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Pattern recognition of single and combined motions from the shoulder complex

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Abstract— **Much research has been done towards developing control systems for artificial hands, elbows, and wrists based on the myoelectric signal (MES). While great effort has gone into developing pattern recognition based control systems for these devices, very little attention has been devoted to the shoulder. This is in part because the majority of amputees are either below elbow or mid-humeral, and true shoulder disarticulations are rare. However, as the level of limb loss increases so does the need for functional replacement. This study investigates pattern recognition concepts for independent control of an artificial shoulder.**

I. INTRODUCTION

MYOELECTRIC signal classification for prosthetic shoulder control is relatively new, in part due to the rarity of shoulder disarticulations. Nonetheless, individuals with shoulder disarticulations are the ones who would most benefit from multifunction myoelectric control.

Conventional prosthetic shoulders are controlled by switches located inside the harness of the prosthesis, which must be activated by the patient when he or she wishes the joint to move. Another strategy is to use 'indirect' myoelectric control, where one healthy muscle is used to activate one degree of freedom of the artificial shoulder joint. While both of these methods can restore some of the missing functionality, neither of them is ideal. The first method relies on the mechanical activation of switches, which involves a high degree of learning on the part of the patient, and depending on the type of activity may not be feasible. The second method, although more intuitive as electrical activity in the muscle is used to initiate motion rather than a switch, is still only an approximation of how the healthy shoulder system would function. Both of these methods lack the intuitive control which is ultimately desirable in the operation of an artificial limb.

In natural movement, the mapping of muscular activity to shoulder motion is far from one to one. The muscles interact in complex patterns to create movements in multiple degrees of freedom simultaneously. Consequently, pattern recognition based control is the obvious choice for an artificial shoulder. This study investigates pattern recognition of myoelectric signals from the shoulder, and attempts to classify a large number of both single and combined shoulder motions of varying force levels.

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II. PATTERN RECOGNITION BASED MYOELECTRIC CONTROL

The design of the classification system plays a paramount role in achieving high accuracy in classification tasks. The classification process involves multiple stages, including the choice of signal representation (feature set), dimensionality reduction, and the choice of classifier, as shown in Fig. 1.

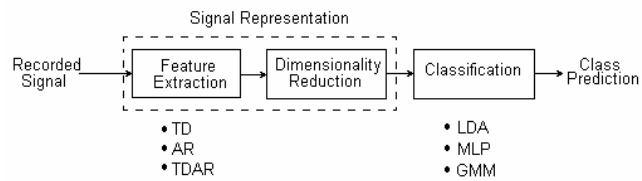


Fig. 1. Block diagram of pattern recognition based classification, showing the three main stages of the classification process: feature extraction, dimensionality reduction, and the classification itself.

The feature extraction stage is the initial transformation of the recorded data into a form more easily separable by the classifier. Both time domain (TD) statistics [1] and autoregressive (AR) coefficients [2],[3] have been found invaluable as a means of myoelectric signal representation when used in conjunction with dimensionality reduction in the form of principal components analysis (PCA) [4]. Statistical classifiers such as Gaussian mixture models (GMM) have proven adept at myoelectric signal classification problems, as have neural classifiers such as the multilayer perceptron neural network (MLPNN) [3],[5-7].

Incorporating GMMs and universal background models (UBMs) is a novel approach to pattern recognition of myoelectric signals. While GMM/UBM pairs have been used with great results in speaker identification/verification applications [8], they have never been applied to myoelectric signal problems. However, the problem of speaker verification/identification bears strong resemblance to the task of motion classification for MES [9]. It is therefore expected that GMM/UBM pairs are capable of performing well on the myoelectric signal classification problem.

III. METHODS

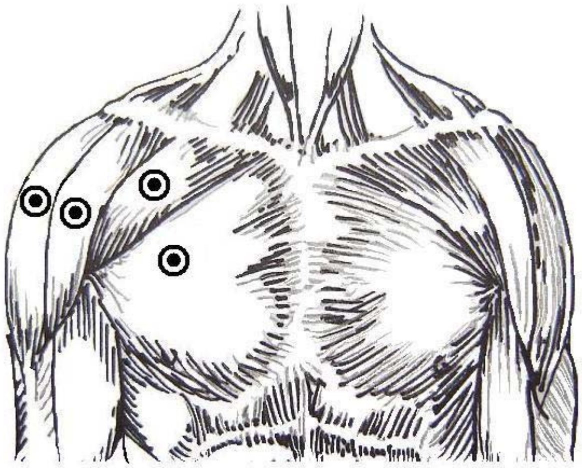
Surface MES were collected from five normally limbed individuals for eight isometric contractions of the shoulder complex. Each contraction had a five second duration and was conducted at light, medium, or strong force, corresponding to approximately 20, 50, and 80% of the participant's maximum voluntary contraction (MVC). The eight shoulder contractions were selected by the frequency with which they are performed in daily living tasks, and are shoulder flexion/extension, medial/lateral rotation, abduction, adduction, and transverse flexion/extension. For all light force motions where the primary resistance is against gravity (flexion/extension, abduction, and transverse flexion/extension), the arm was held at 45 degrees to the body. The angle between the body and the limb was 90 degrees for the medium force, and for the strong force the angle remained the same, but the participant held a 1.5kg weight at arm's length. The motions in which the shoulder and limb are not opposed by gravity (medial/lateral rotation and adduction) were performed with the participant pressing the limb against a solid object with the required percentage MVC. This ensured that the different force levels of the same motion were all accompanied by appropriate force proportional activity of the muscles associated with that motion.

