Muscle Synergies Based Gait Phase Classification during Kinematically Constrained Walking on Slackline

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Abstract—**The study aims to develop an state estimation framework for the detection of stance and swing phases of gait cycle during walking on a perturbed platform, i.e. a slackline. We use Support Vector Machine (SVM) classifier for the detection of stance and swing phase in gait cycle. Surface Electromyography (EMG) data was recorded from nine different muscles in the lower extremity from five healthy subjects. The proposed structure utilizes the hypothesis of Muscle Synergies (MS) where the movement intent is modelled as hidden state of the state space framework. We employ time domain modeling of the neural drive that excites the task-dependent muscles. To cater for the naturally existing physiological bounds (the non-negative muscle activations), the state estimation process is executed using a constrained form of the Kalman filter. Principal Component Analysis (PCA) is used for dimensional reduction of reconstructed EMG signal. We evaluated performance of SVM classifier, and the detection accuracy was later enhanced with post processing. Our preliminary experimental results demonstrate a reconstruction and classification accuracy greater than 95%.**

Index Terms—**walking over slackline, electromyography, neural drive, muscle synergies, Kalman filter, Principal Component Analysis, Support Vector Machine**

I. Introduction

Movement is generated in the human body through the contraction of skeletal muscles. The discrimination between the muscular activation patterns underlying movement gains immense significance when it comes to the myoelectric control of powered prostheses. Pattern classification techniques have been applied in the past for the classification of finite number of movements with a classification accuracy exceeding 90% [1]. However, the practical results on acceptance of prosthetic devices do not support the reported accuracies [2]. The collected sEMG data represents electrical signals that are transmitted from the Central Nervous System (CNS) towards the muscles in order to generate movements, therefore, estimating the neural command and muscular activations could be of significant importance in the development of artificial powered limb prostheses [3], [4].

The basic function of a nervous system is to coordinate all activities in the body. The CNS plays fundamental role in actuating smooth and accurate muscle movements that are continuous in nature by utilizing complex spinal cord structures. The pattern classification techniques possess a discrete nature since the information is passed on to the controller at discrete time intervals which could potentially result into discontinuous movements [2]. A classifier can be trained for a specific set of movements [1], however, increasing set of movements makes it prone to overfitting which is a limitation to such an approach. In case of human locomotion, multiple DOFs are activated simultaneously [2]. In our earlier study, we applied pattern classification algorithms such as Support Vector Machines (SVM), Decision Tree (DT), and Nave Bayes (NB) to discriminate between swing and stance phase during constrained walking on a perturbed platform, i.e. a slackline, where the accelerometer data had been modeled as input to the Kalman filter in order to estimate the movement intent [5].

MS are defined to be the fixed relative levels of activation of muscles. Combinations of such synergies are capable of generating movements by activating multiple DOFs simultaneously rather than following a sequential control regime [6]. The myoelectric prosthetic devices currently available allows to perform basic movements with lesser stride to stride variability. Since our daily tasks involve high gait transition variability, therefore, the aim of this study is to develop a framework that is capable of detecting changes in gate transition with great accuracy for a high variability task.

To cater for the discontinuous movements resulting from the pattern classification techniques, we propose the postulation of MS for the estimation of movement intent modelled as hidden state of the state space network. Since the muscle activations can either be zero or positive, we have designed a constrained form of Kalman filter for the state estimation process. This paper presents

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promising preliminary results of our research where the EMG signal is reconstructed for five gait trials via state space estimation of the movement intent using a modified time varying Kalman filter. Gait discrimination is performed for the classification of swing and stance phase using the SVM classifier.

The paper is assembled as follows. Section II talks about modelling based on state space framework, and design of Kalman filter. Section III involves the methods used for performing the task. In Section IV, test results are introduced with the end goal to delineate the practicality of our work. Section V talks about discussion of results obtained and conclusions are expressed in Section VI.

II. Mathematical Modeling

In this work, we have modeled the movement intent as the unknown hidden state to be estimated from the surface myoelectric data. In order to explain the dynamics of the system, we have used a random walk model while the output model has been constructed by utilizing the postulation of MS. Since muscle activations are non-negative in nature, we have utilized the state constrained Kalman filter to gauge the non-negative hidden state, i.e. the movement intent [3].

