

Fuzzy Fast Time Simulation Model of Ship's Manoeuvring

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ABSTRACT: The paper presents a concept of fuzzy FTS (fast time simulation) model of twin-screw ship manoeuvring autonomously (without tugs) in confined waters. The conceptual model has been based on the fuzzy logic controller with expert database formed by manoeuvres obtained from the real-time non-autonomous trials classified in relation to expert manoeuvre impact on ship's advance, lateral and rotation speed and her position in reference to the present ship status. Exemplary pitch controller for vessels with two propellers at specified hydro-meteorological conditions has been presented.

1 INTRODUCTION

Fuzzy set theory has been used successfully in virtually all the technical fields including control, image/signal processing and expert systems. One of the most successful applications however seems to be in the control field where the theory can utilize the human control operator's knowledge and experience to intuitively construct models so that they can emulate human control behaviour to a certain extent (Ying 2000, Zadeh 1996).

Simulation studies give perfect opportunity to record the expert knowledge of pilots commanding vessels in the relevant area. An essential problem of the acquisition and representation of navigator's knowledge referring the conduct rules (procedural knowledge) and the analysis and evaluation of navigational situation (declarative knowledge) can be solved by gaining knowledge directly from electronic records made during such research and creation of the expert knowledge database can finally lead to finally to the concept of autonomous ship control during FTS in confined waters. Fast time simulation can

be achieved easily by applying shorter period of state change than established in the ship's hydrodynamic model, for instance $dt = 0.01s$, which is not a problem for contemporary computers (Gucma et al. 2008), but ship's fuzzy control in confined waters requires further analysis.

2 FUZZY LOGIC CONTROLLER

In autonomous FTS the manoeuvring decision finding can follow the procedure described in Zalewski (2003). However if any of the present ship state vector parameters comes outside the scope of the expert database it is assumed that the optimum manoeuvre should lead the ship to regain safe values of state vector parameters. For this purpose the fuzzy discrete-time controller can be designed. The major components of the typical fuzzy controller are fuzzification, fuzzy rule base, fuzzy inference, and defuzzification. These components will be described further in an exemplary MISO (multiple input single output) controller of pitch for vessels with two propellers.

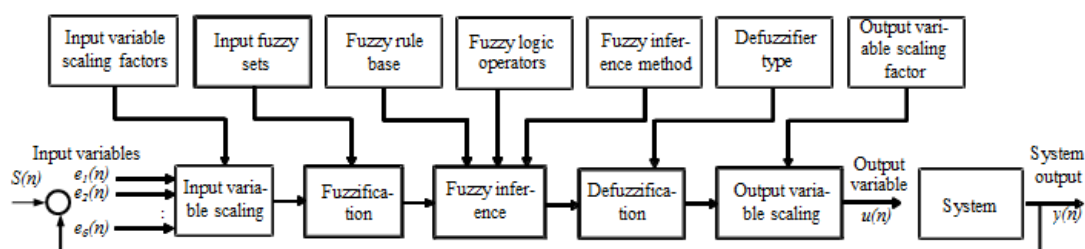


Figure 1. Structure of a MISO fuzzy control system which is composed of a Mamdani fuzzy logic controller and a system under control (based on Ying (2000)).

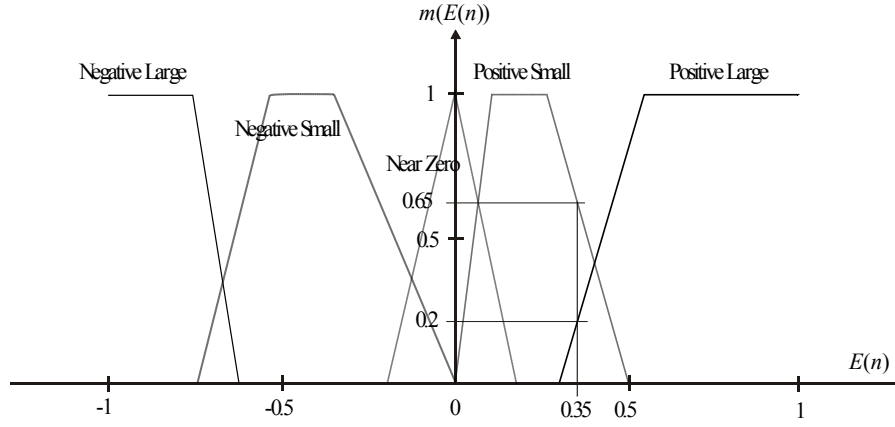


Figure 2. Illustration of the Δv_x input variable fuzzification.

