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A genetic algorithm based nonlinear guidance and control system for an uninhabited surface vehicle

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There is an increasing drive to develop uninhabited surface vehicles (USV) as cost effective solutions to a number of naval and civilian problems. In part, the resolution of these problems relies upon such vehicles possessing robust guidance and control (GC) systems. Furthermore, the vehicles need to be operated under tight performance specifications satisfying multiple constraints simultaneously. This requires vehicle nonlinearities and constraints to be explicitly considered in the controller design. Nonlinear model predictive control (NMPC) is well suited to satisfy these requirements. This paper reports the design of a novel GC system based on NMPC for use in a USV named *Springer* which is benchmarked against a linear proportional-integral-derivative counterpart. The NMPC combines a recurrent neural-network model and a genetic-algorithm-based optimiser. Common to the two GC systems is a waypoint line-of-sight (LOS) guidance subsystem. The control objective is to guide the vehicle through different waypoints stored in a mission planner. The performances of the guidance and control systems are evaluated and compared in simulation studies with and without appropriate disturbances. From the results presented, it is concluded that the GC system based on NMPC is more efficient and more capable to guide the vehicle through LOS waypoints particularly in the presence of disturbances.

AUTHORS' BIOGRAPHIES

Dr Sanjay K Sharma is a lecturer in the School of Marine Science and Engineering. Previously Sharma was employed as a Signal and Telecommunication Engineer for Indian Railways where he was involved with Route Relay and Solid State interlocking design projects. Prior to joining Plymouth University in 2004, he held a position as a Research Engineer in the Intelligent Systems and Control Research Group at Queen's University of Belfast. His main research activities include the application of soft computing techniques in optimisation, fault diagnosis and parallel computing for neural and local model network training, evolutionary approaches to multiple-modelling and control of non-linear systems, and multivariate statistical process control.

Prior to joining the Royal Navy, **Robert Sutton** served general engineering and student apprenticeships with Firth Cleveland Fastenings Limited, Pontypridd, UK, then as a research student at UWIST, Cardiff. On completion of his service in 1992 in the rank of Lieutenant Commander Royal Navy, he joined Plymouth University. Currently, Sutton is Professor of Control Systems Engineering in the School of Marine Science and Engineering. In addition, he is a member of the International Federation of Automatic Control Technical Committee on Marine Systems and the Society for Underwater Technology Underwater Robotics Group Committee.

INTRODUCTION

In his book *Sailing Alone Around The World*[1] which was published in 1900, Slocum cites an incident where a highly experienced shipmaster of that era served as a government expert witness in a famous maritime murder trial in Boston, USA, in which he stated that a particular sail ship could not hold her course long enough for the helmsman to leave the wheel of the vessel to cut the throat of its captain! Clearly since those days practical automatic marine control systems for ships have been and are being designed and developed to meet the needs of the marine industry which historically can be traced back to the work of both Minorski[2] and Sperry[3] in 1922. Although modern ship automatic systems are endowed with a high degree of control sophistication, they also possess manual override facilities in case of emergencies and unforeseen events. However, when functioning in a truly autonomous mode, the luxury of such facilities does not exist on board uninhabited surface vehicles (USVs). Thus USVs are totally reliant upon the integrity of their navigation, guidance and control (NGC) systems.

As previously reported[4], at Plymouth University the *Springer* USV has been built and continues to be evolved by the Marine and Industrial Dynamic Analysis Research Group. The USV being designed primarily for undertaking pollutant tracking, and environmental and hydrographical surveys in rivers, reservoirs, inland waterways and coastal waters, particularly where shallow waters prevail. In order for the vehicle to have such a multi-role capability, *Springer* requires robust, reliable, accurate and adaptable NGC systems.

The intention of this paper is to focus on the design of potential guidance and control (GC) systems for the *Springer* vehicle since candidate adaptive navigation systems have already been described.[4] Herein a nonlinear GC system based on NMPC is proposed, compared and gauged against a linear proportional-integral-derivative (PID) equivalent. A common guidance subsystem based on a waypoint line-of-sight (LOS) algorithm is coupled with each of the controllers. It is considered that the nonlinear GC system based on NMPC offers a novel contribution to the field of marine control system design.

NONLINEAR YAW DYNAMICS OF THE *SPRINGER* VEHICLE

Since full details of the *Springer's* hardware have been published in the *Journal of Marine Engineering and Technology*[4], only the nonlinear yaw dynamic model of *Springer* used in this study will be presented here. The model having been developed and reported recently.[5] Like all marine vessels the yaw dynamics of the *Springer* vehicle are nonlinear, therefore, it was not surprising to find in the previous study[5] that the most appropriate model to describe such behaviour was a recursive neural network (RNN). Thus a model was developed using a dataset recorded during full scale trials. A steady-state GA[6] was used to obtain the unknown parameters of the models which had a population of 20 chromosomes and a crossover probability of $p_c = 0.65$ and mutation probability of $p_m = 0.03$. The GA was run till a maximum of *5000* generations or MSE (mean-square-error) of less than $MSE <= 0.00001$ was achieved on normalised training data set. A parallel architecture network model was then tested on validation and test data to check its predictive capability. After trial and error, a parallel architecture network was obtained with four hidden nodes and represented in generic form as:

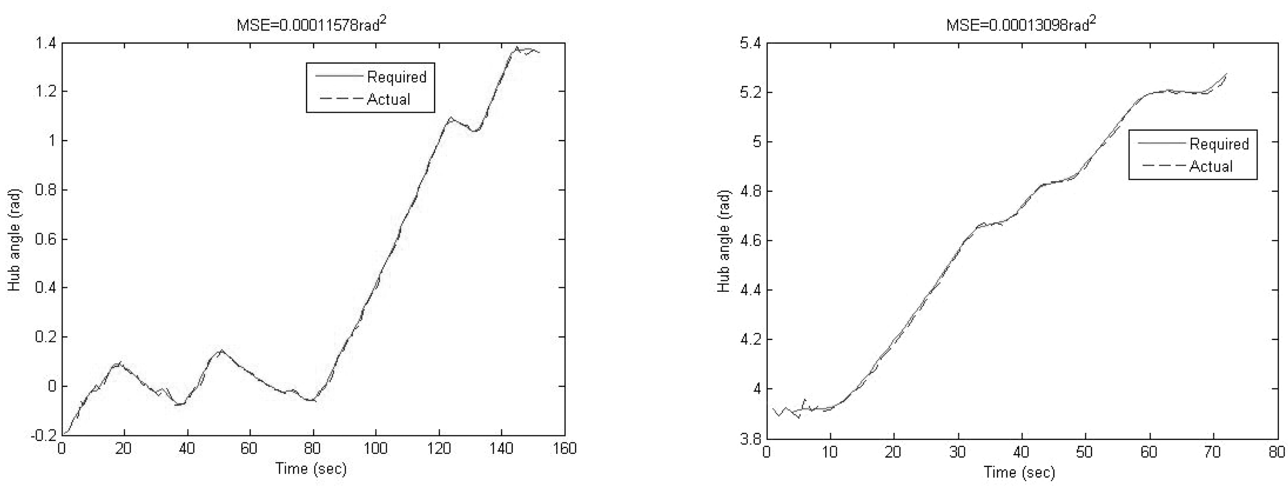
$$\hat{y}(t) = f_{NN}\left\{\begin{matrix} u(t-1), u(t-2), u(t-3), u(t-4), \\ \hat{y}(t-1), \hat{y}(t-2), \hat{y}(t-3), \hat{y}(t-4), \\ e(t-1), e(t-2), e(t-3), e(t-4) \end{matrix}\right\}$$

where

$$e(t) = y(t) - \hat{y}(t) \tag{1}$$

Figures 1a and 1b illustrate the predictive capability of the RNN model on validation and test data which produced mean-squared errors of $0.000115\ rad^2$ and $0.000130\ rad^2$ respectively.

