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

Chetas D. Joshi, Uttama Lahiri, *Member, IEEE,* and Nitish V. Thakor, *Fellow, IEEE*

*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

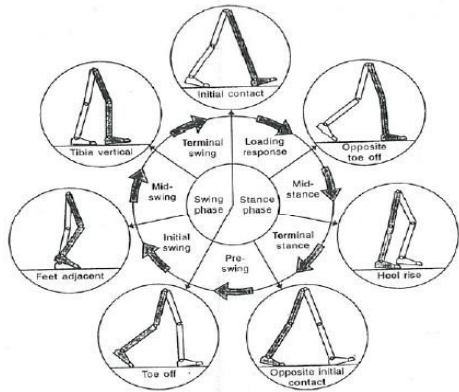previous study [10] has shown that the controller delay is

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
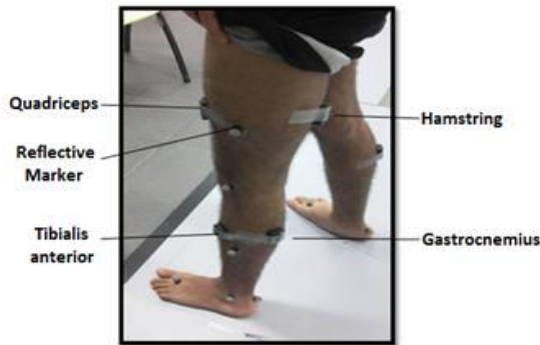

Fig. 3. Quadriceps, Hamstring, Gastrocnemius and Tibialis Anterior are the muscles of the lower limb; the reflective markers were used to get angular data.

Classification Accuracy is quantified from the number of times the test data is classified into their corresponding gait-cycle phases correctly.

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.
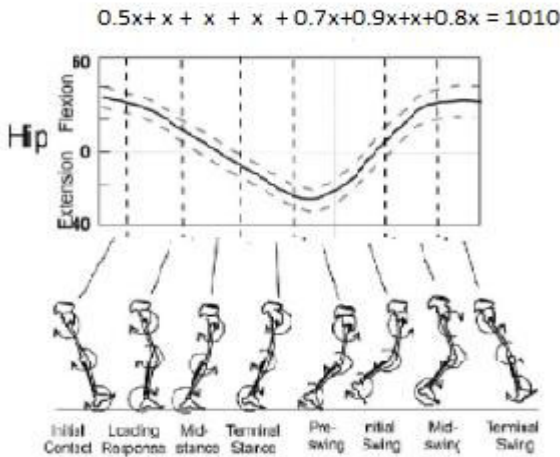
$$0.5x + x + x + x + 0.7x + 0.9x + x + 0.8x = 1010$$

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

229

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[1] absolute value, Waveform[2] length, Variance,[3] Slope sign changes[4] [17]) (ii) Auto-Regressive model (4th 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. *What are the other 4 features? a1, a2, etc or y[n-1]*

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 $X = x_i \in R^d$, $i = 1, 2, . . .,N$ 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 $x_1, . . . , x_b$ and $x_{b+1}, . . . , x_N$, respectively. The decision rule to check and locate the boundary is $\Delta BIC_b = 0.5*(N \log |\Sigma| - b \log |\Sigma1| - (N - b) \log |\Sigma2|) - 0.5*\lambda (d + 0.5*d (d + 1))\log N$, $b = \max (\Delta BIC_b)$ and $\Delta BIC_b \geq 0$; where Σ denotes the covariance matrix of the extracted feature vectors, $\Sigma1$ and $\Sigma2$ 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

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

window.

As a proof of concept of our system, here we present the results of analysis of one participant. Here, we chose λ (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
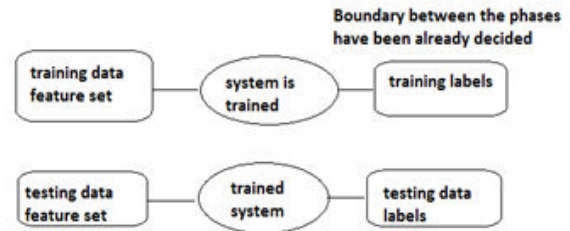

Fig. 5. The sequence followed during PR technique

concept of leave-one-out and train on the rest.

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 (2nd column of the Tables IV and V) and after (3rd column of the Tables IV and V) applying the time-synchronization and the BIC

230

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

REFERENCES

[1] W.K. Timoszyk, R.D. de Leon, et al "Robot-assisted Locomotion Training after Spinal Cord Injury: Comparison of Rodent Stepping in Virtual and Physical Treadmill Environments", Robotica, vol. 21, pp. 25-32, 2003.

[2] G.M. Yarcony, R.J. Jaeger, E. Roth, A.R. Krajly, J. Quintern, "Functional neuromuscular stimulation for standing after spinal cord injury," Arch Phys Med Rehab, vol. 71, pp. 201-206, 1999.

[3] S. Hesse, C. Bertelt, A. Schaffrin, et al. "Restoration of Gait in Nonambulatory Hemiparetic Patients by Treadmill Training With Partial Body-Weight Support," Arch Phys Med Rehab., vol. 75, pp. 1087-1093, 1994.

