A FUZZY-BASED DYNAMIC THRESHOLD ALGORITHM FOR MOTION INTENTION DETECTION SYSTEM FOR UPPER-LIMB ELECTROMYOGRAPHY (EMG) SIGNAL CHARACTERIZATION

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ABSTRACT: *Dynamic threshold is a method of determining a normal behavior range of a certain performance metric. In robotic rehabilitation devices, motion intention detection is an important parameter to consider. The robot's active participation through its assistance is dictated by the electromyography (EMG) threshold signal level in which this signal can be measured using the mean EMG signal (mV). This paper presents a fuzzy-based dynamic threshold algorithm for motion intention detection system used in the characterization of the upper-limb EMG signal. The fuzzy output is obtained mainly from the two inputs: initial position and movement velocity. Results were analyzed statistically to observe its dynamic behavior using different test subjects.*

Keywords: Computer simulation, electromyography (EMG), fuzzy logic, motion intention detection, rehabilitation robotics.

1. INTRODUCTION

Rehabilitation robotics, as shown in Figure 1, is a specific field in biomedical engineering that is designed to assist patients that requires skeletal-muscular assistance [1]. Nowadays, the current trend in robotic devices include powered-exoskeletons for aiding limb or hand movement to perform their daily task activities like eating, walking, etc. [2,3]. Designing such system will not only require mechanical design and controls, these robots need to be adaptable and programmable at the same time to perform multi-operation jobs.

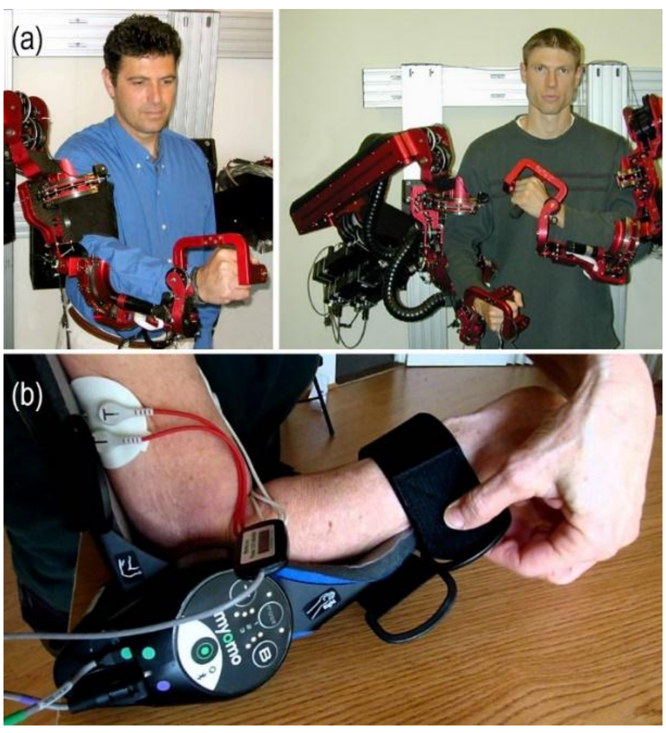

Fig. (1) Sample wearable exoskeletons [3]

In any robotic rehabilitation devices, one parameter need to determine is motion intention detection or recognition [4,5]. Motion intention is a requirement in the active participation of the patient in physical rehabilitation. This parameter will tell the robot if there is a need for robotic intervention during the need for assistance. This is very essential especially in robot-assisted therapy that will assist patients to actively participate in training exercise instead of depending on passive motions. This human-robot interaction and coordination is critical to their overall wellness and physical recovery [6].

In predicting a patient's skeletal muscular activity, the dynamic threshold value of electromyography (EMG) signal is required [7]. EMG is measuring the electrical signal associated with the muscle activation. With that, this study will determine the bicep EMG signal behavior using its threshold level via fuzzy logic approach. The study will make use of the *initial position* or the degree of flexion and the *movement velocity* as factors or fuzzy inputs. Moreover, the study will provide a control surface plot that will describe the behavior and relationship of the threshold level in respect with these inputs. This methodology will be helpful in conducting future optimization runs for the active control of robotic therapy in the upper-arm rehabilitation.

