Interface Prostheses with Classifier-Feedback based User Training

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Abstract—It is evident that user training significantly affects performance of pattern-recognition based myoelectric prosthetic device control. Despite plausible classification accuracy on off-line datasets, online accuracy usually suffers from the changes in physiological conditions and electrode displacement. The user ability in generating consistent EMG patterns can be enhanced via proper user training strategies in order to improve online performance. This study proposes a clustering-feedback strategy that provides real-time feedback to users by means of a visualised online EMG signal input as well as the centroids of the training samples, whose dimensionality is reduced to minimal number by dimension reduction. Clustering-feedback provides a criterion that guides users to adjust motion gestures and muscle contraction forces intentionally. The experiment results have demonstrated that hand motion recognition accuracy increases steadily along the progress of the clustering-feedback based user training, while conventional classifier-feedback methods, i.e. label-feedback, hardly achieve any improvement. The result concludes that the use of proper classifier-feedback can accelerate the process of user training, and implies prosperous future for the amputees with limited or no experience in pattern-recognition based prosthetic device manipulation.

Index Terms—User Training, Classifier-Feedback, Human-machine System, Prostheses, Electromyography, Pattern Recognition, Hand Motion

I. INTRODUCTION

Electromyographic (EMG) signal is the electrical manifestation of the activity of muscle fibres [1]. EMG signals can be decoded into control commands for smart prosthetic devices, using either proportional or pattern recognition (PR) methods. With the increase of degrees of freedom (DoFs) of prosthetic devices, conventional proportional control faces extreme difficulty in coping with simultaneous and collaborative control. With the increase of degrees of freedom (DoFs), conventional proportional control faces extreme difficulty in simultaneous and collaborative control. Over the past decade, PR approaches are preferred in both industry and academia for its convenience in solving the typical problem with multiple inputs of EMG signals and multiple outputs of DoFs based prosthetic devices. However, the changes of physiological and physical conditions, like muscle fatigue, limb posture and electrode displacement, severely impede the advancement of pattern recognition in user intention prediction [2]–[6].

Furthermore, pattern consistency in training and testing phases remains a heavy burden for prosthesis users to follow.

User adaptation is defined as the cognitive and behavioural efforts performed by users to cope with significant information technology events that occur in their work environment [7]. User adaptation plays a critical role in EMG based motion recognition. The significance of user training has been spotlighted in enhancing the performance of prosthetic control [8]–[11].

More studies, however, still concentrates on the design of adaptive classification system by means of either unsupervised or supervised approaches. Unsupervised adaptive classifiers can reduce the impact of slow pattern deviation, while facing the risk of catastrophic failure because incorrect labels are used for adaptation. In contrast, supervised adaptation is more robust, though somewhat cumbersome due to explicit user-interaction [12]. Khezri, *et al.* [13] proposed a supervised adaptive neuro-fuzzy inference system integrated with a real-time trainer unit that received teacher reference signals from the operator and updated the state of pattern recognition unit. Pilarski, *et al.* [14] proposed a general value functions (GVFs)-based reinforcement learning method to implement real-time prediction learning during myoelectric interaction with a multi-joint robot arm, in which sensory information, including EMG signals and the states of the robotic arm, were used to update a set of GVFs online. Liu [15] proposed an unsupervised domain adaptation framework that used the testing data to update the trained models in an off-line setup. Amsüss, *et al.* [16] conceived a self-correcting PR system via taking advantages of an artificial neural network to evaluate the confidence of the classification output and removed misclassifications. Chen *et al.* [17] proposed a self-enhancing classification method based on linear discriminate analysis (LDA) and quadratic discriminant analysis. Moreover, Sensinger *et al.* [18] and Zhang *et al.* [19] compared a variety of adaptive algorithms in EMG based motion classification and achieved better performance than non-adaptive ones. However, it remains to be seen whether the algorithms can also be efficiently used in online situation with great uncertainties. Moreover, these studies tended to consider users' effort as a negative factor and ignored user adaptation towards a PR-based prosthetic system.

A recent study disclosed a significant phenomenon about user adaptation in long-term, open-loop myoelectric training [9]. With an offline recorded EMG dataset over 11 consecutive days from both able-bodied subjects and amputees, they trained a classifier from one day and tested on data

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from the following day. The classification error decreased exponentially until four to nine days. The result indicates that the relative changes in EMG signal features over time become progressively smaller, and implies the importance of user adaptation characteristics in myoelectric control applications.

