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FUZZY COURSE-KEEPING AUTOPILOT FOR SHIPS

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Abstract: In this paper a course-keeping autopilot for a containership designed with fuzzy logic theory is presented. The autopilot control strategy is deduced heuristically by exploiting expert knowledge and is implemented by means of fuzzy logic. In order to facilitate analytical analysis of the closed loop system non-linear control theory is used to guide the choice of control structure. An interpretation in terms of Fourier analysis of the control strategy is given and used in order to improve the performance of the autopilot in different sailing conditions while preserving the grey nature of fuzzy systems. The final autopilot is proved to be locally stable in the Lyapunov sense while a set of simulation results on a non-linear model of a containership shows the viability of the proposed approach. *Copyright © 2002 IFAC*

Keywords: Ship motion control, Fuzzy control, Lyapunov stability.

1. INTRODUCTION

The fast development of small and inexpensive microcomputers and advances in computing technology have fuelled the so-called “Intelligent Control” theory, in which control algorithms are developed by emulating certain characteristics of intelligent biological systems (i.e. learning and adaptation). Within the framework of intelligent control systems, neural networks and fuzzy logic systems have been widely used for the design of more sophisticated and reliable control systems (White and Sofge 1982). The primary advantage of fuzzy logic based systems compared to neural networks is their ability to manipulate imprecision and uncertainty through the definition of pertinent linguistic variables. Moreover, it has been proved that under some assumptions fuzzy logic systems are universal approximators, i.e. they are able to approximate any continuous function defined in a compact set. As a consequence, fuzzy logic based controllers are intrinsically robust, furthermore provided the use of a proper learning algorithm, they can also guarantee the optimality of a desired system’s performance. However, owing to their high non-linear nature both neural networks and fuzzy logic based systems are difficult to be studied analytically (i.e. in terms of stability). Consequently, the majority of the papers presented in the literature rely on a large number of simulation trials to test the effectiveness of the proposed fuzzy approach while others tend to adapt well known non-linear stable design methods for a sub-class of fuzzy systems at the cost of loosing the system’s interpretability (Wang L. 1993), (Tang Y. et al. 1997) and (Zirilli et al. 2000).

When focusing on the functional evaluation of the above intelligent systems, little difference between neural networks and fuzzy logic systems can be appreciated. The two systems can be described in the common framework of adaptive networks, where the same learning algorithms are applied and synergistic combinations of neural networks and fuzzy systems are defined. Different papers address and propose the design of fuzzy logic controller by extending and combining well known results achieved in the field of neural networks. However, by following this approach the interpretability of the resultant fuzzy system is reduced if not compromised (Yen et al 1998). A different way for the synthesis of a fuzzy based controller, is to use a cognitive based approach. In this instance, the aim is to design a control system based on a model of the expert, who is able to specify the general properties of the system, rather than on a mathematical model of the system to be controlled. The control strategy is then specified by a set of rules deduced by *a-priori* knowledge of the system, that constitutes the knowledge rule base of the controller. Based on this stored knowledge, the actual situation is evaluated in order to infer the appropriate control action. The deduced control action, performed by the inference machine, is based on fuzzy logic where uncertainties are easily handled. While the former approach is more suitable for analytical analysis, the latter although preserving the system interpretability, results in a highly non-linear system.

In this paper, by following the cognitive based approach, a heuristic description of course-keeping manoeuvres is given and fuzzy set theory is used for the design of a course-keeping autopilot for a ship. Although, with the above approach, the interpretability of the overall system is still preserved the tuning of the controller parameters is somewhat heuristic and is mainly based on trial and error. Therefore, the optimality of the overall system's performance is not always guaranteed. To overcome this drawback, the heuristic description of the manoeuvre is interpreted by means of a Fourier transform while the proposed control strategy is analysed by means of the Lyapunov method. The resultant autopilot is shown to be locally stable in the Lyapunov sense and then tested for a different range of sailing conditions in a simulation study involving the non-linear model of a containership (Tiano and Blanke 1997). It is shown that the proposed fuzzy autopilot is able to steer the ship acceptably well and represents a viable control structure for further implementation of adaptive and learning algorithms.

