Human Locomotion Activity and Speed Recognition Using Electromyography Based Features

Seyed Mostafa Rezayat Sorkhabadi, Prudhvi Tej Chinimilli, Daniel Gaytan-Jenkins, and Wenlong Zhang*

***Abstract*— Human locomotion recognition methods based on electromyography (EMG) signals have not shown robust and accurate classification performance. This is due to the limitations of EMG signals such as its stochastic nature and sensitivity to placement of the sensors, as well as the number of sensors, feature extraction and classification algorithms. In this paper, a robust classification approach with only two features derived from EMG signals is developed to recognize locomotion activities and detect changing speeds. The root means square (RMS) and energy of the EMG signals are the features adopted in this method. The energy of the EMG signal is extracted using energy kernel method. The proposed approach uses a low number of sensors and features, online unsupervised classification, and is generalizable to different lower-limb muscle groups. To evaluate the benefits of the proposed approach, it is initially tested on a public dataset of five participants with two EMG sensors on biceps femoris and gastrocnemius, doing separate trials on the treadmill at various speeds and slopes. We performed additional experiments on two participants with EMG sensors on vastus laterialis and vastus medialis, as treadmill speeds changed online within each trial. The proposed approach achieved significant classification accuracy (above 90%) using the standard unsupervised K-means clustering, for both locomotion activity and speed recognition with the public dataset and our collected data.**

I. Introduction

Rehabilitation training has shown a positive impact on neurological restoration of limb functions [1]. Conventional rehabilitation training is labor intensive especially for lower-extremity joints. In recent years, assitive devices for rehabilitation have gained significant popularity [2]. Rehabilitation training with proper robot assistance plays a significant role in recovering the limb motor functions. An active interaction control strategy that can provide appropriate assistance as needed is essential for satisfying training performance.

The EMG based control strategy is widely adopted in rehabilitation, prosthetic control, and human-robot interaction [3]. EMG signals contain important information of the muscle activities, and thereby, will be helpful to estimate human intentions. Multiple methods have been proposed to extract useful information from EMG signals to control the assistive devices [4]. In hybrid assistive limb (HAL), a voluntary control strategy is developed to estimate the user's intentions based on the detection of muscle activities through EMG signals [5]. In [6], intention estimation algorithm based on EMG signals was integrated into high-level controller strategy of the knee exoskeleton. Although the aforementioned assistive devices exhibited fair performance in terms of providing appropriate assistance using EMG signals, there are certain limitations associated with number of EMG sensors, types of locomotion activities, and generalization of the approach. Many human activity recognition (HAR) methods were proposed in the literature based on the features extracted from EMG signals [7]. Some employed eight EMG sensors around the thigh and adopted convolutional neural network (CNN) to perform walking activity classification [8]. The combination of linear discriminant analysis (LDA) and a two-layered artificial neural network (ANN), was used to identify the locomotion activities with twelve EMG sensors [9]. Finite state machines using EMG signals from six muscles were able to recognize level-walking, ramp ascent, and ramp descent [10]. There is a need to develop human activity recognition algorithm with minimal number of EMG sensors and to extract less number of features to make the algorithm real-time and easily integrable to the assistive device.

The time domain and frequency domain features are the most commonly extracted features from the time windows of EMG signals [7]. Using sliding time window has been proven to be more robust compared to the fixed time window [11]. The time domain features such as mean absolute value (MAV), root mean square (RMS), integrated EMG (iEMG), and zero crossing (ZC) are used in supervised learning [12]. Although time domain features are easy to compute, they yield less classification accuracy. However, RMS and MAV are proven to be intuitive in classification of locomotion activities. Others used frequency domain features such as mean frequency (MF) and median frequnecy (MDF) [13]. Some performed wavelet decomposition of the EMG signals to extract wavelet features to train the algorithm [14]. The frequency and wavelet features generally require more computational effort than time domain features. In [15], energy of the EMG signal is derived using energy kernel method to improve the transparency of an exoskeleton knee joint based on the understanding of motor intent. The energy kernel method seems more intuitive compared to other methods, which inspired us to use energy of the EMG signal as one feature in our approach. This feature is intuitive because locomotion speed or activity depends on the energy of the muscle activation level. We hypothesize that human efficiently changes the energy of the muscles based on the

This work was supported in part by the National Science Foundation under Grant IIS-1756031, and in part by Science Foundation Arizona under a Bisgrove Early Tenure-Track Faculty Award.

