35th Annual International Conference of the IEEE EMBS
Osaka, Japan, 3 - 7 July, 2013

Motion Recognition for Simultaneous Control of Multifunctional Transradial Prostheses

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Abstract— **Electromyography (EMG) pattern-recognition based control strategies for multifunctional myoelectric prosthesis systems have been studied commonly in a controlled laboratory setting. Most previous efforts concentrated on evaluating the performance of EMG pattern-recognition algorithms in identifying one signal movement at a time. Therefore, the current motion classification methods would be limited with the difficulties in identifying the combined upper-limb motion classes that are commonly required in performing activities daily. In this paper, four improved classifier training schemes were proposed and investigated to address the difficulties mentioned above. Our preliminary results showed that three of the four proposed training schemes could improve the classification performance. The average classification accuracies of the three methods were 75.10% ± 9.71%, 76.95% ± 8.02%, and 77.56% ± 6.55% for the able-bodied subjects, and 63.38% ± 7.51%, 62.55% ± 9.06%, and 62.50% ± 9.36% for the transradial amputees, respectively. These results suggested that the proposed methods could provide better classification performance in identifying the combined motions than the current methods.**

I. Introduction

Upper-limb prostheses are very essential for transradial amputees to improve their life quality, and many studies have been focused on the development of more intuitive and natural control of prostheses. As a kind of non-invasive signal, electromyogram (EMG) is considered suitable for prosthesis control. Several appreciable results on myoelectric upper-limb prostheses have been reported [1–4], where the transradial amputees could do some upper-limb motions with prostheses according to their mind through a pattern recognition method. However, as limited by the classifier, only basic movements could be conducted and the classification accuracy would decrease obviously with the increased number of motion classes if the electrode number was fixed. Several possible improvements were suggested, one of which was to study the relationship between the EMG and the moment & angle information of the related arm joint, and process the results through the Mirrored Bilateral method [5–7]. However, this approach was limited due to some disadvantages such as the lack of enough degree of freedom (DOF). Another approach was to regard a forearm motion as the combination of hand motion and wrist motion, and improve the degree of intuition by selecting suitable features [8]. But in this way the number of motion classes was not enough.

Considering that people often conduct combined motions such as a wrist pronation together with a hand closing to hold a bottle and drink water, a simultaneous control of different joints (DOFs) for multifunctional transradial prostheses is necessary. In this paper, four new schemes for classifier training were presented, and some primary results were discussed.

II. Methods

A. Subjects and Data Acquisition

Four able-bodied subjects (marked as AB, 3 male and 1 female) and three unilateral transradial amputees (marked as TR, 2 male and 1 female) were recruited (Table I). The protocol of the research was approved by the Institutional Review Board of the Shenzhen Institutes of Advanced Technology, Chinese Academy of Science. All subjects gave written informed consent and provided permission for publication of photographs with a scientific and educational purpose.

A wireless signal acquisition system (*Delsys Inc. Boston, USA*) with 16 bipolar EMG electrodes (15 electrodes for some amputees in case of no-enough residual limb) was used to acquire EMG signals with a sampling rate of 1 kHz. For intact arms, 8 electrodes were placed on the proximal forearm, 4 on the wrist, and 4 between the proximal forearm and the wrist, as shown in Fig. 1(a). For amputated arms, 8 electrodes were placed on the proximal forearm, 4 (3 for some amputees) on

TABLE I. Demographic Data of the Subjects

Subject	Age	Gender	Amputated or Experiment Arm	Residual Forearm Length	Number of Electrodes
AB1	24	Male	Right	\	16
AB2	23	Male	Right	\	16
AB3	24	Male	Right	\	16
AB4	26	Female	Right	\	16
TR1	25	Male	Left	18 cm	15
TR2	43	Female	Right	5.5 cm (Residual Palm)	16
TR3	23	Male	Right	12.5 cm	15

*This work was supported in part by the National Natural Science Foundation of China under Grant (#61135004), the Shenzhen Governmental Basic Research Grand (#JC201005270295A), Shenzhen Public Platform for Patient-specific Orthopedic Technology and Manufacturing Service, and the Guangdong Innovation Research Team Fund for Low-cost Healthcare Technologies.

