-fixed frame of surge-sway (X_0Y_0) and a global reference frame of North-East (XY), illustrated in Fig.1. The three degrees of freedom non-linear ship motion equations can be written as[4].

$$\begin{aligned} m(\frac{du}{dt} - vr - x_G r^2) &= X(u, v, r, \frac{du}{dt}, \delta, n) \\ m(\frac{dv}{dt} + ur + x_G \frac{dr}{dt}) &= Y(v, r, \frac{dv}{dt}, \frac{dr}{dt}, \delta) \\ I_z \frac{dr}{dt} + m x_G(\frac{dv}{dt} + ur) &= N(v, r, \frac{dv}{dt}, \frac{dr}{dt}, \delta) \end{aligned} \tag{1}$$

where t is time index. u, v denote surge and sway velocity. r is yaw angular velocity. m and I_z are mass of ship and the moments of inertia about the normal axis of X_0Y_0 plane. x_G is the Cartesian coordinate of the center of gravity along X_0 axis. δ denotes the rudder deflection angle and n is the shaft velocity. $X(\bullet)$, $Y(\bullet)$ and $N(\bullet)$ are external forces (along the surge X_0, sway Y_0 axis) and

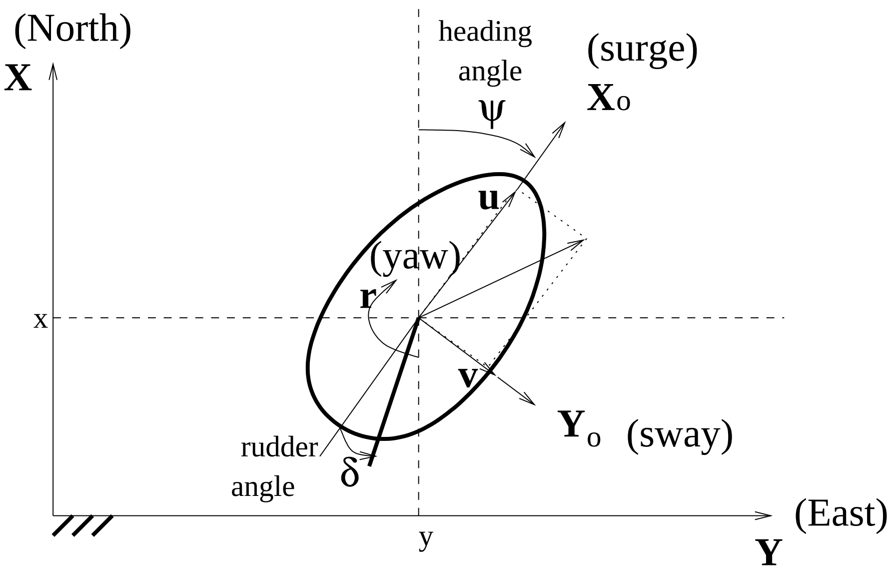

Figure 1: Coordinate system for surface ship motion

moment (for yaw rotation $X_0 \hookrightarrow Y_0$). Eq.(1) however does not include the progression of the ship position. It can be seen, from Fig.1, that the global reference frame based ship kinematics can be expressed as

$$\begin{aligned} \frac{dx}{dt} &= u\cos\psi - v\sin\psi \\ \frac{dy}{dt} &= u\cos\psi - v\sin\psi \\ \frac{d\psi}{dt} &= r \end{aligned} \tag{2}$$

where $[x, y]$ denotes the ship coordinates in the global reference frame, and ψ is the ship heading angle. The terms $X(\bullet)$, $Y(\bullet)$ and $N(\bullet)$ in Eq.(1) can be expanded in Taylor series expansion to derive a lower order polynomial nonlinear model, such that Eqn.(1) and (2) can also be written in a general form as

$$\begin{aligned} \frac{d\mathbf{x}}{dt} &= \mathbf{f}(\mathbf{x}, \mathbf{u}) + \mathbf{w} \\ \mathbf{z} &= \mathbf{C}\mathbf{x} + \mathbf{v} \end{aligned} \tag{3}$$

where $\mathbf{f}(\bullet)$ is a vector valued function. $\mathbf{x} = [u, v, r, \psi, x, y, \delta, n]^T$, $\mathbf{u} = [\delta_d, n_d]^T$, in which the subscript 'd' denotes the command signals. $\mathbf{C}$ is a constant matix with appropriate dimension. $\mathbf{w}$ and $\mathbf{v}$ denote appropriately dimensioned uncorrelated model mismatch and state and observation disturbances.

