33rd Annual International Conference of the IEEE EMBS
Boston, Massachusetts USA, August 30 - September 3, 2011

Improving the Performance of a Neural-Machine Interface for Artificial Legs Using Prior Knowledge of Walking Environment

He Huang*, *Member, IEEE*, Zhi Dou, Fan Zhang, *Student Member, IEEE,* Michael J. Nunnery

***Abstract*—A previously developed neural-machine interface (NMI) based on neuromuscular-mechanical fusion has showed promise for recognizing user locomotion modes; however, errors of NMI during mode transitions were observed, which may challenge its real application. This study aimed to investigate whether or not the prior knowledge of walking environment could further improve the NMI performance. Linear Discriminant Analysis (LDA)-based classifiers were designed to identify user intent based on electromyographic (EMG) signals from residual muscles of leg amputees and ground reaction force (GRF) measured from the prosthetic leg. The prior knowledge of the terrain in front of the user adjusted the prior possibility in the discriminant function. Therefore, the boundaries of LDA were adaptive to the prior knowledge of the walking environment. This algorithm was evaluated on a dataset collected from one patient with a transfemoral (TF) amputation. The preliminary results showed that the NMI with adaptive prior possibilities outperformed the NMI without using the prior knowledge; it produced 98.7% accuracy for identifying tested locomotion modes, accurately predicted all the task transitions with 261-390 ms prediction time, and generated stable decision during task transitions. These results indicate the potential of using prior knowledge about walking environment to further improve the NMI for prosthetic legs.**

I. Introduction

LOWER limb amputation is a major cause of disability [1]. Recent advancements in powered artificial legs have made it possible to allow leg amputees to perform versatile tasks efficiently [2-3]. To switch the performing task, the users must "tell" their intent to the prosthesis so that the correct control mode can be selected. This is achieved by using manual approaches (i.e. extra body motions[4] or a remote key fob[5]), intent recognition based on mechanical sensing[6], or "echo control" strategy[5, 7](i.e., prosthetic leg simply repeats the motion of the sound leg). These approaches are, however, inadequate for leg amputees to perform safe, smooth task transitions due to system time delay or unreliability for recognizing user intent.

In order achieve intuitive control of artificial legs, an interface between human neuromuscular system and powered prosthetic device is essential. Our research group has developed a novel neural-machine interface (NMI) for prosthetic legs based on surface electromyographic (EMG) signals, one of the major neural control sources [8]. A phase-dependent EMG pattern recognition strategy was employed for locomotion mode identification [8]. When the Linear Discriminant Analysis (LDA)-based classifier was used, around 90% average accuracy for identifying seven locomotion modes was achieved. The performance of NMI was further improved by fusing EMG signals from the residual limb with the mechanical information measured from prostheses [9]. We called this method neuromuscular-mechanical fusion. The preliminary evaluation showed that the NMI based on neuromuscular-mechanical fusion produced 95.6% average accuracy for identifying individual tasks in the static states (i.e. the states when subjects continuously performed the same task) and accurately predicted 96% of tested task transitions with an average of 260ms prediction time. Although these results are promising, the real application of designed NMI for artificial legs was challenged by three types of observed errors: (1) unstable decisions during task transitions, (2) delayed decisions in task transitions, and (3) false task transitions in static state.

One of the potential solutions to further reduce the errors in NMI is to introduce the information about walking environment to the intelligent intent recognition system. This concept is inspired by the locomotion mechanism in biological systems. Animals and human rely on the vision system to obtain the information of walking terrain in front them and then modulate the locomotion patterns to adapt to the walking environment [10-12]. If our designed NMI can "know" the walking terrain in front of the user, this prior knowledge might further improve the performance of NMI for recognizing user's locomotion mode and predicting mode transitions. The information of walking terrain can be obtained by various sensors and techniques. For example, computer vision techniques could provide information of the terrain in front of the user based on real-time video data [13]. However, before selecting sensors for terrain recognition, two fundamental questions facing us are (1) whether or not the NMI performance can be improved by introducing the prior information about type of terrains in front of the user, and (2) how to apply this prior knowledge to the pattern recognition algorithm in NMI.

