Real Time Level Ground Walking vs Stair-Climbing Locomotion Mode Detection

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***Abstract*— This paper presents a real-time classification method of ground-level walking and stair climbing, which is a crucial information of natural human locomotion in robotic prosthesis control. Two Inertial Measurement Units (IMU) were mounted on an earlier developed measurement exoskeleton system (one IMU in the shank and the other IMU on the thigh) to monitor the locomotion states. A pair of force-sensing resistors were also incorporated into the shoe insole for plantar pressure measurement. The sensors were interfaced with an STM32L476RG microcontroller powered by a rechargeable battery. The data collection was performed on two healthy subjects. Three features (Thigh IMU x-axis accelerometer minimum value, Shank IMU z-axis gyroscope maximum value, and x-axis gyroscope variance) were computed from the sensors signal. Classification of ground-level walking vs. stair climbing events was performed using Linear Discriminant Analysis (LDA). The accuracy, sensitivity, and specificity were obtained on the training set as 96.50%, 96.32%, and 96.66%, respectively. After implementing the classifier in the embedded system, the sensor system was tested in real-time for 26 minutes with an accuracy of 87.21%, the sensitivity of 90.48%, and the specificity of 86.75%. The results indicate that the system can detect the locomotion states with reasonable accuracy, which could be further implemented in determining the control strategy of a powered intelligent prosthesis in the real-time.**

Keywords*— *real-time activity recognition; wearable sensors; prosthesis

I. INTRODUCTION

There are about 2 million people living with limb loss in the United States who are suffering from mobility issues [1]. Powered lower limb prosthesis is a promising technology that can provide greater ability and mobility to transfemoral amputees [2]. One major concern of research on robotic lower limb prostheses is the locomotion mode recognition, which is very important for the effectiveness of the high-level controller to allow amputees to perform automatic, seamless transitions between locomotion modes. However, current methods to detect modes, such as visual or movement commands, are unintuitive and impose a cognitive burden. An ideal system would provide a safe, automatic, and seamless detection locomotion modes without any cognitive burden imposed on the user. To accomplish this, an activity recognition software must infer the user's locomotion mode in real-time [2][3][4][5]. The most frequently used sensors for activity recognition include surface electromyogram (sEMG) sensors and mechanical sensors. Motion activity recognition based on the sEMG was first reported in [6]. Huang et al. [7] first used sEMG to classify seven motion states using an artificial neural network (ANN). Later, they used a combination of sEMG and load cell information for the classification [8]. However, sEMG-based systems for prosthesis usually have poor performance due to the presence of electrode shifts and changes in electrode position [9]. Liu et al. [10] use a mechanical sensor-based system consisting of an accelerometer, gyroscope, and two pressure sensors. Young et al. [11] also built an activity and intend recognition system using mechanical sensors only (six-axis inertial measurement units (IMUs) and axial load). They collected steady state and transitional data from six transfemoral amputees, while five locomotion modes were performed.

The goal of this study was to develop a wearable locomotion mode recognition system capable of recognizing level-ground walking and stairs ascending in real-time. Two IMUs were placed on the healthy leg of the lower limb using an earlier developed wearable exoskeleton system which allows us to monitor the locomotion of the healthy leg. The wearable exoskeleton system ensured reliable locomotion data collection, which is a comfortable, portable user interface for a variety of limb sizes without restricting the natural range of motion of the user. The scope of this research encompasses the sensory system development, sensor interfacing, the development of a microcontroller-based data acquisition framework to capture sensor signals. Two volunteers participated in the data collection, and a classifier was developed using the data obtained. After that, the classifier was embedded in a microcontroller to detect ground-level walking and stair climbing. Finally, the system was tested on a healthy volunteer to validate the proposed method.

II. METHODOLOGIES

A. Wearable Exoskeleton

A wearable exoskeleton system [12] is used to mount the sensors for accurate lower-limb motion data collection, which consists of three segments, including a thigh segment, a shank segment, and a foot segment. These segments are connected by two joints. The shape of the thigh and shank segment can be adjusted to align with the user's calf curvature using orthotic bending irons. The height of the exoskeleton is adjustable with a range of approximately 7.6 cm which enables the device to fit subjects at different heights in a configuration that ensures the joint sensor is fixed on-axis with the rotation of the measured joint. Two IMUs of the data acquisition system were placed on

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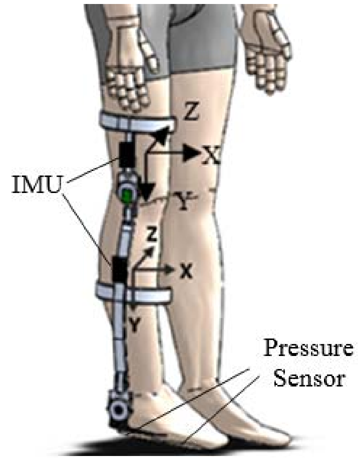

Fig. 1. An illustration of sensors placement with skeleton system

the shank segment and on the thigh segment, respectively (shown in fig. 1) to effectively perceive the movement information. The FSRs (Force Sensing Resistor) are embedded under the shoe sole were installed at the main force points to measure heel and ball pressures under the foot.