A. State-Space Model

State space model for a discrete-time linear system is given as

$$x(n+1) = Ax(n) + Bu(n) + w(n) \tag{1}$$

$$y(n) = Hx(n) + v(n) \tag{2}$$

$x(n)$ represents the states where each synergy coefficient represents a state variable to be estimated, $y(n)$ is the output, $u(n)$ is the input to the system, $w(n)$ and $v(n)$ represent the process and observation noise respectively.

Since there does not exist any mathematical model that can explain the ideal dynamics of CNS, therefore, a random walk model is postulated to satisfy performance requirements for the estimation of a smoothed activation co-efficient, thus we have

$$x(n+1) = x(n) + w(n) \tag{3}$$

The output model presented in this work is based on the postulation of MS [3]. A linear model form emerges normally because of the additive nature of the spinal force fields [7]. Thus, we have,

$$z(n) = W \times h(n) \tag{4}$$

where $z(n)$ represents the EMG signal, 'W' is a $(m \times p)$ matrix in which 'm' constitutes the number of muscles and 'p' amounts to the number of synergies used in the problem. While $h(n)$ is the 'p'-element neural drive to be estimated. Once we are able to compute the matrix 'W', we then utilize it in the output equation of our state space model as follows

$$y(n) = Wx(n) + v(n) \tag{5}$$

We have utilized the Non-negative Matrix Factorization (NMF) algorithm [7] for the computation of the MS matrix W and eq. (5) shows how it relates the state vector $x(n)$ to the output vector $y(n)$. Once the muscle synergy matrix W is known, information regarding $x(n)$ can be used for the reconstruction of movement intent.

B. Kalman Filtering

Kalman filter is known to be the optimal filter in mean square error sense in non-stationary environment [8]. Practically, the Kalman filter requires prior knowledge of $A[n], B[n], C[n], Q[n]\ and\ R[n]$ where $Q[n]\ and\ R[n]$ represent the covariance matrices for process and observation noise ($w(n)\ and\ v(n)$) respectively. In case of the problem under investigation, we suggest the process noise $w(n)$ and observation noise $v(n)$ with a Gaussian process. Some assumptions used in this work regarding process and observation noise are,

$$\begin{aligned} w(n) &\sim \mathcal{N}(0, Q_n), \\ v(n) &\sim \mathcal{N}(0, R_n), \\ Q_n &= E[w_n w_n^T], \\ R_n &= E[v_n v_n^T], \\ E[w_n v_n] &= 0 \end{aligned} \tag{6}$$

The recursive algorithm followed by Kalman filter is classified into two parts, i.e. prediction and correction. Utilizing the state space model described in (3) and (5), we have

[PREDICT]

$$\hat{x}(n|n-1) = \hat{x}(n-1|n-1)$$

$$\hat{P}(n|n-1) = \hat{P}(n-1|n-1) + Q_n \tag{7}$$

[CORRECT]

$$K_n = \hat{P}(n|n-1)W_n^T[W_n\hat{P}(n|n-1)W_n^T + R_n]^{-1}$$

$$\hat{x}(n|n) = \hat{x}(n|n-1) + K_n(y_n - W_n\hat{x}(n|n-1))$$

$$\hat{P}(n|n) = (I - K_nW_n)\,\hat{P}(n|n-1) \tag{8}$$

K_n represents the gain of the Kalman filter. $\hat{P}(n|n-1)$ and $\hat{P}(n|n)$ represent the a-priori and a-posteriori state estimation error. Initial conditions for $x(0|0)$ and $P(0|0)$ were provided and the Kalman filter estimated the state vector recursively.

The physiological non-negativity constraint demands our estimation scheme to be modified in a way so that desirable results could be achieved. State estimation problems can be modified by introducing constraints [9], similarly, we have used a constrained form of Kalman filer derived by following the estimate projection approach [9], which projects the estimated state vector onto a non-negative sub space to get $\tilde{x}$ and is given by

$$\tilde{x} = argmin_{\tilde{x}}(\tilde{x} - \hat{x})^T(\tilde{x} - \hat{x}) \tag{9}$$

Such that $\tilde{x} \geq 0$ where the symbol '$\geq$' represents the element-wise inequality.

