Correlation Analysis of Electromyogram (EMG) Signals for Multi-User Myoelectric Interfaces

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***Abstract*—An inability to adapt myoelectric interfaces to a novel user's unique style of hand motion, or even to adapt to the motion style of an opposite limb upon which the interface is trained, are important factors inhibiting the practical application of myoelectric interfaces. This is mainly attributed to the individual differences in the exhibited Electromyogram (EMG) signals generated by the muscles of different limbs. We propose in this paper a multi-user myoelectric interface which easily adapts to novel users and maintains good movement recognition performance. The main contribution is a framework for implementing style-independent feature transformation by using Canonical Correlation Analysis (CCA) in which different users' data is projected onto a unified-style space. The proposed idea is summarized into three steps, to: 1) train a myoelectric pattern classifier on the set of style-independent features extracted from multiple users using the proposed CCA-based mapping, 2) create a new set of features describing the movements of a novel user during a quick calibration session, and 3) project the novel user's features onto a lower-dimensional unified-style space with features maximally correlated with training data, and classify accordingly. The proposed method has been validated on a set of eight intact-limbed subjects, left-and-right handed, performing ten classes of bilateral synchronous fingers movements with four electrodes on each forearm. The method was able to overcome individual differences through the style-independent framework with accuracies of >83% across multiple users. Testing was also performed on a set of 10 intact-limbed and 6 below-elbow amputee subjects as they performed finger and thumb movements. The proposed framework allowed us to train the classifier on a normal subject's data while subsequently testing it on an amputee's data after calibration with a performance of >82% on average across all amputees.**

***Index Terms*—Myoelectric interface, EMG, Multi-user interface, Feature extraction**

I. Introduction

DURING the last few years, significant attention has been paid to pattern recognition based myoelectric interfaces among researchers, with applications in controlling powered prosthetics and rehabilitation systems [1], [2], [3], speech recognition [4], and in computer games [5]. The main assumption is that at a given surface electrode location, the set of variables, i.e., the extracted features, describing the Electromyogram (EMG) signals will be similar for a given pattern of muscle activation. However at the same electrode location, there are differences between patterns or modes of muscle actuation [6]. Based on these assumptions, a significant amount of research focus has been devoted to various aspects of myoelectric control such as signal preprocessing [2], feature extraction and reduction [7], [8], [9], classification and many other areas in EMG pattern recognition [10], [11]. Nonetheless, despite these advancements, there are considerable challenges in applying research findings to a clinically viable implementation [12]. Therefore, researchers are investigating the clinical usability of EMG pattern recognition through studies related to proportional myoelectric control algorithms [13], the effect of simultaneous and dynamically changing movements [14], the effect of the changes in EMG characteristics on pattern recognition accuracy [12], [15], the effect of limb position [16], [17], and electrode shift [18] on pattern recognition, just to mention few of the reasons for the lack of usability of these systems in practice [11].

The EMG signals also have a user-dependent nature [19]; a factor causing the measured signals, at the same electrodes positioning and for different users performing the same motion, to be largely different to each other. Such differences in the EMG signals are also evidenced even when a user deploys both hands for performing the same motion when using a bilateral-mirrored contractions training scheme. The aforementioned scheme was used previously to associate the EMG features from the amputated limb with the actual movements on the contralateral limb using a data glove [20], [21] or with the force produced by the contralateral limb [22]. However, such a scheme has not been used before in associating the EMG features from both hands with each other due to the inhibited differences between their corresponding EMG signals. Asymmetries between the arms related not only to muscle strength but also, among other factors, muscle geometry and tone, specific motor unit sizes, length/size of the innervating nerves and muscle innervation locations justify the variations in the EMG patterns [3]. Thus, the significant challenge of developing adaptable myoelectric interfaces which work on multiple users's hands, or even on the both hands of the same user, is what this paper focuses on. To this end we make a significant contribution to the growing research in this area by proposing a framework that allows a myoelectric controller that has been built on background data from other users, to adapt to the changes in the EMG signal characteristics from a different user with minimal efforts, making it suitable for clinical implementations and practical applications. Tommasi *et al.* [23] reported that the benefits of such a model are apparent and the perspective is that of shipping a pre-trained prosthesis which would very quickly adapt to the patient, with the effect of enabling him/her to a higher comfort and aid during daily-life activities. The proposed framework can also be applied to associate the EMG patterns of specific muscles activations related to an actual or imagined set of movements on one upper limb with that of the actual movements on the

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contralateral limb of the same user, or between different users.

Among multi-user adaptable EMG controller researchers, Orabona's *et al.* [24] model adaptation has been applied by constraining at each step a new model close to one of a set of pre-trained models stored in the memory of the prosthesis. The adaptation process attempts to modify the best matched model from a pool of stored datasets to fit a new subject; however, the process is executed in a high dimensional parameter space of the classifier, that requires a large amount of data to make the adaptation complete. Chattopadhyay *et al.* [25] also presents, using myoelectric signals, a subject independent computational feature selection framework for monitoring muscle fatigue. A search mechanism toward the vicinity of the best feature subset is guided by an objective function based on the ratio of between subject to within subject variance for the specific features, and this identifies movements across multiple subjects. However, the main limitations here include the time taken to find the best feature subset and the large variance of EMG signals, which limit the applicability of feature selection algorithms to the EMG classification problems [9], [26]. On the other hand, Matsubara and Morimoto [27] have recently proposed a projection approach based on Bilinear modeling of EMG signals that is composed of two linear factors: a user-dependent factor (style) and a motion dependent factor (content). Here performance is improved upon previous models including those based on adaptable Least-Squares Support Vector Machine (LS-SVMs) [19], [27]. However, the dimensions of the style and content variables were experimentally selected by trial-and-error. In addition, it is reported that the positioning of electrodes, the type of features extracted and their dimensionality could significantly impact the model's performance [27].

We present in this paper a novel multi-user myoelectric interface that can adapt to multiple users by adopting an approach using Canonical Correlation Analysis (CCA) [28]. CCA is a well-established method which utilizes two views of the same set of objects, in our case two feature sets extracted from the hands of different users. This describes the same set of hand motions or movements, and projects the two feature sets onto a lower-dimensional space whereby features are maximally correlated. Our proposed model is simple in terms of its computational requirements as it does not require significant training and storing of matrices of multiple user features as proposed in [24]. The model is also parameters free and provides analytical solutions, unlike the iterative model proposed by Matsubara and Morimoto [27] that requires to learn the style and content matrices in addition to the need for proper initialization of the dimensions of the style and content matrices.