The authors are with the Robotics and Intelligent Systems Laboratory, The Polytechnic School, Ira A. Fulton Schools of Engineering, Arizona State University, Mesa, AZ, 85212, USA. (E-mail: srezayat@asu.edu; Prudhvi.Chinimilli@asu.edu; Daniel.Gaytan-Jenkins@asu.edu; Wenlong.Zhang@asu.edu).

* Address all correspondence to this author.

locomotion speed and activity.

The surface EMG (sEMG) sensors are generally preferred to record muscle activities due to its non-invasive nature and easy to mount on the body. There are certain limitations associated with EMG sensors: 1) placement of the EMG sensors, 2) repeatability of the measurements during various sessions, and 3) cross-talk between the muscles. Therefore, there is a need for a robust method to recognize locomotion modes with minimal number of EMG sensors to avoid cross talk and recognize locomotion modes irrespective of the trail or subject. In this paper, we propose such a robust method that can perform locomotion mode recognition with minimal number of sensors and features. The contributions of this paper include:

1) A locomotion recognition approach is developed based on the energy of damped harmonic oscillator EMG model, and the RMS of EMG signal
2) Formulated an online approach that does not require training of the model with features extracted from EMG signals.
3) Generalized the algorithm in terms of placement of the EMG sensor and number of participants.

The rest of the paper is organized as follows. The damped harmonic oscillator formulation is given in section II. section III introduces the approaches used in the experiments and features extraction. Section IV details the experiment protocol and gives the classification results of the algorithm. Section V discusses the results of this paper and talks about the impact of the proposed approach in real-time control of assistive robots. Section VI concludes this paper and presents future work.

II. Approach

The RMS and energy of the EMG signal are the two features proposed to perform classification of locomotion speed and activities. The RMS of EMG signal is attributed to the muscle force [16]. The energy of the EMG signal is derived using energy kernel method given in [15]. The energy kernel method is based on the assumption that EMG signal governs a harmonic oscillator model. There is a physical intuition between energy and force/power of muscle explained in [15]. In this paper, we hypothesize that the change in energy of the EMG signal per gait cycle with locomotion speed or activity follows damped harmonic oscillator model. Therefore we should be able to classify different activities based on their energy level. In [17] it is suggested that the energy kernel method combines the advantages of both RMS and mean power frequency methods and provide better Physical intuition of EMG. However, regarding the uncertainties associated with EMG signal, we believe that using the RMS and energy of EMG signal as two features for identifying the gait speed or activity change would lead to more accurate and robust prediction than using individually, and can be expanded to broader applications.

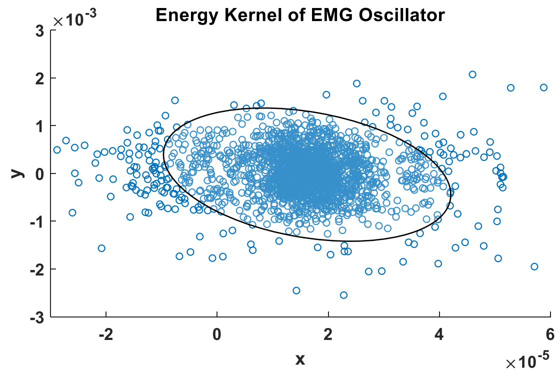


Fig. 1. The energy kernel of the EMG signal of vastus laterialis

A. Damped Harmonic Oscillator Model of EMG

This model is inspired from the simple harmonic oscillator model of the EMG given in [15]. The behavior of the EMG signal can be recognized as a oscillator whose amplitude is featured by the reciprocating motions accompanied by a noise, as it is a zero-averaged stochastic wave signal. The energy of simple harmonic oscillator with mass m, stiffness k is given as:

$$E_0 = \frac{1}{2}kx^2 + \frac{1}{2}my^2 \tag{1}$$

or in an elliptic form as:

$$\frac{x^2}{2E_0/k} + \frac{y^2}{2E_0/m} = 1 \tag{2}$$

The phase portrait of EMG signal of vastus laterialis (amplitude signal on x and derivative of the amplitude on y) for a segment is shown in Fig. 1. The length of the time window chosen for this portrait is equal to one gait cycle. Gait cycle events are obtained from force plates data.

