Promise of using surface EMG signals to volitionally control ankle joint position for powered transtibial prostheses

Baojun Chen, Student Member, IEEE, Qining Wang, Member, IEEE and Long Wang, Member, IEEE

Abstract-Improving the intuitiveness of the interaction between human and machine is an important issue for powered lower-limb prosthesis control. In this research, we aimed to evaluate the potential of using surface electromyography (EMG) signals measured from transtibial amputees' residual muscles to directly control the position of prosthetic ankle. In this research, one transtibial amputee subject and five able-bodied subjects were recruited. They were asked to control a virtual ankle to reach different target positions. The amputee subject finished these tasks in an average time of 1.29 seconds for different target positions with the residual limb, which was comparable with that using the amputee's sound limb and those with able-bodied subjects' dominant legs. Due to human's strong adaptability, the amputee subject was able to adapt to the control model trained one day before or trained in a posture which was different from that during performing control tasks. These results validate the promise of using surface EMG signals to volitionally control powered transtibial prostheses.

I. INTRODUCTION

The life of lower-limb amputees has greatly benefited from the development of prostheses. However, most of the commercially available lower-limb prostheses are energetically passive. Amputees can not walk as naturally as ablebodied people with these passive prostheses, mainly due to more metabolic power consumption and asymmetrical gait pattern [1]. Therefore, the research on powered lower-limb prostheses is gaining more and more attentions. However, the powered lower-limb prostheses not only require more complicated control strategy than the passive ones, but also need to "know" users' movement intents to work appropriately. The lack of sufficient interaction between amputee users and prostheses might be one challenge for clinical application of powered prostheses. Therefore, how to improve the intuitiveness of the human-machine interface (HMI) for powered lower-limb prosthesis control is an important issue to be addressed.

Some studies on HMI for powered lower-limb prosthesis control have been carried out in recent years. Most of them used pattern recognition architecture to recognize human's locomotion modes or movement state of ankle/knee joints with mechanical signals, EMG signals and other signals [2]–[6]. Though some of the results were promising, essential limitations exist for the finite-state-recognition based control strategy. First, the number of studied locomotion modes is

finite, while human's movement states are infinite. Therefore, the controller might work inappropriately when walking on irregular terrains. Second, user's movement intents can only be conveyed to the prosthesis in an indirect way (i.e. through pattern recognition). In this case, users have no clear idea what actions will cause false recognition, and how to improve the recognition accuracy during walking. Furthermore, when movement intents are falsely recognized, there is no definite way for users to correct them. Thus, expressing human's movement intents in a more direct way is necessary for the design of HMI aiming at powered lower-limb prosthesis control.

Direct EMG control, which uses EMG commands to directly control the mechanical output of prosthetic joints [7], can provide more intuitive interaction between users and prostheses. Several recent studies have tested the promise of using EMG signals measured from residual limbs to directly control powered above-knee prostheses [7]–[9]. The control architecture used in [9] combined proportional myoelectric torque control with a state-determined knee impedance to estimate knee torque, and it was tested on a transfemoral amputee subject during stair ascent. In [7], the authors proposed a new control model, which mapped impedancecontrol parameters directly to the user's co-contraction patterns, enabling the user to exploit the full performance capability of the prosthetic knee. Studies of using EMG signals to directly control powered transtibial prostheses were relatively less [10], [11]. [11] proposed a hybrid controller which combined proportional EMG control with the existing intrinsic controller for a powered transtibial prosthesis. The hybrid controller was tested during level-ground walking at different speeds. However, the user had limited freedom to volitionally control the prosthesis, as EMG signals were only used to determine the gain parameter for powered plantar flexion, which lasted for only a short time.

The focus of this research is to evaluate the promise of using EMG signals measured from residual muscles of transtibial amputees to directly control the position of prosthetic ankle. Position control is important for transtibial prosthesis during swing phase, as it improves walking stability by preventing the foot from dragging along the ground and better absorbing impacts from the ground in initial contact (IC) period. The subjects were required to control a virtual ankle displayed on the screen to reach target positions. Finish time of each trial was recorded to quantitatively evaluate the performance of direct EMG control. Average finish time of the amputee subject using residual limb was comparable with that using sound shank and those of able-bodied subjects

This work was supported by the National Natural Science Foundation of China (No. 61005082, 61020106005), the 2011 R&D Project of the Beijing Disabled Persons' Federation and the Beijing Nova Program (No. Z141101001814001).