The design and implementation of an intelligent guidance and control system for ship collision avoidance with obstacles in congested waters is a complex task due to many limitations and/or constraints generated by ship kinematics, mechanics and manoeuvrability, hydrodynamics, and ship environment. An intelligent ship guidance and control system should (a) according to some system optimization criterion J, determine an obstacle free path subject to these constraints (e.g. a desired trajectory denoted as $\mathbf{z}_d(t)$ if $\mathbf{z} = [x, y]^T$); and (b) determine some control strategy (method of solving $\mathbf{u} = [\delta_d, n_d]^T$ subject to physical constraints) so that the trajectory can be followed. It is however difficult and impractical to find a closed form of $\mathbf{z}_d(t)$, if $\mathbf{z} = [x, y]^T$, due to the strong non-linearities, coupling the ship dynamics, and the uncertainty and complexity of the constraints imposed by the environment.

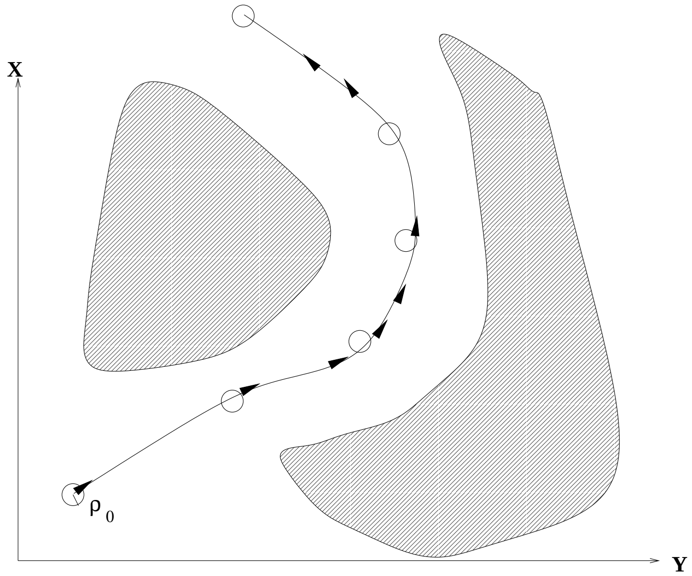

Figure 2: Path planning using line of sight (LOS)

A practical and simple alternative is the concept of a waypoint guidance scheme based on line-of-sight (LOS) guidance which has been used in missile guidance for many years and was used in ship guidance[5] (see Fig. 2). Rather than use a direct guidance scheme for the ship Cartesian coordinates, this guidance scheme aims to control the ship heading angle $\mathbf{z} = \psi$ by predetermining a set of way points $[x_k^d, y_k^d], k = 1, \cdots, N$, which are generated by a sensor fusion system[2] that provide an obstacle free trajectory in the form of discrete waypoints. At time t, a desired heading angle command is given by

$$\psi_d(t) = \arctan\left[\frac{y_k^d - y(t)}{x_k^d - x(t)}\right] \tag{4}$$

where $[x_k^d, y_k^d]$ is the waypoint aimed by the ship heading. If the ship location $[x(t), y(t)]$ lies within a circle of acceptance with radius ρ_0 around $[x_k^d, y_k^d]$, the waypoint proceeds to $[x_{k+1}^d, y_{k+1}^d]$. It is clear that in this scheme the guidance problem is simplified by reducing the output dimension, and the guidance law is given adaptively based on the accurate feedback of state variables (not the heading angle only). A practical philosophy widely applied in classical ship control, such as course-keeping and turning, is that the propulsion system is responsible for speed and that steering (i.e. the rudder deflection angle) is responsible for the ship heading angle δ. Linear course-keeping and turning control methods, etc. are described in[4], the aims of which involve stabilising or control heading using rudder based on heading measurements feedback. However, the relationship between ship heading angle and rudder deflection angle is a highly complicated nonlinear function, and to achieve a better performance than classical linear modelling and controller, nonlinear modelling and control may be required. By utilising the conventional means of ship control, steering by rudder motion, a practical intelligent guidance and control system can be introduced based on an input affine single-input-single-output (SISO) non-linear neurofuzzy multi-step ahead predictor model (with the heading angle as output and rudder deflection angle as input). This will be introduced in the sequel.

