Arm prosthetic control through electromyographic recognition of leg gestures

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Introduction

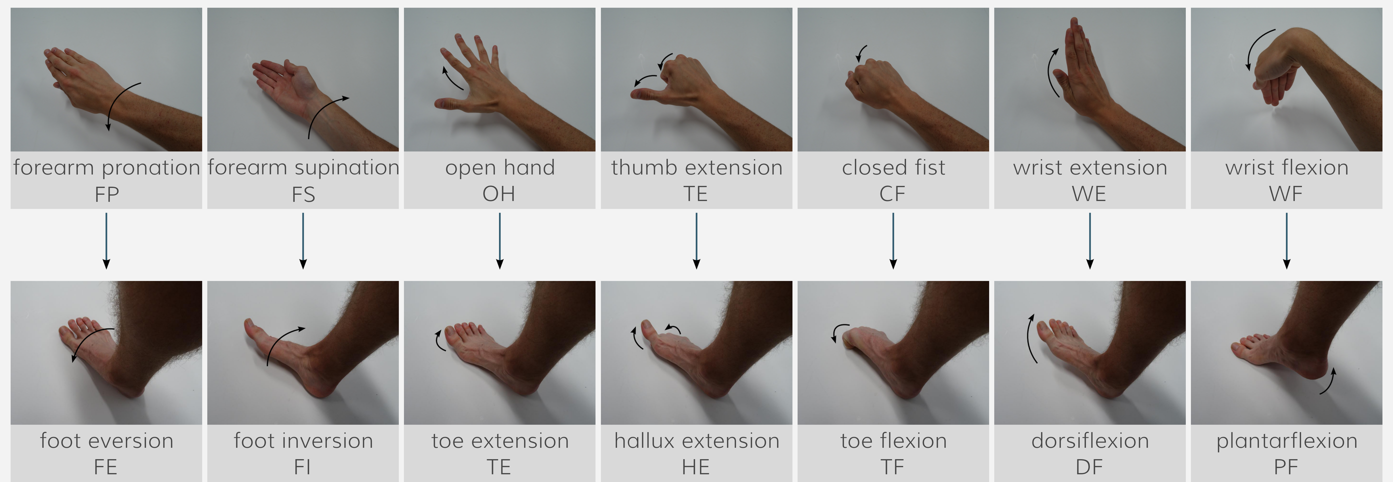
Currently, the only technique offering intuitive myoelectric control of upper-limb prostheses to transhumeral or shoulder disarticulation amputees is a surgical procedure called targeted muscle reinnervation (TMR) [1].

We propose a new approach that is completely non-invasive, where *users command an upper limb prosthetic with analogous leg gestures* that are recognized by surface elctromyography (EMG).

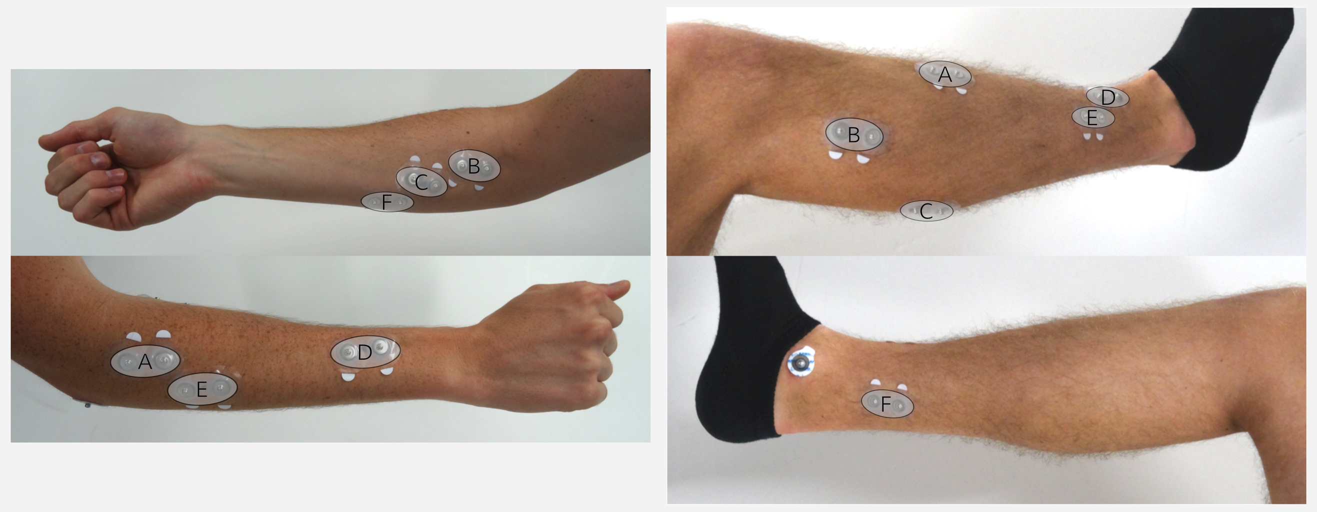
As a preliminary step toward this goal, we developed an *intuitive mapping between movements and muscles of the arm and the leg*, then we used standard methods in EMG-based gesture recognition [2] to test the ability of naive subjects to produce recognizable leg gestures in open loop.