The authors are with the Intelligent Control Laboratory, Center for Systems and Control, College of Engineering, Peking University, Beijing 100871, China. (E-mail: qiningwang@pku.edu.cn)

using dominant legs. To further validate the robustness of this control method, the amputee subject was asked to control the virtual ankle using the model trained on a separate day or trained in postures that were different from those during testing. We found that the amputee subject was able to adapt to these changes and still achieve satisfactory control performance. These results indicated that direct EMG control was promising for powered transtibial prosthesis control in daily life.

II. METHODS

A. Signal measurement

Five able-bodied subjects (3 male, 2 female; age: 23.0 ± 1.7 years; height: 1.68 ± 0.05 m; mass: 63.0 ± 9.1 kg) and one male transtibial amputee subject (age: 31 years; height: 1.72 m; mass: 65 kg) were recruited in the research, and provided written and informed consent. The amputee subject had been amputated (left leg) for 15 years. The length of his residual shank was 12 cm (from patella to the amputated site), while the length of his sound shank was 42 cm (from patella to malleolus lateralis).

Two muscles were measured in the experiment for both able-bodied subjects and the amputee subject: Tibialis Anterior (TA) and Gastrocnemius (GAS). Positions of electrodes were determined by palpation when subjects were asked to perform plantar flexion and dorsiflexion (the amputee subject still had the intents to perform plantar flexion and dorsiflex-ion of the "phantom ankle"). EMG signals were collected at 1000 Hz sampling rate using a wireless EMG system (Trigno wireless EMG system, Delsys Inc.), and translated to a desktop computer through a data acquisition (DAQ) card (National Instruments, NI-USB-6009). The measured raw signals were full wave rectified, and low-pass filtered with a third-order Butterworth filter (2.5-Hz cut-off frequency).

B. Experiment protocol

To collect the data for control model training, subjects were asked to consciously perform plantar flexion and dorsiflexion of the ankle (or phantom ankle). A total of 10 training trials were performed (5 trials of dorsiflexion and 5 trials of plantar flexion, they were alternatively taken). In each trial, dorsiflexion/plantar flexion with different contraction intensity were performed for four times. For each time, subjects were required to held the muscle contraction for 2 seconds, and then relaxed for 6 seconds before the next contraction.

To evaluate the performance of direct EMG control, subjects were asked to control a virtual ankle displayed on the screen (see Fig. 1(a)) to reach target positions by consciously performing dorsiflexion or plantar flexion of the ankle (or phantom ankle). If the virtual ankle was kept at the target position ($\pm 2^{\circ}$ error was allowed) for at least 200 ms, the control task was successfully completed. Finish time of the task was recorded and used for performance evaluation. If the task was not completed within 5 seconds, it was judged to be failed. In each trial, 7 target ankle angles (14° , 10° , 5° , -5° , -10° , -15° and -19° , positive angles

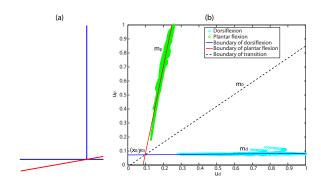


Fig. 1. (a) The virtual ankle used in control tasks. The blue lines represent ankle and foot, while the red line denotes the target position of foot (the shank was unmovable). (b) The control model trained with the data measured from residual muscles of the ampute subject. u_p is the normalized EMG signals of GAS, and u_d is the normalized EMG signals of TA.

indicate dorsiflexion while negative angles indicate plantar flexion) were performed, whose test orders were randomly determined.