2.1 Fuzzification

Fuzzification is a mathematical procedure for converting an element in the universe of discourse into the membership value of the fuzzy set.

In the Figure 1 controller output is designated by $u(n)$ and system output is designated by $y(n)$, where n is a positive integer representing sampling time dt . The desired system output trajectory is denoted as $S(n)$.

In case of system being a ship, steered in accordance to expert passage, $u(n)$ will be pitches setting, $y(n)$ will be a vector containing six variables defining actual motion in 3-degrees of freedom: P_{xy} - actual position of selected waterline point stored as two variables, v_x - actual longitudinal (advance) velocity, v_y - actual transverse (lateral) velocity, ω - actual angular (rotation) velocity, ψ - actual ship's heading; and $S(n)$ will be a vector containing six variables defining required motion in 3-dof: P_{xyr} - required position of selected waterline point stored as two variables, v_{xr} - required advance velocity, v_{yr} - required lateral velocity, ω_r - required rotation velocity, ψ_r - required ship's heading. At time n , $y(n)$ and $S(n)$ are used to compute the input variables of the fuzzy controller (effect of pitches setting on motion): ΔP_{xy} - deviation between required and actual position, Δv_x - difference or deviation between required and actual longitudinal (advance) velocity, Δv_y - difference or deviation between required and actual transverse (lateral) velocity, $\Delta \omega$ - difference or deviation between required and actual angular (rotation) velocity, $\Delta \psi$ - difference or deviation between required and actual ship's heading. So generally the input variables vector can be designated by:

$$e(n) = S(n) - y(n) \quad (1)$$

Input variable scaling factors are used to conveniently manipulate the effective fuzzification on the scaled universes of discourse. The scaled factors used for $e(n)$ vector in presented research are normalization constants of the five mentioned devia-

tions, with their preserved positive or negative sign, as accepted in Zalewski (2003). Assuming the scaling factors for deviations as vector K_e the scaled input vector is:

$$E(n) = K_e e(n) \quad (2)$$

The scaled variables are then fuzzified by input fuzzy sets defined on the scaled universes of discourse: $[0,1]$. Figure 2 shows five input fuzzy sets for one of the $E(n)$ parameters that are used by the fuzzy controller. At this conceptual phase of FTS model development the research on the most suitable fuzzy sets is still ongoing so the most popular membership functions types found in literature have been selected, namely triangular and trapezoidal.

The fuzzification results for normalized Δv_x value of $E(n)$, $E_2(n) = K_{e2} \times \Delta v_x$, shown in Figure 2, are membership value of 0.65 for fuzzy set Positive Small (PS) and 0.2 for fuzzy set Positive Large (PL). The linguistic names "Positive" and "Negative" are related directly to faster advance speed than required and slower advance speed than required respectively. The membership values for Near Zero (NZ), Negative Small (NS) and Negative Large (NL) are 0.

Fuzzification can be formulated mathematically replacing linguistic naming system by a numerical index system, for instance five fuzzy sets used may be represented by A_i , $i = -2$ (NL), -1 (NS), 0 (NZ), 1 (PS), 2 (PL). The example fuzzification of $e_2(n)$ with $K_{e2} = 0.7s/m$ at time t : $e_2(n) = \Delta v_x = 0.5m/s$, $E_2(n) = 0.35$ can be described as:

$$m_{A_{-2}}(e_2(n)) = 0 \quad (3)$$

$$m_{A_{-1}}(e_2(n)) = 0 \quad (4)$$

$$m_{A_0}(e_2(n)) = 0 \quad (5)$$

$$m_{A_1}(e_2(n)) = 0.65 \quad (6)$$

$$m_{A_2}(e_2(n)) = 0.2 \quad (7)$$

No mathematically rigorous formulas or procedures exist to accomplish the design of input fuzzy

sets – the proper determination of design parameters is strictly dependent on the experience with system behaviour, hence the expert data coming from ship manoeuvring trials is necessary.

2.2 Fuzzy rules

Fuzzification results are used by fuzzy logic AND operations in the antecedent of fuzzy rules to make combined membership values for fuzzy inference. An example of a Mamdani fuzzy rule used for control of simulated ship advance speed is:

IF $E_2(n)$ is PL AND $E_1(n)$ is NS
THEN $u(n)$ is SAs (8)

where PL and NS are input fuzzy sets and SAs (Slow Astern) is an output fuzzy set. In essence rule (8) states that if ship's advance speed is significantly larger than the desired advance speed and the ship's position is a little back of the desired one (calculation of vector connecting both positions must be done) the controller output should be the pitch setting corresponding to Slow Astern fuzzy set.