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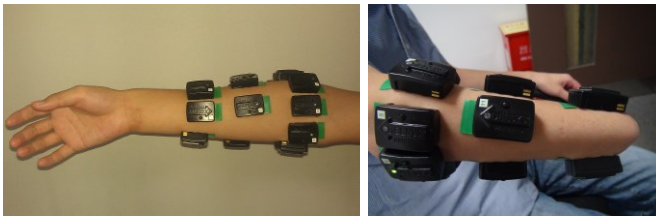


(a) (b)

Figure 1. Position of 16 bipolar EMG electrodes (15 electrodes were used for amputees in some cases) on (a) an intact arm and (b) an amputated arm.

the distal end, and 4 between the proximal forearm and the distal end, as shown in Fig. 1(b). The recorded EMG signals were filtered with a bandpass of 20-450 Hz, processed with a data acquisition card (*USB-6218, National Instruments Corp.*), and then transferred to the computer.

Each subject was asked to accomplish 25 combined forearm motions in a random order following a video instruction. EMG data were recorded in three consecutive trials, where in each trial every motion class was repeated four times (twice for training and twice for testing) and held for 4 s. There was a rest of 4 s between neighboring data acquisition of every motion class, and a rest of 5 min between neighboring trials.

25 combined forearm motion classes were specified in the experiments and each one consisted of a hand motion class and a wrist motion class, i.e. the subject did a hand motion simultaneously with a wrist motion. The five basic hand motion classes were no-movement (NM), hand-closing/-opening (HC/HO), and key-/chuck-grip (KG/CG). The five basic wrist motion classes were no-movement (NM), wrist-pronation/-supination (PRO/SUP), and wrist-flexion/-extension (WF/WE). All combined motion classes were listed in Table II.

B. *Classification Based on Pattern Recognition*

According to the previous studies [1–4, 9], four time-domain features (mean absolute value (MAV), number of zero-crossings (ZC), number of slope sign changes (SSC), and waveform length (WL)) were applied in this work for the classification calculation. Besides, the length of analysis window was 150 ms with an overlap of 100 ms.

All classifiers were obtained from training data and tested by testing data. In this work, there were an Original Single Classifier training scheme and four improved schemes. The pattern recognition algorithms for the calculation of the improved classifiers were the Linear Discriminant Analysis

TABLE II. 25 CLASSES OF COMBINED FOREARM MOTIONS

Hand Motion	**Wrist Motion**				
	NM	***PRO***	***SUP***	***WF***	***WE***
NM	NMNM	NMPRO	NMSUP	NMWF	NMWE
HC	HCNM	HCPRO	HCSUP	HCWF	HCWE
HO	HONM	HOPRO	HOSUP	HOWF	HOWE
KG	KGNM	KGPRO	KGSUP	KGWF	KGWE
CG	CGNM	CGPRO	CGSUP	CGWF	CGWE

(LDA) and the Support Vector Machine (SVM) [10]. All classifiers were built as follows:

1) *Original Single Classifier:* There were 9 basic motion classes, including no-movement (NM), hand-opening (HO), hand-closing (HC), key-grip (KG), chuck-grip (CG), wrist-pronation (PRO), wrist-supination (SUP), wrist-flexion (WF), and wrist-extension (WE). The LDA was used as the pattern recognition algorithm to make the classifier.

2) *Improved Single Classifier:* Compared with the Original Single Classifier, the number of motion classes was increased. There were 25 combined motion classes applied in this classifier, as shown in Table II.

3) *Simple Double Classifier:* One classifier was obtained based on the data of five basic hand motion classes while the other one was obtained based on the data of five basic wrist motion classes. The final result would be achieved according to the results of these two classifiers by applying the testing data from 25 combined motions.

