Identification of Upper Limb Movements through EMG Signals with Fuzzy Logic Algorithm

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Abstract: Electromyography consists on recording the electrical potential generated by the activation of muscle fibers when performing voluntary or involuntary movements. Thus, EMG signals (EMGs) are directly linked to the human intention of motion. However, due to the random nature of EMGs, the correct prediction of the intention of motion is considered the most difficult part of the myoelectric control. A movement identification algorithm to distinguish among nine different movements of the upper limb is presented. Three fuzzy stages were developed. The if-then rules at each stage reflect the behavior of muscle fibers when performing a particular movement. This algorithm was evaluated using surface EMG recordings measured over the Deltoid, Bicep and Pronator Teres muscles. Three main features were extracted from each channel, the root mean square, the contractility characteristic and the onset value. Results have shown a high percentage of accuracy.

Keywords: Electromyography, root mean square, onset, fuzzy logic.

1. Introduction

EMGs are directly linked to human intention of motion. In the past decades, Electromyography is considered a valuable and indispensable technique in studying the human movement as well as a diagnostic tool for identifying neuromuscular diseases and many disorders related to motor control. In the last decade, a rapid increase on human-machine interaction research and project development have been observed specially towards exploiting EMGs to develop new types of human-machine interaction [1], including emotion recognition (Cheng & Liu, 2008). However, it has been mainly focused on developing systems that help people overcome difficulties encountered on their daily lives such as:

- Human power augmentation or human power assist: allows workers to carry loads heavier than their allowable physical conditions.
- Robotic rehabilitation: towards bilateral rehabilitation to help patients who have been diagnosed with a stroke to regain their motor control and motor function.
- Prosthesis: provides impaired person who has suffered a loss of a limb to perform daily functions.

However, unlike machines found in industry, the robotic exoskeletons and prosthesis used for rehabilitation have to directly interact with the user [2]. In such application, the most popular approach regarding the myoelectric control of such human-machine interaction is on using EMG signals to represent human intention of motion.

Due to random nature of EMG signals, in the present field, it has been reported that finding the correct prediction of movement is the most difficult part in myoelectric control. EMGs tend to vary from person to person and even within a single person at different conditions. As reported in [1], most of the developmental area is based on pattern recognition using neural networks. Despite of the great capability of learning from examples that neural network presents, it imposes a tedious training program prior to the use in the assistive robotic machines. Moreover, there is a broad lack of understanding of the classification process, which post reliability concern in medical application.

The organization of this paper is as follows. First, a brief introduction to fuzzy logic theory is presented, followed by the acquisition, onset detection and preprocessing of EMGs description. Lastly a classification algorithm of nine movements of upper limb based on fuzzy logic theory is presented. These movements are: abduction (AB), adduction (AD), flexion of the upper limb (FUL), extension of the upper limb (EUL), extension of the forearm (FF), extention of the forearm (EF), supination and pronation.

The algorithm consists of three fuzzy stages. Stage one determines which segment of the upper limb is moving, the forearm or the arm. In the second stage, the algorithm is used to distinguish movements performed by the arm (AB, AD, FUL, EUL or AB+FUL). Meanwhile the third stage identifies which movement of the forearm is being performed (supination, pronation or extension of the forearm).

The fuzzy set theory is used as the tool needed to reflect the behavior of the muscle fibers within a single muscle, a motor muscle, in order to develop a robust and repeatable pattern recognition algorithm. In other words, fuzzy logic allows us to teach machine the human way of reasoning.

2. Theory

Fuzzy logic is a logic referring to the study of methods and principles of human reasoning. Fuzzy Logic provides a simple way to arrive at a definite conclusion based upon vague, ambiguous, imprecise, noisy or missing input information. Fuzzy logic presents many advantages such as its inherent robustness. It does not require precise, noise-free inputs and can be programmed to fail safely if a feedback sensor quits or is destroyed. Moreover, any sensor data that provides some indication of a system's actions and reactions is sufficient. Because of the rule-based operation, any reasonable number of inputs can be
processed and numerous outputs generated.

