REAL-TIME RECOGNITION OF USER INTENT FOR NEURAL CONTROL OF ARTIFICIAL LEGS

Fan Zhang, He (Helen) Huang
Department of Electrical, Computer, and Biomedical Engineering, University of Rhode Island, Kingston, RI, USA, 02881

INTRODUCTION

Lower limb amputation significantly affects the quality of the leg amputee's daily life. Recent advancements in embedded electronics and electromechanical actuators have propelled the recent development of powered artificial legs [1-3]. Usually, finite-state machine (FSM) is utilized in the design of powered prosthetic legs to control the knee joint impedance or knee position in each gait phase [2, 4]. The impedance adjustment of the powered knee depends on the locomotion modes [2-3], since the dynamics and kinematics of the knee joint varies across different locomotion modes. Thus, in order to allow the prosthetic leg appropriately select the prosthetic control mode and smoothly transit the activities from one to another in time, the user must "tell" the prosthetic leg the locomotion intent before execution of the transitions. Currently, the artificial legs are manually controlled by using exaggerated hip and trunk motion [4], which is cumbersome and sometimes unreliable. Accurately recognizing the leg amputee's locomotion intent is required in order to realize the smooth and seamless control of prosthetic legs.

An intent recognition approach for the real-time control of a powered lower limb prosthesis, which utilized the mechanical sensor information, has been reported in a recent study [5]. One patient with transfemoral (TF) amputation performing level-ground walking, sitting, and standing was tested. The study reported 100% accuracy of recognizing the mode transitions and only 3 misclassifications during a 570s testing period. However, over 500ms system delay was reported, which may be inadequate for users to perform safe and smooth locomotion transitions. In addition, gait initiations and terminations were the only locomotion transitions tested. Only using mechanical information may not be able to promptly recognize the transitions between different locomotion modes because this type of information may not necessarily correspond with the user's intent. Alternatively, utilizing the neural control signal may enable the true intuitive control of the artificial limbs.

As one of the major neural control sources for the powered prosthesis, surface electromyographic (EMG) signals have been successfully applied in the control of upper limb prosthesis [6-9]. However, the EMG pattern recognition methods used in upper limb control cannot be directly applied on the lower limb prostheses, due to the non-stationary characteristic of EMG signals measured from the lower limb muscles during dynamic locomotion movement. In order to address this challenge, a phase-dependent EMG pattern recognition strategy was developed in our previous study [10]. This approach was tested on eight able-bodied subjects and two subjects with TF amputation. About 90% accuracy was obtained when recognizing seven locomotion modes. In addition, the user intent recognition accuracy was further improved by a neuromuscular-mechanical fusion algorithm [11], which fused EMG signals measured from the residual thigh muscles and the ground reaction forces/moments collected from the prosthetic pylon. The algorithm was tested in real-time to recognize three locomotion modes (level walking, stair ascent, and stair descent) on one able-bodied subject with 99.73% accuracy.

Although the experiment on the able-bodied subject has demonstrated promising results, whether or not the designed intent recognition system can be used for neural control of artificial legs is unclear. This is because there might not be enough EMG recording sites available for neuromuscular information extraction due to the muscle loss in patients with leg amputations, which may cause the accuracy of user intent recognition to be inadequate for robust prosthetics control. Therefore, in order to evaluate the potential of the intent recognition system for prosthetic legs, the designed system was evaluated on one TF amputee subject via real-time testing. In addition, besides the previous tested tasks, another two tasks: sitting and standing, were also included in this study. It is hoped that the results of this study could aid the further development of neural-controlled artificial legs.

METHODS

Structure of User Intent Recognition System

The whole structure of the intent recognition system is demonstrated in Fig.1. The multichannel EMG signals and mechanical measurements are simultaneously streamed into the system and then segmented into continuous, overlapped analysis windows. EMG features from each channel and the mechanical features from individual degree of freedom were extracted in each analysis window and further concatenated into one feature vector. The fused feature vector is then sent into a phase-dependent classifier. The phase-dependent classifier consists of multiple sub-classifiers, each one of which is established based on the data in one defined gait phase. The gait phase detector detects the current gait phase and switches on the corresponding sub-classifier. A post-processing algorithm is applied to the decision stream to produce smoothed decision continuously.

