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# Motion Intent Recognition for Control of a Lower Extremity Assistive Device (LEAD)

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***Abstract* - This paper presents a motion intent recognition method to control a wearable lower extremity assistive device (LEAD) intended to aid stroke patient during activities of daily living (ADL) or rehabilitation. The main goal is to identify user's intended motion based on sensor readings from the limb attached to the assistive device, so as to execute the right control actions to aid the user in his intended action effectively. A database of a healthy subject performing various motion tasks is collected. Subsequently, the features of the signals are extracted and Principal Component Analysis (PCA) is performed to reduce the number of dimensions. Using the transformed signal, a multi-class Support Vector Machine (SVM) with Radial Basis function (RBF) kernel is trained to classify the different motion patterns. A Nelder-Mead optimization algorithm is used select the appropriate parameters for each SVM. Test results shows that the SVM can correctly classify each motion pattern with an average accuracy rate of 95.8±4.1%. An offline classification result of a healthy subject performing a series of motion task while wearing the LEAD shows that the proposed method can effectively recognize different motion intent of the user.**

***Index Terms -Assistive device, lower extremities rehabilitation, intention detection, pattern recognition.***

## I. INTRODUCTION

Robots for gait rehabilitation are seen as a solution to conventional manually assisted gait rehabilitation, which is a highly repetitive and labor-intensive task. While the training duration of conventional therapy is limited to personnel shortage and therapist fatigue, robotic gait rehabilitation is able to overcome these deficiencies. They are normally designed for automated gait training on a treadmill to take over the physical aspect of the therapist's task. Gait trainers like the AutoAmbulator (Motorika, USA), Lokomat (Hocoma, Switzerland) [1], LOPES (University of Twente, Netherlands) [2] and ALEX (University of Delaware, USA) [3], are commonly controlled to follow or generate a guiding force field about a prescribed trajectory to move the patient's leg. However, they are not widely available, due to their large size and non-portability. It would be advantages to have a portable rehabilitation system as it can be taken home to assist with gait training at home. Moreover, the increase in accessibility of the rehabilitation device can allow therapist to administer high intensity, task oriented rehabilitation which have been shown to enhance walking distance and walking speed of patient after stroke, particularly for those with moderate walking deficits [4, 5].

Wearable assistive devices, also known as exoskeletons, have shown promising results in providing portable rehabilitation. A few lower extremity exoskeletons have been successfully developed over the past decade, namely the BLEEX (U.C. Berkeley, USA) [6] and HAL-3 (Tsukuba University, Japan) [7]. The BLEEX uses a force amplification method to allow the device to shadows the movement of the user [8]. The HAL-3 provides assistive force based on the estimated intended force from surface electromyography (sEMG) signals [7].

These exoskeleton laboratories have spun off companies to commercialize their products. The designers of the BLEEX setup Berkeley Bionics to market two enhanced version of their exoskeletons, namely the HULC and the EKSO. HULC is meant for augmenting the strength of an able-bodied user, while the EKSO is designed to help paraplegic patients walk. Meanwhile, the developers of HAL-3 setup Cyberdyne in order to market and distribute an improved version of their exoskeleton, named as HAL-5 which is design to help elderly and disabled people walk. Other commercially available exoskeletons are mainly designed to provide mobility to paraplegic patients. They include the Rewalk (Argo Medical, Israel), and the Vanderbilt exoskeleton (Vanderbilt University, USA) that will be made commercially available soon.

Among all the control methods developed for exoskeletons, not all of them are made available to public and not all existing method maybe suitable for users suffering from stroke. To our knowledge, no literature could be found for commercially available products. Force amplification method by the BLEEX cannot be used for rehabilitation since the device will appear to be passive from the point of view of the user. As stroke affects the normal function of the brain, the EMG signal which is further downstream in the neurological pathway gets affected as well. Therefore, sEMG to torque conversion method by HAL-3 will be a more challenging task. In upper limb rehabilitation for stroke patients, sEMG signals are commonly only used as a trigger [9]. Other devices uses manual controller to maneuver the exoskeleton, limiting the user's freedom during operation.

