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Effect of Two Adjacent Muscles of Flexor and Extensor on Finger Pinch and Hand Grip Force*

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***Abstract*— Hand grip force and motion pattern classification using bio signal such as Electromyogram (EMG) has been very important in current studies. EMG based pattern classification has gain the utmost consideration especially in the commercial prostheses. Developing an intuitive hand control with fast response both in time and space are the major challenges. These challenges are due to the lack of information gathered from adjacent muscles. The study of adjacent muscles is crucially needed as it will allow to provide optimised hand grip and motion pattern classification without redundancy in the use of muscle information. The main aim of this paper is to investigate the effect of two adjacent flexor muscles; flexor digitorum superficial (FDS) and flexor carpi radialis (FCR), two adjacent extensor muscles: extensor carpi radialis longus (ECRL) and extensor digitorum communis (EDC) providing the perspective view of individual muscle performance compared to their adjacent muscle with respect to finger pinch and hand grip force. Practical classification results prove the significance of the study, both adjacent muscles perform almost similar with approximately 95% of similarities across different subjects. The results achieved lead to the conclusion, that the use of adjacent muscles can be reduced to only single muscle channel providing an optimised data for pattern recognition or classification.**

I. INTRODUCTION

Electromyography (EMG) is one of the major components in the nerve conduction studies. EMG is one of the techniques for detecting, recording and evaluating the action potential produced by the muscles of the body. It is also known as the diagnostic procedure for the muscle health assessment and the motor neurons control. The origin of EMG action potential or pulse comes from the central nervous system (CNS) [1]. The brain signal is transferred along the nerves through the motor neurons carrying information in pulse repetition or known as frequency. The action potentials generated from this occasion is known as Motor Unit Action Potentials (MUAPs) [2], [3].

Hand prosthetic control is one of the technologies benefitting from the use of EMG such as people with amputated arm or hand. It can be used to help people with disability to use their own hand, or perhaps amputated people for daily activities. However, the main current challenge is to built a good and sophisticated prosthetic control, which could offer better hand movements and fast response.

EMG pattern classification has attracted significant interest in current research activities due to its consolidation with the human machine controls. Noticeable research has been conducted in this area and some have reported improvements in the human machine controls such as prosthetic hand [4], [5], [6], [7]. Lots of studies have reported that the real time accuracy is generally within 90% to 97%. However, despite the promising performance gained from simulated works, real clinical implementations are limited. This is the major drawback faced by many researchers, as as the process involves many channels or data from neighbouring muscles. This will create overlapping or redundancy pattern activity as adjacent muscles generate almost similar signal in response to hand grip or movement. This will lead to an impaired pattern classification performance. There are several other factors that may affect the performance of pattern classification and these have been studied by many researchers. For example, the effect of electrode location [8]. Khushaba in his work [9], analyzed two EMG channels to recognise ten hand movements, but using various muscle positions, which implicate their results especially in time.

This work is introduced to propose a new approach, which is believed to resolve some of the issues mentioned previously. Accuracy and time processing will be improved as the muscle usage is reduced. Most of the studies on EMG nowadays are liberally focused on the quality of the features extraction. These include time domain [10], [11], frequency domain [12], [13], and time-frequency domain [14], [15]. It is proved that the features are the main factors contributing towards real time application. However, the use of adjacent muscles is merely important as this will improve the clinical practicability, as well as reduce the number of channels to be used in the data collection.

In this study, the users' hand grip force and arm movements from flexor (FDS and FCR) and extensor (ECRL and EDC) muscles were recorded. These two muscle in their specific functionality was acknowledged as the neighbouring muscles.The general view of human upper forearm and their muscles are divided into four layers as shown in Figure 1, from first to fourth layers, and two compartments (anterior and posterior). Anterior compartment is separated by posterior compartment by two bones (ulna and radius), interosseous membrane, and lateral intermuscular septum [16]. FDS and FCR muscles lies between each other without any disturbance at the supreme position of the forearm, while ECRL and EDC at the bottom region. The interest is to study and explore the impracticability of using of adjacent muscles such as FDS and FCR for flexing, while ECRL and EDC for extension. The findings will be concluded in the result section.