[4] D. Uhlenbrock, T. Sarkodie-Gyan, F. Reiter, M. Konrad, S. Hesse, "Development of a servo-controlled gait trainer for the rehabilitation of non-ambulatory patients," Biomed Tech, vol. 7-8, no. 42, pp.196-202, 1997.

[5] C. MacDonald, D. Smith, R. Brower, M. Ceberio, T. Sarkodie-Gyan, "Determination of Human Gait Phase Using Fuzzy Inference", Int. Conf. on Rehab. Robotics, 2007.

[6] Smith BT, Coiro DJ, Finson R, Betz RR, McCarthy J. "Evaluation of force-sensing resistors for gait event detection to trigger electrical stimulation to improve walking in the child with cerebral palsy", IEEE trans. on Neural Systems Rehabilitation Engineering, vol 10, no 1, 2002.

[7] A. Mannini, A. Maria Sabatini, "A Hidden Markov Model-based technique for gait segmentation using a foot-mounted gyroscope", Int. Conf. IEEE EMBS, Boston, Massachusetts USA, 2011.

[8] A. M. Sabatini,C. Martelloni, S. Scapellato, F. Cavallo, "Assessment of walking features from foot inertial sensing", IEEE Trans. On Bio. Med. Eng. vol. 52, no. 3, pp. 486-94, 2005.

[9] D. Y.R. Chong, "Biomechanics of Human Locomotion", PhD Thesis, Division of Bioengineering, NUS.

[10] L.H. Smith, L.J. Hargrove, B.A. Lock, T.A. Kuiken, "Determining the Optimal Window Length for Pattern Recognition-Based Myoelectric Control: balancing the Competing Effects of Classification Error and Controller Delay", IEEE Trans. Neural Sys. Rehabil. Eng., vol. 19, no. 2, pp.186-92, 2011.

[11] T.R. Farrell, R.F. Weir, "The Optimal Controller Delay for Myoelectric Prostheses", IEEE TNSRE, vol. 15, no. 1, 2007.

[12] D. Graupe, J. Salahi, K. H. Kohn, "Multifunctional prosthesis and orthosis control via microcomputer identification of temporal pattern differences in single-site myoelectric signals," J. Biomed. Eng., vol. 4, pp. 17–22, 1982.

[13] D. Peleg, E. Braiman, E. Yom-Tov, G. F. Inbar, "Classification of finger activation for use in a robotic prosthesis arm," IEEE Trans. Neural Syst. Rehabil. Eng., vol. 10, no. 4, pp. 290–293, 2002.

[14] R. Boostani, M.H. Moradi, "Evaluation of the forearm EMG signal features for the control of a prosthetic hand," Physiol. Meas., vol. 24, pp. 309–319, 2003.

[15] B. Hudgins, P. Parker, R. N. Scott, "A new strategy for multifunction myoelectric control," IEEE TBME, vol. 40, no. 1, pp. 82–94, 1993.

[16] K. Englehart, B. Hudgins, P. A. Parker, M. Stevenson, "Classification of the myoelectric signal using time-frequency based representations," Med. Eng. Phys., vol. 21, pp. 431–438, 1999.

[17] S.W. Lee, T. Yi, J.S. Han, H. Jang, H.H. Kim, J.W. Jung, Z. Bien, "Walking Phase Recognition for People with Lower Limb Disability" Int. Conf. on Rehab. Robotics, 2007.

[18] U. Lahiri, R.F. Labadie, C. Liu, R. Balachandran, O. Majdani, N. Sarkar, "A Step Toward Identification of Surgical Actions in Mastoidectomy", TBME, vol. 19, no. 4, pp. 443-452, 2011.

[19] M. Baillie, J.M. Jose, "An Audio-based Sports Video Segmentation and Event Detection Algorithm", Computer Vision and PR Workshop, 2004.

[20] S. Balakrishnama, A. Ganapathiraju, "Linear Discriminant Analysis-A brief tutorial", Institute for Signal and Information Processing, Department of Electrical and Computer Engineering, Mississippi State University.

[21] Y. Huang, K.B. Englehart, B. Hudgins, A.D. Chan, "A Gaussian mixture model based classification scheme for myoelectric control of powered upper limb prostheses," TBME,, vol. 52, no. 11, pp. 1801–1811, 2005.

[22] K. Englehart, B. Hudgins, P.A. Parker, M. Stevenson, "Classification of the myoelectric signal using Time frequency based representation", Med. Eng. Phys.,vol. 21, pp. 431-438, 1999.

[23] L. J. Hargrove, K. Englehart, B. Hudgins, "A comparison of surface and intramuscular myoelectric signal classification," IEEE Trans. Biomed.Eng., vol. 54, no. 5, pp. 847–853, 2007.

[24] K. Englehart, B. Hudgins, "A robust, real-time control scheme for multifunction myoelectric control," IEEE Trans. Biomed. Eng., vol. 50, no. 7, pp. 848–854, 2003.

231