EMG-Based Energy Expenditure Optimization for Active Prosthetic Leg Tuning*

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***Abstract*—In recent years, active prosthetic legs have been developed and deployed commercially that help amputees to initiate gait with less effort and more symmetry in the pattern. However, the process of initial set up and tuning is highly time and cost consuming. It requires prosthetic experts to observe the gait and the feedback from amputees to manually tune the parameters subjectively. In this study, an electromyography (EMG)-based energy expenditure optimization method was presented to automatically tune the prosthetic limb. For this purpose, a wide variety of lower body muscles were observed and the energy expenditure was modeled based on their electrical activity. The tuning optimization was implemented based on a grid-searching protocol designed in this study. This method resulted in a power value comparable to manual tuning, which provided enough force to facilitate gait for amputees. This study shows the feasibility of automatic tuning and removal of the need for referral to an expert.**

I. Introduction

Amputation of the leg, the most common amputation process, is the surgical removal of all or part of a limb. This happens because of poor circulation due to narrowing or blocking of arteries, which results in lack of adequate oxygen and nutrients in the cells. Thus, the effected tissue begins to die and infection may set in. In the United States, an estimated 185,000 subjects undergo the amputation process of either an upper or lower limb each year [1]. In 2005, 1.6 million persons were living with the loss of a limb and it is estimated that this number will be more than double by the year 2050 to 3.6 million [2].

With the loss of the limb, the patients use prosthetics to supplant the damaged part. Using a prosthesis demands an increase in energy consumption from the residual proximal muscles [3]. Conventionally, passive prosthetic limbs replace the lost limb. However, they are unsuccessful in mimicking the natural gait due to lack of active force. In recent years, several researches have been focused on developing active prosthetic limbs [4-9]. Active prosthetics provide a positive power to facilitate the steps during the gait process. It has been shown that active prosthetic limbs provide more symmetry to the amputee gait and reduce the burden on the residual limb. The bionic leg made by Herr et al [5] is commercially available and it is being used by amputee subjects. This prosthetic limb has shown to emulate the function of a biological ankle during level-ground walking by providing net positive work required for a range of walking velocities. To utilize this prosthetic leg, subjects are required to go through a training process to adapt to walking with it. It has several adjustable parameters. The adjustment and tuning process requires trained experts. The human experts tune the leg based on their observations and the feedback from the subjects. The tuning process is highly time consuming and the referral to the specialist drastically increases the costs. In addition, this process does not consider the neuro-muscular activity and kinematics of the gait for amputees. Exploration of this feedback would provide direct information regarding the gait symmetry, energy expenditure and pressure on the body. In this study, an EMG-based energy expenditure optimization method was presented for automatic tuning of prosthetic legs.

In the past decade, there has been a focus on how to optimize the prosthetics, but very limited studies have focused on the tuning of them. Aghasadeghi et al. [10] proposed an impedance parameter learning algorithm based on a hybrid system model for walking. They only used observed unimpaired kinematic trajectories from a subject. Simon et al. [11] developed a modified intrinsic control strategy and controlled the impedance using the angle of ankle, angle of knee and load on the prosthesis. Their approach also depended on the previous states. A table for changes in desired kinematics was presented and it resulted in a fewer number of parameters to change. Huang et al. [12] developed a cyber expert system and used the human expert knowledge to encode it. They used knee joint angle, knee joint angular velocity and ground reaction forces to develop a rule-based cyber expert system to automatically tune the control parameters. These approaches can tune the prosthesis, achieving preset kinematic requirements; however, they cannot directly determine how much effort the amputees spend, and thereby the amputees' efforts in term of energy expenditure can't be minimized.

The current study, a neuro-muscular activation-based technique was proposed to measure, and minimize metabolic energy expenditure for the prosthetic tuning. Previously, it was shown that various muscle groups have different sensitivities to deviation from normal [13]. A wide range of muscle groups were inspected to model the energy expenditure and use it as a measure to tune the prosthetic leg. The outcome of this work will improve the prosthetic fitting and tuning process.

