A Method for Locomotion Mode Identification Using Muscle Synergies

Taimoor Afzal, *Student member, IEEE*, Kamran Iqbal, Gannon White and Andrew B. Wright

***Abstract*— Active lower limb transfemoral prostheses have enabled amputees to perform different locomotion modes such as walking, stair ascent, stair descent, ramp ascent and ramp descent. To achieve seamless mode transitions, these devices either rely on neural information from the amputee's residual limbs or sensors attached to the prosthesis to identify the intended locomotion modes or both. We present a new approach for classification of locomotion modes using the framework of muscle synergies underlying electromyography (EMG) signals. Neural information at the critical instances (e.g. heel contact (HC) and toe-off (TO)) was decoded for this purpose. Non-negative matrix factorization (NMF) was used to extract the muscles synergies from the muscle feature matrix. The estimation of the neural command was done using non-negative least squares (NNLS). The muscle synergy approach was compared with Linear Discriminant Analysis (LDA). There was no significant difference ($p > 0.05$) in transitional and steady state classification errors during stance phase. The muscle synergy approach performed significantly better ($p < 0.05$) than LDA during swing phase. These results suggest that the muscle synergy approach can be used to discriminate between locomotion modes for transfemoral prosthesis control.**

***Index Terms*—Intent recognition, Muscle synergies**.

I. INTRODUCTION

LOSS of lower limb is a matter of great concern as it affects the ability of the amputee to perform basic daily activities. According to an estimate, there were 1.6 million persons living without a limb in USA in 2005 and 65% of this number represented people having an amputation of one or both lower limbs [1]. This number is expected to rise to 2.2 million by 2020 as each year approximately 185,000 people undergo an amputation of lower limb or upper limb.

Recent years have seen much advancement in the field of lower limb prosthesis. The development of powered prostheses has provided a potential gateway for lower limb transfemoral amputees to walk on different terrains [2]. The prosthetic users are likely to encounter different kinds of terrains that include but are not limited to level ground, ramps and stairs. Efficient utilization of a powered prosthesis for walking on different terrains requires seamless transition between different locomotion modes. Commercially available devices make use of either a remote-controlled button press, tapping the foot, or non-intuitive muscle contractions to signal the prosthesis to change modes [3]. In order to achieve seamless transition between modes, neural information is essential. As the neural information precedes the movement [4], it is useful in predicting task transitions. In case of the lower limb amputation, the electromyography signals from the residual muscles of the thigh are a source of neural information.

To address the problem of locomotion mode transitions, numerous techniques have been developed. Earlier work for achieving transition from one mode to another included an 'echo control' approach in which the sound side of the amputee was instrumented and knee angle profile was measured [5]. For achieving various gaits the amputated side mimicked the behavior of the sound side. The drawbacks of this technique are that the sound leg is instrumented and is applicable to only unilateral amputees. An intent recognition system that uses mechanical sensors on the prosthetic device to switch between level walking, sitting and standing was developed in [6]. In an extension of this work, walking on five and ten degrees slopes was added in [7]. These methods only utilized mechanical sensor information from the prosthesis and did not include stair ascent and descent modes. A strategy using EMG signals to switch between two walking modes, level ground walking and stair descent, was developed in [3]. For level walking to stair descent transition, the amputee flexed the *gastrocnemius* muscle and to switch from stair-descent to level ground walking the amputee flexed the *tibialis anterior* muscle. The advantage of this technique is that the user can voluntarily control the prostheses at any given time, but it requires training to flex the desired muscles at appropriate instants. This technique was tested on an active ankle prosthesis donned by a transtibial amputee. Adaptation of this technique for transfemoral amputees would require amputees learning to control the residual thigh muscles as more degrees of freedom are controlled in the case of ankle-knee prostheses as opposed to the active ankle prostheses.

A real-time implementation for locomotion mode detection using EMG signals and mechanical sensors (6-DOF load cell) from the prosthetic knee was presented in [8]. In this technique the gait cycle was divided into four phases. The stance phase included three sub-phases, and the fourth phase was the swing phase. A separate classifier was then trained for each phase. The disadvantage of this technique is that identification of sub-phases during a gait cycle requires extra information during the prosthetic foot's contact with the ground. The authors reported a higher classification error for the swing phase as compared to the stance phase. Similar work has been done in [9], where the signals from the mechanical sensors (six-axis inertial measurement unit, axial load sensor, motor potentiometers and encoders) attached to the prosthetic device were used to classify locomotion modes based on time history information. The authors implemented the technique using dynamic Bayesian networks that are useful for integrating time series information over time. The authors reported that this technique performed better than the majority voting technique and the single analysis window technique. However, only mechanical sensor data was used leaving aside the neural information. In a subsequent paper, data from the mechanical sensors attached to the prosthetic limb was used in Linear Discriminant Analysis (LDA) technique to classify transitions between five walking modes [10]. This effort showed that single window at heel contact (HC) and toe-off (TO) provides higher classification as compared to using multiple windows. A neuromuscular fusion approach similar to [8] was implemented in [11] where a combination of 9 EMG signals and 13 mechanical sensors were used to classify transitions and steady-state for 5 locomotion modes based on time history information.

