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Decoding Movement Intent of Patient with Multiple Sclerosis for the Powered Lower Extremity Exoskeleton

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Abstract—**This study aims to recognize movement intent of patients with multiple sclerosis (MS) by decoding neuromuscular control signals fused with mechanical measurements as a method of powered lower extremity exoskeleton control. Surface electromyographic (EMG) signals recorded from the lower extremity muscles, ground reaction forces measured from beneath both feet, and kinematics from both thigh segments of a single MS patient were used to identify three activities (level-ground walking, sitting, and standing). Our study showed that during activity performance clear modulation of muscle activity in the lower extremities was observed for the MS patient, whose Kurtzke Expanded Disability Status Scale (EDSS) was 6. The designed intent recognition algorithm can accurately classify the subject's intended movements with 98.73% accuracy in static states and correctly predict the activity transitions about 100 to 130 ms before the actual transitions were made. These promising results indicate the potential of designed intent recognition interface for volitional control of powered lower extremity exoskeletons.**

I. INTRODUCTION

MULTIPLE sclerosis (MS) is a nervous system disease that affects the brain and spinal cord. MS is caused by damage to the myelin sheath, which slows or stops electrical signal conduction between nerve cells [1]. Population surveys indicate that approximately 75% of patients with multiple sclerosis experience mobility problems, mainly caused by muscle weakness, spasticity, ataxia, imbalance, sensory loss, and pain [2]. There are approximately 400,000 people with MS, and every week, about 200 people are diagnosed in the United States [3]. World-wide, MS affects about 2.5 million people. Therefore, there is a pressing need to enhance the mobility of individuals with MS and to improve the quality of their life.

In order to restore some degrees of lower extremity mobility, passive lower extremity exoskeletons have been developed and widely used by MS patients. The simplest example of a passive device is a long-leg brace coupling with a pair of ankle foot orthoses (AFOs) which provide support at the ankle joint and lock the knee joints against flexion. The hip joint is stabilized by the tension in the ligaments and musculature on the anterior aspect of the pelvis [4]. These passive exoskeletons require high level strength from the user's upper extremity, and usually can only generate slow walking speeds. With the rapid advancement of electronics and electromechanics, powered lower extremity exoskeletons have emerged both in commercial market (e.g. HAL-5 exoskeleton developed by CYBERDYNE, Inc., ReWalk powered orthosis designed by Argo Medical Technologies, eLEGS developed by Berkeley Bionics, and REX powered exoskeleton from Rex Bionics) and research fields [4-8]. Unlike the passive devices, the powered lower extremity exoskeletons can actively generate power at the joints. Therefore, the powered lower extremity exoskeletons are able to allow the MS patients to perform activities which are difficult or even impossible when wearing passive devices, enabling them to walk more naturally and/or efficiently [9].

To command the exoskeleton to the desired activity state (e.g. sitting, standing, and level-ground walking), an interface between the user and the device is necessary so that the user can "tell" the exoskeleton his or her intended movement and then the device can adjust control to coordinate with user intent. Many approaches based on body motions [10], a manual switch [11], and external sensors on the upper extremity [12] have been reported for the lower extremity exoskeleton control. For instance, *Quintero et al.* [4] used the distance between the user's center of pressure (COP) and the location of the forward ankle joint as the primary command input to switch the activity states. A group at the University of California, Berkeley designed a human machine interface to sense the user's natural arm gestures and crutch motions to allow the safe mode transitions [12].

To enable more intuitive control of powered lower extremity exoskeleton, one potential approach is to recognize the user's intent by decoding the neuromuscular signals. *Sankai et al* [13]. developed a full-body hybrid assistive leg (HAL)-5 exoskeleton, which recognized the user's intent by sensing surface electromyography (EMG) signals from thigh muscles, and kinematics from both lower limbs and torso from healthy subjects. In our group, a neuromuscular-mechanical fusion based on a user intent recognition interface was developed to recognize transfemoral amputees' intent to control powered lower limb prostheses [14-16]. Inspired by this approach, several questions were raised: can this previously designed interface be used to recognize the MS patient's movement intent for the powered lower extremity exoskeleton control? Is there sufficient neuromuscular information that can be extracted from MS patients, since the nervous system may be damaged

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by MS diseases? To address these questions, this preliminary study (1) investigated activity of bilateral lower extremity muscles in MS patients during different activity performance, and (2) implemented our previously designed interface to identify the MS patient's movement intent. The results of this study could aid the future design of volitional control of powered lower extremity exoskeletons and eventually enhance the mobility and quality of life of MS patients.

