Adaptive myoelectric pattern recognition for arm movement in different positions using advanced online sequential extreme learning machine

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***Abstract*— The performance of the myoelectric pattern recognition system sharply decreases when working in various limb positions. The issue can be solved by cumbersome training procedure that can anticipate all possible future situations. However, this procedure will sacrifice the comfort of the user. In addition, many unpredictable scenarios may be met in the future. This paper proposed a new adaptive myoelectric pattern recognition using advance online sequential extreme learning (AOS-ELM) for classification of the hand movements to five different positions. AOS-ELM is an improvement of OS-ELM that can verify the adaptation validity using entropy. The proposed adaptive MPR was able to classify eight different classes from eleven subjects by accuracy of 95.42 % using data from one position. After learning the data from whole positions, the performance of the proposed system is 86.13 %. This performance was better than the MPR that employed original OS-ELM, but it was worse than the MPR that utilized the batch classifiers. Nevertheless, the adaptation mechanism of AOS-ELM is preferred in the real-time application.**

I. INTRODUCTION

The development of the prosthetic device for the hand rehabilitation is very advanced. The researchers have been able to build a dexterous prosthetic hand that is very close to resemble the hand functionality precisely. Few commercial dexterous hands have been produced, such as iLimb [1], a bebionic hand [2] and so on. Inevitably, the achievement on the hardware side should be followed by the development of the controller side.

So-called myoelectric pattern recognition (MPR) has been developed to control the prosthetic hand. The advantage of the MPR is that it can predict user's intention to move a particular movement. The efficacy of MPR is very noticeable in the laboratory environment. However, it is facing a serious problem in the real-time application. There is the big gap between the real success of the laboratory experiments and the clinical applications. Farina*, et al.* [3] noted that the primary causes of the gap are related to the robustness of MPR in the clinical applications.

Furthermore, Ning*, et al.* [4] explained that the robust MPR can be achieved by fulfilling four conditions. Firstly, major MPRs should provide the simultaneous and proportional controller that can handle multi-degrees of freedom. Secondly, MPR has to have sensory feedback. Thirdly, MPR should adapt to the changes of EMG signal characteristic, and the last, MPR should integrate with sensor modalities to allow complex actions.

The need of adaptive MPR can be avoided by involving all possible conditions that will be possibly faced in the training session. Unfortunately, this method leads a cumbersome training process [5]. Besides, no one can guarantee that conditions can be covered at the beginning due to a variation of the user's pattern over time. The changes can be influenced by the muscle fatigue, humidity, electrode displacement, different limb positions and other potential causes. In this situation, the adaptive myoelectric pattern recognition is needed.

Some adaptive myoelectric pattern recognitions have been developed. For instance, Nishikawa*, et al.* [6] proposed supervised adaptation technique using three layers feed-forward neural networks to predict forearm motions. Chen*, et al.* [7] proposed a new adaptive MPR using self-enhanced linear and quadratic discriminant analysis (SLDA and SQDA). Furthermore, Sensinger*, et al.* [8] investigated different schemes of adaptation. They suggested that the supervised adaptation mechanism should be considered to be applied in a clinically feasible pattern recognition system. Different from previous approaches that used a batch machine learning, Gijsberts*, et al.* [9] utilized an incremental machine learning as the classifier, which is called Ridge Regression with Random Fourier Features (iRFFRR). Following Gijsberts's work, Anam*, et al.* [10] proposed an adaptive MPR using online sequential extreme learning machine (OS-ELM).

OS-ELM that was used in Anam's work does not have a mechanism to reject bad training results. Whenever data comes as training package must be employed to update the classifier. In fact, the data may be corrupted by noise so that can reduce the performance of the system. To overcome this situation, in this paper, we propose a myoelectric pattern recognition using advance online sequential extreme learning machine (AOS-ELM). AOS-ELM has a mechanism to evaluate the training results by using entropy. Low entropy indicates that the output of the OS-ELM is profoundly correct. In this, the new adaptive MPR will be implemented to problem of MPR dealing with different limb position for classification of the hand movements. As discussed in [5], the different limb position highly affected the classification performance. Therefore, the adaptation is needed to tackle this situation and to avoid cumbersome training proses.