3. Signal Acquisition

The EMG signals were recorded using a four channel surface Delsys Bagnoli desktop EMG system. In order to eliminate artifacts, a main amplifier unit filter is used to filter the signals within bandwidth between 20 Hz and 450Hz. It is important to mention that with this filter, it does not cause any loss of the signal information since most the power and frequency contents of the EMGs are within this region [3].

The sampling frequency was set at 1000Hz and the selectable gain was set to 1000 for each channel. Two surface electrodes were placed over the Deltoid muscle; over the middle part and the anterior part of the deltoid muscles, respectively referred as channel one (CH1) and channel two (CH2). Moreover, the third electrode was placed over the bicep brachii (CH3) and the fourth electrode over the pronator teres muscle (CH4), as shown in figure 1. Ten subjects were measured, seven males and three females. Each of the ten different movements of the upper limb was recorded five times, each period lasts for five seconds. Three recordings were performed while the subject was standing and two recordings were conducted when the same subject was sitting. Two of the ten subjects were asked to perform each movement five times when standing and five times when sitting, respectively. The purpose of such arrangement is to allow us to observe repeatability of the results within a single person regardless of the initial position.

![Fig.1. Electrode Placement](image)

4. Feature Extraction

The root mean square (RMS) of 500ms EMG signal containing 500 samples after onset detection was calculated. The RMS of the EMG signal is considered to be the parameter that more completely reflects the motor unit behavior during a muscle contraction [3]. The second feature extracted was the contractility characteristic of the muscle. The contractility of the muscle refers to the characteristic that presents the condition when muscle fibers are at the beginning of a moment. If the muscle fibers were not contracted, which is at rest, or if the muscle fibers were contracted at the beginning of a particular movement, a value of 01 and 10 were assigned respectively. The contractility value was determined from a simple comparison between the averages of a determined number of peaks from the envelope of the signal. It is important to note that the envelope was also obtained using a 4th order low-pass butterworth filter with a cutoff frequency of 50Hz so as to ensure that the envelope follows closely the behavior recorded on the EMGs. Lastly, the onset value of each measure was calculated using the method explained in [4].

5. Algorithm

In order to develop a coherent and robust algorithm which identifies the intention of motion of a particular subject, it is essential to understand the origin of the signal, or the point when muscle fibers start to engage. Since the objective is to translate the behavior of the muscle fibers to if-then rules, the fuzzy logic, it is proposed to use EMGs recordings from agonist muscles, where we can obtain most motor muscles, to differentiate between different movements of the upper limb. A comparison between extensors and flexors muscles is often preferred [5]. The proposed algorithm primary focuses on the behavior depicted by the activation of the muscle fibers within a muscle when performing different movements. In order to explain the algorithm, two important properties were considered which are defined as follows:

- Property number one: depending on the work that a muscle is required to perform, variable number of muscle fibers need to contract (Scanlon & Sanders, 2010a).
- Property number two: there exists a quasi-linear relationship between the root mean square (RMS) value of the EMGs and its magnitude [6].

Fuzzy Stages

The fuzzy stages were developed using Matlab fuzzy logic toolbox. Moreover, it is important to note that the inference process selected was the Mamdani’s method. The bisector defuzzification was implemented at all stages. Operations of each stage are explained in details below:

Stage One:

The purpose of fuzzy stage one is to determine which part of the upper limb is producing the movement: the arm or the forearm. The RMS and onset value of CH1 and CH3 signals are used to calculate the variable inputs in this stage. The calculation of the input variable is based on the fact that if the arm is moving a shoulder muscle Middle Deltoid (MD), which apparently leads to a greater RMS value in CH1 as compared to the Bicep EMG signal in CH3. On the other hand, if the forearm is moving (flexion of the forearm, extension of the forearm, supination or pronation), the RMS of the Bicep muscle is going to show a particularly high value as compared to the MD, which in this case will produce a slight movement or no movement at all.

