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Improving the Performance of a Neural-Machine Interface for Prosthetic Legs Using Adaptive Pattern Classifiers

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Abstract—**Pattern classification has been used for design of neural-machine interface (NMI) that identifies user intent. Our previous NMI based on electromyographic (EMG) signals and intrinsic mechanical feedback has shown great promise for neural control of artificial legs. In order to make this NMI practical, however, it is desired that classification algorithms can adapt to EMG pattern variations over time, caused by various physical and physiological changes. This study aimed to develop an adaptive pattern recognition framework in the NMI to improve the robustness of NMI performance over time. Two adaptive algorithms, i.e. entropy-based adaptation and Learning From Testing Data (LIFT) adaptation, were presented and compared to the NMI with non-adaptive classifiers. Support vector machine (SVM) was selected as the basic classifier. Gradual change of EMG signals was simulated over time on EMG data collected from four transfemoral (TF) amputees. The preliminary results showed that the NMI with adaptive classifiers produced more consistent performance over time than the classifier without adaptation. The results of this preliminary study indicate the potential of using adaptive classifiers to improve the NMI reliability for neural control of powered prosthetic legs.**

I. Introduction

Lower limb amputation is one of the major causes of disability [1]. In order to restore mobility and stability of lower limb amputees, it is desired to develop bionic prosthetic legs that provide (1) active power around the prosthetic joints and (2) coordinate with user intent. Recent efforts in developing of powered artificial knee or ankle have enabled lower limb amputees to climb stairs, rising from chairs, and even running, which are difficult, if not impossible, when amputees use passive devices [2-4].

However, none of current lower limb prostheses is neurally controlled. The users must "tell" the prostheses their intent for task transition using manual approaches, which is limited in function and cumbersome-to-use. Electromyographic (EMG) signals are commonly used neural control source for artificial limbs [5-7]. Several recent studies have reported neural-machine interface (NMI) based on EMG signals for artificial legs; these NMIs were designed to identify either the intended joint motion [8-9] or task modes [2, 10]. Specifically, our group developed a NMI for identifying the user's performing task mode using a phase-dependent pattern classification strategy [10] and neuromuscular-mechanical fusion [11]. When the support vector machine (SVM)-based classifiers were applied to EMG recorded from the residual muscles of leg amputees and mechanical feedback measured from the prostheses, over 95% accuracy has been achieved to classify 6 tested locomotion modes [11].

Although the reported NMIs based on EMG signals have shown a great potential for artificial legs [10-11], the robustness of these NMIs over time has rarely been evaluated. One of the challenges in design of NMI based on EMG recordings is the gradual variation of EMGs over time, caused by physical (e.g. electrode shift and impedance change) and physiological changes (e.g. human adaption and muscle fatigue). For instance, the electrode location shifts may cause magnitude change in EMG [12-13]; muscle fatigue leads to EMG medium frequency and magnitude drift [14-15]. The gradual changes of EMG influence the NMI robustness for its application for robust prosthetic leg control. Usually, the pattern classification task is composed of two steps: training and testing. The goal of training is to collect the calibration data to build the parameters in classifier. The limited number of calibration data for training cannot accommodate to the EMG pattern variations during long-period testing. Therefore, a specific classification strategy that adapts to the changes of EMG signals as time progresses, is demanded. Several adaptive EMG pattern recognition algorithms have been reported for control of upper limb prosthesis [16-17]. For example, Sensinger *et al.* [17] compared four supervised and three unsupervised adaptation paradigms on EMG pattern recognition and concluded that monitoring the entropy value of classification decision can assist classifier adaptation to EMG variation and improve NMI robustness. However, there has been no report on design of adaptive NMI based on EMG signals for powered prosthetic leg control.

In this preliminary study, we investigated two adaptive pattern recognition algorithms in dealing with gradual EMG magnitude change in neuromuscular-mechanical fusion-based NMI designed for artificial legs. Gradual magnitude changes of EMG signals were simulated over time on data collected from four transfemoral (TF) amputees. Comparative study was conducted on the two adaptive NMIs and the NMI without using adaptive strategy. The results of this study may lead to a new design of NMI that is reliable and practical for neural control for artificial legs.

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II. METHODOLOGY

A. Data Collection and Experiments

Four subjects with unilateral TF amputations (TF01-TF04) were recruited with IRB approval. Signed consent forms were obtained from subjects. All the TF subjects participated in the experiments wearing the hydraulic passive prosthetic legs.