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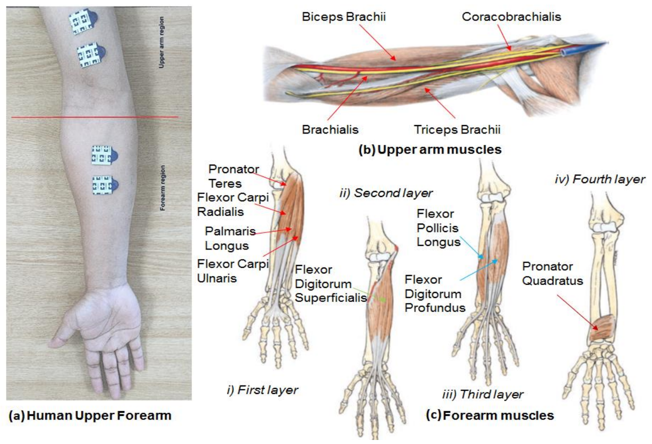

Fig. 1: (a)Human upper forearm; (b)the layers of decomposition of human upper forearm muscles

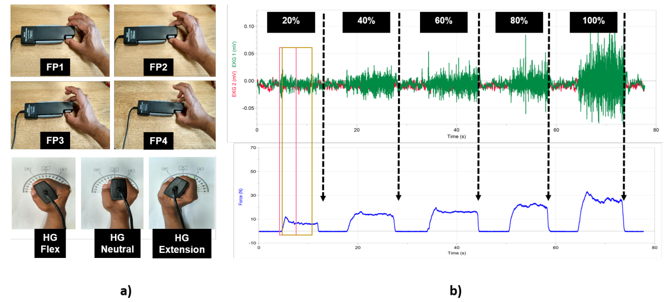

Fig. 2: (a)Seven types of hand movements used in this study: Thumb-Index finger pinch (FP1), Thumb-Middle finger pinch (FP2), Thumb-Ring finger pinch (FP3), Thumb-Little finger pinch (FP4), neutral hand grip (HGN), flexion hand grip (HGF) and extension hand grip (HGE); (b) percentages of MVC applied in the data collection, 20%, 40%, 60%, 80% and 100%

II. Methodology

Nine subjects, seven males and two females, aged between 20-40 years were chosen to perform several finger pinches and hand grasping movements. The subjects were clearly indicated as normally limbed with no muscle disorder within two years back. This study has been rewarded an ethical approval by the Ethical Committee of the University of Sheffield, United Kingdom (Department of Automatic Control and Systems Engineering). All participants observed and acknowledged the university research ethics committee approvals and gave informed consent to participate in the study.

The data has been recorded using five EMG channels from Vernier sensor with 12 bit resolution and $5V$ input. It was sampled at 2000 Hz frequency sampling. The electrodes was placed at the centre area of each muscle, and electrodes were equally space within $20mm$ distance accordance to SENIAM protocols [17]. No filter were implemented in this EMG data as the acquisition procedures was done with minimal effects of power line interference. Two types of arm movement (finger pinches and hand grip force), with a total of seven hand movements were considered in this study. These prescribed as FP1, FP2, FP3, FP4, HG Neutral, HG Flex and HG Extension. Each subject maximum voluntary contraction (MVC) for each class was recorded. They were asked to performed different percentage of MVC (20%, 40%, 60%, 80%, 100%) as shown in Figure 2.

Subject sat in front of battery powered computer with vernier Labquest Mini software. We therefore displayed the raw signals and force power on the portable monitor to help the subject to perform the hand movement with the necessary MVC contraction. Three trials of each hand movement were recorded while each motion was sustained for a period of 5 sec only with a resting period of 5 sec given between motions. The subject movements recorded signal were conducted at different days for the different muscle.

