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The effect of electrode displacements on pattern recognition based myoelectric control

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***Abstract*—Pattern recognition based myoelectric controllers rely on a fundamental assumption that the patterns detected under a given electrode are repeatable for a given state of muscle activation. Consequently, electrode displacements on the skins surface affect the classification accuracy of the pattern based myoelectric controller. The effects of electrode displacement can be mitigated by using a training set of data which consists of patterns detected over a range of plausible displacement locations to train the control system.**

I. INTRODUCTION

INFORMATION extracted from the amplitude [1] or rate of change [2] of the surface myoelectric signal (MES) has been used to successfully control upper limbed powered prostheses for many years. These 'direct' control systems map the extracted amplitude feature or rate of change feature to a specific degree of freedom of the prosthesis. Although these control schemes have been successfully implemented, they are limited in they require source signal independence and can typically only control one or at most two degrees of freedom [3].

Information extracted from patterns contained within the MES has been investigated as an alternative form of myoelectric control. Pattern recognition myoelectric control systems are beneficial in that they do not require independent signals and can potentially control more degrees of freedom than direct control systems; however they have an added complexity in that they have to be properly trained to recognize specific patterns on a patient by patient basis. These control systems operate on the assumption that at a given electrode location the set of features describing the myoelectric signal over an analysis window will be repeatable for a given state of muscle activation [4]. Consequently, one of the many factors that the performance of the control system is dependent upon is electrode location. Each time a user dons the prosthesis it is likely that the electrodes will be in a slightly different location due to socket/residual limb misalignment. As well, during use, it is common that electrode position may change slightly when the prosthesis is used in various orientations. This study attempts to simulate the electrode displacement due to socket/residual limb misalignment and determine the effect it has on the pattern recognition classification accuracy.

II. PATTERN RECOGNITION BASED MYOELECTRIC CONTROL

Figure 1 depicts a block diagram of the state-of-the-art pattern recognition myoelectric control process.

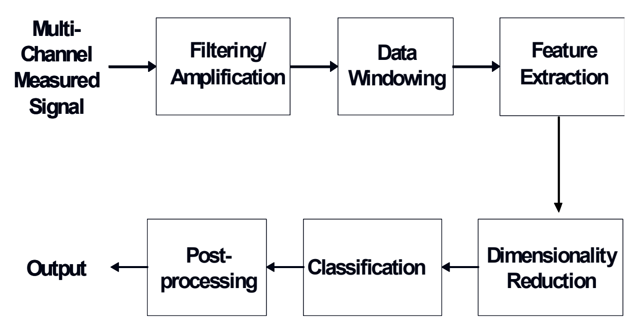

Fig. 1. Block Diagram of Pattern Based Myoelectric Control Process

Feature sets formulated from time domain (TD) statistics [3], autoregressive (AR) coefficients [5], and

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time-frequency information [6], have been shown to provide accurate signal representation when combined with dimensionality reduction in the form of principal components analysis (PCA) [6].

ANN's [3], linear discriminant analysis (LDA) classifiers [6], Gaussian mixture models (GMM) [5], and fuzzy logic classifiers [7] have all been shown to be acceptable classifiers for pattern-based myoelectric control. The size of the data analysis window and the number of majority votes used in post-processing are determined by processing speed and the acceptable delay perceived by a prosthetic user and if chosen properly have been shown to provide a modest increase classification accuracy [8].

III. METHODS

Surface MES were collected from four normally limbed male subjects for ten medium force isometric contractions of five seconds duration, corresponding to the motions: wrist flexion\extension, wrist abduction\adduction, forearm pronation\supination, keygrip, chuck grip, pen hand, and gently move fingers. An arm brace was constructed to hold the arm stationary during the contractions. The brace supports the arm at the elbow and wrist while the hand is inserted into a padded slot. During contractions, the padded slot provides some resistance for the hand to push against while keeping the forearm immobilized. Four Duotrode Ag-AgCl electrodes (3M Corp.) were placed around the circumference of the upper forearm in the electrode configurations depicted in Figure 2. Previous research has shown that for the motions under investigation the specific locations of the electrodes are not important so long as at least four channels are spaced symmetrical around the circumference of the limb [9].

For each electrode displacement location, software guided each subject through data acquisition sessions which consisted of two trials of two repetitions of each motion (corresponding to 40 contractions in all). All channels were band-pass filtered between 10 -500 Hz and amplified with a gain of 2000.

Data were processed with three different feature sets: TD, 6th order AR, and a concatenation of TD and 6th order AR (TDAR), in combination with a LDA classifier. For each combination, data analysis windows of 256 ms were used to extract features and a conservative estimate of 16 ms was used as a processing delay which allowed for at least 17 decisions to be used in a majority vote while keeping the user perceived delay less than 300 ms [4]. Each control scheme was trained using two different methods. In the first method, the classifier was trained with features extracted from trial one of data collected