In this study we address the problem from the perspective of how the central nervous system controls different muscles to perform a limb movement. Our focus lies on the framework of muscle synergies to identify locomotion modes. In this context muscle synergies are defined as a fixed relative activation level of different muscles [12]. This implies that for different movements, the muscles involved are activated in a synergistic manner and the central nervous system generates neural commands to control muscles using a combination of muscle synergies [13]. For muscles in lower limbs, it has been shown that during human locomotion five basic activation patterns account for the muscle activity during walking [14]. In [15], motor patterns in human walking and running were considered. The muscle synergy framework has been utilized in upper limb task discrimination for discriminating between hand postures [16] and for the control of a virtual prosthetic arm [12]. To extract muscle synergies, the root mean square (RMS) values of the EMG signal have been used to discriminate between tasks [12, 16]. There has been no explicit effort on using the muscle synergy hypothesis for lower limb locomotion mode detection that includes identification of transitions between different locomotion modes. The goal of this study is to use this hypothesis to classify five locomotion modes (level walking (WK), stair ascent (SA), stair descent (SD), ramp ascent (RA) and ramp descent (RD)), and the transitions between them. We also compare the muscle synergy approach with LDA to seek significant difference between the two approaches.

II. Muscle Synergy Extraction and Estimation of Neural Commands

We hypothesize that basic muscle patterns which exist for locomotion modes such as level walking, stair ascent/descent, and ramp ascent/descent may be used for discrimination between the various locomotion modes.

A. Muscle Synergies

In their basic form, the muscle synergies may be represented as:

$$f_i(k) = \sum_{j=1}^{N} w_{ij}\, c_j(k), \quad i = 1, \dots, M; \tag{1}$$

Where, N is the number of muscle synergies, M is the number of muscles, $f_i(k)$ represents the activation level of the i^{th} muscle at time k, w_{ij} is the gain of the j^{th} element of the neural command for the i^{th} muscle, and $c_j(k)$ is the applied neural command at time k. (1) is written in vector form as:

$$\boldsymbol{f}(k) = \boldsymbol{W}\boldsymbol{c}(k) \tag{2}$$

Where, $\boldsymbol{f}(k)$ represents activation levels of M muscles at time k, $\boldsymbol{W}$ is a $M \times N$ matrix whose columns are the muscle synergies, $\boldsymbol{c}(k)$ is the neural command vector corresponding to $\boldsymbol{f}(k)$ at time k. We further assume that and all elements of $\boldsymbol{f}(k)$, W and $\boldsymbol{c}(k)$ are non-negative i.e. $\{f_i, w_{ij}, c_j\} \geq 0$. The relation can be extended by including activation levels at multiple times, i.e., for $k = 1, \dots, K$. In such case vectors $\boldsymbol{f}(k)$ and $\boldsymbol{c}(k)$ become matrices with one column devoted to muscle activation at each time instant k i.e.,

$$\boldsymbol{F} = \boldsymbol{W} \times \boldsymbol{C} \tag{3}$$

Where, $\boldsymbol{F}$ is a $M \times K$ matrix and $\boldsymbol{C}$ is $N \times K$ matrix. We also note that $\boldsymbol{W}$ and $\boldsymbol{C}$ are unknown matrices, whereas $\boldsymbol{F}$ is known.

In order to represent the muscle activation matrix $\boldsymbol{F}$, researchers have used the Root Mean Square (RMS) of the EMG signal [14, 16, 12]. We seek to extend this by including other time-domain features that include waveform length (WL), number of zero-crossings (ZC), variance (VAR) and maximum (MAX) value. Our offline analysis showed that using a combination of time-domain features to represent $\boldsymbol{F}$ resulted in lower classification error than using only the RMS value. See Appendix A for a description of the time domain features. We propose to include these time-domain features in $\boldsymbol{F}$. Other classification techniques such as LDA particularly rely on time-domain features of the EMG signals. Thus, $\boldsymbol{F}$ is composed of RMS, WL, and MAX. From here on we refer to $\boldsymbol{F}$ as the feature matrix. The estimation of unknown matrices $\boldsymbol{W}$ and $\boldsymbol{C}$ from one known matrix $\boldsymbol{F}$ is known as the problem of Blind Source Separation (BSS).

B. Muscle synergy extraction algorithm

Numerous algorithms have been developed to address the problem of BSS. The algorithms proposed for extracting the muscle synergies include principal component analysis (PCA), independent component analysis (ICA), factor analysis (FA), probabilistic independent Component Analysis (pICA) and non-negative matrix factorization (NMF) [17]. We use the fast NMF algorithm developed in [18]. The reason for using the NMF is that the feature matrix $\boldsymbol{F}$ has all non-negative values and the NMF imposes the non-negativity constraint for extracting non-negative synergy matrix. In particular, using the NMF for P locomotion modes, we extract P corresponding muscle synergy matrices.

$$[\boldsymbol{W}_i, \boldsymbol{C}_i] = NMF(\boldsymbol{F}_i) \quad i = 1, \dots, P \tag{4}$$

Where, $\boldsymbol{F}_i$ is the muscle activation matrix, $\boldsymbol{W}_i$ is the muscle synergy matrix, and $\boldsymbol{C}_i$ is the neural command matrix for the i^{th} movement. We store $\boldsymbol{W}_i$ for neural command estimation and discard $\boldsymbol{C}_i$.