In this study, we only used the first part of MVC data that is 20% MVC. This is because, we would like to have an analysis which will give us the best understanding on muscle performance. The 20% MVC is consider as the EMG signal gain from the fresh muscle, and would be highly useful in our current case study. We investigated the variation of two muscles with respond to the feature performances. Both muscle were tested using the same technique and approach. This will acknowledge each individual muscle performance for the specific task for flexor and extensor muscles.

III. EMG Signal Analysis

A. Feature Extraction

In digital domain, EMG signal were preprocessed before the feature extraction procedure. We employed a technique which will minimise the complexity of the processing by using $5s$ epoch window for each movements. We had selected the $5s$ signal for each hand movement, and combined all the movement in specific order so that they are correctly labeled. All of the other subject EMG signal will be the same. This kind of preprocessing scheme is employed as the continuous control of prosthesis requires the feature extraction to be done in a sliding window manner [18]. We used $5s$ epoch window to make sure that no data are neglected since our acquisition protocols require the subject to perform hand movement task in $5s$ time frame. $100ms$ overlapped window increment was used for the whole signal in the feature extraction.

Feature extraction is considered as the main part of this study. It will gives the most compact and informative set of indicators, especially when dealing with the most condensed signal such as EMG. The features selected to be used in this study is the feature that able to involve with EMG based control, attained maximum class separability, showed robustness in noisy environment, and must be associated with computationally low complexity [9]. This is crucially needed as the features will have to work in real time environment, as introduce by [19], yielded better pattern classification performance in EMG.

Therefore, we employed several feature techniques as a significant method to extract useful information and to avoid redundancy. Six (6) time domain (TD) features; root mean square (RMS), integrated absolute value (IAV), zero crossing (ZC), waveform length (WL), slope sign change (SSC), auto regression 6th order ($AR6$), and six (6) frequency domain (FD) features; root square zero order moment (m_0), root square second (m_2) and fourth order moments (m_4), sparseness (S), irregularity factor (IF), and lastly waveform length ratio (WLR), were used in this study. This features was deliberately discussed and used by many researchers such as [20], [21], [22].

B. Dimensional Reduction

Principal component analysis (PCA) is a technique that compressing the high dimensional dataset into something that captures the essence of the original data. It is a generalization of Fisher's linear discriminant, a method used in statistics [23]. PCA solve the eigen problem in the dataset of sample distributions or known as features. PCA calculates the eigenvalues and eigenvectors of the covariance matrix of the features. The direction should maximise the variance and orthogonal to the features. PCA has been used widely in many pattern classification, especially in bio-engineering field and robotic controls [24], [25].

If we have an X dataset with n samples $\times$ m measurements. The dimensional mean vector (μ) and covariance matrix of X (ΣX) will be computed for the full data set. PCA will calculates the eigen decomposition of the covariance matrix of (ΣX=$X^T X$), producing the eigenvectors (W), and eigenvalues (λ), which will be sorted as the highest magnitude will be at first. Eigenvalues are important for future analysis as it will help in the deciding the number of orthogonal components, while eigenvectors will establish the connection between the new components and the original variables.

Another type of dimensional reduction technique employed in this study is one of a variant of linear discriminant analysis (LDA) known as uncorrelated linear discriminant analysis (ULDA). LDA as widely discussed in [26], [27], [28], is a linear combination of variables that best separate classes or targets. The idea of proposing ULDA by [29] in 2001, because of the limitation problems in classical LDA requires the scatter matrices to be non singular, and lack of supervision of the dataset decorrelation. This will give poor results when dealing with high sets of redundancy information of datasets. Then Ye et al. in 2004 continued with this new approach of dimensional reduction, namely ULDA, which employs the Generalized Singular Value decomposition technique to deal with undersampled data by producing the features in the transformed space are uncorrelated. The details of ULDA theories is rigorously explained in [30].

In this study, the features extracted from the TD and FD sets were computed. The content of the features were then was subjected to the dimensional reduction using PCA and ULDA. The features number was dimensionally reduced to 10 as to not overload the classifier in pattern classification. Two types of dimensional reduction was used in this study to compared the performance of stated reduction technique. These was discussed in the result section.