This elliptic shape of the phase portrait given by (2), can be seen in Fig. 1 for the EMG signal per gait cycle. It is not possible to compute E_0 directly as k and m are unknown. However, the area of the ellipse will be useful in calculating the energy of the harmonic oscillator. The area of the ellipse can be expressed as

$$S = \frac{2\pi}{\sqrt{km}}E \tag{3}$$

Equation (3) shows that the area of the ellipse is proportional to the energy of the harmonic oscillator. The ellipse of the phase portrait is referred as the energy kernel [15].

It is expected that during gait or any periodic locomotion activity, the energy of EMG per cycle, which is a representation of muscle activity, will stay in the same level, and will change when the activity changes. This change can be modeled by the harmonic damped oscillator. The energy of a damped harmonic oscillator with damping b is given as:

$$E = E_0 e^{\frac{bt}{m}} \tag{4}$$

Here t is time, and E and E_0 are the energy of the damped harmonic oscillator and simple harmonic oscillator, respectively. The smaller value of b in (4) makes E to be approximated as E_0, the energy of the simple harmonic oscillator. We hypothesize that at a constant speed of a locomotion activity, the damping of the muscles exhibit small value. Therefore, it can be approximated as a simple harmonic oscillator. However, the change in locomotion speed and activity will change the damping value to a higher positive or negative value causing decay or increase in the muscular energy governed by damped harmonic oscillator model. We want to validate this model in the experiments with locomotion speed or activity change, and using the result to detect those changes.

III. Methods

To initially evaluate the generalization and performance of this method, it has been tested on a public dataset on which EMG data of participants are collected as they were walking on the treadmill in different slopes and speeds. Furthermore, an additional set of experiments and data collection are done, to evaluate the performance of this method on: 1) clustring if the walking speed changes online and 2) different muscle groups around knee joint. The later will examine the generalization of the proposed method to other muscle groups.

A. Public Data Set

The chosen dataset contains leg joint kinematics, kinetics, and EMG activity of able bodied subjects walking on a instrumented treadmill in different combination of slopes (-10 degree to +10 degree) and speeds (0.8 m/s to 1.2 m/s) in each trial. The study was done at the University of Texas at Dallas [18].

Among all the trials, four trials of five subjects have been considered for speed and activity change detection: level and uphill walking at speeds 0.8 and 1.2 m/s. Each trial contains EMG data of four muscle groups: rectus femoris (RF), biceps femoris (BF), tibialis anterior (TA), and gastrocnemius (GC). The EMG signals were collected with a sampling rate of 2000 Hz, and rectified and low-pass filtered (fc=40 Hz) with a zero-phase digital filter. The EMG data are broken down into individual gait cycles which begin and end at heel strikes. Each gait cycle contains 150 EMG data points which are used to extract the proposed features for each stride. As some issues with right leg EMG sensors have been reported in this study, left leg EMG sensors are chosen for all subjects.

B. Data Collection and Pre-processing

Two level walking experiments were performed on two participants, as the treadmill speed changed online, and their EMG data were collected. For the vastus lateralis (VL) and vastus medialis (VM), one surface EMG (sEMG) wireless sensors (Delsys Trigno Avanti) were placed on each muscle group based on Seniam placement protocol [19].

The sampling rate for both sEMG was 2000 Hz. The sensors placement is shown in Fig. 2. This study has been done at Arizona State University (ASU) and has approved by its Institutional Review Board (IRB).

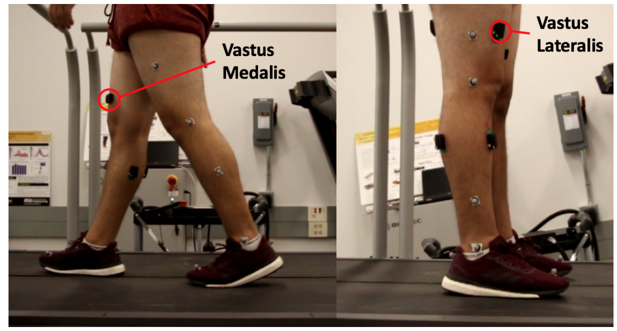


Fig. 2. The sensors placement for EMG signal acquisition of VL and VM muscle groups during the speed change trials

Each participant walked on an instrumented dual belt treadmill with integrated force plates. Along with the EMG data, force plates data were collected to detect heel strike events. The collected raw EMG data were rectified and processed using a 4th order Butterworth filter with the cut-off frequency of 40 Hz. The data were broken down into individual cycles based on heel strike events detected by the force plates.

