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An Intelligent Integrated Navigation and Control Solution for an Unmanned Surface Craft

Wasif Naeem[†], Tao Xu[‡] and Robert Sutton^{*}

[†]*Intelligent Systems and Control Group
School of Electronics, Electrical Engineering and Computer Science
Queen's University Belfast, Belfast, UK
w.naeem@qub.ac.uk*

[‡]*Department of Engineering
University of Durham, Durham, UK
tao.xu2@durham.ac.uk*

^{*}*Marine and Industrial Dynamic Analysis Research group
School of Engineering
University of Plymouth, Plymouth, UK
r.sutton@plymouth.ac.uk*

Abstract — An adaptive navigation and control algorithm is presented in this paper based on fuzzy logic and optimal control techniques and applied on an unmanned surface vehicle platform. The navigation system consists of an extended Kalman filter with time-varying parameters. Whilst the autopilots include a fuzzy logic based linear quadratic Gaussian controller and a model predictive controller optimized using a genetic algorithm. Both the controllers use the output of the adaptive navigation system as their feedback and therefore creates an integrated system. A multiple waypoint following scenario is considered and tested in real time. Experimental results are shown that demonstrate the efficacy of the proposed system.

Keywords — guidance, unmanned surface vehicles, model predictive control, Kalman filter, LQG, covariance matrices

I INTRODUCTION

Unmanned marine vehicles have found a widespread interest in diverse missions ranging from subsea pipeline inspection, rescue operations, mines clearing, surveillance and environmental monitoring tasks such as oil spills and pollutant tracking. Autonomous underwater vehicles (AUVs) are largely popular because of their covertness and subsea operation capabilities which may be too difficult or dangerous for a human diver to conduct. On the other hand, unmanned surface vehicles (USVs) are platforms that could be used in conjunction with underwater vehicles to provide them with guidance signals in the form of GPS fixes or other navigation solutions. Surface craft are also very versatile in

dealing with missions such as tracking the extent of an oil spill, coast patrolling, surveillance to name but a few.

In this paper, the main focus is on the formulation of the navigation, guidance and control (NGC) system of a USV named *Springer* which has been designed and developed to monitor the environment. A waypoint guidance system [1] based on line-of-sight (LOS) is normally adopted for a simple point-to-point manoeuvre. However, for environmental monitoring tasks, for instance to locate the source of contamination, the guidance system could be replaced by chemical signatures found in the water. An onboard environmental monitoring unit e.g. [2] manufactured by YSI Incorporated measures various parameters such as

turbidity, salinity and dissolved oxygen and guides the vehicle to the source of the pollutant based on chemical concentration.

A plethora of NGC solutions have been reported in the literature developed for unmanned marine craft. For instance, an H2 controller for coastline following has been simulated on a full nonlinear model of *Delfimx* vehicle [3]. In [4], a simple PID controller together with an extended Kalman filter is employed for tasks such as heading and speed control on the *Charlie* USV using only a GPS and a compass. SSC San Diego demonstrated the direct transfer of technology developed originally for autonomous ground vehicles [5]. A PID controller with a standard Kalman filter is employed for way-point following tasks. The covariance matrices of the Kalman filter are dynamically adjusted so that the influence of GPS heading on the Kalman filter output at very low speeds is reduced. Herein, advanced control strategies such as a fuzzy-tuned linear quadratic Gaussian (LQG) and a genetic algorithm-based model predictive (GA-MPC) controllers are implemented on the *Springer* USV. An intelligent multisensor data fusion (MSDF) algorithm based on a fuzzy tuning mechanism is integrated with the aforementioned controllers and tested in real time.

The organisation of the paper is as follows. Section II details *Springer* USV development including its dynamics and modelling. The MSDF based navigation solution employed herein is briefly explicated in section III. Whilst in section IV, the optimal control strategies applied to the vehicle are presented. Section V outlines experimental results where a performance comparison is made of the aforementioned control strategies. Concluding remarks and future work is highlighted in section VI.

II *Springer* USV

The *Springer* USV depicted in Fig. 1 is a twin-hull catamaran shaped vessel developed for undertaking environmental monitoring tasks. Issues such as measuring the extent of the oil spill and tracking pollutants are the types of missions envisaged for *Springer*. In general, the vessel can be used for tasks that are too risky or dangerous for human divers to perform. *Springer* is 4 metres in length, 2.3 metres wide and weighing approximately 600 kg. The onboard electronics including computers and navigation sensors are contained within pelicanes which are secured in a bay area between the crossbeams. The onboard computers are linked through an ad-hoc wireless network which is also connected to a laptop on a support boat. This link is normally used for defining a mission, changing mission parameters or even intervention in the case of erroneous behaviour. Since there is no obstacle detection and avoidance system currently onboard

the vehicle, this intervention capability has a primary significance.

