An Assessment of a Modified Optimal Control Strategy as Applied to the Control of an Unmanned Surface Vehicle

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Abstract: Unmanned surface vehicles (USVs) are now being used in a variety of missions including, surveillance, weapon delivery, shallow water surveying, coordination with underwater vehicles to name but a few. The performance of these unmanned systems is crucial in obtaining the required information from a given mission. The onboard navigation, guidance and control (NGC) systems, working in tandem, dictates this performance measure. Degradation in effectiveness of one system can severely affect the efficiency of the overall system. Hence the requirement of the NGC system is that of a robust type which includes fault tolerance as an integral part of the system. This paper presents results of the application of a modified optimal control strategy to an USV named *Springer* which has been designed and developed at the University of Plymouth for the purpose of environmental data monitoring. The performance of the proposed autopilot is compared with the standard control system in terms of real time results.

Keywords: Optimal control, LQG, unmanned surface vehicle, guidance system, experimental results

1. INTRODUCTION

Optimal control is a powerful control technique used in a variety of applications such as process control, robotic manipulators, disk drive head control and airborne and underwater vehicles to name a few. However, the improvement in performance and robustness comes at the price of increased parameters tuning. Generally, optimal control systems require a performance measure and a maximisation or minimisation algorithm that provides an optimal result in some sense. For instance, in a time optimal system, time is the performance measure which should be kept to a minimum. An example would be a missile launched to destroy an airborne target in minimum target intercept time.

Linear quadratic Gaussian (LQG) is one of the several optimal control strategies which has been used for controlling such systems. The main advantage of the LQG, unlike the state feedback regulator, is the presence of a Kalman filter which provides an estimate of all the unmeasured states of the system. The linear quadratic regulator (LQR) generally works well with excellent stability margins, however, in practice, the presence of process noise or the unavailability of an onboard sensor necessitates the use of the LQG controller. Four different parameters are required to be tuned for this type of control strategy. These include state weighting matrix **Q**, input weighting matrix **R**, process noise and measurement noise covariance matrices, **W** and **V**, respectively.

The **Q** and **R** matrices are generally straightforward to adjust. On the other hand, tuning the covariance matrices, **W** and **V**, could be tedious and time consuming. A properly tuned Kalman filter is vital for the proper operation of the LQG autopilot. Hence there is a need to automate the tuning of these variables so that satisfactory performance can be obtained.

This paper presents an alternate way of achieving the above outcome by employing a soft computing methodology based on fuzzy logic. Collins and Selekwa (2002) have considered an input and output variance constrained LQG design problem using fuzzy logic. Shao *et al*. (1994) have implemented a similar approach to generate an LQG control law where the state and control weighting matrices are determined using a fuzzy logic adaptation mechanism. In other literature, the fuzzy logic is used to tune the **W** and **V** matrix of the Kalman filter (see for example Loebis *et al*. (2004a) where the fuzzy membership functions are selected by a heuristic procedure). The Kalman filter in this particular instance is being used for a multi-sensor data fusion (MSDF) algorithm. Another enhancement to this approach is also proposed by Loebis *et al*. (2004b) wherein multi-objective genetic algorithms are utilised to determine the fuzzy membership function parameters.

The intention herein is to apply a heuristically tuned fuzzy logic to adjust the covariance matrices and hence determine the Kalman gain. This Kalman filter is then integrated with the LQR to form an adaptive LQG control strategy which is implemented and tested in real time on an autonomous surface craft. Please note that the feedback data is obtained from a novel form of MSDF technique, however, the details of this algorithm are out of the scope of this paper. The data is assumed to be available for feedback for control system implementation.

The organisation of the paper is as follows. The next section provides a brief description of the *Springer* USV to which the resulting autopilot is implemented. Section 3 outlines process modelling using system identification (SI) techniques whereas the development of the proposed control strategy is covered in Section 4. Section 5 presents experimental results and concluding remarks are made in Section 6.