II. METHODS

A. Participant and Experimental Measurements

This study was conducted with Institutional Review Board (IRB) approval at the University of Rhode Island and written, informed consent of the subject. One female patient with multiple sclerosis (MS) was recruited. The Kurtzke Expanded Disability Status Scale (EDSS) of the patient subject was 6.0.

Sixteen channels of surface EMG signals from muscles on lower extremities were collected. The monitored muscles included the *gluteus maximus* (GMA), *gluteus medius* (GME), *rectus femoris* (RF), *biceps femoris long head* (BFL), *adductor magnus* (ADM), *tibialis anterior* (TA), *peroneus longus* (PERO), and *gastrocnemius lateral head* (GASL) on both sides. The locations of the electrode placement were determined by anatomical locations [17] and muscle palpation. A ground electrode was placed on the bony area near the anterior iliac spine. Active bipolar surface EMG electrodes were used to record the EMG signals; the electrodes contained a preamplifier that band-pass filtered the EMG signals between 10 and 1000 Hz with a pass-band gain of 20. A 16-channel EMG system (MA 300, Motion Lab System, U.S.) was used to collect the EMG signals. The EMG system filtered signals between 20 and 450 Hz with a pass-band gain of 1000 and, then, sampled at 1000 Hz.

A foot pressure measuring system ((Pedar-X, Novel Electronics Inc., Germany) was placed under both feet to measure the vertical ground reaction force and detect gait events. In addition, two inertial measurement units (IMUs) (Xsens Technologies B.V., Enschede, The Netherlands) were used to measure the kinematics of the subject's thigh segment. Both IMUs were tightly affixed to the lateral side of the thighs and aligned with the coordinate system in the standing position (see Fig. 1). Three-degree-of-freedom linear accelerations and the angular velocity of each thigh segment were directly measured by the IMUs. Both foot pressure and kinematic measurements were sampled at 100 Hz and were synchronized with the EMG signals.

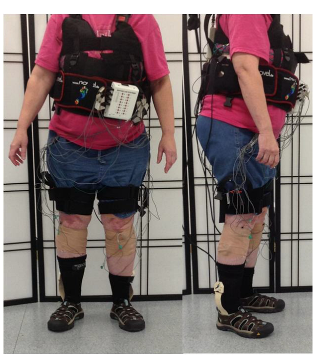

Fig. 1. Experimental setup on the recruited MS patient subject

B. Experimental Protocol

Three activities and four mode transitions were investigated in this study. The activities included level-ground walking (W), standing (ST), and sitting (S); the resultant transitions included standing up (S→ST), gait initiation (ST→W), gait termination (W→ST), and sitting down (ST→S).

For level-ground walking, the subject was instructed to walk along a straight walkway at her comfortable walking speed with a cane. For sitting and standing activities, the subject was asked to transition between sitting and standing. When in standing positions, the subject was allowed to make small steps and shift her weight; during sitting, the subject was allowed to move her lower extremities. In each experimental trial, the subject was asked to transition between different activities in a fixed sequence: sitting, standing, level-ground walking, standing, and sitting. Each trial lasted about 50 seconds and a total of 15 testing trials were conducted. During the experiment, the subject was protected from falling by a railing harness system. Rest periods were allowed between trials to avoid fatigue.

C. Recognition of MS Patient's Movement Intent

A neuromuscular-mechanical fusion based user intent recognition interface had been designed to interpret transfemoral amputees' intended movements in our previous studies [14, 15]. The system architecture of designed interface is demonstrated in Fig. 2. The multichannel measurements are preprocessed and segmented into sliding, overlapped analysis windows. Features representing the signal patterns are extracted and fused into one feature vector. The feature vector is then fed to a phase-dependent pattern classifier, composed of multiple subclassifiers corresponding to individually defined gait phases for intent recognition. The classification decisions are further post-processed to eliminate erroneous predictions.