The quantity, linguistic names, and membership functions of output fuzzy sets are all design parameters determined by the controller developer. Similarly to input fuzzy sets the most popular membership functions of singleton type have been used (Fig. 3).

The exact number of fuzzy rules is determined by the number of input fuzzy sets. For the considered system of ship control the total number of fuzzy rules will be the combination of 5 input variables and 5 fuzzy sets (if for all variables the same number of fuzzy input sets is designed): $5^5=3125$; quite a large amount for only pitches setting. Actually this number of fuzzy rules can be significantly reduced by treating each input variable independently and combining the output during defuzzification. This can be achieved by utilizing coupled fuzzy controllers.

2.3 Fuzzy inference

The resultant membership values of input sets produced by fuzzy logic AND operation (Zadeh or product operator can be used (Ying, 2000)) are then related to the singleton output fuzzy sets by fuzzy inference. The four common inference methods produce the same inference result if the output fuzzy set is singleton. Assuming that for fuzzy sets A_i membership values are given by (3)-(7), and for fuzzy sets B_i , corresponding to position deviation, the membership values are:

$$m_{B_{-1}}(e_1(n))=0.5 \quad (9)$$

$$m_{B_0}(e_1(n))=0.3 \quad (10)$$

if four fuzzy rules similar to (8) will be activated at time n , using the Zadeh fuzzy logic AND operator and Mamdani minimum inference method (Ying 2000) yields the following inference results:

for $u_1(n)=DSAs$ (Dead Slow Astern):

$$\begin{aligned} m_{Z_1} &= \min(m_{A_1}(e_2(n)), m_{B_{-1}}(e_1(n))) = \\ &= \min(0.65, 0.5) = 0.5 \end{aligned} \quad (11)$$

for $u_2(n)=STOP$:

$$\begin{aligned} m_{Z_2} &= \min(m_{A_1}(e_2(n)), m_{B_0}(e_1(n))) = \\ &= \min(0.65, 0.3) = 0.3 \end{aligned} \quad (12)$$

for $u_3(n)=SAs$ (Slow Astern):

$$\begin{aligned} m_{Z_3} &= \min(m_{A_2}(e_2(n)), m_{B_{-1}}(e_1(n))) = \\ &= \min(0.2, 0.5) = 0.2 \end{aligned} \quad (13)$$

for $u_4(n)=HAs$ (Half Astern):

$$\begin{aligned} m_{Z_4} &= \min(m_{A_2}(e_2(n)), m_{B_0}(e_1(n))) = \\ &= \min(0.2, 0.3) = 0.2 \end{aligned} \quad (14)$$

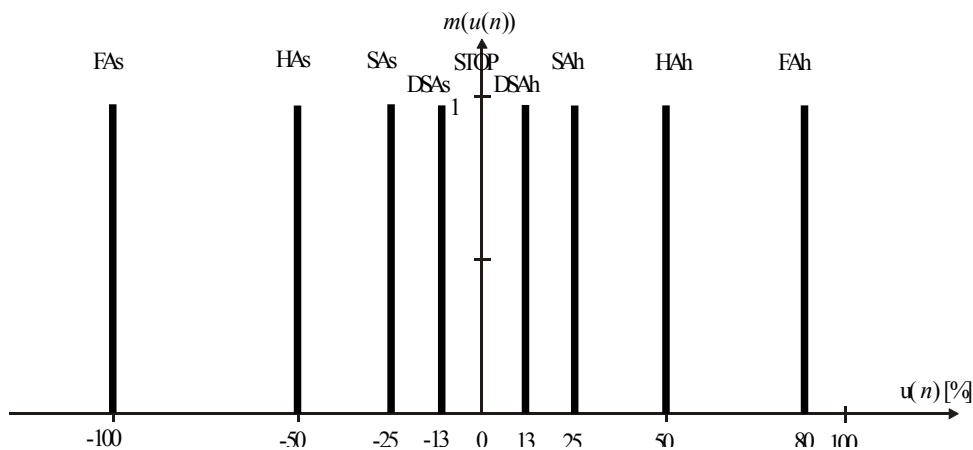


Figure 3. Singleton fuzzy sets as output fuzzy sets in the designed controller.

If output fuzzy sets in rules are the same fuzzy logic OR operation can be used to combine the memberships. In the presented example all four output singleton sets are different (DSAs, STOP, SAs, HAs) so the calculation will continue without it.

