A Characterization of the Effect of Limb Position on EMG Features to Guide the Development of Effective Prosthetic Control Schemes

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Abstract— **Electromyogram (EMG) pattern recognition has long been used for the control of upper limb prostheses. More recently, it has been shown that variability induced during functional use, such as changes in limb position and dynamic contractions, can have a substantial impact on the robustness of EMG pattern recognition. This work further investigates the reasons for pattern recognition performance degradation due to the limb position variation. The main focus is on the impact of limb position variation on features of the EMG, as measured using separability and repeatability metrics. The results show that when the limb is moved to a position different from the one in which the classifier is trained, both the separability and repeatability of the data decrease. It is shown how two previously proposed classification methods, multiple position training and dual-stage classification, resolve the position effect problem to some extent through increasing either separability or repeatability but not both. A hybrid classification method which exhibits a compromise between separability and repeatability is proposed in this work. It is shown that, when tested with the limb in 16 different positions, this method increases classification accuracy from an average of 70% (single position training) to 89% (hybrid approach). This hybrid method significantly (p<0.05) outperforms multiple position training (an average of 86%) and dual-stage classification (an average of 85%).**

I. Introduction

The surface electromyogram has been one of the major neural control sources for powered upper limb prostheses for many decades. Various EMG signal processing methods have been used to extract the user's intended movement. Conventional myoelectric control schemes employ measures such as the root mean square or mean absolute value of the EMG to quantify the intensity of contraction in the underlying muscles. Control is elicited by mapping this activity to the desired prosthetic function. Although such control schemes have been widely used commercially, they are incapable of controlling more than one or two degrees of freedom (DOF). If more than one DOF is to be controlled, mode switching techniques are used which can be slow and counterintuitive [1-3].

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Pattern recognition-based myoelectric control is an advanced signal processing technique that can potentially be used to control multiple DOFs. This technique has shown great promise for improved dexterity of control in upper-limb prostheses. In this approach, a set of features containing spatial and temporal information about the acquired signals are extracted and form an input pattern to a classifier which determines the user's intended movement [4, 5].

Many researchers have used myoelectric pattern recognition to control upper limb prostheses and reported high classification accuracies using various combinations of pre-processing, feature extraction, classification, and post-processing algorithms [4, 5]. These studies were done under ideal conditions, eliciting static contractions in constrained positions. In real-world prosthetic use, however, those ideal conditions do not exist, as the focus is on task execution in dynamic environments [6]. Newer studies have shown that several conditions, such as electrode shift [7-9], variation in force [10], transient changes in EMG [11, 12], and variation in the limb position [13-17] might affect signal patterns and erode the clinical robustness of the EMG pattern recognition. The focus of this work is the effect caused by the limb position variation.

The so-called "*position effect*" is the degradation of myoelectric pattern recognition performance when the classifier is trained with limb in one fixed position but is tested or used with limb in other positions. This degradation is due to the impact of arm position variation on the muscular activation pattern when performing activities [18-20]. A review of the literature shows that many researchers have demonstrated the position effect and proposed solutions to resolve it [13-17, 21-23]. The aim of this work is to explore and analyze the etiology of the position effect problem, rather than solely to demonstrate this problem, and to propose solutions to reduce that effect.

Myoelectric pattern recognition methods look for patterns in the features used to represent the EMG. The robustness of these methods relies on two important characteristics of these feature patterns; distinctness (or separability), and repeatability. Distinctness is the difference in the features between motion classes, relating to their separability. Repeatability is the degree of coincidence between features extracted from training and testing data of each class, relating to their reproducibility. The higher the separability and repeatability of features, the more robust the classifier is.

This work investigates the effect of limb position variation on the separability and repeatability of data in the feature space. It is assumed that limb position variation

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reduces these characteristics of the feature patterns and that minimization of such reduction would result in a more robust control scheme.

Multiple position training (single classifier trained in multiple positions) and dual-stage classification (multiple classifiers each trained in a single position) are two existing solutions [13-17] to the position effect problem. This work investigates how these methods affect separability and repeatability of data. It is hypothesized that a combination of these methods can optimize the classification accuracy by capitalizing on the trade-off between separability and repeatability of data.