Further details concerning the RNN can be found in Sharma and Sutton.[5]



(a) Validation

(b) Test data

Fig 1: Predictive capability of the RNN model on (a) validation and (b) test data

GUIDANCE AND CONTROL SYSTEM DESIGN

A GC system forms an integral component in effectively piloting a vehicle between desired locations. The guidance system yields suitable trajectories whereas the autopilot keeps the vessel on the desired path whilst rejecting any disturbances. It may not be possible to avoid the external influence altogether such as winds and currents. In such events, the navigation system with the aid of additional sensors such as an anemometer, provides suitable information to the guidance system. This will then generate optimal paths to reach the target which may or may not be in a straight line. A generic block diagram of a NGC system for a vehicle is depicted in Fig 2.

An obstacle detection and avoidance subsystem is also imperative for a fully autonomous vehicle operation and should be fully integrated within the system. However, as this subsystem has not yet been installed in the craft, it will not be discussed any further.

Springer's guidance subsystem utilises a waypoint LOS as discussed in following subsection.

Waypoint guidance by line-of-sight

LOS is the most widely used guidance strategy in missile systems today[7] and is gaining in popularity the marine field for both autonomous underwater vehicle[8,9] and USV[10,11] applications. Ideally, the design of GC systems should be fully integrated. Although this is not the case here, it is assumed that each autopilot has a sufficiently wide bandwidth to track the commands from the guidance subsystem.

With this particular approach, guidance is achieved between two points $[x(t_0), y(t_0)]$ and $[x(t_f), y(t_f)]$ by splitting the path between them into a number of waypoints $[x(k), y(k)]$ for $k = 1,2,......,N$ that are stored in the mission planner as shown in Fig 2.

Fig 3 shows such an example stored in the mission planner where $A\,[x(t_0), y(t_0)]$ is the starting point and $D\,[x(t_f), y(t_f)]$ is the final point. The vehicle follows different paths to cover intermediate waypoints in sequence starting from *A* to arriving finally at *D*. L_{AB} is the ideal path to arrive from waypoint *A* to point *B* but because of dynamics, inertia and disturbances, the vehicle will follow some other path to arrive at the next waypoint. In the figure a trajectory connecting between points *A* and *B′* shows such a path. θ_0 denotes the *circle of acceptance* for the waypoints. When the vehicle is within the circle of acceptance it is considered to have arrived at that waypoint and then travels towards the next. In the figure B', C' and D' are the points inside circle of acceptance where the vehicle arrives at waypoints *B*, *C* and *D* respectively. $L_{B'C}$ is the ideal path to travel from the waypoint *B* to *C* whereas $L_{C'D}$ from waypoint *C* to *D* and so on for other waypoints stored in the mission planner.

Determining when the vehicle reaches the vicinity of a waypoint is achieved by checking if the USV lies within a circle of acceptance with a radius θ_0 around the waypoint $[x(k), y(k)]$. If the vehicle's curent location $[x_d(t), y_d(t)]$ satisfies:

$$\theta^2 = \left[x(k) - x_d(t)\right]^2 + \left[y(k) - y_d(t)\right]^2 \le \theta_0^2 \qquad (2)$$

the next waypoint $[x(k+1), y(k+1)]$ is selected. In this case the circle of acceptance is taken as twice the length of *Springer*.

As the vehicle will move forward in the lateral plane, the LOS in terms of desired heading angle λ can be defined as:

$$\lambda = tan^{-1}\left[\frac{\left[y(k) - y_d(t)\right]}{x(k) - x_d(t)}\right] \qquad (3)$$

Where $[x_d(t), y_d(t)]$ is the current location of the vehicle. Care must be exercised to ensure the heading angle λ is in the proper quadrant.

If on the other hand, $d\theta/dt$ goes from negative to positive without the above condition being met, then the waypoint has not been reached. At this point, the guidance law must decide whether to keep the same destination waypoint and direct the vehicle to the circle or choose the next depending on mission planning decisions. In this study, the mission planner does not undertake any decision making tasks but simply supplies the waypoints. Also when performing mapping operations, such as during pollutant tracking, the vehicle will be guided through the water by the prevailing chemical signatures.

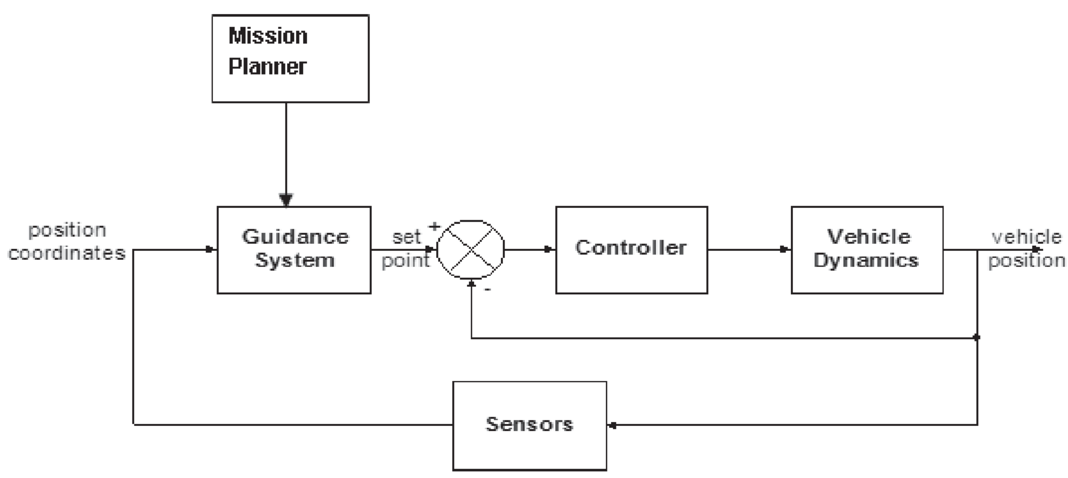


Fig 2: A generic block diagram of a navigation, guidance and control system for a vehicle