2. AUTOPILOT DESIGN

Traditionally in the design of steering control systems, it is common practice to distinguish between two modes of operation, namely *course-changing* and *course-keeping*. In the former operating mode the ship's heading angle is changed in a way that the ship can sail in the new (desired) direction. While engaged in a course-changing manoeuvre, the control signal must be such that a good transient response (which implies minimum time for changing sailing direction) and minimum overshoot (which infers good precision) can be achieved. On the contrary while in the course-keeping mode of operating the autopilot has to maintain a fixed direction of sailing. The rudder as the control signal, is therefore used in order to compensate for the different external disturbances (i.e. wind, waves and current) bearing in mind that an excessive rudder signal will introduce additional drag force and consequent loss of speed. The control aim is therefore to maintain the course error as small as possible and at the same time minimising the number of rudder calls. Figure 1 shows a possible rudder sequence where the different rudder calls in terms of amplitude and period are in general a function of the external disturbances and the desired course precision.

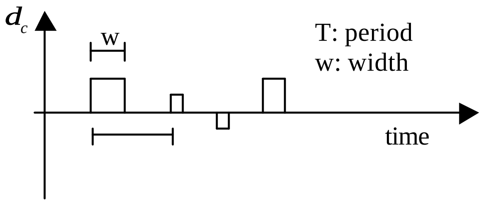

Fig.1: Rudder sequence during course-keeping

For the determination of the rudder calls, the low-pass nature of the yaw dynamics has to be considered and rudder movements that are too fast must be avoided. The control action produced by the rudder should be aimed at compensating the yaw acceleration induced by the external disturbances (mainly the effect of the waves). A rudder angle which is proportional and in counter phase with the yaw rate is then a possible solution.

An interpretation of the above control strategy can be attempted by considering the series expansion of the pulses sequence. Equation (1) and (2) express the Fourier transformation and its coefficients respectively.

$$\boldsymbol{d}(t) = \frac{1}{T}\sum_{n=-\infty}^{\infty} F_n e^{jnwt} \qquad (1)$$

$$F_n = \int_{-T/2}^{T/2} \boldsymbol{d}(t) e^{-jnwt}\,dt = 2\boldsymbol{d}_{\max} w \frac{\sin(n\boldsymbol{w}w)}{n\boldsymbol{w}w} \qquad (2)$$

From equation (2) it is clear that the amplitude of the Fourier coefficients is proportional to the width (w) of the pulses, while the number of harmonics in the first lobe are inversely proportional to w. Increasing w therefore will increase the amplitude of the harmonics whilst the number of the significant harmonics will be reduced. For a fixed period T this is equivalent to increasing the low frequency contribution. On the other hand, if roll damping is attempted, higher frequencies of the control signal are of interest. The value of w therefore needs to be reduced. However, this will reduce the amplitude of each harmonics that can be re-amplified by increasing the value of $\boldsymbol{d}_{\max}$. This is why, for roll damping faster and larger rudder movements are needed.

Provided that the amplitude and the period of the pulse sequence are fixed, the control law reduces to modulation of the pulse width. The rudder sequence as described above may be expressed as:

$$\boldsymbol{d}(t) = [\boldsymbol{d}_{\max}(t - kT) - \boldsymbol{d}_{\max}(t - kT - w(k))](-sign(r)) \quad (3)$$

for $kT < t < (k+1)T$, where T is the rudder sequence period, $w(k)$ the width signal modulator and *r* is the yaw rate.

To study analytically the behaviour of the heuristically deduced control law (expressed by equation 3), let a linear approximation of the ship dynamics in diagonal state space form be expressed as equation 4:

$$\dot{x} = \Lambda x + b\boldsymbol{d}(t) \quad (4)$$

The general solution of the state equation is:

$$x(t) = e^{(t-t_0)\Lambda}x(t_0) + \int_{t_0}^{t} \boldsymbol{d}(\boldsymbol{t})e^{(t-t)\Lambda}bd\boldsymbol{t} \quad (5)$$

where t_0 is an arbitrary initial instant and Λ is the diagonal matrix of eigenvalues. Substitution of the following two set of values for t_0 and t

$$t_0 = kT \qquad t = kT + w(k)$$
$$t_0 = kT + w(k) \qquad t = (k+1)T$$

yields:

$$x(kT + w(k)) = e^{w(k)\Lambda}x(kT) + sign(\boldsymbol{d}) \int_{kT}^{kT+w(k)} e^{(kT+w(k)-t)\Lambda}bd\boldsymbol{t} \quad (6)$$

$$x((k+1)T) = e^{(T-w(k))\Lambda}x(kT + w(k)) \quad (7)$$

combining equation (6) and (7) gives:

$$x((k+1)T) = e^{T\Lambda}x(kT) + $$
$$+ \sin g(\boldsymbol{d})e^{(T-w(k))\Lambda} \int_{kT}^{kT+w(k)} e^{(kT+w(k)-t)\Lambda}bd\boldsymbol{t} \quad (8)$$