2. *SPRINGER* USV DESCRIPTION

The *Springer* USV is a twin hull catamaran shaped vessel of length and width of 4m and 2.3m respectively. Each hull is divided into three watertight compartments containing the electronics and batteries. The data acquisition (DAQ) and NGC systems are carried within watertight Pelicases that are placed in a bay area between the cross beams as shown in Figure 1. This facilitates the quick substitution of systems on shore or at water.

The propulsion system consists of two trolling motors which are capable of generating up to 8 knots of speed (Please see Figure 1). The steering of *Springer* is based on differential thrust. Any difference in the propellers' speed will make the vehicle turn in one direction or the other. To maintain the speed of the vessel at all times, it is important that the average speed of the propellers is kept constant. Manoeuvres can be obtained by changing the revolution rates of both motors whilst maintaining the average speed at all times. For a detailed description of the *Springer* hardware, please refer to Naeem *et al*. (2007).

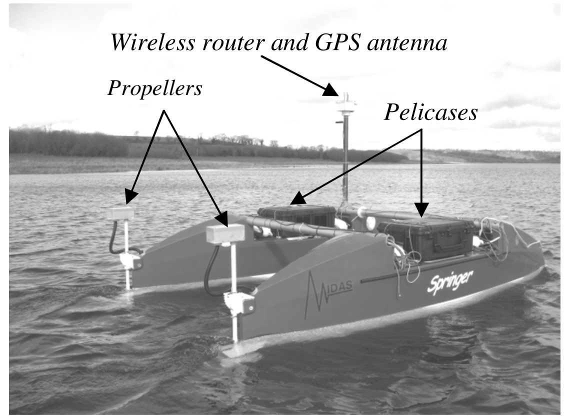

Fig. 1. *Springer* USV during trials at Roadford Reservoir, UK

2.1 Steering Mechanism

The vehicle has a differential steering mechanism and thus requires two inputs to adjust its course. This can be simply modelled as a two input, single output system in the form depicted in Figure 2.

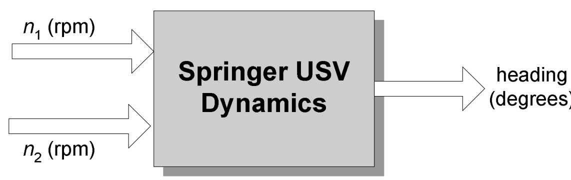

Fig. 2. Block diagram representation of a two-input USV

where n_1 and n_2 being the two propeller thrusts in revolutions per minute (rpm). Clearly, straight line manoeuvres require both the thrusters running at the same speed whereas the differential thrust is zero in this case. In order to linearise the model at an operating point, it is assumed that the vehicle is running at a constant speed of 3 knots. This corresponds to both thrusters running at 900 rpm. To clarify this further, let n_c and n_d represents the common mode and differential mode thruster velocities defined to be

$$n_c = \frac{n_1 + n_2}{2} \tag{1}$$

$$n_d = \frac{n_1 - n_2}{2} \tag{2}$$

In order to maintain the velocity of the vessel, n_c must remain constant at all times. The differential mode input, however, oscillates about zero depending on the direction of the manoeuvre.

In the following section, the SI procedure is applied to data acquired from the *Springer* vehicle through experiments conducted at Roadford Reservoir, Devon, UK.

3. MODELLING AND SYSTEM IDENTIFICATION

The model of the vehicle is developed using SI techniques on actual trials data. For this purpose, several sea trials needed to be performed where the vessel was driven for some calculated manoeuvres and data was recorded. Similar approach was adopted by Naeem (2004) to extract the model of an underwater vehicle and was proved to be quite successful.

A multi-input single-output model is the most obvious choice in this case, however, taking advantage of an additional piece of hardware present in the vehicle, the model is restricted to single-input single-output only. This hardware is the RoboteQ controller (RoboteQ website, 2007) which maintains the common mode speed of the motors throughout. The differential thrust is the only variable manipulated by the autopilot to generate the required steering.