III. Experimental Design

The study received approval from the Institutional Review Board (IRB) of University of Arkansas at Little Rock, USA under protocol number 17-098. Five healthy participants (2 Male & 3 Female) volunteered for the study by signing a consent form. The individuals in our study performed a postural stability task with multiple degrees of freedom. R and MATLAB 2017 programing languages were used to process the data in this study. The experiment involved walking and balancing on a 19 feet long slackline and 0.46 meter above the ground. Every task required at least five trials in order to be labelled as completed.

A. EMG and Data Collection

Noraxon, Direct Transmission System (DTS) was used to acquire EMG data at a sampling rate of 1500 Hertz (Hz) using wireless sensors. Nine muscles shown in Fig. 1 from different compartments of the thigh and lower limb of the dominant leg were identified by palpation.

Table I demonstrates the muscles included in our study.

TABLE I. Lower Extremity Muscles Involved in Study

Tibilais Anterior (TA)	Gracilis (GR)
Vastus Medialis (VAS(M))	Rectus Femoris (REC(F))
Gastrocnemius Medial (GAS(M))	Vastus Laterialis (VAS(L))
Biceps Femoris (BF)	Gastrocnemius Laeral (GAS(L))
Semitendinosus (ST)	

Eight shaped circular silver/silver chloride (Ag/Agcl) self-adhesive snap electrodes with inter electrode distance of 2cm were placed on the surface of the skin after cleaning it with isopropyl alcohol. DTS Foot switch sensor with two force sensitive resistors were placed at the heel and forefoot for the identification of gait cycles.

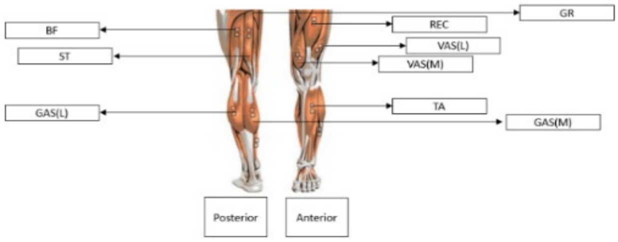

Figure 1. (A) Tilted (B) Anterior (C) Posterior (D) Side view of the muscles where the electrodes were placed.

B. Experiment and Trials

The prototype is available in the Human Performance and Rehabilitation Lab (HPRL) located at UA Little Rock, The task included walking and balancing on a perturbed surface [5]. The participants were asked to sign a consent form before the experiment was conducted. The task was conducted on five healthy subjects (two males and three females) aged between 18-30 years, where every participant was asked to walk on slackline which is 19 feet long and 0.46 meters above ground surface. The neural constraints while walking on such a platform increases variability in the EMG data with each gait cycle. The EMG data recording was initiated from the time when the participant stepped on the slackline taking the first stance with dominant leg. A single trial consisted of one gait cycle and each individual walked on an average of five gait cycles/trials to complete the task.

C. Data Processing and Analysis

Once the data collection phase is over, the very next step is pre-processing of data in order to get it ready to be analyzed. Data processing involves noise filtering, rectification, smoothing, and normalization. The first step is noise filtering where we remove the external noise in the raw EMG data. The second step involves rectification where we take the absolute number of EMG signal so that all values become positive since muscle activations can either be positive or zero. Third step involves smoothing of data and final step is the normalization where we normalize the EMG value to the EMG data during maximum contraction.

The acquired EMG was first filtered with a fourth order band pass filter with a cutoff frequency ranging from 20 Hz to 500 Hz to remove baseline noise and movement artifact. EMG data was then rectified and smoothed using a moving average filter where the Root Mean Square (RMS) envelopes were extracted later with a non-overlapping window of 66 samples. The window size was chosen depending on the weak sense of stationarity and avoiding any phase shift. The raw EMG data was finally normalized knowing the fact that it is not possible to tell if a muscle is contracting hard or not based on the EMG amplitude data. A comparison of raw and processed EMG data is shown in Fig. 2.

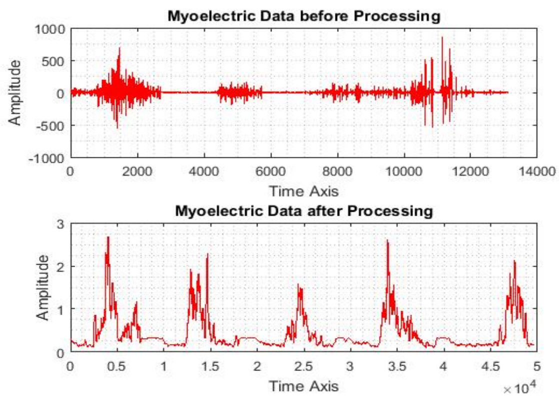

Figure 2. Comparison between raw and processed EMG data. The x-axis represents the no. of samples while the y-axis represents the amplitude of.