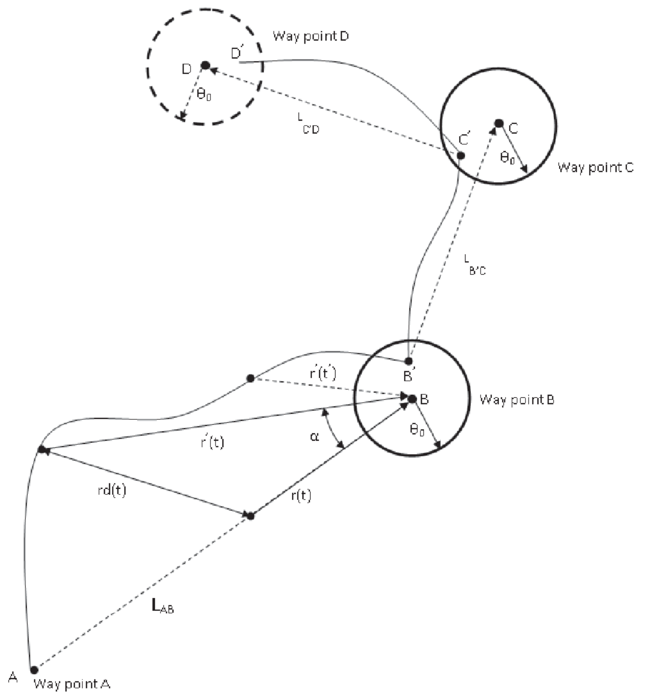


Fig 3: Waypoint guidance by line-of-sight

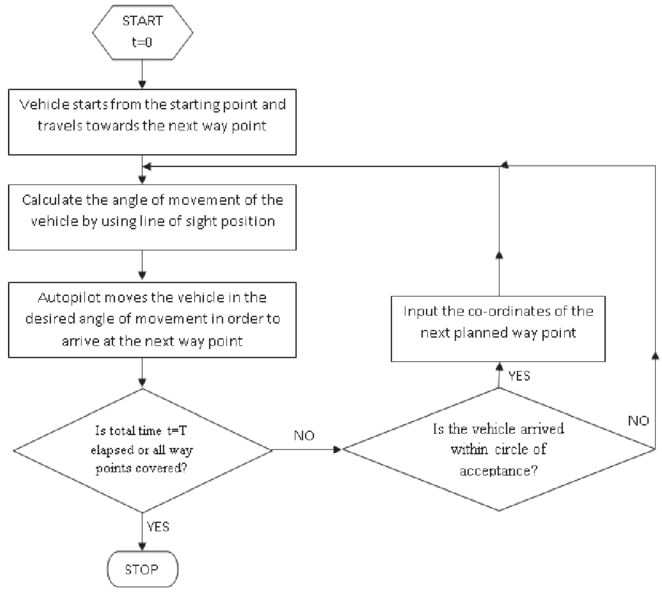


Fig 4: Flow diagram of the waypoints following by the *Springer* USV

As described earlier, the vehicle normally follows the path different from the ideal path between two waypoints and the deviation of the vehicle from the ideal path at time t is mathematically expressed as:

$$rd(t) = \sqrt{r^2(t) + r'^2(t) - 2r(t)r'(t)cos\alpha} \tag{4}$$

Where

$r(t)$ is the position of the vehicle in the ideal path from next waypoint at time t,

$r'(t)$ is the actual position of the vehicle from next way point at time t and

α is the angle between $r(t)$ and $r'(t)$.

If the vehicle follows the ideal path then the total deviation from the next waypoint will be zero and the vehicle will arrive in the shortest time; otherwise the vehicle will take longer time to arrive at the next waypoint. $r'(t')$ as shown in Fig 3 is the LOS distance of the vehicle at time t' from the desired next waypoint. The GC system guides the vehicle in a sequence of waypoints stored in the mission planner. The following steps as shown in Fig 4 are followed to guide the vehicle through different waypoints:

The GC systems operate the vehicle till all waypoints stored in the mission planner are either covered or the maximum allowable time to operate the vehicle has elapsed.

NONLINEAR MODEL PREDICTIVE CONTROL AUTOPILOT DESIGN

The concepts and techniques of model predictive control (MPC) have been developing for over three decades and are shown to be popular in many sectors such as the process and automotive industries, and in academia as illustrated in the text of Maciejowski[13], Rawlings and Mayne[14], Wang[15]and Allgower et al.[16] In addition, the marine control system design fraternity have also embraced this approach since it offers the advantage of being capable of enforcing various types of constraints on the plant process as exemplified by Naeem et al[17], Perez[18], Oh and Sun[19], Liu et al[20], Li and Sun[21], and Naeem et al.[22]

Although MPC is well established and has provided solutions to a number of problems, in its linear approach, however, it does have its limitations particularly when dealing with nonlinear plant. Many systems are, however, inherently nonlinear and operate under tight performance conditions with many satisfying constraints. These demands require systems to operate over a wide range of operating conditions and linear models are often not sufficient to describe the system dynamics adequately and hence nonlinear models must be used. This inadequacy of linear models is one of the motivations for the increasing interest in nonlinear model predictive control. Note that even so the system is linear in the MPC; the closed loop dynamics are nonlinear due to the presence of constraints. NMPC based on nonlinear models consider non-quadratic cost-functional and general nonlinear constraints. An excellent introductions to such techniques can be found in Tatjewski and Lawrynczuk[23] and Grune and Pannek.[24]

Principle of NMPC

At the heart of MPC are the model of the system and the concept of open-loop optimal feedback. The model is used to generate a prediction of future behaviour of the system. At each time step, past measurements and inputs are used to estimate the current state of the system. An optimisation problem is solved to determine an optimal open-loop policy from the present (estimated) state. Only the first input move is applied to the plant. At the subsequent time step, the system state is re-estimated using new measurements. The optimisation

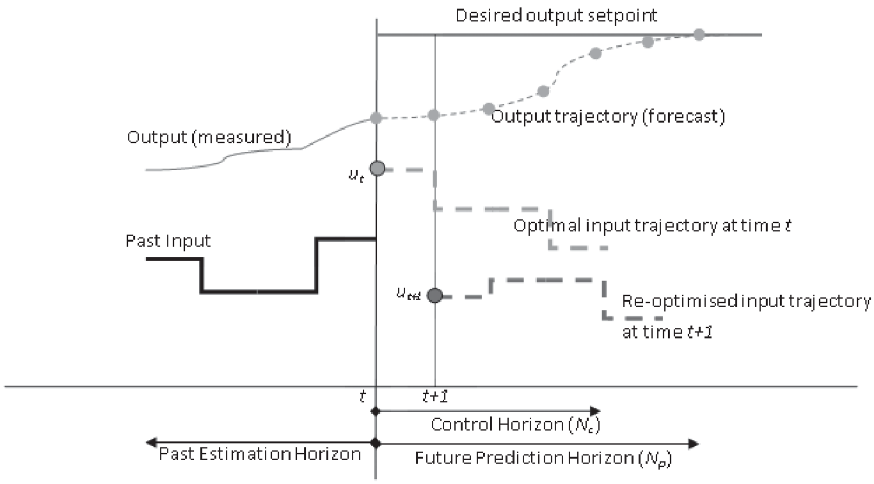


Fig 5: A conceptual picture of MPC. Only $(u_t|t)$ is injected into the plant at time t. At time $t + 1$, a new optimal trajectory is recomputed.