In the recent years, some research efforts towards intent based detection using the user's kinetic and kinematic information have been made. HAL utilizes a phase sequence approach which assumes sequential motion of the user and infers the transition to the next motion state based on joint angles and ground reaction force (GRF) information [10]. They have shown it effectiveness in sit-to-stand and stand-to-

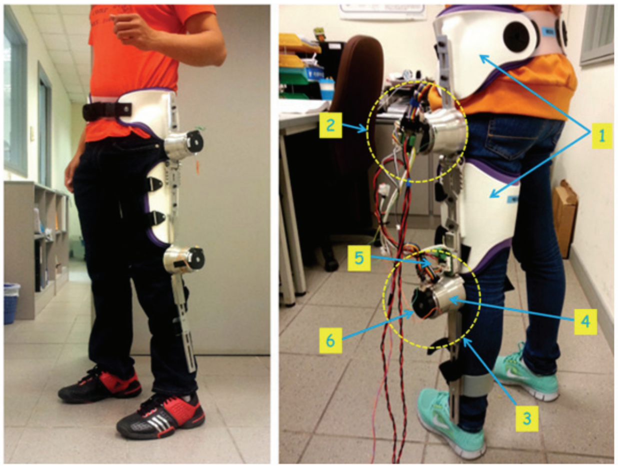


Figure 1 The Lower Extremity Assistive Device (LEAD) prototype on different users. 1: Orthotic cuffs; 2: Hip joint actuator module; 3: Knee joint actuator module; Each module consist of, 4: Housing for DC motor and harmonic gear; 5: Digital servo drive; 6: Incremental encoder.

sit transfers [10], and in supporting walking [11]. However, transition between walking motion to other motion states is not address. Moreover, the user motion may not be sequential, for example a premature termination of a sit-to-stand motion.

In this paper, we propose a multi-class motion intent recognition method to control a wearable lower extremity assistive device (LEAD). The multi-class motion intent classifier acts as a supervisory controller to determine which motion state the user is in. In this work, we aim to detect and assist the patient in sit-to-stand, stand-to-sit, and level-walking tasks. The assistive joint torques within the each motion state follows that described in [12].

## II. DESIGN OF HARDWARE

The LEAD is a powered assistive device design to provide active assistance to the user's hip and knee joints in the sagittal plane. Its adjustable frame is derived from the anthropometrical data provided in [13], to ensure that it can fit a wider range of users. Orthotic cuffs are used as the attachment interface between the device frame and the user. The actuator module at each joint, could deliver up to 35 Nm of torque and it is powered by a DC motor coupled with a harmonic drive of 50:1 reduction ratio. Optical incremental encoder at 1000 counts/rev is also equipped at the pre-reduction stage of each actuator module to measure the hip angle ($\theta_h$) and knee angle ($\theta_k$). Three resistive force sensors are attached on the insoles of the wearer's shoe at the first and fourth metatarsal, and the calcaneus positions to detect the GRF of the limb attached to the device. Mechanical stops at each joints limits the range of motion of each joint to ensure that the device moves within the normal range of motion of a normal human, for safety reasons. A summary of the LEAD is shown is table I.

A reconfigurable embedded control and acquisition system which consist of a real-time processor, reconfigurable field-programmable gate array (FPGA), and analog and digital I/O is used for the control the device. A digital servo drive at each actuator module performs close-loop current control to control the torque output at each actuated joint. CAN communication at 1Mbits/s is implemented between the controllers to allow for scalability in future iterations of the device.

Table I Specifications of the LEAD

| **Actuator Module** | | |
|---|---|---|
| **Max. Output Speed** | 877 °/s | |
| **Max. Continuous Torque** | 35 N.m | |
| **Power** | 347 W | |
| ***Range of motion (Sagittal):*** | **Flexion** | **Extension** |
| **Hip** | 130 ° | -15 ° |
| **Knee** | 130 ° | 0 ° |

## III. METHODOLOGY

The control architecture of the LEAD is shown in Fig 2. At the joint level, the torque controller utilizes a close-loop proportional-integral (PI) current control to track a desired torque input provided by a sub-state controller. The sub-state controller determines the magnitude and direction of the desired torque for each joint base on the current motion state and the sensor information. More details on the sub-state controller can be found in [12]. On the supervisory level, a motion intent classifier determines which motion state the user is in so as to switch to the appropriate sub-state controller for effective motion assistance. The following sections focus on the motion intent classifier that uses a multi-class SVM to distinguish between the following states, namely, sit, stand, walking, sit-to-stand and stand-to-sit.