To address these fundamental questions, in this study the prior knowledge of walking environment was used to adaptively adjust the discriminant functions of pattern

This work is supported by NSF/CPS #0931820, NIH #RHD064968A, and DoD/TATRC #W81XWH-09-2-0020.

H. Huang, Z. Dou, and F. Zhang are with the Neuromuscular Rehabilitation Engineering Laboratory at the Department of Electrical, Computer, and Biomedical Engineering, University of Rhode Island, Kingston, RI 02881, USA

* Corresponding author: H. Huang, Ph.D., phone: 401-874-2385; fax: 401-782-6422; e-mail: huang@ele.uri.edu

M. J. Nunnery is with Nunnery Orthotic & Prosthetic Technologies, LLC, North Kingstown, RI 02852, USA.

recognition algorithm. We investigated the effects of prior knowledge on the performance of adaptive NMI. The prior possibility were simulated and tested on the data collected from a transfemoral (TF) amputee. The preliminary result of this study may lead to an adaptive NMI for prosthetic legs with improved accuracy and reliability.

II. METHODS

A. Fusion based Neural-Machine Interface (NMI)

Multichannel EMG signals recorded from the residual thigh and load measurements from a 6-DOF load cell were simultaneously streamed into the NMI and segmented by continuous, overlapped analysis windows. In each analysis window, four EMG features (mean absolute value, number of slope sign changes, waveform length, and number of zero crossings [14]) were extracted from each EMG signal; mechanical features (maximum, minimum, and mean values) were computed from individual DOFs. Both EMG and mechanical features were fused into one feature vector, which was then sent to a phase-dependent classifier to decide the user's locomotion mode. Detailed description of this previously designed NMI can be found in [8] and [9].

B. Pattern Recognition Algorithm

Linear Discriminant Analysis (LDA) was investigated in this paper to classify the user's locomotion mode. LDA has been reported as having a comparable classification performance to more complex types [15-17] and as being computationally efficient for real-time myoelectric prosthesis arm control [18]. The main idea of LDA is to classify observed data to a locomotion mode (class), in which the posterior probability can be maximized. For a G-class classification problem, the posterior probability $P(C_g \mid \bar{x})$ is the probability of class C_g ($g \in [1, G]$) given the observed feature vector $\bar{x}$ and can be expressed as

$$P(C_g \mid \bar{x}) = \frac{P(\bar{x} \mid C_g)P(C_g)}{P(\bar{x})} \tag{1}$$

where $P(C_g)$ is the prior possibility, $P(\bar{x} \mid C_g)$ is the likelihood, and $P(\bar{x})$ is the possibility of observed vector $\bar{x}$. Given the locomotion mode C_g, the observed feature vector was assumed to conform to a multivariate normal distribution. Here, every class shares the same covariance. Thus, the maximization of posteriori possibility in (1) equaled the maximization of the linear discriminant function defined as

$$d_{C_g} = \bar{x}^T \Sigma^{-1} \mu_g - \frac{1}{2} \mu_g{}^T \Sigma^{-1} \mu_g + \ln p(C_g) \tag{2}$$

where μ_g is the mean vector in C_g, and Σ is the common covariance matrix. Both μ_g and Σ can be estimated from the training data set.

C. Adaptively Adjusting Prior Probability based on the Knowledge of Walking Environments

In many applications, equal prior probabilities in (2) were assumed for all classes and therefore, can be ignored. When the prior probabilities were not the same across classes, the discriminant function in (2) must consider $P(C_g)$ [19]. In this study, the prior knowledge of walking environment was used to adaptively adjust the the prior probability of discriminant function of LDA. The designed NMI considered 6 locomotion modes (classes): level walking (W), stepping over an obstacle (O), stairs ascent (SA), stairs descent (SD), ramp ascent (RA), and ramp descent (RD). Assume the initial task was level ground walking. The prior possibilities of these classes were 30% for W, 14% for the other tasks, respectively. At time *t*, given that there was a stair in front the user, we modified the prior probabilities from that moment to be 45% for SA, 26% for W and RA, and 1% for other tasks as they were unlikely to happen.