The integration of (8) results in:

$$x((k+1)T) = e^{T\Lambda}x(kT) + \sin g(d)e^{T\Lambda}\Lambda^{-1}\left[I - e^{-w(k)\Lambda}\right]b \quad (9)$$

where *I* is the unit matrix. If $T << -1/\boldsymbol{l}_i$, $i = 1,2,..n$ then,

$$w(k) \approx \frac{1 - e^{-w(k)l_i}}{\boldsymbol{l}_i} \quad (10)$$

so that equation (9) can be rewritten

$$x((k+1)T) = e^{T\Lambda}x(kT) + \sin g(\boldsymbol{d})e^{T\Lambda}w(k)b \quad (11)$$

In order to study the stability conditions for the system described by equation (11), consider the Lyapunov function candidate $V(x(kT)) = \langle x(kT), x(kT)\rangle$. The first, derivative along equation (11) is then:

$$W = V(x((k+1)T)) - V(x(kT)) = \langle [e^{T\Lambda}x(kT) +$$
$$+ sign(r)e^{T\Lambda}w(k)b], [e^{T\Lambda}x(kT) + sign(r)e^{T\Lambda}w(k)b]\rangle -$$
$$- \langle x(kT), x(kT)\rangle = -\langle x(kT), x(kT)\rangle +$$
$$+ 2sign(r)w(k)\langle x(kT), e^{2T\Lambda}b\rangle + w^2(k)\langle b, e^{2T\Lambda}b\rangle. \quad (12)$$

Letting

$$sign(\boldsymbol{d}) = -sign\langle x(kT), e^{2T\Lambda}b\rangle \quad (13)$$

equation (12) can be rewritten in the following form:

$$W = -\langle x(kT), x(kT)\rangle - 2w(k)\left|\langle x(kT), e^{2T\Lambda}b\rangle\right| +$$
$$+ w^2(k)\langle b, e^{2T\Lambda}b\rangle. \quad (14)$$

Since the first term on the right hand side of equation (14) is negative definite**,** *W* has its most negative value for any *x* if:

$$w(k) = \frac{\left|\langle x, e^{2T\Lambda}b\rangle\right|}{\langle b, e^{2T\Lambda}b\rangle} \quad (15)$$

Since $w(k)$ cannot exceed T, the best choice is:

$$w(k) = Tsat\left\{\frac{\left|\langle x, e^{2T\Lambda}b\rangle\right|}{T\langle b, e^{2T\Lambda}b\rangle}\right\} \quad (16)$$

For a system with linear dynamics as expressed by equation (4), the control law expressed by equation (3) with the constraints expressed by equations (13) and (16) result in the equilibrium point of the system being asymptotically stable.

3. FUZZY COURSE-KEEPING AUTOPILOT

The control strategy along with all the above considerations about the frequency component as well as the stability conditions for the rudder pulse sequence will be used in this section to present a solution for the course-keeping control problem based on the implementation of equation (3) by means of fuzzy logic.

In order to implement the above control strategy it is necessary to define adaptively the rudder pulse characteristic (i.e. width (w), period (T) and amplitude (d_{max}) see Fig 1) which will be a function of the actual ship state. Based on equations (3) , (13) and (16), a fuzzy system with inputs being yaw error and yaw rate (equivalently the change in the error) and output width (w), period (T) and amplitude (d_{max}) will be defined. Since any multi-input multi-output (MIMO) fuzzy systems with *m* outputs can be represented by *m* multi-input single-output (MISO) fuzzy systems the course-keeping autopilot will be constituted by three MISO fuzzy systems with outputs width (w) the period (T) and the amplitude (d_{max}) of the rudder sequence. Based on equation (16) the fuzzy system determining the width of the rudder pulse will have its rule base knowledge constituted by rules of the form:

IF *abs(yaw_rate)* is *Big* THEN *width* is *Big*

With respect the determination of the rudder amplitude it is necessary that phase lags between the rudder angle and the yaw rate signal are not introduced by the limited rudder speed. In van Amerongen and van Naute Lemke, (1980) it is suggested that in order to avoid rudder rate saturation and consequent phase lags the following inequality must hold:

$$\frac{d_{max}}{\dot{d}_{max}} < 0.2t \qquad (17)$$

where t is the main time constant of the ship. For a value of $t \approx 15$ seconds and $\dot{d}_{max} = 2.5$ deg/sec, the maximum allowed rudder angle is approximately 7.5^o.