3 Neurofuzzy predictor modelling and controller design

The prime task of the ship control system isto implement the requirement set by the guidance system in a smooth and effective manner. This frequently involves the computation of the inverse function of $\mathbf{f}(\bullet)$ in Eq.(3) to find a suitable control signal $\mathbf{u}$ given a desired trajectory $\mathbf{z}_d(t)$. Difficulties arise due to the highly nonlinearity and coupling of the real dynamics. Here a practical intelligent guidance and control system is introduced based on an input affine single-input-single-output (SISO) non-linear multistep ahead predictor using a neurofuzzy network with ANOVA decompostion (with the heading angle as output and rudder deflection angle as input). It is well known that nonlinear models such as neural networks possess strong approximation ability for unknown nonlinear functions. A wide class of nonlinear models can be represented as a linear-in-the-parameters structure so that linear learning methods and control methods can be readily applied[1]. Most of the difficulties can be circumvented by ship steering modelling using the neurofuzzy predictor model which can arbitrarily approximates the ship dynamics, be easily identified and used for controller design. The diagram of a practical intelligent ship guidance and control

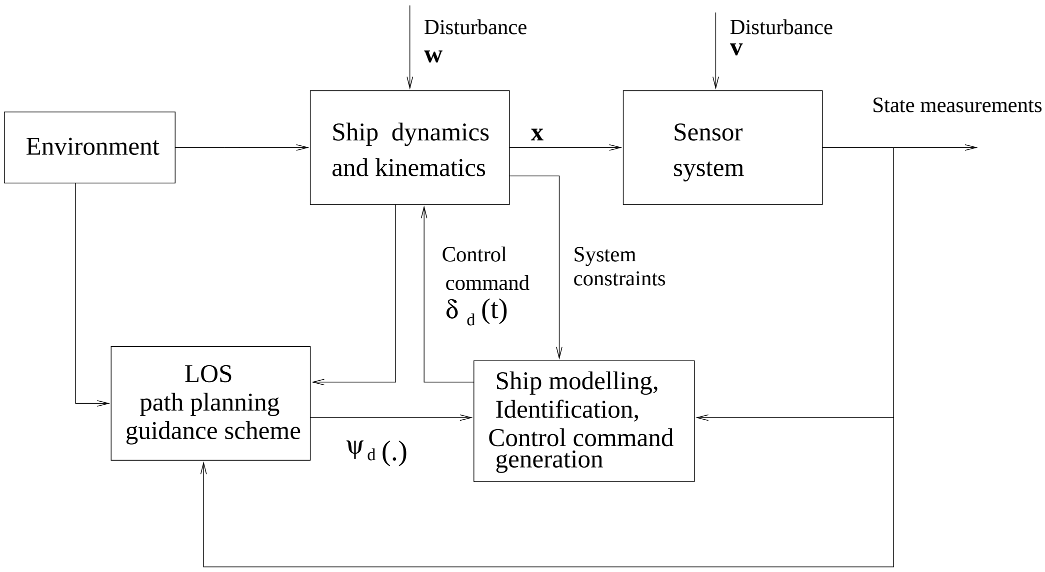

Figure 3: Intelligent ship guidance and control system

system is plotted in Fig.3. Suppose that the ship steering equation can be expressed as a nonlinear regression in discrete time as

$$\psi(t) = g(\psi(t-1), \cdots, \psi(t-n_\psi), \delta(t-d), \cdots, \delta(t-d-n_\delta+1)) \tag{5}$$

where $g(\bullet)$ is nonlinear function. n_ψ, n_δ are assumed known positive interger representing lag in system output and input. d is the assumed known system time lag. In this paper, a neurofuzzy self-tuning predictive controller is introduced. The basic idea is to construct a predictive model based on an neurofuzzy input affine model structure, followed by the controller design which aims to minimise the prediction error. In the present application, the d step ahead predictor at time t can be constructed using system observables $\{\delta(t), \psi(t)\}$ up to time t. In simulation study, the data sequence can be generated by discretization of the ship dynamics and kinematics model of Eq.(1) and (2). Initially define

$$\begin{aligned} x_i &= \psi_d(t-i+1) - \psi(t-i+1), \qquad i = 1, \cdots, n_\psi \\ \overline{x}_i &= \frac{x_i}{\mid x_i \mid +1} \end{aligned} \tag{6}$$