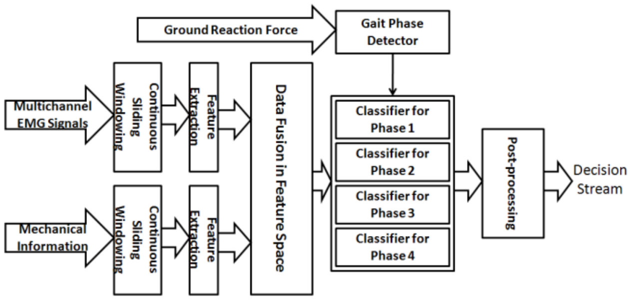

Fig. 1. Structure of intent recognition system based on neuromuscular-mechanical fusion.

Sensor Data Pre-processing and Feature Extraction

An eighth-order band-pass Butterworth filter with cut-off frequency between 25 and 450 Hz is applied on the raw EMG signals. The mechanical forces/moments recorded from the load cell mounted on the prosthetic pylon are low-pass filtered with a 50 HZ cut-off frequency. Then, the signal streams are segmented by sliding analysis windows as shown in Fig. 2. In this study, the length of the analysis window is 150 ms and the window increment is 50 ms.

Four time-domain (TD) features were extracted from the EMG signals: (1) the mean absolute value, (2) number of zero crossings, (3) number of slope sign changes, and (4) waveform length as described in [8]. For mechanical signals, the mean, minimum, and maximum values in each analysis window were extracted as the features.

Phase-dependent Classification Strategy

Different from the discrete gait phases with constant 200ms duration proposed in our previous study [10], continuous gait phases were used in this study. Four clinical gait phases are defined (shown in Fig. 2). The real-time gait phase detection is implemented by monitoring the vertical ground reaction force (GRF) measured from the load cell mounted on the prosthetic leg. The detection criteria are shown in Fig. 3. The applied contact threshold is 2% of the subject's weight. If one analysis window is located between two defined gait phases (e.g. the window W2 Fig. 2), the activated classifier is associated with the gait phase, in which it incorporates the data more than half of the window length (e.g. the classifier associated with the phase 2 should be used for the data in W2).

A Support Vector Machine (SVM) classifier with a nonlinear kernel is used in this study. A multiclass SVM with "one-against-one" (OAO) scheme [12-13] and C-Support Vectors Classification (C-SVC) [14] are used to identify different locomotion modes. The applied kernel function is the radial basis function (RBF). A 5-point majority vote scheme is applied to eliminate the erroneous decisions from the classifier. More detailed information about SVM algorithm can be found in [13-14].

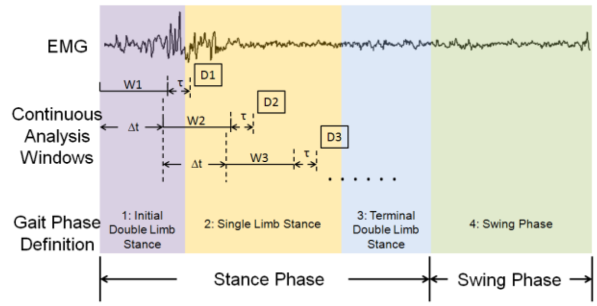

Fig. 2. Continuous windowing scheme for real time pattern recognition and definition of gait phases. For each analysis window (W1, W2, and W3), a classification decision (D1, D2 and D3) is made Δt seconds later. τ is the processing time required of the classifier, where τ is no larger than Δt.