4) *Single-Stage Parallel Double Classifier Based on Superimposed Data:* Different from the classifier in *3)*, the data used here were mixed from 25 combined motions. For instance, combined motion classes of hand-opening were HONM, HOPRO, HOSUP, HOWF and HOWE. After data processing, several data matrices could be obtained:

$$X_{HONM} = [x_{honm,1}, x_{honm,2}, \ldots, x_{honm,n}] \quad (1)$$

$$X_{HOPRO} = [x_{hopro,1}, x_{hopro,2}, \ldots, x_{hopro,n}] \quad (2)$$

$$X_{HOSUP} = [x_{ho\sup,1}, x_{ho\sup,2}, \ldots, x_{ho\sup,n}] \quad (3)$$

$$X_{HOWF} = [x_{howf,1}, x_{howf,2}, \ldots, x_{howf,n}] \quad (4)$$

$$X_{HOWE} = [x_{howe,1}, x_{howe,2}, \ldots, x_{howe,n}] \quad (5)$$

where n was the label number of electrodes. The component of each matrix was from the processed data of corresponding electrodes during training. Meanwhile, each component was also a matrix consisted of four column vectors. The method to superimpose the data was as follows:

$$X_{HO} = [X_{HONM}; X_{HOPRO;} X_{HOSUP}; X_{HOWF;} X_{HOWE}]$$
$$= \begin{bmatrix} x_{honm,1} & x_{honm,2} & \cdots & x_{honm,n} \\ x_{hopro,1} & x_{hopro,2} & \cdots & x_{hopro,n} \\ x_{ho\sup,1} & x_{ho\sup,2} & \cdots & x_{ho\sup,n} \\ x_{howf,1} & x_{howf,2} & \cdots & x_{howf,n} \\ x_{howe,1} & x_{howe,2} & \cdots & x_{howe,n} \end{bmatrix} \quad (6)$$

and therefore the combined data of hand-opening could be obtained. Similarly, the combined data of all motion classes could also be achieved and used to calculate the hand classifier and wrist classifier.

5) *Two-Stage Sequential Double Classifier:* The first stage was to train a hand (wrist) classifier with the method in *4)*. The second stage was to build and select one of the five corresponding wrist (hand) classifiers referring to the Simple Double Classifier training scheme, according to the classification results of the first stage. The final result was attained according to the results of these two stages.

In addition, the training data and testing data were both from 25 combined motion classes.

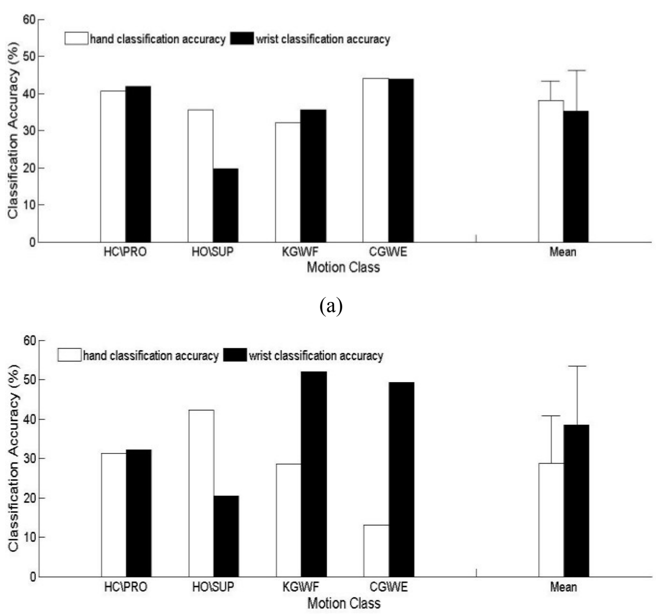
III. Results and Discussion

A. Original Single Classifier

As shown in Fig. 2, with the Original Single Classifier, a combined motion class was judged incorrectly as a hand motion class, a wrist motion class, or the no-movement motion class. The correct classification could not be achieved since the Original Single Classifier was formed from only 9 basic motion classes. For the able-bodied subjects and amputees, the average classification accuracies were less than 50% both for hand and wrist. Besides, for the amputees, the classification accuracy of hand was less than that of wrist. This classifier training scheme should be improved in order to achieve better classification performance.