The first part of Eq.(6) involves the past known heading command $\psi_d(t-i+1)$ (given in Eq.(4)) in order to ensure the stationarity of the network input, since it is also assumed that the constraint such as $x_i \in [-\pi/4, \pi/4]$ must be satisfified (for an appropriate LOS path planning scheme). The second part of Eq.(6) is a one-to-one mapping[7] ensuring that $\overline{x}_i \in (-1,1)$. The d step ahead predictor is constructed as the multidimensional B-spline basis function models given as the following form

$$\begin{aligned} \psi(t+d) &= \hat{\psi}(t+d|t) + e(t+d|t) \\ &= g_0(\psi(t), \cdots, \psi(t-n_\psi+1)) + \sum_{k=0}^{n_\delta -1} \omega_{p+k}\delta(t-k) + e(t+d|t) \\ &= g_0(\overline{x}_1, \cdots, \overline{x}_{n_\psi}) + \sum_{k=0}^{n_\delta -1} \omega_{p+k}\delta(t-k) + e(t+d|t) \end{aligned} \tag{7}$$

where $\hat{\psi}(t+d|t)$ denotes model prediction and $e(t+d|t)$ is the model residual. $g_0(\bullet)$ can be modelled using a B-spline neurofuzzy network[1] where the overall number of basis functions in g_0 will be denoted as p, and ω_{p+k}'s are constant weights. For a one-dimensional variable $\overline{x}_i$ the B-spline model is formed as a linear combination of L_i B-spline basis functions as

$$f(\overline{x}_i) = \sum_{k=1}^{L_i} \omega_k B_{k,m}(\overline{x}_i) \tag{8}$$

The coefficients ω_k's represent the set of adjustable parameters associated with the set of basis functions $B_{k,m}(\overline{x}_i)$. The set of basis functions $B_{k,m}(\overline{x}_i)$'s in the model Eq.(8) is a polynomial of a given degree m and is uniquely defined by an ordered sequence of real values denoted by a knot vector $\tau = \{\tau_1, \tau_2, \cdots, \tau_{L+m+1}\}$. The knot sequence forms a partitioning of the input domain into $(L+m)$ disjoint intervals. The definition of basis functions set can be expressed as a recursion[8]

$$B_{k,m}(\overline{x}_i) = \frac{\overline{x}_i - \tau_k}{\tau_{k+m} - \tau_k} B_{k,m-1}(\overline{x}_i) + \frac{\tau_{k+m+1} - \overline{x}_i}{\tau_{k+m+1} - \tau_{k+1}} B_{k+1,m-1}(\overline{x}_i) \tag{9}$$

with

$$B_{k,0}(\overline{x}_i) = \begin{cases} 1 & \tau_k \le (\overline{x}_i) < \tau_{k+1} \\ 0 & otherwise \end{cases}$$

The multidimensional B-spline basis functions are formed by a tensor product of univariate basis functions with an analysis of variance (ANOVA) decomposition[3] as

$$= \underbrace{B_{k_i,m}(\overline{x}_i) \cdots B_{k_j,m}(\overline{x}_j)}_{n_l}, \qquad i \ne j \tag{10}$$

where $n_l = 0, 1, \cdots,$ up to a predetermined number denoting polynomial degree. $k_i = 1, 2, \cdots, L_i$, L_i is the number of B-spline basis functions defined in $\overline{x}_i$. To overcome the curse of dimensionality, the maximum number of n_l will be limited to 3 or less. $g_0(\bullet)$ can be expressed as

$$\begin{aligned} g_0(\overline{x}_1, \cdots, \overline{x}_{n_\psi})) &= \sum_{k=0}^{p-1} \omega_k N_k^{(n_l)} \\ &= \omega_0 + \sum_{i=1}^{n_\psi} \sum_{k_i=1}^{L_i} \omega_k B_{k_i,m}(\overline{x}_i) + \sum_{i=1}^{n_\psi -1} \sum_{j=i+1}^{n_\psi} \sum_{k_i=1}^{L_i} \sum_{k_j=1}^{L_j} \omega_k B_{k_i,m}(\overline{x}_i) B_{k_l,m}(\overline{x}_j) \\ &\quad + \sum_{i=1}^{n_\psi -2} \sum_{j=i+1}^{n_\psi -1} \sum_{l=j+1}^{n_\psi} \sum_{k_i=1}^{L_i} \sum_{k_j=1}^{L_j} \sum_{k_l=1}^{L_l} \omega_k B_{k_i,m}(\overline{x}_i) B_{k_j,m}(\overline{x}_j) B_{k_l,m}(\overline{x}_j) + \cdots \end{aligned} \tag{11}$$