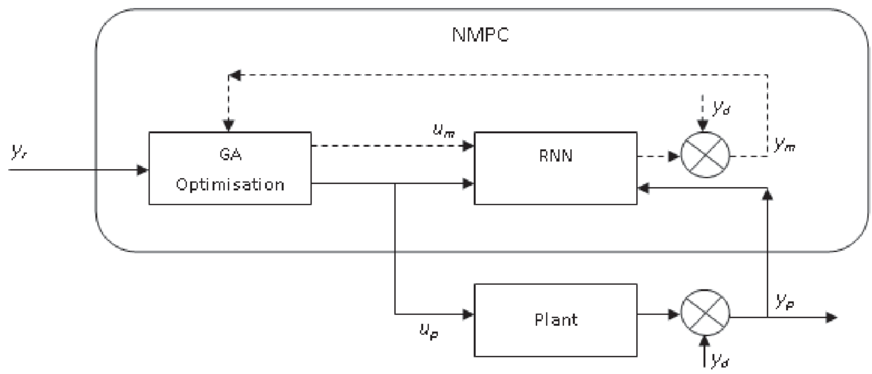


Fig 6: The model predictive control process

problem is resolved and the first input move to the plant is calculated again. Fig 5 presents the working scheme of a MPC. Here the controller predicts the dynamic behaviour of the system in the future over a prediction horizon N_p and determines the input over a control horizon ($N_c \leq N_p$) based on the measurements obtained at time t such that an open-loop performance objective J is minimised.

The block diagram in Fig 6 illustrates the nonlinear model predictive control process used in this paper. The NMPC consists of the RNN model and the GA optimisation block. The u_m variable is the tentative control signal, y_r is the desired response, y_d is the disturbances in the output, and y_m is the network model response. The GA optimisation block determines the values of u_m that minimise J, and then the optimal u_p is input to the plant.

The objective function J mathematically describes the control goal. In general, good tracking of the reference trajectory is required with low control energy consumption. The predictions are used by a numerical optimisation program to determine the control signal that minimises the following performance criterion over the specified horizon:

$$J = \sum_{i=N_0}^{N_p} \left[y_m(t+i) - y_r(t+i) \right]^2 + \rho \sum_{j=1}^{N_c} \left[u_m(t+j-1) - u_m(t+j-2) \right]^2 \quad (5)$$

where N_0, N_p and N_c define the horizons over which the tracking error and the control increments are evaluated. The ρ value determines the contribution that the sum of the squares of the control increments has on the performance index.

The key characteristics and properties of NMPC are:

- NMPC allows the direct use of nonlinear models for prediction.
- NMPC allows the explicit consideration of constraints.
- In NMPC a specified time domain performance criteria is minimised on-line.
- In NMPC the predicted behaviour is in general different from the closed loop behaviour.
- For the application of NMPC typically a real-time solution of an open-loop optimal control problem is necessary.
- To perform the prediction the system states must be measured or estimated.

Many of these properties can be seen as advantages as well as drawbacks of NMPC. The possibility to directly use a nonlinear model is advantageous if a good nonlinear model is available.

NMPC requires the repeated online solution of a nonlinear optimal control problem. In the case of linear MPC the online solution of the optimal control problem can be efficiently obtained by a quadratic program whereas NMPC requires a solution of a nonlinear program, which is in general complex and computationally expensive and is one of the key limiting factors for a successful practical application of NMPC. NMPC thus has been applied almost only to slow systems. For fast systems where the sampling time is considerably small, the existing NMPC algorithms cannot be used. Therefore, solving such a nonlinear optimisation problem efficiently and fast has attracted significant research interest in recent years.[25, 26, 27, 28]

The conventional iterative optimisation method requiring initial values based on gradient descent such as sequential quadratic programming (SQP) has been applied to NMPC.[29] These techniques can succumb to local minima and can lead to infeasible solution. Genetic algorithms (GAs) on the other hand is a global stochastic search technique that applies the concept of biological evolution to find an optimal solution in a search space and has proved to be efficient in solving complicated nonlinear optimisation problems compared to the more conventional optimisation techniques such as SQP. Furthermore the search range of the input variable constraints can easily be incorporated in the search space of a GA during optimisation, which makes it easier to handle the input constraint problem than other descent-based methods.

However the computational burden in the case of a GA is much heavier and increases exponentially with the increase of the horizon length of the NMPC making it difficult to implement in the conventional form thus only a few applications of GAs to nonlinear MPC[30, 31] are available in literatures. In this paper a modified NMPC algorithm based on a GA is proposed for the design of an autopilot for the *Springer* USV. In place of seeking the exact global solution for NMPC at every sampling time, suboptimal control sequences satisfying the constraints are implemented. The GA decreases the cost function within the sampling interval and the best chromosome represents the optimal control sequence at that time and so on. This requires less computational demands without deteriorating much to the control performance.[32]

GA optimised NMPC algorithm

Here a GA is used to obtain a sequence of optimal control signals. More specifically, a steady-state GA with floating point encoding and special genetic operators, including initialisation, mutation, crossover and termination, were used. The fitness function of the GA is derived from the objective function of the NMPC. Mutation and crossover operators are designed with built-in constraints in order not to violate the constraints of the control inputs. A convergence measure is introduced as a termination condition. The operation of the GA used here is explained as follows.

Encoding

Every individual chromosome $\{ o_i;\ i = 1, ..., Npop \}$ in the population of the GA determines a control trajectory: $\{ o_i = \left[u_i(t),\ u_i(t+1),\ ....,\ u_i(t+N_c-1) \right] \}$.

An individual chromosome o_i is described by a set of N_c floating point numbers which are selected within the admissible control interval $[\, u_{min}, u_{max} \,]$ and with absolute difference $\{ \Delta u_i(t+j);\ j = 1, ..., N_c - 1 \}$ not exceeding a prescribed value Δu_{max}. Here u_{min} and u_{max} are constraints limiting the range of the control signal whereas Δu_{max} limits the gradient of the control signal.

Initialisation

A suitable initialisation procedure at every sampling interval is required in order to obtain a better solution from the GA optimisation. Here the best solution of the last optimisation cycle with shift in the sequence of control signals as shown in Fig 7 is used to initialise the half of the chromosomes in a population and the rest of the chromosomes are randomly initialised with control sequence within the admissible constrained as defined in the encoding. Fig 7 shows the previous optimised control trajectory u_t as a chromosome with genes: $\{ gene_1, gene_2, ..., gene_{N_C-1} \}$ representing the optimal control sequence at time *t*. The optimal chromosome at $t+1$ is created by shifting the control sequence as shown in the figure. The last gene at $t+1$ is randomly added in u_{t+1} satisfying limiting constraints. Now the remaining half of the chromosomes in the population are created by randomly adding a floating number within range of $\pm\Delta u_{max}$ to each gene of u_{t+1}. The value of a gene is then adjusted to restrict it within the admissible control interval $[\, u_{min}, u_{max} \,]$.