The organization of the paper is as follow. The next section presents the method proposed in this paper consisting

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of the feature extraction, dimensionality reduction, the classifier and the mechanism to update the classifier online. Afterward, the result and discussion are presented. Finally, the last section provides the conclusion.

II. METHOD

A. Adaptive myoelectric pattern recognition

The scheme of the adaptive myoelectric pattern recognition (Adaptive MPR) is presented in Fig. 1. The adaptive MPR follows the state-of-the-art of MPR that consists of an EMG collection, feature extraction, dimensionality reduction and the classification. When the user thinks that the recognition system does not classify the movement properly, the user provides the target class to the trainer unit. The trainer unit will collect the features related to the target class given by the user and then employ the target class and the features to update the classifier. The user should not provide a large data to the trainer unit. Five minutes data collection from all movements may be enough to update the classifier.

1) Data acquisition

The EMG signals were collected in [5]. Eleven (11) subjects participated in the data collection were two females and nine males, aged between 20 and 37 years of age. They were asked to perform eight movements (Fig. 2) with duration of 5 seconds for each action. Seven EMG channels were put across the circumference of the forearm using Delsys De 2.x series EMG sensors. The EMG signals were sampled and sent to the PC using A 12-bit analog-to-digital computer at a sampling frequency of 4000 Hz. Furthermore, there are five different limb position involved in the data collection, as depicted in Fig. 3.

2) Feature extraction

This proposed system extracted wavelet features from electromyography (EMG) signals using fuzzy wavelet-packet based feature [11]. The features were extracted using the overlapped segmentation methods with the window length of 200 ms and incremented every 50 ms. The fuzzy-wavelet packet yielded in 19176 samples with 113 features in each position. The data will be divided into training and testing data with an equal number. Therefore, the number of training and testing data is 9588 each.

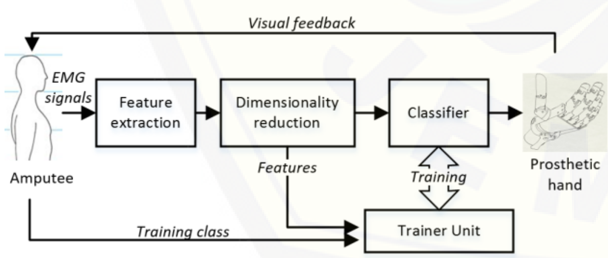

Fig. 1. The scheme of the proposed adaptive myoelectric pattern recognition

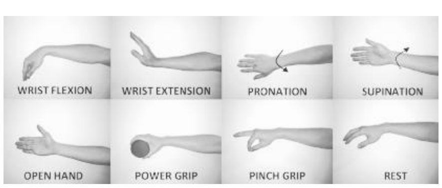

Fig. 2. Eight different hand movements considered in the experiments

Fig. 3. Five different limb positions

3) Dimensionality reduction

The proposed adaptive MPR employed a new dimensionality reduction proposed by Anam, *et al.* [12] called spectral regression extreme learning machine (SR-ELM). SR-ELM is an extension of linear discriminant analysis that can improve the class separability.

The feature extraction produced 113 features from seven channels. These features will be projected to new feature representation with a smaller dimension. Using SR-ELM, the number of features will be reduced to c-1 features where c is the number of classes. Therefore, the number of new features is seven features only.

4) Advanced online sequential extreme learning machine (AOS-ELM)

The advanced online sequential extreme learning machine (AOS-ELM) is an improvement of online sequential extreme learning machine (OS-ELM). OS-ELM is extreme learning machine that trains the weight incrementally using chunk-by-chunk data.

Assume, there are N arbitrary samples $\{(x_i, t_i)\}_{i=1}^{N} \in \mathbf{R}^{\mathbf{n}}$ x $\mathbf{R}^m$, the output of a single hidden layer feed-forward network (SLFN) with L hidden nodes is

$$f(\boldsymbol{x}_i) = \sum_{j=1}^{L} \beta_j G(\boldsymbol{a}_j, b_j, \boldsymbol{x}_i) = \boldsymbol{h}(\boldsymbol{x}_i)\boldsymbol{\beta} = \boldsymbol{t}_i, \qquad i = 1,..N \tag{1}$$

where f is an output of ELM, G is a hidden layer output, $\mathbf{h}(\mathbf{x}_i) \in \mathrm{R}^{\mathrm{NxL}}$ is a matrix of hidden layer output, and $\boldsymbol{\beta} \in \mathrm{R}^{\mathrm{Lxm}}$ is a matrix of output weight.

