A Strategy for Labeling Data for the Neural Adaptation of a Powered Lower Limb Prosthesis

John A. Spanias – *IEEE Student Member*, Eric J. Perreault – *IEEE Member*, and Levi J. Hargrove – *IEEE Member*

***Abstract*—Pattern recognition algorithms that use EMG signals have been proposed to help control powered lower limb prostheses. These algorithms do not automatically compensate for disturbances in EMG signals, resulting in deterioration of algorithm accuracies. Supervised adaptive pattern recognition algorithms can solve this problem, but require correct labeling of new data. Information from embedded mechanical sensors can be compared to the characteristic gait profiles of the different modes to identify the mode of the user's most recent stride and provide a label for new data. The purpose of this study was to develop a gait pattern estimator (GPE) that could automatically make such a comparison. The GPE output was used to supervise an adaptive EMG-based pattern recognition algorithm. Our results indicate that using GPE-based adaptation helped prevent classification errors that would otherwise occur between experimental sessions. The GPE could accurately label new data with a low error rate of approx. 2%. The low error rate of the GPE was reflected in the accuracy of an adapted pattern recognition algorithm. The error rate of the adapted algorithm that was supervised by the GPE was not significantly different from one that used perfect supervision.**

I. Introduction

Surface electromyography (EMG) signals have not yet been clinically implemented as a control signal for lower limb prostheses despite their frequent use in powered upper limb applications [1]. Powered prosthetic legs have recently become commercially available (OSSUR, BiOM) and several other advanced prototypes have been developed [2], [3]. These devices are capable of restoring a variety of locomotion modes (e.g., level walking, stair ascent, ramp descent) and assist the user by generating positive mechanical work at the knee and ankle joints [4]. The potential of these devices is diminished by the lack of a seamless and automatic method to select different modes during normal use. Accurate EMG pattern recognition algorithms may be able to address this need.

EMG signals have been integrated into control systems for powered leg prostheses as inputs to a pattern recognition algorithm that predicts the desired locomotion mode (i.e., locomotion mode prediction) [5]. Recent studies have shown that EMG signals complement the kinematic and kinetic information from mechanical sensors embedded within the prosthesis and significantly reduce the prediction error rates of pattern recognition algorithms [6]–[8]. However, these control strategies do not compensate for disturbances in EMG that occur during daily prosthesis use, such as those caused by electrode shift during donning and doffing, fatigue, or loss of skin contact due to volume fluctuation [9], [10]. These factors may result in the deterioration of prediction accuracy, which can endanger patient safety unless an adaptive mechanism to compensate for their effects is developed.

Adaptive frameworks that learn from new patterns must be able to "label" those patterns with the correct locomotion mode (i.e., supervised learning). Previously proposed adaptive frameworks that compensate for EMG disturbances have not been implemented because there are no clinically acceptable and accurate methods to supervise new data used for adaptation [11]–[13]. Fortunately, human gait and the locomotion modes of the prosthesis are cyclic. Thus, kinematic and kinetic data acquired from embedded mechanical sensors can be compared to the characteristic gait profiles of the different modes to determine the mode of the user's most recent stride (i.e., gait pattern estimation) [14]. This estimation can be performed automatically after the completion of each stride by using pattern recognition to classify gait patterns from the mechanical sensors. This technique could be used to correctly and automatically supervise the data used to update an adaptive system. This strategy, which identifies the locomotion mode *after* stride completion, is contrasted with locomotion mode prediction, which identifies the mode *before* the stride begins.

The objective of this study was to develop and evaluate a gait pattern estimator (GPE) for supervision of an adaptive pattern recognition system for a powered leg prosthesis. This analysis was completed by evaluating the performance of a locomotion mode prediction algorithm that uses the GPE to adapt algorithm between experimental sessions.

This work was supported in part by the US Army's Telemedicine and Advanced Technology Research Center under grant number 81XWH-09-2-0020. J.A. Spanias was supported by a John N. Nicholson fellowship.

J.A. Spanias, is with Center for Bionic Medicine at the Rehabilitation Institute of Chicago, Chicago, IL 60611 USA and with the Department of Biomedical Engineering at Northwestern University, Chicago, IL, 60611, USA(e-mail: john.spanias@u.northwestern.edu).

