Design of Fuzzy Logic Parameter Tuners for Upper-Limb Assistive Robots

Christopher Coco Jr., Jonathan Spanos, Hamid Osooli, and Reza Azadeh

***Abstract*— Assistive Exoskeleton Robots are helping restore functions to people suffering from underlying medical conditions. These robots require precise tuning of hyper-parameters to feel natural to the user. The device hyper-parameters often need to be re-tuned from task to task, which can be tedious and require expert knowledge. To address this issue, we develop a set of fuzzy logic controllers that can dynamically tune robot gain parameters to adapt its sensitivity to the user's intention determined from muscle activation. The designed fuzzy controllers benefit from a set of expert-defined rules and do not rely on extensive amounts of training data. We evaluate the designed controllers with three different tasks and compare our results against the manually tuned system. Our preliminary results show that our controllers reduce the amount of fighting between the device and the human, measured using a set of pressure sensors.**

I. Introduction

Assistive robotics is a growing field that aims to help people in need. Among others, exoskeleton robots and assistive orthoses can help restore some daily actions (e.g., picking objects or opening doors) that may be difficult or impossible due to underlying medical conditions [1], [2]. Although these robots are usually equipped with effective low-level controllers (e.g., PID controllers), the high-level parameters of the device (and sometimes the low-level control parameters such as the PID gains) need to be re-tuned manually to feel natural to the user. The device parameter tuning process can be done by experts. However, training the user or their caregivers to perform the parameter tuning for different tasks under different circumstances is a challenging process and could be tedious. As a result, researchers have been studying methods for hyper-parameter tuning using high-level controllers. A common theme in this area is the employment of the data-driven control methods. For instance, several reinforcement learning-based methods have been developed to learn sEMG-based control policies for upper-limb exoskeletons [3]–[5]. Several other methods rely on the advantages of neural networks [6], [7]. Both categories include algorithms that require extensive amounts of data for performing system identification and training.

Our study, on the other hand, seeks to integrate the benefits of data-driven methods with the robustness of rule-based methods [8]. To achieve this goal, we propose a fuzzy logic system [9]–[11] that can utilize the expert knowledge in the form of a set of rules designed by a human expert. For this study, we focus on the parameter tuning of upper-limb assistive robots and consider the MyoPro 2 device (Myomo Inc., Cambridge, MA) in our experiments. This device is an elbow and hand exoskeleton designed to help restoring functionality to the wearer's paralyzed or weakened upper body. To enhance user experience, the hyper-parameters of the robot, two gains in this case, must be tuned properly. We design two fuzzy logic controllers, one for each gain, to enable real-time parameter tuning. The ultimate goal of this research is to enable the robot to adapt from task to task under different conditions, improving the quality of human assistance experience. In this paper, we identify the hyper-parameters and critical factors affecting them. We then explain our controller design process and experimental setup. We evaluate the designed controllers with three tasks under several different conditions and compare the results against scenarios where the robot was tuned manually. Our preliminary results show the effectiveness of the proposed controllers for the hyper-parameter tuning.

Authors are with the Persistent Autonomy and Robot Learning (PeARL) Lab, University of Massachusetts Lowell, Lowell, MA 01854, USA {christopher_coco, jonathan_spanos, hamid_osooli}@student.uml.edu, reza@cs.uml.edu

Fig. 1: MyoPro 2 orthosis used in our research. (a) integrated sEMG sensors and (b) integrated pressure sensors for the arm joint.

II. Device Overview

The MyoPro 2 orthosis (Fig. 1) is an upper-limb exoskeleton designed to help with everyday activities. The device has two motor-controlled degrees of freedom (DoF). The elbow joint governs arm movements (i.e., extension and flexion) while the wrist joint enables hand movements (i.e., open and close). The device reads and interprets the muscle activation patterns into motor commands using two surface electromyography (sEMG) sensors. In this paper, we only focus on the arm movements which are continuous.