The reason why dimensional reduction crucially needed from this study is twofold. At first, we involved with nine subjects, producing relatively good data for training and testing. Seconds, various number of features has been used, these affect the high dimensionality problems and implicating the suitable data processing to be acceptable in ranges. This is important in any classification study.

C. EMG Muscle Pattern Classification

The approaches for EMG pattern classification in this study were inspired by [31], [32]. However, this study discovers the variability of two adjacent muscles at flexor and extensor region. The objectives are to determine the properties of individual adjacent muscle while performing the same task, and to identified a good feature vector with the classifier performance. Findings from this study, could improves the use of EMG applications such as hand prosthesis and control. This could lead towards minimising the numbers of channel used or redundancy issues in EMG data collection. LDA as a classifier, is famous when dealing with pattern classification as it helps to reduce the dimensional projection problem of features. LDA preserves as much of information or class determination while performing the reduction.

Since we acquired the EMG signal from nine subjects, the dataset from first 5 subjects was used as training, and the testing dataset will be from the last 5 subjects. This will includes the overlapping dataset for the training and testing for fifth subject. This type of dataset arrangement will be used in our pattern classification analysis to evaluate the muscle performance.

IV. Results

At first section of our analysis began by inspecting the separability of the chosen features used in this study. The EMG features extracted from the different hand movements was plotted using scatter plot by Matlab. We showed the example observation of the FCR,FDS, ECRL and EDC muscles of first subject, their features distribution across seven types of hand movements as in Figure 3 to Figure 10. The scatter plot figures was displayed to show that different types of muscle features especially in time and frequency domains were exhibiting distinctive classes of separability performance with respect to feature reduction technique applied. These figures represent TD and FD and scatter plots were constructed upon the most three discriminant feature components after the dimensionality reduction method using PCA and ULDA respectively.

In comparison as in Figures 5,6,9,and 10, the figures show an example of analysed FD features when projected with PCA and ULDA. It is very obvious that both features have larger variance when ULDA reduction is used as compared to the PCA. PCA gave poor class separability where the features look compact in the same region especially for flexor muscle. Fortunately, all muscles performing well when using ULDA, where the distribution seem to form clear class of hand movement.