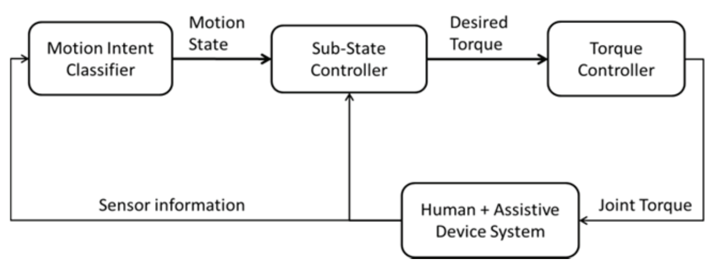


Figure 2 Control Architecture of the LEAD

### A. *Experiment Protocol*

As SVM is a form of supervise learning, the data captured needs to be labeled with its corresponding motion state label. Therefore, a database of a subject preforming a series of known motion trials needs to be collected. The subject in this study is a 28 years old male with no known medical condition. His height and weight is 171 cm and 65 kg respectively.

The subject is required to perform the motions in list of motion trials as shown in Table II while wearing the LEAD. The trial motions are split into static and dynamic processes. Sitting and standing is a static process, however to improve the robustness of the classifier to disturbance, we include dynamic sitting and standing motion trials. During those trials,

Table II List of Motion Trials

| Motion State | | Number of Trials | State Label |
|---|---|---|---|
| **Static** | **Sitting** | 4 | SIT |
| | **Standing** | 4 | STAND |
| **Dynamic** | **Sitting (with front sway)** | 4 | SIT |
| | **Standing (with front sway)** | 4 | STAND |
| | **Sit-to-Stand** | 4 | SIT-TO-STAND |
| | **Stand-to-Sit** | 4 | STAND-TO-SIT |
| | **Walking on treadmill at 2 km/h** | 4 | WALKING |
| | **Walking on treadmill at 3 km/h** | 4 | WALKING |

the subject is required to slightly sway front and back at a pace of 1 Hz while sitting or standing. A digital metronome is used to provide audio feedback to the subject for maintenance of pace. The classification of other motion states as dynamic is self-explanatory. For each motion state, the subject is asked to repeat the same motion for four times. The first three trials will be used to train the SVM while the last trial will be used for test the SVM.

During the data capturing process, the LEAD is controlled under friction compensation mode to minimize its influence on the subject's motion. Five signals are recorded during the trials. They include the flexion angles of the hip and knee joints, and the GRF sensor readings from the first and fourth metatarsal, and the calcaneus positions which we shall henceforth refer to as front, mid and back GRF respectively. All data is recorded at the rate of 500 Hz. The length of each trial last 30 seconds, expect for sit-to-stand and stand-to-sit task where the data recording stops once the task is completed.

### *B. Feature Extraction across Entire Motion*

From the five sensor data, the derivative of each sensor reading is obtained by taking the difference between the current and previous readings. To reduce the effect of noise during differentiation, the readings are passed through a digital $4^{th}$ order Butterworth low pass filter with a cutoff frequency of 20 Hz before taking its derivative. Taking the value of all available data result in a total of 10 features, namely, hip position and velocity, knee position and velocity, back GRF, mid GRF, front GRF and the rate of change of all the GRFs. Each feature is normalized from 0 to 1 to eliminate the effect of scaling between different features.

For static processes, the feature vector is expected to maintain relatively constant. Hence, the feature vectors are randomly selected from each static trial. A total of 120 feature vectors are select for each static sitting and standing motion state.

For dynamic processes, feature vector selected should cover the entire space of the motion state for better classification results. Therefore, for dynamic sitting, standing, sit-to-stand and stand-to-sit motion states, feature vectors are selected every 10 ms interval. For walking, the feature vector at every 3 percentage gait cycle is recorded. A heel strike detector based on the threshold of back GRF, in order to classify each step in terms of gait cycle. The result of the heel strike detector is shown in Fig 3. The percentage gait cycle is

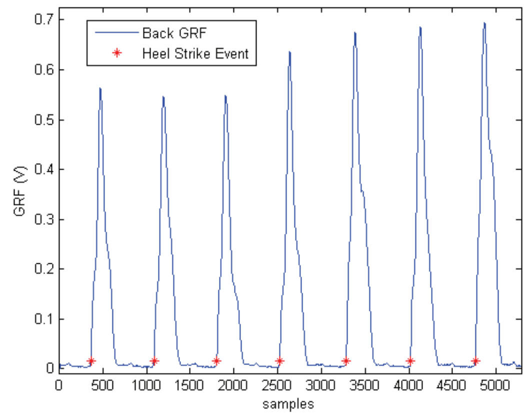


Figure 3 Graph depicting heel strike detection base on Back GRF (Motion state: Walking on treadmill at 2km/h)

computed based on the time period across two consecutive heel strike events.