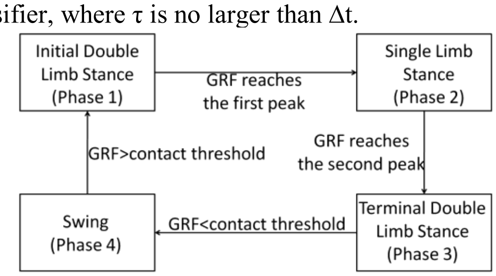

Fig. 3. The real-time gait phase detection criteria.

Subject and Experimental Setup

This study was conducted with Institutional Review Board (IRB) approval and informed consent of the subject. One female patient with unilateral transfemoral (TF) amputation was recruited. Eight channels surface EMG signals from the residual thigh muscles were collected by an EMG system (Motion Lab System, US) and used for intent recognition. The EMG electrodes were embedded in customized gel liners (Ohio Willow Wood, US) for both comfort and reliable electrode-skin contact and placed at locations where strong EMG signals could be recorded. A ground electrode was placed on the bony area near the anterior iliac spine. The EMG system filtered signals between 20 Hz and 450 Hz with a pass-band gain of 1000 and then sampled at 1000 Hz. Mechanical ground reaction forces and moments were measured by a six–degree of freedom (DOF) load cell (Bertec Corporation, OH, US) mounted on the prosthetic pylon. The forces/moments were also sampled at 1000 Hz. All data recordings were synchronized and streamed into a PC through data acquisition system. The real-time algorithm was implemented in MATLAB and the real-time locomotion predictions were displayed on a flat Plasma TV. In addition, the states of sitting and standing were indicated by a pressure measuring mat which was attached to the gluteal region of the subject.

Experimental Protocol

The subject wore a hydraulic passive knee during the experiment period. Experimental sockets were duplicated from the subject's ischial containment socket with suction suspension. The subject received instructions and practiced the tasks several times prior to experiment.

Three locomotion modes including level-ground walking (W), stair ascent (SA), and stair descent (SD) and two tasks such as sitting (S) and standing (ST) were investigated in this study. The resultant mode transitions included W→SA, SA→W, W→SD, SD→W, S→ST, ST→W, W→ST, and ST→S. The experiment consisted of two sessions: training session and testing session. The training data collection for building the classifiers was performed in the training session. At least three training trials for each task were required in order to collect enough training data. During the real-time testing session, the subject was asked to continuously transit among the five different tasks. Each trial lasted around one minute. Totally 15 real-time testing trials were conducted. For the subject's safety, she was allowed to use hand railing. Rest periods were allowed between trials to avoid fatigue.

Real-time Performance Evaluation

The real time performance of intent recognition system is evaluated by the following parameters.

1) *Classification Accuracy (CA) in the Static States:* The static state is defined as the state of the subject continuously walking on the same type of terrain (level ground and stair) or performing the same task (sitting and standing). The classification accuracy in the static state is quantified by

$$CA = \frac{Number\ of\ correctly\ classified\ observations}{Total\ number\ of\ observations} \times 100\% \tag{1}$$

2) *The Number of Missed Mode Transitions:* For the transition between different locomotion modes, the transition period starts from the initial prosthetic heel contact (phase 1 in Fig. 2) before switching the negotiated terrain and terminates at the end of single stance phase (phase 2 in Fig. 2) after the terrain switching; for the transition between different tasks such as sitting and standing, the transition period begins from the subject starting to switch the task and ends when the subject completely sit/stand. A transition is missed if no correct transition decision is made within the defined transition period.

3) *Prediction Time of the Transitions:* The prediction time of a transition is defined as the elapsed time from the moment when the decisions of the classifier changes locomotion mode to the critical timing for the investigated task transitions. For the transitions between walking on level-ground and staircase (W→SA, SA→W, W→SD, and SD→W), the critical timing is defined as the beginning of the swing phase of the prosthetic side in the transitional period; for the transition ST→W, the critical timing is chosen as the beginning of the swing phase (prosthetic leg toe-off); for the transition W→ST, if the last standing leg was the prosthetic leg, the beginning of initial double limb stance phase was used as the critical timing; if the last standing leg was the sound leg, we defined the critical timing at the beginning of terminal double stance phase. For the transition S→ST and ST→S, the critical timing is the moment that the pressure under the gluteal region of the subject starts to drop to zero reading or exceed the zero reading.