2. REHABILITATION BIOFEEDBACK

Biofeedback is a method used in learning to control a certain body function like heart, muscle, body temperature, etc. One good example of a biofeedback signal that is commonly used in stroke rehabilitation is detection of muscle signal behavior [8]. As demonstrated in Figure 2, this method involves placing surface electrode sensors over a skeletal muscle with an EMG in monitoring the electrical activity that causes muscle contraction then send it back to the user for further analysis.

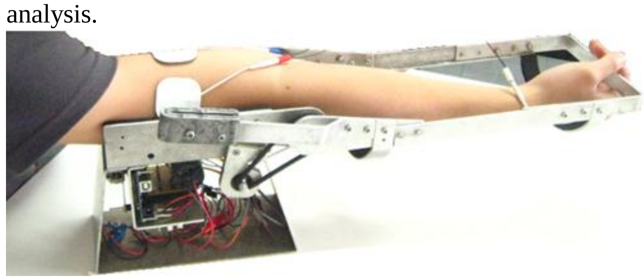

Fig. (2) EMG surface electrodes attached to the biceps.

Figure 3 displays a sample bicep EMG signal response using the Biopac instrumentation systems wherein four signal data were generated for 16 seconds. Biopac is a modular and powerful data logger or acquisition system used in academic and scientific research.

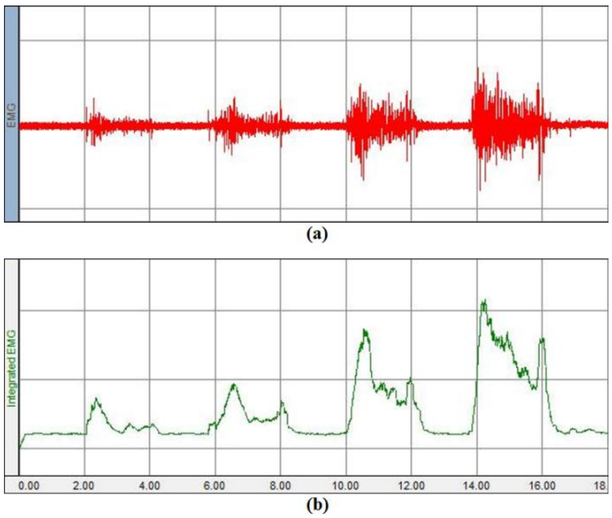

Fig. (3) Sample bicep a) EMG (mV) and b) iEMG (mV-s) signal response.

The first graph (see Fig. 3a) is the actual mean EMG signal (mV). On the other hand, the second graph (see Fig. 3b) corresponds to the integrated EMG (mV-s) in which its value is mathematically computed from the first curve.

$$RMS\,\{m(t)\} = \left(\frac{1}{T}\int_t^{t+T} m^2(t)dt\right)^{0.5} \qquad (1)$$

Integrated EMG, or iEMG, is defined as the area under the rectified EMG signal curve. From Eq. 1, it is the mathematical integral of the absolute raw EMG signal. Moreover, using maximum iEMG, it will be easier in interpreting the signal visually and approximates the envelope of the iEMG signal.

3. FUZZY LOGIC

Fuzzy logic control is merely the application or implementation of fuzzy logic to control system [9]. The main idea is purely based on the concepts of fuzzy sets, linguistic variables and reasoning or inferences [10]. Figure 4 displays the schematic diagram of a fuzzy logic control system.