### *C. Dimension Reduction*

To reduce the computation speed for real-time implementation of the motion intent classifier, the feature vector dimension must be kept small. In order to reduce the overall dimension of the feature vector, principle component analysis (PCA) [14] is applied to the entire set of feature data collected. The PCA transformations represent a high-dimensional data in such a way that the first principal component has the largest possible variance, and each succeeding component has the highest variance under the constraint that it is orthogonal to the preceding components.

### *D. Multi-class RBF-SVM*

SVMs is a pattern classification technique proposed by Vapnik [15]. Besides minimizing the training error, SVM aims to maximize the margin between the separating hyper-plane and the data, thus giving a more robust performance. Furthermore, its ability to condense information in the entire training data into a small number of support vectors makes it attractive for our application. SVM is a linear classifier within its parameter space, but it could be extended to a nonlinear classifier with the application of kernels that maps the inputs of the SVM into a feature space [16]. The hyper-plane is then found by the SVM in the feature space.

Given a training set of N data points $\{y_i, x_i\}_{i=1}^{N}$, where $x_i$ is the $i^{th}$ input pattern and $y_i$ is the $i^{th}$ output pattern, the support vector machine approach aims to construct the decision function,

$$f(x) = sign\left(\sum_{i=1}^{N} \alpha_i y_i\, \varphi(x, x_i) + b\right) \tag{1}$$

where $\alpha_i$ are positive real constants and b is the bias term which is a real constant. The kernel function, $\varphi(\cdot,\cdot)$, used is the RBF kernel which is given as

$$\varphi(x, x_i) = \exp\left(-\frac{\|x - x_i\|^2}{2\sigma^2}\right) \tag{2}$$

where $\sigma$ is a positive real number that specifics the scaling factor in the RBF kernel.

For a hyper-plane with soft margin, $\alpha_i$ that maximizes the hyper-plane margin is found by maximizing

$$\sum_{i=1}^{N} \alpha_i - \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N} y_i y_j \varphi(x_i, x_j)\, \alpha_i \alpha_j \qquad (3)$$

Subjected to

$$\sum_{i=1}^{N} \alpha_i y_i = 0, 0 \ \leq \alpha_i \leq c$$

where $c$ is a positive real number that correspond to the constrain for the soft margin.

For classification problems consisting of k-classes, k number of classifiers can be constructed, one for each class [17] . A one-against-all approach is used in this paper which constructs k binary SVM classifiers, each of which separates one class from the rest. The resulting classification follows the following priority sequence, SIT, STAND, WALKING, SIT-TO-STAND and STAND-TO-SIT.

### *E. Optimizing parameters of SVM*

For each SVM classifier there are 2 parameters that needs to be tuned, namely the scaling factor $\sigma$ and the soft margin constrain $c$. Five motion states yield a total of 10 SVM parameters to be tuned for classification. Thus, a Nelder-Mead optimization routine [18] is employed to identify the parameters that gives the best classification results. Nelder-Mead optimization is a non-linear technique that can find a locally optimum solution for systems with several variables. As it only finds the local optimum, the algorithm is repeated a few times with random initial points and the parameters which yield the lowest error in classification result is recorded.

### *F. State Switch Filter*

To avoid rapid switching between motion states, an additional filter is implemented to smoothen the switching of motion states. In the state switch filter, a window containing classification results of a period of previous time step is constructed. The LEAD will maintain in its previous state of motion unless if more than 90% of the classification result in the constructed window agrees to switch to a specific new motion state. The diagram in Fig. 4 depicts the logic of the state switch filter. Selecting an appropriate period for windowing requires a balance between undesirable rapid state switching if the window period is too small, and the delayed response time if the window period is stretched. In this paper, 30 previous samples are taken, which translate to a period of 60 ms.

## IV. Results & Discussions

### *A. Result of PCA Dimension Reduction*

From Table III, the PCA result shows that the first 7 principle components account for more than 95% of the variance. This means that we can reduce the dimension from 10 to 7 key components after the PCA transformation. A reduction of only 3 dimensions may not seem significant, however it is to be noted that the number of combination of features varies exponentially with the dimensions.