RESULTS

The intent recognition system was tested on one patient with transfemoral amputation. For the studied five tasks, the overall classification accuracy in static states across 15 real-time testing trials is 98.25%. For all the 15 trials, none of the mode transitions was missed during the defined transition period. The prediction time for 8 types of transitions is shown in Table 1. This result showed that the user intent for the locomotion transitions can be accurately predicted about 76-295 ms before the critical timing for switching the control of prosthesis.

Table 1. Predication time of mode transitions before critical timing

Transition	W → SA	SA → W	W → SD	SD → W	W → ST	ST → W	ST → S	S → ST
Estima-tion Time (ms)	126.7 ± 28.6	136.5 ± 25.7	138.8 ± 30.5	108.3± 27.4	92.8 ± 35.6	127.6± 25.3	295.6± 40.8	76.2 ± 22.8

The real-time intent recognition result in one representative trial is shown in Fig. 4. During the 56 second real-time testing, totally four decision errors in static states were observed when the subject performed the stair descent task. These four errors were misclassified as level-ground walking. All the transitions are correctly recognized before the defined critical timing within the transition period.

DISCUSSION

Similar to the experimental results observed in our previous able-bodied subject testing, the designed intent recognition system produced a 98.25% accuracy in static states and 108-138ms transition prediction time (for W→SA, SA→W, W→SD, and SD→W), although the tested amputee only has a 68% of residual limb length. This implies that the muscles in the amputee's residual limb still present different activation pattern among studied locomotion modes, which can be potentially used for neural control of artificial legs.

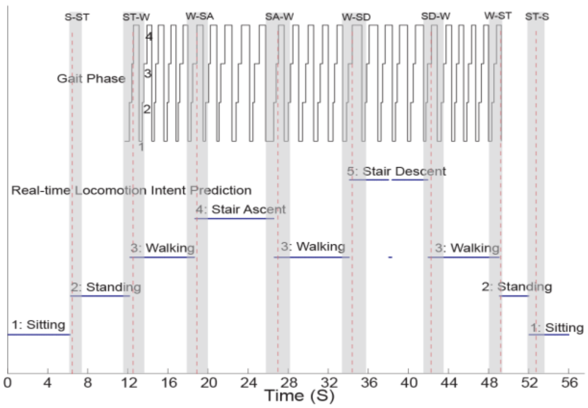

Fig.4. Real-time recognition results in one representative testing trial. The white area denotes the static states period; the gray area represents the transitional period. The red dash line indicates the critical timing for each transition.

Different from the discrete gait phases used in the previous study [10], continuous gait phases were used in this study, which makes the real-time implementation of the designed system feasible and practical. It is noteworthy that the gait phase is determined only based on the vertical ground reaction force measured from a load cell mounted on the prosthetic pylon. This design enables the system to be self-contained, which makes the integration of intent recognition system into prosthetic legs possible.

Additional efforts are needed, including (1) investigation of importance of the information carried by each sensor, (2) testing more subjects with various levels of TF amputations, and (3) study of the effects of errors of the intent recognition on the prosthetic leg control.

CONCLUSION

In this study, an intent recognition system was implemented in real-time on one patient with a transfemoral amputation. The system achieved 98.25% accuracy for indentifying the locomotion modes in static states and showed fast response time (76-295ms) for predicting the task transitions. These preliminary results demonstrated potentials of designed intent recognition system to aid the future design of neural-controlled artificial legs and therefore improve the quality of life of leg amputees.

ACKNOWLEDGEMENTS

The authors thank Zhi Dou, Andrew Burke, and Ming Liu at the University of Rhode Island, and Michael Nunnery and Becky Blaine at the Nunnery Orthotic and Prosthetic Technology, LLC, for their suggestion and assistance in this study.

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