C. Neural command estimation algorithm

The muscle synergy model in (2) shows that feature vector $\boldsymbol{f}$ and the neural command vector $\boldsymbol{c}$ are linearly related with each other. The muscle synergy matrix $\boldsymbol{W}$ provides the linear mapping from the parameters of $\boldsymbol{c}$ into $\boldsymbol{f}$. Since $\boldsymbol{c}$ is non-negative and $M > N$, therefore the system of linear equations can be solved using a Non-Negative Least Square (NNLS) approach.

The NNLS problem can be stated as follows: Given a $M \times N$ matrix $\boldsymbol{W}$ and a $M \times 1$ vector $\boldsymbol{f}$, find a non-negative $M \times 1$ vector $\boldsymbol{c}$, which minimizes the norm of $\boldsymbol{Wc} - \boldsymbol{f}$, i.e.

$$Minimize\ ||\boldsymbol{Wc} - \boldsymbol{f}||\ subject\ to\ \boldsymbol{c} \geq 0 \qquad (5)$$

Features extracted from each trial are stored in a vector $\boldsymbol{f}(k)$. We intend to estimate the command vector $\hat{\boldsymbol{c}}^i(k)$ from all the synergies extracted from the feature matrix $\boldsymbol{F}$. In this work we use the algorithm developed by Lawson and Hanson [19]. A faster version of this algorithm is also available known as fast non-negativity-constrained least square (FNNLS). FNNLS performs better than NNLS when the size of command vector is large, but, since in our case the size of the estimated neural command vector is 6x1 we chose NNLS. In fact, NNLS performed better than FNNLS in this case.

D. Locomotion Mode Classification

As we have '*P*' locomotion modes, then the most accurate reconstruction of the actual feature vector $\boldsymbol{f}(k)$ for a particular locomotion mode '*L*' is only possible using the mode-specific feature synergy matrix and its corresponding estimated neural command vector $[\boldsymbol{W}_L, \hat{\boldsymbol{c}}^L(k)]$, where '*L*' is the mode to be detected. The NNLS estimated neural command vector $\hat{\boldsymbol{c}}^L(k)$ is multiplied with the muscle synergies to reconstruct the feature vector estimate $\hat{\boldsymbol{f}}^{\boldsymbol{L}}(k)$. This estimated feature vector $\hat{\boldsymbol{f}}^{\boldsymbol{L}}(k)$ should possess the closest similarity with $\boldsymbol{f}(k)$ than the reconstruction from all other pairs$[\boldsymbol{W}_i, \hat{\boldsymbol{c}}^i(k)]_{i=1, i\neq L}^{P}$. Using the NNLS we estimate the *P* neural command vectors $[\hat{\boldsymbol{c}}^i(k)]_{i=1}^{P}$. Using (6) we find the reconstructed feature vectors for all the *P* locomotion modes.

$$\hat{\boldsymbol{f}}^{\boldsymbol{i}}(k) = \boldsymbol{W}_i \hat{\boldsymbol{c}}^i(k), \qquad i = 1, \ldots, P \qquad (6)$$

The cosine similarity measure S_k^i between the reconstructed feature vectors $[\hat{\boldsymbol{f}}^{\boldsymbol{i}}(k)]_{i=1}^{P}$ and actual feature vector $\boldsymbol{f}(k)$ in (7) is used to evaluate which pair reconstructs the feature vector most accurately. Cosine similarity measure gives an outcome between 0 and 1 that represents the similarity between the two vectors $\hat{\boldsymbol{f}}^{\boldsymbol{i}}(k)$ and $\boldsymbol{f}(k)$.

$$S_k^i = \frac{\hat{\boldsymbol{f}}^{\boldsymbol{i}}(k)^T \boldsymbol{f}(k)}{\sqrt{(\hat{\boldsymbol{f}}^{\boldsymbol{i}}(k)^T \hat{\boldsymbol{f}}^{\boldsymbol{i}}(k))(\boldsymbol{f}(k)^T \boldsymbol{f}(k))}}, \qquad i = 1, \ldots, P \qquad (7)$$

TABLE I
TRANSITIONS BETWEEN LOCOMOTION MODES

Mode Transitions	Gait phase	Critical instant
RA to WK	stance to swing	End of HC
RD to WK	stance to swing	End of HC
SA to WK	stance to swing	End of HC
SD to WK	stance to swing	End of HC
WK to RA	stance to swing	End of HC
WK to RD	stance to swing	End of HC
WK to SA	stance to swing	End of HC
WK to SD	stance to swing	End of HC