2.4 Defuzzification

The membership values computed in fuzzy inference must be finally converted into one number by a defuzzifier. In the ongoing research the most prevalent defuzzifier in literature – centroid defuzzifier has been used (Piegat 2003, Ying 2000). In the presented example the defuzzifier output at time n is:

$$u(n) = \frac{m_{Z_1} \cdot u_1 + m_{Z_2} \cdot u_2 + m_{Z_3} \cdot u_3 + m_{Z_4} \cdot u_4}{m_{Z_1} + m_{Z_2} + m_{Z_3} + m_{Z_4}} \quad (14)$$

where:

$u_1 = -13\%$ of pitch/throttle position (DSAs),

$u_2 = 0\%$ of pitch/throttle position (STOP),

$u_3 = -25\%$ of pitch/throttle position (SAs),

$u_4 = -50\%$ of pitch/throttle position (HAs),

so $u(n) = -18\%$ of pitch/throttle position.

$u(n)$ is the new output of the fuzzy controller at time n which will be applied to the ship system to achieve control. In comparison with conventional controllers, what is lacking is the explicit structure of the fuzzy controller behind the presented procedure. On the other hand utilizing expert knowledge for such a black box is much more straightforward and comprehensive.

3 MIMO SYSTEM

The controller's design process is further complicated by its multidimensional output. The possible solution of this problem has been presented in [6] by utilizing coupled controllers. Also usage of independent fuzzy controllers in the control of a MIMO system (multiple input, multiple output) can give good results.

Figure 4 presents exemplary structure of a coupled fuzzy controller for 5 input variables and 2 output variables (pitch settings of both propellers). Each controller utilizes its own fuzzy sets membership functions and fuzzy rules covering impact of pitches settings on the rotation and lateral speed of the vessel.

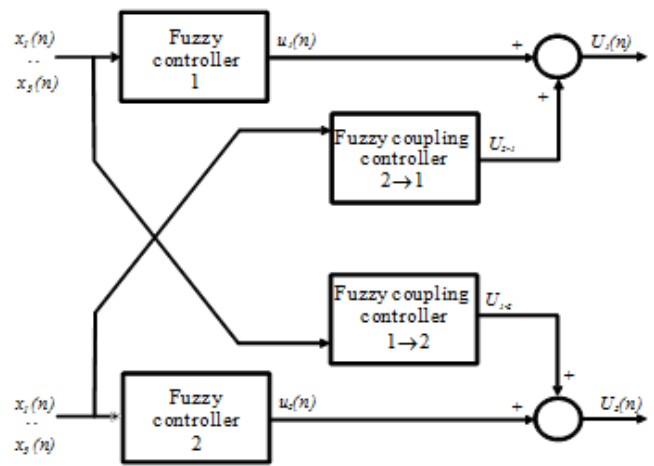


Figure 4. MIMO coupled fuzzy controller.

4 CONCLUSIONS

The human shiphandling expertise and knowledge can be captured and utilized in the form of fuzzy sets, fuzzy logic and fuzzy rules. The expertise and knowledge are actually nonlinear structures of physical systems which are represented in an implicit and linguistic form rather than an explicit and analytical form, as dealt with by the conventional system modeling methodology. That is why fuzzy controllers can be suitably implemented into nonlinear dynamic model of ship control. Fast time simulation based on such model should give satisfactory results even after logging only one or few expert passages in relevant area and conditions. Afterwards the FTS model can run autonomously provided that the proper ship safety limits are achieved by designed fuzzification (membership functions) and inference (fuzzy if-then rules and operators) processes.

BIBLIOGRAPHY

- [1] Gucma S., Gucma L., Zalewski P., "Symulacyjne metody badań w inżynierii ruchu morskiego", Wydawnictwo Naukowe Akademii Morskiej w Szczecinie, Szczecin 2008.
- [2] Piegat A., "Modelowanie i sterowanie rozmyte", Akademicka Oficyna Wydawnicza EXIT, Warszawa, 2003.
- [3] Ying H., "Fuzzy Control and Modelling - Analytical Foundations and Applications", IEEE Press, New York, 2000.
- [4] Zadeh L. A., "The evolution of systems analysis and control: a personal perspective", IEEE Control Systems Magazine, 16, 95-98, 1996.
- [5] Zalewski P., "Construction of the Knowledge Base for an Expert System Supporting Navigator's Manoeuvre Decision in Confined Waters", in 9th IEEE MMAR, Międzyzdroje, Technical University of Szczecin, pp. 195-200, 2003.