1) Signal Preprocessing and Feature Extraction: Raw EMG signals were band-pass filtered by a 20–450 Hz sixth-order Butterworth digital band-pass filter. The ground reaction force was filtered by a low-pass filter with a 45 Hz cut-off frequency. The linear accelerations and angular velocities of the thigh segment were low-pass filtered with a

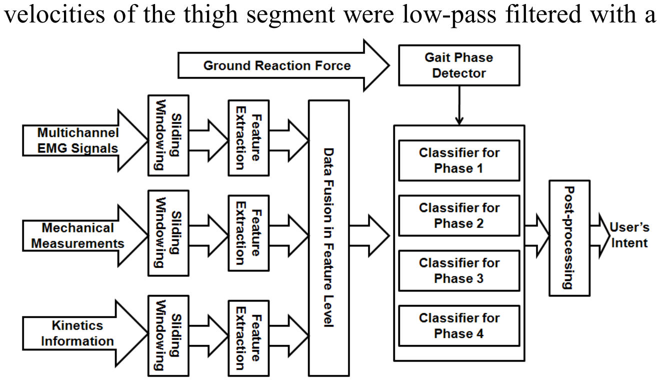

Fig. 2. Architecture of intent recognition interface based on neuromuscular-mechanical fusion.

20 Hz cut-off frequency. The multichannel data were then segmented into several overlapped analysis windows with a 160 ms window length and 20 ms window increment. Each window was assigned a gait phase index and an activity label. One gait cycle was separated into four gait phases by the two gait events of both feet: heel-strike and toe-off, which were detected by the foot pressure measuring system. The labeling of activities was done by manual indication of mode transitions from an experimenter. Four time-domain (TD) features [18] (mean absolute value, number of slope sign changes, waveform length, and number of zero crossings) were extracted from each EMG signal in each analysis window. The mean, maximum, and minimum values of ground reaction force and thigh kinematics were extracted as features from each measurement.

2) Pattern Recognition Algorithm : A multiclass nonlinear support vector machine (SVM) with "one-against-one" (OAO) scheme [19] and C-Support Vectors Classification (C-SVC) [20] were used to classify different intended activities. The applied kernel function was the radial basis function (RBF). More details about SVM algorithm can be found in [19, 20]. Leave-one-out cross-validation (LOOCV) [21] was used to evaluate intent recognition performance. During this procedure, data from one experimental trial were used as the testing data; data in all other trials were used as the training dataset. This procedure was repeated 15 times until each trial was used as the testing set. In addition, a 5-point majority vote scheme is applied to eliminate erroneous decision outputs from the classifier.

D. *Evaluation*

The performance of the intent recognition system was evaluated using three parameters: (1) recognition accuracy in static states, (2) the number of missed activity transitions, and (3) transition prediction time. The static state is defined as the state that subject continuously performed the same activity (e.g. level-ground walking, sitting, or standing). The transition prediction time was defined as the elapsed time from the moment when the interface correctly predicted the intended activity to the critical timing for the targeted transitions. For the transitions between sitting and standing, the critical timing was defined as the moment that the subject started to sit down or stand up, which was detected by the large change of angular velocity of thigh segment; for transition from standing to walking, the critical timing was defined as the toe-off of the leading leg; for transition from walking to standing, the beginning of initial double limb stance phase was regarded as critical timing. A transition was missed if no correct transition decision was made before the defined critical timing. More details about the definition of evaluation parameters can be found in a previous study [14].

III. Results

A. *Muscle Activity of Lower Extremities on MS Patient*

An example of preprocessed EMG signals measured from lower extremity muscles during one stride cycle is shown in

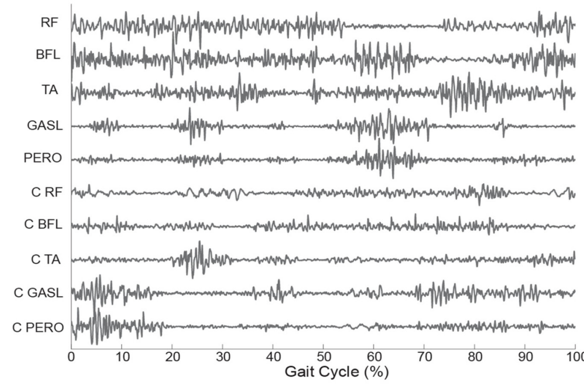

Fig. 3. Example of EMG signals measured from several lower extremity muscles during one gait cycle. "C" represented contralateral side.