C. Feature Extraction

The RMS and energy feature of EMG were calculated per gait cycle, from the collected and processed EMG for all trials. For a given number of data points, the RMS of the signal will be:

$$RMS = \sqrt{\frac{1}{n}\Sigma_{i=1}^{n} x_i^2} \tag{5}$$

where x represents the signal over the cycle and n is the number of data points within the cycle. The energy of the EMG signal at each gait cycle, would be the area of the ellipsoid which was represented in section II. To calculate the area, the phase portrait of each cycle was extracted by taking the x as the amplitude of the signal and y as its derivative. A discrete box counting method proposed in [15] has been used to calculate the ellipsoid of the phase portrait.

TABLE I
DETAILS OF THE HEALTHY PARTICIPANTS JOINED THE STUDY.

ID	Gender	Age	Height (cm)	Weight (kg)
1	Male	21	175	94
2	Male	20	176	78

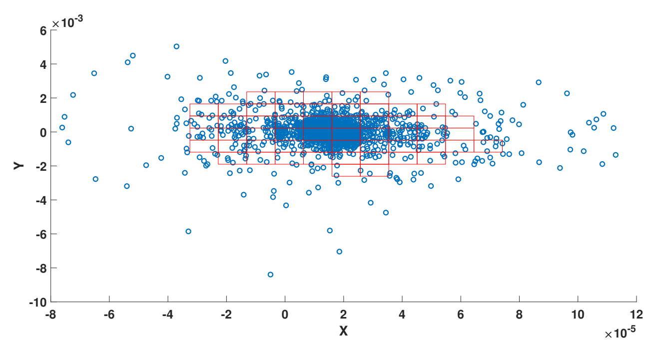
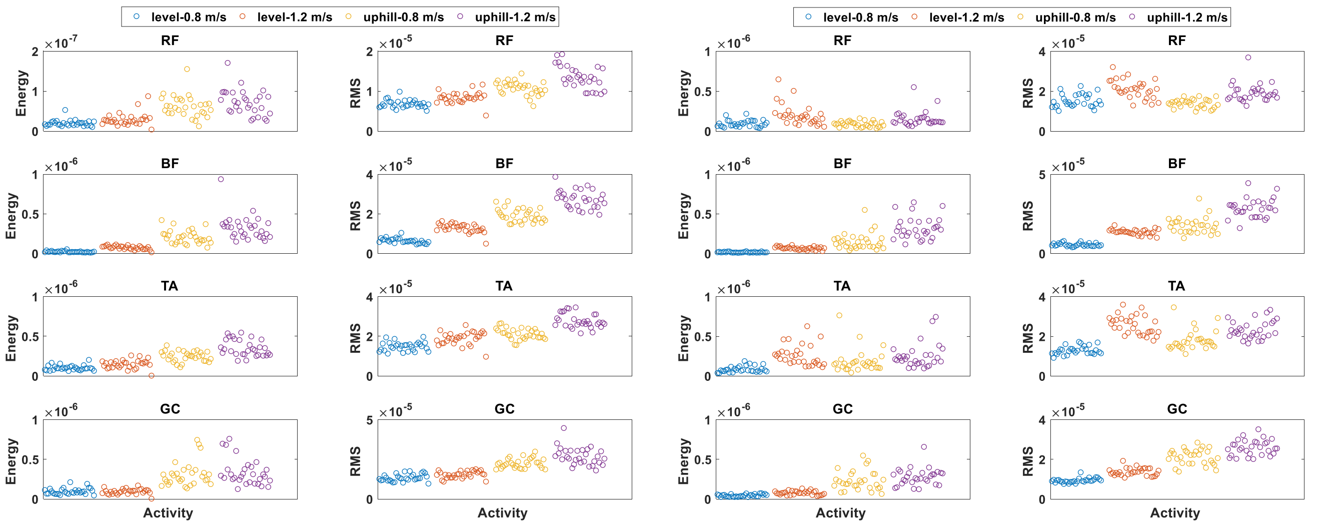


Fig. 3. The discrete box counting method to calculate the ellipsoid area of the EMG signal of the VM muscle groups for one gait cycle.