II. Methodology

A. Population and Data Acquisition

EMG data corresponding to eight classes of motion were collected from 10 right-handed, healthy, normally-limbed subjects (9 male, 1 female) within the age range of 19 to 32 years. All experiments were approved by the University of New Brunswick's Research Ethics Board.

A Trigno Wireless System (Delsys Inc., USA) was used to record surface myoelectric signals. Six wireless electrodes were equally spaced placed around the dominant forearm, proximal to the elbow, at the position with largest muscle bulk. The six channels of EMG were band-pass filtered (20-450Hz Butterworth) and sampled at 1 kHz by a custom data collection system.

Subjects were prompted to elicit contractions corresponding to eight classes of motion including wrist flexion/extension, wrist supination/pronation, power grip, pinch grip, hand open, and no movement. Each contraction was sustained for three seconds at a moderate and repeatable force level, and a three second rest was given between subsequent contractions. This set of contractions was repeated in the 16 static limb positions, shown in Fig. 1. These positions cover the workspace in which most activities of daily living (ADL) are performed. Positions with odd numbers were located on a plane parallel to the sagittal plane, passing through the subject's humerus, and positions with even numbers were located on the sagittal plane. P3-P6 were carried out with the elbow bent, P9-P16 were carried out with the elbow straight, and the rest were carried out somewhere in between.

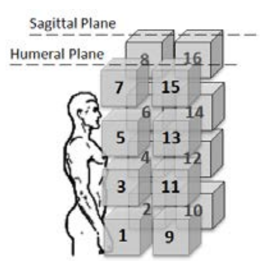

Figure 1. Subjects were asked to perform four sets of contractions corresponding to eight classes of motion while holding their arm in each of the 16 static positions shown, which are labelled P1 through P16.

To ensure that all subjects moved their arms to the same set of 16 positions, the subjects were asked to stand in front of a white board, on which a grid of 8 cells corresponding to positions P1-P8 was drawn, and move the limb as if they want to reach the center of each cell. When data from all eight of these positions were collected, the board was moved away from the subject to elicit the other 8 positions (P9-P16) and data were collected from those positions as well. Before each session, the height of the board and the spatial distribution of the cells were adapted to the height and reach of the subject.

Four sets of contractions were collected in each of the 16 static positions. Two of these sets were used for training and two were used for testing.

Four time-domain (TD) features including mean absolute value, waveform length, zero crossings, and slope sign changes, combined with a linear discriminant analysis (LDA) classifier were used in this study. This combination, introduced by Englehart and Hudgins [4], was chosen because it has been widely reported in the literature for pattern recognition based EMG control. EMG data were digitally notch filtered at 60Hz using a 3rd order Butterworth filter in order to remove any power line interference. Data were segmented for feature extraction using analysis windows of length 200ms, an ideal window length for real-time application [24], with processing increments of 100ms.

B. Analysis of Limb Position Impact on EMG Features

Two metrics – Separability Index (SI) and Repeatability Index (RI) – introduced by Bunderson and Kuiken [25] were used to quantify the characteristics of training and testing data in the feature space. The SI indicates the distinctness of classes in the feature space by measuring interclass distances. The RI measures degree of coincidence between training and testing datasets, each possibly consisting of data from several repetitions. In order to more intuitively relate the RI metric to this ideological definition of repeatability, the reciprocal of the definition introduced by Bunderson and Kuiken [25] was used, such that a higher RI indicates better repeatability.

To analyze the effect of limb position variation on EMG features, in the first step, data collected from each contraction class in one fixed position were used as the training data and data collected in the same position were used as the testing data. Then, data collected from a new position were successively added to the testing data until all 16 positions were included. After each addition, the separability and repeatability of the data were measured to study the changes in the characteristics of the features as more variation in the limb position was added.

