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Classification of Gait Phases from Lower Limb EMG: Application to Exoskeleton Orthosis

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***Abstract*-This paper describes the use of Bayesian Information Criteria (BIC) along with some standard feature extraction methods and Linear Discriminant Analysis (LDA) classification algorithm to separate 8 different phases of gait by using electromyographic (EMG) signal data of the lower limb. Four time domain features along with 4th order Auto-Regressive model were used to get feature vector set from the EMG data of each leg of an able bodied person. Window of 50 ms (millisecond) was used such that it is within the controller delay limit. Then, the BIC segmentation algorithm was applied on the feature vector sets of 10 different gait cycles one by one to find out the locations of the boundaries between the phases. Due to the differences in the identified boundary locations for different gait cycles, the ambiguous part around each boundary was removed. The LDA classifier was then applied to the EMG feature vector set to classify 8 phases of gait. The classification accuracy increased by a significant amount in comparison to when BIC algorithm was not used. The work is our first step towards making an EMG signal driven foot-knee exoskeleton orthosis for the stroke patient having hemiparesis.**

I. Introduction

Traumatic brain injury, stroke or as well certain neurological disorderes can produce locomotor impairments. For example, patients having post-stroke hemiparesis are unable to walk without assistance. Many rehabilitative strategies like partial weight bearing treadmill training and functional electrical stimulation are employed in the clinical settings [1-4]. Majority of the research work has been done using kinematics and kinetics data (accelerometers, gyroscopes, foot inertial sensors, force detectors etc.) during locomotion [5-8]. In this paper, we have used the electromyographic (EMG) signal data to detect the phases of the gait cycle. The "EMG signals" resulting from the "motor unit action potential" generated in the muscle fibers are responsible for the muscle movements. We captured the EMG signals from four different muscle groups of each leg using surface electromyography. The information available in the EMG signals was used to detect phases of human gait. In normal gait, there is a well understood relationship (implying synchronization) between the phases of both legs; whereas the synchronization is lost in the case of post-stroke hemiparesis. Therefore exoskeleton or orthotic device may be useful to such patients. Accurate phase information obtained using EMG data taken from the leg which is in a proper working condition, may be used to drive the actuators at hip, knee and ankle joints of the exoskeleton (Fig. 1) which is wore on the impaired leg. Subsequently, normal gait (walking pattern) may be achieved by obtaining synchronization between the legs.

The objective of our present work is to acquire EMG data from the lower limb of individuals, extract relevant features, and analyze the features through machine learning techniques to achieve improved prediction accuracy of different phases of gait cycle. Here, we present our preliminary findings that we achieved by applying Bayesian Information Criteria (BIC) along with feature extraction technique and classification algorithm (e.g. LDA) to the EMG data.

Fig. 1. Exoskeleton orthotic device (courtesy Dr. Yu Haoyong, National University of Singapore)

II. BACKGROUND

Here, we present brief on each of the terms that we will come across in this paper. A single cycle of human gait can be divided into 7 (1st and 8th phase are clubbed) different phases as shown in Fig. 2 [9]. So far as our data acquisition and analysis is concerned, we will also come across the terms such as controller delay and classification accuracy.

Controller delay is the time elapsed between the generation of the EMG signals in the muscle fibers of the body and the generation of output after signal acquisition, feature extraction and pattern recognition is done. A

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previous study [10] has shown that the controller delay is

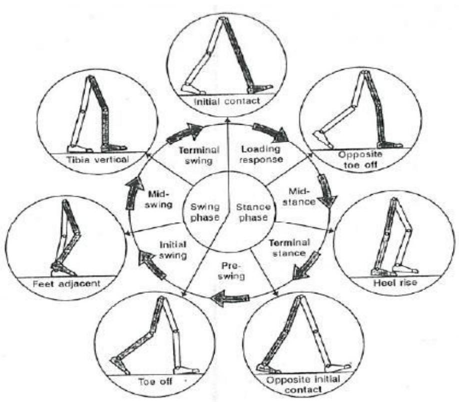

Fig. 2. Human gait cycle divided into 7 phases

proportional to the window-size if the increment in the window size is very small compared to the actual size of the window. Another study [11] has shown that if controller delay is above the maximum limit of 125 ms, then that delay becomes perceivable as a disruption in the gait cycle synchronization between the legs. In our work, we overcame this problem by choosing the EMG signal window length of 50 ms and an increment of window size of only 1 ms. Our objective is to acquire improved Classification accuracy while predicting different phases of the gait cycle. The *Classification Accuracy* is quantified from the number of times the test data is classified into their corresponding gait-cycle phases correctly.

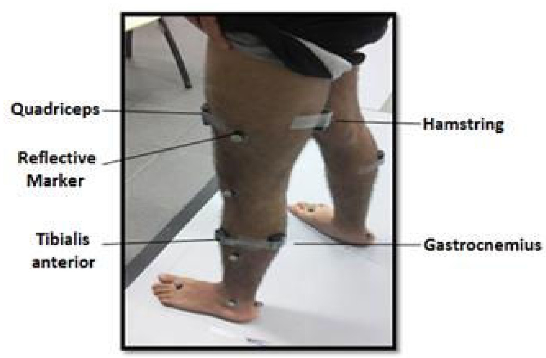

Fig. 3. Quadriceps, Hamstring, Gastrocnemius and Tibialis Anterior are the muscles of the lower limb; the reflective markers were used to get angular data.