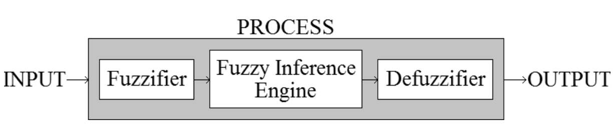

Fig. (4) Fuzzy logic control architecture. ***[11]***

As displayed in Figure 5, the structure of fuzzy logic, when applied to control system, is almost identical to an open-loop or straightforward-based controller that contains an input, process and output. Inside the process block is the fuzzy control that has the following components: fuzzifier or fuzzy input, fuzzy inference or process engine and defuzzifier or fuzzy output.

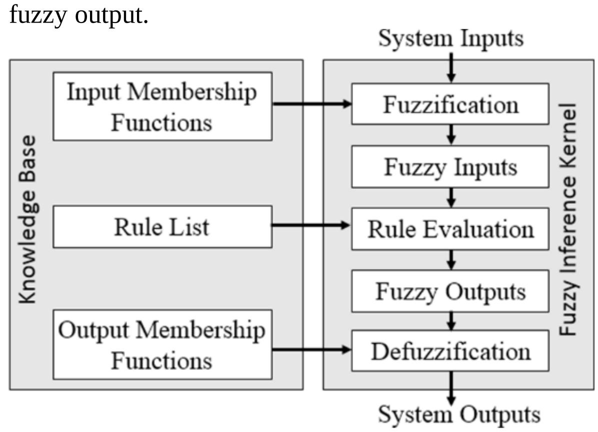

Fig. 5: Knowledge-based to fuzzy inference. ***[12]***

In the fuzzifier, the fuzzy controller receives the physical input data, then analyzes and converts it into fuzzy values. It contains the membership function and the label. The membership function is a multi-valued characteristic function that defines the fuzzy set to a certain grade. It uses shapes like triangular (Δ), trapezoidal (Π) or Gaussian. Meanwhile, the label defines the membership function. Figure 6 displays a sample fuzzy input or fuzzifier containing five triangular (Δ) membership functions with labels very low, low, zero, high and very high.

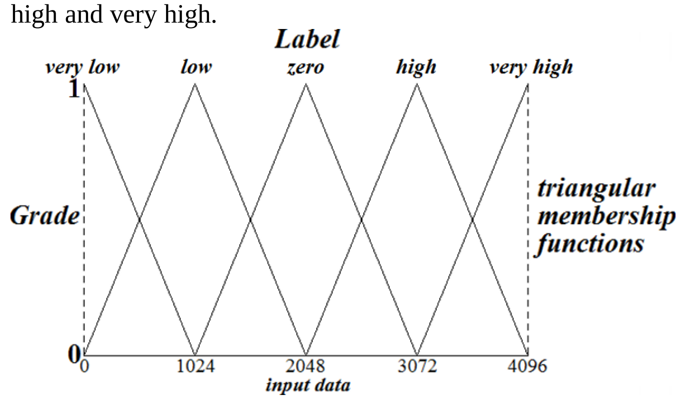

Fig. (6) Fuzzifier with 5 triangular functions.

After that, these fuzzy values will be used by the next stage which is the fuzzy inference engine. This engine is used to develop a certain response output based on natural language.

1	IF temperature is very cold THEN fanspeed is very slow
2	IF temperature is cold THEN fanspeed is slow
3	IF temperature is normal THEN fanspeed is average
4	IF temperature is hot THEN fanspeed is fast
5	IF temperature is very hot THEN fanspeed is very fast

Fig. (7) Sample design rule block ***[12]***

This type of rule evaluation consists of series IF-THEN rules that are logically connected using AND. It will only activate or trigger a certain THEN rule once an input condition satisfies the IF part. This is where the programmer will develop the fuzzy rules through rule evaluation design. As described in Figure 7, designing the set of fuzzy rules could be in terms of a rule matrix or rule block.