E.J. Perreault is with the Departments of Physical Medicine and Rehabilitation and Biomedical Engineering at Northwestern University, Chicago, IL, 60611, USA

L.J. Hargrove is with Center for Bionic Medicine at the Rehabiliation Institute of Chicago, Chicago, IL 60611 USA and with the Department of Physical Medicine and Rehabilitation at Northwestern University, Chicago, IL, 60611, USA (e-mail: l-hargrove@northwestern.edu).

978-1-4244-7929-0/14/$26.00 ©2014 IEEE

II. METHODS

A. Experimental Protocol

Four subjects with unilateral transfemoral amputations completed the experiment, which was approved by the Northwestern University Institutional Review Board. Subjects' ages ranged from 30 to 66, heights between 1.75 and 1.87 m, and weight between 77.1 and 96.6 kg.

A skin-fit suction socket was custom made for each such subject. The socket had embedded stainless-steel electrodes that recorded EMG signals from nine muscles: semitendinosus, biceps femoris, tensor fasciae latae, rectus femoris, vastus lateralis, vastus medialis, sartorius, adductor magnus, and gracilis. The electrodes were inserted into the socket based on locations identified by a physical therapist. A certified prothestist attached and aligned a powered knee and ankle prosthesis to the subject's socket. The Center for Intelligent Mechatronics at Vanderbilt University designed the prosthesis used for this experiment [3]. Published strategies were used to tune the leg in each mode for each subject in previous sessions [4], [6], [15].

The data collection procedure for this experiment has been described before in previously published literature [7]. Briefly, each subject completed 20 repetitions of a locomotion circuit that included level-ground, ramps, and stairs. An experimenter triggered the prosthesis between modes at heel contact and toe-off [5]. These 20 repetitions were repeated in a separate session during a different day.

B. Signal Processing

Kinetic and kinematic information from thirteen embedded mechanical sensors embedded in the prosthesis were recorded at 500 Hz. Nine EMG signals from the nine aforementioned muscle sites were recorded at 1000 Hz using a custom-built EMG system. This system used a Texas Instruments TI-ADS1299 instrumentation chip and also used a hardware bandpass filter with between 20 and 450 Hz.

For locomotion mode prediction, data were segmented into analysis windows of 300 ms before heel contact and toe off. Mechanical sensor features and EMG features were extracted from each analysis window. Mechanical sensor features included mean, maximum, minimum, and standard deviation [6]. EMG features included mean absolute value, waveform length, zero crossing, slope sign changes and the first two autoregressive coefficients of a third order autoregressive model [10], [16]. Thus, the information prior to each step (i.e. the 300 ms analysis window) is a vector of features that is classified by a pattern recognition algorithm that predicts the desired mode, i.e., a locomotion mode predictor. The predictor can use either mechanical sensors features only, or the combination of EMG features and mechanical sensor features to make its prediction. The predicted locomotion mode determines the behavior of the prosthesis over the next stride.

For gait estimation, mechanical sensor data were segmented by stride (i.e., from one heel contact or toe off to the next heel contact or toe off). For each of the thirteen mechanical sensor channels, the following features were used to characterize each stride: initial, final, minimum, maximum and mean value as well as the standard deviation of the channel across the stride. Thus, the information over the entire stride is a vector of mechanical sensor features that is classified as one of five locomotion modes by a GPE. The GPE is simply a pattern recognition algorithm that estimates the locomotion mode of the user's most recent completed stride, instead of predicting the mode of the upcoming stride.

C. Supervision Strategies and Adaptive Framework

We investigated two potential supervision strategies. The first method used to supervise adaptation was to assume that the label provided by a locomotion mode predictor that only used mechanical sensors was correct. This strategy of using the predictor's decision (i.e., the output of the control system itself) as data labels has been proposed in previous literature, and will be used as a standard of comparison [12].

The second method used the output of the GPE to supervise adaptation. The GPE uses mechanical sensor data collected throughout the most recent stride to estimate that stride's locomotion mode. The motivation for this approach is that each locomotion mode has a unique set of kinematic and kinetic characteristics that are captured by the mechanical sensors of the prosthesis. The estimated locomotion mode can supervise data used to update an adaptive system.

In this study, adaptive locomotion mode prediction was implemented by adding data collected from the second experimental session to a training set that originally comprised of data from the first experimental session. Either the GPE or the locomotion mode predictor was used to supervise these new data. We can evaluate the performance of the adapted predictor (and consequently the impact of the chosen supervision strategy) by observing its error rate on a testing set comprised of data from the second session.