Based on equation (13) and (17) the rule base knowledge of the fuzzy system for determining the rudder amplitude is constituted by rules of the form:

IF *course-error* is *Positive_Big* and *yaw_rate* is *Positive_Big* THEN d_{max} is *Positive_big*

The determination of the rudder sequence period (T) is in general more complicated. It must be related not only to the ship state vector but also to the sea condition (i.e. relative angle of encounter, sea state etc.). Since for a fixed sailing condition the rudder sequence period is fixed, it is possible to construct a look-up table relating the period of the rudder sequence to the different angles of attack. Table 1 gives approximate figures of the rudder sequence period for a sea state characterised with respect a Pierson-Moskowitz spectral density by a mean period of 8 seconds and an significant wave height of 4 meters.

For the design of the two fuzzy systems a normalised universe of discourse has been chosen, along with a first order Sugeno-type fuzzy inference system with triangular input membership functions, singleton fuzzification and weighted average defuzzification. The completeness of the rule knowledge base therefore is guaranteed by a proper adjustment of the associated input and output gains. The course-keeping autopilot, so designed, is then tested in a simulation study involving the non-linear model of a containership which is described in appendix A.

TABLE 1

Angle of attack (degree)	Period (seconds)
145	50
130	45
110	30
90	10
70	25
50	45
30	45

4. SIMULATION RESULTS

Figure 2 shows an example of the fuzzy course-keeping autopilot operating with an angle of encounter of 70 degrees with a period of the pulse sequence equal to T=25 sec. as given by table I .

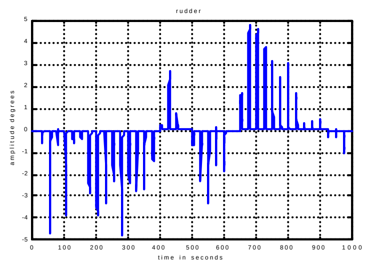

Fig.2.a: Rudder sequence amplitude

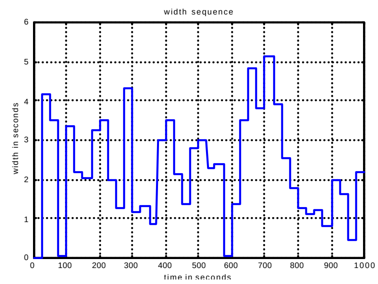

Fig.2.b: Rudder sequence width

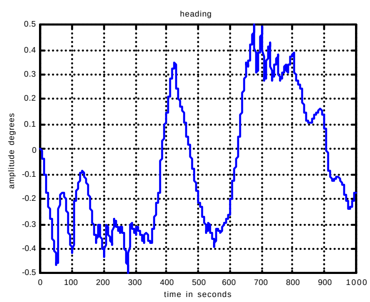

Fig.2.c: Yaw angle

Figure 2.a shows the rudder sequence amplitude, while figure 2.b and 2.c shows respectively the rudder sequence width and the yaw angle. Figure 3 shows the same signals for a course-keeping with an

angle of encounter of 145 degrees (following sea) and the pulse sequence period of 45 seconds.

In both manoeuvres of figure 2 and 3, the rudder amplitude never saturates to the limit of 7.5 degrees and the yaw angle is maintained within an acceptable course error. On the contrary, the rudder sequence width in the second manoeuvre is higher then the first, by a factor of about five. According to the discussion of section 2 this implies an increasing of the low frequency contribution of the rudder signal, in accordance with the following sea sailing condition.

