EXPLORATION OF FUZZY LOGIC AS A MEANS TO HANDLE IMPRECISE EMG SIGNALS IN PATTERN RECOGNITION CLASSIFIERS

Stephanie A. Lorelli & Richard F. *ff*. Weir

University of Colorado Denver: Department of Bioengineering

ABSTRACT

Myoelectric pattern recognition systems have the potential to offer intuitive selection and nearly seamless switching between different prosthetic hand grip patterns. This is made possible by using surface electromyogram (sEMG) signals to decode the user's intent each moment in time instead of the user sequentially switching between pre-programmed patterns via a unique motion. However, despite many advances in machine learning algorithms, myoelectric hands face numerous clinical barriers which prevent widespread user acceptance and adoption [2]. These clinical barriers include accuracy declines from sEMG signal shifts, imprecise control, operation lag times, and daily retraining time burdens [3,2].

Fuzzy Logic is a powerful tool which can transform ranges of numerical values into linguistic variables for performing mathematical approximations much like how we use language to describe subsets of populations without having exact numbers [4,5]. Therefore, since sEMG signals are notoriously noisy and have imprecise ranges, Fuzzy Logic may offer a way to account for this inherent signal property yet still be able to decipher the overall control signal command. This quality has the potential to address some of the clinical challenges of being able to reliably differentiate between active contraction and rest states, even if the sEMG signal has shifted due to fatigue or untrained arm positions which other machine learning algorithms seem to struggle with handling [3,7].

Based on promising results from Ajiboye & Weir, we seek to re-explore Fuzzy Logic as a rule-based pattern recognition system [1]. Our preliminary data shows that a Fuzzy C-Means (FCM) system is able to maintain higher accuracies across multiple bin sizes with averages ranging from 76-82% for the resting & momentary "OFF" data compared to a Linear Discriminant Analysis (LDA) system with averages ranging from 53-73%. Therefore, progress from a control perspective seems to have been made as it is easier to reliably return to a resting state before making a desired posture again instead of waiting for the control system to determine if the desired state is actually "OFF". While this is intriguing, more optimization still needs to be done to have this FCM system obtain higher "ON" postural contraction accuracies closer to the clinical standard-of-care LDA system.

INTRODUCTION

Clinical Problem

Machine Learning is a powerful tool for finding underlying patterns in large quantities of data. This has led to impressive technologies such as facial recognition, computer vision, AI speech technology, and other forms of data analysis in the medical research fields. Despite the best advances in machine learning, there is still a low adoption rate for myoelectric prosthetic hand systems [2]. However, this is not due to producing low accuracy rates. In fact, greater than 95% "ON" classification rates have been produced since the 1980s [2]. So the puzzling thing is, why do people prefer to not use myoelectric pattern recognition hands? One answer points toward the fact that these high accuracies achieved in a lab setting decrease significantly when the system is used in daily life with many other external factors to account for [3]. Even training neural networks with more extensive data does not necessarily solve these clinical problems as many would have hoped for. To date, researchers are still struggling to find a machine learning algorithm that presents a robust solution for dealing with changing noise and EMG patterns in daily use while minimizing the training burden on the user.

Research Rationale

Humans produce muscle contractions to perform different hand postures. When our brains are forming, we learn how to produce repeatable muscle patterns reliably. Therefore, the same neuron connections for muscle memory are strengthened every time we produce the same action, acting almost like a rule. However, each time the muscles contract to produce a posture, there will be some slight variation in the final signal due to human imprecision. In addition, myoelectric signals fluctuate throughout the day and as a result, produce patterns that are different from initial training data. These factors challenge pattern recognition systems as it is difficult to account for all possible scenarios of fatigue, accumulation of sweat, and different arm positions without requiring a person to spend hours training and recalibrating each day.

We hypothesize that FCM may offer more robustness in the face of imprecise EMG signals compared to the standard-of-care LDA system since Fuzzy Logic offers a way to handle noisy data by not needing to calculate exact numerical values and can accept values that are within similar rules, memberships, and ranges. This is done by transforming hard numbers into linguistic variables which is similar to how we utilize adjectives to refer to portions of populations without performing computations to reduce brain energy consumption [4,5]. Therefore, we are exploring how an FCM system can classify hand postures with imprecise sEMG ranges while reliably separating those from momentary rest states and minimizing the amount of data that is necessary to train the system.