The pattern classification involved two procedures: training and testing. During the training session, μ_g and Σ were estimated based on the feature vectors derived from the training data collected from two experimental trials. In the testing procedure, the observed feature vector of each analysis window and our simulated adaptive prior knowledge were fed into the classifier to calculate the d_{C_g} in (2) for each class. The observed feature vector was classified into the class that can maximize the linear discriminant function.

III. EXPERIMENTS AND EVALUATIONS

A. Participant and Data Collection

This study was conducted under Institutional Review Board (IRB) approval and consent of the subject. One male subject (age: 51, height: 177.8 cm, weight: 80.3 kg) with a unilateral transfemoral (TF) amputation (TF01) was recruited.

Nine EMG electrodes were placed surrounding the residual limb. Two gluteal muscles (*gluteus maximus* and *gluteus medius*) were also monitored. A 16-Channel EMG System (Motion Lab System, US) was used to collect and filter EMG signals between 20 Hz and 420 Hz with a band-pass gain of 1000. Mechanical ground reaction forces and moments were measured by a 6 degrees-of-freedom (DOF) load cell mounted on the prosthetic pylon. EMG signals and mechanical loads were digitally sampled at a rate of 1000 Hz and synchronized.

B. Experiment Protocol

In the experiment, the TF subject wore a hydraulic passive knee. Six locomotion modes (W, O, SA, SD, RA, and RD) and four mode transitions (W→ SA, W→RA, SD→W, and RD→W) were investigated. For each locomotion mode, 15 trials were conducted. Rest periods were allowed between trials to avoid fatigue.

C. Evaluation Methods

A transition between two locomotion modes (e.g. from level walking to stairs ascent) was a dynamic process and cannot be distinctively separated, which makes the system performance evaluation difficult. Thus, we separated data into the static states (the states when subjects continuously performed the same task) and transitional periods (one and half stride during the transition between two task modes [9]) and evaluated the system individually for the two states.

The studied task modes (classes) in the static state include W, SA, SD, RA, and RD. Note that the task of stepping over an obstacle was not included because this task only consisted of one stride cycle. The overall classification accuracy (CA) in the static states was then quantified by

$$CA = \frac{Number\ of\ correctly\ classified\ testing\ data}{Total\ number\ of\ applied\ testing\ data} \times 100\% \tag{3}$$

Two parameters were used to quantify the performance in the transitional periods: (1) the number of missed transitions and (2) prediction time of the transitions (T_{pre}). The T_{pre} is defined as the elapse time from the moment when the last stabilized task transition was recognized (t_d) in the transitional period to the critical timing for the investigated task transitions (t_c). We identify critical timing as: For all transitions from level walking (W→ SA, W→RA), the desired transition should be identified before the prosthetic foot leaves the ground to allow the knee to produce the proper flexion torque and prevent tripping; For transitions to level walking (SD→W, RD→W) the transition should be identified prior to weight acceptance. The detailed definition of these parameters can be found in [9].

D. Simulation of Prior Knowledge of Walking Environment

The prior knowledge of walking environment was simulated by modifying the prior possibilities of individual classes in LDA. The simulation was tested on the data recorded during both static states and transitions.

In the mode transitional periods, we assumed that the prior knowledge of next walking terrain was obtained starting from the initial prosthetic foot contact before switching the negotiated terrain and terminating at the end of single stance phase after switching the terrain. The prior possibilities of individual classes were modified accordingly based on the type of task transitions.

In real applications, the prior information could be noisy. In order to test the robustness of our design to the errors of prior knowledge, we simulated the false terrain information by applying incorrect prior possibilities to the classifier during static state. The type of false terrain was selected based on the classification confusion matrix in static state, obtained in our previous study. For example, during the static state of level-ground walking (W) task, an incline was chosen as the false terrain in front of the user because the class of level walking was most confused with ramp ascent. Then the prior possibility for each class was modified accordingly, starting from a heel contact of a gait cycle. The simulated false information lasted for the whole time during level walking.