The training procedure of OS-ELM involves an initialization and a sequential stage. In the initialization stage, a small amount of data $\{(\boldsymbol{x}_i, \boldsymbol{t}_i)\}_{i=1}^{N_0}$is extracted from the training dataset with condition $N_0 \geq L$. Below is the procedure for the initialization stage.

a. Set the hidden node parameters randomly (weight a and bias b)
b. Compute the initial hidden layer output matrix $\mathbf{H}_0$.

$$H_0 = \begin{bmatrix} G(\boldsymbol{a}_1, b_1, \boldsymbol{x}_1) & \cdots & G(\boldsymbol{a}_L, b_L, \boldsymbol{x}_1) \\ \vdots & \cdots & \vdots \\ G(\boldsymbol{a}_1, b_1, \boldsymbol{x}_{N_0}) & \cdots & G(\boldsymbol{a}_L, b_L, \boldsymbol{x}_{N_0}) \end{bmatrix} \tag{2}$$

c. Calculate the initial output weight $\beta^{(0)}$

The goal of ELM is to minimize $\|\boldsymbol{H}_0\beta - \boldsymbol{T}_0\|$ where the target $\boldsymbol{T}_0 = [\boldsymbol{t}_1, \dots, \boldsymbol{t}_{N_0}]^T_{N_0xm}$,. The solution is $\beta^{(0)} = \boldsymbol{M}_0\boldsymbol{H}_0^T\boldsymbol{T}_0$, where $M_0 = (H_0^T H_0)^{-1}$ and $K_0 = H_0^T H_0 = M_0{}^{-1}$. k=0 is set as the initial sequent.

The second stage is the sequential learning. A new observation for (k+1)*th* chunk of data will involve:

$$N_{k+1} = \{(\mathbf{x}_i, \mathbf{t}_i)\}_{i=\left(\sum_{j=0}^{k} N_j\right)+1}^{\sum_{j=0}^{k+1} N_j}.$$

Below are some procedures involved.

a. Compute the output matrix of the partial hidden layer $\mathbf{H}_{k+1}$.

$$H_0 = \begin{bmatrix} G\left(\boldsymbol{a}_1, b_1, \boldsymbol{x}_{(\sum_{j=0}^{k} N_j)+1}\right) & \cdots & G\left(\boldsymbol{a}_L, b_L, \boldsymbol{x}_{(\sum_{j=0}^{k} N_j)+1}\right) \\ \vdots & \cdots & \vdots \\ G\left(\boldsymbol{a}_1, b_1, \boldsymbol{x}_{\sum_{j=0}^{k+1} N_j}\right) & \cdots & G\left(\boldsymbol{a}_L, b_L, \boldsymbol{x}_{\sum_{j=0}^{k+1} N_j}\right) \end{bmatrix}_{N_{k+1} x L} \quad (3)$$

b. Compute the output weight
The target is:

$$\mathbf{T}_{k+1} = \left[\mathbf{t}_{(\sum_{j=0}^{k} N_j)+1}, \ldots, \mathbf{t}_{\sum_{j=0}^{k+1} N_j} \right]^T_{N_{k+1} x m} \quad (4)$$

$$\mathbf{K}_{k+1} = \mathbf{K}_k + \mathbf{H}_{k+1}^T \mathbf{H}_{k+1} \quad (5)$$

$$\beta^{(k+1)} = \beta^{(k)} + \mathbf{K}_{k+1}^{-1} \mathbf{H}_{k+1}^T \left(\mathbf{T}_{k+1} - \mathbf{H}_{k+1} \beta^{(k)} \right) \quad (6)$$

In the recursive process, the inverse of $\mathbf{K}_{k+1}^{-1}$ should be avoided. Therefore,

$$\begin{aligned} \mathbf{K}_{k+1}^{-1} &= \left(\mathbf{K}_k + \mathbf{H}_{k+1}^T \mathbf{H}_{k+1} \right)^{-1} \\ &= \mathbf{K}^{-1} - \mathbf{K}^{-1} \mathbf{H}_{k+1}^T \left(\mathbf{I} + \mathbf{H}_{k+1} \mathbf{K}_k^{-1} \right)^{-1} \mathbf{H}_{k+1} \mathbf{K}_k^{-1} \end{aligned} \quad (7)$$

And $\mathbf{M}_{k+1} = \mathbf{K}_{k+1}^{-1}$.

