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A New Technique to Improve the Operation of Prosthetic Limbs during Muscle Fatigue

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Running Title: Improved Technique for Operation of Prosthetic Limbs

Abstract

Prosthetic limbs hold a promise to renew the quality of life for the amputee. Neural commands are decoded via a classifier to generate control signals for the prosthetic devices. In the literature, many challenges and limitations have been identified that affect the prosthesis operation. One such drawback is muscle fatigue which degrades the surface electromyogram (sEMG) signals, and consequently, the performance of the deployed classification algorithm declines from 90% to 50% of average accuracy. We used a new technique using the Linear Discrimination Analysis (LDA) algorithm and the muscle synergy-based task discrimination (MSD) algorithm to improve the classification accuracy. In this technique, during muscles contraction/fatigue, we used the LDA algorithms in the beginning and the MSD algorithms later. The applied technique exhibited better movement classification performance during normal and muscle fatigue conditions. However, more work needs to be done to effectively solve the muscle fatigue problem in prosthesis design.

Introduction

Although many research studies have shown promising results in the performance of myoelectric-controlled prosthesis, there is still a gap between that academic success and the real need of the amputee population in terms of the prosthesis reliability (Jiang et al. 2012). An internet survey that continued for four years revealed that many amputees were dissatisfied with mmyoelectric prosthesis functionality (Pylatiuk, et al. 2007). A similar study that reviewed 55 subjects with upper limb impairment found that they wore their prosthesis only for an average of 7.9 hours/day (Gaine et al. 1997). In addition, the study stated that most of the amputees with myoelectric-controlled prosthesis were not satisfied due to the poor performance of their prosthesis (Gaine et al. 1997). All these complaints towards the prosthetic limbs lead us to a discussion about challenges/factors that cause such limitations in the operation of the myoelectric-controlled prosthesis.

In the literature, the following factors were stated that they impact the performance of the prosthesis:

1- Muscle fatigue (Jiang et al. 2012, Scheme and Englehart 2011).
2- Sweat or perspiration (Jiang et al. 2012).
3- The electrodes' movement (Jiang et al. 2012, Scheme and Englehart 2011).
4- Fit of the socket (Scheme and Englehart 2011).
5- Variation of muscles' force or contraction level (Scheme and Englehart 2011).
6- sEMG signal's transient change (Scheme and Englehart 2011).

The performance of myoelectric prosthesis is extremely affected by the behavior of the sEMG signal which represents the electrical activity of muscles. The sEMG signal can be changed adversely due to the produced efforts by muscles. When muscles fatigue, a significant change occurs in the features of the sEMG signals—both time and frequency domain features are changed. Accordingly, the change in the sEMG signals affects the performance of a used classification algorithm which is utilized for subsequent control of prosthesis [master thesis].

The myoelectric controlled prosthesis utilizes supervised machine learning algorithms—classification algorithms to make a decision about intended tasks or movements. These algorithms assume the training data (the data used by a classification algorithm as a reference to compare with a real-time data or the validation data) has a static statue which means they are not changed overtime. In the literature, under such assumption, the classification accuracy of these algorithms was reported greater than 90%. However, as mentioned earlier, these data can be changed due to muscle fatigue. Therefore, such assumption is no longer valid when muscles fatigue.

Problem Statement and Related Work

The most commonly algorithms mentioned in the literature, which are used for task discrimination, are linear discriminant analysis (LDA), support vector machine (SVM), multiplier perceptron (MLP), artificial neural network (ANN) and hidden Markov model (HMM) (Scheme and Englehart 2011, Ortiz-Catalan, Brånemark, and Håkansson 2013, Rasool et al. 2015, Reaz, et al. 2006). Moreover, two new classification algorithms based on a muscle synergy hypothesis were proposed and applied in real time to discriminate between tasks—one was used for classification tasks of upper limbs and the other was used for classification tasks of lower limbs (Rasool et al. 2015, Afzal et al. 2015). The main difference between them that the first one was used for lower limb task classification, and it uses Non-Negative Least Square (NNLS) approach for neuron estimation. However, the second one was used for upper limb tasks classification, and it uses Kalman filter for neuron estimation. All aforementioned algorithms showed very high performance. For upper limb task discrimination, the used algorithm is called muscle synergy-based task discrimination (MSD). The MSD algorithm has shown a very promising performance when compared to 3 pattern recognition algorithms (SVM, AND, LDA), and indeed it displayed the best performance (Rasool et al. 2015).

Although, in normal operations, most of the proposed supervised machine-learning algorithms work to a sufficient level of accuracy (>90%) to classify the intended tasks, the performance of these algorithms declines significantly in muscle fatigue (Albunashee et al. 2016). The reason behind this declination belongs to the fact that these algorithms were tested under normal operation that the sEMG signals stay unchanged over time.