Fig. 3. Clear EMG modulation in lower extremity muscles was observed during walking.. This implied that neuromuscular control information was still represented in leg EMG signals, which can be potentially used for recognizing a user's intent.

B. *Performance of Intent Recognition on MS Patient*

The intent recognition accuracy in static states was calculated and averaged across all the 15 testing trials. The overall accuracy for recognizing the level-ground walking, standing, and sitting was 98.73%. All the activity transitions were predicted before the subject actually transited from one activity to another. The prediction times of four types of transitions was shown in Table I.

TABLE I. Prediction Time of Mode Transitions before Critical Timing

Transition	W→ ST	ST→ W	ST→ S	S → ST
Prediction Time (ms)	112.7 ± 23.4	131.5± 27.2	103.6± 32.9	126.3 ± 40.2

The intent recognition results in one representative testing trial were shown in Fig. 4. During about 45 seconds testing trial, a total of five decisions (indicated by red circle in Fig. 4) were misclassified. These errors happened between

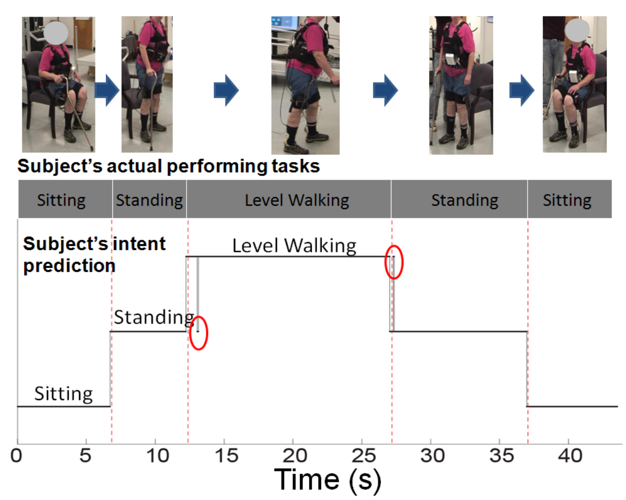

Fig. 4. Intent recognition results in one representative testing trial. The red dash line indicates the critical timing for each type of activity transition.

level-ground walking and standing. All transitions were correctly recognized before the defined critical timing (indicated by the red dash line in Fig. 4).

IV. Discussion

To enable volitional control of powered lower extremity exoskeletons, a reliable and safe interface between the user and the robotic devices is needed to recognize the user's movement intent. Inspired by the promise of the neuromuscular-mechanical fusion-based user intent recognition interface previously developed in previous study for powered lower limb prosthesis control, we are interested in extending this technology to lower extremity exoskeletons in order to improve the mobility of MS patients. To address this question, we first need to know whether or not sufficient neuromuscular information can be extracted from MS patients, since the nervous system may be damaged caused by MS diseases. Based on the observation of recorded EMG signals measured from the lower extremities of MS patient (see Fig. 3), it was found that the modulation of leg muscle activity still existed on the recruited subject even though her EDSS is 6.0 (i.e. patient needs assistive device for walking). This may imply the potential use of EMG signals as an interface for accurate intent recognition in MS patients.

A previously designed user intent recognition interface based on neuromuscular-mechanical fusion was used to recognize the MS patient's intended movements. The offline analysis results showed that the algorithm can recognize the subject's intent (including sitting, standing, and level-ground walking) to high accuracy in static states. Additionally, the interface can predict activity transition about 100-130 ms before the subject actually switched the activity mode without any missed transitions. These preliminary results imply the potential of the designed interface for volitional control of lower extremity exoskeletons.

Our future efforts will focus on (1) quantification of the performance of designed intent recognition system on more individuals with different stages of MS disease, (2) investigation of more activities (e.g. stair ascent/ descent, and ramp ascent/ descent), and (3) further development of volitional control of powered lower extremity exoskeleton for improved mobility in MS patients.

V. Conclusion

In this study, our previously designed user intent recognition interface was applied to recognize the movement intent of a patient with multiple sclerosis (MS). The modulation of lower extremity muscle activity was clearly observed in this recruited MS patient (EDSS=6). Offline analysis showed that the designed interface can recognize 3 activity modes (e.g. sitting, standing, and level-ground walking) with a high accuracy and accurately predict the mode transitions with sufficient predication time. These preliminary results demonstrate the potential of volitional control of powered lower extremity exoskeleton by MS patients to assist their mobility.

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