Recent years, co-adaptive learning systems have been proved to be effective in the context of brain-computer systems [20], [21]. Inspired from this, Hahne *et al* [12] firstly demonstrated a significant work to implement EMG-based 2-D proportional control based on a co-adaptive closed-loop real-time learning scheme. The study highlighted that the performance gain from the interaction between two concurrent learners: human and machine. With an adaptive learning algorithm, however, the learning speed of the human is still unclear, and it is hard to distinguish the contribution of user adaptation from system adaptation. The current study aims to evaluate humans' learning ability in generating consistent EMG patterns towards a PR-based myoelectric control via the strategy of classifier-feedback based user training.

The remainder of this paper is organised as follows. Section II introduces the classifier-feedback in the context of human-machine system. Section III-A describes a classifier-feedback solution of a real-time hand motion recognition system. Section III-B describes the experimental methodology. Section IV and V analyse and discuss the experimental results. Section VI concludes the study and presents future works in the end.

II. CLASSIFIER-FEEDBACK

The learning procedure of a human-machine interface (HMI) involves two learners: human and machine. Neither aspect should be ignored for improving the performance of HMIs [12]. On the one hand, the human who generates unlabelled bio-signal samples, is able to change the signal according to his/her intention. However, the classification output might mismatch users' intention because of two primary reasons: 1) the original bio-signals are corrupted with noise before being fed to a classifier; 2) ambiguity remains in the transformation from user intention to bio-signals. For example, when generating the motion of "fine pinch", users can either extend or flex the resting fingers, which may result in two patterns of EMG signal but with the same intention. User training is to unify potentially changeable motions under the similar user intention. The user training in this study is different from algorithm training, it is referred to a cognitive learning process of users to enhance ones' skill in generating stable bio-signals, herein EMG signals, and avoid inconsistency between bio-signals and its correspondingly represented intention. On the other hand, the classifier, as a part of the machine in PR-related human-machine systems, learns knowledge through algorithm/system training to predict user intention through decoding measured bio-signals. The discussion of user training and system training can be also found in [22].

As demonstrated in Fig. 1, classification output $\hat{l}$ is considered as the feedback for both the classifier and the human perception system to implement adaptive classifier and user adaptation exploitation. The current study diverts the focus from adaptive classifier design to user adaptation exploitation

Fig. 1: The diagram for a generalised PR-based myoelectric prosthetic control system. The central nervous system and peripheral nervous system determine users' effort in muscular control. The classifier input is the measured EMG signal $v(t)$ contaminated by the noise $n(t)$. $x(t)$ is the desired EMG signal. Classification output $\hat{l}$ is the estimated intention. Meanwhile, $\hat{l}$ is adopted as the feedback signal to the central nervous system and the classifier.

by utilising the feedback information. An additional feedback path is developed to deliver classifier-related information to users in real-time. The path accordingly is termed as classifier-feedback in this study. Classifier-feedback allows users to learn from their mistakes and accelerates users' adaptation. In this study, two types of classifier-feedback are investigated: label-feedback and clustering-feedback. Label-feedback is a typical classifier-feedback method, which provides users with discrete class labels from the classifier. Depending on the class label, users can identify the occurrence of misclassification. However, with limited information in label-feedback, even when a misclassified output is identified, users are not sure how to adjust themselves. Therefore, this study proposes a novel classifier-feedback approach: clustering-feedback. In addition to the class label, it provides users with a visualised online EMG signal input as well as the centroids of the training samples. Fig. 2 demonstrates an instance of clustering-feedback map for hand motion recognition, where a clear trajectory is displayed, reflecting the hand motion transformation from rest to wrist flexion. Given the clustering-feedback map, users can accordingly shorten the distance between the intended centroid and the input point with their own strategies, to achieve the intended classification output.

Classifier-feedback is different from motion feedback in prosthetic manipulation. The sensory information of motion feedback is prostheses' states, such as the torque and the angle of joints. In contrast, the source of classifier-feedback is from the classifier itself before being the movements of prostheses. In this study, classifier-feedback is a type of visual feedback, while motion feedback can be vibrotactile, electrotactile feedback via stimulation on the skin as well [23]–[25]. In addition, the classifier-feedback in this study is for the purpose of assisting user training for PR-based prosthetic device control and it is not a necessary module in practical prosthetic control.

Fig. 2: An instance of clustering-feedback map. Nine solid dots with different colours are the centroid representations of nine classes of hand motions (1 hand at rest, 2 hand open, 3 hand close, 4 index finger point, 5 fine pinch, 6 wrist flexion, 7 wrist extension, 8 supination, 9 pronation). The black solid dot is the current input sample point, and the following trial of small dots are the previous input samples. The number under each solid dot is the class label. All the mentioned elements compose the visual clustering-feedback map.