For all the TF subjects, the EMG signals from their residual limb muscles were collected by seven bipolar EMG electrodes embedded in a gel liner. The targeted muscles included *sartorius* (SAR), *rectus femoris* (RF), *vastus lateralis* (VL), *vastus medialis* (VM), *biceps femoris long head* (BFL), *semitendinosus* (SEM) and *biceps femoris short head* (BFS). The locations of electrodes were approximately confirmed by EMG recordings when subjects were attempting hip motions and knee extension/flexion. The ground electrode was positioned on the anterior iliac spine. A 16-channel EMG system (Motion Lab System, Boston Rouge, LA) was used to record EMG signals. The collected EMG signals were filtered by the recording system between 20 and 420 Hz with a band-pass gain 1000. Mechanical signals were measured by a six-degree-of-freedom (DOF) load cell (Bertec Corporation, Columbus, OH) mounted on the prosthetic pylon. Both EMG and load cell measurements were sampled as 1000 Hz and synchronized as well.

Five locomotion modes and eight mode transitions were investigated. The locomotion modes were level-ground walking (W), stair ascent (SA), stair descent (SD), ramp ascent (RA) and ramp descent (RD). The mode transitions included W→SA, W→SD, W→RA, W→RD, SA→W, SD→W, RA→W and RD→W. The experiment consisted of two parts: training and testing. The calibration data used to build the classifier were collected during training. In the testing part, subjects began with level-ground walking, ascended the stair/ramp, turned 180 degrees, and walked back to the initial position for one testing trial. Ten testing trials were conducted for each subject and rest periods were allowed during the experiments.

B. Feature Extraction and Pattern Recognition

Based on neuromuscular-mechanical fusion strategy reported in our previous study [10], the EMG and mechanical signals were segmented into sliding window 160 ms in length and overlapped at 20 ms intervals. Four commonly-used time-domain features (i.e., mean absolute value, waveform length, number of zero-crossing, and number of slope sign changes) were extracted from each EMG channel [5]. For the mechanical loads, the maximum, minimum and mean values were selected as the features. Then the fused feature vectors were sent into a phase-dependent classifier associated with each gait phase to identify the locomotion mode. In this study, a multiclass SVM [18] with "one-against-all" structure and radial basis function kernel function was used as the basic classifier.

C. Adaptive Classification Algorithms

In this study, two adaptive algorithms: entropy-based algorithm [17] and Learning From Testing Data (LIFT) [19] algorithm are introduced in the following part.

- *Entropy-based Adaptation*

Entropy [17], which is a measurement of confidence for classification decisions, can be defined as

$$E(n) = -\sum_{k=1}^{K} p_k(n)\ln(p_k(n)) \qquad (1)$$

where, $p_k(n)$ is the probability of the n*th* decision belongs to class k and K (K=5) is the total number of considered classes. A low-entropy decision is highly confident and mostly like a correct classification; a decision with high entropy value means low confidence. The entropy-based adaptive algorithm monitors the entropy of each classification decision and chooses testing data with low-entropy decisions to enlarge the training data. In this study, the data collected in the initial training session were first used as the training dataset to build the classifier. Then the classifier was used to test the data collected during the first testing trial. The data associated with the decisions of low entropy value were then added into the training dataset as the augmented data to re-train the classifier. After that, the updated classifier was applied to test the data collected from the second testing trial. This procedure was repeated until all of the testing trials were tested. To ensure the high classification accuracy, a threshold was defined and optimized to find the sufficiently low entropy value. Details on defining the threshold was described in Section II *E.*

- *Learning From Testing data (LIFT) Adaptation*

The basic concept of LIFT [19] is to recover the labels of the testing data using several binary classifiers, and enlarge the training data adaptively by the recovered data. The procedure of this algorithm is summarized as follows.

Initialization of Three Datasets

(1) Training dataset $D_{TR} = \{x_q, y_q\}, q = 1, \dots, N_{tr}$, where x_q is a feature vector, $y_q \in \{1,2,3,4,5\}$ is the label of x_q; N_{tr1} is the total number of training data samples. The initial data samples in D_{TR} were collected in the training procedure.

(2) Available testing trials $D_{TE_i}(i = 1, .., T) = \{x_p\}, p = 1, \dots, N_{te_i}$. Wherein, T is the number of testing trials (T=10); N_{te_i} is the total number of data samples in one testing trial.

(3) Recovered testing dataset D_{RE} that is empty before testing, i.e. $D_{RE} = \emptyset$.

Classifier Testing and Adaptation Procedure

(1) Set $i = 1$, i.e. the first testing trial in the experiment.