The structure of this paper is organized as follows: Section II first reports a background on CCA feature projection and then describes how we fit this method to our problem. Section III describes the data collection procedure. Section IV presents the experimental results and finally, Section V presents our conclusions.

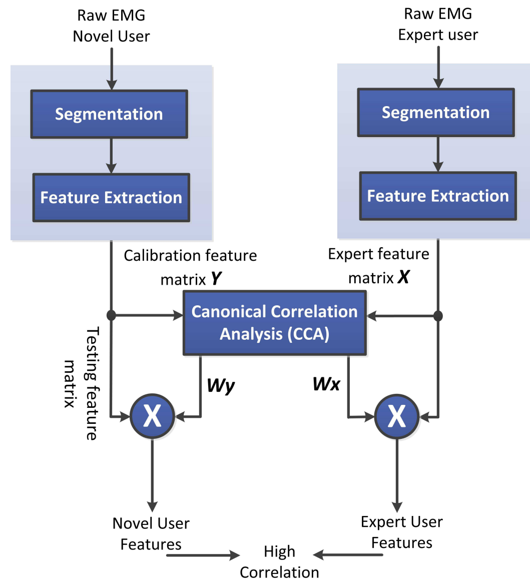


Fig. 1. Schematic diagram of the general CCA-based framework.

II. Canonical Correlation Analysis in EMG Pattern Recognition

Canonical correlation analysis [28] is commonly used for finding the correlations between two sets of multi-dimensional variables. CCA seeks a pair of linear [29] or nonlinear transformations [30], one for each set of variables, such that the data are maximally correlated in the transformed space. As a result, it can extract the intrinsic representation of the data by integrating two views of the same set of objects. CCA has been applied successfully in various applications [31]. However, to the best of the author's knowledge, the application of CCA in developing multi-user myoelectric interfaces is novel. In this section, we map the presentation of CCA theory into one that directly utilizes EMG feature matrices as shown in Fig.1.

Let us assume two different feature matrices, $X \in \mathbb{R}^{d\times n}$ collected from the expert hand, and $Y \in \mathbb{R}^{k\times n}$ collected from a new user hand in a calibration session, with the same number of samples n, and similar or different dimensions d and k respectively[1]. Both of these feature matrices are extracted from the EMG signals of two users' implementing the same hand motions, i.e., two representations of the same set of objects, with x_i and y_i corresponding to the i'th object or motion class. Our goal here is to find two projection matrices $w_x \in \mathbb{R}^d$ and $w_y \in \mathbb{R}^k$ that will maximize the following correlation coefficient:

$$\rho = \frac{w_x^T XY^T w_y}{\sqrt{((w_x^T XX^T w_x)(w_y^T YY^T w_y))}} \tag{1}$$

Since ρ is invariant to the scaling of w_x and w_y, CCA can be formulated equivalently as

[1] X and Y may also have different number of dimensions or features d and k respectively. CCA usually limits the projected features' dimensionality to the minimum of the ranks of the X and Y

$$\max_{w_x, w_y} \quad w_x^T X Y^T w_y \tag{2}$$
$$\text{Subject to} \quad w_x^T X X^T w_x = 1, w_y^T Y Y^T w_y = 1.$$

In the following, we assume that YY^T is nonsingular. It can be shown that w_x is obtained when the following optimization problem is solved:

$$\max_{w_x} \quad w_x^T X Y^T (YY^T)^{-1} Y X^T w_x \tag{3}$$
$$\text{Subject to} \quad w_x^T X X^T w_x = 1.$$

Both formulations in Eqs. 2 and 3 attempt to find the eigenvectors corresponding to top eigenvalues of the following generalized eigenvalue problem:

$$XY^T (YY^T)^{-1} Y X^T w_x = \eta X X^T w_x \tag{4}$$

where η is the eigenvalue corresponding to the eigenvector w_x. Within certain orthonormality constraints, multiple projection vectors can be computed simultaneously when the following optimization problem is solved:

$$\max_{W} \quad \text{trace}(W^T X Y^T (YY^T)^{-1} Y X^T W) \tag{5}$$
$$\text{Subject to} \quad W^T X X^T W = I,$$

where $W \in \mathbb{R}^{d \times l}$ is the projection matrix, l is the number of projection vectors, and I is the identity matrix. The solution to the optimization problem in Eq.5 consists of the top l eigenvectors of the generalized eigenvalue problem in Eq.3. A regularized version of CCA (rCCA), could also be constructed by employing two regularization terms, $\lambda_x I$ and $\lambda_y I$, with $\lambda_x I > 0$, $\lambda_y I > 0$, that are added in Eq.2 to prevent overfitting and avoid the singularity of XX^T and YY^T. Specifically, rCCA solves the following generalized eigenvalue problem:

$$XY^T (YY^T + \lambda_y I)^{-1} Y X^T w_x = \eta (XX^T + \lambda_x I) w_x. \tag{6}$$

It is worth mentioning here that the aforementioned CCA-based approach utilized in this paper is unsupervised, i.e., CCA does not observe the class label from the training set when constructing the w_x and w_y projection matrices, with the main goal being to maximize the correlation among the dimensions of X and Y. However, a supervised version could also be implemented by correlating the feature matrix with a class-indicator matrix and by using a binary representation of entities, e.g. for an example with 4 classes and x_i belonging to class 1, then x_i will be appended with $[1, 0, 0, 0]$, and $[0, 1, 0, 0]$ for class 2 and so on.