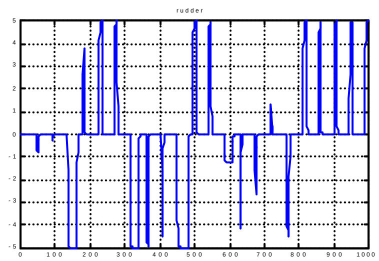

Fig.3.a: Rudder sequence amplitude

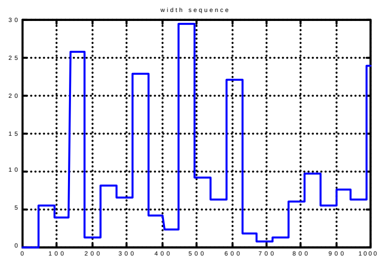

Fig.3.b: Rudder sequence width

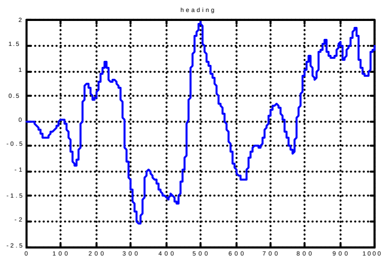

Fig.3.c: Yaw angle

5. CONCLUDING REMARKS

In this paper a solution for the course-keeping control problem is presented. The aim is to combine the cognitive model design approach with more rigorous analytical methods. Therefore the course-keeping autopilot design is divided into two steps. First the control strategy of the proposed fuzzy autopilot is described heuristically in terms of an experienced helmsman behaviours. Then a more rigorous interpretation of the control strategy, in term of Fourier transform as well as by means of Lyapunov methods is given. The latter analysis while preserving the grey box nature of fuzzy logic based systems and giving a rigorous interpretation of the control law, is of fundamental help during the tuning phase of the fuzzy controllers. The effectiveness of the proposed fuzzy autopilot is finally shown with a simulation study by means of a non-linear model of a containership.

APPENDIX 1

The mathematical model of a container ship used in this study is described in detail in (Tiano and Blanke 1997) and (Blanke and Jessen 1997). The non-linear equations describing the motion of the rigid body in four degree of freedom are as follows:

$$\begin{aligned} &m\left(\dot{u} - vr - x_g r^2 + z_g pr\right) = X + X_w \\ &m\left(\dot{v} + ur - z_g \dot{p} + x_g \dot{r}\right) = Y + Y_w \\ &I_{zz}\dot{r} + m x_g\left(ur + \dot{v}\right) = N + N_w \\ &I_{xx}\dot{p} - m z_g\left(ur + \dot{v}\right) = K + K_w - \rho g \Delta R_z(\varphi) \end{aligned} \qquad (A.1)$$

The above equations with reference to the co-ordinate system shown in figure A.1, describe the coupled surge, sway, yaw and roll motions, where Δ is the displacement, g the gravity constant, ρ the water mass density, $R_Z(\varphi)$ is the action of the rightening arm that depends on the roll angle φ, while $(x_G, 0, z_G)$ are the co-ordinates of the mass centre. The mass is denoted by m whereas Ixx and Izz are the inertial moments about x and z, respectively. The linear velocity of surge and sway are u and v and the angular ones of yaw and roll are respectively r and p. The rightening arm function can be expressed as:

$$R_z(\varphi) = \sin\varphi\left(GM + \frac{BM}{2}\tan^2\varphi\right) \qquad (A.2)$$

where GM is the ship metacentric height and BM is the distance from the centre of buoyancy to the metacentre. Terms X, Y denote the deterministic forces acting along x e y while N and K are the deterministic moments around z and x, which takes into account the hydrodynamic effects from the hull movements and forces exerted on the ship by the rudder and by the propulsion system. Such forces and moments are usually described by regarding X,Y,N,K as polynomial expansion in terms of state variables, control actions and hydrodynamic coefficients (Lewis 1988).

The effects of external disturbances, i.e. wind and waves, consist of related forces X_w, Y_w and moments N_w, K_w acting as perturbation terms in the corresponding right hand parts of equation (A.1). Such terms, owing to their intrinsically random nature, are generally quite difficult to be characterised through explicit mathematical relations.

By limiting attention to sea waves, which are by far the dominant disturbance, it is possible to regard a long crested irregular sea height $V(t)$, at time t, as described by a one-dimensional amplitude spectrum, the main parameters of which are the significant wave height, h and the average wave period T. This spectrum, accepted by the International Ship Structure Congress (ISSC) is given by:

$$G_V(w) = \frac{173h^2}{w^5 T^4} \exp\left(\frac{-691}{T^4 w^4}\right) \tag{A.3}$$

The response of each individual component of the wave induced ship state vector $\mathbf{x_w}=[u_w\ v_w\ r_w\ p_w]^T$, can be obtained in terms of the receptance operator, which is assumed to be known from experimental tests. They describes the response of the ship i[th] motion to the waves (Blanke and Jessen 1997). Once the waves induced ship state vector x_w is computed the total ship state vector is represented by:

$$x_{tot}=x_w+x$$

According to this approach, it is possible to implement an accurate and numerically reliable simulation of sea wave induced ship motions.

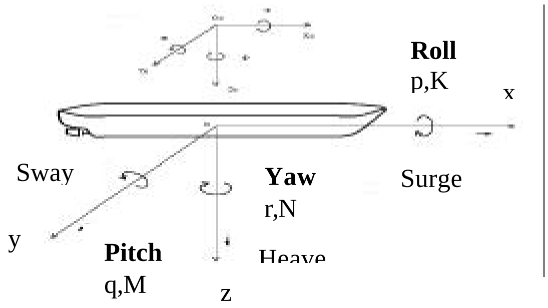

Figure:A.1 Ship's system frame

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