D. Classifier Evaluation

In this study, linear discriminant analysis (LDA) classifiers were used for both the locomotion mode predictor and the GPE. Leave-one-out cross validation of the 20 circuit trials was used to determine the error rates of the locomotion mode predictor and the GPE (19 trials in the training dataset and 1 trial in the testing dataset and repeated until each trial was in the test set once). Error rates reported are the pooled misclassification rates at heel contact and toe off as these are the transition points for the prosthesis.

Three different comparisons were made for this study. The first comparison was between the error rates of the locomotion mode predictor that used EMG and mechanical sensors between experimental sessions. The locomotion mode predictor was trained exclusively on data collected during the first experimental session. Performance in the second experimental session is the performance of the locomotion mode predictor that is tested on data from the second experimental session. Misclassifications were categorized as either steady-state or transitional misclassifications [7]. A paired t-test was performed for both steady-state and transitional error with classification error as the response and experimental session as a fixed within subject variable. The second comparison was made between the error rates of the two aforementioned supervision strategies, i.e., the locomotion mode predictor that uses only mechanical sensors, and the GPE, between experimental sessions. A repeated measures ANOVA was performed with classification error as the response and the experimental session and supervision strategy as fixed within subject variables with interaction terms. Lastly, we compared the performance of the adapted locomotion mode predictor on the testing dataset from the second experimental session under two different conditions representing the two supervision strategies, as well as performance when perfect labels are used. A repeated measures ANOVA was performed with classification error as the response and the supervision strategy as a fixed within subject variable. Variances between groups were not homogeneous based on a Levene's Test, thus all the data were log transformed to fit the homogeneity assumption for ANOVA. Post-hoc tests (pairwise comparisons with Bonferroni corrections) were conducted on statistically significant variables of interest.

III. Results

The steady-state error of the locomotion mode predictor that used both EMG and mechanical sensors was significantly higher (p=0.04) in the second experimental session than in the first (Figure 1). The difference in transitional error between experimental sessions for this predictor was not significant (p>0.05). In both the first and second experimental sessions, the GPE had a significantly lower error rate than the predictor that used mechanical sensors only (p=0.0001) (Figure 2). Neither strategy had significantly different error rates between sessions (p>0.05).

The adapted predictor had the lowest error rate when all the labels of the added data from the second experimental session were correct (Figure 3). When the predictions of the mechanical sensors were used to label the data, the error rate of the adapted predictor was significantly higher (p=0.004). The error rate of the adapted predictor is significantly lower when the GPE supervised the data (p=0.039), and this error rate was not significantly different from its performance when perfect labels were used (p>0.05).

IV. Discussion

This preliminary study demonstrates the effects of using different supervision strategies to label data that is used to update a locomotion mode predictor. The steady-state error rate of the predictor that used EMG substantially increased when it was tested on data from the second experimental session. This result is expected because donning and doffing

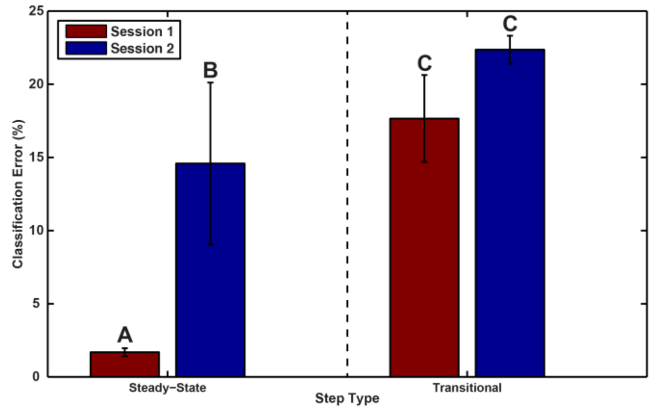

Fig. 1: Performance of the locomotion mode predictor between experimental sessions. The predictor uses the combination of EMG and mechanical sensors. Misclassifications are separated into steady-state and transitional errors. Data are averages of four subjects and error bars represent +/- 1 SEM. Within step type, groups that do not share a letter are statistically different.