TABLE II
FEATURE MATRIX SIZE FOR DIFFERENT LOCOMOTION MODES

Locomotion mode	Feature matrix size	Transitions
RA	36 x 18	WK to RA
RD	36 x18	WK to RD
SA	36 x 18	WK to SA
SD	36 x 18	WK to SD
WK	36 x 45	WK, RA to WK, RD to WK, SA to WK and SD to WK

To find the locomotion mode we compute the Locomotion Mode Index (LMI) as the maximum of all similarity measures using (8). The locomotion mode corresponding to the LMI is chosen to be the desired mode. The block diagram of the muscle synergy extraction algorithm is shown in Fig. 1.

$$LMI = index(max[S_k^1, S_k^2, S_k^3, \ldots, S_k^P]) \qquad (8)$$

E. Muscle synergy approach comparison with LDA

The muscle synergy approach was compared with LDA under same conditions i.e. using an analysis window size of 200 ms before HC and TO. Four time domain features RMS, WL, MAX and ZC were extracted for predicting modes using LDA. We used One-Way ANOVA to check for any significant differences between the two approaches.

III. EXPERIMENTAL PROTOCOL

Seven able-bodied subjects (5 males and 2 females) participated in this experiment approved by the Institutional Review Board at the University of Arkansas at Little Rock. All participants gave written consent to take part in the study and were free to withdraw at any time during the data collection. All participants were right leg dominant with average height of 172.7 cm, maximum height being 189 cm and minimum height being 168 cm and average mass of 75.65 kg, maximum mass being 97.2 kg and minimum mass being 60.9 kg. The thigh of the non-dominant leg was instrumented

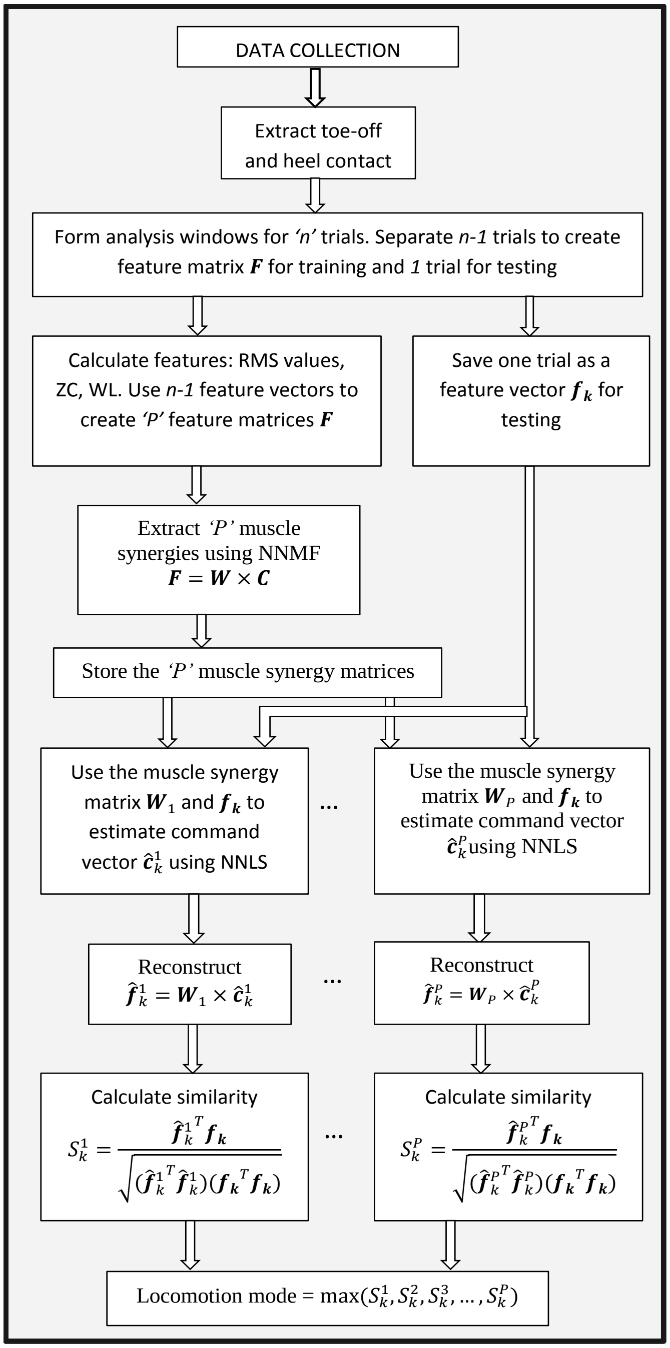

Fig. 1. Block diagram for the muscle synergy extraction algorithm

and the transitions between modes were performed with the dominant leg as the leading leg. Nine muscles were targeted through palpation namely: *Sartorius* (SART), *Rectus Femoris* (RF), Bicep *Femoris longhead* (BFL), *Bicep Femoris shorthead* (BFS), *Vastus Medialis* (VM), *Vastus Lateralis* (VL), *Semitendinosus* (ST) *Gracilis* (GR) *Semimembranosus* (SM), while three electrodes were placed on untargeted random locations on the thigh. These locations were consistent for all the 7 participants. EMG signals from 12 locations on the thigh were collected. To separate the stance phase and the swing phase, two foot switches were placed under the heel and metatarsals. A Noraxon TeleMyo Direct Transmission System (DTS) (Noraxon U.S.A. Inc) with twelve wireless sensors was