(2) Train and test a multiclass classifier: Use D_{TR} to train a five class classifier C_{MAIN}. Apply the testing dataset D_{TE_i} to C_{MAIN} and return the predicted labels y_p for testing data x_p.

(3) Formulate binary training datasets: For each class $g\ (g = 1, \dots, 5)$: Partition D_{TR} into D_{TR}^g and $\overline{D}_{TR}^g$, where $D_{TR}^g = \{\{x_k, y_k\}: \{x_k, y_k\} \in D_{TR}, y_k = g\}$ and $\overline{D}_{TR}^g = \{\{x_l, y_l\}: \{x_l, y_l\} \in D_{TR}, y_k \neq g\}$. Then label all the data samples in D_{TR}^g as class 1 and all samples in $\overline{D}_{TR}^g$ as class 2 to form a binary classification training dataset, i.e. $\widehat{D}_{TR}^g = \{\{x_k, 1\}: y_k = g\} \cup \{x_l, 2\}: y_l \neq g\}$. Therefore, there were totally five binary training datasets $\widehat{D}_{TR}^g(g = 1, \dots, 5)$.

(4) Build binary classifiers, i.e. C_{RE_g}(g=1,…or 5, and is also defined as the label of the binary classifiers) based on binary training datasets $\widehat{D}_{TR}^g(g = 1, \dots, 5)$.

(5) Apply the testing dataset D_{TE_i} to five binary classifiers $C_{RE_g}(g = 1, \dots, 5)$ and return the predicted labels

$\hat{y}_{p,g}$ (i.e. the label of p^{th} sample from the g^{th} binary classifier). The binary label $\hat{y}_{p,g}$ can be 1 or 2.

(6) Select recovery testing data: If a testing sample results in only one label out of five binary decisions as class 1, this testing sample was selected and added into the recovery testing data set D_{RE}. The label of this sample was the label of the corresponding classifier, i.e. g in C_{RE_g}.

(7) Update the training data set D_{TR} by including the new recovery testing dataset D_{RE}.

(8) Set $i = i + 1$ and $D_{RE} = \emptyset$.

(9) Repeating (2)-(8) until finishing testing D_{TE_T}.

D. The Simulation of EMG Variations

In this study, EMG signal variations were simulated to investigate the NMI performance with and without adaptation. Although there were many causes of EMG variation [20], the EMG signals change due to electrode location shifts was simulated here because it has been observed and reported in upper limb myoelectric control [12]. The position shifts of electrodes could be simulated as EMG signal magnitude changes [20]

$$y(i) = (1 \pm a) \cdot y(i) \quad (2)$$

where, $y(i)$ is the raw signal of the i^{th} channel, '$+$' means the increase of signal magnitude, '$-$' means the decrease of signal magnitude and a is the percentage of magnitude variation. An example of an EMG signal with magnitude variations is shown in Fig.1. Among all the EMG channels in the last five testing trials, b (b<=7) channels were randomly selected as candidate channels. For each candidate channel, the percentage of magnitude variations was also randomly simulated within three ranges: -10%~10%, -20%~20% and -30%~30%. For each range, the disturbance was simulated five times.

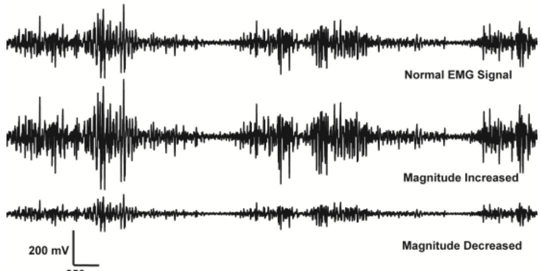

Fig. 1. An example of EMG signals with magnitude variations.

E. Parameter Selection and Evaluation

For the entropy-based adaptation, the entropy threshold should be determined before testing. The experimental data from TF04 was used to optimize this threshold. The values from 0.01 to 1.60 with an interval 0.04 were scanned and optimized to maximize the classification accuracy defined as equation (3).

Data collected from TF01-03 were used to quantify the performance of NMI with and without adaptive classifiers. The NMI performance was quantified separately for static states and transition periods [11]. Static states were defined as states when subjects continued performing one task. The transitional period was the period when subjects changed modem which included a full stride cycle and two stance phases of the prosthetic leg. For the static states, the overall classification accuracy was defined as

$$CA = \frac{\text{Number of correctly classified samples in testing data}}{\text{Total tested samples in testing data}} \times 100\% \quad (3).$$

For transitions, the number of missed transitions was computed [11]. A missed transition was identified if no correct or stable task transition was recognized within the transitional period. A stable task transition was a correct transition decision recognized for at least 18 decisions.