Fig. 3: The difference of classifier feedback and motion feedback in the context of PR-based prosthetic device manipulation. C1 represents the motion feedback that obtains feedback information directly from the prosthetic devices, while C2 indicates classifier-feedback that acquires feedback information from the classifier algorithm.

III. METHODS

A. Online EMG based Hand Motion Recognition

To verify the effectiveness of clustering-feedback in user training, this study proposes an online EMG pattern recognition solution for hand motion recognition. Surface EMG (sEMG) signal is captured by the customised device, published in [26]. It consists of 16 bi-polar sEMG channels with 3000 gain, 1 kHz sampling frequency and 12 bits ADC resolution. sEMG signals are restricted between 10 Hz and 500 Hz by a hardware based band pass filter, and the power line noise is filtered via a hardware based notch filter and a software based comb filter.

Four stable time domain features [3], including Mean Absolute Value, Zero Crossings, Slope Sign Changes and Waveform Length and 4th-order autoregressive coefficients feature were employed in this study. Feature normalisation was applied on these features in real time according to the historical minimum and maximum values. These features have been proved to achieve decent performance in hand motion recognition [27], although more sophisticated features have been investigated in our previous study [28], [29]. Sliding windows with 300 ms

Fig. 4: The software flowchart for hand motion recognition. For a run of the software, it firstly loads the training data set to train the LDA classifier and calculate the PCA covariance matrix. The software also conducts online sEMG capturing, pre-processing, feature extraction, LDA based classification, PCA-based dimension reduction and classifier-feedback map display. Three feedback options (non-feedback, label-feedback and clustering-feedback) can be selected to meet different experimental scenarios.

length and 50 ms increments were applied to calculate feature extraction and predict user intention [30].

Classifier-feedback information was displayed on the screen with free access for users during operation. In label-feedback, estimated labels were displayed on the screen, while in clustering-feedback, the clustering-feedback map (as seen in Fig. 2) was displayed. To generate the clustering-feedback map in 2D space, the centroids of each class and the input points were dimensionally reduced by principal component analysis (PCA) without compromising the amount of information [31]. The commonly used Fisher's LDA was applied in this study to estimate users' intention from the real-time EMG inputs. Fig. 4 illustrates the software diagram of the proposed solution.

B. Experimental Protocol

Twelve able-bodied subjects [age: 32.4 ± 6.7 , weight: 64.7 ± 8.8 kg, height: 170.7 ± 7.2 cm, forearm Size: 24.2 ± 1.7 cm, gender: 8 males and 4 females] were employed in the experiment. None of them had experience of PR-based myoelectric control. The subjects were randomly separated into two groups to implement two user training tests: label-feedback user training (LF-UT) test and clustering-feedback user training (CF-UT) test. Before the experiment, subjects were informed that the aim of the experiment was to acquire higher hand motion recognition accuracy during user training test, which would encourage subjects' enthusiasm and let them know the importance of their effort in the experiment.

After wearing the electrode sleeve in the approach as described in [26] and getting familiar with the hand motion recognition system, subjects started to conduct a training data set recording session. Nine images indicating nine hand motions (Rest, Open, Closed, Index Finger Pointing, Fine Pinch,

Wrist Flexion, Wrist Extension, Supination and Pronation) were displayed on the screen as cue signals to guide subjects to conduct corresponding motions. Each recording session lasted 100 seconds. During the first 10 seconds, subjects were required to ensure that every channel provided stable EMG signal via screening. The first cue signal popped up at the time point of 10 seconds. Subjects were allowed to respond to the cue signal and performed the corresponding hand motion within 5 seconds, during which the collected sEMG signals were excluded from the training dataset. In the following 5 seconds, subjects were asked to maintain the hand motion until the next cue signal was given. All cue signals would be given in a random order.

The procedure of hand motion recognition session was the same as the training dataset recording session, except that the classifier started to predict user intention after loading the training data set, instead of simply recording the data. The accuracy (acc) of a recognition session was calculated by the following equation,

$$acc = \frac{\sum_{i=1}^9 Cor_i}{9N}, \quad (1)$$

where N was the number of testing samples for each motion, and Cor_i was the number of correctly predicted samples for motion i , and $i = 1, 2, \dots, 9$. In the experiment, the value of N was 95 that can be obtained from the testing duration for each motion (5 s), the length (300 ms) and increment (50 ms) of the sliding window.