III. EMG SIGNAL PROCESSING

A. Data Acquisition

A 16 channel wireless EMG system from Delsys was used to acquire EMG signals. Out of the available 16 channels, 8 channels were used, 4 for each leg with 1 channel corresponding to EMG data from one muscle. The measurements of the hip, knee and ankle joint angles were made using the VICON 3D motion analysis system. The anatomical data were recorded using the spatial location of the reflective markers and the motion capture system. For this work, the sagittal components of the angles were extracted for processing. The angular data and the EMG data were synchronized and were acquired simultaneously on the same time-line. As shown in Fig. 3, activity of the four muscles of the lower limb was captured during the gait cycle.

Myoelectric signals have frequencies ranging from 20 hertz to 450 Hz, and voltage ranging from approximately 100 μV to 10 mV (peak to peak). Therefore, the sampling frequency of the EMG acquisition system was set to 1000 samples/sec (second). Sampling frequency of motion capture system was 100 samples/sec. Thus, 1 sample of angular data corresponds to 10 samples of the EMG data.

B. Assigning labels to the EMG data using hip angle graph

The angular data from the hip was used to assign labels to the EMG data. The division of 8 phases of gait [9] as shown in Fig. 4 was used to decide boundary (acts as reference for the boundaries obtained using BIC which has been explained later in the paper) between the different phases. The gait period was 1.01 sec, so we got total 1010 samples for each gait cycle. After applying the window of 50 ms, we got 961 samples for each gait cycle and subsequently we obtained the predicted transition boundaries as shown in table I.

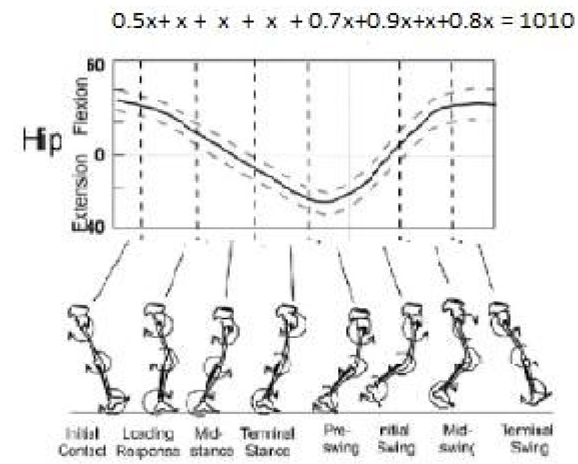

Fig. 4. Hip angle graph used for dividing one gait cycle into 8 different phases.

TABLE I
LOCATION OF BOUNDARIES BETWEEN THE PHASES

Boundary between phases	Sample number
1 and 2	50
2 and 3	196
3 and 4	343
4 and 5	489
5 and 6	592
6 and 7	724
7 and 8	870

Note that the system starts capturing motion data or tracking the markers when they come under the vision of the cameras. It might happen that for some gait cycles, it starts capturing data before the beginning of the gait cycle. In order to have initial phase synchronization among the EMG data of all the gait cycles, we pruned or eliminated some initial samples for some gait cycles.

C. *Feature Extraction*

Literature indicates that different EMG features, including autoregression coefficients [12], time-domain features [15], frequency domain features [13], and time–frequency-domain features [14], [16] have been used in the EMG Pattern Recognition for upper limb prosthesis control. Lee et al. [17] have indicated certain features which might give good results even in different environmental conditions. Thus, in this work we have selected features such as, four coefficients of the fourth order autoregressive model and four time domain features. We chose these features because their computation does not require signal transformation which consequently also satisfies the requirement of fast time-response.

The following features were studied: (i) Time domain features (Mean absolute value, Waveform length, Variance, Slope sign changes [17]) (ii) Auto-Regressive model (4^{th} order) (Y[n] = a1*y[n-1] + a2*y[n-2] + a3*y[n-3] + a4*y[n-4] [17]). Thus, for each window, we extracted 8 features for every channel and hence a total of 32 features for every window.

D. *BIC Segmentation Algorithm*

The feature vector set of each gait cycle was applied to BIC one by one to detect the location of boundaries between different phases of gait. As explained in [18] and [19], the algorithm works as follows:
Let us assume that $X = xi \in Rd,\ i = 1, 2, \ldots, N$ is the sequence of vectors in which there is at most one segment boundary. We wish to consider if there is a position $b \in (1,N)$ that is the boundary between two phases generating the two segment outputs $x_1, \ldots, x_b$ and $x_{b+1}, \ldots, x_N$, respectively. The decision rule to check and locate the boundary is $\Delta BIC_b = 0.5*(N \log|\Sigma| - b \log|\Sigma 1| - (N - b) \log|\Sigma 2|) - 0.5*\lambda\ (d + 0.5*d\ (d + 1))\log N$, b = max (ΔBIC_b) and $\Delta BIC_b \geq 0$; where Σ denotes the covariance matrix of the extracted feature vectors, Σ1 and Σ2 are the covariance matrices of the features of the first and the second segment respectively. The variables d and λ represent feature dimension and penalty weight factor, respectively.