Moreover, the primary motor muscle will present a slightly faster or earlier onset than the secondary motor muscles. The secondary motor muscle will collaborate to complete the movement. This is another key characteristic used in this stage to calculate the corresponding input variables. Fuzzy stage one has a total of three inputs and two outputs which are described below:

- Onset: This variable represents the differentiation between the MD onset value and the Bicep onset value. Hereafter the differentiation of these two values (i.e MD_onset – Bicep_onset) will be negative when performing a movement produced by the shoulder muscles.
Due to the fact that the MD muscle fibers will activate first, a positive value is expected. When the primary motor muscle is the bicep muscle, it is then expected that the subject is performing the flexion of the forearm.

- **Differentiation (DIF):** It represents the differentiation of MD_rms and the Bicep_rms values. The same idea as the onset variable is used. If the movement is produced by the shoulder, a positive value is expected. On the other hand when performing the flexion of forearm, a negative value is expected.
- **Middle Deltoid RMS (MD_rms):** The MD_rms is calculated using 500 samples after the onset to evaluate the power of the muscle put together to perform a movement. Thus, stage one has two outputs, namely (1) shoulder: the arm is moving; (2) Forearm: when the forearm is moving. The If-Then rules of stage one are presented in the Table 1.

<table>
<thead>
<tr>
<th>If</th>
<th>Then</th>
</tr>
</thead>
<tbody>
<tr>
<td>Onset</td>
<td>Differentiation</td>
</tr>
<tr>
<td>Positive</td>
<td>negative</td>
</tr>
<tr>
<td>Negative</td>
<td>positive</td>
</tr>
<tr>
<td>Negative</td>
<td>positive</td>
</tr>
</tbody>
</table>

| Table 1. If-then rules. Fuzzy Stage One. |

<table>
<thead>
<tr>
<th>Rule</th>
<th>If</th>
<th>Then</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>High</td>
<td>N</td>
</tr>
<tr>
<td>2</td>
<td>High</td>
<td>VN</td>
</tr>
<tr>
<td>3</td>
<td>High</td>
<td>P</td>
</tr>
<tr>
<td>4</td>
<td>High</td>
<td>VP</td>
</tr>
<tr>
<td>5</td>
<td>High</td>
<td>N</td>
</tr>
<tr>
<td>6</td>
<td>Low</td>
<td>P</td>
</tr>
<tr>
<td>7</td>
<td>Low</td>
<td>VP</td>
</tr>
<tr>
<td>8</td>
<td>Low</td>
<td>N</td>
</tr>
</tbody>
</table>

| Table 2. Stage 2-A Fuzzy rules (N: negative, VP: very positive). |

<table>
<thead>
<tr>
<th>Pronator</th>
<th>Bicep</th>
<th>Low</th>
<th>High</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Extension</td>
<td>pronation</td>
<td></td>
</tr>
<tr>
<td>Low</td>
<td>Supination</td>
<td>Pronation</td>
<td></td>
</tr>
<tr>
<td>Middle</td>
<td>Supination</td>
<td>supination</td>
<td></td>
</tr>
</tbody>
</table>

Fuzzy Stage 2:

It is at this stage that fuzzy logic is implemented to distinguish among the movements of the arm (AB, AD, FUL, EUL, AB+FUL). It is subdivided into fuzzy stage 2-A and stage 2-B.

Fuzzy Stage 2-A: To differentiate among the AB, FUL and EUL.

Inputs: (1) Addition of MD RMS (ch1) and AD RMS (ch2): It is calculated in order to represent with a value the total effort performed by the deltoid muscle when performing different movements. (2) Differentiation (DIF): Calculated in order to determine which part of the deltoid muscle is exerting more force when performing a particular movement. (3) Anterior Deltoid RMS (AD_rms): In order to ensure robustness, the AD_rms is also used at this stage.

Stage 2-B: If the output of fuzzy stage 2-A is AB (Abduction).