Arm-Leg Mapping

Intuitive control of an arm prosthetic with leg movements begins with a mapping between the arm and leg. Seven of the gestures that subjects performed in our experiment are shown below, demonstrating the natural relationship between the degrees of freedom of both limbs.



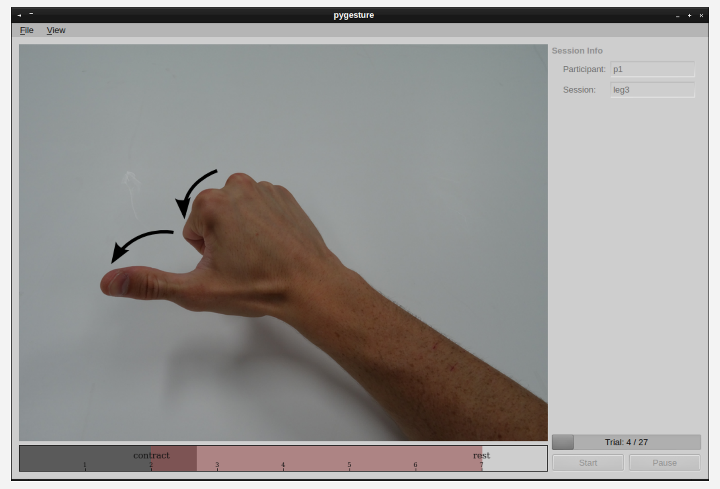
In addition to the gesture mapping, we have also identified a set of muscles of the arm and leg which have analogous primary functions on the corresponding limb. These muscles are the ones targeted by surface EMG in our gesture recognition system.



Methods

Subjects performed gestures with the leg in three different conditions: sitting, standing, and standing with the leg lifted from the ground (open-loop kinematic chain). For comparison, they also performed the analogous gestures with the arm. All recording was done in a single session for each subject.

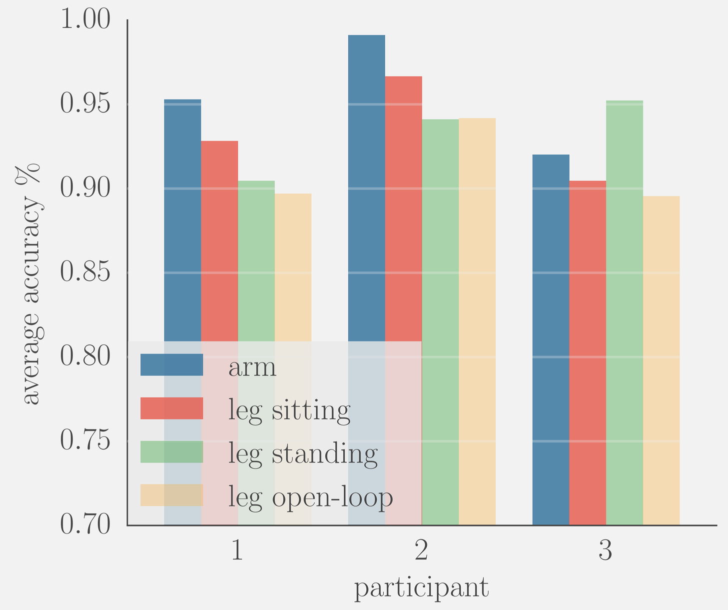
Six EMG sensors recorded the activity of specific muscles. The recordings were divided into segments, and for each segment, a feature vector was calculated using four time-domain features for each channel: mean absolute value (MAV), waveform length (WL), zero crossings (ZC), and slope sign changes (SSC). Linear discriminant analysis (LDA) classified the gestures offline.