In our previous work, the impact of muscle fatigue on the classification accuracy was quantified. The classification accuracy declined from (>90%) to an average of 50% during muscle fatigue (Albunashee et al. 2016). In this study, the performance of two algorithms (LDA and MSD) during normal and muscles fatigue was monitored. Then, in order to improve the overall classification accuracy, we used both algorithms (instead of using one) during different periods of time of muscle fatigue. LDA algorithm was used in the beginning and the MSD algorithms later.

Muscle Synergy Hypothesis

Performing an intended task by a human hand is an extremely complex process. In order to perform an intended task, there are 38 muscles and 22 joints in the human hand and thousands of embedded sensors facilitating the integration (Ziegler-Graham et al. 2008). No single movement can be performed based solely on one muscle or one specific neuron signal (Rasool et al. 2015). This leads us to a discussion of "*how the nervous system overcomes these complexities to produce movement effortlessly and efficiently*" (Tresch et al. 1999). In human hands, different muscles cooperate together to perform the intended tasks based on weighted coefficients (brain/nerve signals) and muscle synergies (Rasool et al. 2015, Bizzi and Cheung 2013, Bizzi et al. 2008, d'Avella and Bizzi 2005, Tresch 2005, Rasool et al. 2013). Muscle synergies have been hypothesized as constant building blocks which are weighted by an unlimited number of neuron command signals (activation coefficients) to recruit the muscles to perform certain tasks/movements (Bizzi and Cheung 2013, Bizzi et al. 2008, d'Avella and Bizzi 2005, Tresch 2005).

MSD Framework

The MSD algorithm is explained in details in the references (Rasool et al. 2013, 2015). In this section, a breif description for the main components of MSD is explained.

The mathematical model of muscle synergy framework is described as follows: Time-varying weighted coefficients (X (k)), neuron drive, is mapped to a particular task (Y (k)) through fixed components, muscle synergies (W) as in (2).

$$Y_{m*k} = W_{m*n} * X_{n*k} \qquad (2)$$

where m, n and k are numbers of muscles/sensors, neuron drive coefficients and sample time respectively. The description of the MSD algorithms is explained as follows:

During the training session, MSD uses muscle synergy (W) as the training dataset after extracting them from the root mean square (RMS) values of the surface electromyogram signal (sEMG).

W is extracted from the RMS values (y) of sEMG using a blind source separation algorithm (BSS) such as non-negative matrix factorization (MNF) algorithm or probabilistic independent component analysis (pICA).

In the end of training session, W(s) of all tasks are saved as training dataset for the MSD algorithm. MSD algorithm, as any classifier, is based on finding the similarity between the training dataset and the validation/testing dataset. Therefore, in real time, having a new sEMG signal (y) and j number of movement, MSD uses (j) of Kalman filters to estimate the neuron command signal (X) for each possible movement (j) based in (2).

Kalman filter uses the measured sEMG signals (y) as the system's observation and a random walk model as the state-space model (given in 3)

$$X_{k+1}=X_k + n1_k$$
$$Y_k = \mathrm{W}\, X_k + n2_k \qquad (3)$$

where $n1_k$ and $n2_k$ are system and measurement noise respectively. The estimation of Kalman filter is subjected with a constrain—the neuron drive (x) must be non-negative which is inherited from physiological bounds (Rasool et al. 2013).

In the end, after j (X) are estimated using j Kalman filters for each sensor of sEMG signal, the algorithm will make a decision of which movement is the intended one, based on measuring the similarity between the new (y) and all (j) constructed (y) using (2).

Experiment Protocol

This work is approved by Institutional Review Board of the University of Arkansas at Little Rock. Five volunteers (age 35±5 years) participated in this study.

In the 1st session, the subjects performed normal tasks, single-degree-of-freedom, 1-DoF (hand open, hand close, wrist extension, wrist flexion, forearm pronation and forearm supination). Each task was performed for five seconds (secs), followed by another five secs of relaxation (four times). There was rest time between every two consecutive tasks. In the 2nd session, the subjects were asked to perform each task one time with maximum voluntary contraction (100% MVC) for five minutes. All the participants were allowed to interrupt this session when they felt uncomfortable during the five minutes of the experiment—the average time of the experiment was 2.5 minutes due to participant discomfort.

Electrodes and Hardware Configuration

Seven electrodes were placed on the forearm. The focus was on the extensor carpi ulnaris (ECU), extensor carpi radialis longus/brevis (ECRL/B), extensor digitorum communis (EDC), flexor carpi radialis (FCR) and flexor carpi ulnaris (FCU), pronator teres (PT), and supinator (SUP). We used Naraxon TeleMyo (DTS) to record the sEMG data with a sampling rate (fs) of 2000 sample/sec. BioPatRec software was used for data acquisitions (Ortiz-Catalan et al. 2013).