IV. Results

A. Matrix Factorization

Synchronous/Time Invariant MS based on the assumption of non-negativity using Non-negative Matrix Factorization Algorithm (NNMF) were extracted from the processed EMG data. The mathematical expression for the model of synchronous MS is shown by (10). The number of MS is not a trivial matter, therefore, prior to extracting synergies, the number of synergies required to be extracted should be identified. The EMG data was reconstructed for 1 to N factors using NNMF. The factor that explains maximum variability in the data ≥ 90% was selected as a threshold to identify the number of synergies or observations for the Kalman filter.

$$EMG_p = \sum_{n=1}^{N} W_n \times H_n \tag{10}$$

where EMG_p is the processed EMG (muscle × time series) matrix, n represents the number of synergies extracted from 1 to N Channels/Muscles. W_n represents synergy vector (Muscle × n) & $H_n(n \times activation\ command)$ represents the activation coefficient/neural commands.

We have utilized the NNMF and eight-fold cross validation scheme in order to extract the number of muscle synergies, whereas, co-efficient of determination R^2 has been utilized for reporting the cross-validation results [3], i.e.

$$R^2 = 1 - \frac{\sum_i (y_i - \widehat{y_i})^2}{\sum_i (y_i - \bar{y})^2} \tag{11}$$

where $\widehat{y_i}$ is an estimate of y_i and $\bar{y} = \frac{1}{n}\sum_i y_i$. It is evident in Fig. 3 that five synergies demonstrate 95% data variability.

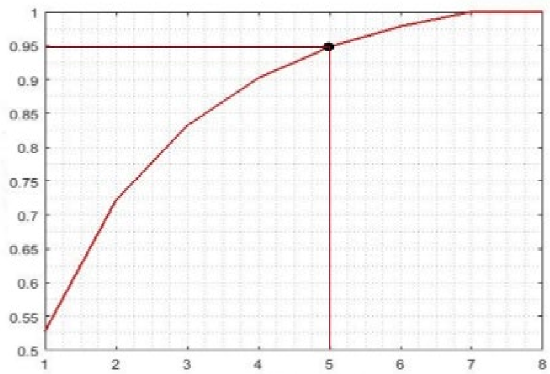

Figure 3. R^2 Cross-validation results (y-axis) Vs No. of muscle synergies (x-axis).

B. Neural Command Estimation

We extracted the MS matrix and the actual neural drive using the NNMF algorithm. The extracted MS matrix 'W' was then deployed as an output matrix into the state space model in (5), while the actual neural drive (ground truth) '$h(n)$' was kept for comparison with the estimated neural drive [3]. Based on (11), we have chosen the number of synergies to be 5, which indicates five state variables, i.e. each synergy represents a state of the system. The surface EMG data was processed, decomposed and fed to the Kalman filter for the state estimation process (the processing of the EMG data can be seen under section III C).

Fig. 4 demonstrates a comparison between the actual neural drive $'h(n)'$ and the estimated neural drive using the Kalman filter for 1000 time points [3], where each time point represents a 66ms window. Our work generated promising results as can be seen in Fig. 4 where the correlation co-efficient (r) showed 98.48% $\pm$ 1% reconstruction accuracy. The Muscle synergies (state vector) was restored with $R^2 = 98.48\%$.

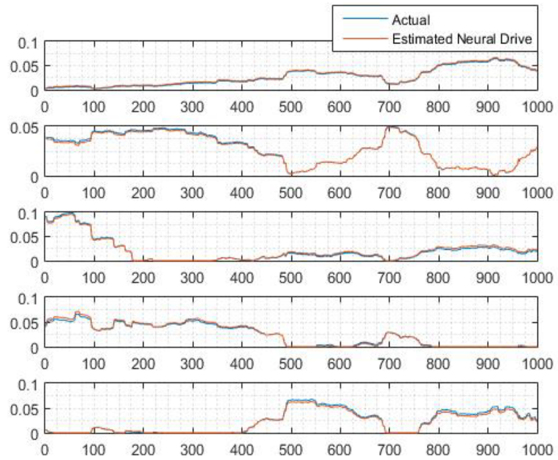

Figure 4. Estimated neural drive using Kalman filter. The actual neural drive in comparison with the estimated neural drive.