IV. Numerical Results and Evaluations

A. Mode Recognition Performance in the Static State

For the classification accuracy test in the static state, the NMI algorithm with accurate, adaptive prior probabilities produced 98.7% accuracy for identifying the five tested locomotion modes, which outperformed the NMI without using the prior information (95.6% classification accuracy).

To test the robustness of LDA with false prior probabilities, incorrect prior probabilities were applied to the data in the static state of level walking. This simulation considered the *worst* scenario (refer to Section III D). The accuracy for classifying level walking task dropped only 6.1% when using incorrect prior possibility, compared to the result without adding any prior information (i.e. equal prior possibility). It indicated that during the static states, the pattern of neuromuscular and mechanical signals dominates the discriminant power than the prior information. However, accurate terrain recognition and modeling of prior probabilities are desired in order to enhance the reliability of intent recognition system.

B. Transition Recognition Accuracy

In the transitions, the NMI with prior information did not miss any transitions, while the NMI without prior knowledge missed 3 transitions in the defined transitional periods among tested transitions.

Table I shows the prediction time for 4 types of transitions. Based on our definition of prediction time, the larger the value, the earlier a stabilized transition was recognized. Missed transitions were not considered for computing the prediction time. The LDA algorithm with adaptive prior probabilities revealed slightly earlier recognition of task transitions partly because it produced more stable decisions than the algorithm without the prior

TABLE I
The Prediction Time of Mode Transitions Before Critical Timing

Unit:ms	W→SA	W→RA	SD→W	RD→W
LDA w/o Prior Knowledge	262 ±79	231 ±145	359 ±174	192 ±94
LDA w/ Prior Knowledge	332 ±105	273 ±151	390 ±93	261 ±132

Note: W, SA, RA, SD, and RD denote level walking, stairs ascent, ramp ascent, stairs descent, and ramp descent respectively.

information.

C. *Representative Result of Continuous Mode Identification*

Fig. 1 compares the performance of continuous locomotion mode identification for fusion-based LDA classifiers with and without using the prior knowledge in a representative trial. A smooth transition was required to be detected before the swing phase (i.e. critical timing) so that the control can promptly instruct the artificial joints and keep the prosthetic foot clear of the staircase during swing. Our investigated approach demonstrated earlier transition predication and more stable classification decision during the transition than the method without using prior knowledge.

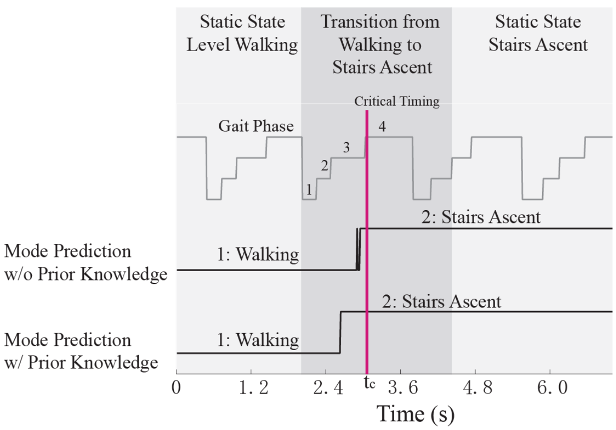

Fig. 1. Results of continuous mode identification from a trial that recoded transition from level ground walking to stairs ascent.

V. Conclusions

The presented study aimed at investigating the effects of additional prior information of walking environment on the performance of a neural-machine interface for artificial legs. The preliminary results showed that the NMI with adaptive prior possibilities outperformed the NMI without using the prior knowledge of walking terrains. Our study also reveals that this algorithm is robust to noisy and imperfect sources of prior knowledge. These results indicate the potential for using prior knowledge about walking environment to improve the performance of NMI for prosthetic legs. However, in this study the testing was limited to one subject, and the presented results lack statistical power. In addition, only a linear discriminant algorithm was used. Further investigations include selecting sensors for accurate terrain recognition and modeling the optimal prior probabilities that find the trade-off between transition recognition accuracy and system robustness. Additionally, we will apply this concept to different pattern recognition algorithm and test more leg amputees.