(a) Subject 03

(b) Subject 06

Fig. 4. The RMS and energy value of 4 muscle groups EMG signal for two subjects in 4 different walking trials: level walking at 0.8 m/s and 1.2 m/s, and uphill walking (10 deg inclined) at 0.8 m/s and 1.2 m/s.

This methods divides the rectangle enclosing all the data points of phase portrait in $n_1 \times n_2$ grids or boxes. The number of points inside each box (p_{ij}) will be counted, and if $p_{ij} > thr$, where thr is a predefined threshold, the box will be included as the area of ellipsoid. In order to make sure that boxes will cover a continuous area, a 2D moving average with one sliding window is performed on p_{ij} for smoothing the counted values of each box before comparing to the threshold. It must be noted that the number of boxes ($n_1 \times n_2$) and the threshold thr depend on the total number of data points in the segment. By many trials and errors, we chose $n_1 = n_2 = 10$ and $thr = 0.5$ for the public data set which contains 150 points per cycle, and $n_1 = n_2 = 20$ and $thr = 2$ for the collected data as 2000 data points were considered for each cycle. Fig. 3 shows the area to calculate the energy kernel of one of the collected gait cycle data.

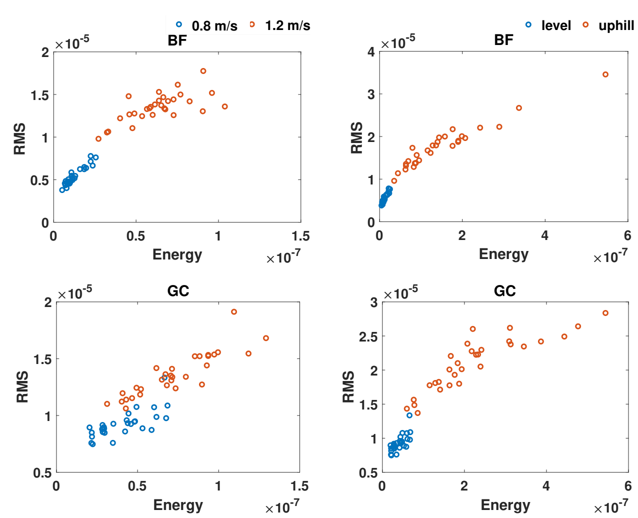
D. K-means Clustering Approach

K-means is a well known unsupervised approach that can cluster n objects into k classes. K-means clustering minimizes the distortion measure, taking the total intra-cluster variance as a cost function. This method iteratively finds the cluster centroids, and then assigns the data according to the Euclidean distance to the cluster centroids until convergence. In our case, we hypothesize that energy-RMS cluster of the EMG signal will be distinguishable for various locomotion speeds and activities.

IV. Results

A. Speed and Activity Change Identification in Separate Trials

The energy and RMS value of EMG signals during each gait cycle are calculated for five subjects in four different trials with different activities and speeds. The subject ID numbers are as given in the public dataset. Fig. 4 shows the RMS and energy of EMG signal of the four muscle groups, for two of the subjects. It can be seen that the RMS and energy values of some muscle groups show more clear distinction in the activities than the other ones. Based on our observation from these figures for all subjects, the muscle groups BF and GC are chosen to extract the features. Fig. 5 shows the 2D feature space (Energy-RMS) of these two EMG signals for gait speed change and activity change. By considering these 2D features for all the four EMG sensors, it seems impossible to use only one EMG sensor to differentiate between speed and activity changes for all subjects. Using two EMG sensors make the classification among the subjects more robust. The energy feature of EMG signal helps with increasing the distance between the clusters and making the classification more accurate, rather than



(a) Speed change (0.8 vs 1.2 m/s)

(b) Activity change (level vs uphill)

Fig. 5. The Energy-RMS plots of RF and GC EMG signals of one of the subjects for gait speed change (a) and activity change (b).

using only RMS feature.