The MyoPro 2 robot has four different control modes: (a) *Standby mode* in which both of the motors do not receive readings from the sEMG sensors, (b) *Bicep mode* where the

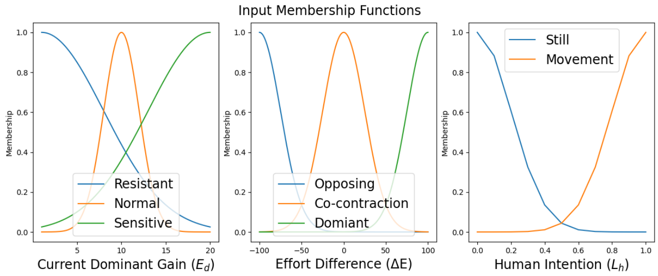

Fig. 2: Designed membership functions for the two controllers.

device only receives information from the bicep sensor which allows only for flexion movement, (c) *Tricep mode* where the device only receives information from the tricep sensor which only allows for extension movement, and (d) *Dual mode* which gets information from both sensors which allows for extension/flexion movements. In this paper, we focus on the *dual mode* which is the mode applicable to most everyday tasks. Although the dual mode can be set with three different movement types: constant, proportional, and exponential, our research focuses on the proportional mode that allows the device to adjust the speed proportionally. In other words, the device activates by measuring the changes in the dominant and opposing effort (E_d and E_o) weighted proportionally by a gain value (k_p) as

$$S = k_p \Delta E, \tag{1}$$

where S is the joint speed, $\Delta E = E_d - E_o$, and effort is defined as the ratio between the current and maximum values of the sEMG signal. The dominant and opposing efforts refer to the maximum and minimum value between the bicep and the tricep efforts, respectively. Whenever the effort difference ΔE surpasses a preset threshold for the muscle of the dominant effort the device then moves in that direction. Besides choosing a movement type and tuning the bicep/tricep effort thresholds, the user can also adjust the bicep/tricep gains. These gains are used to amplify the sEMG signal. In this paper, we consider tuning the gains instead of the thresholds. The reason is that the gains have a more direct effect on the sensitivity of the sEMG sensors, while the thresholds change upon muscle activation.

III. Fuzzy Controller Design

The overall parameter tuning process of the device depends on three main factors: (a) human intention, (b) current dominant gain E_d, and (c) effort difference ΔE. To dynamically tune the parameters of the MyoPro robot, we designed two controllers for adjusting the dominant gain, δE_d and the changes in the opposing gain, δE_o. For both controllers, we used a Takagi-Sugeno-Kang (TSK) fuzzy system [12] comprising the product inference engine, singleton fuzzifier, and the center average defuzzifier [9]. The controller that deals with the dominant gain takes two inputs: the human intention I_h and the current dominant gain E_d. We defined two Gaussian Membership Functions (MFs) to represent the human intention. The *still* MF describes the human intention to stay still, whereas the *movement* MF describes the intention to move. The second input (the current E_d) is in range $[1, 20]$. For this input, we define three Gaussian MFs: *resistant*, *normal*, *sensitive*. The output of this controller is a continuous value in range $[-3, 3]$ defined using five constant MFs: *decrease*, *small decrease*, *no change*, *small increase*, and *increase*. This controller can be defined as

$$\delta E_d = f_{E_d}(I_h, E_d). \tag{2}$$

We construct a rule-base for this controller including six IF-ELSE rules. This rule-base, as reported in Table I, is continuous, complete, and consistent [9].

TABLE I: Fuzzy rule-base for dominant gain controller, f_{E_d}.

		Current Dominant Gain E_d		
		Resistant	Normal	Sensitive
Human Intention I_h	Movement	Increase	Increase	Small Increase
	Still	No Change	Small Decrease	Decrease

The second controller that deals with the opposing gain also takes two inputs: the human intention I_h and the effort difference ΔE. The human intention input in this controller was defined similar to the one in the previous controller. We define the effort difference input, in range $[-100, 100]$, using three Gaussian MFs: *opposing*, *co-contraction*, and *dominant*. Similarly, the output of this controller is also a continuous value, in range $[-3, 3]$, defined using five constant MFs: *decrease*, *small decrease*, *no change*, *small increase*, and *increase*. This controller can be defined as

$$\delta E_o = f_{E_o}(I_h, \Delta E). \tag{3}$$

We construct a rule-base for this controller including six IF-ELSE rules. This rule-base, as reported in Table II, is also continuous, complete, and consistent [9]. The designed MFs and the corresponding control surfaces can be seen in Fig. 2 and Fig. 3, respectively.

TABLE II: Fuzzy rule-base for opposing gain controller, f_{E_o}.

		Effort difference ΔE		
		Dominant	Co-contraction	Opposing
Human Intention I_h	Movement	No Change	Small Decrease	Decrease
	Still	No Change	Decrease	Decrease

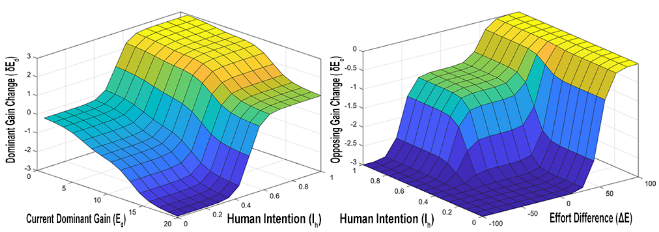

Fig. 3: Control surfaces for the controllers: (left) f_{E_d}, (right) f_{E_o}.