Subjects were prompted to perform the gestures with a custom graphical user interface which displayed a picture of the prompted *arm gesture* regardless of whether they were moving the arm or the leg, establishing the intuitive nature of the arm-leg mapping.

Results

The results for three randomly selected participants are presented. The bar plot to the right shows classification accuracy averaged across gesture classes for each participant in the four different experimental conditions.



This establishes that accuracy for leg gestures in the sitting condition is close to that of the arm gestures, though it is somewhat lower across participants.

predicted class

actual class	NC	TF	FE	FI	TE	HE	DF	PF
NC	0.97 ±0.02							
TF		0.95 ±0.08		0.05				
FE			0.91 ±0.07	0.05	0.01			0.02
FI		0.04		0.95 ±0.03				
TE	0.01			0.03	0.86 ±0.01	0.09		
HE	0.01	0.04		0.01	0.05	0.89 ±0.05		
DF				0.01			0.98 ±0.02	
PF		0.03	0.05					0.92 ±0.06

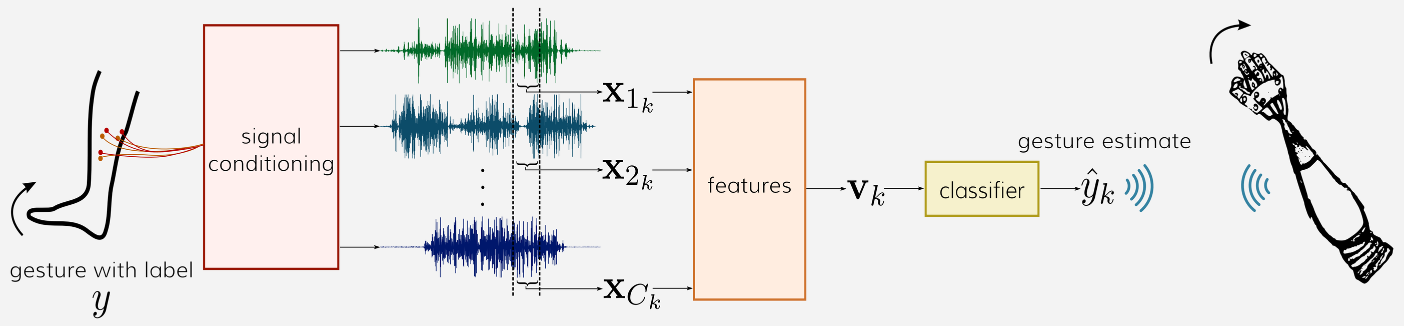
The confusion matrix to the left shows the classification rates for the primary set of gesture classes when participants performed leg gestures in the sitting condition. These accuracies are comparable to results in targeted muscle reinnervation studies.

High misclassification rates, such as toe extension being misclassified as hallux extension, may be caused by the proximity of the two different toe extensor muscles targeted and the relative difficulty of measuring their activity via surface EMG.

Discussion

With this initial work, we have demonstrated that it is possible to classify leg gestures using current standard techniques in electromyographic gesture recognition. Furthermore, the classification accuracy of leg gestures in a seated position compares well with the same system classifying arm gestures.

We have also developed a mapping between the arm and leg which is natural and intuitive enough for naive subjects to convert images of arm movements to the corresponding leg movements with no training. This could lead to an intuitive prosthetic control system which recognizes leg gestures and transmits the analogous arm gestures to an upper-limb prosthetic.



The main limitation of this study is that it is based on offline analysis only, meaning subjects received no feedback regarding classifier output during the gesture recording trials. Providing such feedback is an essential part of evaluating a prosthetic control scheme, so in the future we will run experiments in which the classifier output is displayed to the user in real time. This will allow us to more accurately determine the feasibility of controlling an upper-limb prosthetic with leg gestures.

References

[1] T. A. Kuiken, G. Li, B. A. Lock, R. D. Lipschutz, L. A. Mller, K. A. Stubblefield, and K. B. Englehart, "Targeted Muscle Reinnervation for Real-time Myoelectric Control of Multifunction Artificial Limbs," *JAMA*, vol. 301, no. 6, pp. 619-628, 2009.

[2] E. Scheme and K. Englehart, "Electromyogram Pattern Recognition for Control of Powered Upper-Limb Prostheses: State of the Art and Challenges for Clinical Use," *J. Rehabil. Res. Dev.*, vol 48, no 6, pp. 643-660, 2011.

Acknowledgments

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