A. Least-Squares CCA-Framework

In order to simplify the aforementioned CCA implementation and provide a generalized solution, it has been shown in the literature that efficient algorithms for solving least-squares problems can be applied to scale CCA to very large data sets [32], [33]. Given the usual least-squares problem with the form of

$$\min_{W} \sum_{i=1}^{n} ||W^T X - T||_F^2, \tag{7}$$

where $T = [t_1, t_2, ..., t_n]$ being the class indicator matrix, W is the projection matrix that minimizes the difference between X and T, it is well known that the optimal W is given by

$$W = \left(XX^T\right)^{-1} XT^T \tag{8}$$

where the pseudo-inverse is used in case $\left(XX^T\right)$ is singular. According to Sun *et al.* [32], a least-squares CCA-framework (LS-CCA) can be easily constructed by replacing the class indicator matrix by

$$T = \left(YY^T\right)^{-\frac{1}{2}} Y = H^T \tag{9}$$

where it follows from Eq.9 that the solution to the least-squares CCA-framework for the above T is

$$W = \left(XX^T\right)^{-1} XH \tag{10}$$

Based on the above equivalence, the LS-CCA can be extended to include regularization techniques to control the complexity and improve the generalization performance of the suggested model. Similarly to ridge regression [34], by using the target matrix T in Eq.9, we obtain the 2-norm regularized least-squares CCA formulation by minimizing the following objective function:

$$L_2(W, \lambda) = \sum_{j=1}^{k} \left(\sum_{i=1}^{n} (x_i^T w_j - T_{ij})^2 + \lambda ||w_j||_2^2 \right), \tag{11}$$

The above formulation is equivalent to finding a projection matrix for X. In this case, one can utilize the features from one subject, denoted as the expert, to represent T and then utilize features from the remaining subjects to make them similar in style to T, i.e., raise the correlation between these feature sets so they have a similar trend resulting in a unified-style-space (with style here referring to the trend of the features across the different classes).

B. EMG Adaptation Scheme

In order to control complex myoelectric prostheses, the EMG patterns must be associated with the correct movements. In previous studies, a specific muscle activation, is usually associated with a specific movement imagined by the subject, and it is then up to the test subject to remember all the imaginary or virtual movements. Experiments were previously conducted to associate the EMG patterns with specific hand movements based on the use of a data glove on the healthy hand contralateral to the amputation (when controlling powered prosthetics by amputees) [20], or on a data glove on the same hand from which the EMG is collected (when teleoperating multi-finger robots) [21]. In this paper, we present a new concept that facilitates the association of EMG patterns with the actual hand movements based on the use of EMG data collected from the contralateral hand to the one been tested, whether from the same or a different user. The proposed CCA-based framework can act as a possible shortcut to high-end control of an advanced multi-user prosthesis by minimizing the efforts spent on training a subject/patient on the use of a prosthetic device. An adaptation scheme is presented here in a way that requires the novel user to go through a calibration session in which the system collects EMG data from the new user while implementing one repetition of each of a predefined set of hand motions. Additionally, the proposed framework extends the previous work in this field by allowing the system to overcome the individual differences in the EMG patterns collected from the different hands, i.e., the prosthesis system could be trained with EMG data from one subject and tested on EMG data from another subject, after using our CCA-based framework. Two schemes of users' adaptation are tested here, one for each set of collected EMG datasets.

- **Within-Subject Experiments**: In the first scheme, simultaneous fingers movements are carried out by each user with both hands while their EMG signals were collected. In this context, the expert and user data in Fig.1 were collected from the same user, with the expert data been collected from the muscles on one hand (intact limb) and the user data been collected from the contralateral hand (from the remaining muscles on contralateral limb). CCA based projection matrices are then computed to make the extracted features from both hands highly correlated. Testing is then performed with and without the proposed CCA adaptation with training/testing data from either hand to measure the usability of the proposed adaptation framework.
- **Subject-Independent Experiments**: In the second scheme and as shown schematically in Fig.2, the leave-one-out cross-validation (LOOCV) method was utilized, with one user's data retained for testing while training the classifier on the data from the rest of the users (more details in the experiments section). In this scheme, we attempt to create a unified-style-space, i.e., attempt to make all training users' style similar to that of the expert. This is done by correlating the feature matrices acquired from each user preserved for training (intact-limbed or amputee) with the feature matrix from an expert user (usually intact-limbed subject). Then the interface is applied on a novel user's hand and CCA projection matrices are computed to make the novel user's features correlated with the expert. The use of pre-trained models is reported in many research articles as being very useful in shortening the time required by the subject/patient to become proficient in using the prosthetic hand [35], [23].

The main benefits with the proposed CCA-based scheme include: Firstly, novel users require minimal training efforts to start using the system or to re-train the system after daily use. In most previous studies, each user must execute long-time experiments to capture a sufficient number of EMG signals in multiple trails to construct the training set for the classifier before starting to use it. In the proposed framework, a small amount of data (usually 3-to-5 sec of EMG data per movement class are enough for calibration, as determined empirically) is required to perform calibration and the system projects the extracted features from the EMG signals onto a new space whereby these are highly correlated with expert features. The calibration set is much smaller than the training set that is usually extracted from the users in the previous experiments, i.e., there are huge benefits gained in training time as we avoided the collection of multiple trials per each movement from the new user. Secondly, the proposed scheme allows for the development of muscle computer interfaces worn on either left or right hand by the user, in addition is the ability to train the system on one user's right (or left) hand while testing on a second user's left (or right) hand. Finally, one can also train the system on the data from intact-limbed subjects and then test the system on the data from an amputee.

III. Data Collection

In order to test the proposed CCA-based EMG pattern recognition system, two sets of EMG studies are utilized here. The first is collected by the author while the second was collected and first used by another research group [36].

A. DATASET-I: Synchronous Bilateral Fingers Movements Study

An experimental protocol has been developed in which EMG data is collected from both hands of each user for testing the CCA-based adaptation scheme within the user, i.e., adaptation among the two hands. Eight subjects, five right handed and three left handed, seven males and one female and aged between 25 and 36 years had been recruited. All participants provided university research ethics committee approved informed consent to participate in the study. Data was collected using four EMG channels (Delsys DE 2.x series EMG sensors) mounted on each of the left and right forearms as shown in Fig.3. This approach endeavoured to cover all muscles of the Extensor Digitorum (channel 1), Extensor Pollicis Longus and Abductor Pollicis Longus (channel 2), Palmaris Longus (channel 3), and Flexor Carpi Ulnaris (channel 4), as these muscles contribute largely to finger movements.

A 2-slot adhesive skin interface was applied to each sensor, and stuck firmly to the skin. A conductive adhesive dermatrode reference electrode was placed on the wrist of the right hand during the experiments. The data was processed by the Bagnoli desktop EMG system from Delsys Inc. with the EMG signals amplified to 1000 using a Delsys Bagnoli-8 amplifier. A 12-bit analog-to-digital converter (National Instruments, BNC-2090) sampled the signal at 4000 Hz; signals were then transferred to Matlab software. and EMG signals bandpass filtered between 20 and 450 Hz.

