Application of Fuzzy Logic Controllers for the Automation of Human Circulatory Systems

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EEL 6681 Fuzzy Systems Design
Fall 2022

Abstract: Medical devices are not typical electronic pieces of equipment. When we apply Fuzzy Logic Controllers to automate human bodily functions, they further step away from the realm of typical devices. Though they do not require precise parameters, they control with multiple layers of data manipulation between the human and the machines to insure survivability during and post-surgery. Having reviewed four articles at which Fuzzy Control is introduced in medical devices, specifically ECSS (Extra-Corporeal Support Systems), it can be shown that the nature of Fuzzy Logic can improve upon existing equipment with far less-complex models that are required in conventional computing. This investigation into Fuzzy Control as it pertains to ECSS, focuses on the proposed need for smaller equipment and adaptive systems to help make surgeries more survivable.

Introduction

Existing ECSS (again Extra-Corporeal Support Systems) such as the Heart Lung Machine, expressed further as HLM, have shown issues with adaptability and portability. Identified by expert perfusionists, portability and adaptability of the equipment may increase the use of such devices to save lives inside and outside of an operating room. This is unlikely as things stand now as all the required equipment is bulky and too large for use outside of the operating room and still requires the presence of skilled perfusionists. The research shows various attempts to automate certain processes of ECSS with specific goals. Of those goals, lessening the burden of the perfusionist by automating support systems while miniaturizing bulky equipment is paramount. Perfusionists are scarce, highly skilled ones are further still. With expert input and the use of simulation, these articles summarize how Fuzzy Logic works to create a control interface between smaller components while delivering adaptive control to create a robust ECSS control. In this text we include a review of four different fuzzy tactics used. The articles reviewed are: “Design of a fuzzy controller for the automation of an extracorporeal support system with the use of a simulation environment” [1], “Automation of a portable extracorporeal circulatory support system with adaptive fuzzy controllers” [2], “Microcomputer-based automatic regulation of extracorporeal circulation: a trial for the application of fuzzy inference” [3], and “A comparative study on extracorporeal circulation control” [4].

History

HLM’s are currently built with large, rotary pumps that cannot be moved once installed. For control purposes, they also require a more energy. Presently, the Proportional-Integral (PI) controller along with the robust Model Predictive controller are used to control this piece of equipment. All of this was an attempt to satisfy providing the patient with optimal perfusion while mitigating the burdens placed on the operator. With technological improvements of modern electrical equipment, it is now possible to improve the adaptability and portability of these bulky systems with body sensors and fuzzy controlled actuators. Fuzzy control is an established method in control engineering and has been applied to a wide range of problems. No precise analytical plant description is needed nor computationally rigorous models for fuzzy logic to be successful. Also, the fuzzy inference logic allows the interpretation of linguistic rules to design controllers based on knowledge obtained from domain experts, in this case, surgeons and perfusionists.

Simulation

To safely create the fuzzy controller, a simulation environment is necessary. This environment must accurately mimic the behavior of a body's cardiovascular system connected with an ECSS. The simulation must be robust and contain the mechanisms of blood flow and blood oxygenation. The authors of "Design of a Fuzzy Controller for the Automation of an Extracorporeal Support System with the use of a Simulation Environment" [1] used the HLM model from the ISR Physiome Project that included HLM component parts: a reservoir, a centrifugal pump, oxygenator, filter, tubing, and venous and arterial cannulas (smaller tubes that can be inserted into a vein or artery).

In our review of the articles, other simulations, including utilizing the circulatory system of local pigs were utilized for the acquisition of hemodynamic parameters during extracorporeal circulation (ECC). A 'CDI 500' gas meter was used to collect data on gas exchange where one sample was taken every six seconds while using an analyzer [2]. Accurate simulations under real world circumstances allows for crisp verification of hypothesized ideas in an experiment. Our author uses several different schemes for simulation, including MATLAB with the Fuzzy Logic Toolbox.