Fig. 1: *Springer* USV during trials at Roadford Reservoir, Devon

The onboard sensor-suite is shown in Fig. 2 depicting the usual sensors such as a GPS, electronic compasses and a depth and speed sensor. In addition to these units, a YSI environmental monitoring sonde [2] has been installed which can take a variety of measurements including turbidity, salinity and dissolved oxygen from a water sample. This can be used to follow a plume of say saline water in fresh water. The redundancy in the compasses is to test the MSDF algorithm. See section III for more details. Heading data from the GPS is also fused with the bearings obtained from the three compasses. For the interested reader, additional details of *Springer* hardware can be found in [6]. The next subsection explicates the basic dynamics of *Springer*.

Fig. 2: *Springer* USV onboard sensor suite

a) *Springer Dynamics and Modelling*

The *Springer* USV has a differential steering mechanism. A difference between the two propeller revolution rates causes the vessel to vary its heading

angle. A six degrees of freedom rigid body equations of motion can be utilised for mathematical modelling of a surface vehicle by ignoring the pitch and roll variations and also the motion along the z-axis (depth). The reduced equations of motion are given by

$$m [\dot{u} - vr - x_G(r^2) - y_G\dot{r}] = X \quad (1)$$

$$m [\dot{v} + ur - y_G(r^2 + p^2)] = Y \quad (2)$$

$$\dot{p}I_x + prI_{xy} + my_G(vp) = K \quad (3)$$

$$rpI_x - \dot{p}I_{xy} - mx_G(vp) = M \quad (4)$$

By coinciding the centre of gravity with the origin, the above equations can be further simplified. See Appendix A for a nomenclature of the variables used.

To model *Springer*, system identification techniques have been employed to formulate a linear parametric model. This requires the availability of input output data from test trials. A simple multi-input, single-output model is the most obvious choice. However, using the following set of equations, the model dimensions can be reduced to single-input, single output only

$$n_c = \frac{n_1 + n_2}{2} \quad (5)$$

$$n_d = \frac{n_1 - n_2}{2} \quad (6)$$

where n_c and n_d are the common mode and differential mode thruster velocities respectively in revolutions per minute (rpm). n_1 and n_2 being the individual thrusters revolution rates. A value of $n_d = 0$ therefore represents the vehicle traversing in a straight line. Based on the above equations, the input and output variables of the model are n_d and heading angle respectively. A decentralised PID controller is tuned to maintain the thrusters' speed as commanded by the autopilot by providing feedback from a shaft speed encoder.

The following sections describe the NGC development of the *Springer* vehicle.

III NAVIGATION SYSTEM

Navigation is defined as measuring the states (position, velocity etc.) of a mobile or stationary vehicle relative to some known reference frame and to process this information to determine and carry out the manoeuvres between the desired locations. Autonomous navigation allows an unmanned vehicle to move along a desired path purposefully without human intervention [7]. This entails the use of a variety of sensors that are able to measure all the vital states of the system. This would further require the development of algorithms to combine or fuse data from different sources to provide one

meaningful output. Hence, the term MSDF is often used.

By default, the MSDF methods provide fault tolerance capability [8]. Techniques have been devised for problems such as noise on the data, temporary sensor fault or transients and sensor fatality. In the latter case, the faulty sensor may be isolated from the list of active sensors. Fuzzy logic adaptive estimation techniques have proved to be very useful in dealing with aforementioned scenarios [9]. By using a FLA-MSDF mechanism, the sensor measurements are represented in the fusion process by allowing each proposition to be assigned a real number to indicate its degree of truth.

To realise a fault tolerant navigation system for the *Springer* vehicle, a modified FLA federated Kalman filter (FKF)-based MSDF architecture proposed in [10] and depicted in Fig. 3 is considered. The FLA-FKF algorithm consists of n local filters and a single master filter where n is the number of sensors. The data from all the sensors is processed in two stages. The first stage constitutes of all n local filters processing the data in parallel according to the difference between the actual and theoretical values of the covariance to yield the best possible estimate. Next, the measurement noise covariance matrix is manipulated using fuzzy logic in order to reduce the sensor fault influence. The master filter then calculates feedback factors $\beta(i)$ for each local filter whose value depends on the accuracy of the output of each local Kalman filter estimate. The most accurate local filter receives the highest feedback from the master filter and hence makes the biggest contribution in the global estimation process. The master filter then fuses all local filters' estimates to generate a global output which can be used as a feedback to the autopilot.

Fig. 3: A fuzzy logic based MSDF strategy.

IV AUTOPILOTS DESIGN

An adaptive LQG based on fuzzy logic and an evolutionary-algorithm based MPC are primarily

chosen to implement in the *Springer* vehicle. LQG is well known for its robustness properties whereas the MPC has been selected due to its success in the process industry. The fuzzy-LQG autopilot was implemented and reported in a paper earlier [11]. However, raw data was used to provide feedback in the actual implementation. Moreover, the results reported consist of a two waypoint scenario and a comparison was made with the standard LQG.