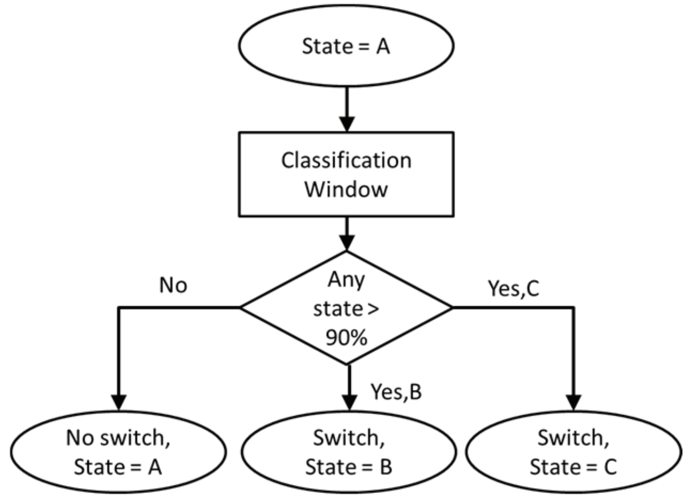


Figure 4 Logic flow chart of state switch filter with example states A,B and C

Table III PCA results on Cumulative Variance

| Principle Components | Cumulative variance |
|---|---|
| 1 | 26.6% |
| 2 | 45.1% |
| 3 | 60.4% |
| 4 | 73.7% |
| 5 | 82.7% |
| 6 | 89.9% |
| 7 | 95.7% |
| 8 | 97.8% |
| 9 | 99.3% |
| 10 | 100.0% |

Table IV Optimized Parameters for SVM

| Classified State | Sit | Stand | Walking | Sit-to-Stand | Stand-to-Sit |
|---|---|---|---|---|---|
| Scaling factor, σ | 5.95 | 1.36 | 30.17 | 3.49 | 13.02 |
| Soft margin constrain, c | 21.27 | 15.66 | 12.93 | 2.98 | 33.27 |

Table V Confusion Matrix in Motion State Classification

| | | **Actual Motion** | | | | |
|---|---|---|---|---|---|---|
| | | Sit | Stand | Walking | Sit-to-Stand | Stand-to-Sit |
| **Estimated Motion** | Sit | 100.0% | 0.0% | 0.0% | 11.6% | 14.3% |
| | Stand | 0.0% | 98.7% | 2.5% | 2.4% | 26.1% |
| | Walking | 0.0% | 6.0% | 97.2% | 14.0% | 7.3% |
| | Sit-to-Stand | 0.0% | 0.0% | 8.7% | 93.1% | 0.0% |
| | Stand-to-Sit | 23.3% | 1.0% | 4.3% | 7.6% | 90.2% |

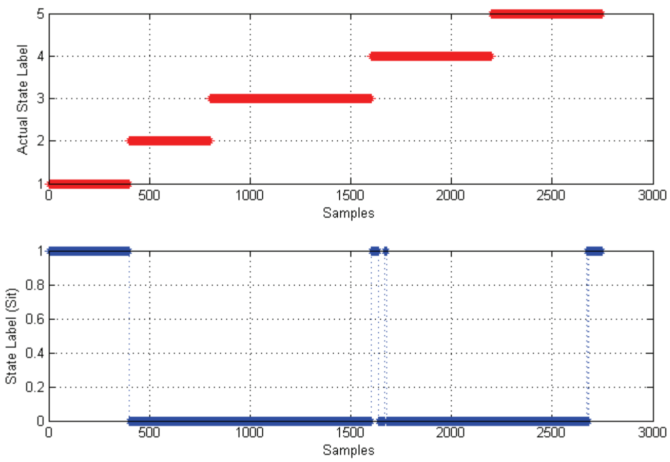


Figure 5 Actual Motion State Label (top) as compared as SVM output for Sit Motion State (below). The motion states are indexed as follows, Sit = 1, Stand = 2, Walking = 3, Sit-to-stand = 4, and Stand-to-sit = 5.

### B. *SVM Classification Results*

The Nelder-Mead optimization routine of 50 iterations with randomize initial points is repeated a few times. Out of the 4 trials for each motion state, the first three trials are used to train the SVM whose parameters are selected follows the Nelder-Mead method. The features captured follows that which is described in the previous section. The last trail is used to evaluate the effectiveness of the SVM. During the evaluation, features are sampled at a higher rate at every 1 ms for dynamic tasks, and 1% gait cycle for walking tasks to ensure good generalization of the classifier. The parameters which yield the lowest error rate are presented in Table IV, and its corresponding confusion matrix is displayed in Table V.