Initialisation of the chromosomes within the close vicinity of the best solution of the previous optimisation cycle facilitates the optimisation procedures by the exploitation of previously accumulated knowledge. This strategy guarantees the quality of the current population and the stability of the NMPC algorithm. Whereas the rest of the population with randomly generated chromosomes add to the genetic diversity and are responsible for exploring the global search space in the solution.

Mutation

The mutation introduces new genetic variations into the population. The selected genes on the basis of mutation probability p_m are randomly replaced within admissible constraints of the control signals $[\, u_{min} \le u \le u_{max} \,]$ and $|\Delta u| \le |\Delta u_{max}|$.

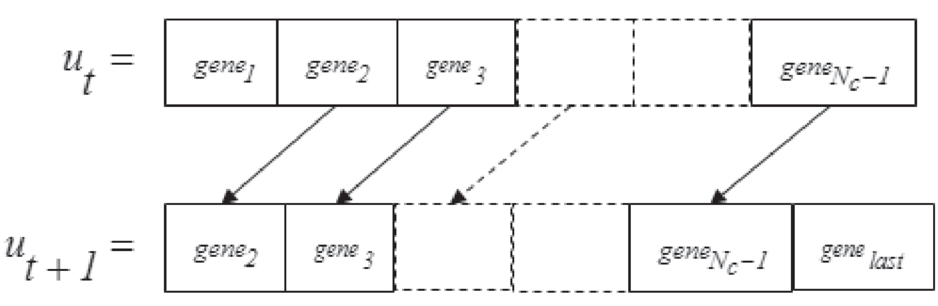


Fig 7: Chromosomes representing optimal control trajectories at time *t* and *t* + *1*

Crossover

The crossover is used to exchange genetic information between the two chromosomes of the population. In this paper, an arithmetic crossover between the two selected parents on the basis of crossover probability p_c is used to produce two offspring. This procedure maintains the control signals within the admissible constraints.

Termination conditions

This determines when the GA optimisation loop should be stopped and first control input from the best chromosome is applied to the plant. Judicious selection of the termination criteria of the GA is the key factor in reducing the computation burden in the design of the suboptimal NMPC algorithm. Here the GA was run till 90% of the sampling interval is either elapsed or evolution converges whichever is earlier. This insures that at every sampling interval, a feasible control signal is always available for the vehicle.

Fitness value and selection

The fitness value of each chromosome is defined as $1/(J+1)$ and the best chromosomes from the current parent and children are selected for the next generation and rest are discarded to keep the number of chromosomes in a population constant.

PROPORTIONAL-INTEGRAL-DERIVATIVE AUTOPILOT DESIGN

A continuous-time PID control law is described by

$$u(t) = k_p e(t) + k_d \dot{e}(t) + k_I \int e dt \tag{6}$$

where k_p, k_d and k_I are the proportional, differential and the integral gains respectively, u is the control action and e is the error. The equivalent PID controller in discrete form is

$$\begin{aligned} u(k) = u(k-1) + k_p[e(k) - e(k-1)] + \\ k_d[e(k) - 2e(k-1) + e(k-2)] + T_s k_I e(k) \end{aligned} \tag{7}$$

where k is the sample number and T_s is the sampling interval.

A GA with a population of 20 chromosomes and a crossover probability of $p_c = 0.65$ and mutation probability of $p_m = 0.03$ was run for a maximum of *3000* generations to obtain the optimal parameters k_p, k_d and k_I for the PID autopilot. For comparison, the same performance criterion and simulation setup was be used as previously to test the effectiveness of the PID autopilot. In NMPC the constraints on the controller signal can be easily accommodated in the design but in case of a PID, a saturation unit is required to limit the controller efforts within an admissible range of u_{min} and u_{max}.

SIMULATION RESULTS AND DISCUSSION

In order to make quantitative comparisons between the two GC designs, the average deviation from the ideal path ($\overline{rd}$) and the average equivalent controller energy ($\overline{CE_u}$) were used. These may be expressed as:

$$\overline{rd} = \frac{\sum_{t=0}^{T} rd(t)}{T} \tag{8}$$

and

$$\overline{CE_u} = \frac{\sum_{t=0}^{T} [u_c(t)/60]^2}{T} \tag{9}$$

Where T is either the maximum allowable time for a vehicle to operate or the total time elapsed to cover all waypoints in the mission planner, and $u_c(t)$ is the controller effort at time t in *rpm*.