If the knot positions of B-spline functions are predetermined, the d-step ahead predictor model Eq.(7) has a linear-in-the-parameters structure. The parameters or weights ω_k's can be estimated on-line using the recursive least squares (RLS) method via the minimization of $E[e(t+d|t)^2]$[9]. It is reasonable to assume that the modelling error of the neural network based predictor can be reduced arbitrarily small by the proper selection of basis function and adjusting the weights by learning. The adaptive on-line controller can be designed based on the predictor according to *the certainty equivalence principle*[10].

The controller design stage initially involves the definition of a cost function which computes quatitatively how well the predicted process output tracks the reference trajectory. The cost function used here is

$$J = E\left[(\psi_d(t+d) - \hat{\psi}(t+d|t))^2 + \lambda\delta^2(t)\right] \tag{12}$$

where λ is constant weighting factor. The optimal control sequence is obtained by minimising J with respect to $\delta(t)$ by setting

$$\frac{\partial J}{\partial \delta(t)} = 0 \tag{13}$$

yielding the optimal control law as

$$\delta_d(t) = \frac{1}{\lambda + \omega_p^2}\left[g_0(\overline{x}_1, \cdots, \overline{x}_{n_\psi}) - \psi_d(t+d) - \sum_{k=1}^{n_\delta - 1} \omega_{p+k}\delta(t-k)\right] \tag{14}$$

Note that the ship rudder is physically constrained by its maximum angle and the maximum angle changing rate, and input constraint was included in the cost function J to prevent unrealistic control command. Taking into account these physical constraints, a rudder limiter is used, given by

$$\delta_d(t) = sign\,[\delta_d(t)] \bullet \min\{|\,\delta_d(t)\,|, |\,\delta_{max}\,|, |\,\delta_d(t-1) + sign\,[\delta_d(t) - \delta(t-1)] \bullet T_s \bullet D\delta_{max}\,|\} \tag{15}$$

where δ_{max}, $D\delta_{max}$ denotes maximum rudder angle and maximum angle changing rate. T_s is the sampling time of the system.

Remarks:

1. Some computational issues; (i) care should be taken to ensure the measurements of yaw angle $\psi(.) \in [0, 2\pi]$; (ii) proper quadrant diagnosis is needed for Eq.(4) to ensure the heading angle command $\psi_d(.) \in [0, 2\pi]$; and (iii) extra care is needed to ensure $x_i \in [-\pi, \pi]$ in Eq.(6) and usually $x_i \in [-\pi/4, \pi/4]$ (by proper selection of way points).

2. A small radius of the circle of acceptance, ρ_0, is needed for guidance precision, but too small a ρ_0 could result in an excessively fast changing heading angle command which is difficult to track by the ship around the waypoints.

3. The ship shaft velocity n is assumed to be constant in the present study, however the adaptive nature of the algorithm could allow n to be slowly changing over its operating region. Note that due to the constraints of the ship manoeuvrability, the selection of waypoints and speed of the ship (related to the shaft velocity n) should allow sufficient system response time for satisfactory tracking. The optimisation of shaft velocity n with fixed waypoints is a topic for further study.

4 Simulation results

The simulation has been based on ESSO 190000 dwt tanker model given in[4, 10]. Euler's numerical integration method was used for the discretization with a sampling time $T_s = 0.2s$. As the first example, the initial contition of the ship was set as $[u, v, r, \psi, x, y, \delta, n]^T = [2.7787, 0.8666, -0.0185, \pi/4, 10, 10, 0.26, 60]$. The initial surge, sway and yaw velocity has been obtained by setting the rudder angle as 0.26, the shaft velocity as 60rpm such that the ship has been in a steady circle movement state. Throughout the actual shaft velocity was maintained as a constant 60rpm. The depth of water is assumed to be constant at 50m. 4 waypoints was set as