As an unsupervised classification approach, K-means clustering has been used to classify the data based on the gait activity or speed change. This approach does not need any training and can group unlabeled data into certain clusters. The only input to this algorithm besides the features, is the number of clusters. Our assumption is that the extracted features of the two EMG signals will remain at almost same level, as far as the gait speed or activity has not changed, independent of subjects or other conditions. The K-means clustering would be ideal to test this assumption.

The RMS and energy of EMG signal of RF and GC muscle groups, were considered as the four features of the K-means clustering. The classification is performed on 30 gait cycles of each trial. The level walking trials at speeds 0.8 and 1.2 m/s are considered together to classify the speed change, and level and uphill walking trials at 0.8 m/s are considered as activity change classification. The accuracy of the two classifications for all subjects is represented in Fig. 6. For all cases, the accuracy of classification is greater than 90%. Depending on the subject, the accuracy of detecting activity or speed change is different, which is expected as different subjects' muscle groups might behave differently in those conditions.

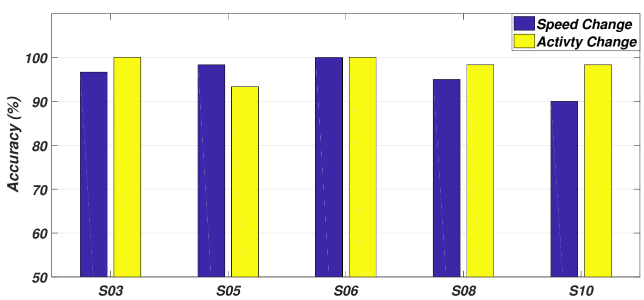


Fig. 6. The accuracy of K-means classification algorithm to predict gait speed or activity change based on a 4 features space consisting of RMS and energy values of two EMG sensors (BF and GC) in the public dataset

B. Online Gait Speed Change Detection using Different Muscle Groups

In order to validate the performance of this method in the case that walking speed changes online in one trial, rather than in separate trials, the same analysis is performed on 2 subjects walking on treadmill while the speed changes twice in the middle of the trial, from slow speed (0.5m/s) to normal speed (0.8 m/s), and then to fast speed (1.2 m/s). Here, EMG signal of VM and VL muscle groups are used to further examine the generalization of this approach. The 2D feature (RMS and energy) of each EMG signal are plotted in Fig. 7 for each subject. 15 gait cycles are considered for each speed (total 45 for each trial), and the transition points are not considered here. The reason is that transition points will make the classification and distinction between clusters much more complicated and difficult, and for now we only focus on speed change from slow walking to normal and fast walking.

From Fig. 7 it is observed that using these muscle groups and the proposed features, it is still possible to have separate clusters as the speed changes during walking. The K-means clustering method is performed on the extracted features of these two EMG signal, to classify three clusters for each experiment and the results are shown in table II. As expected, the classification accuracy for all 4 trials is high (more than 97%).

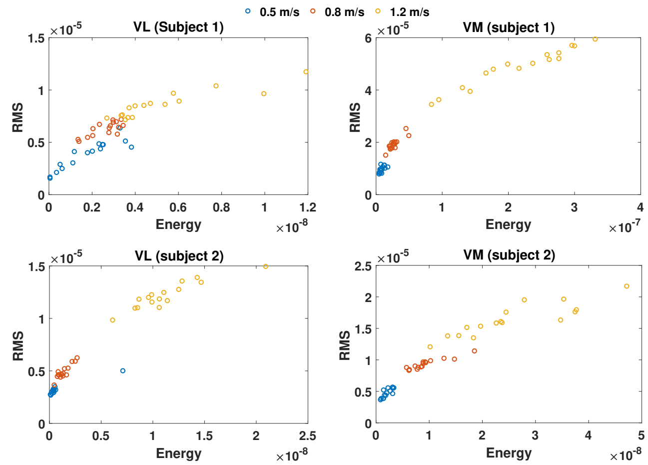


Fig. 7. The energy-RMS of EMG signal plots for two subjects walking on treadmill as the speed changes twice: From 0.5 m/s to 0.8 m/s and then to 1.2 m/s. The EMG signal are acquired from two muscle groups, VL and VM. The gait cycles in speed transitions are not considered.