For data acquisition, several form of inputs including a pseudo random binary sequence were applied to the thrusters and the heading response was recorded. Figures 3 and 4 depict two data sets obtained from those trials. The input shown is the differential rpm, n_d, which causes the vehicle to manoeuvre as required. The acquired data is processed and down sampled to 1 Hz since this frequency is deemed to be adequate for controller design.

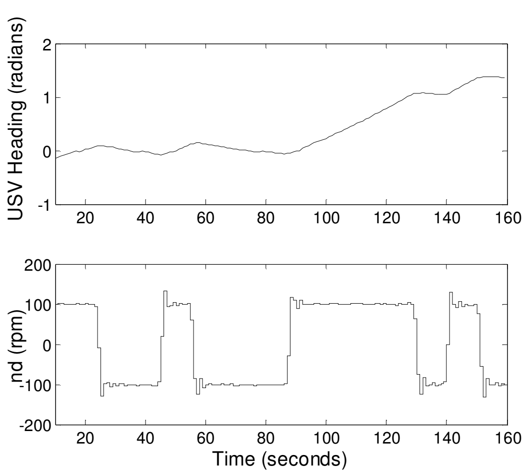

Fig. 3. One of the several data sets acquired from *Springer* through trials conducted at Roadford Reservoir in Devon, UK

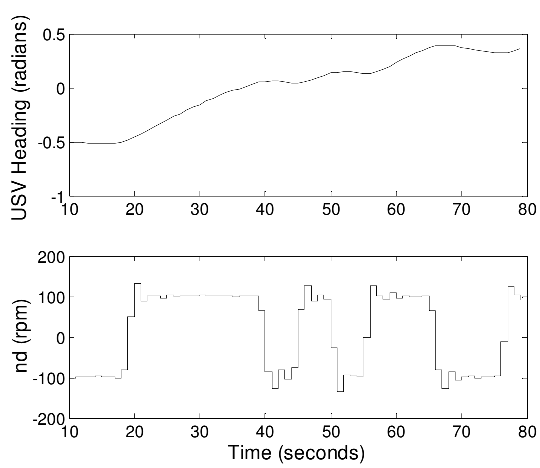

Fig. 4. Another data set acquired from *Springer* through trials conducted at Roadford Reservoir in Devon, UK

SI is then applied to the acquired data set and a dynamic model of the vehicle is obtained using a prediction error method in the following form.

$$y(z) = G_1(z)u_1 + G_2(z)u_2 \qquad (3)$$

where G_1 and G_2 denotes the discrete transfer functions from inputs u_1 and u_2 respectively and y being the output of the system. In this case, only n_d has been manipulated and therefore act as the sole input to the system. This alters both n_1 and n_2 whereas n_c is maintained to conserve the operating regime. Two models of second and fourth order were identified from the data, however, subsequent simulation study reveals that there is no significant advantage of using a more complex fourth order model. Hence, the second order model shown in Equations (4) and (5) in state space form is selected for further analysis and controller design.

$$\begin{aligned} \boldsymbol{x}(k+1) &= \mathbf{A}\boldsymbol{x}(k) + \mathbf{B}u(k) \\ y(k) &= \mathbf{C}\boldsymbol{x}(k) + \mathbf{D}u(k) \end{aligned} \qquad (4)$$

where

$$\mathbf{A} = \begin{bmatrix} 1.002 & 0 \\ 0 & 0.9945 \end{bmatrix}, \quad \mathbf{B} = \begin{bmatrix} 6.354 \times 10^{-6} \\ -4.699 \times 10^{-6} \end{bmatrix}$$
$$\mathbf{C} = \begin{bmatrix} 34.13 & 15.11 \end{bmatrix}, \qquad \mathbf{D} = \begin{bmatrix} 0 \end{bmatrix} \qquad (5)$$

4. FUZZY LQG AUTOPILOT DEVELOPMENT

In this section, the fuzzy LQG control algorithm is outlined for the *Springer* USV. A similar work was carried out earlier by Naeem *et al.* (2006) where the algorithm was developed for the *Delfim* USV and the performance was assessed in a simulation environment only. However, the intention here is to design the controller for the *Springer* vehicle and test it in real time. A comparison of the resulting controller is also made with the standard control scheme in terms of control effort and measured response. Figure 5 presents the fuzzy LQG autopilot in a block diagram format.