Three experiments were designed in this research to validate the promise of using EMG signals measured from residual muscles to directly control prosthetic ankle. In the first experiment, we aimed to compare the performance of virtual ankle control using signals measured from the impaired side of the amputee subject with that from the sound side and those from the dominant side of able-bodied subjects (right side for all of them). Control model training and virtual ankle control tasks were performed in sitting posture. A total of 20 trials of control tasks were tested. In the second experiment, we evaluated whether control performance significantly decreased when model training and control tasks were performed in different postures. The amputee subject was asked to train the control model in sitting and standing postures, respectively. 20 trials of virtual ankle control tasks were separately performed in sitting and standing postures using these two trained models. In the third experiment, we intended to test the robustness of the method to changes of electrode positions and muscles' status. The amputee subject was asked to perform control tasks using the model trained one day before, and the control performance was compared with those when model training and control tasks were performed in the same day. Note that the amputee subject determined electrode positions himself in the second day.

C. Control model

The control model used in this research is similar with the one proposed in [7]. We used 10-ms adjacent sliding windows to calculate the means of filtered signals. They were normalized to maximum voluntary contraction (MVC) of plantar flexion and dorsiflexion. Normalized EMG signals of GAS and TA were marked as u_p and u_d , respectively. Principle component analysis (PCA) was performed for plantar flexion data and dorsiflexion data. The two lines representing the first principle component of plantar flexion and dorsiflexion were obtained (see Fig. 1(b)). Slopes of these two lines were m_p and m_d , and the the intersection point of these two lines was marked as (x_0,y_0) . The slope of the transition boundary separating plantar flexion and dorsiflexion was calculated by

$$m_0 = \tan(\frac{\arctan m_p + \arctan m_d}{2}). \tag{1}$$

The desired ankle angle was estimated by

$$\theta_{est} = \begin{cases} -K\theta_{pmax} \cdot \frac{m - m_0}{m_p - m_0}, & m \ge m_0, \quad (2a) \end{cases}$$

$$\begin{cases} K\theta_{dmax} \cdot \frac{m - m_0}{m_d - m_0}, \qquad m < m_0, \quad (2b) \end{cases}$$

where

$$K = K_0 \sqrt{u_p^2 + u_d^2} \tag{3}$$

and

$$m = \frac{u_p - y_0}{u_d - x_0}.$$
 (4)

 K_0 is a constant ($K_0 > 1$) to avoid muscle fatigue, as EMG signals of residual muscles could not reach the maximum voluntary contraction potential repeatedly during testing. Its value was determined by each subject's own preference, and it ranged from 1.5 to 2.5 for different subjects in this study.

Angular velocity of the virtual ankle joint displayed on the screen was determined by

$$\omega = \frac{\theta_{est} - \theta}{dt},\tag{5}$$

where θ is the current ankle angle, and dt is the interval between two adjacent estimations, which is 10 ms in this study. If the estimated joint angles or calculated angular velocities exceeded the predefined movement range $(-20^{\circ} \sim 15^{\circ})$ or maximum angular velocity $(100^{\circ}/s \text{ in both directions})$ of the virtual ankle, they were set to the extreme values.

III. RESULTS

A. Experiment 1

Average finish times of using EMG signals measured from the amputee's residual limb, the amputee's sound leg and able-bodied subjects' dominant limbs (see Table. I) were close to each other. It implies that the amputee subject was able to accurately convey his movement intents and make quick response to new tasks with the residual limb as well as able-bodied people in spite of the degeneration of some muscles and nerves.

B. Experiment 2

When control model was trained in sitting posture, average finish time of performing control tasks in sitting posture (1.29 s) and that in standing posture (1.22 s) were close to each other, and the difference was not statistically significant (p = 0.197, Wilcoxon signed-rank test). Similar results were also obtained when the model was trained in standing posture

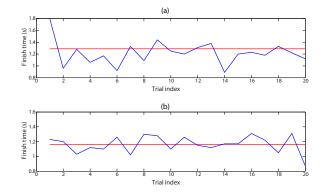


Fig. 2. Control performance of the amputee subject using control model trained in a different posture. (a) Red line denotes average finish time when both model training and testing were performed in sitting posture. And blue line shows the performance when model was trained in seated position while tested in standing posture. (b) Red line denotes average finish time when both model training and testing were performed in standing posture. And blue line shows the performance when model was trained in standing posture while tested in sitting posture.