C. Reconstruction of Muscle Activations

Once we had the estimated neural drive, we reconstructed the muscle activation patterns using the muscle synergy matrix 'W' and the estimated neural drive '$h(k)$'. In Fig. 5, we demonstrate the reconstructed muscle activation patterns for all the nine muscles using estimated activation co-efficient. Similar to the neural drive estimation process, this process was also carried out for 2000 time points where the correlation co-efficient (r) demonstrated 97.36% $\pm$ 3% accuracy.

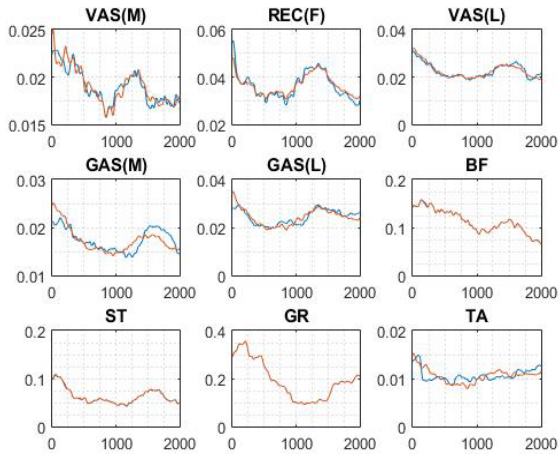

Figure 5. Reconstructed muscle activation using the estimated neural drive and the muscle synergy matrix 'W'. 'Blue' represent the actual while 'red' represents the estimated.

D. Pattern Classification

Before beginning with the classification process, the reconstructed EMG signal was passed through the feature extraction step i.e. extracting additional features by using RMS of 50 samples moving window for each gait trial. The feature extraction step is termed as post processing step in Fig. 6. The scheme involved PCA with SVM as a classifier. We used to foot switch data to differentiate between stance and swing phase. PCA dimensionally reduced the reconstructed EMG signal into three principal component feature space depending on the 90% cumulative variance of each component [5]. The PC scores were further divided in a way such that 70% of data was used for the training and remaining 30% data was used for testing of the SVM classifier. Fig. 6 demonstrates a schematic layout of the proposed control structure.

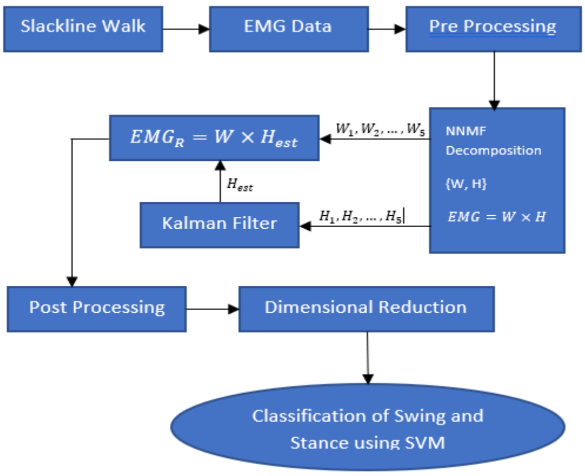

Figure 6. Schematic layout of pattern classification process using the reconstructed EMG signal.

E. *Classification of Gait Cycle*

In order to detect the swing and stance phase, we have successfully implemented the SVM classifier and split swing and stance into their respective classes. The SVM classification plot for the principal component 1 and 2 in Fig. 7 explains maximum variance in the data. The different colors or regions (blue and pink) represent different classes (stance and swing) separated by the classification line or decision boundaries. The points x on the graph are support vectors that effect this classification line. The decision boundaries explained by the SVM can be used to train the control mechanism to distinguish between stance and swing phase of the gait cycle. 70% of the data was evaluated for training of the classifier. The fitted model was then examined on the 30% testing data in order to validate the effectiveness of proposed scheme. The SVM classifier, prior to the post processing step, demonstrated an accuracy of $79.76\% \pm 5.26$. We further enhanced the performance of classifier by extracting additional features by using RMS of 50 samples moving window for each gait trial as a post processing step. The classification accuracy after post processing increased to $96.6\% \pm 3.7$.