B. Comparison of Different Improved Classifier Training Schemes Based on the LDA Algorithm

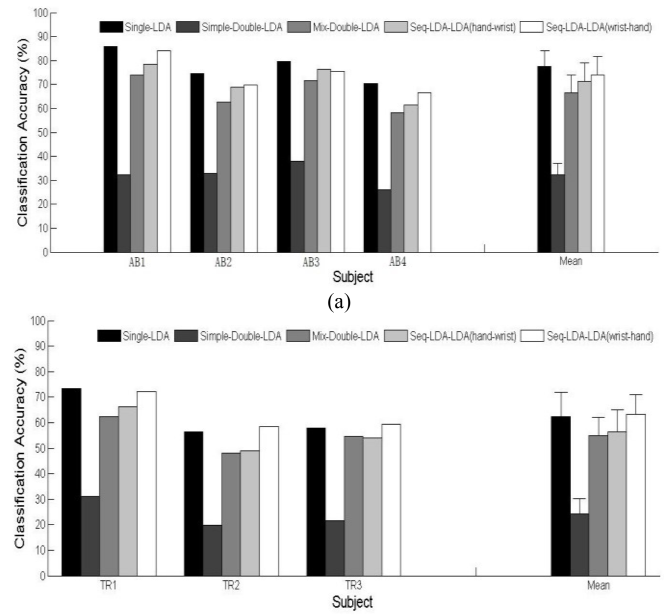
With the LDA algorithm, classification accuracies of classifiers could be obtained, as shown in Fig. 3. The Single-LDA and Seq-LDA-LDA (wrist-hand) showed the highest average accuracies for both the able-bodied subjects and the amputees. For the able-bodied subjects, the average accuracy was 77.56% ± 6.55% and 73.96% ± 7.63%, respectively. By applying the *t*-test to the significance analysis, it was found that the former scheme was better than the latter one ($p<0.01$). For the amputees, the difference was insignificant ($p>0.05$), and the average accuracy was 62.50% ± 9.36% and 63.38% ± 7.51%, respectively. Meanwhile, the Simple-Double-LDA showed the lowest average accuracy of 32.26% ± 4.93% for the able-bodied subjects and 24.13% ± 6.07% for the amputees. In addition, its difference from all other classifiers' average accuracy was significant ($p<0.01$).



(a)

(b)

Figure 2. Hand and wrist classification accuracies using the testing data of the combined motion classes for (a) the able-bodied subjects and (b) the amputees.The pair of hand and wirst histogram was random and no-movent motion class was ignored.



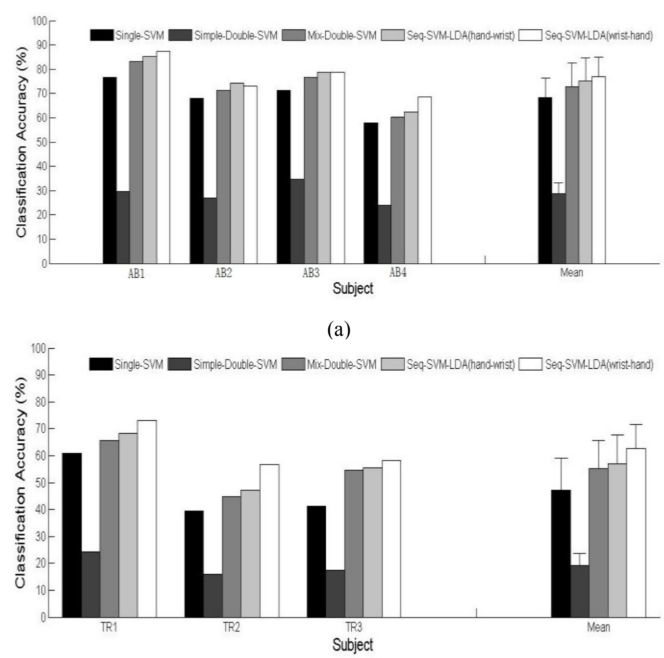
(a)

(b)

Figure 3. Classification accuracies of different schemes based on the LDA algorithmfor (a) the able-bodied subjects, and (b) the amputees.

C. Comparison of Different Improved Classifier Training Schemes Based on the SVM Algorithm

Similar as the results of section B, the Simple-Double-SVM showed the lowest average accuracy of 28.80% ± 4.52% for the able-bodied subjects and 19.18% ± 4.54% for the amputees, as shown in Fig. 4. Besides, in comparison with all other classifiers' average accuracy, the difference was significant ($p<0.01$). The best schemes were the Seq-SVM-LDA (hand-wrist) and the Seq-SVM-LDA (wrist-hand).