The experiment involved three types of hand motion recognition sessions: non-feedback session (NF-session), label-feedback session (LF-session) and clustering-feedback session (CF-session), in which different feedback strategies were provided. In NF-session, the subjects were blind to the predicted results during operation, while in LF or CF sessions, subjects could access the predicted classification label or the clustering-feedback map, respectively. Moreover, the experiment involved two types of tests: LF-UT test and CF-UT test. Both tests consist of 10 NF-sessions and 10 classifier-feedback (either LF or CF session) sessions. Subjects conducted NF-session and LF/CF-session alternatively, starting with NF-session. The experimental setup was to evaluate whether classifier-feedback user training could positively influence NF-based hand motion recognition accuracy. Half of subjects implemented LF-UT test, and the other half carried out CF-UT test. Fig. 5 demonstrated an experimental scenario during a CF-session in CF-UT test.

After the experiment, each subject was required to fill the Paas Cognitive Load Scale that was a typical single-item measure of total cognitive load [32]. It rates the perceived intensity of their mental effort along a 9-point scale (1 = very, very low mental effort; 9 = very, very high mental effort). The questionnaire was initially designed to investigate whether classifier-feedback would bring in more cognitive load to users.

C. Evaluation Indicators

$acc_{i,j}$ indicated the hand motion recognition accuracy of the j^{th} session of the i^{th} subject. $\overline{acc_j} = \frac{1}{6} \sum_{i=1}^6 acc_{i,j}$

Fig. 5: An experimental scenario of a clustering-feedback based hand motion recognition session, in which the subject was performing wrist flexion.

was the average accuracy of 6 subjects who conducted the same user training test. $\overline{acc} = \frac{1}{60} \sum_{j=1}^{10} \sum_{i=1}^6 acc_{i,j}$ was the overall accuracy of all sessions of 6 subjects who conducted the same user training test. To further analyse the change of accuracy during different user training phases, we defined another three average accuracies on homogeneous sessions. $acc_{initial,i} = \frac{1}{3} \sum_{j=1}^3 acc_{i,j}$ was the average accuracy of the first 3 homogeneous sessions of the i^{th} subject. $acc_{middle,i} = \frac{1}{4} \sum_{j=4}^7 acc_{i,j}$ was the average accuracy of the middle 4 homogeneous sessions of the i^{th} subject. $acc_{last,i} = \frac{1}{3} \sum_{j=8}^{10} acc_{i,j}$ was the initial accuracy of the last 3 homogeneous sessions of the i^{th} subject. For better comparison among different subjects, relative accuracy is defined. $racc_{initial,i} = 0$ was the relative accuracy of the first 3 sessions of the i^{th} subject. $racc_{middle,i} = acc_{middle,i} - acc_{initial,i}$ was the relative accuracy of the middle 4 sessions of the i^{th} subject. $racc_{last,i} = acc_{last,i} - acc_{initial,i}$ was the relative accuracy of the last 3 sessions of the i^{th} subject. Student's t-test was applied to check whether two testing groups differ significantly. Paired t-test was employed in the accuracy comparison between NF-session and classifier-feedback session, while unpaired t-test was used for the comparison between LF-session and CF-session because accuracies for the comparison were from two different groups of subjects. The sample size of the above test was 60 (6 subjects with 10 sessions) for each group. Paired t-test with 6 samples in each group was applied in the accuracy comparison between the first and the last homogeneous session to check the significance of user training in improving hand motion recognition accuracy. Unpaired t-test was applied to compare the cognitive load between CF-UT and LF-UT.

IV. RESULTS

A. The Accuracy Trend of Classifier-Feedback Sessions

The accuracy trends of LF-sessions and CF-sessions could be described by a 2-order polynomial function ($y = aj^2 + bj + c, j = 1, 2, \dots, 10$), where j indicated the j^{th} classifier-feedback session in LF-UT or CF-UT test. The least squares

(a) Clustering-feedback

(b) Label-feedback

Fig. 6: The accuracy trend of CF-sessions and LF-sessions in CF-UT test and LF-UT test, respectively.

method was applied to fit the curve. For the accuracies of CF-sessions, the fitting function was $y = -0.27j^2 + 4.49j + 68.82$ ($R^2 = 0.73$), and the highest accuracy around 85% appeared at $j = 9$ (Fig. 6(a)). It depicted that the average hand motion classification accuracy $\overline{acc}_j$ increased along the user training procedure and reached to the plateau at the ninth session. For the accuracies of LF-sessions, the fitting function was $y = 0.35j^2 - 4.20j + 86.83$ ($R^2 = 0.72$), and the lowest accuracy appeared at $j = 6$ of about 75% (Fig. 6(b)). LF-UT faced an accuracy decrease during the first 6 sessions, and then started to rise. Comparing $\overline{acc}_1$ with $\overline{acc}_{10}$, the accuracy significantly increased ($p < 0.05$) by 15% from $69.5 \pm 13.8\%$ to $84.9 \pm 5.8\%$ in CF-UT test, whereas reduced by 4.4% from $83.2 \pm 9.7\%$ to $78.8 \pm 10.3\%$ in LF-UT test. In sum, clustering-feedback user training achieved better performance than label-feedback user training in classifier-feedback based hand motion recognition via a short-term user training.