TABLE II

THE SPEED CHANGE DETECTION ACCURACY FOR SUBJECTS WALKING ON TREADMILL AS ITS SPEED CHANGES TWO TIMES

Subject	Trial number	Accuracy
1	1	97.8%
	2	100%
2	1	97.8%
	2	97.8%

V. DISCUSSION

Essentially RMS and energy of EMG signal are not completely independent features as they are both attributed to the muscle activation level. However, regarding the noisy and stochastic nature of EMG signal, each of them might behave differently, and our result showed that having them as two different features would lead to better classification accuracy.

Based on the results showed in Fig. 6, the energy kernel of EMG per gait cycle for lower-limb muscles will remain in certain level or cluster during constant gait activity or speed, and will go to different clusters if the speed or activity changes. Therefore the energy kernel of each gait cycle, during the gait activity or speed change, can be described by damped harmonic oscillators rather than mass-spring model.

The robustness of the proposed method to detect gait speed or activity changes is tested in three ways: across different subjects, across different experimental and data acquisition conditions (two different data set and separate trials), and across two groups of different muscle groups (VM-VL, and BF-GC). We obtained high classification accuracies for all those conditions, suggesting a robust performance of the purposed method. It must be noted that EMG based classification methods are not usually robust, regarding the stochastic and noisy nature of EMG signal, and its sensitivity to the experiment and data acquisition condition. Further experiments can be performed to address the effects of human physiological change such as muscle fatigue, to examine the robustness of this EMG classification method, in more details.

This method has the potential to be implemented in real time. Both features can be extracted in real time and an online unsupervised classification algorithm can use the proposed 2D feature space to identify changes in the gait. Although the update rate might not be very fast (at least one gait cycle), this method can possibly be used for gait assistive robot applications. Given its accuracy, robustness, few number of sensors, and applicability to different muscle groups, it can be used to detect any changes in the muscle activation level, and the robotic exoskeleton would alter its policy or level of assistance accordingly.

VI. Conclusion and Future Work

In this paper, a damped harmonic oscillator model was proposed based on a previously developed harmonic oscillator model for EMG signals, to account for the change in energy level of EMG signal due to gait activity changes. It was shown that the energy level of EMG of lower-limb muscle groups remain at the same level for each activity and changes as the activity changes, therefore they could be classified into different clusters. Inspired by these ideas and observations, the energy of EMG was considered as a feature, along with the RMS of the signal, to classify human gait based on activity and speed. The method was tested on a public dataset containing different walking activity and speed trials. The result showed that by taking the data from two EMG sensors, placed on biceps femoris and gastrocnemius, the change in speed and activity in separate trials could be detected using K-means clustering as an unsupervised classification method, with more than 90% accuracy for five participants. To further evaluate the generalization and robustness of the proposed method, experiments were performed on two subjects walking on a treadmill as the speed change online. This time the EMG data of vastus laterialis and Vastus medialis were collected, and the RMS-energy features were extracted. Using the same method, the accuracy of detecting speed change for both subject was more than 97%.

In the future, this work can be extended to control of lower-limb robotic exoskeletons, to adopt to different gait activities and speeds [20]. The applicability of this method will be further investigated by testing in an outdoor environment, and/or with a larger number of gait activities. The integration of this method with other joints kinematic data to gain better gait activity and speed recognition, will be explored.

References

[1] G. Morone, S. Paolucci, A. Cherubini, D. De Angelis, V. Venturiero, P. Coiro, and M. Iosa, "Robot-assisted gait training for stroke patients: current state of the art and perspectives of robotics," *Neuropsychiatric disease and treatment*, vol. 13, p. 1303, 2017.

[2] T. Yan, M. Cempini, C. M. Oddo, and N. Vitiello, "Review of assistive strategies in powered lower-limb orthoses and exoskeletons," *Robotics and Autonomous Systems*, vol. 64, pp. 120–136, 2015.

[3] W. Meng, Q. Liu, Z. Zhou, Q. Ai, B. Sheng, and S. S. Xie, "Recent development of mechanisms and control strategies for robot-assisted lower limb rehabilitation," *Mechatronics*, vol. 31, pp. 132–145, 2015.