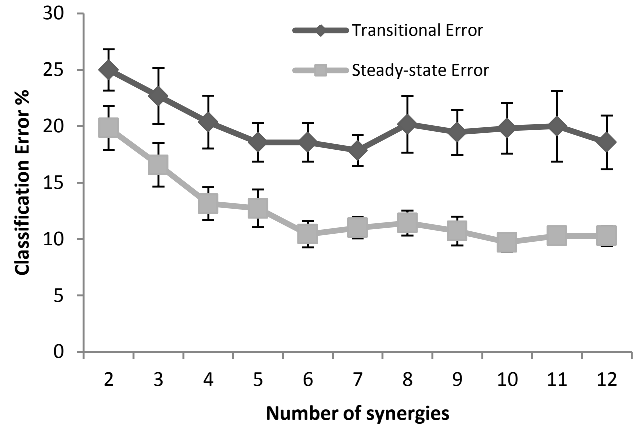

Fig. 2. Effect of the number of synergies on classification error. Both the transitional and steady-state errors decreased as the number of synergies was increased from 2 to 6. From 6 onwards the effect flattened. Data are averages for seven subjects.

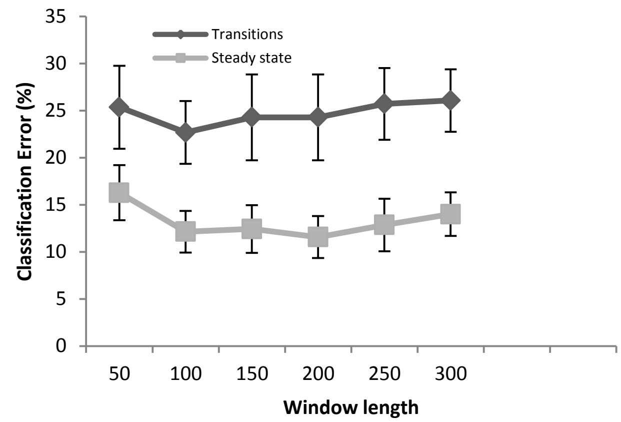

Fig. 3. Effect of analysis window size on classification error. Both the transitional and steady-state errors increased as the size of the analysis window increased. Significant increase in steady state error was observed for window size above 300 ms. Data are averages for seven subjects.

used to record the EMG data. We used disposable, self-adhesive silver/silver chloride (Ag/AgCl) snap electrodes with two circular conductive areas of 1 cm each and an inter-electrode distance of 2 cm.

The subjects completed 10 trials each for two circuits. In the first circuit the subjects walked four steps, climbed four step stairs, walked four steps and stopped; then they turned around, again stood for 5 sec, walked four steps, went down the four step stairs and walked four steps and stopped. In the second circuit the subjects walked two steps, climbed ramp and walked two steps and turned around; then, they walked one step on level ground, walked down ramp and walked one step and stopped.

The data for each subject included eight transitions (four transition 'from' level walking and four transitions 'to' level walking from each of the other four locomotion modes) and five locomotion modes namely: walking, ramp ascent/descent, and stair ascent/descent. The leading limb in all cases was the sound/uninstrumented limb. The participants were asked to use their sound leg while making all transitions. We assumed that all transitions would be detected at the end of the stance

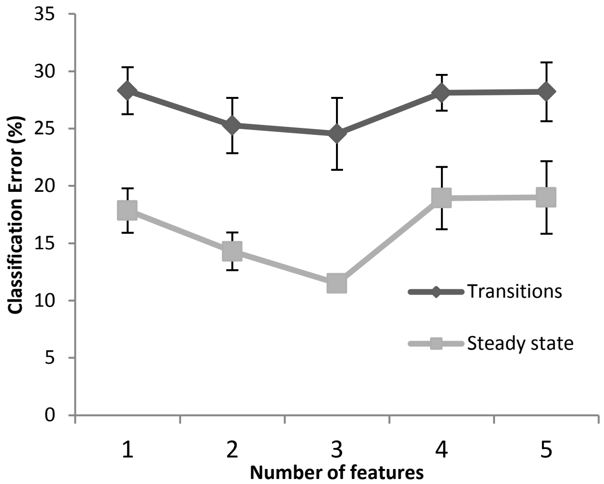

Fig. 4. Effect of number of features for extraction of muscle synergies. Three features produced the lowest transitional and steady state error.