In fuzzy logic, the defuzzification or the defuzzifier is the final stage where it converts back fuzzy values or expressions to real data values [13]. Several defuzzifier methods are available and all are based purely on mathematical concepts and algorithms [14,15].

$$Fuzzy\_Output = \frac{\sum_{n=1}^{n=N}\left[(FO_n)(FGrade_n)\right]}{\sum_{n=1}^{n=N}(FGrade_n)} \qquad (2)$$

The middle of maximum (MOM) and the center of gravity (COG) are two of the most common defuzzification techniques. From Eq. 2, COG states that the final fuzzy output value is equal to the ratio of the sum of each rule outcome's grade multiply with the actual output counts to the sum of outcome's grade.

4. METHODOLOGY

In this study, experimentation is composed of four major blocks as shown in Figure 8. The data gathering phase is the part where each test subjects will perform an upper-arm rehabilitation exercise. Then, this will be followed by the data acquisition for EMG signal characterization which will be performed and executed in a biomedical instrumentation device. In this study, the device or platform used to perform muscle data acquisition is the Biopac MP-35 system. Using the Biopac, the electrodes and transducers employ sensors in allowing the software to communicate with the user.

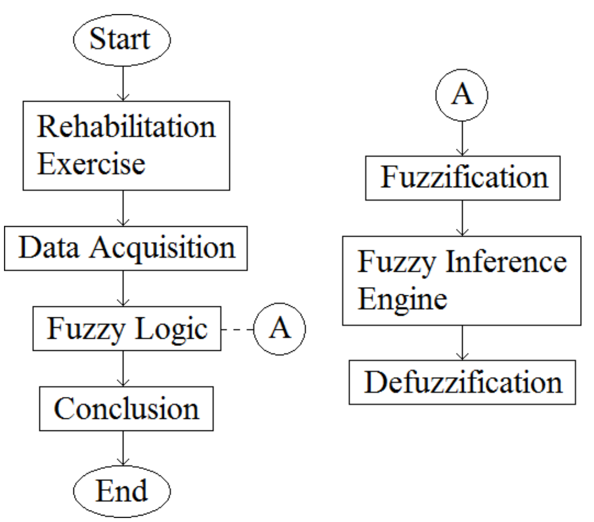

Fig. (8) System flowchart.

In the data acquisition phase, test subjects will be undergoing an upper-arm rehabilitation exercise. A total of eight healthy subjects were used in this study to perform repetitive forearm movements, as shown in Figure 9a, using different combinations of *initial position* and *movement velocity*. Figure 9b displays the data communication transfer of the EMG signal data to a workstation using the Biopac that serves as the integration platform and data acquisition unit. In collecting real-time EMG signal, non-invasive EMG surface electrodes were used.

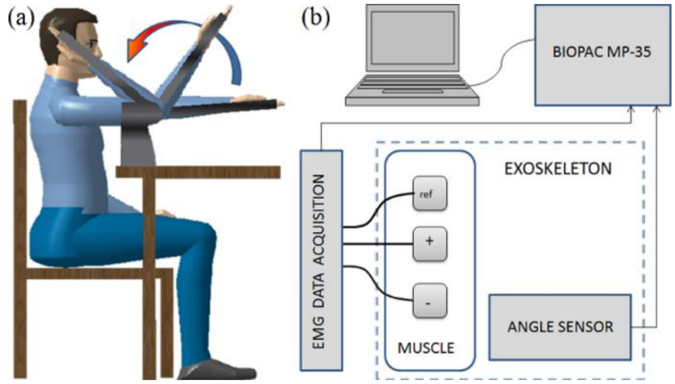

Fig. (9) Setup used for a) experimental data gathering and b) layout of EMG data acquisition. *[16]*

For the fuzzy system (see Fig. 10), two inputs, which are the *movement velocity* and *initial position*, were used in the analysis to provide the threshold level which represents the fuzzy response or output. The design of each membership function and labels were based statistically from the previous study conducted in the bicep EMG signal characterization [16].