METHODS

<u>How Fuzzy Logic and Clustering Works</u>

There are two parts to the FCM system. First, there is the Fuzzy Clustering where multiple centers are spread across a feature's data cloud to capture the whole space instead of reducing it to one point like how an LDA system works. This is done by sharing the membership (U) of each point as a percentage based on the relative closeness to each center. The data then pulls the centers apart through an iterative process such that each data point tries to obtain the highest U possible [8].

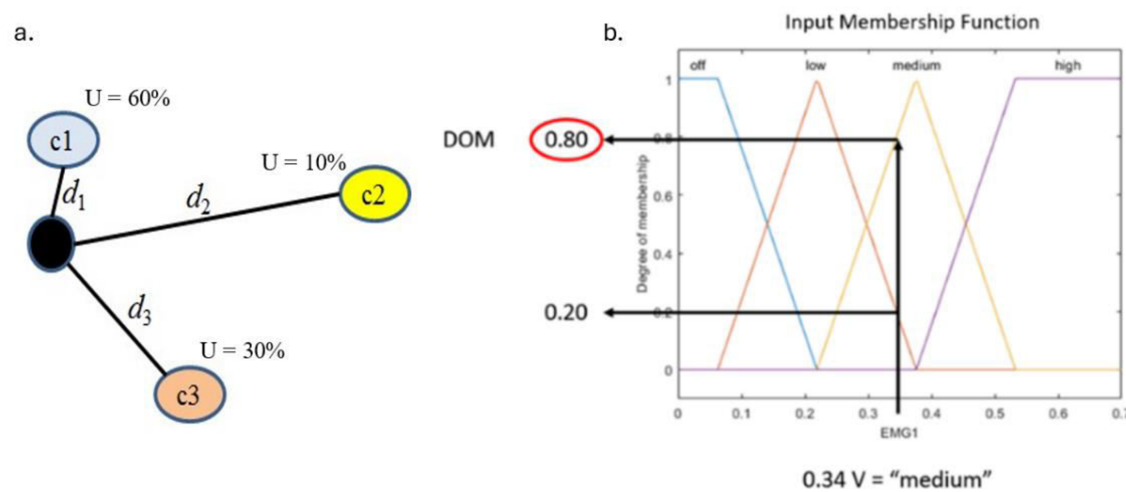

Figure 1:(a.) Fuzzy Clustering membership is shared between all cluster centers based on the relative distance to each center [8]. (b.) Converting cluster center numeric values into linguistic values via a membership function. Here we have 0.34 Volts being inputted into the membership function which is converted into "MEDIUM" via the highest degree of Degree of Membership (DOM) [8].

The second part is the Fuzzy Logic System where each center is transformed into a linguistic variable. Once the locations of the feature centers are determined, then their numeric values are converted into linguistic variables such as "OFF", "LOW", MEDIUM", or "HIGH" via an input membership function. Once we have converted each cluster center into a linguistic variable, we can now create rules that describe what each sEMG channel is doing when a certain posture is being performed. Such as, *If* [EMG_1 is "LOW" & EMG_2 is "HIGH" & EMG_3 is "OFF"] *then* Posture = "Hand Close", to describe a Root Mean Square (RMS) feature's center. Then we determine how well a new point matches to the rule via a degree of membership (DOM). The highest DOM produces the final hand posture's classification. While Ajiboye only used RMS, we are also exploring the use of a common time-domain (TD) feature set of RMS, zero-crossings (ZC), slope-sign-change (SSC), and wavelength (WL) paired with this approach.

Once we have a rule base of "IF/THEN" rules, we have a computationally inexpensive way to see how well each new numeric value matches to a rule within a posture's EMG set [1]. Ultimately, this can decrease controller delay times and potentially decrease the amount of data required to initially train the system since all that is required is a mean and range of data which can be produced by even one EMG contraction. In practice, multiple contractions would be beneficial for reproducibility purposes. Also once set up, membership functions can accommodate EMG shifts due to already being trained on a spread of data for each posture.