The diagonal of the confusion matrix shows that the SVM classifiers are able to correctly classify their respective motion pattern with an average accuracy rate of 95.8±4.1%. The off-diagonal values indicate the misclassification result. Relatively large misclassification is observed in estimates of Sit motion and Stand motion. A closer examination of the test results (Fig. 5) shows that misclassification occurs of Sit motion happens during early stages of sit-to-stand and late stages of stand-to-sit, where the subject is truly in sit position since dynamic tasks are sampled progressively at every 1 ms for testing of SVM. Test results on stand motion shows similar outcome in misclassification.

### C. *Result of Motion Intent Classifier*

To evaluate the feasibility of the motion intent classifier in identifying the user's motion state, the subject is asked to perform a series of motion task while attached to the LEAD. The data is captured and processed with the motion intent classifier constructed with optimized SVM parameters.

Fig. 6 depicts the result of motion intent classifier. The actual state labels are labelled based on the task prescribed to the subject. The on-set of the actual state label is taken as when the data starts changing for a static to dynamic motion state change, and when the data stabilizes for a dynamic to static motion state change. The offline classification test shows that the motion intent classifier can effectively recognize different motion intent of the user during the series of task. Some misclassifications are observed during the starting and ending of walking motion. A possible explanation could be that since low speed walking data are not supplied during training of the SVM, hence the motion intent classifier might have some difficulty in distinguishing it as walking. Nonetheless, apart from that, the motion intent classifier can

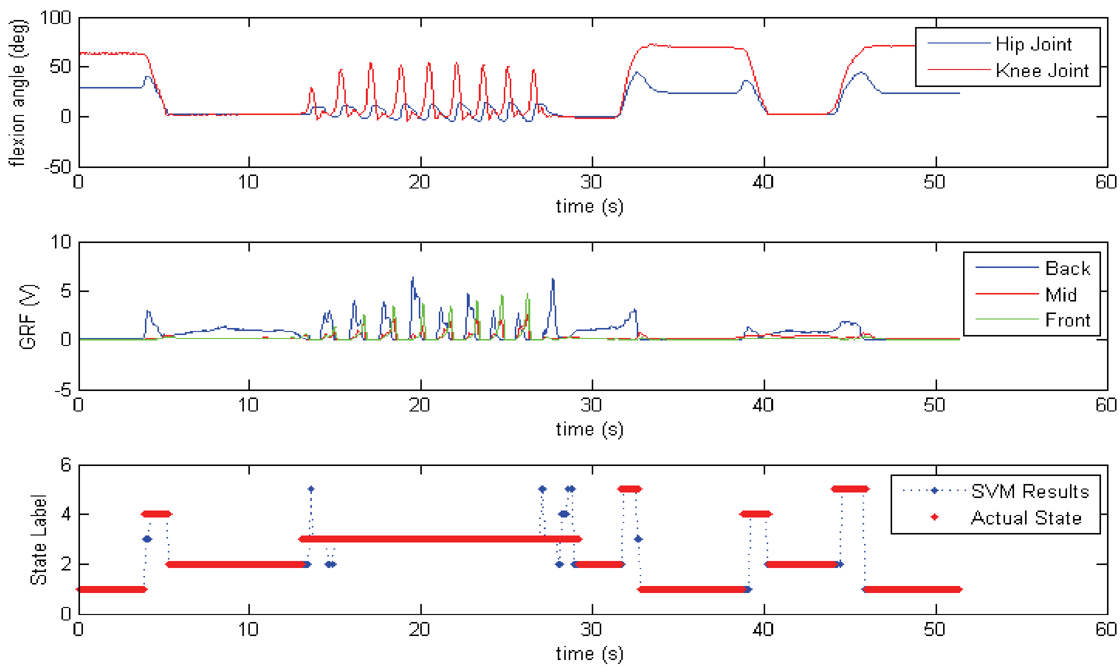


Figure 6 Result of the motion intent classifier for a subject conducting a series of task. The motion states are indexed as follows, Sit = 1, Stand = 2, Walking = 3, Sit-to-stand = 4, and Stand-to-sit = 5

correctly classify the motion states of the user.

## V. Conclusion

This paper presents a motion intent recognition method using multi-class SVM with RBF kernel to control a wearable lower extremity assistive device (LEAD) to aid stroke patient during activities of daily living (ADL) or rehabilitation. Features of the signal extracted from a healthy subject performing the various motion tasks are extracted and PCA is applied to reduce its dimension. The transformed signal is used to train the SVM classifier. Test results shows that the motion intent classifier can effectively distinguish each motion pattern during a series of motion task. An actual implementation of this motion intent classifier to the LEAD will be done in future works.

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