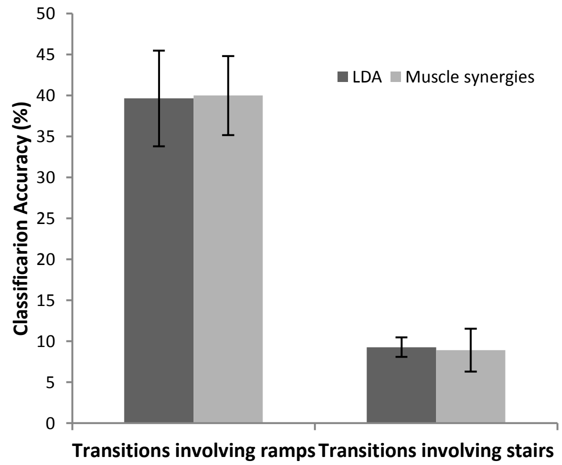

Fig. 5. Classification accuracy for transitions involving ramps and stairs are shown for both LDA and muscle synergy approach. Data are averages for seven subjects.

phase. The transition instants during various phases of gait are shown in table 1.

A. Feature Extraction and Pattern Classification

The data from the 12 sensors was recorded at a sampling rate of 1500 Hz. We used a 200 ms analysis window before HC and TO. The feature matrix was formed using three features, i.e., RMS, ZC and WL. Each feature matrix consisted of the steady-state of that mode and transitions that led to that mode. Since we measured EMG signals from twelve muscles, the feature matrix had 36 rows. The number of columns depended upon which locomotion modes and their transitions were used to construct the feature matrix. Table 2 shows the feature matrix size corresponding to each locomotion mode.

The size of the muscle synergy matrices corresponding to each locomotion mode was 36 x 6. The choice of the number of muscle synergies was a result of the analysis that showed that classification error reduced as number of synergies was increased to 6 (Fig. 2).

B. Classifier Performance Evaluation

The performance of the muscle synergy algorithm was evaluated via leave-one-out cross validation (LOOCV) with 10 trials collected from each subject, i.e., 9 trials were used to extract the synergies, and one trial was used to estimate the command vectors corresponding to all synergies. These command vectors were then used to reconstruct five feature vectors. The reconstructed features vectors were compared with the original feature vector containing features of the test trial, and the one having the highest similarity measure was chosen to be the locomotion mode. For each subject the LOOCV was performed ten times. The classification errors reported in the results section are averages of all ten runs of all participants.

The classification errors were divided into transitional and steady-state errors. Transitional error was defined as misclassification of the transition data occurring at a transition, and the steady-state error was defined as misclassification of steady-state data not occurring at a transition.

$$Transition\ Error\ (\%) = \frac{Total\ misclassified\ transition\ steps}{Total\ transition\ steps} \tag{9}$$

$$SS\ Error\ (\%) = \frac{Total\ misclassified\ SS\ steps}{Total\ SS\ steps} \tag{10}$$

IV. Results

A. Number of task specific muscle synergies

The performance of the classifier was evaluated for different number of muscle synergies. As the number of muscle synergies increased from 2 to 6, a decrease in classification error for both transitional and steady-state locomotion was observed. No significant change was observed as the number of synergies was increased beyond 6. Therefore, we chose 6 muscle synergies for our locomotion mode classifier (Fig. 2).

B. Analysis window size

The analysis window size was varied from 50 to 300 ms and no significant difference in estimation accuracy was observed. The error increased as the size of window was increased beyond 200 ms. In literature, machine learning algorithms such as LDA have usually produced higher classification accuracy for a window size between 200 ms to 300 ms [4, 8]. The least classification error for the muscle synergy approach was found at a window length of 200 ms, therefore we chose this length for the remaining analysis (Fig. 3).

C. Analysis of number of features for synergy extraction

We tried different combinations of time-domain features for synergy extraction. We found that when the feature matrix *F* was composed of three features, the transitional and steady state errors were the lowest. We repeated the analysis with different feature combinations and found that combination of RMS, WL and MAX yielded the least classification error in both transitions and steady-state phases (Fig. 4) therefore we chose to construct the feature matrix *F* with three features.

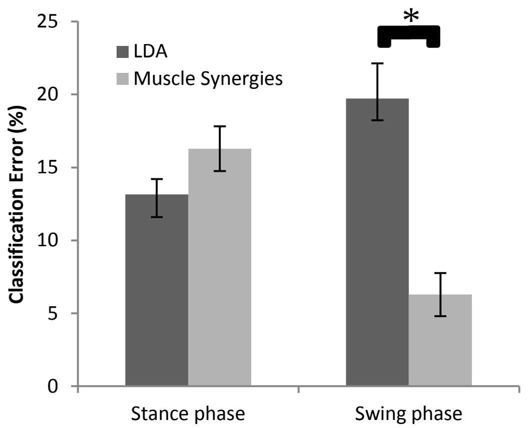

Fig. 6. Steady-state classification for steady state during stance phase and swing phase for both LDA and muscle synergy approach. Star indicates significant difference of $p < 0.05$. Data are averages for seven subjects.