$$[x_1^d, y_1^d] = [400, 500]$$

$$[x_2^d, y_2^d] = [1250, 700]$$

$$[x_3^d, y_3^d] = [1800, 300]$$

$$[x_4^d, y_4^d] = [2500, 0]$$

The radius of the circle of acceptance was set as $\rho_0 = 20m$. Set $n_u = 1$. An order-1 ($m = 1$) B-spline neuro-fuzzy network was used to approximate the $g_0(\bullet)$. The 3 dimensional input vector to the neurofuzzy network basis function was generated via the transformation Eq.(6) from lagged system output $[\psi(t), \psi(t-5), \psi(t-10)]^T$. For the sake of simplicity the input vector are stilled called as $[\overline{x}_1, \overline{x}_2, \overline{x}_3]^T$. The knot vector τ for the input domain was defined as

$$\{-1.2, -1, -0.3, 0, 0.3, 1, 1.2\}$$

for $\overline{x}_i$'s, resulting 5 one-dimensional basis functions for each $\overline{x}_i$. The ANOVA decomposition was used to form the neurofuzzy network and the maximum number of input interactions $\max(n_l) = 2$. The prediction step was set as d=10. The parameters ω_k's are adaptively estimated using recursive least squares (RLS) method with a forgetting factor 0.98. The control law was generated using Eq.(14) and (15) where $\lambda = 10$. The trajectory of the ship in earth-fixed coordinate was plotted in Fig.4 demonstrating that ship moves smoothly along the waypoints as expected. The evolution of ship actual heading angle and the desired heading command was plotted in Fig.5 demonstrating the excellent tracking performance. The evolution of surge, sway and yaw velocity and rudder deflection angle were shown in Fig.6.

In the second example, the initial condition of the ship was set as $[u, v, r, \psi, x, y, \delta, n]^T = [1.5487, 0.4730, -0.0057, \pi/4, 10, 10, 0.1, 30]^T$. The initial surge, sway and yaw velocity has been obtained by setting the rudder angle as 0.1, the shaft velocity as 30rpm such that the ship has been in a steady circle movement state. Throughout the shaft velocity was maintained at a constant 30rpm. The depth of water is assumed to be constant 50m. 4 waypoints was set as

$$[x_1^d, y_1^d] = [200, 200]$$

$$[x_2^d, y_2^d] = [350, 500]$$

$$[x_3^d, y_3^d] = [300, 800]$$

$$[x_4^d, y_4^d] = [200, 1000]$$

The radius of the circle of acceptance was set as $\rho_0 = 20m$. Set $n_u = 1$. An order-1 ($m = 1$) B-spline neuro-fuzzy network was used to approximate the $g_0(\bullet)$. The 3 dimensional input vector to the neurofuzzy network basis function was generated via the transformation Eq.(6) from lagged system output $[\psi(t), \psi(t-5), \psi(t-10)]^T$. For the sake of simplicity the input vector are stilled called as $[\overline{x}_1, \overline{x}_2, \overline{x}_3]^T$. The knot vector τ for the input domain was defined as

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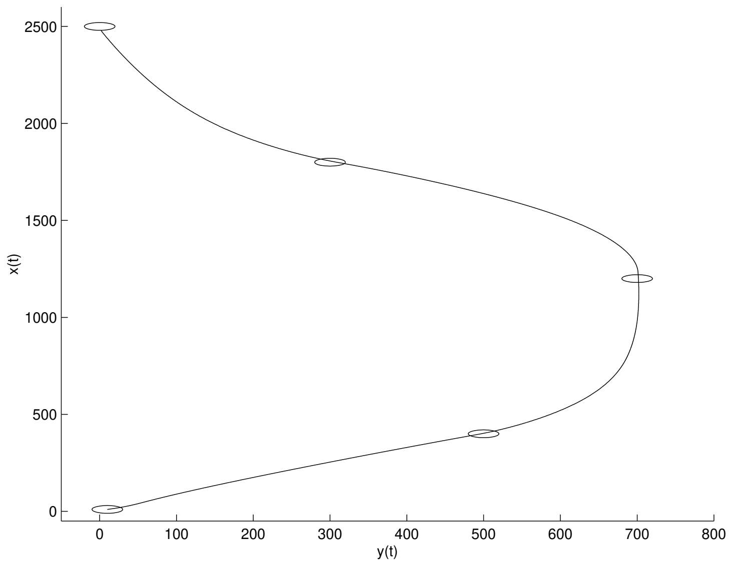