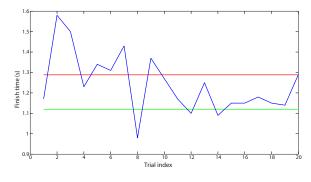


Fig. 3. Control performance of the amputee subject using control model trained in a different day. Red line denotes the average finish time achieved in the first day, immediately after model training completed. Blue line shows the finish time of different trials achieved in the second day, using the model trained one day before. Green line denotes the average finish time achieved in the second day, using the newly trained control model.

(1.16 s for testing in standing posture while 1.24 s for testing in sitting posture, and p = 0.125 for significance testing). In both situations mentioned above, control performance during standing is a little better than that during sitting. Ignoring this influence, the posture for model training had little influence on the control performance. In addition, the amputee subject was able to adapt to the model trained in a different posture, as finish time didn't decrease as trial index increased (see Fig. 2(a) and (b)).

C. Experiment 3

With the model trained one day before, control performance varied a lot (ranged from 0.98 s to 1.58 s) for the first 10 trials, while changed less for the last 10 trials (ranged from 1.09 s to 1.29 s). And average finish time of the last 10 trials (1.17 s) was shorter than that of the first 10 trials (1.32 s). This implies that the subject could adapt to the control model after a few trials of testing. Compared with the results of using the model trained in the same day, the overall performance (1.24 s) was worse than that of the first day (1.29 s).

	TABLE I	
FINISH TIME OF CONTROLLING VIRTUAL	L ANKLE TO REACH DIFFERENT TARGET ANGLES (SECOND)	

	-19º	-15°	-10°	-5°	5°	10 ^o	14°	Average
Able-bodied 1	0.98	1.47	1.61	1.89	0.92	1.19	1.03	1.30
Able-bodied 2	2.02	2.39	1.39	1.34	1.04	1.25	1.25	1.53
Able-bodied 3	1.22	1.47	0.97	1.29	0.90	1.14	0.91	1.13
Able-bodied 4	1.31	2.64	1.46	1.23	1.16	1.10	0.95	1.41
Able-bodied 5	1.12	1.54	1.47	1.28	0.91	0.92	1.43	1.24
Mean of able-bodied $1{\sim}5$	$1.33 {\pm} 0.41$	$1.90 {\pm} 0.57$	$1.38{\pm}0.24$	$1.41{\pm}0.27$	$0.99 {\pm} 0.11$	$1.12{\pm}0.13$	$1.12{\pm}0.22$	$1.32{\pm}0.15$
Sound side of amputee	1.33	1.27	1.23	1.00	1.27	1.27	1.38	1.25
Amputated side of amputee	1.03	1.36	1.54	1.56	1.12	1.23	1.18	1.29

The transtibial amputee subject was also asked to control a powered transtibial prosthesis without worn, and a video was included in the supplementary.

IV. DISCUSSION AND CONCLUSION

In this preliminary research, we evaluated the potential of using surface EMG signals measured from residual muscles to volitionally control the position of prosthetic ankle. By comparing the finish time of controlling a virtual ankle to reach target positions under different experiment conditions, we verified that the control method was robust to limited changes of electrode positions and muscles' status. In addition, the amputee subject was able to accurately and intuitively express his movement intents with the residual limb, just as able-bodied subjects did. Testing in a posture that was different from training doesn't impact control performance. These results indicate that the proposed method is promising for powered transtibial prosthesis control.

Compared with finite-state-recognition based approaches, the proposed direct EMG control model has following advantages for powered prosthesis control. First, amputees can express their movement intents in a more intuitive way, which is similar with controlling intact limbs. This makes it easier for amputees to accept powered prostheses. In addition, the control model is not complicated and computation burden is very low. Prostheses are able to make accurate and fast response to unexpected situations. Second, the full performance capability of powered prostheses can be utilized. Rather than just recognizing the direction of joint rotation or finite locomotion modes, direct EMG control allowed amputees to control prosthetic joints to any position they want. This is very important in clinical application, especially for walking on irregular terrains. Third, amputees are able to adapt to new control tasks and gradually improve control performance through learning. [12] found that the performance of proportional myoelectric control could be greatly improved after a short training period. Our results agreed with this conclusion, as control performance in the second day was better than that of the first day (see Fig. 3).