A set of ten classes of fingers movements, specifically fingers flexion movements, were carried on during the experiments. These included the flexion of: Thumb (T), Index (I), Middle (M), Ring (R), Little (L), Thumb-Index (T-I), Thumb-Middle (T-M), Thumb-Ring (T-R), Thumb-Little (T-L), and Hand Close (HC). Each subject was instructed to carry out one movement at a time using both hands, with cues issued by software to implement a specific finger motion lasting five seconds, followed by a five second relax. Six trials were

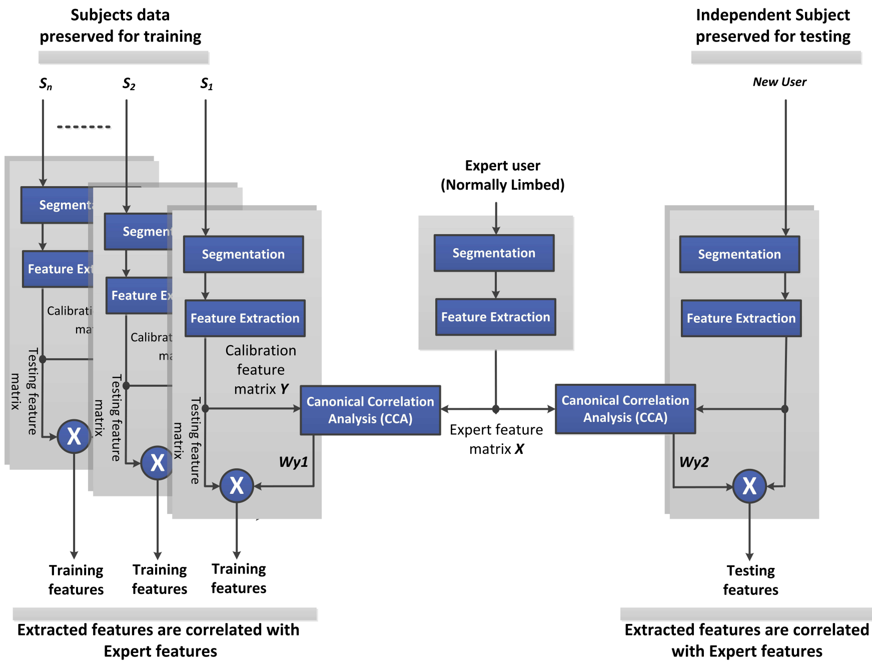


Fig. 2. The proposed subject independent CCA-framework for adaptation.

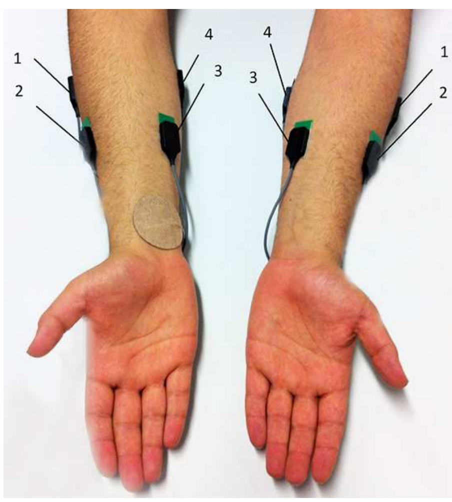


Fig. 3. Positions of electrodes on both forearms (sensors wires removed for clarity).

collected for each class of movement using both left and right hands simultaneously; the training and testing distribution is discussed in the experiments.

B. DATASET-II: Individual and Combined Fingers Movement Classification

In addition to testing on our own EMG data from intact-limbed subjects, we aimed to test our proposed CCA-framework on amputees and for this purpose we have utilized the EMG studies that were collected and first utilized by Timemy *et al.* [36]. EMG signals were recorded from the right forearm of ten intact-limbed subjects (referred to as N1-to-N10), including six males and four females ages 21 to 35 years. The study also includes EMG data collated from six traumatic below-elbow amputees (referred to as A1-to-A6), ages 24 to 34 years. Data from intact-limbed subjects was collected from participants based at Plymouth University, United Kingdom (UK), while the amputee data was collected at the Artificial Limbs and Rehabilitation Centres in Baghdad and Babylon, Iraq. Before placing electrodes on the subjects, alcohol and abrasive skin preparation gel was applied to the forearm for cleaning the skin. Electrode locations were chosen to maximize the quality of recording. For intact-limbed subjects, 12 EMG channels were used with pairs of self-adhesive Ag-AgCl electrodes (Tyco healthcare, Germany) placed around the circumference of the upper part of the forearm (Fig.4 A and B). To reproduce electrode positions, European recommendations for sEMG (SENIAM) [37] had been followed to determine electrode locations prior to placement. To mark the electrode locations, elbow joints were used as a reference point. By contrast, only 11 EMG channels had been recorded for amputee persons, this is due to the limited upper forearm surface area. The same self-adhesive Ag-AgCl electrodes (Tyco healthcare, Germany) had been used to acquire signals from amputee persons. The level of transradial amputation differed for each amputee person. For A1, the 11 pairs of electrodes were placed around the circumference of the upper forearm, whereas the electrodes were placed into two rows around the circumference of the upper forearm for the rest of the amputees. The ground reference electrode was placed on the wrist for healthy subjects and at the Olecranon process of the Ulna for the amputee persons. The type of amputation was transradial amputation for all of the amputee persons apart from amputee person A3, who had undergone a wrist disarticulation amputation (Fig.4 C). To minimize the cross-talk, bi-polar EMG measurements were used with inter-electrode distance of 24mm as recommended by Young *et al.*

and the SENIAM [37], [38]. The intact-limbed and amputee subjects had not been trained on EMG recording prior to the study. All amputees had a strong muscular structure in the arm and forearm, apart from (A3). The EMG activity was strong since no-one suffered nerve damage.

While intact-limbed subjects performed actual finger movements, amputee persons were instructed to produce a specific imagined finger movement. This was sometimes helped by mirror movements of the fingers of the intact hand. In total, 12 classes of finger movements had been carried out by amputees (11 individual finger movements as well as the rest position, which is considered in this study as one of the movement classes). Index and thumb flexion were recorded on a different day for A3 only with the same number of channels. The intact-limbed subjects performed 15 classes of finger movement from which we selected the same 12 classes of movements performed by the amputees. The 12 individual finger movements performed both by amputee persons and intact-limbed subjects are as follows: little flexion (f1), ring flexion (f2), middle flexion (f3), index flexion (f4), rest position, little extension (e1), ring extension (e2), middle extension (e3), index extension (e4), thumb flexion (f5), thumb extension (e5), thumb abduction (a5).