Figure 4: Simulated ESSO 190000 dwt tanker's trajectory in earth-fixed coordinate in the first example. (circle: way points used in path planning)

5 Conclusions

In this paper, a practical intelligent guidance and control system for ship obstacle avoidance is introduced. The main idea is using neurofuzzy network multistep ahead predictor model to model the ship steering dynamics, with rudder deflection angle as system input and ship heading angle as system output using a waypoint guidance scheme based on line-of-sight (LOS). Simulation results for an illustration system of an ESSO 190000dwt tanker model are included to demonstrate the effectiveness of the system. Since this approach, including the generation of waypoints, is entirely data based, then it can be readily extended to higher dimensional control and guidance problems such as flight management of aircraft and missiles where the dynamics may change significantly and unpredictably during flight.

6 Acknowledgement

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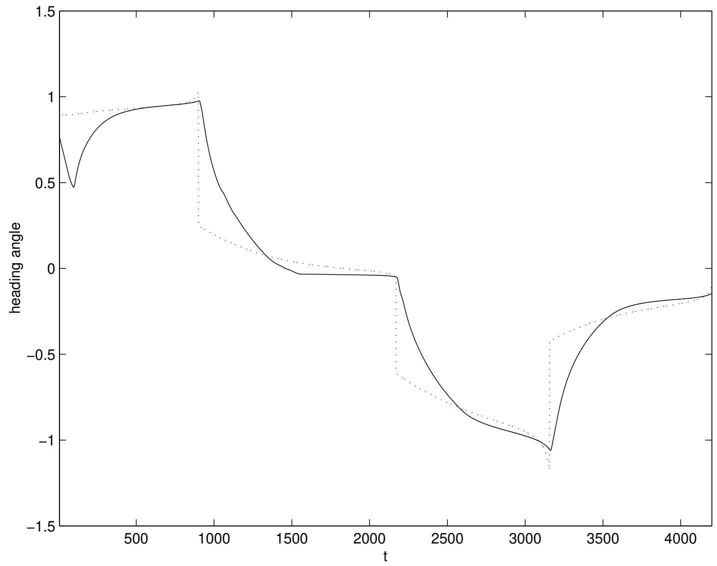

Figure 5: The performance of heading angle tracking in the first example. (Solid Line: actual heading; and Dotted Line: desired heading command)

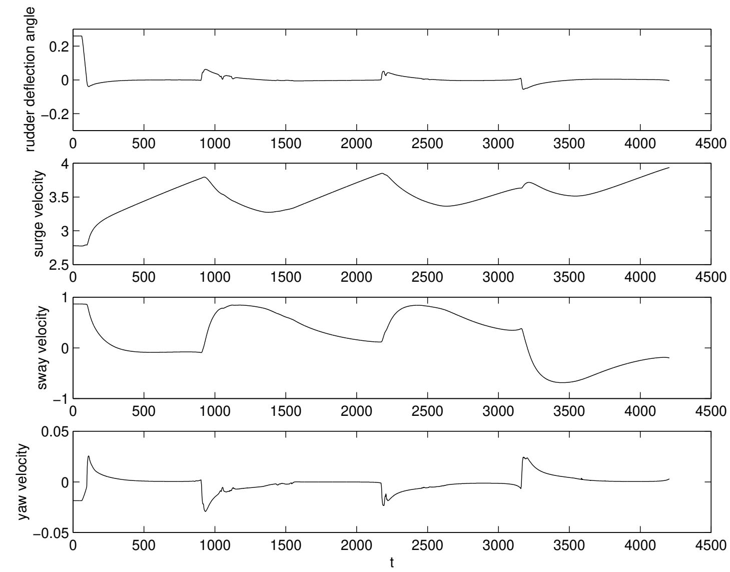

Figure 6: The evolution of surge, sway and yaw velocity and rudder deflection angle in the first example.