Controller Modeling

The main advantage of Fuzzy logic is to create a system of membership functions and rules that can be mapped to or interpret a stable output by means of common linguistic references, rather than creating complex mathematical models. In this realm of ECSS, the mathematical models are extremely intricate and involve subjects like flow rate, pressure, temperature, concentration, and more mechanisms of hemodynamics and blood distribution to be further accurate. With fuzzy logic, these concepts do not need to be as mathematically or computationally rigorous. It is just necessary to map inputs and outputs using a Fuzzifier and De-fuzzifier that is determined to use membership functions to define its fuzziness. The described method chosen by the authors (1,2, and 4) was the Mamdani Inference method, which is described in our text as the various IF-THEN statements used to create their fuzzy rule base. They then use Max-Min Method and the Centroid Method for fuzzification and de-fuzzification. Secondly, they found it necessary to add adaptive components for regulation and control. The authors seem to be using the Learning from Example, or LFE, method or the Modified Learning from Examples, or MLFE, approach of automating fuzzy control. They state that adaptive mechanisms enhance the controller's responsiveness. When the present input values are being integrated into the adaptive controller, where no rule reaches a predetermined threshold, results in a learning process where a new rule is implemented, and the knowledge controllers are generated. If a rule already exists, an adaptive procedure is used to modify the rules and enhance control effectiveness. The output of the adaptive controller, via feedback, is then used to tweak the value of the control variables. The authors use a variety of equations to model and analyze the behavior of the systems. Some are listed below:

> "Individual elements (reservoir, centrifugal pump, oxygenator, filter, tubing, venous cannula, and arterial cannula) are fed into function to describe the difference in pressure in terms of the flow going through each component:
>
> $$\Delta P_i = Ca_i Q^2 + Cb_i Q$$
>
> $$P_S(rpm) - \frac{\Delta P_{CVM}}{\rho g} = \left(\frac{\sum_{i=1}^{7} Ca_i}{\rho g} + \frac{1}{2A^2 g}\right) Q^2 + \left(\frac{\sum_{i=1}^{7} Cb_i}{\rho g} - P_D(rpm)\right) Q$$
>
> The values of C_a and $C_b$are fed from the HLM manual, Q is the resulting flow, P_s and P_D are factors obtained depending on the RPM of the centrifugal pump and ΔP_{CVM} is the difference of pressure obtained from the input and output of the cardiovascular model previously discussed in the simulation section. A is the pump output area, ρ is the blood density and g is gravity."
>
> $$\frac{dP_G}{dt} = \frac{\dot{V}_G \cdot (P_{G,i} - P_G) + P_{atm} \cdot D_G \cdot (BloodP_{G,i} - P_G)}{V_G} \quad (2)$$
>
> According to the authors, [1], "The subindex G corresponds to either O_2 or CO_2. V_G is the flow of the gas mixture introduced into the oxygenator and is determined by the oxygen blender. $P_{G,i}$ is the input partial pressure of O_2 (PO_2) and CO_2 (PCO_2). The input of PCO_2 is 0 mmHg. The input PO_2 is determined by the oxygen blender obtained by multiplying FiO_2 times the atmospheric pressure P_{ATM} (760mmHg). D_G is the diffusion factor for O_2 and CO_2. $BloodP_{G,i}$ corresponds to the gas partial pressure of the blood entering the oxygenator. This is obtained from the gas partial pressures at the pulmonary artery from the gas exchange model of the cardiovascular system."

Controller Integration:

Adaptive Model

The below figure (Fig. 1 obtained from [2]- "Automation of a portable extracorporeal circulatory support system with adaptive fuzzy controllers") depicts a block diagram of the fuzzy control system consisting of four components. As we know, Fuzzification converts given crisp inputs into fuzzy sets, then passes them into control system for further processing. The Inference Mechanism allows the users to find matching degrees between fuzzy inputs and rule bases. The Rule Base contains the set of rules that govern the decision-making system. Defuzzification takes the fuzzy inputs generated by the inference mechanism and transforms them into crisp output values. According to the authors, the collection of reference models were compiled, then used as input parameters. The second is a smaller group of fuzzy controllers that include the perfusionist's rules. According to specific input signals, each sub-controller specifies how a control variable should be changed. The authors refer to these sets of controllers as Knowledge controllers. A controller that is adaptable is the third element. The rule set for this controller is empty at first. It includes additional signals that might be pertinent to the parameter under control in addition to the same inputs as the knowledge controllers. The authors refer to a special PI-Fuzzy type of controller described by LI ("Approximate model reference adaptive mechanism for nominal gain design of fuzzy control system." IEEE Trans Syst Man Cybern B Cybern 1999;29(1):41–6)