The fuzzy-LQG controller is designed by adapting the measurement noise covariance matrix online based on actual sensor data. On the other hand, the GA-MPC autopilot uses an online GA to optimize the objective function based on a model of the vehicle obtained using system identification techniques. Each controller design is now briefly described in the following subsections.

a) Fuzzy LQG

The LQG controller requires four tuning parameters; state weighting and control weighting matrices and process noise and measurement noise covariance matrices. The weighting matrices are rather straightforward to adjust, however, the tuning of the covariance matrices is tedious and time consuming. To automate this process, a fuzzy logic tuning mechanism is developed which adjusts the parameters based on actual sensor data characteristics. This is equivalent to developing an adaptive Kalman filter since it is an integral part of the LQG controller (see section III for local Kalman filter design). A block diagram of the approach is depicted in Fig. 4. For the interested reader, the analytical details of the controller can be found in [12].

Fig. 4: Fuzzy LQG controller block diagram.

b) GA-MPC

The MPC controller originally developed by Richalet *et al.* [13] from Shell Oil uses a model of the plant as an integral part of the controller. The algorithm is based on prediction of the output up to a certain time called the prediction horizon. The controller optimizes an objective function given by equation 7 over the prediction horizon and computes control moves online based on the output of

the integral plant model over that time. Only the first control input is then applied to the physical process and the same procedure is iterated for the next sampling time. The regressors in the model are updated at every sampling interval by actual plant measurements.

$$J = \sum_{i=1}^{H_p} e(k+i)^T \mathbf{Q} e(k+i) + \sum_{j=1}^{H_c} \Delta u(k+i)^T \mathbf{R} \Delta u(k+i) \quad (7)$$

where e is the error between the actual and model outputs. $\mathbf{Q}$ and $\mathbf{R}$ represents weighting matrices whereas H_p and H_c are the prediction and control horizons respectively.

Generally, quadratic programming is used to optimize the objective function in an MPC framework for a linear model. However, a GA is used here to generalise the MPC for nonlinear models. This has been demonstrated earlier in [12] where a nonlinear neural network based model of an AUV is integrated in the MPC control strategy. More details of the algorithm can be found in [14] and the block diagram of the controller is depicted in Fig. 5.

Fig. 5: GA-MPC controller block diagram.

V EXPERIMENTAL RESULTS

The strategies presented in this paper have been implemented in the *Springer* USV as an intelligent integrated navigation, guidance and control solution and tested for a waypoint following guidance scenario.

Two onboard computers were responsible for executing the control code and navigation algorithms including data acquisition. The sampling time of the model is 1 second which is adequate given the slow dynamics of the vehicle (approximately 3 knots forward speed). The guidance and control code was running in Matlab whereas data acquisition and fuzzy-MSDF calculations were carried out on a Labview platform. Four waypoints

were selected which were placed at a distance of approximately 200 metres from each other. A circle of acceptance (COA) of radius 10 metres was assumed around each waypoint. If the vehicle reaches within the COA, the guidance system raises a flag and the next waypoint is selected. For visual confirmation of target acquisition, GPS coordinates of the buoys, already present on the lake, were determined and programmed into the mission control software.

Fig. 6 depicts *Springer's* trajectory for all the aforementioned controller types. By comparing the fuzzy LQG with its standard counterpart, its performance in terms of accuracy and speed of response is superior. On the other hand, the GA-MPC has a sluggish and poor response. Although the vehicle did manage to arrive at all the waypoints, the trajectory taken is far from optimal. Please note that a mild south-easterly wind was blowing causing the vehicle to sway towards the starboard side evident in all the trajectories.

The controllers' outputs, n_d are compared in Fig. 7 where both the LQG controllers generate similar control efforts. The fuzzy-LQG saturates slightly longer for each manoeuvre causing the vehicle to respond faster. The GA-MPC output seems very restricted which could be due to excessive weighting of the n_d variable in the objective function. In addition, it is noisy and not consistent in contrast with the LQG output which can be possibly linked to randomness inherited because of the use of GA.

Fig. 6: Performance comparison of LQG and MPC control strategies for a waypoint following scenario.

VI CONCLUSIONS

This paper presents new results of the application of an advanced navigation and control algorithm to an unmanned surface craft. Trials data shows

Fig. 7: Comparison of the manipulated inputs generated by the controllers in real time.

promising performance of the controllers and navigation algorithm in terms of speed of response and accuracy. Although the GA-MPC autopilot performance is far inferior to that of the fuzzy-LQG, the vehicle still manages to complete the mission. This could be improved by reducing the weight on the control input in the MPC objective function. The fuzzy logic and GA algorithms are shown to be running in real time which was made possible primarily due to the slow plant dynamics.

Although the *Springer* is an autonomous vessel, a support boat must be present for every mission due to the lack of an obstacle detection and avoidance system. This feature is crucial in rendering any unmanned vehicle truly autonomous. Work is currently being carried out to develop a collision detection and avoidance module which could even be used for automatic berthing operations. Only the implementation of such a system could help to remove the human factor from the loop of any uninhabited system.

A NOMENCLATURE

m	mass of the vehicle
p	angular velocity along the x -axis
r	angular velocity along the z -axis
u	surge velocity
v	sway velocity
x_G	x -coordinate of the centre of gravity
y_G	y -coordinate of the centre of gravity
I_x	moment of inertia about the x -axis
I_{xy}	product of inertia about x and y axes
X, Y	external forces along the x and y axes
K, M	external moments along the x and y axes

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