B. The Accuracy Trend of Non-feedback Sessions

The experimental results also indicated the effect of classifier-feedback user training on the accuracies of NF-

(a) Clustering-feedback

(b) Label-feedback

Fig. 7: The accuracy trend of NF-sessions in CF-UT test and LF-UT test, respectively.

sessions. The average initial accuracy ($\overline{acc}_1$) of NF-sessions was $71.8 \pm 19.8\%$ and $78.8 \pm 13.4\%$ for CF-UT test and LF-UT test, respectively. In the last session, the accuracy ($\overline{acc}_{10}$) reached to $75.3 \pm 22.9\%$ with an increase of 3.5% for CF-UT, while reduced by 7.8% to $71.0 \pm 8.8.0\%$ for LF-UT, despite that the change was not statistically significant. Two linear functions $y = 0.45x + 72.6$ and $y = -0.04x + 74.5$ were used to describe the trend, as seen in Fig. 7(a) and 7(b). The result showed that CF-UT provides positive impact on the hand motion recognition accuracy for NF-sessions, while LF-UT did not.

C. Overall Accuracy among Different Types of Sessions

Classifier-feedback based hand motion recognition could achieve higher classification accuracy than non-feedback ones, as seen in Fig. 9. In LF-UT tests, the average accuracy of NF-sessions was $74.3\% \pm 10.8\%$, while that of label-feedback sessions was $76.7\% \pm 11.7\%$, showing an improvement of 2.4% after using label-feedback, though the increase was not found to be statistically significant. In CF-UT tests, the average accuracies were $75.1\% \pm 15.0\%$ and $82.6\% \pm 19.4\%$ for

Fig. 8: The relative hand motion recognition accuracies during three training phases in LF-UT test and CF-UT test.

Fig. 9: Comparisons of the average accuracies between NF-sessions and LF-sessions in LF-UT test, NF-sessions and CF-sessions in LF-UT test, and LF-sessions and CF-sessions in LF-UT test and CF-UT test, respectively.

NF-sessions and CF-sessions, respectively, which disclosed a significant improvement by 7.5% after employing clustering-feedback in hand motion recognition ($p < 0.005$). It was also found that clustering-feedback was more effective ($p < 0.05$) than label-feedback in classifier-feedback based hand motion recognition, as seen in third comparison columns in Fig. 9. The results showed that classifier-feedback improved the performance of online hand motion recognition, and clustering-feedback outperformed label-feedback.

D. Individual Differences

The changes of hand motion recognition accuracy varied with subjects, as seen in Fig. 8. For NF-sessions in LF-UT test (Fig. 8(a)), Subject 2 and Subject 6 obtained accuracy increase both from initial phase to middle phase then to final phase, while the accuracy decreased for Subject 4 and Subject 5. Subject 2 started with an obvious accuracy increase, then faced a severe decrease, which was just opposite to Subject 1. For NF-sessions in CF-UT test (Fig. 8(b)), only two subjects (Subject 9 and Subject 11) demonstrated accuracy increase from the initial phase to the middle phase. However, from the middle phase to the final phase, most subjects obtained increased accuracy except Subject 12. For LF-sessions in the

LF-UT test, hand motion recognition accuracy of subject 1 and Subject 3 dropped from the initial phase to middle phase, then started to increase after the middle phase; Subject 5 achieved continuous but limited accuracy increase less than 3%; Subject 4 obtained a slight increase firstly but suffered from a dramatic decrease later on. For CF-sessions in CF-UT test, 3 subjects (Subject 8, 11 and 12) achieved continuous accuracy increase, with a total improvement by more than 5%; Subject 9 achieved accuracy increase by about 5% from the initial phase to the middle phase and then the accuracy kept stable; a slight accuracy reduction was observed in Subject 11, and followed by a remarkable increase about 10%; Subject 10 obtained an accuracy increase firstly and then suffered from an obvious accuracy decrease by about 8%.

V. DISCUSSION

A. Feedback in User training

Feedback based motor learning has been investigated for decades, and the presentation of the feedback information varies among studies. In [11], multi-channel myoelectric signals are displayed in conceptual training phase to emphasise the importance of performing proper muscle contraction. In [8], confusion matrix was disclosed to the subjects after a training session to promote users to generate consistent and distinguishable EMG patterns. Although it has been demonstrated that the learning procedure could happen without any external feedback, it is still believed that the learning ability can be further enhanced when proper external feedback is provided during user training [9]. Clustering-feedback map is right the external feedback in the current study, and has demonstrated positive impact.