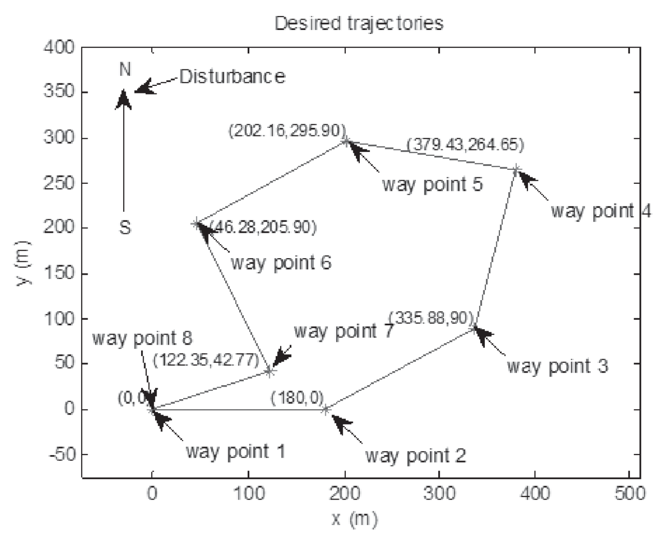
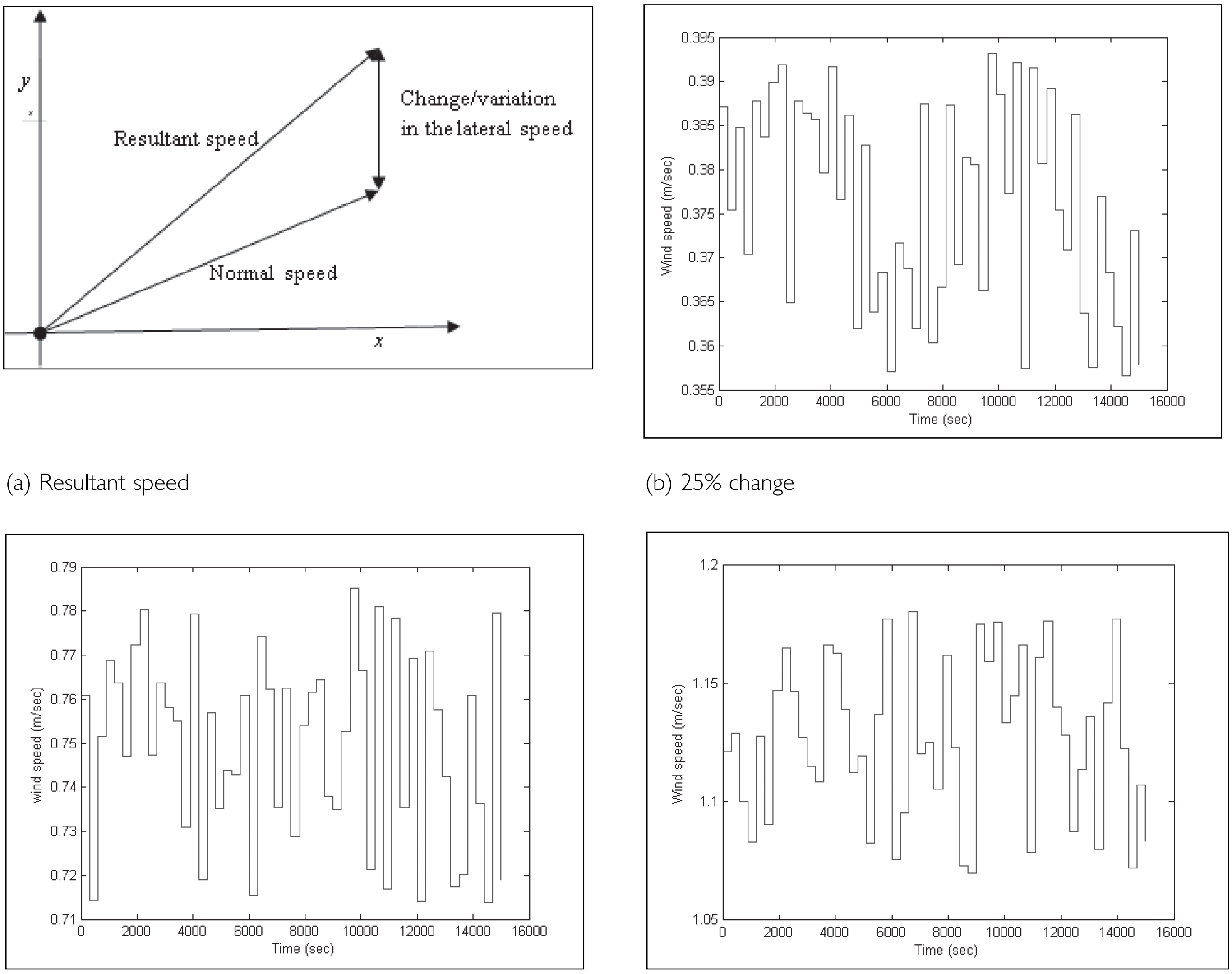


Fig 8: *x-y* co-ordinates of the waypoints stored in the mission planner



(a) Resultant speed

(b) 25% change

(c) 50% change

(d) 75% change

Fig 9: Random variation/change in lateral speed of the vehicle

A large value of $\overline{rd}$ indicates that the vehicle has deviated more from the ideal path and taken a longer time to travel or cover the way points.

Springer travels at constant speed of three knots (1.5m/s) and weighs 600kg. For this simulation study, different sea conditions which change the lateral speed of the vehicle will be considered to test the viability of the GC systems. The changes/variations in the lateral speed of the vehicle will be caused by random disturbances/sea-conditions running from the south in a northerly direction. The variation/change in lateral speed of the vehicle owing to various sea-state conditions were around 25%, 50% and 75% of the normal speed. The variations/changes were assumed constant for five minute periods and spanned the whole planned mission. The simulated trajectory considered in such a way that it follows the close path covering all directions. The maximum allowable simulation time for *Springer* to operate in a GC mode is considered four hours (14400s) in this paper. *Springer* can be operated for maximum of eight hours in a fully battery charged mode. If the vehicle covers all desired way points before the maximum allowable time then the simulation stops otherwise the GC system is allowed to guide the vehicle for maximum allowable operating time of four hours.

Fig 8 shows *x-y* co-ordinates of the waypoints stored in the mission planner for the simulation studies. The vehicle starts from waypoint 1 and then travels through waypoints 2, 3, 4, 5, 6 and 7 in sequence to arrive finally at waypoint 8 completing a closed path. The ideal paths to be followed will be straight line connecting the two way points. Fig 9a shows the effect in the normal speed of the vehicle because of change/variation in the lateral speed. The resultant speed of the vehicle as shown in the figure is more than the normal speed and also changes the course of direction and thus represents a challenging task for a GC system to guide the vehicle through different waypoints. Figs 9b, 9c and 9d show the random variation/change in of 25%, 50% and 75% in the lateral speed of the vehicle.

In the study, several predictive horizons were heuristically changed to investigate the optimal predictive control strategy. It was observed that too short a prediction horizon

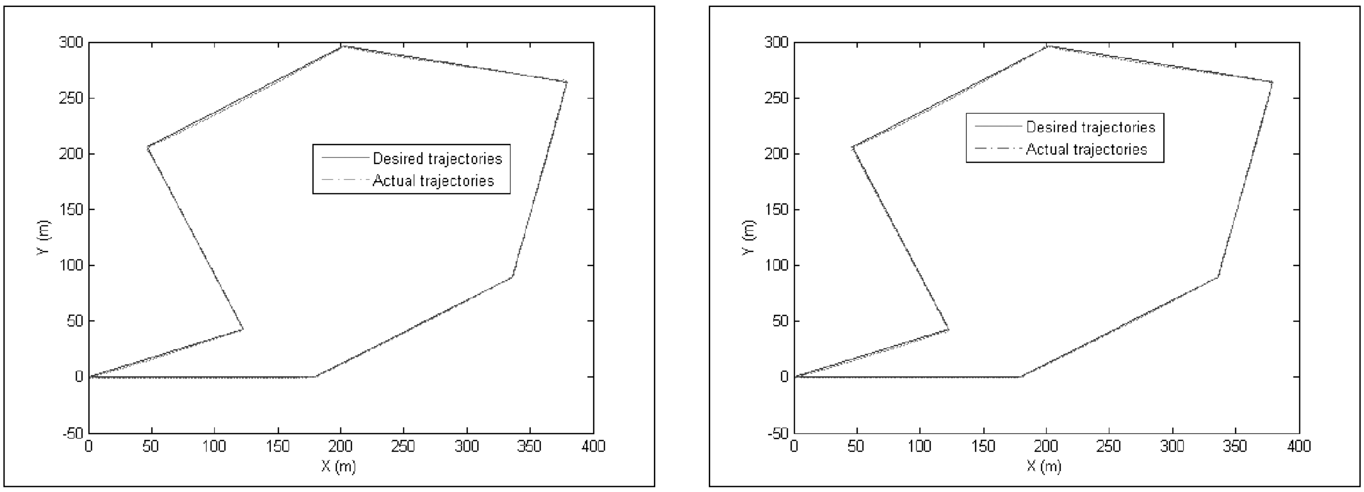
($N_p = 2$) provided an intensively oscillatory prediction with a large root mean square (RMS) prediction error. NMPC with horizon ($N_p = 6$) resulted in near-optimal control and increasing the prediction horizon above $N_p = 6$ added only a slight improvement in RMS error but with more increased computational time. A prediction horizon $N_p = 6$ and control horizon $N_c = 3$ were found appropriate for this application and were selected for the simulation. The simulations were run using Visual C++ on a desktop PC with Intel Core 2 CPU 1.86GHz processor and 1.97Gb of RAM. The maximum simulation time was four hours and the sampling time is $T_s = 1.0s$. Mutation probability is $p_m = 0.03$ and crossover probability is $p_c = 0.65$, population size is *20*, maximum time to run a GA generation is 0.90*s*, and the fitness value is $1/(J+1)$. The range of controller input and gradient of the controller input were {u_{min}, u_{max}}={*−132*, *132*} and $|\Delta u_{max}| \leq 20$ respectively. The weighting parameter ρ for performance objective was selected as *0.01*.