The EMG signals were acquired with the custom-built multichannel EMG amplifier. Each EMG channel was sampled at a rate of 2000 Hz with 16-bit resolution. A Virtual Instrument (VI) was developed in LABVIEW (National Instruments, USA) to display and store the EMG signals. During the recording, each participant sat on a chair in front of a computer with the LABVIEW interface screen to see all the EMG channels in real-time while performing the movements. Their arm position was fixed and it was resting on a pillow. They were asked to produce a succession of different finger movements separated by 5-second periods of rest. Both groups of participants were asked to produce finger movements with a moderate, constant-force, and non-fatiguing contractions to the best of their ability. The final position of a movement was held for a period of 8-12 seconds by intact-limbed subjects. However, this time was limited to 5-10 seconds for amputees to avoid fatigue. Each holding phase is referred as a ”trial”. Six trials were recorded for each movement; the distribution of training and testing trials are described in the experiments.

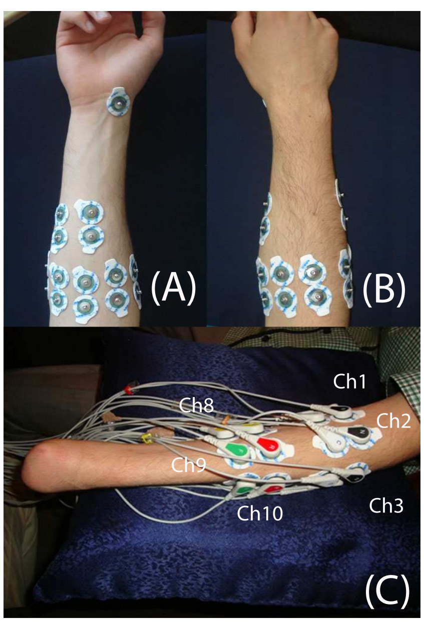


Fig. 4. Example of electrode location. A. Anterior view of the right forearm of an intact-limbed subject. B. Posterior view of the forearm of an intact limbed subject. C. Anterior view of amputee person A3.

IV. Experiments and Results

In the experiments, an overlapping windowing scheme was utilized when extracting features with a window size of 150 msec overlapped by 50 msec. The extracted features cover the recently proposed time-domain derivations of spectral moments by Khushaba *et al.* [17] including 5 features/channel consisting of a normalized version of the zero, second, and forth order power spectral moments in addition to a sparsity measures and the irregularity factor measure (this is the number of zero crossings divided by the number of peaks). Additionally, the correlation factor between each two possible raw EMG signals was also added as features by concatenating all the features together to form one large feature set. These features have demonstrated power against many other feature sets while having small computational requirements and dimensionality (for more info the interesting reader may refer to [17]). For the EMG studies for both hands, as collected by the author, the extracted feature set had a dimensionality of 26 features/hand, i.e., 26 features/hand = [5 features/channel (time-domain moments) $\times$ 4 channels/hand+ 6 correlation features (6 unique values from the correlation coefficients matrix)]. For the EMG studies acquired from [36], the dimensionality of the extracted feature set totaled to 110 features/hand when 11 channels were utilized, i.e., 110 features/hand = [5 features/channel $\times$ 11 channels/hand+ 55 correlation features (55 unique values from the correlation coefficients matrix of size 11 $\times$ 11)], and similarly to 126 features/hand when 12 channels were utilized. In terms of the classification, three different classifiers were tested including: Linear Discriminant Analysis (LDA), k-Nearest Neighbor (kNN), and the well-known LIBSVM library of support vector machine [39]. The performance metric employed is classification accuracy of the testing feature set, this is completely independent from the training and the calibration set i.e., the unseen testing data. In order to increase stability and robustness of the class decision stream, we also implemented post-processing using majority voting. Majority voting stipulates that the output of the controller is not simply the most recent class decision but the class that appears the most often in the previous n class decisions (n = 8 in our experiments).

In the following subsections, different experiments have been evaluated including testing within the subject, i.e. train on left (or right) hand and test on right (or left) hand for the same subject; then across the hands of the different subjects i.e. hand train on a normal limbed subject and test on an amputee.

A. Experiments on DATASET-I

In this section, the classification performance of the system is first evaluated without using CCA-framework, i.e., what is the classification performance of individual hands separately (baseline accuracy for each hand). In this case, only the EMG data from the first trial (for each movement) is used to extract the training feature set, while the remaining five trials (for each movement) are used to extract the testing feature set i.e., completely independent feature sets. In addition to the baseline for each hand, we compare our proposed CCA framework with the simple-SVM utilized by Matsubara and Morimoto [27]. The simple-SVM provides an indicator of the classification performance when a classifier is trained on the left hand data and tested on the right hand data, also vice versa. In addition to simple-SVM, we have included what we call 'global-SVM', this is where an SVM classifier is provided with training data from both hands. Additionally, the results achieved through the Bilinear model of Matsubara and Morimoto [27] were also included. The classification results for each of the subjects with the aforementioned simple-SVM, global-SVM, and Bilinear models are shown in Table.I, in addition to the left and right hands baselines.

These results clearly indicate a few important points, firstly it is not feasible to implement the hand independent classification scheme directly using EMG features from one hand to infer what movement of the other hand will be, that is simple-SVM fails to deal with the current problem despite good performance individually for the baseline of each hand. This is justified by the different EMG signals extracted from each hand with different data distributions, though both hands are implementing the same movement simultaneously. Secondly, in comparison to simple-SVM and individual baselines for each hand, the global-SVM has powerful performance. This is mainly attributed to the fact that the classifier was made aware of the distribution of the EMG features from both hands by including EMG features extracted from both hands in the training set. It is also important to mention here that using more training data could further enhance the baseline classification results for both hands, as only one trial per movement has been allocated for training. However, our main point is not devoted to enhancing the baseline classification results, but to enhancing the cross-hands classification results when using training and testing data from different hands. Thirdly, the Bilinear model performed better than simple-SVM, but performed worse than the global-SVM. Matsubara and Morimoto [27] indicate clearly that there are some current limitations to the Bilinear model including its sensitivity to the type of features extracted from the EMG channels. In this case, although training data was allocated from both hands, the Bilinear model representation of the extracted content variables has resulted in lower classification accuracies than the global-SVM.