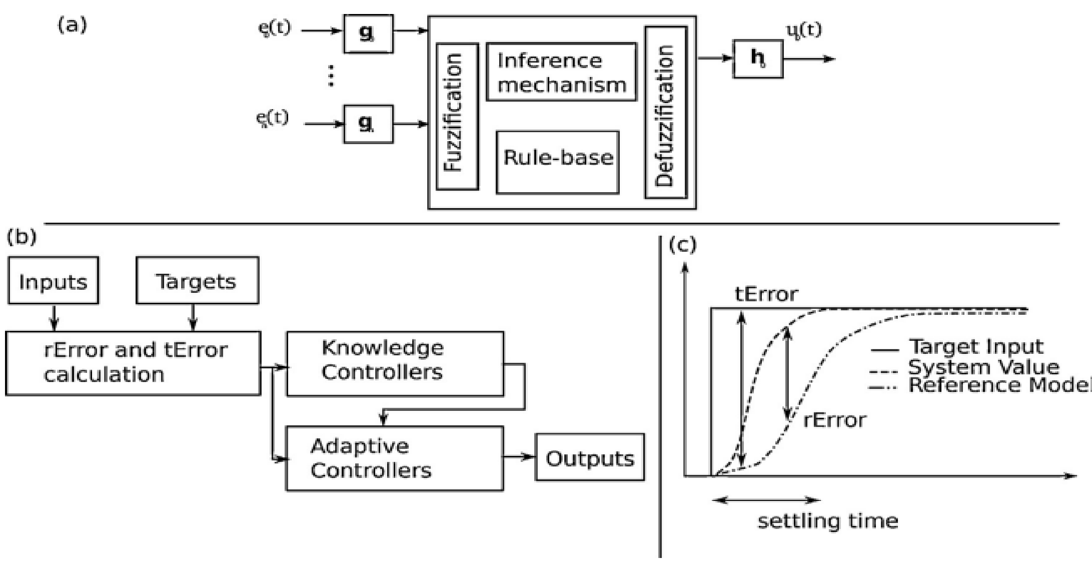

Figure 1. From [2]

The ECSS was automated utilizing four adaptive controllers, one oversees changing the centrifugal pump speed, a second for the gas mixer FiO_2, third for the delivery of medication, and the last one for gas flow. The chosen input parameters are listed in the table below, together with the configured minimum, maximum, and target values. Control parameters are defined as vital signals that are maintained at a given range to assure organ perfusion. The values of the different parameters are predefined by the operator and are referred to as target values. A target error ($tError$ or tE. Fig 1.) is defined as the difference between the target value and the current value of the patient. As previously stated, the authors suggest the following,

> "the input and output sets were chosen of triangular shape to reduce computational cost. The sets are spread covering the range of values configured for each input. In the knowledge controllers 5 triangular sets are used for each input and 11 sets for the outputs. In the adaptive controllers 7 sets are used for the inputs and 31 triangular sets are used for the output to enable the adaptive algorithm to do small corrections."

This is in refence to the Mamdani and Max-Min factors of fuzzy previously introduced.

Input and control variables.

Name	Min	Normal	Max	Units
Input parameters				
MAP	50	60	80	mmHg
EFR	3	5	6	l/min
SVR	500	960	1600	dyn s/cm^5
SpO_2a	70	99	100	%
SpO_2v	50	80	80	%
PO_2a	90	100	200	mmHg
PO_2v	30	40	60	mmHg
PCO_2a	30	40	50	mmHg
PCO_2v	30	41	50	mmHg
Control variables				
Pump speed	1000	–	3900	rpm
FiO_2	20	–	100	%
Gas vol.	2	–	10	l/min
SNP	0	–	2	µg/kg/min
NEP	0	–	0.1	µg/kg/min