C. Classification Methods

1) Multiple position training

When a classifier is trained with the limb in one position, the EMG of each motion class shapes a cluster in feature space. Ideally, the EMG patterns of a testing dataset collected in the same position should coincide with those of the training clusters. In this case, given that the classes are distinct, the classifier would be capable of correctly identifying those patterns. When the limb position changes, the EMG may be affected and the location of the resulting features might be different from those of the training clusters, as illustrated in Fig. 2. Therefore, adding data from multiple positions to the testing dataset might have the effect of decreasing the repeatability. To avoid this problem, data from several limb positions can be incorporated into the training dataset.

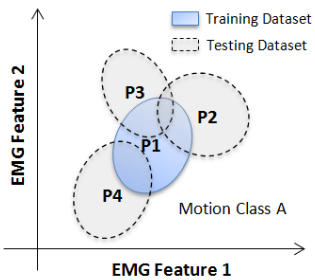

Figure 2. An illustration demonstrating how changing the limb position affects the EMG features and moves their location in the feature space. This makes the training dataset (including data from position P1) and the testing dataset (including data from positions P2-P4), dissimilar.

In this section, the effect of adding data from multiple positions to the training dataset was investigated using classification accuracy as well as RI and SI indices. Classifiers were trained in one position to begin with, and more positions were successively added for training until all 16 positions were represented in the training dataset. A brute force method was applied, meaning that for each distinct number of training positions, the results were acquired for every possible subset of the 16 positions and then the average was computed.

2) Dual-stage classification

In a dual-stage classification approach, multiple positions are still involved in training, but their data are used to train multiple position-specific classifiers. Therefore, training clusters within each classifier are smaller in size and more separable in feature space, as illustrated in Fig. 3.

This multi-classifier approach requires that, first, the originating limb position of a given test sample be determined. Once this is known, an EMG motion classifier, which is trained using data from only the detected position, is used to classify the test sample. Different strategies can be used to detect the limb position in the first stage of this method. It has been shown before [13] that accelerometers may be used to detect five limb positions with 100% accuracy. With this high degree of accuracy, for the purposes of this investigation, the limb position was assumed to be known. The focus herein was therefore the effect of using separate position-specific EMG motion classifiers on the separability and repeatability of classes in feature space. Data from each of the positions were used to train a single classifier resulting in generation of 16 separate position-specific classifiers.

3) Hybrid classification

A hybrid approach which uses multiple classifiers each trained using multiple positions is proposed. It is expected that, this approach increases both the separability of the classes (due to multiple classifiers), and the repeatability between training and testing datasets (due to the inclusion of multiple positions within each classifier). This is illustrated in Fig. 4.

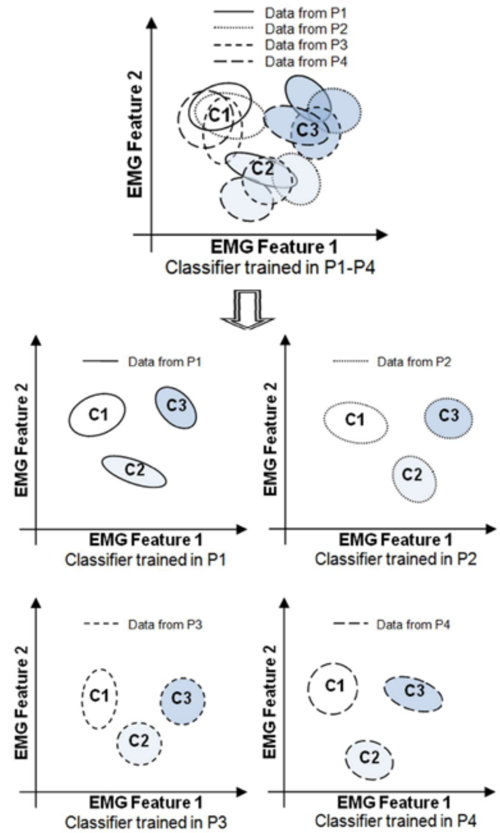

Figure 3. An illustration demonstrating that collecting data from multiple positions increases the size of clusters in the feature space If data from each position is used to train a separate classifier, separability between the classes (C1-C3 in the above figure) of each classifier might be increased.