Figs 10a and 10b illustrate the waypoints followed by the *Springer* USV under the PID and NMPC GC schemes with no variation/change in the lateral speed. The *circle of acceptance* is *8.0m* in all cases. Both schemes were able to guide the *Springer* vehicle through the waypoints stored in the mission planner.

Figs 11a and 11b indicate the distance of the *Springer* from the next waypoint and the time taken to arrive at different waypoints. It is clear from the graphs that both GC systems guided the vehicle through all seven waypoints of the mission planner however overall time taken by NMPC GC system was slightly better than that of the PID version.

Figs 12a and 12b show the amount of deviation of the vehicle from the ideal path before arriving at the next waypoints. As indicated later in Table 1, the NMPC GC system outperformed the PID GC system in terms less mean average deviation ($\overline{rd}$).

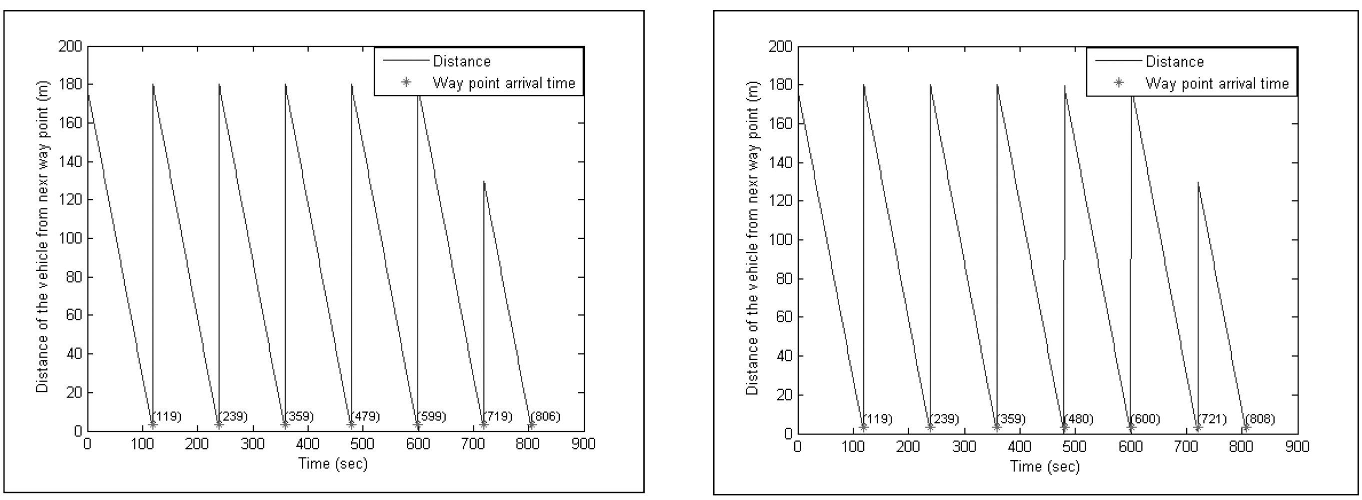
Figures 13a and 13b show the average equivalent energy ($\overline{CE_u}$) consumed by each system while guiding the vehicle



(a) NMPC GC system

(b) PID GC system

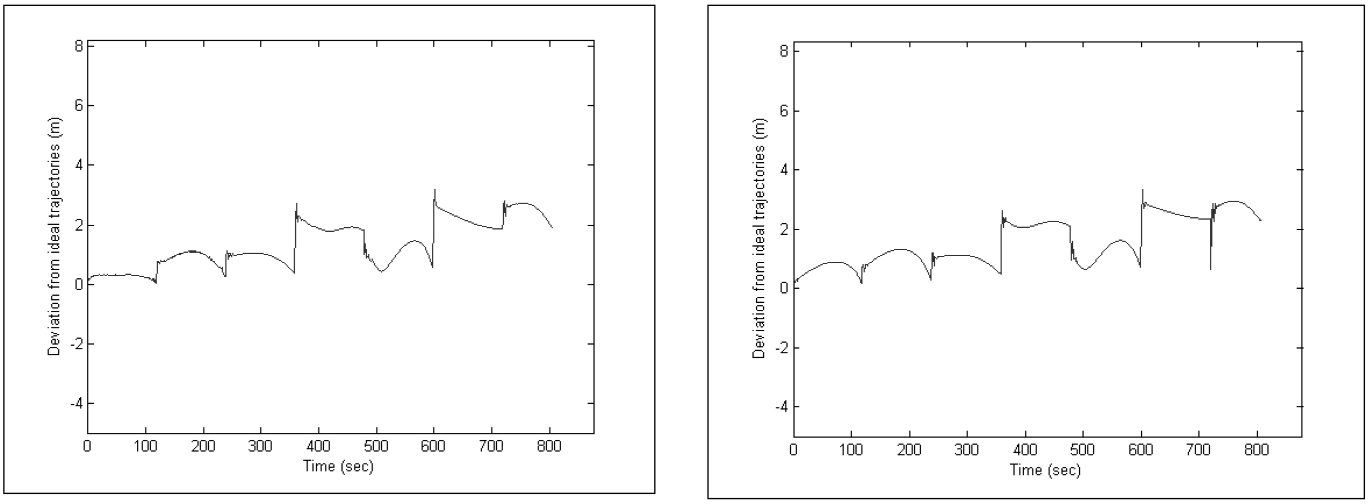
Fig 10: Waypoints followed by the GC systems