Table 1. From [2]

Our author, [2], then found it necessary to automate medication delivery using fuzzy. We find: These values may change depending on the precondition and medical history of the patient. Fig. 2 shows the reference models used in the automation system, with the four adaptive controllers created, described as follows:

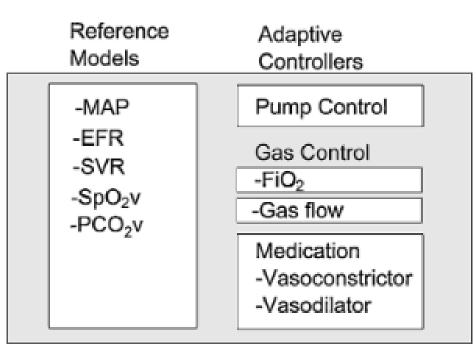

Figure 2. from [2]

The main inputs of the centrifugal pump controller are MAP (Mean Arterial Pressure) and EFR (Extracorporeal Flow Rate). The control rules consist of increasing pump speed if MAP or EFR are lower than the target value and decrease pump speed if MAP or EFR are higher. Oxygen saturation is also used as input were the pump speed may be increased to generate more flow if the FiO2 is already at 100% with a gas flow at 10 l/min and the venous oxygen saturation is lower than the target value. Fig. 3 shows the pump control structure.

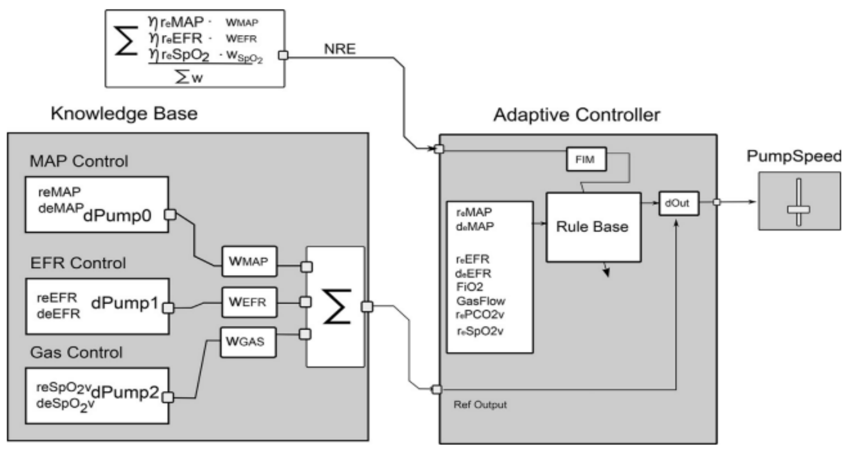

Figure 3. From [2]

For the medication controllers, a systemic vascular resistance (SVR) was approximated by considering the MAP together with central venous pressue (CVP) and replacing the cardiac output with the EFR:

$$SVR \approx \frac{MAP - CVP}{EFR}$$

Utilizing this, the Mamdani Inference can be updated by,

> "Once the pump speed is stabilized the medication control is activated. A vasodilator and vasoconstrictor is used to produce contrary effects and are exclusive: If one substance is used the other substance is not. A unified medication variable was used (Meds). When this variable is positive this corresponds to the vasoconstrictor dosage, while the vasodilator remains on 0; if the variable is negative it corresponds to the vasodilator using an absolute value. The rules of the controllers consist on modifying this variable: if the current SVR is higher than the target SVR then Meds is decreased, if the current SVR is lower than the target then Meds is increased."

PI- Fuzzy Conroller

Another application of fuzzy into the realm of ECSS was introduced in a comparative analysis as well as an implementation of ECSS automation with the PI-Fuzzy controller [1,4]. In the below figure, we have a block diagram of this system;

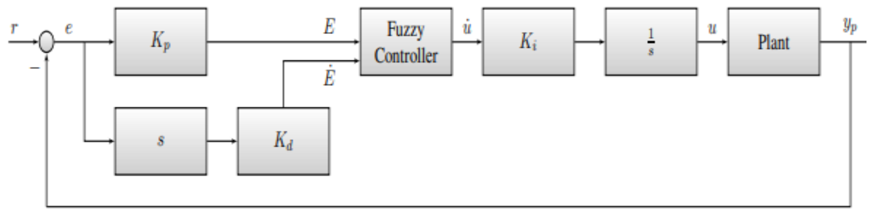

Figure 4. From [4]