B. Sensors

The sensor system used in data collection consists of two IMUs (MPU-9250, InvenSense Inc, San Jose, CA), two FSRs (FSR 406, Interlink Electronics, Camarillo, USA) and data acquisition electronics with a 3.7 V Li-polymer battery of 300 mAh capacity. This system employed STM32L476RG, a Cortex-M4 Ultra-low-power ARM processor (ST Microelectronics, Geneva, Switzerland); a 16 GB micro-SD card to store data sampled at 1 kHz. The sensor suite was capable of monitoring accelerations in all three directions, rotations around each axis and change in resistance upon applying pressure or mechanical stress. The IMUs were interfaced with the MCU through two SPI interfaces. The polymer thick film FSR is capable of measuring pressure utilizing its property of decreasing resistance with the increase in the applied force on its active surface. A resistive divider was formed by each FSR and a 500Ω resistor and applied to op-amp based voltage followers. The Op-amp output of FSRs was interfaced with the MCU's two ADC channels (with 12 bits of resolution).

C. Data Collection and Labeling

To collect data for this study, volunteers were recruited. Two volunteers having age, height, and the weight of 31 and 27 years, 1.72 and 1.77 meters, 172 and 160 pounds, respectively, with no physical and cognitive abnormalities participated in the data collection. The study was approved by the Institutional Review Board (IRB) at the University of Alabama. First, each subject was asked to wear the sensor system. Before starting the data collection, the subjects were asked to walk normally for 5-10 minutes to get comfortable with the device. After that, they performed following locomotives activities in the following order: a) Level ground walking in self-selected moderate and fast cadence and b) Stair ascending (starting at ground floor to the third floor). All participants repeat the same activity sequence for 20 times. The participants were free to take rest whenever necessary. A total of 85 minutes of data (approximately 51 minutes of ground walking and 34 minutes of stair climbing) was recorded by the system from the subjects. The data contains values of accelerometer and gyroscope for x, y, and z-axes from both IMUs as well as heel and ball pressure from FSRs. Fig. 2 shows an instance of thigh IMU sensor responses while a participant was walking, then stopped for a moment and started stair ascending at a self-selected speed. The dataset was manually reviewed and then labeled by a custom MATLAB application for model training and validation.

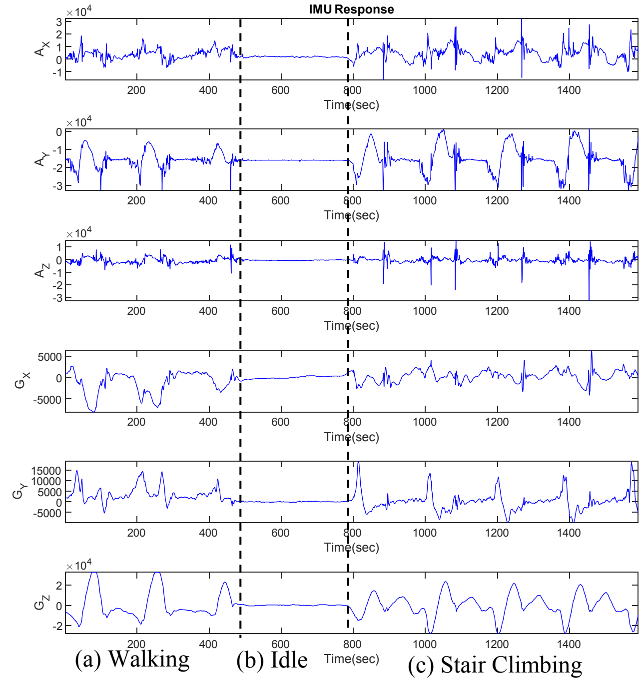

Fig. 2. The response of IMU sensor while a participant was (a) walking over ground (b) Idle and (C) Stair Climbing.

D. Feature Extraction and Selection

Initially, 112 (8 features from each signal) features were defined and extracted from all the sensors signals. Simple and computationally less intensive time domain features were explored for the easy real-time microcontroller implementation. The features were: 1) standard deviation, 2) variance, 3) RMS, 4) maximum, 5) minimum, 6) slope sign change, 7) number of mean crossing and 8) wavelength. To find out the most significant features, a forward feature selection technique was implemented. This was an iterative method, which started with having no feature in the model. In each iteration, a new feature was added which best improved the model till an addition of a new variable did not improve the performance of the model. A total of ten features were initially determined from the forward feature selection method, which are: 1) Fea1 (AX2-Minimum value), 2) Fea2 (GZ1- Maximum value), 3) Fea3 (GX1- Variance), 4) Fea4 (GY2- Variance), 5) Fea5 (AZ2- Maximum value), 6) Fea6 (GZ2- Mean crossing), 7) Fea7 (AZ1- Variance), 8) Fea8 (AY1- Slope sign change),

9) Fea9 (AX1- Mean crossing), and 10) Fea10 (Toe pressure - Standard deviation). Since too many features may lead to overfitting, to find out the best performing set of features, the accuracy of the model for different combinations of the features were investigated.