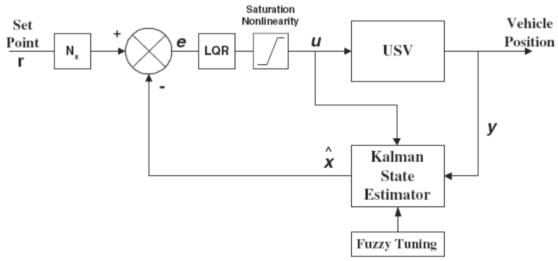

Fig. 5. Fuzzy LQG controller block diagram

The additional element that can be observed in the above diagram as compared to the standard LQG is the fuzzy tuning block which manipulate the covariance matrices until a suitable solution is obtained. The block N_x denotes the forward block which transforms the reference input **r** to a reference state x_r that is an equilibrium one for that **r**, u is the differential thrust input, n_d to the USV and y represents the output of interest which is the heading of the vehicle. The next subsection expands the fuzzy logic tuning methodology used in this algorithm.

4.1 Parameter Adjustment Methodology

The fuzzy logic based Kalman filter used in this paper is based on the innovation adaptive estimation (IAE) approach using a technique known as covariance matching (Mehra, 1970). In this technique, a comparison is made between the actual and theoretical covariances. The actual covariance is defined as the Inn_k sample covariance through averaging inside a moving estimation window of size M (Mohamed and Schwarz, 1999). Mathematically, it can be stated as

$$C_{Inn_k} = \frac{1}{M} \sum_{j=j0}^{k} Inn_k Inn_k^T \qquad (6)$$

where Inn_k is the innovation sequence defined to be the difference between the measured response and estimated output of the Kalman filter i.e.,

$$Inn_k = z_k - \hat{z}_k \qquad (7)$$

Also the theoretical covariance of the innovation sequence is defined as

$$S_k = H_k P_k^- H_k^T + R_k \qquad (8)$$

Once the covariances are defined, the decision to alter the **V** matrix is based on their difference δk. A small δk means that only a small change is required in the tuning parameters to maintain the performance. On the other hand, if the actual covariance is greater or less than the theoretical covariance then the controller parameters are adjusted accordingly. If the actual covariance is greater than its theoretical value, the value of **V** should be decreased and vice versa. A fuzzy rule base of the kind:

$$IF < antecedent > THEN < consequent > \qquad (9)$$

is very well suited for this type of adaptation behaviour.

where the antecedent and consequent are of the form $\mathbf{X} \in M_i$, $\mathbf{Y} \in N_i$, $i = 1,2, \cdots$ respectively where **X** and **Y** represents the input and output variables respectively and M_i and N_i are the fuzzy sets.

To implement the above covariance matching technique using the fuzzy logic approach, the following three fuzzy rules similar to above are used:

IF $<\delta_k \approx 0>$ THEN $<\mathbf{V}_k$ is unchanged $>$,
IF $<\delta_k > 0>$ THEN $<\mathbf{V}_k$ is decreased $>$,
IF $<\delta_k < 0>$ THEN $<\mathbf{V}_k$ is increased $>$

Thus **V** is adjusted according to

$$\mathbf{V}_k = \mathbf{V}_{k-1} + \Delta\mathbf{V}_k \qquad (10)$$

where $\Delta\mathbf{V}_k$ is added or subtracted from $\mathbf{V}_k$ at each instant of time. Here δ_k is the input to the fuzzy inference system (FIS) and $\Delta\mathbf{V}_k$ is the output. The FIS is implemented using three fuzzy sets for input δ_k; *N = Negative*, *Z = Zero* and *P = Positive*. For $\Delta\mathbf{V}_k$ the fuzzy sets are specified as *I = Increase*, *M = Maintain* and *D=Decrease*. The membership functions of these fuzzy sets which are designed using a heuristic approach are shown in Figures 6 and 7.