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II. PROTOCOL AND DATA COLLECTION

A. Participants

Seven non-amputee subjects with normal gait were recruited (age: 23±3 and BMI=24.4±6). None of the subjects had a history of lower limb injuries, neurodegenerative diseases or any skin conditions. The choice for non-amputee subjects was based on the fact that their residual muscles were not damaged or missing and the properties of normal gait were available for observation.

The prosthetic leg used in this study has several parameters to ameliorate the impaired gait. The main parameters for the prosthetic leg are impedance controlled stiffness of the ankle and the amount of power for slow and fast cadences. The subjects were inexperienced in operating the active prosthetic limb, and they went through at least 150 minutes of training until they felt comfortable walking on a treadmill. The training was done by two human experts, and each expert individually tuned the prosthetic limb based on their personal experience and the feedback from the subject. Informed consent was obtained from subjects prior to training and recording. The study was approved by the institutional board review at Florida International University.

B. Data Collection

The neuro-muscular activity of the muscles was investigated using the surface electromyography (EMG) signals. EMG is an investigational practice which is related to the development, recording, and analysis of myoelectric activity. Myoelectric activities are formed by physiological variations in the state of muscle fiber membranes [14]. EMG signals are summation of myoelectric activity around the area it is collected and, contain information regarding neuro-muscular activation of muscles. EMG signals can be simply and non-invasively collected using surface electrodes. The data was collected and monitored on a treadmill inside the lab configuration while subjects initiated gait with a speed they felt comfortable walking.

Twelve channels of EMG signals from main muscle groups on the lower body were considered to provide a comprehensive investigation to determine the perfect muscle groups. EMG signal was collected from the following muscle groups: Soleus (Sol), Tibialis Anterior (TA), Gastrocnemius Lateralis (GL), Gastrocnemius Medialis (GM), Vastus Lateralis (VL), Vastus Medialis (VM), Rectus Femoris (RF), Biceps Femoris (BF). The EMG signals were collected using the Shimmer platform with the sampling rate of 1024 Hz and 24-bit resolution with a gain of 8 [15].

C. Procedure

The setup for recording consisted of a treadmill, a harness to avoid injuries from possible loss of balance, EMG sensors, IMU sensors, piezo-electric pressure sensors and a bent-knee active prosthetic lower limb. Prior to the recording session, subjects were trained under supervision of experts to operate the prosthetic limb. Following the training, two experienced experts tuned the prosthetic limb individually without the knowledge of each other’s results, and they were used as the goal values. Mean of the expert tuned values were used as the target.

Based on the human expert knowledge, three grid groups have been considered for subjects with various BMI values in the protocol. The grid contained twenty different parameter combinations for stiffness and power. This consideration was done to prevent any discomfort or falling from over or under powering of the leg. The parameter grid for subjects based on their BMI is shown in Table I.

The sensors mentioned in previous sections were set up on different parts of the lower body for each subject. The data was collected while the subject operated the prosthetic limb on the treadmill. Each recording was done for a duration of 40 seconds for each grid of parameters. Since the non-impaired subjects were used, data was also collected from their normal gait. The data was assessed and portioned to each session by manual inspection to avoid any error in data collection. Also, the broken data was excluded from further analysis in the study to avoid outliers. Moreover, subjects were provided with enough rest in between data collection grids to prevent the data from being contaminated by the fatigue effect.

TABLE I. the amount of power and stiffness for grids of the parameters in the protocol.

Subject group	BMI	Stiffness (%)	Power (%)
Underweight	BMI < 19	20, 25, 30, 35	5, 10, 15, 20, 25
Normal	19 < BMI < 25	20, 25, 30, 35	20, 25, 30, 35, 40
Overweight	BMI > 25	20, 25, 30, 35	30, 35, 40, 45, 50

III. Methods

The presented method contains several steps to remove noisy outliers and extract simple measures to reduce complexity and finally provide a model to observe the energy expenditure. The steps for this method are illustrated in Figure 1.