So, (5) and (6) can be modified by:

$$\mathbf{M}_{k+1} = \mathbf{M}_k - \mathbf{M}_k \mathbf{H}_{k+1}^T \left(\mathbf{I} + \mathbf{H}_{k+1} \mathbf{M}_k \mathbf{H}_{k+1}^T \right)^{-1} \mathbf{H}_{k+1} \mathbf{M}_k \quad (8)$$

$$\beta^{(k+1)} = \beta^{(k)} + \mathbf{M}_{k+1} \mathbf{H}_{k+1}^T \left(\mathbf{T}_{k+1} - \mathbf{H}_{k+1} \beta^{(k)} \right) \quad (9)$$

c. Calculate the output of ELM using $\beta^{(k+1)}$ and $\beta^{(k)}$. Then compute the entropy E(k+1) and E(k) using:

$$E(n) = \sum_{j}^{N} o_j(n) \ln\left(o_j(n)\right) \quad (10)$$

where $o_j(n)$ is the output unit *j* at data *n*.

If E(k+1)>E(k) then $\beta^{(k+1)} = \beta^{(k)}$, to achieve the output with low entropy. Otherwise, $\beta^{(k+1)}$ is equal to Eq. (9).

d. Set k=k+1 and go to (a) in this phase.

III. Result and Discussion

In this paper, the proposed adaptive M-PR using AOS-ELM was applied to classify eight hand movements on various limb positions. Some experiments were conducted to examine and investigate the efficacy of the proposed method.

A. *Classification performance on various positions*

This experiment aims to test the performance of the incremental learning compared to the batch learning. The incremental learning allows the MPR to be trained using a small number of training data. This is very useful to update the MPR bit-by-bit without collecting a large number of data in the beginning.

Table I. The accuracy of the system using various classifiers

Position	OS-ELM	AOS-ELM	ELM	SVM	LDA	kNN
1	93.55	95.42	96.40	96.56	96.10	96.50
2	91.39	91.40	91.92	91.48	89.85	91.92
3	91.99	92.10	92.29	92.64	92.01	92.63
4	93.17	93.67	93.87	94.00	93.29	94.13
5	93.00	92.97	93.28	92.98	92.06	93.18
Average	**92.62**	**93.11**	**93.55**	**93.53**	**92.66**	**93.67**

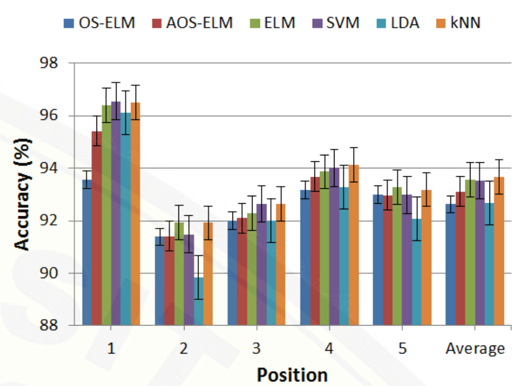

Fig. 4. The accuracy of different classifiers across five different positions

To validate the performance of the incremental learning, a comparison between the incremental learning and the batch learning should be conducted. This experiment involved two incremental learnings, OS-ELM, and AOS-ELM and four batch learnings, extreme learning machine (ELM), support vector machine (SVM), linear discriminant analysis (LDA), and k-nearest neighbor (kNN). The experimental results are described in Table I and Fig. 4.

Table I describes the accuracy of the MPR using various classifiers. In general, the batch learning performs better than the incremental learning. However, the difference is not significant. One-way analysis of variance (ANOVA) test on all classifiers results in p = 0.8736. The p value is more than 0.05. Therefore, the performance difference between the batch and incremental learning is not significant. As for the comparison between AOS-ELM and OS-ELM, Table 1 shows that AOS-ELM is better than OS-ELM. The additional procedure in AOS-ELM using entropy to evaluate the validity of the update enhances the performance of OS-ELM.