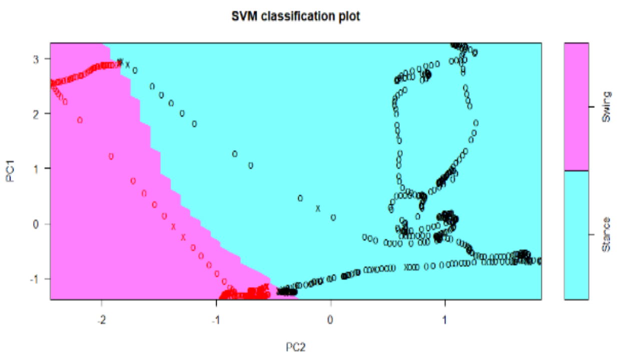

Figure 7. Classification of swing and stance using SVM classifier.

V. Discussion

Myoelectric control possesses immense importance when comes to the invention of powered prostheses. We have investigated the problem by employing time domain modeling of the neural drive that excites task dependent muscles by utilizing hypotheses of muscle synergies in state-space framework. In the past researchers have utilized the concept of muscle synergies for task discrimination in the upper limb [3] [4], however, we have investigated a novel task (i.e. walking on a slackline) where each gait trial represents a different mode and corresponds to higher stride by stride variability [5].

We modelled the movement intent as hidden state of system which was later estimated by using a constrained form of kalman filter. Muscle synergies and the neural drive were extracted from the EMG signal through the NNMF algorithm. The muscle synergy matrix (W) was then incorporated as observation matrix in (5), while the neural drive matrix 'h' in (4) was stored as reference (the actual neural drive). The processed EMG data (see Section II F) was then fed to the kalman filter for the estimation of neural drive. The reconstruction of state vector yielded an amazing accuracy of $R^2 = 98.46\%$ which outperformed the accuracies reported in literature. Once estimated the neural drive, we then further estimated the muscle activations using the estimated neural drive and the muscle synergy matrix (W) with $R^2 = 97.36\%$. We have successfully implemented the SVM classifier and split swing and stance into their respective classes.70% of the data was evaluated for training of the classifier. The fitted model was then examined on the 30% testing data in order to validate the effectiveness of proposed scheme. The SVM classifier, prior to the post processing step, demonstrated an accuracy of $79.76\% \pm 5.26$. The post processed reconstructed EMG signal demonstrated a classification accuracy great than 95%.

Our preliminary results have demonstrated high performance accuracy in the classification of swing and stance phase during a gait trial. Classifiers reported in literature can classify only a specific set of movements with limited DOF, whereas the proposed structure can perform task discrimination by eliminating the limitation of limited DOF. Fig. 5 and Fig. 6 witness the outstanding performance of our work and the next step of our research is to develop neuromusculoskeletal models that could perform state tracking in real time.

VI. Conclusion

In this study, we have successfully modelled our problem of designing a gait phase detection system in the state-space framework where we described system dynamics by a random walk model and output dynamics of the system were extracted from the recoded myoelectric data using the postulation of muscle synergies. A state-constrained Kalman filter was designed and the movement intent along with muscle activations were estimated successfully with a promising reconstruction accuracy of $R^2 = 98.46\%$ and $R^2 =$

97.36% respectively in the lower extremity which outperformed the accuracies reported in literature. SVM classifier was implemented on reconstructed EMG signal and the classification error was reduced by discriminating the swing and stance phases. Our proposed framework is robust and can be very efficiently used in generating control signals for powered prosthetic limb applications. Preliminary results have been presented to illustrate the effectiveness of our research.

Conflict of Interest

There is no conflict of interest from any author for publishing this work. The authors declare that the research was conducted in absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Author Contributions

Safi Ullah: Literature review, mathematical modelling, experimental design and simulations, paper writing, paper revision, and paper submission. Kamran Iqbal: Research supervision and paper revision. Rajat E. Singh: EMG data collection, post processing of data and classification.

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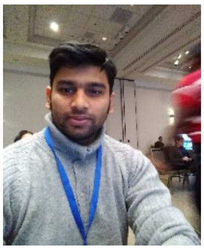
Dr. Iqbal is a member of IEEE, IET (UK), BMES, ASEE, IASTED, and Sigma Xi (past president of Central Arkansas Chapter). He is an editor of Journal of Engineering (Hindawi).



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