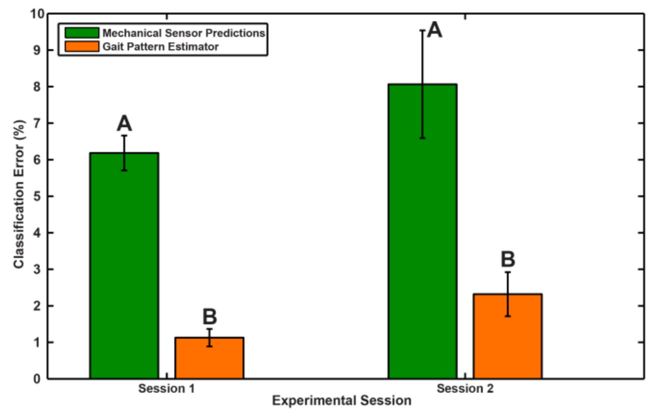

Fig. 2: Error rates of the two supervision strategies. Two different types of supervision strategies are shown, a locomotion mode predictor that uses mechanical sensors only, and a GPE. Data are averages of four subjects and error bars represent +/- 1 SEM. Groups that do not share a letter are statistically different.

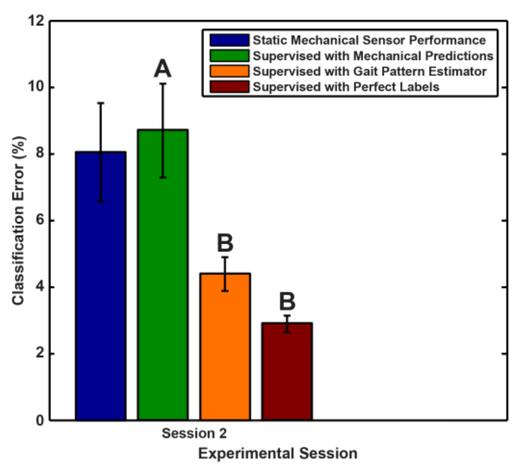

Fig. 3: Effect of different supervision strategies on adapted locomotion mode predictor error. The GPE or a locomotion mode predictor that uses mechanical sensors only were used to supervise data from the second experimental session that were added to the training set. Adapted predictor performance when all labels are correct, as well as the performance of a locomotion mode predictor that uses mechanical sensors only are shown. Data are averages of four subjects and error bars represent +/- 1 SEM. Groups that do not share a letter are statistically different.

the device would result in shifts in EMG electrode position, and subsequently signal changes that compromise performance. This highlights the critical need for adaptive strategies for EMG-based pattern recognition algorithms. Proposed myoelectric pattern recognition interfaces do not compensate for such disturbances, and the negative impact is observed in this study. Interestingly, a significant increase in error was not observed for transition steps.

The comparison between the different supervision strategies showed that there was a slight increase in error when only mechanical sensors were used to make locomotion mode predictions between sessions, though this difference was not determined to be statistically significant. This result is expected because the readings from the embedded mechanical sensors should not change substantially between sessions. Differences in error could be due to changes in the walking behavior of the subject in the second experimental session, or alignment changes.

We also showed that a GPE that estimates the locomotion mode of the user's most recent completed stride could accurately and automatically supervise data that are used to update a locomotion mode predictor. The error rate of the GPE was significantly lower than that of the predictor that used mechanical sensors in both sessions, meaning that most of the data used for updating were correctly labeled. Previous literature has demonstrated the negative impact of incorrectly labeled data on adaptation [12], so it is promising that the GPE had a low error rate. Moreover, the error rate of the GPE was not significantly different between experimental sessions (Figure 2). This means that subjects' gait patterns do not change very much between sessions, and thus a GPE could be used to supervise new data.

The error rate of the chosen supervision strategy was reflected in the error rate of the adapted locomotion mode predictor (Figure 3). Very few data were incorrectly labeled when the GPE was used, and thus the adapted predictor that used the GPE had an error rate that was not significantly different from that when perfect labels are used. When the predictions of the mechanical sensors were used, the error rate of the adapted predictor significantly increased. This highlights the importance of correctly labeled data. We would expect the error rate of our adapted predictor to be proportional to the error rate of the supervision strategy, i.e., the adapted predictor can only predict as accurately as its training data is labeled. Such findings are consistent with previous work [12], which showed that label accuracy impacts supervised pattern recognition algorithms.

The presented work focused on potential supervision strategies for adaptive locomotion mode prediction in a powered leg prosthesis. In this study, data from all steps from the second experimental session were used to update the locomotion mode predictor. Future work should investigate whether specific steps should be used while others are not included in the training dataset. This study is also limited in the small amount of recruited subjects. Future work should expand the number of subjects. Lastly, this study used batch learning to update the locomotion mode predictor. This is clearly not an automatic method for adaptation, and would be better characterized as re-training. Future work should investigate online learning paradigms where the parameters of the pattern recognition algorithm are updated sequentially with each step.