In order to detect multiple segmentation boundaries, a moving window was considered that swept through the stream. We used a window of 50 samples. Then, the window is shifted by 1 sample if no boundary exists and a new window is started from the detected boundary as the next window.

TABLE II
IDENTIFIED BOUNDARIES USING BIC ON THE EMG DATA OF LEFT LEG

Boundary between phases	Boundary identified between Sample numbers
1 and 2	51-96
2 and 3	164-214
3 and 4	343-388
4 and 5	477-527
5 and 6	566-620
6 and 7	698-739
7 and 8	844-910

TABLE III
IDENTIFIED BOUNDARIES USING BIC ON THE EMG DATA OF RIGHT LEG

Boundary between phases	Boundary identified between Sample numbers
1 and 2	51-61
2 and 3	172-217
3 and 4	323-364
4 and 5	466-508
5 and 6	580-626
6 and 7	697-738
7 and 8	866-870

As a proof of concept of our system, here we present the results of analysis of one participant. Here, we chose $\boldsymbol{\lambda}$ (penalty weight vector) = 1.68, for which all 7 boundaries were identified for most of the gait cycles. The results are presented in Tables II and III.

E. *Pattern Recognition*

After locating the transition boundaries between the different phases, our objective was to identify different phases of the gait cycle. For that we used Pattern Recognition (PR) technique. Fig. 5 shows the sequence followed during PR. The feature vectors appearing in the ambiguous portion (identified using BIC) in the vicinity of each boundary were pruned while training and testing the classifier.

The EMG feature data of 10 gait cycles collected from the participant were segmented into train dataset (data of 9 gait cycles) and test dataset (data of 1 gait cycle). We used the concept of leave-one-out and train on the rest.

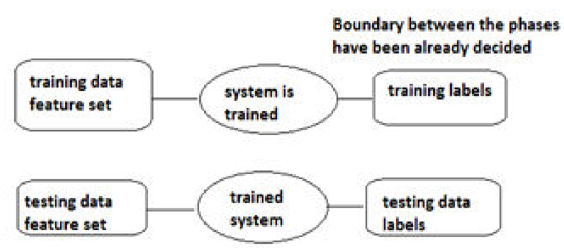

Fig. 5. The sequence followed during PR technique

We chose LDA PR classifier. As explained in [20], it uses a transformation technique that maximizes the ratio of between class variance and within class variance. Between-class variance is found by the covariance of dataset whose members are the mean vectors of each class. Within class variance is the covariance of data set of a particular class. We used LDA since it gives comparable classification performance to more complex types [21]–[23] and is computationally efficient for real-time myoelectric prosthesis control [24].

IV. RESULTS OF THE CLASSIFICATION ACCURACY

Here we present a comparative analysis of the results of classification accuracy that we achieved prior to (2^{nd} column of the Tables IV and V) and after (3^{rd} column of the Tables IV and V) applying the time-synchronization and the BIC

TABLE IV
CLASSIFICATION ACCURACY FOR DIFFERENT GAIT CYCLES FOR LEFT LEG EMG DATA

Test cycle	Accuracy before	Accuracy after
1	50.02%	60.17%
2	55.27%	77.00%
3	57.41%	93.83%
4	55.46%	89.17%
5	57.14%	84.83%
6	58.17%	65.33%
7	36.41%	68.67%
8	53.03%	87.83%
9	44.52%	87.67%
10	58.50%	46.67%

TABLE V
CLASSIFICATION ACCURACY FOR DIFFERENT GAIT CYCLES FOR RIGHT LEG EMG DATA

Test cycle	Accuracy before	Accuracy after
1	60.60%	70.80%
2	71.43%	84.02%
3	58.63%	70.25%
4	69.19%	91.60%
5	35.85%	64.74%
6	37.54%	77.27%
7	45.19%	79.34%
8	53.50%	84.16%
9	31.00%	57.02%
10	63.59%	72.04%

segmentation algorithm. Improved accuracy of prediction of different phases of gait was observed.

V. DISCUSSION AND CONCLUSION

The results show an improvement in the classification accuracy but also some uncertainty in the accuracy is obtained when different gait cycles were used as the testing cycles. In future, we are planning to address this problem by combining the EMG data with the data of foot sensors and IMU (Inertial Measurement Unit) sensors. Additionally, we plan to extend our data analysis to more participants (able bodied and stroke patients) which will provide us a platform to cross validate our results. Also, we plan to implement the algorithms on the micro-controller which can serve as a very useful tool in controlling the exoskeleton prosthetic in real life.

VI. ACKNOWLEDGEMENT

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