Preprocessing the sEMG signal

For the LDA algorithm, 4 features were extracted from the sEMG signal after segmenting the raw sEMG in the size of 250 milliseconds (ms). The features are the waveform length (WL), zero crossing (ZC), mean absolute value (MAV), and slope sign change (SSC) (Rasool et al. 2015, Ortiz-Catalan et al. 2013). Then the features were divided into training and testing parts for evaluation purpose. The same approach was followed for MSD algorithm using the RMS values of the sEMG to extract muscle synergies.

Improving the Classification Accuracy

During normal operation, we confirmed that the 2 algorithms introduced a promising performance (>90%). During muscle fatigue, we used the recorded data during the first 50 seconds of the 2nd session to update the LDA algorithm. For the MSD algorithm, we used the extracted synergies during the 40-50 secs. The performance of the 2 algorithms was monitored for 150 seconds during the second session. Each algorithm was performing better for a period of time during muscle fatigue, as will be explained in the next section.

Results

When the MSD and LDA algorithms were updated with the new training dataset, both algorithms performed very well as shown in Figure 1. LDA, in the beginning, showed very good performance but in the end, the classification accuracy started declining. On the other hand, MSD showed poor performance in the beginning but it started getting better with time progression.

The two algorithms were used simultaneously. LDA algorithm was used for classification during the first 60-70 secs because it performed better than MSD and gave an accuracy of greater than 90% as shown in Figure 2. After 60 seconds, the MSD was used and it showed better performance than the LDA (>90% except in the last 10 secs, it showed 87%) as illustrated in Figure 2.

Discussion

In the beginning, the classification accuracy of LDA was higher than MSD not only because the muscles were not fully fatigued but also because LDA

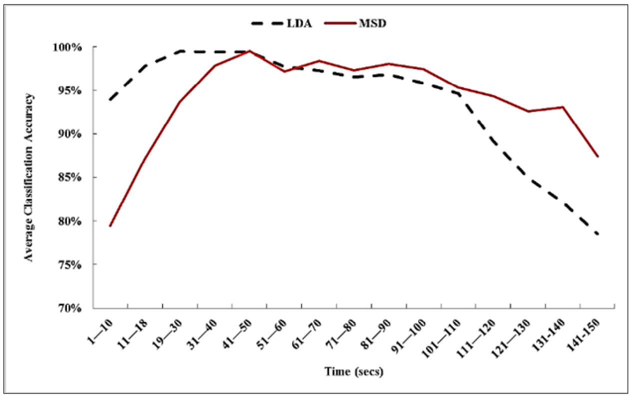

Figure 1. LDA and MSD algorithms during session 2

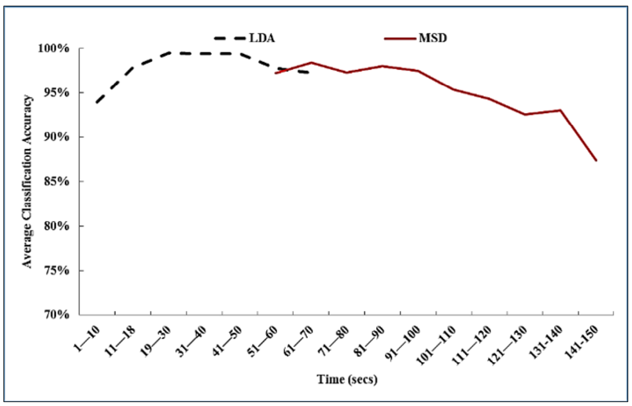

Figure 2. The performance of LDA during the first 60 secs and MSD during the rest of the 150 secs

uses more training features than MSD. On the other hand, when muscle fatigue, the performance of both algorithms declined (after 40 seconds). However, the declination in LDA was faster than in MSD, and for that reason, MSD was used instead of LDA. The fast declination in the LDA when muscle fully fatigued could be regarded to the fact that LDA is parametric classifier and MSD non-parametric classifier.

In order to apply the proposed technique in myoelectric-controlled prosthesis, the subjects (amputees) are required to perform an additional training session similar to the 2nd session (section 2). However, to avoid this issue, the training dataset which are used during muscle fatigue, should be generated from the training dataset which are collected during the 1st session.

Based on our investigation, we believe that using the MSD algorithm, *under same conditions*, is more applicable than the LDA algorithm because MSD requires updating only one feature instead of five features (in LDA case).

Conclusion

A new technique for task discrimination to control myoelectric controlled prosthesis was presented. In this technique, we used two supervised machine learning algorithms (LDA and MSD) to work during different times of muscle fatigue. In the first 60-70 seconds, we used LDA, and for the rest of the time, MSD was used. The overall performance of this technique was very good during muscle fatigue.

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