(a) NMPC GC system

(b) PID GC system

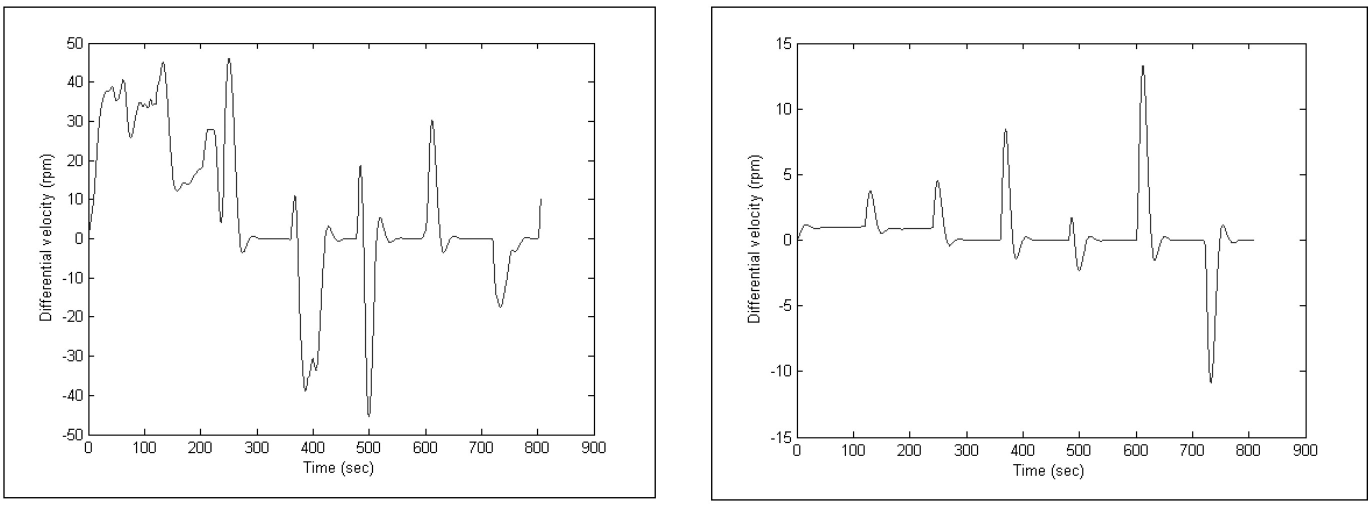
Fig 11: Distance of the vehicle from next waypoint and total time taken to operate



(a) NMPC GC system

(b) PID GC system

Fig 12: Mean average deviation of the waypoints



(a) NMPC GC system

(b) PID GC system

Fig 13: Average equivalent energy consumed by the GC systems

through the different waypoints. The NMPC based system was a more efficient and used less energy (see Table 1) to track the waypoints compared to the PID version.

Table 1 shows the comparative results of the effectiveness of the two autopilot schemes under different operating conditions. It was observed that the PID scheme was unable to move vehicle through waypoints and totally deviated from the desired path for external disturbances causing change/variation in the lateral speed of 75% or more whereas the NMPC version successfully guided the vehicle. In all cases, NMPC GC system was able to restrict the vehicle deviating from the desired waypoints and also consumed less energy thus proving to be an efficient system for the USV compared to its PID variant.

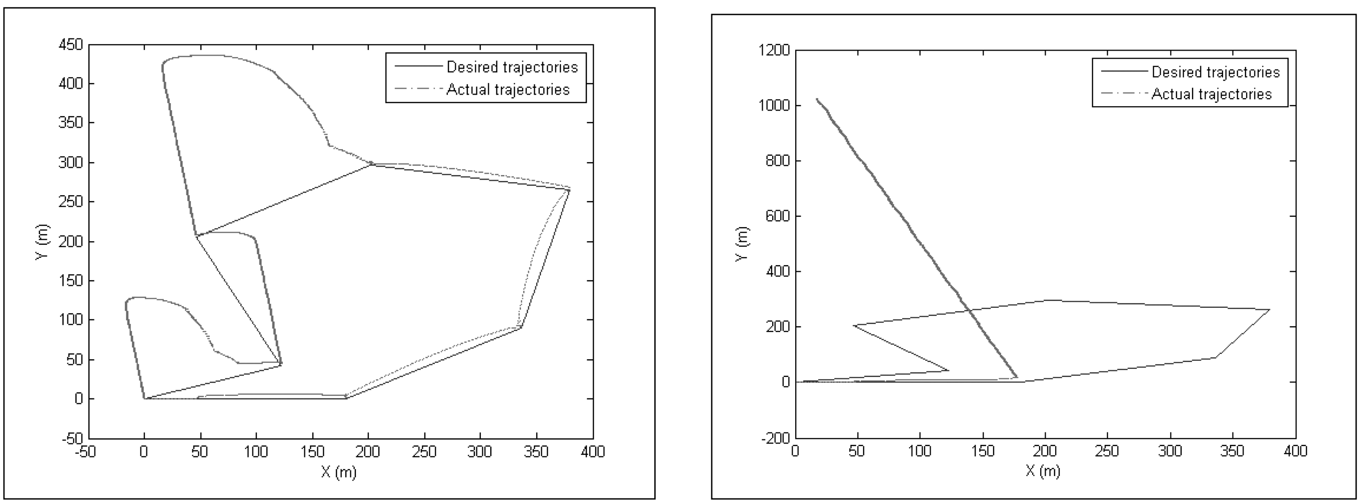
Figs 14a and 14b show the waypoints following results with 75% variation/change in lateral speed of the vehicle. It can clearly be seen that NMPC GC system was able to guide the vehicle through all waypoints whereas PID scheme failed to keep the vehicle on track. In the case of the NMPC based system, the vehicle had to change the course of direction to travel from waypoint 5 to 6 and deviated first in the direction of external disturbance and then arrived at waypoint 6. Similar deviations can also be observed while travelling from waypoint 6 to 7 and finally from 7 to 8. This confirms that NMPC GC system is significantly better than conventional PID GC system since it was able to guide the vehicle through the desired sequence of waypoints.

CONCLUDING REMARKS

A novel nonlinear GC system based on NMPC and a waypoint line-of-sight guidance strategy has been presented and benchmarked against another that includes a PID control algorithm in its architecture. Guidance and control of a USV in the presence of disturbances is a challenging problem. Hence in the study herein, a disturbance was applied which simulated a random sea condition disturbance that run from the south to the north to produce a lateral impact

PID GC scheme				
Disturbance *(m/sec)*	**Missed way points**	**Total time travelled (T)** *(sec)*	$\overline{CE_u}$ *(rps)²/sec*	$\overline{rd}$ *(m/sec)*
No disturbance	None	789	0.0219	1.5525
25% disturbance	None	1119	1.7008	30.6556
50% disturbance	None	5112	3.0051	82.8806
75% disturbance	All	14400	3.7505	1079.6835
NMPC GC scheme				
No disturbance	None	788	0.0163	1.4825
25% disturbance	None	1050	0.4188	24.9719
50% disturbance	None	2797	1.2848	59.2168
75% disturbance	None	13549	1.6289	96.0856

Table 1: Results of the two GC systems under different operating conditions



(a) NMPC GC system

(b) PID GC system

Fig 14: Waypoints followed by the GC systems

on the *Springer* vehicle of varying degrees of severity whilst transiting around the waypoints. From the results, the NMPC based GC system is shown to outperform its PID alternative. Thus the nonlinear GC system is considered as a suitable candidate for application in full scale real-time trials in the near future.

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