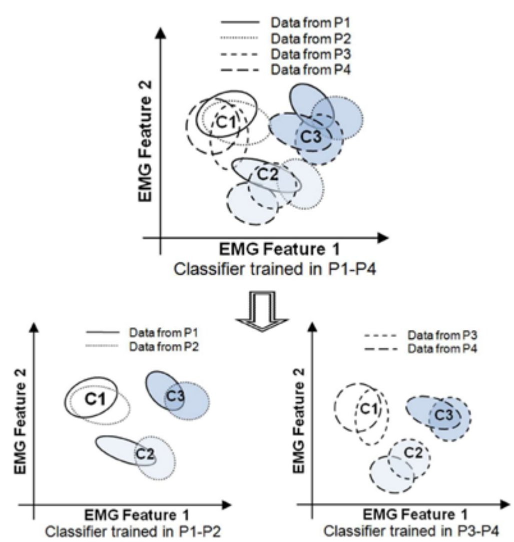

Figure 4. An illustration demonstrating that if multiple classifiers are trained each using data from multiple positions, both repeatability between training and test datasets and separability between the classes (C1-C3 in the above figure) of each classifier might be increased.

Three different configurations were investigated: 1) training two classifiers each with eight positions, 2) training four classifiers each with four positions, and 3) training eight classifiers each with two positions. The position groupings for these configurations were as shown in the three rightmost images of Fig. 5. Each of the classifiers was used to classify only the portion of the test data that was collected in the same positions as those used to train that classifier.

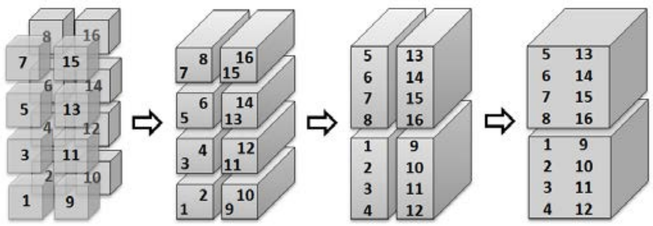

Figure 5. Position groupings used for hybrid classification method.

III. Results

A. Position Variation Effect on EMG Feature Space

Fig. 6 shows the effect of increasing the number of test positions, as measured using separability and repeatability indices, when the classifier was trained in only one position. The test was repeated with the classifier trained in each position and the results were averaged. The results showed that both separability between the motion classes of the test dataset and repeatability between training and testing datasets decrease as more positions are incorporated in the test data. Therefore, the ability of a classifier trained in a single position to discriminate the classes from each other suffers, and the classification accuracy decreases.

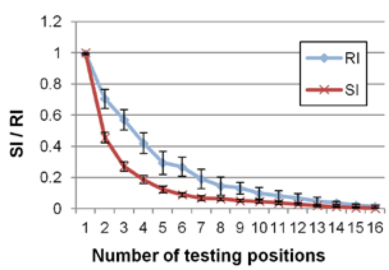

Figure 6. Illustration of how, when the classifier is trained in a single position, increasing the number of test positions causes the separability between motion classes and the repeatability between training and testing data to decrease. For visualization purposes, the indices have been normalized between zero and one. The error bars indicate the standard error of the measurements.

B. Multiple Position Training

The classification accuracies when including varying numbers of positions (1-16) for training of the classifier are shown in Fig. 7. In each case, the classifier was tested with data from all 16 positions. For each number of training positions, the classification accuracies of the best possible subset of positions and of the average of all subsets are shown. These results suggest that, on average, increasing the number of training positions improves classification performance. However, the results of using the optimal subset of training positions indicate that there is a finite number of training positions beyond which classification accuracy drops.