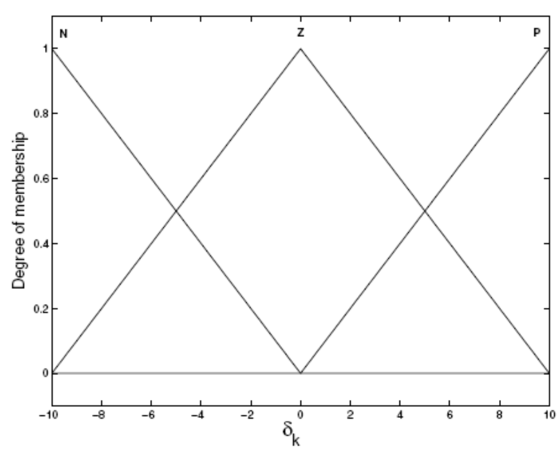

Fig. 6. Input membership functions

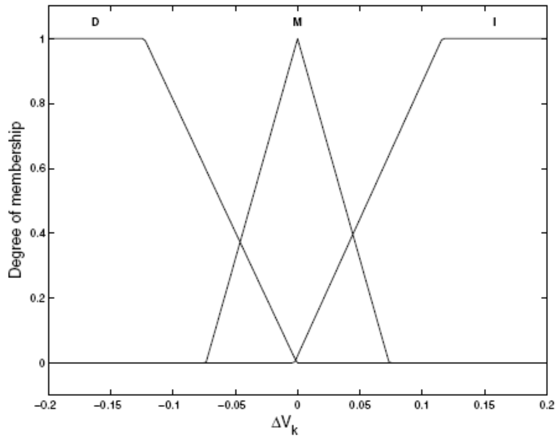

Fig. 7. Output membership functions

The Kalman filter developed in this section is now incorporated into the LQG autopilot and the performance is assessed in real time experiments.

5. EXPERIMENTAL RESULTS

The LQR controller is first designed to obtain a suitable value of the settling time and overshoot characteristics. Next, the Kalman filter is tuned by keeping the **W** matrix fixed at 0.001 whilst an initial value of unity is selected for the measurement noise covariance matrix **V**. An empirical estimation for the value of M in Equation 6 is carried out which suggests a value of 10 to achieve satisfactory performance.

A guidance system based on waypoint following as proposed by Healey and Lienard (1993) is considered and integrated with the proposed controller. The intention is to launch the vehicle at one of the three marked waypoints and the vehicle is required to reach all the remaining waypoint by following the desired trajectory as closely as possible. A circle of acceptance (COA) is also defined around the waypoints so that when the vehicle arrive within that circle, it can proceed to the next point. The radius of the COA is taken to be 10m.

Figure 8 depicts the path taken by the *Springer* USV for both control strategies. Please note that the GPS data has been post-processed and converted to body-fixed frame of reference. Moreover, the waypoints were deliberately chosen not to be in a straight line for a fair assessment of autopilots' performances. It is clearly seen from the plot that the performance of the proposed autopilot shows marked improvement over the standard LQG. The fuzzy logic based control scheme has closely tracked the ideal trajectory i.e. a straight line when maneouvring from one waypoint to another. However, the standard LQG is prone to external disturbances caused by winds and surface currents, hence a curved trajectory is observed.