The proposed CCA-framework was then applied in this experiment. In such a case, each subject could be requested to go through a calibration session in which he/she shows the system an example of how they perform a specific finger movement (the style of movements) with both hands simultaneously or one hand only, if the interface is applied on that specific hand. Features are then extracted from both hands and were submitted to CCA to find two projection matrices that would increase the correlation between the two feature sets, as shown in Fig.1. Training data is allocated from one hand and testing data from the opposite hand and the classifier makes decisions on the new unseen testing data from the opposite hand that has been multiplied by the precomputed projection matrix from CCA. Out of the six trials collected from each user for each movement, only the first trial of each movement is used in the calibration process, i.e., get one trial's features from the right hand and one from the left hand, apply CCA-framework, extract the projection matrices that would make both hands features correlated and classify unseen testing data. In this case, the training data was again allocated from the first trial only while testing data was acquired from the remaining five trials (completely unseen during calibration). In this case, the results from different scenarios are shown in Table.II while using the LIBSVM classifier. This table again shows the baseline accuracy for both hands after CCA was applied in addition to two more scenarios: The first in which the training feature set includes samples from opposite hand to the one being tested on (comparable to simple-SVM) and the second in which the training feature set includes samples from both hands after CCA (comparable to global-SVM). These results indicate the significance of the proposed CCA-based scheme that managed to raise the correlation between the projected features from both hands resulting in similar features trends across the different classes with average accuracies of 80.64$\%$ and 81.39$\%$ in comparison to 26.80$\%$ and 25.66$\%$ for simple-SVM when testing on the left and right hands respectively. On the other hand, when training on both hands after CCA, the classifier is made aware of the distribution of the EMG data from both hands which in turn allowed the classifier to better generalize on the unseen testing data with accuracies of 84.25$\%$ and 88.35$\%$ with CCA in comparison to 80.68$\%$ and 86.34$\%$ for global-SVM without CCA and 72.11$\%$ and 71.5$\%$ respectively on the left and right hands for the Bilinear model.

All of the aforementioned results were verified by an analysis of variance test with a significance level at 0.05. ANOVA tests outcome indicated that the classification results when training on one hand and testing on the opposite with CCA are significantly different from those with simple-SVM with $p << 0.01$. The same significance level also applied to the case where we train the classifier on EMG features from both hands and test on either hand, indicating the significant differences between our CCA-framework and the Bilinear model and the global-SVM with $p < 0.01$. Thus, the proposed approach allows the development of myoelectric interfaces that the user can wear on either hand. The testing classification results using LDA and kNN classifiers also showed similar results to these exhibited by the LIBSVM classifier as shown in Fig.5.a when training on the right hand features and testing on the left hand features with CCA and Fig.5.b when training on the left hand features and testing on the right hand features respectively.

The effect of the number of samples used in the calibration process on the testing set classification accuracy was also analyzed. In such a case, we randomly pick up a certain number of samples from the available calibration data and test the classification accuracies with CCA-framework applied (with training data from the contralateral hand to the one

TABLE I
CLASSIFICATION ACCURACIES (LIBSVM): WITHIN SUBJECT EXPERIMENT, WITHOUT CCA SCHEME

	Baseline-Left	Baseline-Right	simple-SVM	simple-SVM	global-SVM	global-SVM	Bilinear	Bilinear
TrainingData →	Train-Left	Train-Right	Train-Right	Train-Left	Train-Both	Train-Both	Train-Both	Train-Both
TestingData →	Test-Left	Test-Right	Test-Left	Test-Right	Test-Left	Test-Right	Test-Left	Test-Right
Subject1	78.04	79.65	22.39	23.92	74.04	73.27	71.40	67.2
Subject2	86.04	93.88	12.69	30.51	79.96	93.39	71.46	71.5
Subject3	77.37	98.22	53.94	27.96	78.27	94.88	73.57	78.8
Subject4	87.88	88.51	12.53	19.65	80.98	86.45	75.10	72.9
Subject5	89.41	80.39	12.86	17.98	81.65	75.73	69.84	61.2
Subject6	86.76	97.22	40.80	32.51	87.55	95.71	64.94	76.6
Subject7	80.96	80.04	12.24	11.41	83.24	78.04	71.49	63.0
Subject8	82.32	90.32	46.97	41.35	79.80	93.30	79.08	81.1
Average	83.60	88.53	26.80	25.66	80.69	86.35	72.11	71.5
Std	4.57	7.73	17.60	9.43	3.89	9.34	4.10	7.3

TABLE II
CLASSIFICATION ACCURACIES (LIBSVM): WITHIN SUBJECT EXPERIMENT, CCA UNSUPERVISED FRAMEWORK APPLIED

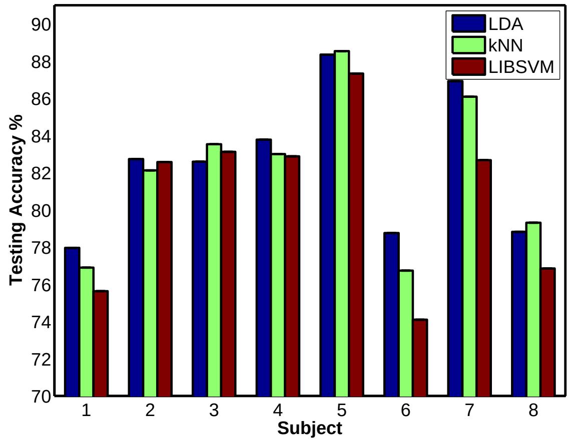
	With CCA	With CCA	With CCA	With CCA	With CCA	With CCA
TrainingData →	Train-Left	Train-Right	Train-Right	Train-Left	Train-Both	Train-Both
TestingData →	Test-Left	Test-Right	Test-Left	Test-Right	Test-Left	Test-Right
Subject1	80.53	77.55	75.63	73.02	81.44	78.97
Subject2	83.42	94.08	82.57	91.95	84.30	95.63
Subject3	81.67	97.18	83.12	87.93	82.61	94.51
Subject4	89.08	89.77	82.87	81.16	86.38	90.83
Subject5	87.06	87.95	87.32	74.71	90.10	86.24
Subject6	87.20	96.63	74.10	81.89	85.59	93.79
Subject7	81.26	79.53	82.67	74.61	81.10	78.14
Subject8	80.23	88.38	76.85	85.82	82.45	88.72
Average	83.81	88.88	80.64	81.39	84.25	88.35
Std	3.47	7.30	4.56	6.91	3.03	6.79