They describe the controller as having two input variables, one output with a feedback loop chosen to affect pump speed as in the previous adaptive model. The membership functions for the two inputs and the output are composed of 7 sets each.What makes this different is that the Fuzzy-PI controller works in the range of -1 to 1. Control gains (K) are used to transfer inputs and outputs to the internal representatives. The authors then tuned the controller by a grid search over the gain parameters. For flow control, the authors set the proportional gain to Kp = 0.225 and the derivative gain to Kd = 0.1 for flow control. Ki = 4 was chosen as the output gain. The parameters Kp = Kd = 0.05 and Ki = 4 were selected for pressure control.

<u>Results</u>:

Several simulations were used to train the adaptive controllers so they could learn and adjust to the behavior of the system. According to the authors,

> "The simulation shows that when the medication controllers were not activated, due to a high SVR, the values of MAP and EFR could not be achieved. An equilibrium point is reached where the MAP is slightly higher (+5 mmHg) than its target and the EFR is lower (−1 l/m). This was corrected with the activation of the medication control by decreasing the SVR and increasing the pump speed to reach the target MAP and EFR. In the case of control without adaptation the target value of SpO_2v was exceeded by 10% and oscillations around the target value were generated. The adaptive control was able to reduce these oscillations and subsequently achieve the target values. Once this was achieved by changing the FiO2 the gas flow was slowly increased to reduce the PCO2. An accumulative mean square error (accMSE) was calculated to compare the performance of each controller, consisting on calculating the error between the current values and the target values. This analysis shows that the adaptive fuzzy control with medication (AFC/Meds) had the lowest accMSE. FC/Meds had the highest error since the response of the medication caused the pressure to drop and the EFR to increase, generating oscillations without reaching stability. The controllers without medication had a constant increase of MSE since the target values of EFR and MAP cannot be achieved due to a high SVR. The adaptive controllers however gave a better response." [2]

This suggests, due to the application of an adaptive fuzzy model, overall accuracy was improved. Fuzzy control allowed for a straight-forward implementation of expert knowledge.

The PI-Fuzzy Controller, when compared to others (4), has issues with oscillations and overshoots when compared with target values in the authors' experiments. In this case, it seems to confirm our texts implication that fuzzy logic shouldn't be applied to problems with verified solutions. This is an exercise in the decision-making process as to whether fuzzy logic can improve already proven control methods.

Conclusion:

We have reviewed different applications of fuzzy controllers in ECSS. For those who experience cardiogenic shock, a portable ECSS could be helpful. While being transferred to a hospital, it supplies the vital oxygen perfusion to the body. The ECSS must be properly and consistently adjusted to do this. This is made feasible by the ECSS's automation. A simple implementation of expert knowledge was made possible via fuzzy control.

PI controller is the one which provides best results on using various adaptive controllers. The concept and methodology behind these fuzzy regulatory systems suggest, again, that PI controllers and other conventional controllers may work with data better when the mathematical models are already proven, and fuzziness may be overlooked. However, the cases where fuzzy is warranted, the models are greatly improved with higher stability ad less cost. This allows for the miniaturization of system components to make it portable without sacrificing reliability.

References:

[1] A Mendoza G, B Baumgartner, U Schreiber, S Eichhorn, M Krane, R Bauernschmitt, A Knoll. Design of a Fuzzy Controller for the Automation of an Extracorporeal Support System with the use of a Simulation Environment.

[2] A Mendoza García, M Krane, B Baumgartner, N Sprunk, U Schreiber, S Eichhorn, R Lange, A Knoll. Automation of a Portable Extracorporeal Circulatory Support System with Adaptive Fuzzy Controllers.

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[4] Benedikt Baumgartner, Alejandro Mendoza, Stefan Eichhorn, Ulrich Schreiber, Alois Knoll. A Comparative Study on Extracorporeal Circulation Control.