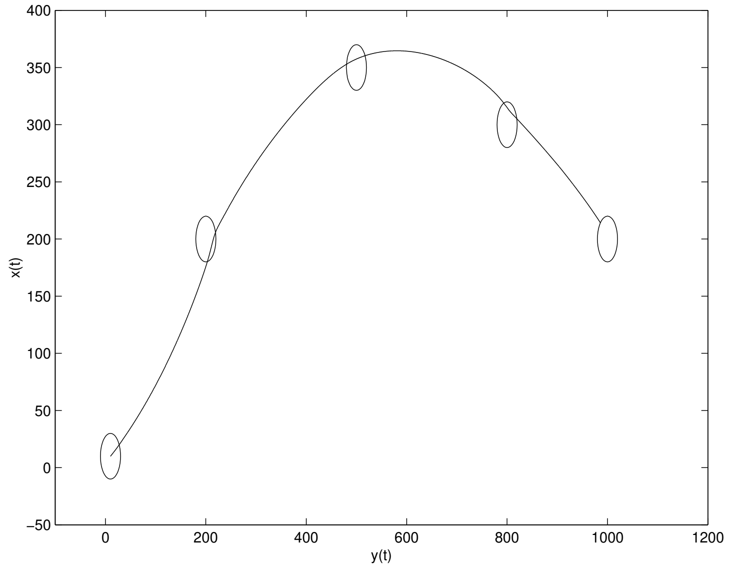

Figure 7: Simulated ESSO 190000 dwt tanker's trajectory in earth-fixed coordinate in the second example. (circle: way points used in path planning)

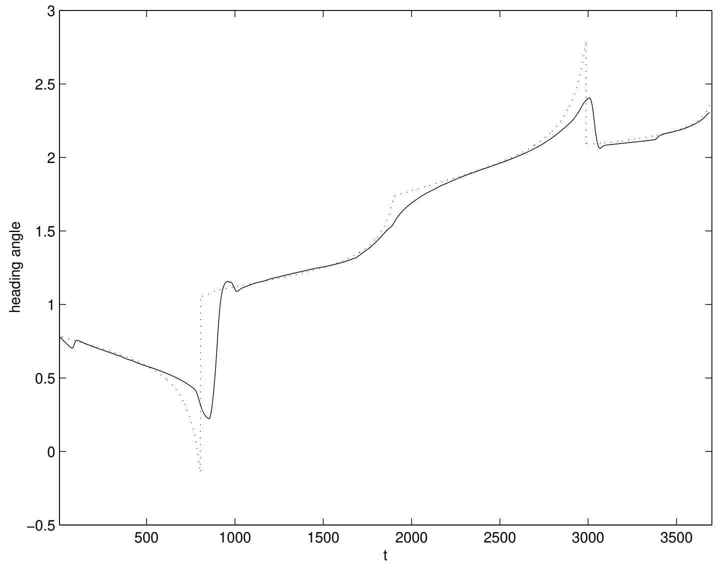

Figure 8: The performance of heading angle tracking in the second example. (Solid Line: actual heading; and Dotted Line: desired heading command)

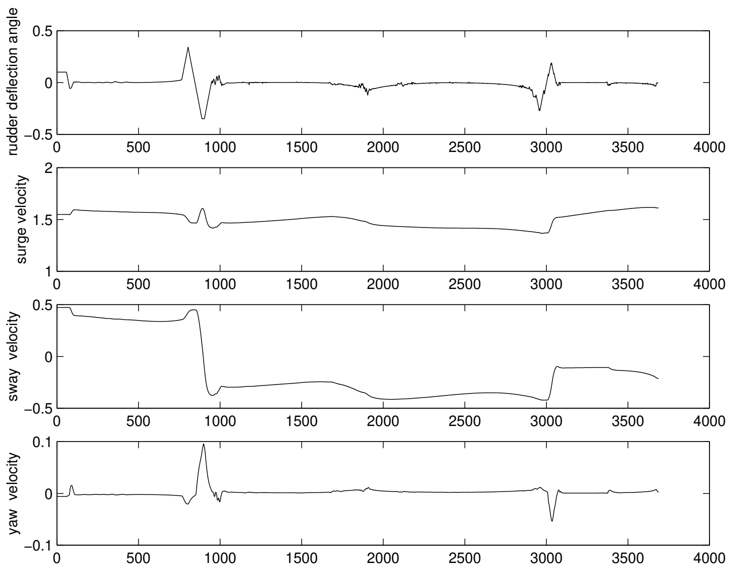

Figure 9: The evolution of surge, sway and yaw velocity and rudder deflection angle in the second example.

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