CF-UT accelerates the accuracy increase in hand motion recognition along the training procedure. As can be seen from Fig. 6, CF-UT achieves better convergence speed towards a stable and higher hand motion recognition accuracy. In terms the trend of accuracy in CF-UT, the current study shows a similar accuracy trend as in [9], [10], although this study focuses more on short-term user training, while the others are based on daily or weekly basis. It implies that a properly selected feedback approach is very likely to achieve the goal of short-term user training, rather than the use of transcranial direct current stimulation intervention [33]. LF-UT, however, leads to an accuracy decrease until the 5th or 6th sessions, which is possibly because the lost short-term muscle memory

Fig. 10: The real-time clustering-feedback trajectory in 6th CF-session in CF-UT test of Subject 9.

encoded during training dataset recording phase, and the lack of relevant reference for motion adjustment in label-feedback.

In the context of PR-based myoelectric control, it is a hard task to introduce the phenomenon of misclassification to naive subjects. In [11], a conceptual training stage is included in user training for pattern recognition introduction. In [8], the concept is explored by the boundaries among separate movements. The current study relies on clustering-feedback map to delivery the same concept, and the boundaries among motions can be measured by the distance between the centroids. Fig. 10 demonstrates the input trajectory in the clustering-feedback map, where the transient EMG samples are included to clarify the procedure of motion transformation. Taking Fig. 10(a) as an example, the subject transfers from Motion 8 (Supination) to Motion 3 (Hand Closed) with three phases: short delay after informed with the cue signal, transient hand movement, and motion maintenance with gesture adjustment.

During motor learning tasks, directing the performer's attention to his or her own movements would disrupt the execution of automated skills and degrade skill learning [34]. Interpreting the mechanics of hand movements by visual feedback allows subjects to pay attention to an external object rather than his or her own movements [8]. Clustering-feedback map is considered as the external object in the current study. Also, clustering-feedback is informative and closely related to the motions for classification. It avoids the problem that users' attention and efforts might be more directed to addressing or responding to the feedback rather than to completing the intended task [35].

It is intuitively expected that users will need more cognitive load on CF-UT, since more elements are presented in clustering-feedback map and required to be processed in **real time**. The results of the Paas Cognitive Load Scale questionnaire, however, showed that the mean amount of perceived mental effort for CF-UT and LF-UT are 3.0 ± 1.26 and 2.83 ± 0.75 , respectively, and there was no cognitive load difference ($p > 0.5$). It might prove that the presentation of clustering-feedback is rational and acceptable, and consequently avoids the increase of users' cognitive load, especially the extraneous cognitive load.

B. User Adaptation

It is the fact that a large proportion of patients give up the use of prosthesis during the user training procedure. The use of virtual reality by means of visual feedback in user training reduces patients' mental effort and eases users' adaptation [36].

The current study discloses that proper muscle contraction force is the key fact that user adaptation functions on. It has been reported that the presence of contractions from unseen force levels leads to considerable error by greater than 32% [37]. To counteract the severe degradation, training sets comprising all force levels is recommended [38]. The current study provides a better understanding of the importance of user training in muscle-contraction-level uniformization, which is consistent with the finding in [8].

This study also discovers that users subjectively apply a similar user adaptation strategy to improve motion recognition accuracy. At the first several sessions, if a misclassified result is found in clustering-feedback map, subjects prefer to apply more muscle contraction force without adjusting the motion itself, because they believe that a correct classification output can be obtained through their efforts (i.e. more contraction force). Their efforts, however, do not bring in an expected result, and even arouse larger error between the target and actual EMG pattern. It is a very confusing phenomenon for the subjects who are exposed to PR-based hand motion recognition systems the first time. This phenomenon can be intuitively reflected by the distance between the targeted centroid and the input point in clustering-feedback map. With the presence of clustering-feedback in user training, most subjects start to properly control the force accordingly after several sessions.

An additional preliminary experiment was carried out to investigate the relationship between the exerted force and the horizontal coordinates in the clustering-feedback map. A force sensor, LUD-050-015-S*C01 (Loadstar sensors, US), was used to measure the force of fine pinch applied on it. Meanwhile, sEMG signals were also synchronously recorded. Fig. 11(a) demonstrated the fine pinch on the force sensor. A subject was employed to take the experiment via increasing the pinch force gradually until the 80% of maximum voluntary contraction (MVC) and then gradually reducing to nearly zero. Based on the analysis of the recorded data set, it was

Fig. 11: A preliminary experiment to disclose the relationship between the first PCA component of EMG signals and the force.

found that the horizontal coordinate in the clustering feedback map is closely relevant to muscle contraction force with a correlation coefficient $r > 0.90$. Fig. 11(b) demonstrates the force information as well as the first PCA component of EMG signal. This result implies that subjects could singly rely on the horizontal axis to adjust contraction force, which releases the cognitive load for users. Moreover, the vertical axis somewhat reflects the motions of wrist flexion and extension in two directions. As can be seen in Figs. 2 and 10, motion 6 (flexion) and motion 7 (extension) usually apart obviously in the vertical axis, while with the similar horizontal coordinates. The information might be utilised during user training to unify motion gestures.