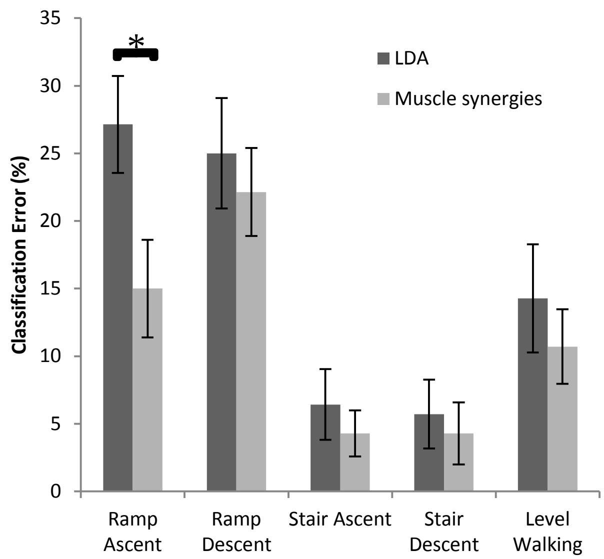

Fig. 7. Classification errors for ramp ascent, ramp descent, stair ascent, stair descent and level walking. Ramp ascent classification error using muscle synergy approach was significantly lower than LDA. Data are averages for seven subjects.

Other feature combinations tested were comprised of RMS (one feature), RMS and WL (two features), RMS, WL, MAX and VAR (four features) and RMS, WL, MAX, VAR and ZC (five features).

D. Comparison with LDA

1) Analysis of transitions involving ramps and stairs

No significant difference *($p>0.05$)* was found in transitions involving ramps and stairs between the two approaches. The classification accuracy of transition involving stairs was, as expected, higher than transitions that involved ramps. This difference was attributed to the fact that ramp walking pattern more closely resembled level ground walking as compared to the stair walking pattern (Fig. 5).

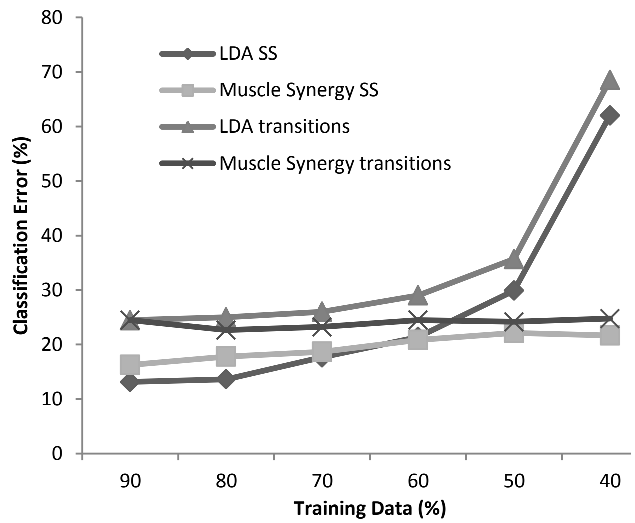

Fig. 8. Effect of training data on classification error for both LDA and muscle synergy approach. Decrease in training data shows a significant increase in classification error for LDA. The classification error for muscle synergy approach increases less rapidly. Training Data is the percentage of trial used for training. Data are averages for seven subjects.

2) Analysis of steady-state classification

LDA and muscle synergy approach were compared for the steady-state classification during stance and swing phases (Fig. 6). No significant difference *($p>0.05$)* was found between the two approaches during stance phase; however, classification error using muscle synergy approach was significantly lower *($p<0.05$)* than LDA for the swing phase. The steady-state classification error was compared for five locomotion modes. We observed that ramp ascent mode was classified significantly better *($p<0.05$)* using muscle synergy approach than LDA. No significant difference among other four modes was found. As expected, stair walking had significantly lower classification error than ramp walking (Fig. 7).

3) Analysis of number of training trials

Both algorithms were tested with different number of training trials (Fig. 8). From the figure it can be seen that as the number of training trials decreased the classification error of both LDA and muscle synergy approach increased. However, the classification error decreased more rapidly in the case of LDA than muscle synergy approach. Both steady-state and transitional error increased significantly with decrease in the size of training data sets for LDA.

V. Discussion

In this study we investigated using muscle synergies to classify locomotion modes for use in transfemoral prostheses control. In this context muscle synergies represent fixed relative activation levels of muscles involved in the movement. The muscle synergies were extracted from a combination of different time-domain features. These synergies were then used to estimate the command vector associated with the feature vector. The feature vectors were reconstructed using all available muscle synergies and the estimated command vectors. The reconstructed feature vectors were compared to the original feature vector using similarity measure, and the locomotion mode corresponding to the highest similarity measure was chosen. The performance of the muscle synergy approach was greatly dependent upon selecting the appropriate number of muscle synergies. We found that six or more synergies provided lower classification errors for both transition and steady state classification of locomotion modes. We used NMF algorithm for extracting the muscle synergies as, all the features used to construct the feature matrix were non-negative. We used NNLS for estimating the command vector due to the non-negativity condition on the vector. Since the muscle synergy matrix linearly maps the feature vector to the command vector, the NNLS successfully estimated the command vector while imposing non-negativity constraint.