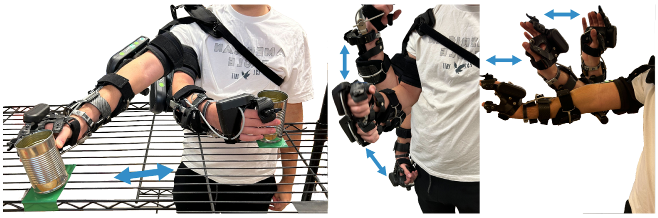

Fig. 4: Three tasks designed for evaluation. From left to right: horizontal motion, vertical motion, and pushing motion.

IV. Experiments

A. Experimental Setup

We evaluated the designed controllers using a MyoPro 2 orthosis in nine experiments. We compared the performance of the controllers against the manually-tuned device. To evaluate the effectiveness of the controllers, we defined a metric that measures the amount of *fighting* between the device and the human measured using two pressure sensors. It should be noted that the integration of pressure and sEMG sensors is common in assistive human-robot interaction scenarios [13]. During the manual tuning, the human used the built-in GUI (called MyConfig) to tune the gains in range $[0.2, 20]$. The default value for each gain was set to 10.

B. Task Design

We designed three tasks to include movements with different varieties. The first task, shown in Fig. 4 (middle), is a vertical motion that resembles a curling exercise. The second task, shown in Fig. 4 (left), is a horizontal motion that includes relocating an empty can. The third task, shown in Fig. 4 (right), is a pushing motion. To collect data, each task was performed three times. Each time we manually set the effort thresholds to a different value to generate different scenarios. The thresholds were set to 10, 20, and 40, representing the *sensitive*, *normal*, and *resistant* scenarios, respectively. For the manual tuning experiments, both gains were set to 10 which is considered the default value for the device. In each test, we collected data for 30 sec. For each scenario, this procedure allowed the user to repeat the vertical, horizontal, and the pushing movements, 5, 6, and 9 times, respectively. After each test, the user rested for a few seconds to reduce the effect of fatigue.

C. Data Collection & Pressure Sensors

To measure the amount of fighting between the user and the device, two MD30-60 pressure sensors were integrated to the MyoPro 2 orthosis. The placement of the sensors can be seen in Fig. 1. These sensors were aligned to make contact with the radius and ulna bones. It is important to note that the sEMG sensors can be used for detecting anticipatory signals for grasp and release despite sensitivity to sensor placement [14], [15]. The sensor placement, however, is a challenge when using pressure sensors. To mitigate this issue, we incorporate a custom 3D-printed sensor holder, ensuring stable positioning. The printed piece was tied down using a string to keep it in a fixed position. The pressure sensors were powered by two 1.5V AA batteries. To monitor the contact with these sensors the voltage is passed into a BTH-1208LS Data Acquisition System (DAQ). In our setup, the voltage increases when the user fighting with the device increases.

D. Results

To evaluate the effectiveness of the designed controller compared to the manual tuning case, we recorded the pressure during each task (i.e., vertical, horizontal, push) over different scenarios (i.e., sensitive, normal, resistant). The recorded data can be seen in Fig. 5 where the blue curves indicate the measured signal for when using the fuzzy controllers, while the red curves are for the manually tuned cases. For each curve, we calculated the area under the curve resulting in A_f and A_m (area for the fuzzy controller signal and area for manual tuning). For comparing the signals, we calculated the ratio $r = \frac{\Delta A}{max([A_f, A_m])}$. Results are reported in Table III and Table IV. Overall, our results show that the designed controllers helped to improve the vertical and the pushing task. It also helped to improve the horizontal task for the bicep but not for the tricep. Looking closer, we noticed the followings:

1) Vertical Task: The vertical task saw the most improvement with the controller because the difference in pressure was above 60% for both sensitive and resistant for the bicep and sensitive and normal for the tricep.

2) Horizontal Task: The horizontal task saw improvement for the bicep however, it saw worst results for the tricep. This is most likely due to the positioning of device during the tests. We plan to investigate this issue in the future.

3) Push Task: For this task, we noticed significant improvement in the bicep and decent improvement in the tricep.

