Investigation of Muscle Activity During Loaded Human Gait Using Signal Processing of Multi-Channel Surface EMG and IMU

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Abstract— **Human gait is a complex process resulting from contraction of various muscle groups with different sizes. With the loss of a lower limb, amputees use passive prosthetics to replace the lost limb and regain function. Operating a prosthetic leg, requires more metabolic energy expenditure and greater pressure on the residual limb. In order to understand the muscle activity during human gait, a set of loads were used to model the amputated gait on normal subjects. The loads comprised of sandbags with weights of 5, 10, and 15 lbs. Using 10 Inertial Measurement Units (IMU) alongside 20 Electromyography (EMG) sensors, physiological and kinetic signals were recorded with non-invasive sensors placed on the lower body. Trials were comprised of recording gait from 8 voluntary subjects, and this data was analyzed in the following steps. First, the data was pre-processed using signal processing techniques and, the steps were extracted using a local extrema detection technique from IMU signal as time stamps. Next, to have a numerical measure for the ease of analysis, several features extracted from the EMG signal for each step. The distribution of the features extracted from the signals while subjects performed gait in different states were compared. The results were obtained using students' t-test and the hypothesis of having the same distribution was rejected with a p-value of less than 0.005. The results revealed that the muscles on the intact limb had more activity and sensitivity as a result of compensation for the loaded leg. Vastus Medialis, Vastus Lateralis and Biceps Femoris for the left leg provided escalation in activity according to the features for 100% of the subjects, even with the addition of the smallest load (5 lbs.). Results of this study will determine the sensitivity of muscles to deviation from normal gait and, fewer number of inputs will be used to calibrate and control an active prosthetic limb. This will reduce the complexity and increase the speed of computation.**

Keywords—Gait analysis; Electromyorgraphy; Inertial measurement unit; statistical signal processing;

I. Introduction

In recent decades, human gait analysis has been one of the major studies for understanding the complex biomechanical and physiological processes while initiating gait. Various equipment and methods have been proposed and applied to obtain the best model for the activity of different sections of body during gait. In order to reach this goal, numerous equipment such as electromyographic (EMG) signals [1], inertial measurement units (IMU), force platforms [2], knee force [3], and center of mass [1] have been used. Previous studies concentrated on presenting a gait model using different sensor inputs, which can be applied in diagnosis as well as prediction for patients suffering from various motor diseases such as Parkinson's, Multiple Sclerosis (MS), prosthetic limb control, etc. In order to have a precise assessment for the purpose of detection, prediction, or control of patients with different conditions, it is crucial to have an accurate gait model.

Gait analysis is aimed at understanding the kinematics and kinetics of locomotion using signal processing from biomechanical or physiological sensors. Herzog et al. [2] used a force platform and measured the variations in pressure on a platform during gait. They presented a symmetry/asymmetry measure and quantified it to evaluate the gait. Lunderberg et al. [4] also collected the contact force data on the knee joint and suggested a model for the sensitivity of abnormal gait based on pressure sensor recordings. Kurayama et al. [1] studied the movement characteristics of the kneeling gait and compared it with the normal gait. They used electromyography (EMG) and center of mass signals. They showed that the kneeling gait is an effective tool for rehabilitation of gait stroke patients. Di Narde et al. [5] also used EMG during gait and studied the co-contractions during the ankle plantar/dorsiflexion. In addition to various gait studies, there has been a lot of focus on gait for the subjects that went through amputation. These studies focused on energy expenditure and symmetry to obtain the most natural gait pattern for the amputee subjects. Using force platforms, TV-computer and pylon transducer systems, Zahedi et al. [6] quantified the degrees of repeatability and observed that the variability was more in amputees and it is augmented as the amputation was more proximal. Torburn et al. [7] analyzed gait of amputees while they wore four different prosthetics and compared their performances. Sacco et al. [8] compared the lower limb EMG signal and ground reaction forces in diabetic subjects and non-diabetic ones during gait, which revealed a different motor strategy in diabetic subjects. Wentik et al. [9] used EMG signals to observe the intention of gait initiation in amputees and, to reach this goal, they used inertial

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measurement units (IMU) to observe gait. Even though this topic has been the issue of major scholars in previous decades, the results are far less optimal and possess less applicable insight and transition into real life. Ongoing research focuses on different parts of gait to provide an optimal and in depth understanding of its neuro-muscular and kinetic processes. These signals are being used to observe the deviation from normal gait pattern that occurs with amputation. Various measurements such as surface electromyography (EMG), inertial measurement units (IMU), motion tracking system and electroencephalogram (EEG) are being used to reach this purpose.