From AB position, three combined movements may be followed: AB+AD, AB+FUL and AB+ EUL. However, the contractility characteristic derived from each movement at each channel is different. The contractility describes if the muscle fibers are at rest or not at a particular time. There is no need on implementing fuzzy theory due to the fact that the contractility characteristic may be considered as a crispy set, on or off.

**Fuzzy Stage 3:** If the output of stage one indicates the subject performs the flexion of the forearm three movements may be followed. These movements are supination, pronation and extension of the forearm. At this stage is a simple comparison on the effort performed by the bicep and the pronator Teres muscle. The fuzzy rules are as in table 3.

6. Results and Discussion

Figures 2, 3, and 4 depict the input variables of stage number one, the onset, differentiation and MD_RMS respectively. It is clearly seen the behavior expected on each variable as described on stage I. Figures 5, 6, 7 depicts variables of stage 2-A; the addition, differentiation and AD_RMS respectively. Moreover, figures 8, 9 depicts the input variables of stage three. It is clearly reflected on each graph the behavior of the muscle fibers per stage. The same behavior inferred by human reasoning.

The success rate of identification per stage is presented on table 4 to table 7. Moreover, to test the repeatability and robustness of the algorithm using fuzzy logic theory, fresh 10 subjects were measured. The subjects were asked to perform each of the movements four times; two times standing and two times sitting. Moreover each subject repeats the process with both arms. The results are presented below on table 8 to table 11.
Fig. 4 Stage one input variable three. MD_RMS

Fig. 5 Stage 2-A input variable One. Addition (AD)

Fig. 6 Stage 2-A input variable Two. Differentiation (Dif)

Fig. 7 Stage 2-A input variable Three. AD_RMS

Fig. 8 Stage three input variable one. Bicep_RMS

Fig. 9 Stage Three input variable two. Pronator_RMS

Table 4. Summary Fuzzy Stage One outputs and success rate.

Table 5. Summary Fuzzy Stage 2-A outputs and success rate.

Table 6. Summary Fuzzy Stage 2-B outputs and success rate.

Table 7. Summary Fuzzy Stage 3 outputs and success rate.

Table 8. Repeatability. Fuzzy Stage One outputs and success rate.

Table 9. Repeatability. Fuzzy Stage 2-A outputs and success rate.

Table 10. Repeatability. Fuzzy Stage 2-B outputs and success rate.
Table 11. Repeatability. Stage Three outputs and success rate.

<table>
<thead>
<tr>
<th>Movement</th>
<th>Expected Output Range</th>
<th>Total Number Measurements</th>
<th>Successfully Identified Movements</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>Percentage of Successful Identification [%]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Supination</td>
<td>0-2</td>
<td>80</td>
<td>77</td>
<td>1.20</td>
<td>0.75</td>
<td>96.2</td>
</tr>
<tr>
<td>Pronation</td>
<td>2-4</td>
<td>80</td>
<td>72</td>
<td>3.17</td>
<td>0.55</td>
<td>90</td>
</tr>
<tr>
<td>IE</td>
<td>4.6</td>
<td>80</td>
<td>80</td>
<td>4.97</td>
<td>0.05</td>
<td>100</td>
</tr>
</tbody>
</table>

7. Conclusions

The pattern recognition algorithm results presented in this work show a high percentage of success rates from 90% to 100% for all the movements. It is then possible to state that the existing gap of the classification process of the movements and intention of motion using neural networks can be fulfilled with the proposed method. Furthermore, the method has also demonstrated that it is robust and effective disregarding the gender or weight of the test subjects.

The repeatability results have also demonstrated that the algorithm can offer good results even when the subjects’ recordings were not used to develop the pattern recognition if-then rules. Thus it is concluded that as opposed to commonly used calibration methods which needs to be customized depending on test subjects, the proposed method with onset detection and fuzzy logic can offer a very general and effective ways in distinguishing upper limb movements using the surface EMG data.

References