[4] A. J. Young and D. P. Ferris, "State of the art and future directions for lower limb robotic exoskeletons," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 25, no. 2, pp. 171–182, 2017.

[5] S. Lee and Y. Sankai, "Power assist control for walking aid with hal-3 based on emg and impedance adjustment around knee joint," in *Intelligent Robots and Systems, 2002. IEEE/RSJ International Conference on*, vol. 2. IEEE, 2002, pp. 1499–1504.

[6] N. Karavas, A. Ajoudani, N. Tsagarakis, J. Saglia, A. Bicchi, and D. Caldwell, "Tele-impedance based assistive control for a compliant knee exoskeleton," *Robotics and Autonomous Systems*, vol. 73, pp. 78–90, 2015.

[7] X. Xi, M. Tang, S. M. Miran, and Z. Luo, "Evaluation of feature extraction and recognition for activity monitoring and fall detection based on wearable semg sensors," *Sensors*, vol. 17, no. 6, p. 1229, 2017.

[8] M. Md Alias, A. Needham, A. A. Dehghani-Sanij, R. Vaidyanathan, U. Martinez-Hernandez, and C. Weston, "Walking activity recognition with semg sensor array on thigh circumference using convolutional neural network," in *2018 International Conference on Intelligent Systems Engineering (ICISE)*. IEEE, 2018.

[9] H. Huang, T. A. Kuiken, R. D. Lipschutz *et al.*, "A strategy for identifying locomotion modes using surface electromyography," *IEEE Transactions on Biomedical Engineering*, vol. 56, no. 1, pp. 65–73, 2009.

[10] M. Islam and E. T. Hsiao-Wecksler, "Detection of gait modes using an artificial neural network during walking with a powered ankle-foot orthosis," *Journal of Biophysics*, vol. 2016, 2016.

[11] A. Merlo, D. Farina, and R. Merletti, "A fast and reliable technique for muscle activity detection from surface emg signals," *IEEE Transactions on Biomedical Engineering*, vol. 50, no. 3, pp. 316–323, 2003.

[12] J. Ziegier, H. Gattringer, and A. Mueller, "Classification of gait phases based on bilateral emg data using support vector machines," in *2018 7th IEEE International Conference on Biomedical Robotics and Biomechatronics (Biorob)*. IEEE, 2018, pp. 978–983.

[13] D. Joshi, B. H. Nakamura, and M. E. Hahn, "High energy spectrogram with integrated prior knowledge for emg-based locomotion classification," *Medical engineering & physics*, vol. 37, no. 5, pp. 518–524, 2015.

[14] Y. P. Ivanenko, R. E. Poppele, and F. Lacquaniti, "Five basic muscle activation patterns account for muscle activity during human locomotion," *The Journal of physiology*, vol. 556, no. 1, pp. 267–282, 2004.

[15] X. Chen, Y. Zeng, and Y. Yin, "Improving the transparency of an exoskeleton knee joint based on the understanding of motor intent using energy kernel method of emg," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 25, no. 6, pp. 577–588, 2017.

[16] A. Christie, J. G. Inglis, G. Kamen, and D. A. Gabriel, "Relationships between surface emg variables and motor unit firing rates," *European journal of applied physiology*, vol. 107, no. 2, pp. 177–185, 2009.

[17] X. Chen, Y. Yin, and Y. Fan, "Emg oscillator model-based energy kernel method for characterizing muscle intrinsic property under isometric contraction," *Chinese science bulletin*, vol. 59, no. 14, pp. 1556–1567, 2014.

[18] K. R. Embry, D. J. Villarreal, R. L. Macaluso, and R. D. Gregg, "Modeling the kinematics of human locomotion over continuously varying speeds and inclines," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 2018.

[19] H. Hermens and B. Freriks, "The state of the art on sensors and sensor placement procedures for surface electromyography: a proposal for sensor placement procedures," *Deliverable of the SENIAM Project*, 1997.

[20] P. T. Chinimilli, Z. Qiao, S. M. Rezayat Sorkhabadi, V. Jhawar, I. H. Fong, and W. Zhang, "Automatic virtual impedance adaptation of a knee exoskeleton for personalized walking assistance," *Robotics and Autonomous Systems*, 2019. [Online]. Available: http://doi.org/10.1016/j.robot.2019.01.013