been tested). The process was repeated for 20 times along each number of samples with the results averaged as shown in Fig.6. These results clearly show that around 400-to-500 samples seem adequate to produce classification accuracies that are not significantly different from those produced by larger sample size. The results also indicate that even with very small samples size of 100 samples our method was still able to perform well with classification accuracies of 71.73$\%$ and 74.57$\%$ when training the classifier on right hand data and testing on left hand data and vice versa respectively. In comparison to the Bilinear model, the number of samples used in calibration did not have a significant impact upon the testing set classification results which is one of the main powerful attributes of the Bilinear model. However, the fact that the classification results achieved by the CCA-framework with 100 samples, with training features from individual hands only, still outperform the Bilinear model trained with EMG features from both hands, warrants its acceptance as a good adaptation framework.

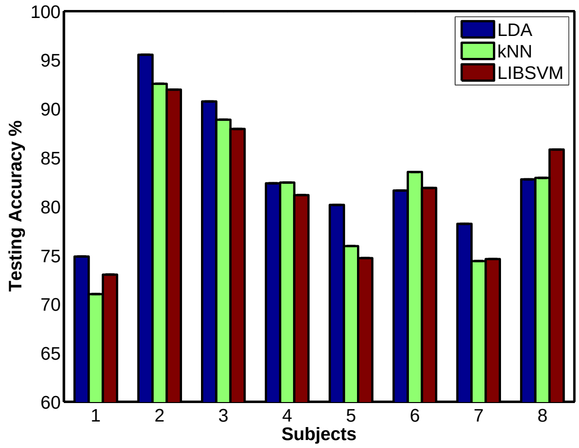
B. Experiments on DATASET-II

In this set of experiments, a leave-one-out cross-validation testing scheme was utilized in which, at each time, five out of the total six amputees' EMG signals features are allocated for extracting the training feature set while the remaining one amputee's EMG signals features are allocated for extracting the testing feature set. According to Fig.1, the CCA-framework is then utilized to increase the correlation between each of the five amputees' features preserved for training and the expert features. As the amputees had different levels of transradial amputation then we decided to use an intact-limbed subject's EMG signals features as the expert features when employing the unsupervised CCA-framework (or the class-indicator matrix for the supervised version). In such a case, we seek feature transformation matrices that would make each of the amputees' EMG features similar to that of the expert, resulting in a unified-style-space, i.e., the five amputees' EMG features are highly correlated to that of the expert now. The remaining one amputee's EMG features matrix is kept for testing and the CCA framework is applied on a small sample of his/her features during calibration to increase the correlation between his/her features and that of the expert. Thus, no training data is acquired from the subject on which we are testing our CCA framework, as the classification performance is evaluated using a classifier trained on background data from other users alone.

As there were multiple trials for each of the movements with a huge amount of collected EMG data, then the first trial for each subject been tested was set aside to acquire the calibration data. Specifically, in this experiment only the data belonging to the first five seconds from each first trial was used for calibration. The data from the remaining five trials was set aside for testing, that is the calibration feature set was completely separated from the testing set. Given the large number of EMG channels and the extracted features from these EMG datasets, then dimensionality reduction was utilized. For this purpose, the Orthogonal Fuzzy Neighborhood Discriminant Analysis (OFNDA) feature projection method by Khushaba *et al.* [9], that have been utilized on these same EMG studies from amputees in [36], is also used in



(a) Training-right and testing-left



(b) Training-left and testing-right

Fig. 5. Testing classification accuracies with the LDA, kNN,and LIBSVM classifiers while using the proposed CCA framework with training data from one hand and testing data from he opposite hand.

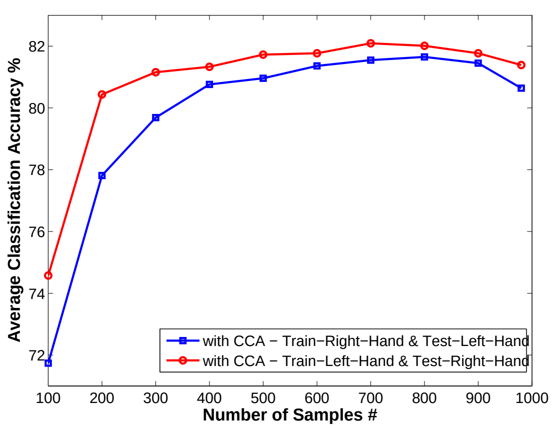


Fig. 6. Effect of the number of samples used in the calibration process on the testing set classification accuracy while using our proposed CCA-framework, with samples taken randomly from all classes. In each of these curves, training is based on data from the contralateral limb to the one been tested.

this research. The baseline classification results, when training and testing data is acquired from the same subject, for the intact-limbed had an average of 98.39% (standard deviation of 2.40%) across all subjects, while the amputees subjects achieved much lower than that as shown in Table.III. As the intact-limbed subjects had powerful classification results, we aimed to investigate whether we can enhance the classification results for the amputees by using the CCA framework, and with each intact-limbed person as an expert. The classification results with the unsupervised CCA framework are given in Table.IV. In such a case, the first row in Table.IV shows an expert N1, the first column shows a testing subject A1, while the remaining subjects (A2-A6) are allocated for training, with a testing accuracy of 85.52%. The second column then shows the accuracy when A2 is preserved for testing and A1, A3, A4, A5 and A6 are used for training with a testing accuracy of 86.31%, and similarly for the remaining entries, with different expert in each row.