This study focused on variations of muscle activity during normal gait for the purpose of determining the sensitivity of muscle groups in response to a change in load, which can then help determine the muscle groups that will be best in future studies for calibration and control of lower limb prosthetics. This will reduce the amount of complexity for control aim, as it will require less inputs. To obtain the sensitivity for the muscle activities and model the amputee condition, several loads were tested on the lower limb for the subjects. A wide range of muscle groups were studied while subjects with normal gait were walking on a treadmill and the EMG and IMU signals were recorded. Results showed the effectiveness of the EMG signal in modeling the muscle activity during gait.

In this study, the gait procedure for lower body was observed using kinetic sensors alongside physiological sensors. These systems have been observed in subjects with normal gait and, to observe and model the muscle activity for lower limb amputees, various loads have been applied on the right ankle. The amputees replace the lost limb with a passive prosthetic and they lack the muscles on the lower limb to facilitate the gait. As a result, they endure more pressure on the residual limb and, the activity of the muscles on the residual limb increases as compared to non-amputees. Based on this reason, a non-invasive way to model increase of load on the muscles is decided to be the addition of load to lower limb. The motor and the battery for the active prosthetics are usually placed on the ankle. So it is fair to model the prosthetic limbs effect on the residual muscles by placing load on the ankle. The addition of the load on the leg presented an increase in muscle activity and sensitivity of several muscle groups were observed. This will provide enough information to optimize the gait pattern for patients who underwent amputation using biomedical and kinetic signal processing techniques.

The rest of this paper is organized as follows: section II presents data acquisition techniques that were used, section III consists of the methods used in this study and, section IV shows the results acquired from processing of the data, and in section V discussion regarding the results is provided.

II. DATA ACQUISITION

Having a reliable data set is one of the major parts of the study. In order to have a good model for the gait and imitate the load of prosthetics on normal subjects, a setup was made in the lab. The setup contains a treadmill and several sandbags to be attached to the leg. Also, physiological and kinematic sensors were used to collect data while subjects were operating on the treadmill. In this study, we focused on the signals from EMG and IMU sensors to highlight the neuro-muscular activation during deviation from normal gait. The setup is shown in Figure 1.

A. Electromyography

EMG is an experimental technique concerned with the development, recording, and analysis of myoelectric signals. Myoelectric signals are formed by physiological variations in the state of muscle fiber membranes [10]. EMG signals contain information regarding neuro-muscular activation of muscles and could be easily and non-invasively recorded using surface electrodes.

Human gait is a complex process during which numerous muscles with various sizes and power collaborate to form each portion of a step. In order to have an in depth look at the muscles on the lower body, a 20 channel setup was made to record surface EMG signals. The following muscle groups were recorded and analyzed in this study: Tibialis Anterior (TA), Soleus (Sol), Gastrocnemious Lateralis (GL), Gastrocenmius Medialis (GM), Vastus medialis (VM), Vastus Lateralis (VL), Rectus femoris (RF), Biceps femoris (BF), Glutes Medius (GMed), Tensor fascia latae (TF), Gluteus Maximus (GMax), Semitendinosus (ST). The first four muscle groups (TA, Sol, GL, and GM) belong to the lower limb. As we placed a load on the lower right leg, these data were recorded only from one leg. Using this approach, asymmetric gait in amputees was modeled. Four different states of walking with load on the lower right leg was studied. Loads consisted of sandbags with a weights of 5, 10 and, 15 lbs., and were placed on the right ankle. Using Shimmer3 EMG unit, the EMG signal for these muscles was recorded using standard silver/silver-chloride surface electrode pads with the sampling frequency of 1KHz from both thighs and left lower limb (right leg was considered as amputated) [11]. Electrodes were placed on the surface of the skin with respect to the sensor locations recommended by SENIAM [12].