The critical points in the gait cycle are the TO and HC instances. Identifying the locomotion mode at these instances led to smooth transitions between modes. Other research studies have shown that using a single analysis window before HC and TO provided significantly higher classification accuracy, as compared to using more than one windows and employing a majority voting scheme [9]. Our investigation on the analysis window size revealed that a single window of 200 ms before HC and TO produced least classification error. This optimal window size is marginally smaller than the value reported in the literature for LDA algorithm.

We demonstrated that using additional features along with the RMS of the EMG signal significantly decreased the classification error. The steady-state classification error went down from 17.8% for one additional feature to 11.5% for three additional features and transitional error decreased from 28.3% to 24.5% (Fig. 4). Studies that have used muscle synergies for upper limb prostheses control or hand posture identification have only used the RMS to represent the muscle activations [16, 12]. The authors are unaware of any study that has used a combination of features to extract the muscle synergies.

The transitions involving stair ascent/descent had a higher recognition rate as compared to the transitions involving ramps. This was attributed to the similarity between ramp walking and level ground walking. Similar results were observed for steady state mode recognition whereby stair walking had a lower classification error compared to ramp walking. Other studies have also reported that ramp transitions have higher classification error as compared to stair ascent [11].

We compared the muscle synergy approach with LDA using different numbers of training and testing data sets (Fig. 8). It was observed that as the number of trials in the training dataset decreased, the classification error of LDA increased more rapidly as compared to the muscle synergy approach. However, there was no significant difference when more than 60% of the data trials were used for training. This result shows that classification strategies such as LDA rely heavily on the availability of training data [10]. Every time an amputee dons the prostheses; he/she requires a training session before using the prostheses in real time. The length of this training session depends upon the number of trials and locomotion modes. For a transfemoral amputee using an active prosthesis, the training session normally includes walking on different terrains and remote switching performed by someone other than the amputee for seamless transitions [9]. Based on our results (Fig. 8), the muscle synergy approach would effectively reduce the amount of data required for training the classifier. It may be noted that even though we reduced the number of training data trials, the number of synergies used in all cases was the same, i.e., six synergies.

A comparison of the swing and stance phases yielded an interesting result. Previous research studies have reported that using LDA the classification error in the swing phase was higher than the classification error in the stance phase [8, 9, 10]. Huang et al. have reported a classification error of nearly 15% during swing phase when using only EMG data with multiple analysis windows [8]. Our result supports the findings of other researchers that for LDA the classification error during the stance phase is higher than the swing phase. In this study, the classification error during swing phase using LDA was around 20% when using a single window for classification while in stance phase the error was around 13%. However, using the muscle synergies approach, the error during swing phase reduced to 6% for a single window, while for stance phase the error was 16% (Fig. 6). The increase in steady-state error during stance phase using muscle synergy approach was not significantly higher than error using LDA *($p>0.05$)*. For the swing phase, however, a significant reduction in error was observed compared to LDA *($p<0.05$)*. Swing phase may be considered as a form of reaching movement where the leg is being moved from one point to another. Muscle synergy approach performs better than LDA during swing phase. In this study we have considered the transitions to occur at the end of the stance phase of the instrumented leg. Based on the better performance of muscle synergy approach during swing phase, it may be inferred that if the transitions for some locomotion modes were to be detected during the swing phase, the transitions classification error would reduce further using the muscle synergy approach.

VI. Conclusion

We have presented a novel approach to identify and predict the locomotion modes and the task transitions underlying gait assisted by a prosthetic device in the case of amputees. The proposed approach that exploits the hypothesis of muscle synergies was compared with the popular machine learning approach, i.e., LDA. Significant improvements were observed in the classification accuracy during swing phase where the muscle synergy approach outperformed the LDA. Performance was relatively similar in all other phases. As expected the classification error for transitions ‘to’ and ‘from’ ramps was significantly higher than transitions ‘to’ and ‘from’ stairs. This study employed healthy participants with instrumented legs to resemble prostheses. Our future work will focus on collecting data from transfemoral amputees and testing the feasibility of our algorithm on active prostheses.

Appendix

Time-Domain Features

The following time-domain features and their combinations were used to extract the muscle synergies. N represents the number of samples in the analysis window and x_k represents the k^{th} sample.

- Root Mean Square: $RMS = \sqrt{\frac{1}{N}\sum_{k=1}^{N}|x_k{}^2|}$
- Number of Zero Crossings: ZC is incremented by 1 if $\{x_k > 0 \; and \; x_{k+1} < 0\} or \{x_k < 0 \; and \; x_{k+1} > 0\}$ $and \; |x_k - x_{k+1}| > \varepsilon$
- Variance: $VAR = \frac{1}{N-1}\sum_{k=1}^{N} x_k^2$
- Maximum: $MAX = \max(|x_1| \ldots |x_k|)$
- Waveform Length: $WL = \sum_{k=1}^{N}|\Delta x_k| \, , where \; \Delta x_k = \; x_k - x_{k-1}$

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