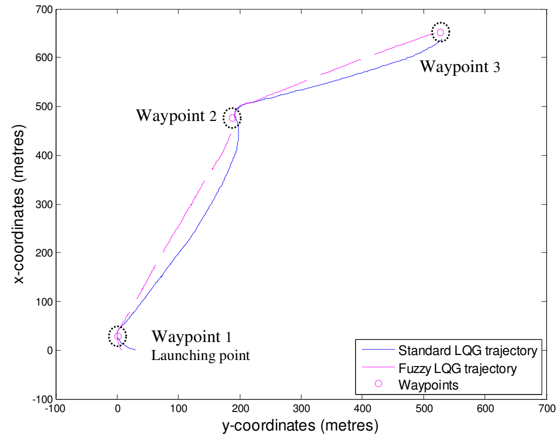

Fig 8. Experimental data sets from trials conducted at Roadford Reservoir in Devon, UK

To further assess the performance of the two autopilots, the control efforts have been plotted and depicted in Figures 9 and 10. It was found during experimentation that there is a small bias in vehicle's movement towards the port side. This is either due to uneven distribution of weight or some misalignment between the two propellers. In any case, a small positive bias in the input is required to counteract this phenomenon. This is clearly seen in both figures, however, the bias introduced by the standard LQG is slightly higher resulting in a curved trajectory. The same phenomenon is repeated when traversing from waypoint 2 to 3. In addition, the control effort generated by the standard control scheme is slightly more aggressive as compared to the proposed autopilot.

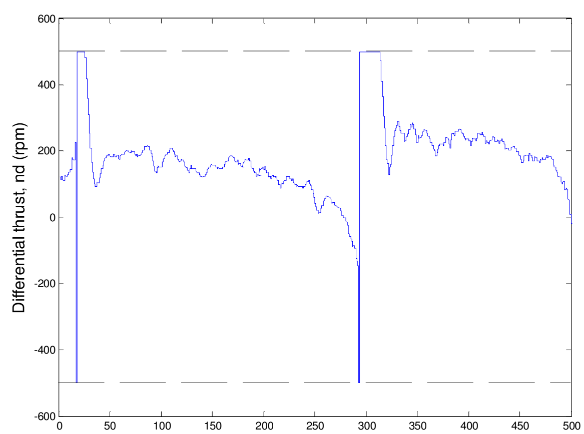

Fig. 9. Differential thrust produced by the standard LQG autopilot

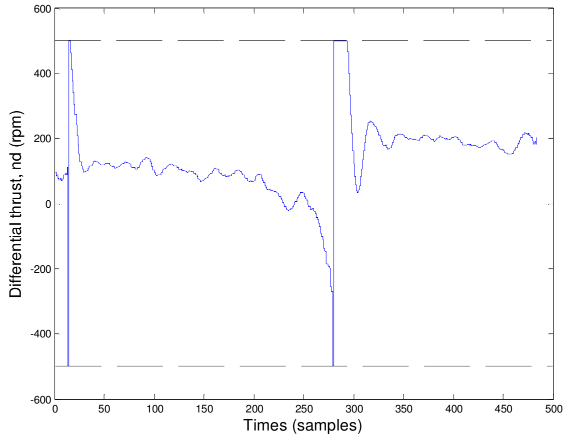

Fig. 10. Differential thrust produced by the fuzzyy LQG autopilot

6. CONCLUSION

This paper presents real time results of the application of an LQG controller modified using fuzzy logic. In particular, the Kalman filter is made adaptive and integrated with the standard LQR to obtain a novel control scheme. This is implemented on the *Springer* USV in real time and a comparison is made with the standard autopilot. To the authors' knowledge, this is the first reported application of a fuzzy LQG application to an autonomous marine vessel. It is shown that the proposed strategy provides improved performance in terms of generating control effort and following the desired trajectory. In addition, the proposed controller copes well with external disturbances and modelling uncertainty. It is hoped that more advanced control schemes will be devised and the performances are compared with the fuzzy LQG as the benchmark controller.

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