Figure 1. Setup for data collection

B. *Inertial Measurement Units*

Navigation is accomplished by recording the accelerations and calculating the change of position after initial alignment [13]. IMUs are the main idea for the navigation and consists of various sensors including; magnetometers, accelerometers, and gyroscopes. In this paper ten, IMU sensors were placed on both thighs and the left lower limb. The IMUs have been recorded using the same Shimmer3 EMG units [11] with the sampling frequency of 1 kHz.

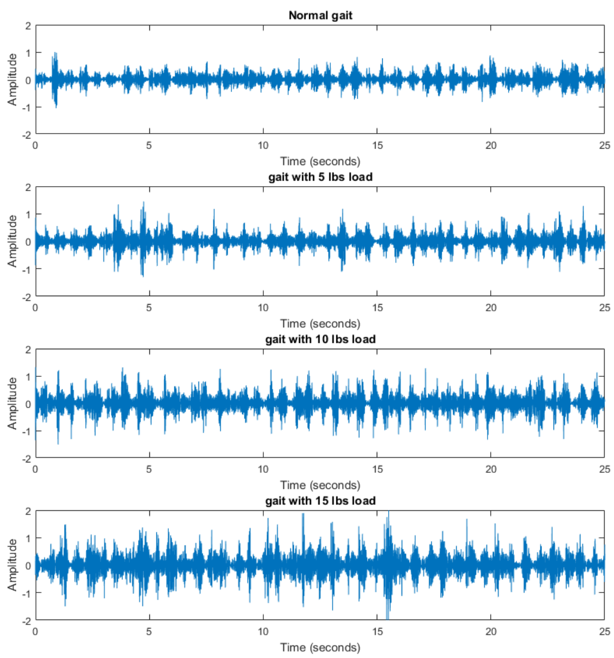

Figure 2. EMG signal recorded from VL muscle of subject 3, while initiating gait on treadmill. EMG activity for four different values of load is illustrated. It is observable that with increase of weight on the ankle, the EMG activity increases (Both in amplitude and frequency content) in this muscle, which indicates increase in energy consumption.

C. *Database*

The physiological and kinetic signals that is proposed in previous section was collected in the lab environment. Eight male subjects were recruited throughout the study (24±2 years old, and BMI of 23.3±1.5). The study was approved by the institutional review board (IRB) of Florida International University. All the subjects signed an informative consent form prior to data collection. Subjects were asked to walk for a minute on a treadmill with the speed they felt comfortable with. During the data collection, 20 channels of EMG alongside 10 channels of IMU signals were recorded with a sampling frequency of 1 kHz. The recordings were done over four different states of walking (0, 5, 10, 15 lbs.). Different walking states were modeled using sandbags, and they were placed on the ankle of the lower right leg of the subject. Figure 2 illustrates the EMG signal for VL recorded from the left leg of subject 3. The increase in the neuro-muscular activity is observable from the amplitude of the EMG signal in the figure. It is worth noting that even though it is not observable from the plot, the frequency of the signals also increases with the addition of load. To illustrate this we extracted some features to show the frequency change in the signal.

III. METHODS

The recorded data in this study was analyzed offline to observe the complex process of human gait in neuro-muscular and kinetic sense. They were statistically evaluated to observe the sensitivity of various muscle groups on different subjects.

A. *Pre-processing and artifact removal*

Prior to any comparison, it is crucial to remove the artifacts and outliers from the signals. The EMG signal is highly sensitive to the noise and it is highly contaminated with the low frequency alternations of motion artifact (0-15 Hz). To eliminate the motion artifact and other high frequency noises from EMG signal, a forth order Butterworth band pass filter with the cut off frequency of 15-450Hz was designed and applied [14]. In order to have a comparable measure between various recordings, each EMG signal was normalized with respect to its maximum value in normal walking for each subject.

From the IMU signals, the magnetometer was chosen to be used as it had smoother content than the gyroscope and accelerometer data. Magnetometer data was utilized to discriminate between each step. Prior to step detection, the magnetometer data was a low pass filtered with the cut off frequency of 20 Hz using the Butterworth approach. A local minima-finding algorithm was applied to the signal and local minimums were determined in a 700ms window. The window size defined by manual inspection of difference between each step. After detection of minimum points, the time difference for consecutive minimums were determined and compared to the mean for all of them. Based on the difference, missed minimums or sporous ones were corrected. Figure 3 illustrates a sample magnetometer signal from the left ankle of subject 3 alongside the EMG signal for his Soleus muscle.