One of the important benefits of applying the proposed CCA-framework on these EMG studies is attributed to the fact that there were different number of EMG channels utilized across the amputees and the intact-limbed subjects. The fact that the proposed CCA-framework can be applied on two feature matrices with different dimensionalities makes it very attractive option, as it is simply not possible using other adaptation frameworks unless the same number of channels is used across all subjects. The second important benefit of the proposed CCA-framework is attributed to its capability for increasing correlations among EMG signals collected from EMG channels at different forearm positions. As mentioned previously, the level of transradial amputation was different for each amputee which in turn necessitated the different placement of electrodes on some amputees (A1 versus the

TABLE III
AMPUTEES' BASELINE CLASSIFICATION RESULTS, TRAINING AND TESTING DATA FROM THE SAME SUBJECT

Subject $\rightarrow$	A1	A2	A3	A4	A5	A6
LIBSVM	83.10	83.75	80.54	81.47	79.65	74.67
LDA	81.09	85.60	82.19	76.44	79.08	78.41
kNN	83.55	85.05	81.44	81.61	79.43	79.17

TABLE IV
SUBJECT-INDEPENDENT CLASSIFICATION RESULTS (LIBSVM), UNSUPERVISED CCA-FRAMEWORK APPLIED, TRAINING DATA FROM BACKGROUND MODEL BASED ON INDEPENDENT SUBJECTS TO THE ONE BEEN TESTED

Subject	A1	A2	A3	A4	A5	A6
N1	85.52	86.31	82.15	81.65	82.79	72.37
N2	85.43	86.81	82.65	81.04	85.55	76.88
N3	85.66	85.06	82.40	78.89	84.69	69.86
N4	84.99	89.32	81.64	82.63	85.36	72.14
N5	86.15	86.06	80.89	81.91	84.71	75.34
N6	84.63	85.61	81.29	82.52	83.98	76.18
N7	86.46	86.26	81.59	82.16	86.69	73.34
N8	86.15	85.81	82.40	81.59	85.02	75.67
N9	86.55	86.06	84.20	82.90	85.86	76.17
N10	85.25	86.36	81.29	81.54	81.86	75.38
Mean	85.68	86.36	82.05	81.68	84.65	74.33
Std	0.64	1.14	0.95	1.14	1.45	2.28

rest of the amputees). This in turn allowed for training on A2-to-A6 features while testing on A1 features, despite different electrodes placements. Matsubara and Morimoto [27] suggested that electrode placement influences the user dependent variables in their bilinear model; they also caution that the method cannot be used if the electrodes are not placed on the same muscles between different users. This is due to different amputee patient conditions (as verified in our experiments). However, different amputees do have different conditions, and for an adaptable interface to be clinically applicable, such an interface should be applicable even under different conditions of amputations, this being the case using our CCA-framework.

In comparison to the classification accuracy results achieved by the unsupervised CCA-framework, we have also computed the results by using a supervised version of our CCA-framework, in which we correlate the amputees' features against the class indicator matrix rather than the expert feature matrix as shown in Table.V. Additionally we have also included the simple-SVM (training data from all amputees, except the one been tested) and global-SVM (training data from all amputees, including the one been tested). The results of the Bilinear model were not competitive with the rest of the results which is possibly due to the aforementioned effect of electrodes placement variations and we decided to remove these results from this comparison. These results clearly indicate the simple-SVM is of no use here due to the variations in the EMG features across different subjects. On the other hand, the accuracy results by global-SVM seem more convincing; however, the fact that training data was required from each subject, including the one the classifier is tested on, made the global-SVM not competitive with our unsupervised CCA-framework. It should be mentioned here that for the subject been tested the amount of data used for calibration with our CCA-framework is the same as that amount of data included in the training set from the testing subject in global-SVM. However, our framework employs this data for calibration and does not include this data with the training set, i.e., training in our framework is completely based on data from other subjects. In comparison to simple-SVM and global-SVM our CCA-framework achieved significantly better results as validated by an ANOVA test with the achieved p-values of $<<$0.05 for the tests against simple-SVM and global-SVM. On the other hand, there was no statistically significant difference between the accuracy results achieved by the supervised vs. the unsupervised versions of our CCA-framework, with ANOVA giving a p-value of > 0.05. Thus, either of the CCA versions can be used.

In the final part of the experiments, the classification results with the LDA and kNN classifiers were also calculated as shown in Fig.7, indicating a similar trend to those exhibited by the LIBSVM classifier. This in turn indicates that the extracted features are robust against the change of the classifier.

TABLE V
AVERAGE AMPUTEES' CLASSIFICATION ACCURACY RESULTS USING DIFFERENT METHODS FOR ADAPTATION

Subject $\rightarrow$	A1	A2	A3	A4	A5	A6
simple-SVM	9.56	63.54	49.69	14.49	27.64	26.84
global-SVM	77.52	71.61	72.76	75.29	70.08	70.51
Unsupervised-CCA	85.68	86.36	82.05	81.68	84.65	74.33
Supervised-CCA	85.65	86.30	81.84	81.55	86.00	76.43

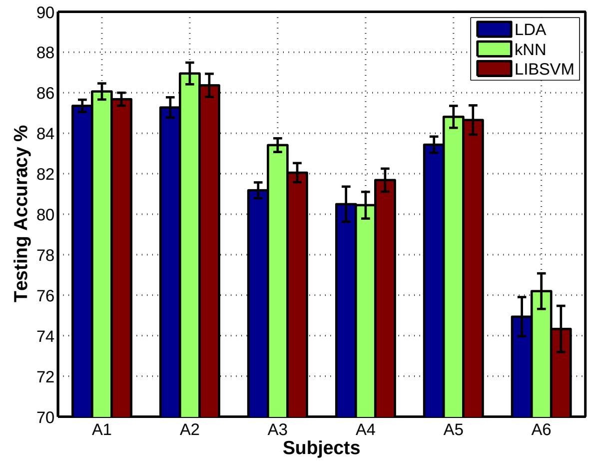


Fig. 7. Average classification results with LDA, kNN, and LIBSVM classifiers, with standard deviation as bars.

V. Conclusions

In this paper, an approach for developing multi-user myoelectric interfaces utilizing a CCA framework has been proposed. Two schemes of adaptation have been tested, one among individual users, in which we tested the possibility of training the classifier on EMG features from either hand while testing the opposite, and a second between users, including training on multiple users data and testing on a novel user. Our initial results clearly indicates the significance of this research, allowing us to train and test on different users with average classification accuracies of $> 82\%$ across all subjects. The performance of the proposed model has also been compared with other models like the simple-SVM, global-SVm and the Bilinear model proving its power as a multi-user adaptation framework. However, further investigation is required into the adaptation approaches for further enhancing the performance of subject-independent EMG classification results and the real-time application of this framework. This will be the basis of our future research.

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