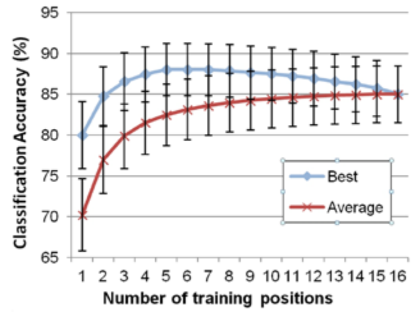

Figure 7. An illustration demonstrating that for a classifier that is tested in 16 positions, increasing the number of training positions improves the classification accuracy on average. However, if the optimal subset of positions is selected, the best performance occurs with as few as 4-6 positions. In the figure above, the error bars indicate the standard error across all subjects.

A multivariate analysis of variance (ANOVA) was completed on the above results and showed that training the classifier in more than one position significantly ($p < 0.05$) increases both the best and average classification accuracy, with diminishing returns once more than five positions are included in the training dataset.

Fig. 8 shows the effect of training the classifier in multiple positions on the repeatability and separability indices. For every given number of training positions, the indices were measured only for the best performing subset of that number of positions. Because the classifier is tested in all 16 positions, increasing the number of training positions makes the testing and training datasets more closely coincide and results in higher repeatability. However, it also increases variance of classes in feature space and, therefore, reduces separability between them.

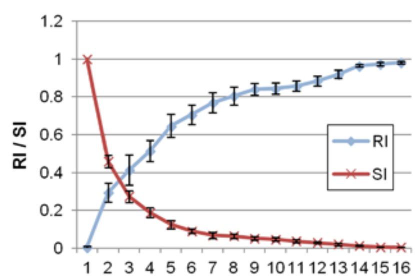

Figure 8. Illustration of how inclusion of more positions in training increases repeatability between training and testing datasets, but reduces the separability between the motion classes in the feature space. For easier visualization of the trends, the indices have been normalized between zero and one. The error bars indicate the standard error of the measurements.

It should be noted that while the subset of training positions determined to be optimal was not common between all users, some generalities were observed. For example, although the optimal combination of two positions was different for most subjects, they all shared a common trend: each subset consisted of one position in which the arm was straight and one in which the elbow was bent.

C. Comparison of Classification Methods

Fig. 9 compares the average classification accuracies for each of the three classification methods discussed in section C. The results of all three configurations of the hybrid classification approach are shown. In all cases, data from all 16 positions were used for testing.

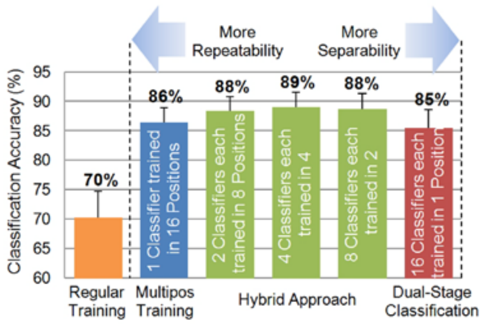

Figure 9. A comparison of the studied methods of resolving the position effect. It is shown that accuracy is improved by training separate position-group specific classifiers, peaking at four subdivisions of the 16 position workspace, after which performance declines. The error bars indicate the standard error across subjects.

The results of Fig. 9 show that the novel hybrid classification approach outperforms the previously proposed methods. An ANOVA test showed that training classifiers using this method produced significantly higher accuracies ($p < 0.05$) than training one classifier in 16 positions or training 16 classifiers each in one position. Training four classifiers each including four positions provided the optimal subdivision of position space (although no significant improvement was found relative to the configurations of two or eight).

The average separability between motion classes and average repeatability between training and testing datasets for different classification methods and different number of classifiers are shown using SI and RI in Fig. 10. The results show that, by separating data from different subdivisions of the workspace and using them to train multiple classifiers (as done in Fig. 9), the separability between the trained clusters of each classifier increases. This is because, when the number of classifiers increases, the number of positions involved in their training and testing data decreases, resulting in a decrease in the variance of the associated clusters in feature space. This causes the classes to be more separable. This, however, results in less repeatability between the training and testing data. When the size of the trained clusters is small, despite the fact that testing data is from the same position, unavoidable inter-repetition variation of the testing data more easily causes divergence from the training data.