Based on the detected points for the magnetometer signal, the EMG signal was chopped into each step. In further analysis, the EMG data for each step was used and the features were extracted from them, and then compared in different states of walking.

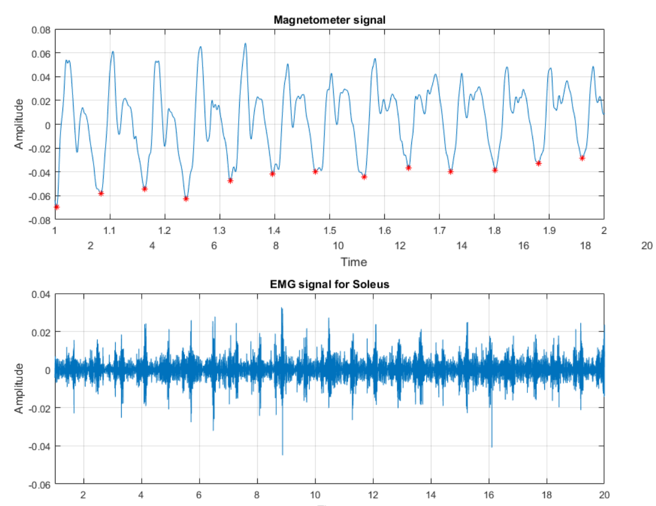

Figure 3. Magnetometer signal with the detected local minimums for the ankle of subject 3, alongside with the EMG for Soleus muscle recorded using the same sensors.