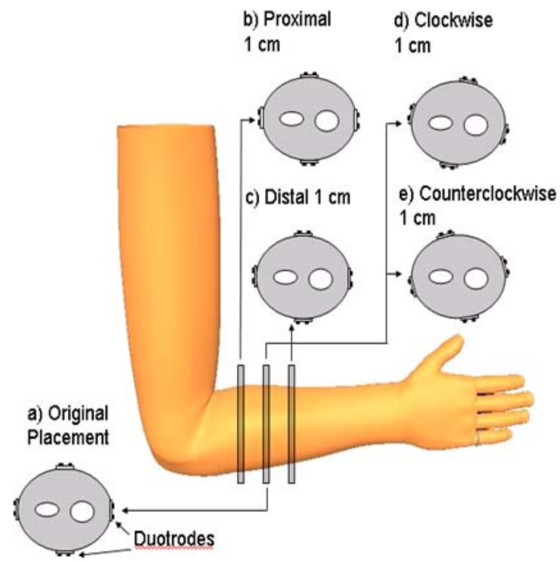

Fig. 2. The above figure displays the original electrode location and four displacement locations. Cross-sections a) - e) depict electrode locations; b) and c) introduce longitudinal displacement, while d) and e) introduce rotational displacement.

only from the nominal electrode placement location. In the second method, the classifier was trained with features extracted from trial one of the data collected from each of the five locations. The classifiers were then tested using features extracted from trial two of the data collected at all locations.

IV. RESULTS

Figure 3a illustrates the classification error when the classifier is trained with patterns detected only at the electrodes over the 'original' locations. Figure 3b illustrates the classification error when the classifier is trained with patterns detected from all displacement locations.

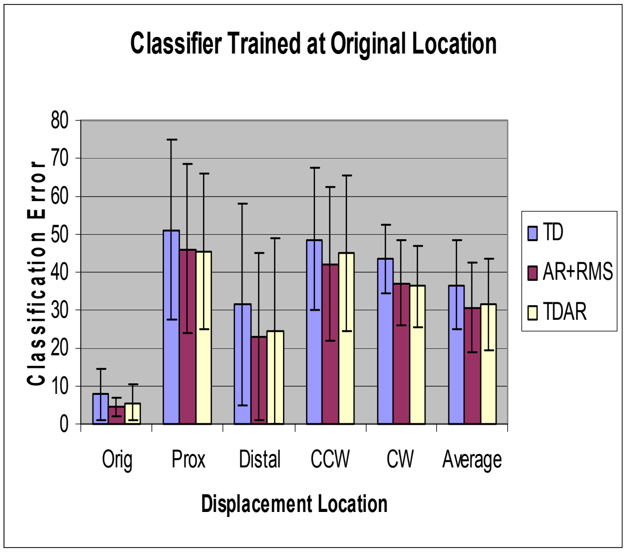

Fig. 3a. The classification error, averaged over all four subjects when, considering data acquired at an original position (Orig), proximal longitudinal displacement (Prox), distal longitudinal displacement (Dist)al), counterclockwise rotational displacement (CCW) and lockwise rotational displacement (CW).

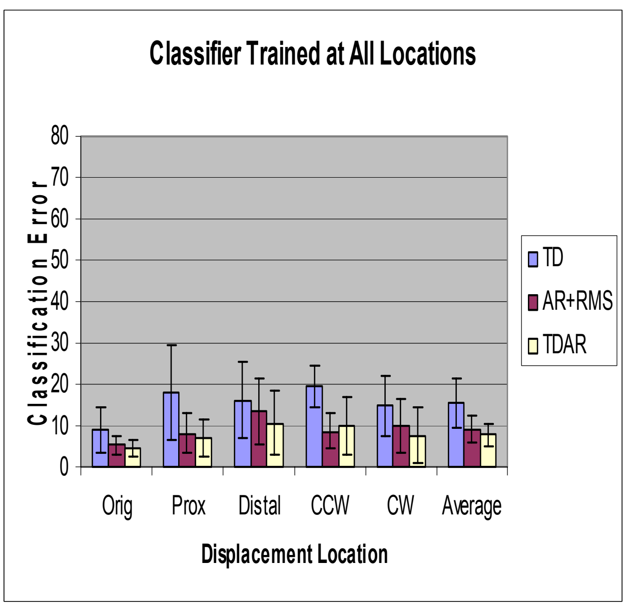

Fig. 3b. The classification error, averaged over all four subjects when, considering data acquired at an original position (Orig), proximal longitudinal displacement (Prox), distal longitudinal displacement (Dist)al), counterclockwise rotational displacement (CCW) and lockwise rotational displacement (CW).

When considering Figure 3a, the case when the classifiers are trained only with data collected at the nominal electrode location, it is obvious that they can recognize test patterns collected from the nominal location with a high accuracy (classification error $\approx$ 5%); however the system is not able to reliably recognize patterns when the electrodes are displaced (average classification error $\approx$ 30%). When considering Figure 3b, the case when the classifiers are trained with patterns detected at both the nominal and displacement locations, it is obvious that the system can reliably recognize patterns generated from any of the electrode displacement locations.

A smaller effect is seen with regard to the feature set used; the AR features consistently outperform the TD features. In the system trained with all electrode locations, the TDAR features show a slight advantage over the AR features.

V. Conclusions

Clearly, pattern recognition performance deteriorates with displacement of electrode position. The situation of 1 cm displacement is likely larger than that typically encountered in practical use, but is a reasonable worst-case scenario. A dramatic improvement is obtained, however, when the classifier is trained with data that represents possible displacements, indicating that the classifier can incorporate this new information and generalize when encountering new data. This is an important practical result, as this method can be used to ensure pattern recognition based MES control systems that are robust to electrode displacement.

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