As adjusting ankle joint position to different terrains in swing phase is important for maintaining walking stability, we intended to develop a position controller for transtibial prostheses. Therefore, unlike previous studies [2], [7], [9], [11], we mapped EMG signals to the desired ankle angle instead of joint torque or other control parameters in this research. However, position controller may perform unsatisfactorily during stance phase. In our future work, we will combined position control and torque control together. The former works in swing phase, while the latter works in stance phase. In addition, we will test direct EMG control on level ground walking and other locomotion tasks with powered transtibial prostheses. And its universality will be validated by testing on more amputee subjects.

REFERENCES

- S. Au, J.Weber, and H. Herr, "Powered ankle-foot prosthesis improves walking metabolic economy," *IEEE Trans. Robot.*, vol. 25, no. 1, pp. 51-66, Feb. 2009.
- [2] 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, no. 3, pp. 542-551, Mar. 2010.
- [3] H. Huang, F. Zhang, L. Hargrove, Z. Dou, D. Rogers, and K. Englehart, "Continuous locomotion mode identification for prosthetic legs based on neuromuscular-mechanical fusion," *IEEE Trans. Biomed. Eng.*, vol. 58, no. 10, pp. 2867-2875, Oct. 2011.
- [4] L. J. Hargrove, A. M. Simon, A. J. Young, R. D. Lipschutz, S. B. Finucane, D. G. Smith, and T. A. Kuiken, "Robotic leg control with emg decoding in an amputee with nerve transfers," *N. Engl. J. Med.*, vol. 369, no. 13, pp. 1237-1242, Sep. 2013.
- [5] B. Chen, E. Zheng, X. Fan, T. Liang, Q. Wang, K. Wei, L. Wang, "Locomotion mode classification using a wearable capacitive sensing system," *IEEE Trans. Neural. Syst. Rehabil. Eng.*, vol. 21, no. 5, pp. 744-755, Sep. 2013.
- [6] D. C. Tkach, R. D. Lipschutz, S.B. Finucane, and L.J. Hargrove. "Myoelectric neural interface enables accurate control of a virtual multiple degree-of-freedom foot-ankle prosthesis," *IEEE 13th International Conference on Rehabilitation Robotics (ICORR)*, 2013.
- [7] J. A. Dawley, K. B. Fite, and G. D. Fulk. "EMG control of a bionic knee prosthesis: exploiting muscle co-contractions for improved locomotor function," *IEEE 13th International Conference on Rehabilitation Robotics (ICORR)*, 2013.
- [8] K. H. Ha, H. A. Varol, and M. Goldfarb, "Volitional control of a prosthetic knee using surface electromyography," *IEEE Trans. Biomed. Eng.*, vol. 58, no. 1, pp. 144-151, Jan. 2011.
- [9] C. D. Hoover, G. D. Fulk, and K. B. Fite, "Stair ascent with a powered transfemoral prosthesis under direct myoelectric control," *IEEE-ASME Trans. Mechatron.*, vol. 18, no. 3, pp. 1191-1200, Jun. 2013.
- [10] S. K. Au, P. Bonato, and H. Herr, "An EMG-position controlled system for an active ankle-foot prosthesis: An initial experimental study," *IEEE 9th International Conference on Rehabilitation Robotics*, pp. 375-379, 2005.
- [11] J. Wang, O. A. Kannape, and H. M. Herr, "Proportional EMG control of ankle plantar flexion in a powered transibilial prosthesis," *IEEE 13th International Conference on Rehabilitation Robotics (ICORR)*, 2013.
- [12] R. E. Alcaide-Aguirre, D. C. Morgenroth, and D. P. Ferris, "Motor control and learning with lower-limb myoelectric control in amputees," *J. Rehabil. Res. Dev.*, vol. 50, no. 5, pp. 687-698, 2013.