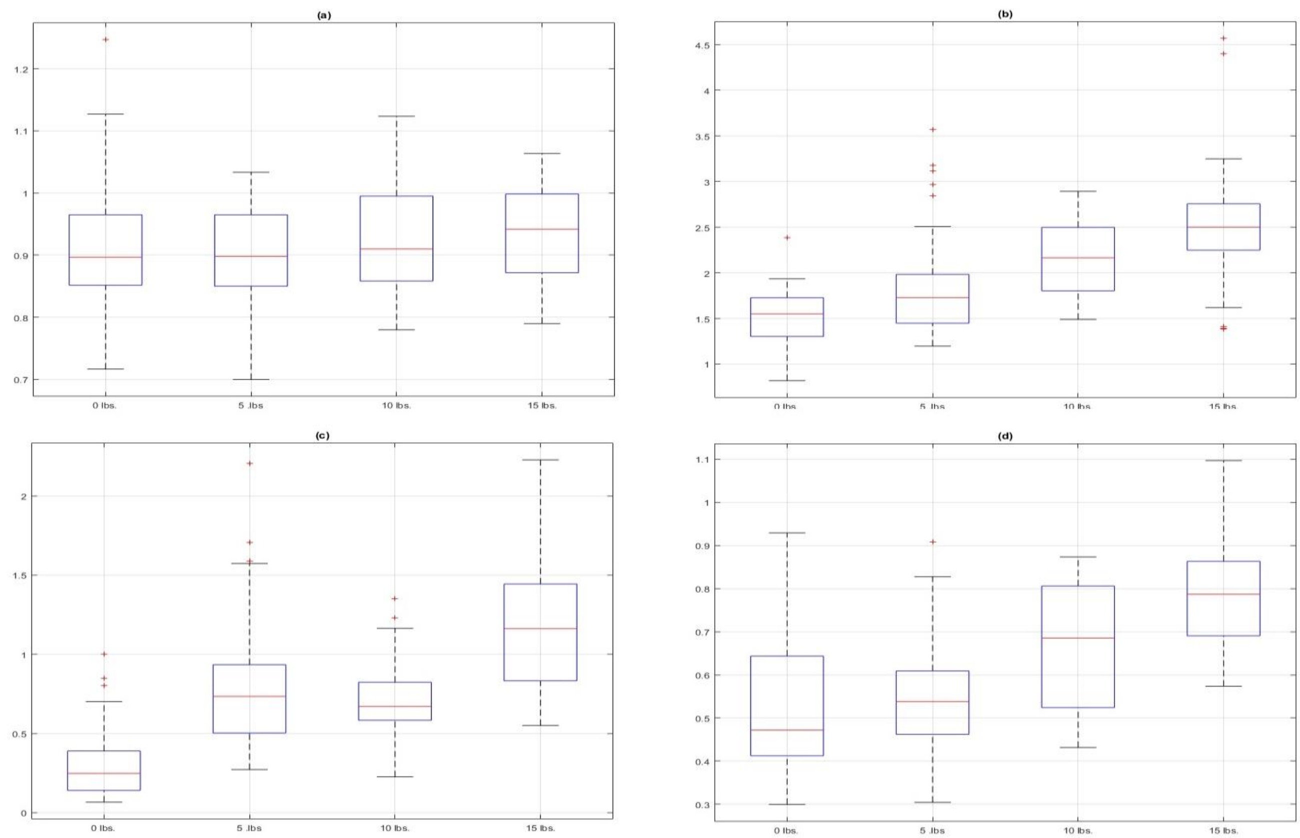

Figure 4 . Sample result of distribution for four different features and subjects. (a) WAMP feature derived from Soleus muscle of subject 8. This muscle does not present an increase in the EMG activity in the means of WAMP feature. (b) MAV feature extracted from VL muscle on the left thigh for subject 1. The EMG activity shows a comparable increase for various load levels. (c) Variance feature for the BF muscle on the left side of subject 4. This muscle also presents augmentation in the EMG activity with addition of more loads. (d) ZC feature for GMax from the right leg of subject 3. This muscle shows an increase in the activity in the sense of zero crossing for 10 and 15 lbs. load but, does not present much variation for 5 lbs. which, shows that GMax has less sensitivity for the 5 lbs. sandbag.

B. Feature evaluation

The EMG signals collected from the surface of skin are highly complex and represent the summation of firing of motor unit action potentials around the area that the electrode was placed. So as a result, the EMG signal contains valuable information regarding the muscles performance and energy expenditure. In order to comprehend the process with less mathematical complexity, several numerical features in time domain have been proposed. These features provide numerical values used to compare different states during gait and to obtain the variations. The following features have been proposed to be used in EMG signal processing [15]:

- Mean absolute value:

$$MAV = \frac{1}{N}\sum_{i=1}^{N} | x_i | \tag{1}$$

Where, x_i is the band pass filtered and N is the number of samples in each step.

- Variance:

$$VAR = \frac{1}{N-1}\sum_{i=1}^{N} x_i^{\,2} \tag{2}$$

- Wilson amplitude, which is defined as number of the times that the EMG signal exceeds a threshold. It is an indicator of the firing of motor unit action potentials. As this feature shows the number of action potentials, it will present information regarding the frequency content using simple calculations in time domain. This feature is defined as follows:

$$WAMP = \sum_{i=1}^{N} f(| x_i - x_{i-1} |) \tag{3}$$

Where, $f(x) = \begin{cases} 1 & x > \varepsilon \\ 0 & x \le \varepsilon \end{cases}$ and ε is the threshold.

- Zero crossing, which is the number of times the EMG signal passes through the amplitude zero. This feature is an indicator of frequency variations in time domain and it is calculated as below:

$$ZC = \sum_{i=1}^{N} sign(-x_i x_{i+1}) \quad (4)$$

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

- Shannon Entropy: this feature measures the uncertainty associated with a random variable [16]. This feature can be calculated using the probability of the signal as followed:

$$SE = p_i \log_2(p_i) \quad (5)$$

Where, p_i is the probability of occurrence of an event x_i.

Later, these features were extracted from the EMG signal of each muscle in each step (detected using magnetometer signal). The extracted features were used to compare the variations in neuro-muscular activity with the addition of load on the right ankle.

C. Statistical analysis

In this study, a statistical approach was implemented to point out the difference between states of walking. To do so, the statistical hypothesis testing of students' t-test was used. This approach tests the distribution for variables with a hypothesis that the random processes have the same distribution and presents the result with the probability of them having the same distribution.

IV. RESULTS

The collected EMG and IMU data were analyzed offline using MATLAB. Signals were collected from 8 subjects while they were walking on a treadmill with the speed they felt comfortable. The recording was for a minute of walking, and it was done for several repetitions using various weights of sandbag on the lower right leg. The data was pre-processed to eliminate noise and baseline drift. Then, the data was normalized for each subject to have comparable scale and, the proposed features have been extracted from all of EMG signals. The features calculated were used to investigate the variation in gait parameters. Each sensor contained two channels of EMG and one channel of IMU. The data was collected from 20 muscles and 10 IMU signals. The magnetometer signal from each sensor was used to detect steps and chop the EMG channels from the same sensor.