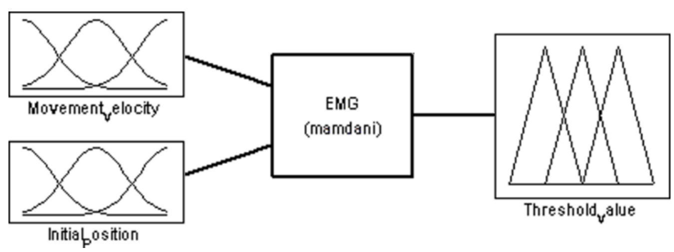

Fig. (10) Design of the 2-input single-output fuzzy system.

Table 1 displays the summary of the two fuzzy inputs used in the study. The input *initial position* was labeled using end, mid and full with range from 0^0 to 150^0 while the input *movement velocity* used the labels slow, normal and fast ranging from 0.028 to 0.314 ^{0}/ms.

Table 1: Summary of the Two Fuzzy Inputs

Item	**Fuzzy Inputs**	
	Initial position	***Movement velocity***
Functions	1 trimf, 2 trapmf	3 gaussmf
Labels	End, mid, full	Slow, medium, fast
Data Range	0 to 150	0.028 to 0.314
Units	Degrees (^{0})	^{0}/ms

5. EXPERIMENTAL RESULTS

For the design of the first fuzzy input, as illustrated in Figure 11, since the end and the full members are located at the endpoints of the *initial position*, they were assigned with a trapezoidal function (trimf). The use of both triangular and trapezoidal (trapmf) functions in the *initial position* is easy to justify since the statistical response is very linear from the study conducted by Sy et al.

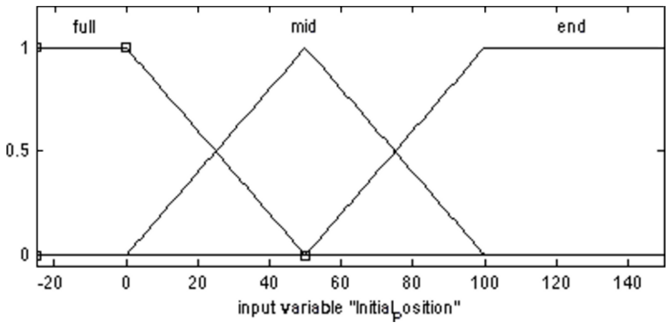

Fig. (11) Initial position fuzzifier input

For the *movement velocity*, as depicted in Figure 12, the labels used (slow, normal and fast) were assigned with Gaussian functions (gaussmf). This is due to the response observed from different test subjects which is almost near to normal distribution. Moreover, during experimentation and testing, *movement velocity* is easy to quantify but difficult to categorize due to the variation of individual's muscle grade, thus, produces wide variation.

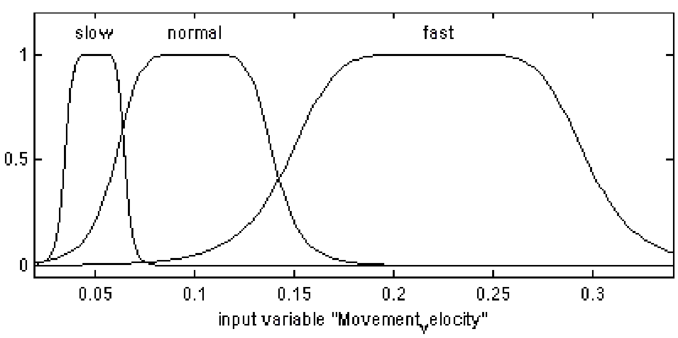

Fig. (12) Movement velocity fuzzifier input

For the defuzzifier, which is the threshold value, its design and configuration were based from the output of a pulse-width modulation (PWM) motor or robot such that the response could be zero, low, normal or high depending on the fuzzy rules (see Fig. 13). PWM is a type of modulation scheme used to control the width of the pulse based on the modular signal information [17,18].