III. RESULTS

For the NMI performance in static states, the overall classification accuracies over time (testing trials) for TF01 derived from non-adaptive and two adaptive classifiers are shown in Fig.2. In Fig. 2 (a)-(c), the range of simulated magnitude variations are -10%~10%, -20%~20% and -30%~30%, respectively. When the variation range was small, both adaptive classifiers could maintain the performance, but the classification accuracy for the NMI without adaptation dropped over time. When the disturbance level was large, the classification accuracy decreased after the EMG variation was introduced for all three algorithms. However, the two adaptive algorithms could achieve higher accuracy

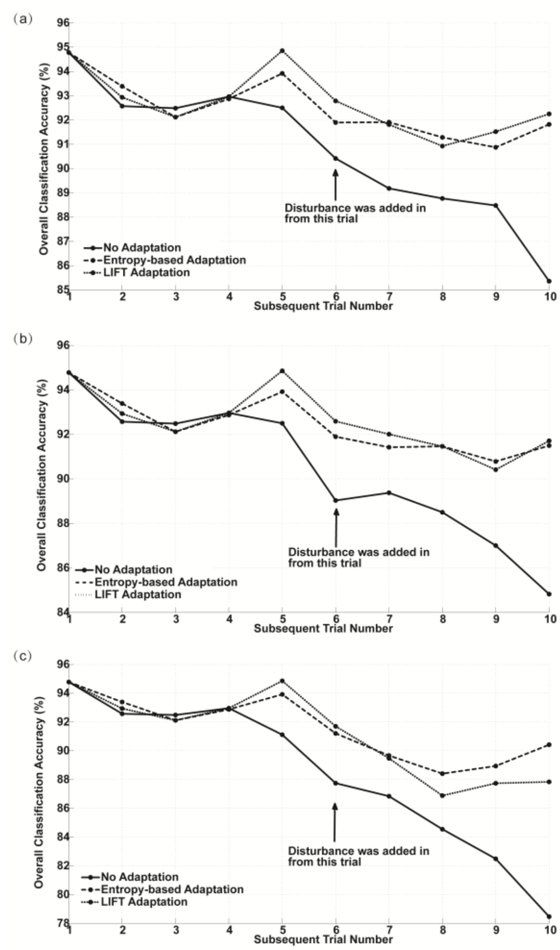

Fig. 2. Example of overall classification accuracy over time of TF01 for different magnitude variation ranges (a:±10%,b:±20%,c:±30%). Entropy-based adaptive (dashed lines) and LIFT adaptive (dotted lines) classifiers have better accuracies than non-adaptive classifier (solid lines) especially after the simulated variations are introduced from the sixth testing trial.

(6.5%~12%) than non-adaptive one. Furthermore, the average classification accuracies computed by non-adaptive and adaptive classifiers across the last three trials are represented in Fig. 3. Both adaptive algorithms can increase the classification accuracies significantly (One-way ANOVA, $p<0.05$). As for the performance in transitional period, both of the tested adaptive algorithms can reduce the number of missed transitions as compared to the non-adaptive classifier (Table I).

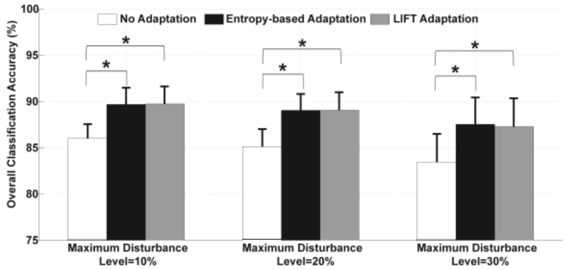

Fig. 3. The average classification accuracies (%) of the last three testing trials across TF01-TF03 for different magnitude variation ranges. The performances of non-adaptive (white bars), entropy-based adaptive (black bars) and LIFT adaptive (gray bars) classifiers are demonstrated. * means a statistically significant difference (one-way ANOVA, $p<0.05$).

TABLE I
THE NUMBER OF MISSED TRANSITIONS AMONG ALL SUBJECTS

No. of Missed Transitions	MVR: -10%~10%	MVR: -20%~20%	MVR: -30%~30%
No Adaptation	5	23	42
Entropy-based Adaptation	1	4	10
LIFT Adaptation	1	3	10

Note: The total number of investigated task transitions is 1200. MVR denotes magnitude variation range.