Acknowledgment

Authors thank Qing Yang, Ph.D., Yan Sun, Ph.D., and Haibo He, PhD. for their assistance in this study.

References

[1] M. M. Lusardi and C. C. Nielsen, *Orthotics and Prosthetics in Rehabilitation*. Boston: Butterworth-Heinemann Publications, 2000.

[2] E. C. Martinez-Villalpando and H. Herr, "Agonist-antagonist active knee prosthesis: a preliminary study in level-ground walking," *J Rehabil Res Dev,* vol. 46, pp. 361-73, 2009.

[3] F. Sup, A. Bohara, and M. Goldfarb, "Design and Control of a Powered Transfemoral Prosthesis," *International Journal of Robotics Research,* vol. 27, pp. 263-73, 2008.

[4] OSSUR, *The POWER KNEE*, The POWER KNEE ed.: http://bionics.ossur.com/Products/POWER-KNEE/SENSE.

[5] S. Bedard and P. Roy, "Actuated leg prosthesis for above-knee amputees," U. S. Patent, 2003.

[6] H. A. Varol, F. Sup, and M. Goldfarb, "Multiclass real-time intent recognition of a powered lower limb prosthesis," *IEEE Trans Biomed Eng,* vol. 57, pp. 542-51, Mar 2010.

[7] W. C. Flowers and R. W. Mann, "Electrohydraulic knee-torque controller for a prosthesis simulator," *ASME J. Biomech. Eng.,* vol. 99, pp. 3-8, 1977.

[8] H. Huang, T. A. Kuiken, and R. D. Lipschutz, "A strategy for identifying locomotion modes using surface electromyography," *IEEE Trans Biomed Eng,* vol. 56, pp. 65-73, Jan 2009.

[9] F. Zhang, W. DiSanto, J. Ren, Z. Dou, Q. Yang, and H. Huang, "A Novel CPS System for Evaluating a Neural-Machine Interface for Artificial Legs," in *Proceeding of the 2nd International Conference on Cyber-Physical Systems*, Chicago, IL, 2011.

[10] A. E. Patla, "Understanding the roles of vision in the control of human locomotion," *Gait & Posture,* pp. 54-69, 1997.

[11] A. E. Patla and J. N. Vickers, "How far ahead do we look when required to step on specific locations in the travel path during locomotion?," *Experimental Brain Research,* vol. 148, pp. 133-138, Jan 2003.

[12] E. J. Wilkinson and H. A. Sherk, "The use of visual information for planning accurate steps in a cluttered environment," *Behavioural Brain Research,* vol. 164, pp. 270-274, Nov 2005.

[13] G. K. Bradski, A., "Robot-Vision Signal Processing Primitives," *IEEE Signal Processing Magazine,* vol. 25, p. 4, 2008.

[14] B. Hudgins, P. Parker, and R. N. Scott, "A new strategy for multifunction myoelectric control," *IEEE Trans Biomed Eng,* vol. 40, pp. 82-94, Jan 1993.

[15] K. Englehart, B. Hudgins, P. A. Parker, and M. Stevenson, "Classification of the myoelectric signal using time-frequency based representations," *Med Eng Phys,* vol. 21, pp. 431-8, Jul-Sep 1999.

[16] Y. H. Huang, K. B. Englehart, B. Hudgins, and A. D. C. Chan, "A Gaussian mixture model based classification scheme for myoelectric control of powered upper limb prostheses," *IEEE Transactions on Biomedical Engineering,* vol. 52, pp. 1801-1811, Nov. 2005.

[17] L. J. Hargrove, K. Englehart, and B. Hudgins, "A comparison of surface and intramuscular myoelectric signal classification," *IEEE Trans Biomed Eng,* vol. 54, pp. 847-53, May 2007.

[18] K. Englehart and B. Hudgins, "A robust, real-time control scheme for multifunction myoelectric control," *IEEE Trans Biomed Eng,* vol. 50, pp. 848-54, Jul 2003.

[19] R. A. Johnson and D. W. Wichern, *Applied Multivariate Statistical Analysis*, 6 ed.: Pearson, 2007.