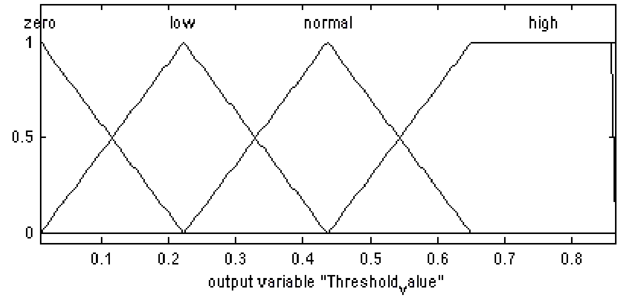

Fig. (13) Threshold value defuzzifier output

As illustrated in Figure 14, rule evaluation was employed to quantify the response via linguistic descriptions. For example, if the *movement velocity* is 0.18 ^{0}/ms and the *initial position* is at 50^{0}, the threshold value is at 0.437 or 43.7%.

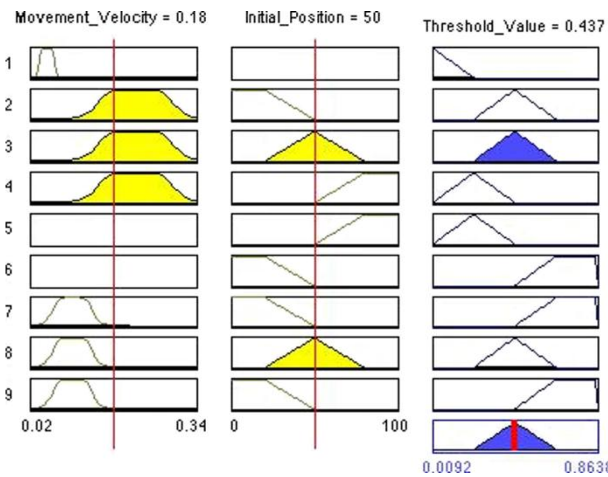

Fig. (14) Rule evaluation for the fuzzy-based dynamic threshold

To further understand the behavior of motion intention detection, a control surface plot was also generated using the Fuzzy Logic Toolbox in MATLAB. This three-dimensional (3d) plot is a type of graphical curve that is used to display a surface. Figure 15 illustrates the 3D control surface plot based on the fuzzy response from *initial position* and *movement velocity*.

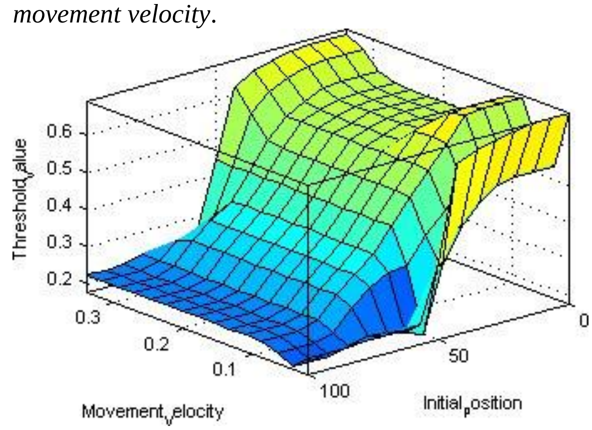

Fig. (15) 3D surface response plot

By mapping the input parameters to the output variable, this control plot helps in predicting the behavior of the output given the varying input-level combinations and in conducting fuzzy optimization runs.

6. CONCLUSIONS

In this study, the implementation of the fuzzy logic concept was successful in determining the threshold level for the bicep EMG signal amplitude under varying degrees of input parameters which are the initial position and the movement velocity. Clearly seen from the results and based from the rules, increasing the movement velocity, the amplitude of EMG signal increases.

For the initial position, which affects the degree of muscle flexion, results show that amount of EMG signal is actively high during the full range of motion which corresponds to a low degree of initial muscle flexion.

7. ACKNOWLEDGEMENT

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