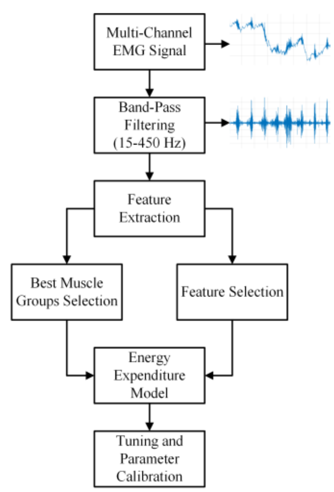

Figure 1. Block diagram of presented method for EMG-based tuning of active prosthetic leg.

A. Pre-processing

The recorded data was corrected and partitioned to seclude each grid. Prior to analysis, a pre-processing and filtering algorithm was implemented to remove outliers and artifacts. These contaminations resulted from movement that lay in lower frequency band of less than 15 Hz, and the EMG activity is shown to lay in the frequency of 15-450 Hz [16]. To remove the alterations regarding the motion artifact, a fourth-order bandpass Butterworth filter with cut-off frequency of 15-450 Hz was designed and implemented. Additionally, data normalization was done per subject to have a comparable range.

B. Feature extraction

Biological signals are highly non-stationary and surface EMG signals are not an exception. Furthermore, EMG signals have a noisy nature, which makes them harder to investigate. To simplify the signals and extract useful information from them, various features have been proposed in the literature. In this study, the following features have been extracted from myographic signals to assess the energy expenditure in muscles:

1. Mean absolute value [17]: Average of the amplitude for the rectified EMG signal.

$$MAV = \frac{1}{N}\sum_{i=1}^{N}|EMG_i|. \quad (1)$$

2. Variance: This feature is the measure of the EMG signal's power [16].

$$VAR = \frac{1}{N-1}\sum_{i=1}^{N}EMG_i^2. \quad (2)$$

3. Zero crossing: number of times the EMG signal changes sign. This feature is a measure of frequency change in time domain.

$$ZC = \sum^{N-1} f(-EMG_i \times EMG_{i+1}). \quad (3)$$

Where, $f(x) = \begin{cases} 1 & x > 0 \\ 0 & otherwise \end{cases}$.

4. First four AR coefficients.

5. Histogram: This shows the number of samples in signal at various amplitude levels in segments of time [18]. This features is an expansion for energy in time domain and frequency domain, and the number of bins was chosen to be 9 [17]. In this study, we used the width of the bins to compare the EMG signals.

Feature extraction was done using a sliding window with the size of one second (1024 samples). The window size was chosen to include at least one gait cycle to properly model the energy. The features used in this study are extracted in time domain and they provide simple measures to investigate the myographic activity and observe energy expenditure in the muscle.

C. Feature selection

Dealing with many features would increase the complexity and result in a dimensionality problem. To avoid this, a method for selecting the features was implemented to choose the best features and remove redundant information. For this purpose, the normal gait was used and a statistical study of variance was done using the students t-test approach. MAV and ZC features resulted in a meaningful difference in distribution for all the grid combinations and normal gait with a p-value of less than 0.05. MAV and ZC features were chosen to be used for further analysis. To simplify the features and fuse them into a single measure, the Mahalanobis distance for the selected features was calculated.

D. Muscle fusion and optimization

Various muscle groups contain different types of fiber and they vary in size. Due to this fact, the amount of energy consumed in different muscle groups varies. Human skeletal muscles consist of two different types of muscle fibers: fast and slow twitch fibers. Fast twitch fibers consume more metabolic energy. To emphasize on the importance of the muscle group in the energy expenditure the percentage of fast twitch fibers in the muscle groups was, used and a weight was calculated for each muscle group. The percentages for fast twitch fibers in the muscles used here are listed below [19]: (a) Soleus: 20%, (b) Gastrocnemius muscles: 50%, (c) Vastus muscles: 50%, (d) Rectus Femoris: 65%,(e) Biceps Femoris: 35%, and (f) Tibialis Anterior: 25%.

These values were normalized to have values between 0 and 1. To find the perfect parameter tuning automatically, a grid approach was implemented to optimize the energy expenditure. The energy expenditure was modeled using the selected features and the following equation was optimized:

$$\underset{s,p}{\operatorname{argmin}}\, W^T \times M^2. \quad (4)$$

Where, W^T is the vector of the weights as:

$$W = [w_1, w_2, \dots, w_i],\ i = 1, 2, \dots, 12. \quad (5)$$

And, M is the vector of the Mahalanobis distances for features of muscles.

$$M = [m_1, m_2, \dots, m_i],\ i = 1, 2, \dots, 12. \quad (6)$$

And, s is stiffness values and p is the power values as of TABLE I. Based on this method, the smallest energy expenditure value was determined to provide the most optimum energy expenditure for bent-knee gait.