<u>"ON" vs. "OFF" Total Real-Time Controller Accuracy Testing</u>

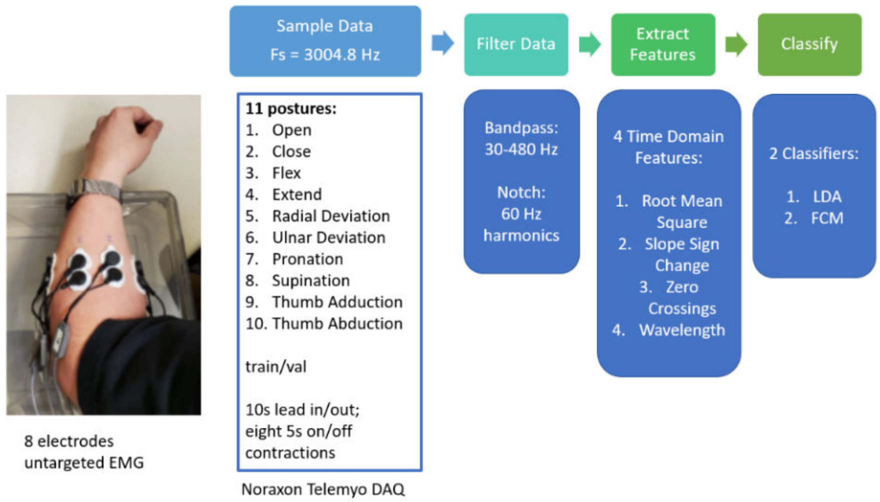

Figure 2: Data Acquisition Protocol for the CU Denver Weir Biomechatronics Development Lab covered under COMIRB No: 14-0838.

The first part of creating a controller is to see if it can reliably differentiate between multiple grasp patterns. These "ON" contractions are typically the ones reported in the literature and achieve very high accuracies within a lab setting [2]. However, in a real-time controller the person is switching between active grasp patterns and resting patterns. Unfortunately, the accuracies reported in literature do not include an overall accuracy comprised of how well the controller switches between a posture and back to a brief resting pattern between contractions. Therefore, we are researching how to report both the "ON" and "OFF" accuracies for any given controller to obtain information on how well each system can reliably and quickly differentiate between active contraction and momentary rest states as a user would experience the system.

We have tested, built, and acquired data (Figure 2) for two control systems and are using cluster computing to fine tune hyperparameters and compare the Fuzzy Logic system to the clinical standard-of-care LDA system.