IV. Discussion

The effect of adding more positions to the test data, when the classifier is trained in only one position, is shown in Fig. 6. This suggests that the "position effect", which results in decreased accuracy, manifests itself by a reduction in both separability and repeatability of the EMG features.

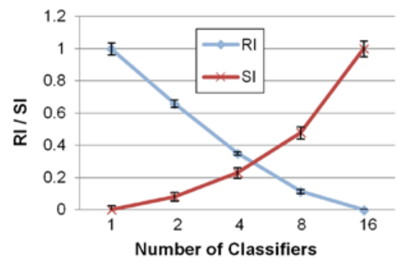

Figure 10. Illustration showing how splitting the workspace into higher numbers of subdivisions, resulting in fewer positions being used in the training of each classifier, increases the separability between the trained classes but decreases the repeatability between training and testing data of each classifier. The indices have been normalized between zero and one to make the trends visually comparable. The error bars indicate the standard error of the measurements.

Training the classifier in multiple (1-16) positions was a previously proposed method to reduce these effects and, as shown in Fig. 7, classification accuracy was shown, on average, to increase with the number of training positions. Fig. 8 shows that this improvement in classification accuracy is related to the increased repeatability between the training and testing data. Also, Fig. 7 shows that when using the best possible combination of positions, classification accuracy quickly climbs to a maximum at 5 positions, after which the relative performance actually decreases. This can be explained by observing the decrease in separability of the data, despite the increase in repeatability, as the number of training positions rises (See Fig. 8). In fact, adding data from more positions to the problem increases the variance of the motion classes in feature space resulting in less separability between the classes and can eventually cause them to overlap. At some point, the decrease in separability has a bigger effect on classification performance than the increase in repeatability and this leads to a reduction in classification accuracy. Therefore, a trade-off exists between repeatability and separability of data, indicating that there is an optimum selection of training positions at which these characteristics of the data are balanced.

Although the results of an ANOVA on the number of training positions showed that four or five positions are best for training, this number of positions still imposes a rather extensive training session for the amputee. For a clinically practical training session, one must weigh the incremental benefit against the added time and effort. Correspondingly, the results suggest that a suitable compromise may be to use only two positions for training. Observation of trends across the subjects indicate that one of these positions should be picked from the positions in which the arm is straight and one from the positions in which the arm is bent.

Another approach to reduce the position effect is dual-stage classification. Fig. 9 showed that when the number of desired positions is high, splitting the workspace into several subdivisions (to use separate position-group specific classifiers) is better than either training one classifier in all positions or training multiple classifiers each in just one position. The number of subdivisions (and therefore classifiers) should be chosen cautiously because the classification accuracy improves as the number of classifiers initially increases, but reaches an optimal number before then decreasing with further subdivision of position space. This can be explained by studying the effect of increasing the number of classifiers on the characteristics of feature space. As shown in Fig. 10, separating data from different positions causes increased separability between the motion classes by reducing their variance. However, reduction in the size of the feature clusters also leads to a reduction in repeatability between training and testing data, which tends to increase classification error. Therefore, again, there is a trade-off between separability and repeatability. The results showed that for the 16 training positions used in this work (chosen to mostly cover the expected workspace of a prosthesis), the optimal number of position subgroupings was four, although two was shown to be similar, and more clinically desirable.

V. Conclusion

In this work, the effect of variation in the limb position on the performance of pattern recognition was analyzed through investigation of its effect on EMG feature space. By using the repeatability and separability indices, it was shown how training the classifier in multiple positions reduces the position effect and that there is an optimum number of training positions to gain the maximum benefit. Since training in multiple positions imposes an extensive training session for the amputee, it is suggested that considerable benefit can be gained by training the classifier using only two limb positions. It was demonstrated that these two positions are ideally comprised of one in which the arm is straight and another in which the arm is bent at the elbow. It was also shown how the position effect can be reduced by using a dual-stage classification scheme that identifies the limb position first, and then selects position-specific classifiers. Finally, a hybrid classification scheme in which multiple position-specific classifiers were each trained using data from multiple positions was shown to outperform previous methods, minimizing the position effect by exploiting a trade-off between repeatability and separability of the data.

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