IV. DISCUSSIONS AND CONCLUSIONS

This study presented two adaptive pattern recognition algorithms for NMI based on neuromuscular-mechanical fusion designed for artificial legs. Gradual magnitude variations of EMG signals were simulated in data collected from TF amputees. The simulated magnitude disturbances on EMG signals would significantly influence the performance of NMI without adaptation. Both adaptive classification algorithms can cope with variations of EMG signals. When simulated magnitude variations were small, the NMI with adaptive classifiers could maintain its accuracy over time. When variations were large, the accuracy of adaptive classifiers would drop over time, but not as much as non-adaptive classifier. These results indicated that adaptive classifiers could improve the robustness of NMI against gradual EMG signal variations caused by physical reasons.

This study is preliminary. First, only simulated variations on EMG signals were considered in this study. Further study should take into account EMG disturbances happened in real experiments. Moreover, this study only considered the data collected from the subjects on passive prosthesis. Experiments should be conducted on powered devices to test the adaptive classifiers. Finally, the data in every testing trial were balanced for each class in this study, because the experiment was conducted in designed laboratory environment. Imbalanced data between classes should be tested by adaptive classifiers in future study.

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REFERENCE

[1] M. M. Lusardi and C. C. Nielsen, *Orthotics and prosthetics in rehabilitation*. Boston: Butterworth-Heinemann, 2000.

[2] S. Au, M. Berniker, and H. Herr, "Powered ankle-foot prosthesis to assist level-ground and stair-descent gaits," *Neural Netw,* vol. 21, pp. 654-66, May 2008.

[3] F. Sup, A. Bohara, and M. Goldfarb, "Design and Control of a Powered Transfemoral Prosthesis," *Int J Rob Res,* vol. 27, pp. 263-273, Feb 1 2008.

[4] 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, pp. 71-8, Feb 2011.

[5] 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.

[6] 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.

[7] M. Zecca, S. Micera, M. C. Carrozza, and P. Dario, "Control of multifunctional prosthetic hands by processing the electromyographic signal," *Crit Rev Biomed Eng,* vol. 30, pp. 459-85, 2002.

[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, pp. 144-51, Jan 2011.

[9] L. J. Hargrove, A. M. Simon, R. D. Lipschutz, S. B. Finucane, and T. A. Kuiken, "Real-time myoelectric control of knee and ankle motions for transfemoral amputees," *JAMA,* vol. 305, pp. 1542-4, Apr 20 2011.

[10] 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.

[11] H. Huang, F. Zhang, L. J. Hargrove, Z. Dou, D. R. Rogers, and K. B. Englehart, "Continuous locomotion-mode identification for prosthetic legs based on neuromuscular-mechanical fusion," *IEEE Trans Biomed Eng,* vol. 58, pp. 2867-75, Oct 2011.

[12] L. Hargrove, K. Englehart, and B. Hudgins, "A training strategy to reduce classification degradation due to electrode displacements in pattern recognition based myoelectric control," *Biomedical Signal Processing and Control,* vol. 3, pp. 175-180, Apr 2008.

[13] B. Vigreux, J. C. Cnockaert, and E. Pertuzon, "Factors influencing quantified surface EMGs," *European Journal of Applied Physiology and Occupational Physiology,* vol. 41, pp. 119-129, 1979/06/01 1979.

[14] D. Tkach, H. Huang, and T. A. Kuiken, "Study of stability of time-domain features for electromyographic pattern recognition," *J Neuroeng Rehabil,* vol. 7, p. 21, 2010.

[15] J. R. Doud and J. M. Walsh, "Muscle fatigue and muscle length interaction: effect on the EMG frequency components," *Electromyogr Clin Neurophysiol,* vol. 35, pp. 331-9, Oct 1995.

[16] O. Fukuda, T. Tsuji, M. Kaneko, and A. Otsuka, "A human-assisting manipulator teleoperated by EMG signals and arm motions," *Robotics and Automation, IEEE Transactions on,* vol. 19, pp. 210-222, 2003.

[17] 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, pp. 270-8, Jun 2009.

[18] V. N. Vapnik, *The nature of statistical learning theory*: Springer-Verlag New York, Inc., 1995.

[19] Y. Cao, H. He, and H. Huang, "LIFT: A new framework of learning from testing data for face recognition," *Neurocomputing,* vol. 74, pp. 916-929, 2011.

[20] H. Huang, F. Zhang, Y. L. Sun, and H. He, "Design of a robust EMG sensing interface for pattern classification," *J Neural Eng,* vol. 7, p. 056005, Oct 2010.