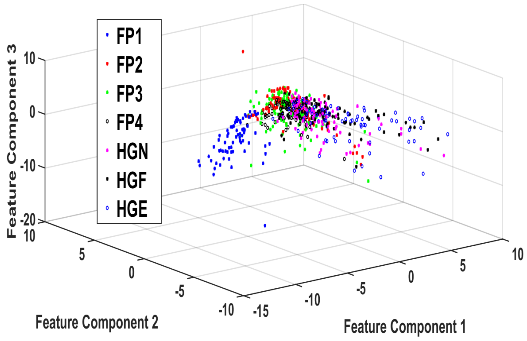

Fig. 3: FCR;TD features with PCA

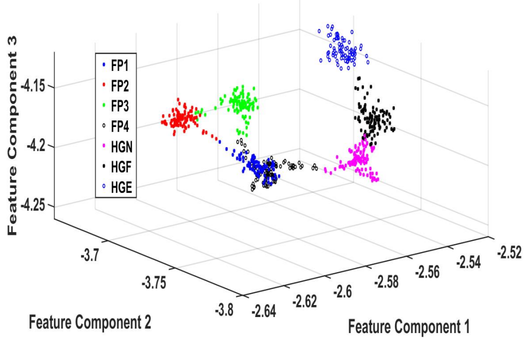

Fig. 4: FCR;TD features with ULDA

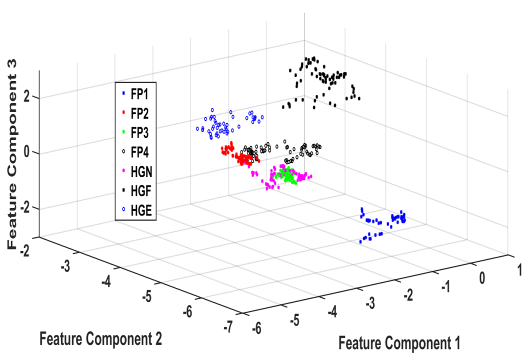

Fig. 5: ECRL;FD features with PCA

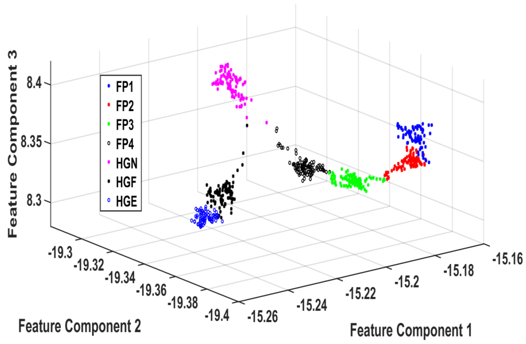

Fig. 6: ECRL;FD features with ULDA

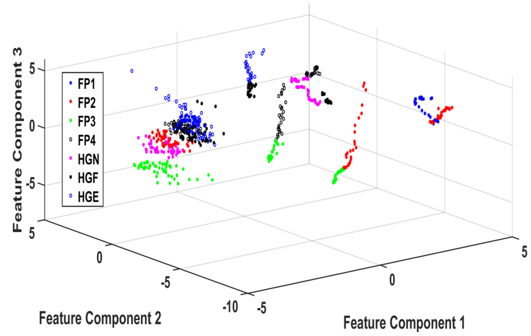

Fig. 7: FDS;FD features with PCA

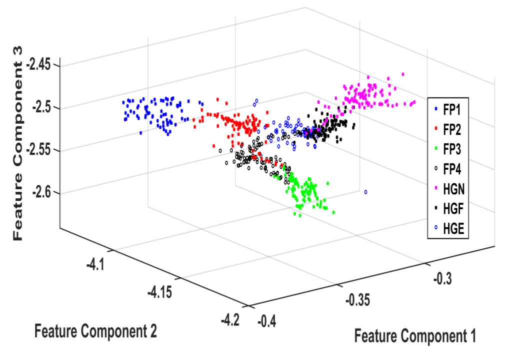

Fig. 8: FDS;FD features with ULDA

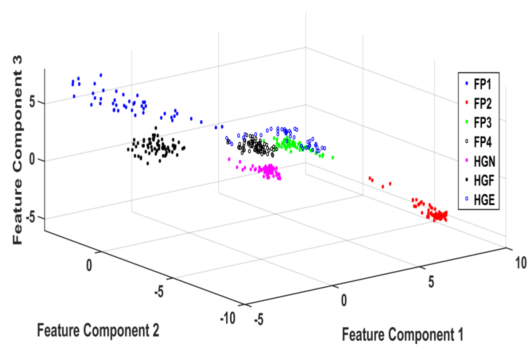

Fig. 9: EDC;TD features with PCA

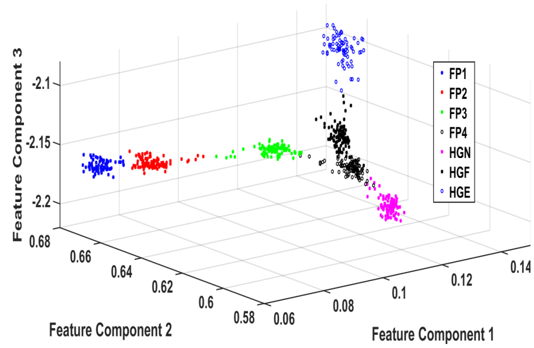

Fig. 10: EDC;TD features with ULDA

A. Pattern Classification

PCA performances in distributing the feature components are inconsistences and ULDA in both features performed very well. The scatter plot of FD feature components show a good consistency and look promising in the class separability. Each muscles showing their own characteristic within class variance in each hand movement. We examined the performances of all subjects, with training and testing, the results is concluded as tabulated in Table I.