REFERENCES

[1] P. Parker, K. Englehart, and B. Hudgins, "Myoelectric signal processing for control of powered limb prostheses.," *J. Electromyogr. Kinesiol.*, vol. 16, no. 6, pp. 541–8, Dec. 2006.

[2] M. a. Holgate, J. K. Hitt, R. D. Bellman, T. G. Sugar, and K. W. Hollander, "The SPARKy (Spring Ankle with Regenerative kinetics) project: Choosing a DC motor based actuation method," *2008 2nd IEEE RAS EMBS Int. Conf. Biomed. Robot. Biomechatronics*, pp. 163–168, Oct. 2008.

[3] F. Sup, A. Bohara, and M. Goldfarb, "Design and Control of a Powered Transfemoral Prosthesis.," *Int. J. Rob. Res.*, vol. 27, no. 2, pp. 263–273, Feb. 2008.

[4] B. Lawson, H. Varol, A. Huff, E. Erdemir, and M. Goldfarb, "Control of Stair Ascent and Descent with a Powered Transfemoral Prosthesis.," *IEEE Trans. Neural Syst. Rehabil. Eng.*, no. c, pp. 1–9, Oct. 2012.

[5] H. Huang, T. Kuiken, and R. Lipschutz, "A strategy for identifying locomotion modes using surface electromyography," *IEEE Trans. Biomed. Eng.*, vol. 56, no. 1, pp. 65–73, 2009.

[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, no. 3, pp. 542–51, Mar. 2010.

[7] A. J. Young, A. M. Simon, N. P. Fey, and L. J. Hargrove, "Intent Recognition in a Powered Lower Limb Prosthesis Using Time History Information.," *Ann. Biomed. Eng.*, vol. 42, no. 3, pp. 631–641, Sep. 2013.

[8] H. Huang, F. Zhang, and L. Hargrove, "Continuous Locomotion-Mode Identification for Prosthetic Legs Based on Neuromuscular-Mechanical Fusion," *IEEE Trans. Biomed. Eng.*, vol. 58, no. 10, pp. 2867–2875, 2011.

[9] L. Hargrove, K. Englehart, and B. Hudgins, "The effect of electrode displacements on pattern recognition based myoelectric control.," *Conf. Proc. IEEE Eng. Med. Biol. Soc.*, vol. 1, pp. 2203–6, Jan. 2006.

[10] L. Hargrove, K. Englehart, and B. Hudgins, "A training strategy to reduce classification degradation due to electrode displacements in pattern recognition based myoelectric control," *Biomed. Signal Process. Control*, vol. 3, no. 2, pp. 175–180, Apr. 2008.

[11] O. Fukuda, T. Tsuji, M. Kaneko, S. Member, and A. Otsuka, "A Human-Assisting Manipulator Teleoperated by EMG Signals and Arm Motions," vol. 19, no. 2, pp. 210–222, 2003.

[12] J. W. Sensinger, B. a Lock, and T. a Kuiken, "Adaptive pattern recognition of myoelectric signals: exploration of conceptual framework and practical algorithms," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 17, no. 3, pp. 270–8, Jun. 2009.

[13] L. Du, F. Zhang, H. He, and H. Huang, "Improving the performance of a neural-machine interface for prosthetic legs using adaptive pattern classifiers.," *Conf. Proc. IEEE Eng. Med. Biol. Soc.*, vol. 2013, pp. 1571–4, Jan. 2013.

[14] B. McFadyen and D. Winter, "An Integrated Biomechanical Analysis of Normal Stair Asecent and Descent," *J. Biomech.*, vol. 21, no. 9, pp. 733–744, 1988.

[15] F. Sup, H. A. Varol, and M. Goldfarb, "Upslope walking with a powered knee and ankle prosthesis: initial results with an amputee subject.," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 19, no. 1, pp. 71–8, Feb. 2011.

[16] Y. Huang, K. B. Englehart, S. Member, B. Hudgins, and A. D. C. Chan, "A Gaussian Mixture Model Based Classification Scheme for Myoelectric Control of Powered Upper Limb Prostheses," *IEEE Trans. Biomed. Eng.*, vol. 52, no. 11, pp. 1801–1811, 2005.