IV. RESULTS

The collected data obtained from seven subjects was investigated offline using MATLAB. The EMG signals were partitioned to each grid by manually inspecting the IMU data. The optimization was done and the grid with the smallest energy expenditure was chosen based on the proposed optimization model. The investigation was done for different muscle combinations. The results for the proposed method and the average result from experts are shown in TABLE II.

TABLE II. RESULTS OF MULTI MUSCLE TUNING AND TUNING USING RF ANF BF MUSCLES FROM BENT-KNEE LIMB VERSUS HUMAN EXPERT TUNING. (S: STIFFNESS, P: POWER IN PERCENTAGES)

Subject	*Expert tuning*	*Multi-muscle tuning*	*Bent-knee RF and BF tuning*
1	*S=15±5, P=27.5±2.5*	*S=30, P=40*	*S=35, P=35*
2	*S=35±5, P=25*	*S=35, P=40*	*S=25, P=25*
3	*S=25±10, P=20*	*S=35, P=20*	*S=35, P=25*
4	*S=22.5±2.5, P=27.5±2.5*	*S=25, P=20*	*S=25, P=25*
5	*S=25±20, P=12.5±2.5*	*S=20, P=25*	*S=35, P=10*
6	*S=40±20, P=45±5*	*S=20, P=55*	*S=30, P=55*
7	*S=25±5, P=30±2.5*	*S=25, P=30*	*S=25, P=30*

The results show a comparable value (±5%) for the power of the leg. The results show that muscles on the bent-knee leg, specifically the antagonist muscles of BF and RF on the bent-knee leg, are the best muscle groups for automatic tuning. Figure 2 illustrates the grid analysis of energy measure for subject 8. It is observable that the parameter combination of 25% stiffness and 30% power is the best. Based on the results,

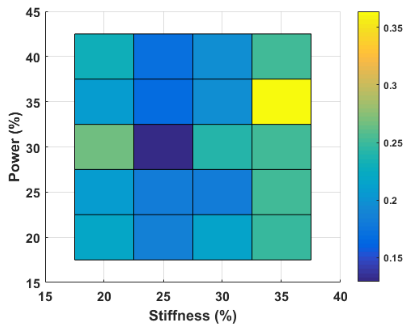

Figure 2. Example of a figure caption.

it is possible to tune the leg using only two channels of EMG from antagonist muscles of RF and BF.

V. DISCUSSION

In this study, the electromyographic activity of various muscle groups was observed in non-amputee subjects. The energy expenditure for muscles was modeled using time domain features and percentage of fast twitch fibers in muscle groups.

Five groups of muscles were considered in this study. This was done to specify the best muscle group for tuning purposes and to reduce the number of muscles and complexity of the method. The muscle groups that were investigated separately are, all 12 muscles, lower intact limb muscles (Sol, TA, GL and GM), intact thigh (RF, VL, VM and BF), bent-knee thigh, RF and BF on bent-knee. The last combination was investigated since it was observed that the pressure of cast affected the signals recorded from VL and VM.

Based on the results, muscles from the first three groups resulted in higher power values than the muscles on the bent-knee leg. The best muscle groups for tuning the leg were RF and BF on the bent-knee leg. They resulted in comparable value for the power, but the amount of stiffness was variable. The reason for less accuracy in stiffness tuning was that non-amputee subjects were not able to feel the variation in this parameter. This also was observed by the experts. They had difficulty in observing the variation in stiffness, and they had a bigger variance in this value. This is expected to be resolved with amputee subjects. The slight higher power value decision for some subjects was due to gait on the treadmill, which forces subjects to walk on a steady state, and a smaller power value is required since they have shorter strides.

Future studies are going to focus on amputees and the method will be extended to real time to provide a more reliable and less complex system.

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