The statistical students' distribution analysis was done over all of the features to observe the change in activity of the muscles. The results were in coherence with the hypothesis that the load would change and have different distribution in comparison with normal gait. It was observed that muscular activation for VL, BF, VM muscles increased for all of the subjects. The muscles that were most sensitive to the change in load are depicted in Table I. In Figure 4, the distribution for four different samples of features from various subjects is presented. In the figure it is observable that the Soleus muscle for the 8th subject, does not present meaningful increase in the EMG activity. Furthermore, the plot shows the increase in distribution for BF and VL muscles on the left foot. It is obvious how the distribution for the feature increased with addition of the weight. Also, distribution for GMax of 3rd subject shows the condition where it does not have a meaningful increase in distribution with addition of 5 lbs. But this muscle presents an augmentation in the activity with addition of other loads.

In addition to the single feature distribution comparison of data, the features have been combined into a single feature by calculating the sum of the square root and fused them into one. The results obtained from the new feature showed the variations in the pattern of activation for muscles. Even though there was difference between subjects, but the new feature still showed the similar increase in the firing of motor units in VM, VL and, BF of the left leg.

Table I. Results for the statistical analysis of muscles using 5 different features. Second column presents the muscles that had sensitivity for all of the sandbag levels and they were compatible for all subjects. Last column shows the muscle that were not sensitive enough to observe variation for 5 or 10 lbs. loads.

Feature	***Muscles that rejected the null hypothesis for addition of all loads (p<0.005)***	***Muscles that rejected the null hypothesis for addition of 15lbs loads (p<0.005)***
MAV	GMed (right), VL (left), BF (left) **except GMed for subject 3, 4*	VM (left), RF (left) **except subject 7*
VAR	GMed (right), VL (left), BF (left) **except GMed for subject 3, 4*	VM (left), RF (left)
ZC	VM (left) **except subject 1*	Gmax (right) **except subject 7*
WAMP	VM (left), GMax (right) **except GMax for subject 7*	GMed (right), TF (right), BF (left) **except TF for subject 3, 8 and, except GMed for subject 2, 7*
SE	GMed (right), VL (left), BF (left) **except GMed for subject 3, 4*	VM (left), RF (left), VL (right), GMax (left) **except VM for subject 1, 2 and GMax for subjects 2, 6 and VL for subject 4*

V. DISCUSSION

The human gait is a very complex process and during it many muscles get activated by neurological stimulations. Current work was designed to investigate the human gait while various loads were attached to a lower limb and present the increase in the muscle energy expenditure. A comprehensive study over 20 channels of EMG and 10 channels of IMU were carried out throughout this study. The results mainly showed that the subjects depend on the leg that doesn't have a load and the EMG data from that leg presented higher activity than the leg with the sandbag on. This observation was in accordance with the visual inspection of the subjects, where they tend to take shorter strides with their right leg. In order to compensate the limitations applied by the sandbags, the muscles on the left leg were more active. Mainly the muscles on the thigh were more sensitive to variations from normal gait. The VM, VL, BF muscle groups showed a good sensitivity and they had statistically meaningful difference in distribution with a p-value smaller than 0.005. Other muscle groups that showed a good sensitivity to the deviation from normal gait were RF, GMed and, GMax.

Gait process is slightly different in every person since the muscle and fat varies, which affects the EMG signals. Keeping this in mind, the difference in the gait pattern in between subjects can be expected. For example, subject 3 and 4, the variations in the GMed muscle was not comparable suggesting this signal is not suitable for gait observation in these subjects. Also this muscle is a small fiber in comparison with the others which influences the positioning and it is more delicate to the fat layer beneath the skin.

Currently, the results obtained from this study is being used to calibrate and optimize an active prosthetic limb. Also, in future works, one can fuzzify the approach by presenting a membership value for each muscle and magnifying their participation in the gait process. This work does not consider the dominant foot. Future studies might keep left or right-footedness in mind and analyze muscle activity.

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