E. Classifier

The Linear Discriminant Analysis (LDA) was chosen in this study. The LDA classifier is simple, easy to implement, and computationally inexpensive. The classification rule for LDA is very intuitive. This method requires a training phase, meaning the computation of the discriminant functions and their parameters. The new real-time data can be classified simply by solving the appropriate discriminant function for each class and applying the classification rule. The training dataset contained feature vectors and labels from ground truth annotation. The feature vectors were computed in the microcontroller environment, and then using those features, a classifier was trained in Matlab. A five-fold cross-validation technique was utilized to train the classifier. The parameters were determined from the training data set and then applied to the microcontroller environment for the real-time application.

F. Real-time Implementation and Testing

For real-time implementation, the trained LDA classifier was implemented in the embedded software. The embedded software was designed to execute the following operations in sequence: a) feature computation, and b) find the response using the trained LDA classifier. The features were computed every after 2.92 seconds of data collections. Once the features were computed, the classifier predicted response in this case ground walking vs. stair climbing and stored the response in the SD card. After the implementation of the classifier in the embedded system, the wearable sensor system was tested on one volunteer. The volunteer performed similar walking and stair climbing sequence as mentioned in the data collection section. In this testing, completely different staircase and ground walking path were used.

TABLE I. PERFORMANCE OF CLASSIFIER USING DIFFERENT FEATURE COMBINATIONS

Combination of features	**Accuracy %**
Fea1	94.1077
Fea1, Fea2	95.3498
Fea1, Fea2, Fea3	96.5001
Fea1, Fea2, Fea3, Fea4	97.0665
Fea1, Fea2, Fea3, Fea4, Fea5	97.8454
Fea1, Fea2, Fea3, Fea4, Fea5, Fea6	98.0989
Fea1, Fea2, Fea3, Fea4, Fea5, Fea6, Fea7	98.4030
Fea1, Fea2, Fea3, Fea4, Fea5, Fea6, Fea7, Fea8	98.5298
Fea1, Fea2, Fea3, Fea4, Fea5, Fea6, Fea7, Fea8, Fea9	98.5805
Fea1, Fea2, Fea3, Fea4, Fea5, Fea6, Fea7, Fea8, Fea9, Fea10	98.6565

III. RESULTS

The accuracy of the model for different combinations of the features were investigated, and the results are presented in Table I. The results show that the addition of new features did not increase the classification accuracy more than 1% after three features, which was determined to be the optimal feature number. Finally, the combination of these top three ranked features (AX2- Minimum value, GZ1- Maximum value and GX1- Variance) was utilized to train the classifier and implement it in real-time. The comparison of performance between training and real-time testing is shown in Table II. The accuracy, sensitivity, and specificity of the testing are comparable with the performance of the model on training dataset. The accuracy of the proposed model was 87.21%, while the sensitivity and the specificity were calculated as 90.48% and 86.75% respectively in real-time testing.

TABLE II. PERFORMANCE OF CLASSIFIER ON TESTING DATA

	Training	Real-time testing
Accuracy	96.50%	87.21%
Sensitivity	96.32%	90.48%
Specificity	96.66%	86.75%

The classification results of the proposed LDA classifier are demonstrated by a confusion matrix, which is presented in Fig. 3.

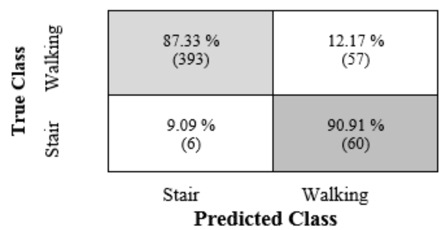

Fig. 3. Confusion matrix of the testing

IV. DISCUSSION AND CONCLUSION

In this paper, we proposed a solution for real-time level ground walking vs. stair-climbing locomotion Mode Detection by successfully implementing in a wearable embedded system. The proposed method is simple, easy to implement, yet effective to level ground walking vs. stair-climbing. Three features were extracted from the sensors signal, and the LDA classifier was used. The proposed model achieves an accuracy of 87.21%, sensitivity of 90.48%, and specificity of 86.75% in real-time testing for around 26 minutes, which shows, the initial proof of the concept and demonstrates great promise. Since the model was trained and tested with a small amount of dataset, to further improve the performance, the model should be trained and tested with more data. In addition, the experiment was performed on two volunteers only, but with a higher number of participants, the model will be more person independent. In this study, two locomotion modes were considered only. However, in the future work other locomotion modes (i.e. stair descending, ramp up, and ramp down, sit to stand) can also be investigated.

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