(a)

(b)

Figure 4. Classification accuracies of different schemes based on the SVM algorithm for (a) the able-bodied subjects, and (b) the amputees.

D. Final Result

In summary, improved training schemes were selected and compared, as shown in Fig. 5. For the able-bodied subjects, the classification algorithm would have a greater impact on the classification accuracy ($p<0.01$) than the order of hand and wrist in two stages, according to the Two-Stage Sequential Double Classifier training scheme. However, for the amputees, the result was completely opposite. The possible reason was that for the amputees, more information of the wrist motion in the residual limbs was reserved than that of the hand motion, but for the able-bodied subjects, most information of both hand motion and wrist motion in the intact limb were retained.

Furthermore, the best schemes for the able-bodied subjects and for the amputees were different. For the able-bodied subjects, the Seq-SVM-LDA (H-W), Seq-SVM-LDA (W-H), and Single-LDA showed the highest classification accuracies of 75.10% ± 9.71%, 76.95% ± 8.02%, and 77.56% ± 6.55%, respectively, and for the amputees, the Seq-LDA-LDA (W-H), Seq-SVM-LDA (W-H), and Single-LDA showed the highest classification accuracies of 63.38% ± 7.51%, 62.55% ± 9.06%, and 62.50% ± 9.36%, respectively. There was no significant difference among these three schemes ($p>0.05$) both for the able-bodied subjects and for the amputees.

Based on the above results, it could be concluded that the Improved Single Classifier training scheme and the Two-Stage Sequential Double Classifier training scheme had the best performance among the schemes discussed in this work, and might overcome the disadvantages of the Original Single Classifier.

Future work would focus on the improvement of the classification accuracy by selecting new features or making new schemes.

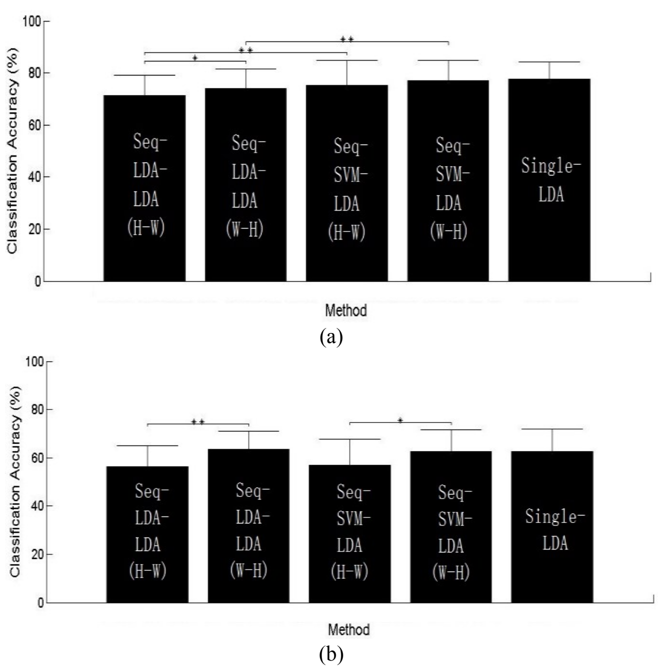


Figure 5. Comparison of several main schemes for (a) the able-bodied subjects and (b) the amputees, where * means $p<0.05$, ** means $p<0.01$.

APPENDIX

TABLE III. SEVERAL ABBREVIATIONS

Abbreviation	Full Name
Single-LDA	Improved Single Classifier using LDA
Simple-Double-LDA	Simple Double Classifier using LDA
Mix-Double-LDA	Single-Stage Double Classifier Based on superimposed Data using LDA
Seq-LDA-LDA (wrist-hand)/(W-H)	Two-Stage Sequential Double Classifier which applying the LDA to the wrist classification in the first stage and then LDA to the hand classification in the second stage
Seq-SVM-LDA (hand-wrist)/(H-W)	Two-Stage Sequential Double Classifier which applying the SVM to the hand classification in the first stage and then LDA to the wrist classification in the second stage

ACKNOWLEDGMENT

The authors would like to thank the members of Neural Engineering Center, Institute of Biomedical and Health Engineering, Shenzhen Institutes of Advance Technology, Chinese Academy of Sciences, for their assistance in the experiments of this research.

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