Fig. 4 provides more information regarding the performance of the system in different positions. It can be inferred that the MPR achieved better accuracy on Position 1 than other positions.

B. *Performance of the adaptation*

This experiment aims to examine the performance of the adaptive MPR using OS-ELM and AOS-ELM. To evaluate the performance of the incremental learning (OS-ELM and AOS-ELM), this section compares their performance with the batch learning methods. They are ELM, SVM, LDA, and kNN.

Five scenarios were considered for the incremental learning system. The first scenario is the system is trained and tested using EMG of position 1. In the next scenario, the trained OS-ELM and AOS-ELM will be retrained using a half of data from position 2 and tested using the rest of data of Position 2. The same procedure was repeated until the last position, which is Position 5.

As for the batch learning, in each scenario, the classifiers were trained using a half of whole data in the scenario and then tested using the rest of it. For instance, in the scenario "1+2+3", the batch classifiers were trained and tested using data from Position 1, 2 and 3. The experimental results are showed in Table 2 and Fig. 5.

Table 2 expresses the fact that involving all positions in the experiment reduces the accuracy of the system. This phenomenon occurred in the incremental and batch classifiers. This table also indicates that OS-ELM and AOS-ELM are able to learn new data from a different position even though the data was presented chunk-by-chunk. It means the adaptive MPR using OS-ELM and AOS-ELM can be a promising a solution for a robust MPR that can adapt to the new environment without conducting a cumbersome training procedure.

Unfortunately, the performance of OS-ELM and AOS-ELM is not as good as the batch classifiers when all positions are involved in the experiment. Fig. 5 explains this fact clearly. On the position 1, the incremental classifiers were able to perform as good as the batch classifiers. However, the accuracy of the incremental classifiers is not comparable to the batch classifiers on the scenario (1,2,3,4) and (1,2,3,4,5). This issue should be solved in future. Inevitably, the adaptation mechanism and the ability to work on a small number of the training data is one advantageous of the incremental.

As for AOS-ELM, Fig. 5 shows that the performance of AOS-ELM is better than OS-ELM in all scenarios. In the beginning, the accuracy of AOS-ELM and OS-ELM are

TABLE II. THE ACCURACY OF THE SYSTEM WHEN DATA WAS ADDED GRADUALLY

Position	OS-ELM	AOS-ELM	ELM	SVM	LDA	kNN
1	93.55	95.42	96.41	**96.56**	96.10	96.50
1+2	90.11	90.72	**92.89**	92.49	91.56	92.88
1+2+3	87.11	87.48	91.08	90.92	89.96	**91.24**
1+2+3+4	86.17	86.27	90.13	89.98	89.04	**90.37**
1+2+3+4+5	86.07	86.13	90.08	89.97	88.93	**90.44**

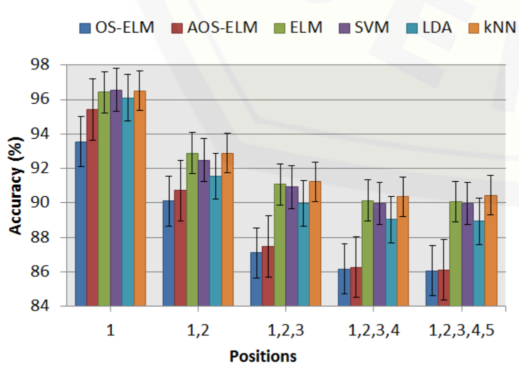

Fig. 5. The accuracy of OS-ELM and AOS-ELM when data was added gradually

95.42% and 93.55%, respectively. At last, after training for all positions, the accuracy of AOS-ELM and OS-ELM are similar, 86.13% and 86.07%, respectively.

IV. CONCLUSION

This paper proposed a new adaptive myoelectric pattern recognition using advanced online sequential extreme learning for classification of the hand movements to five different positions. In the position 1, the proposed adaptive MPR was able to classify eight different classes from eleven subjects by accuracy of 95.42 % and 93.55% using AOS-ELM and OS-ELM, respectively. After learning the data from all positions, the performance of the proposed system is 86.13 % and 86.07% using AOS-ELM and OS-ELM, respectively. This performance was worse than the MPR that utilized the batch classifiers. Nevertheless, the adaptation mechanism of AOS-ELM and OS-ELM is preferred in the real-time application.

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