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VI. CONCLUSION AND FUTURE WORK

The concept of classifier-feedback based user training was proposed method to achieve better control performance for PR-based prosthetic hand system with enhanced user ability. The proposed was evaluated by two types of classifier-feedback based user training: label-feedback and clustering-feedback. The experiment confirmed that clustering-feedback outperforms label-feedback in online hand motion recognition. Label-feedback user training did not show a rising trend in terms of recognition accuracy in non-feedback sessions, while clustering-feedback user training achieved significant improvement. Moreover, it demonstrated that clustering-feedback map contained feasible information that guided users to apply proper force and gestures on motion patterns. It indicated that user adaptation can be fully exploited towards the proposed online hand motion recognition system.

Future work has been planned as follows: a) The proposed clustering-feedback user training will be applied to amputee to evaluate its feasibility in PR-based myoelectric hand prostheses. b) The clustering-feedback map will be used to deliver

haptics information through skin stimulation instead of visual feedback, so that users potentially could achieve the sense of body ownership. c) Varying muscle contraction force will be taken in account for clustering-feedback user training.

REFERENCES

- [1] D. Farina and A. Holobar, "Human-machine interfacing by decoding the surface electromyogram," *IEEE Signal Process. Mag.*, vol. 32, no. 1, pp. 115–120, 2015.
- [2] A. Danna-Dos Santos *et al.*, "Influence of fatigue on hand muscle coordination and emg-emg coherence during three-digit grasping," *J. Neurophysiol.*, vol. 104, no. 6, pp. 3576–3587, 2010.
- [3] D. Tkach, H. Huang, and T. A. Kuiken, "Study of stability of time-domain features for electromyographic pattern recognition," *J. Neuroeng. Rehabil.*, vol. 7, no. 1, p. 1, 2010.
- [4] 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, 2008.
- [5] C. Castellini and P. van der Smagt, "Surface emg in advanced hand prosthetics," *Biol. Cybern.*, vol. 100, no. 1, pp. 35–47, 2009.
- [6] T. R. Farrell *et al.*, "A comparison of the effects of electrode implantation and targeting on pattern classification accuracy for prosthesis control," *IEEE Trans. Biomed. Eng.*, vol. 55, no. 9, pp. 2198–2211, 2008.
- [7] A. Beaudry and A. Pinsonneault, "Understanding user responses to information technology: A coping model of user adaptation," *Manag. Inf. Syst. Q.*, pp. 493–524, 2005.
- [8] M. A. Powell, R. R. Kaliki, and N. V. Thakor, "User training for pattern recognition-based myoelectric prostheses: Improving phantom limb movement consistency and distinguishability," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 22, no. 3, pp. 522–532, 2014.
- [9] J. He *et al.*, "User adaptation in long-term, open-loop myoelectric training: implications for emg pattern recognition in prosthesis control," *J. Neural Eng.*, vol. 12, no. 4, p. 046005, 2015.
- [10] R. Clingman and P. Pidcoe, "A novel myoelectric training device for upper limb prostheses," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 22, no. 4, pp. 879–885, 2014.
- [11] A. M. Simon, B. A. Lock, and K. A. Stubblefield, "Patient training for functional use of pattern recognition-controlled prostheses," *J. Prosthet. Orthot.*, vol. 24, no. 2, p. 56, 2012.
- [12] J. M. Hahne *et al.*, "Concurrent adaptation of human and machine improves simultaneous and proportional myoelectric control," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 23, no. 4, pp. 618–627, 2015.
- [13] M. Khezri and M. Jahed, "Real-time intelligent pattern recognition algorithm for surface emg signals," *Biomed. Eng. Online*, vol. 6, p. 45, 2007.
- [14] P. M. Pilarski *et al.*, "Adaptive artificial limbs a real-time approach to prediction and anticipation," *IEEE Robot. Autom. Mag.*, vol. 20, no. 1, pp. 53–64, 2013.
- [15] J. Liu *et al.*, "Reduced daily recalibration of myoelectric prosthesis classifiers based on domain adaptation," *IEEE J. Biomed. Health Inform.*, vol. 20, no. 1, pp. 166–176, 2016.
- [16] S. Amsüss *et al.*, "Self-correcting pattern recognition system of surface emg signals for upper limb prosthesis control," *IEEE Trans. Biomed. Eng.*, vol. 61, no. 4, pp. 1167–1176, 2014.
- [17] X. Chen, D. Zhang, and X. Zhu, "Application of a self-enhancing classification method to electromyography pattern recognition for multifunctional prosthesis control," *J. Neuroeng. Rehabil.*, vol. 10, no. 1, p. 1, 2013.
- [18] 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. 270–278, 2009.
- [19] Y. Zhang *et al.*, "Comparison of online adaptive learning algorithms for myoelectric hand control," in *Proc. Int. Conf. Hum. Mach. Syst.*, 2016, pp. 69–75.
- [20] C. Vidaurre *et al.*, "Toward unsupervised adaptation of lda for brain-computer interfaces," *IEEE Trans. Biomed. Eng.*, vol. 58, no. 3, pp. 587–597, 2011.
- [21] —, "Machine-learning-based coadaptive calibration for brain-computer interfaces," *Neural Comput.*, vol. 23, no. 3, pp. 791–816, 2011.
- [22] A. Fougner *et al.*, "Control of upper limb prostheses: terminology and proportional myoelectric control: a review," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 20, no. 5, pp. 663–677, 2012.