LDA classifier architectures is proven to perform the equivalent performance as k-nearest neighbour (kNN) or multilayer perceptron neural network (MLPNN) [33]. We performed an analysis of training and testing data for the LDA classifier based on the features extracted from time and frequency domain components. There is high accuracies has been generated by both reduction methods. ULDA has shown the utmost classification performances by giving >98% average for both TD and FD training features. While for PCA, less than 92% average achieved for both TD and FD training features. The trend appeared almost the same on testing data with ULDA performing much better than PCA.

TABLE I: Training and testing data classification accuracies using PCA and ULDA for both time and frequency domain features. Training data has an excellent performance for both domain and reduction technique. However, performances of testing data are slightly low.

Analysis Domain	Muscles	Training Data (%)		Testing Data (%)	
		PCA	ULDA	PCA	ULDA
Time Domain	**FCR**	86.9432	99.5392	85.3403	90.8377
	FDS	85.4071	98.9247	87.8272	92.0157
	ECRL	98.6175	99.6928	93.7173	94.2408
	EDC	97.0814	99.3856	94.3717	99.8691
Frequency Domain	**FCR**	91.5515	97.3886	81.4136	87.9581
	FDS	88.0184	98.1567	91.0995	93.9791
	ECRL	97.3886	99.232	80.6283	84.8168
	EDC	94.7773	98.4639	81.6754	76.8325

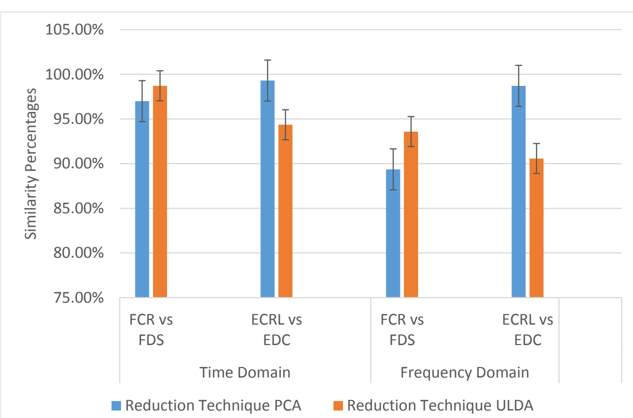

Fig. 11: Similarity performances between adjacent muscles of flexor (FDS and FCR) and extensor (ECRL and EDC) using PCA and ULDA for both time and frequency domain features. Both type of muscles has shown significant results for TD and FD.

V. Conclusion

There are reciprocal trends appeared in the performance of adjacent muscles where different reduction technique gaves unlikely performances. FCR and FDS muscles tends to perform well when ULDA are applied. Meanwhile, ECRL and EDC muscles responded very well on the PCA compared to ULDA. This has been illustrated as in Figure 11. These phenomenon however, does not affect the objective of the study, where the overall performance between muscles could be the ultimate justification. These could be seen in the bar graph, the similarity performance between both adjacent muscles are high, less than 5% gap for both flexor (FCR and FDS) and extensor (ECRL and EDC) muscles in average. These are applicable for both domains of feature analysis.

Based on these findings, this study concluded that the adjacent muscles performing almost similar at all subject (in this study contexts). It is suggested that, the number of muscles used in the data collection could be reduce as it would make the analysis better. This also would help the researchers to be efficient in the time and money spending in the data collection. However, the deservedness of reducing the number of channels or muscles used should reflect the study objectives. An early study in assessing the forearm muscles has been done and published in 2017 [34]. The study explored and evaluated the new approaches of data collection and assessing the human upper forearm muscles with force variations, as well as muscle fatigue. It is suggested that the most applicable use of muscle is to establish the inter-relation between two regions of human upper forearm. The protocol strategy set up for the study has given a good compatibility for the current research interest.

VI. Future Work

Future works are suggested to includes time-frequency domain in the classification with fatigue consideration. Fatigue study is important as it is the major contribution of the destruction of muscle capability. This is believe to be beneficial for the development of control strategy of prosthetic arm.

VII. ACKNOWLEDGEMENT

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