PRELIMINARY DATA & OBSERVATIONS

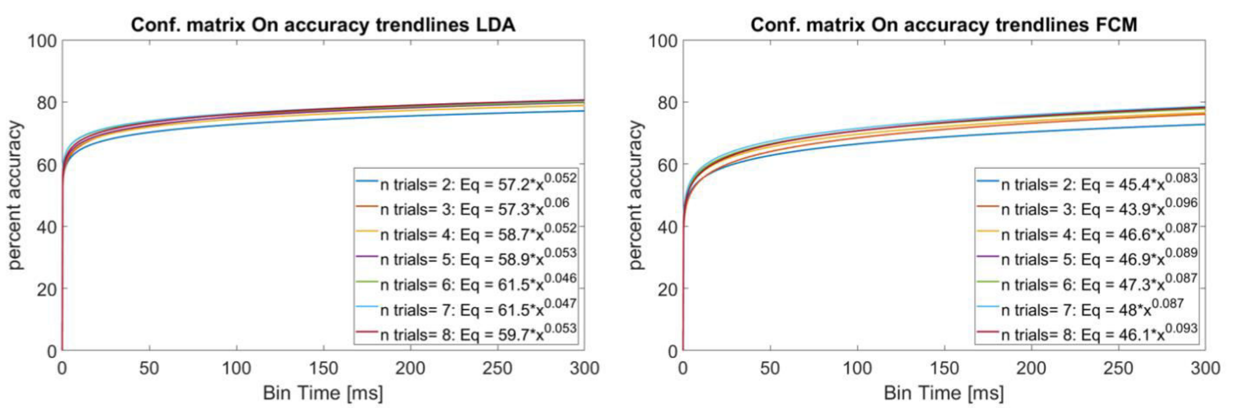

Figure 3: LDA & FCM "ON" Data testing across different bin time sizes and numbers of contractions to train each posture. From 7 people, LDA averages range from 60-80% while FCM averages range from 43-78%. We reach a tight accuracy band after 100ms bins generally agreeing with Ajiboye & Weir and Smith, Hargrove, Lock, & Kuiken and if "n trials" is greater than four [6, 1]. However, minimal accuracy improvements happen even if more contractions are included all the way up to 8 contractions per posture in training data. Therefore, we may be able to reduce the training time burden on the users by requiring only 5 or 6 contractions per posture instead of 8 or more.

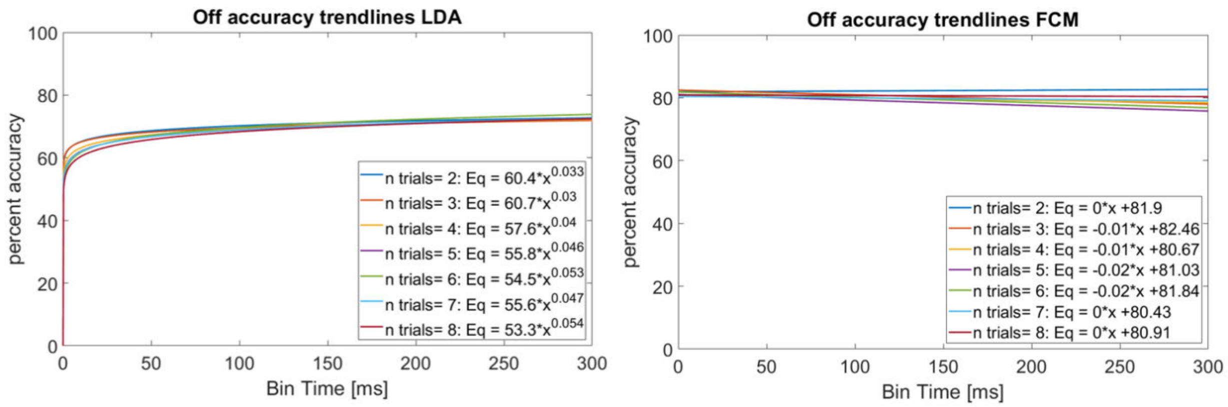

Figure 4: Averages from 7 people range from 53-73% for the LDA "OFF" Data testing across different bin time sizes and numbers of contractions to train each posture. We reach a tight accuracy band with minimal improvement after 100ms bins. For the FCM "OFF" Data testing, averages range from 76-82%. We reach a declining accuracy after 50ms bins, however overall FCM "OFF" accuracies start out higher than the LDA "OFF" accuracies.

This work used the computing resources at the Center for Computational Mathematics, University of Colorado Denver, including the Alderaan cluster, supported by the National Science Foundation award OAC-2019089. The averages for each of the "n trials" are from using 7 people's sEMG data, each run with varying numbers of bin sizes and numbers of contractions per posture to train the algorithms. Trendlines with explanations are plotted in Figures 3 & 4.

CONCLUSION

We see that the Fuzzy Logic system may offer ways to reliably control a prosthetic hand by making it easier to differentiate between active contractions and momentary rest states. In addition, it may be possible to reduce the obligations on the amount of data and time required by the user to train the system. For example, only needing the user to train the system on 6 contractions per posture instead of 8 or more.

While this is useful, "ON" accuracies for the FCM across the board need to be improved by around 10% to be comparable to the LDA "ON" accuracies. Therefore, further research will be done to continue to optimize the FCM algorithm and test different feature combinations in hopes of providing a future controller that is intuitive, robust, and responsive for prosthetic hand users.

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