- [23] A. Blank, A. M. Okamura, and K. J. Kuchenbecker, "Identifying the role of proprioception in upper-limb prosthesis control: Studies on targeted motion," *ACM Trans. Appl. Percept.*, vol. 7, no. 3, p. 15, 2010.
- [24] A. J. Westerveld *et al.*, "Selectivity and resolution of surface electrical stimulation for grasp and release," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 20, no. 1, pp. 94–101, 2012.
- [25] M. D'Alonzo, F. Clemente, and C. Cipriani, "Vibrotactile stimulation promotes embodiment of an alien hand in amputees with phantom sensations," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. PP, no. 99, pp. 1–1, 2014.
- [26] Y. Fang *et al.*, "A multichannel surface emg system for hand motion recognition," *Int. J. Humanoid*, p. 1550011, 2015.
- [27] A. Phinyomark *et al.*, "Emg feature evaluation for improving myoelectric pattern recognition robustness," *Expert Syst. Appl.*, vol. 40, no. 12, pp. 4832–4840, 2013.
- [28] G. Ouyang *et al.*, "Dynamical characteristics of surface emg signals of hand grasps via recurrence plot," *IEEE J. Biomed. Health Inform.*, vol. 18, no. 1, pp. 257–265, 2014.
- [29] Z. Ju *et al.*, "Surface emg based hand manipulation identification via nonlinear feature extraction and classification," *IEEE Sens. J.*, vol. 13, no. 9, pp. 3302–3311, 2013.
- [30] K. Englehart and B. Hudgins, "A robust, real-time control scheme for multifunction myoelectric control," *IEEE Trans. Biomed. Eng.*, vol. 50, no. 7, pp. 848–854, 2003.
- [31] I. Jolliffe, *Principal component analysis*. Wiley Online Library, 2002.
- [32] F. G. Paas, "Training strategies for attaining transfer of problem-solving skill in statistics: A cognitive-load approach," *J. Educ. Psychol.*, vol. 84, no. 4, p. 429, 1992.
- [33] L. Pan *et al.*, "Improving myoelectric control for amputees through transcranial direct current stimulation," *IEEE Trans. Biomed. Eng.*, vol. 62, no. 8, pp. 1927–1936, 2015.
- [34] N. H. McNevin, G. Wulf, and C. Carlson, "Effects of attentional focus, self-control, and dyad training on motor learning: implications for physical rehabilitation," *Phys. Ther.*, vol. 80, no. 4, pp. 373–385, 2000.
- [35] R. A. Schmidt and R. A. Bjork, "New conceptualizations of practice: Common principles in three paradigms suggest new concepts for training," *Psychol. Sci.*, vol. 3, no. 4, pp. 207–217, 1992.
- [36] F. E. Mattioli *et al.*, "Classification of emg signals using artificial neural networks for virtual hand prosthesis control," in *Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, 2011, pp. 7254–7257.
- [37] 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. 643–659, 2011.
- [38] A. H. Al-Timemy *et al.*, "A preliminary investigation of the effect of force variation for myoelectric control of hand prosthesis," in *Proc. Annu. IEEE Int. Conf. Eng. Med. Biol. Soc.*, 2013, pp. 5758–5761.