TABLE III: Calculated area ratio for bicep pressure

		Tasks		
		Vertical	Horizontal	Pushing
Scenarios	Sensitive	65.31%	83%	40.1%
	Normal	44.4%	74%	51%
	Resistant	63%	69%	47%

TABLE IV: Calculated area ratio for tricep pressure

		Tasks		
		Vertical	Horizontal	Pushing
Scenarios	Sensitive	60%	-38%	20%
	Normal	61%	0.02%	43.3%
	Resistant	38%	-34.2%	38%

V. Conclusions & Future Work

We proposed a hyper-parameter tuning method for assistive robots using fuzzy logic and designed two fuzzy controllers to dynamically change the sensitivity of the MyoPro 2 orthosis. We evaluated these controllers across three tasks in various scenarios, comparing their effectiveness to manual tuning by measuring user-device fighting during

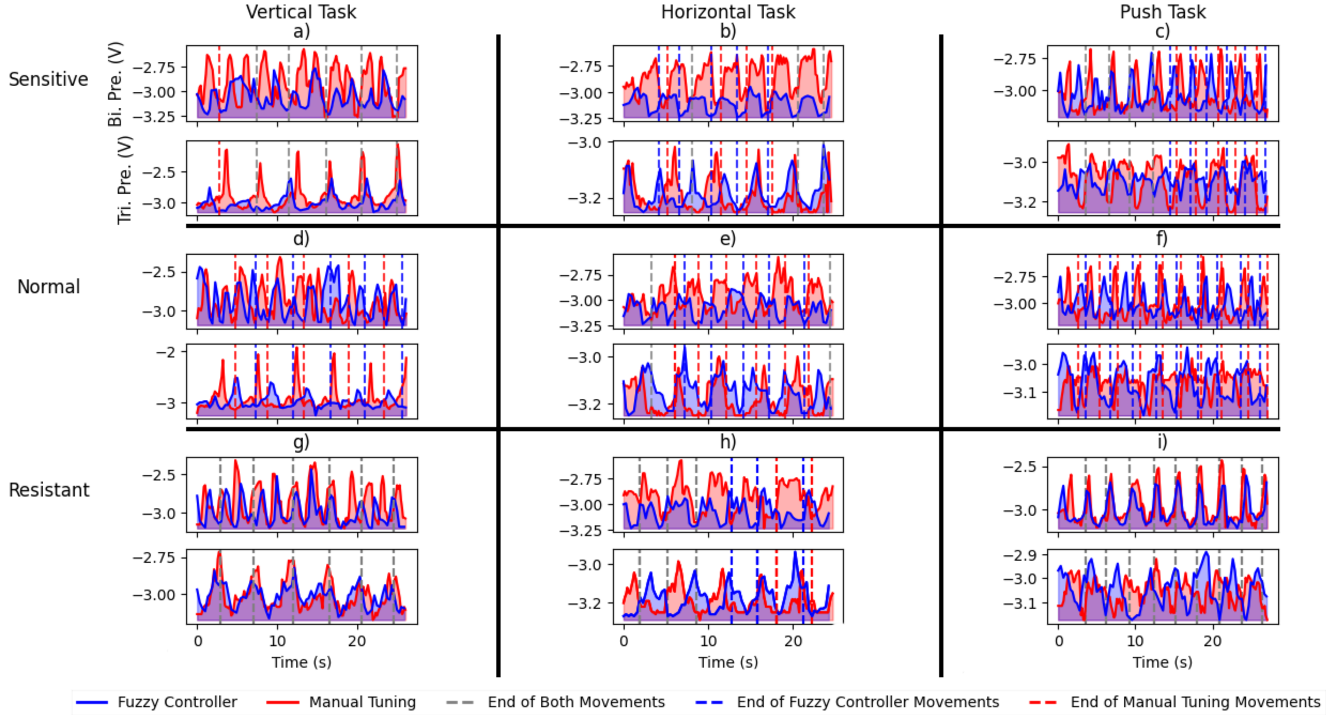

Fig. 5: Recorded pressure sensors signals for the sensitive (top row), normal (middle row), and resistant scenarios (bottom row). The plots correspond to the vertical (left column), horizontal (middle column), and pushing tasks (right column). In each task, the joint angle trajectory is plotted. The vertical dashed lines indicate when one trial of each task was completed and the next one started.

movement. Preliminary results indicate a positive performance enhancement, particularly for vertical and push tasks. However, no significant improvement was observed for the horizontal task involving the tricep. Further investigations will address controller shortcomings through additional experiments incorporating varied movement features and data collection from multiple human subjects.

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