Eight Duotrode Ag-AgCl electrodes (3M Corp.) were placed on the musculature of the shoulder girdle. The eight chosen sites were the anterior and lateral deltoids, the clavicular and sternal heads of the pectoralis major (Fig. 2 (a)), the posterior deltoid, trapezius, the latissumus dorsi, and the infraspinatus/teres major (Fig. 2 (b)). These sites were chosen as they are the primary muscle groups involved in shoulder motion. It is feasible to use all of these locations as control sites, as in the event of a shoulder disarticulation, all of these muscles remain at least partially present.

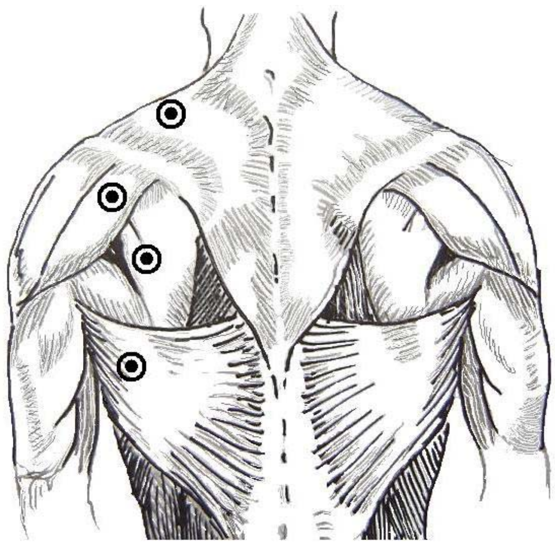
Clear MES was observed on each channel separately prior to the data collection. The participant was guided through the data collection sessions by software specifying which contraction was to be performed at a given time. Each force level of each contraction was repeated five times, making for a total of 120 contractions. All channels were sampled at 1024 Hz and amplified with a gain of 2000.

The data were represented by three feature sets: TD, 6^{th} order AR, and a concatenation of TD features and the 6^{th} order AR features (TDAR). Data analysis windows of 256ms were used in conjunction with an estimated processing delay of 32ms, making for a dense decision stream. Both overlapped and non-overlapped data were classified. The overlapped data provided eight decisions per analysis window, and the non-overlapped data provided one decision per analysis window. Two forms of classifiers were used: MLPNN, and GMM/UBMs. The classifiers were each tested on overlapped and non-overlapped data from all three feature sets, and all force levels of all eight motions being classified separately, for a total of 24 classes.

Next, the outputs of the MLPNN were trained to targets proportional to force. Conventionally, the neural network output of the desired class is trained to one and the outputs associated with all other classes are trained to zero.



(a)



(b)

Fig. 2. The eight chosen electrode locations for data collection from the shoulder complex. (a). Anterior view, showing electrodes on the anterior and lateral deltoids, and on the clavicular and sternal heads of the pectoralis major. (b). Posterior view, showing electrodes on the posterior deltoid, the trapezius, the latissumus dorsi, and the infraspinatus/teres major.

When testing the conventional neural network, the output corresponding to a given class will be one when that class is present, and zero at all other times. The outputs of the MLPNN used in this work however were trained to one third, two thirds, or one, depending on the force level of the input signal. This was done to investigate the MLPNN as a means of proportional myoelectric control.

Next the MLPNN and GMM/UBM were investigated as a means of multifunction control. When collecting real combination data from a participant, it is impossible to know the exact proportion of involvement of each of the singular motions which produce the combination. Thus there is no practical way of obtaining data to train the network to recognize proportional involvement. Therefore combined motion data were artificially generated by assuming that a combined motion (such as the simultaneous shoulder flexion and medial rotation required to position the upper arm for feeding tasks) is the average of the two singular motions involved in the combination. This approximation was made for the sake of having training combination data where the proportions of class involvement are known precisely.

Four classes of combinations were created, each with five repetitions of the three force levels. The four combinations are shoulder flexion and medial rotation, shoulder extension and lateral rotation, shoulder flexion and transverse flexion, and shoulder extension and transverse extension. These motions were chosen for their relevance to daily living tasks, such as feeding and dressing.

An MLPNN was trained to distinguish these combinations by using specially defined targets. The targets were defined such that the outputs associated with the two classes involved in a combination would each be equal to one half when the input pattern x belongs to a combination. When the current input pattern does not belong to a combination, the network was trained in the usual fashion. During testing, the presence of combination data was assumed if two outputs of the neural network were high simultaneously. A similar classification was also attempted using the GMM/UBM, although the GMM/UBM was not trained to specific targets. Since GMM/UBM outputs are the likelihood ratio that the input pattern x was generated by a given class, ideally combinations should be recognized as the equal likelihood of two classes being present simultaneously.

All classifications were done using the three features sets and both overlapped and non-overlapped data.

IV. RESULTS

Fig. 3 illustrates the classification error of three classification schemes which are trained to distinguish the force with which a motion is executed. The first is an MLPNN which was trained to recognize each force level as a separate class, making for a total of 24 classes (eight motions times three force levels). The GMM/UBM is trained in the same way. The third classification scheme is an MLPNN which is trained to force proportional targets, meaning it recognizes first that the data came from one of eight classes, and then it attempts to select the force level with which the motion was performed. It makes the force decision based on the neural network outputs, which have been trained to be proportional to the force with which a motion is executed. This system distinguishes between two force levels instead of three.

When considering Fig. 3, it is evident that the three force MLPNN model cannot distinguish forces reliably in comparison with the three force GMM/UBM model. The two force MLPNN model which employs force proportional outputs demonstrates an improved classification rate over the other MLPNN model with the tradeoff of one force state. There is no significant difference between the performance of the three force GMM/UBM and the two force MLPNN in terms of classification accuracy, with both having average classification errors of approximately 7% on the best feature set.

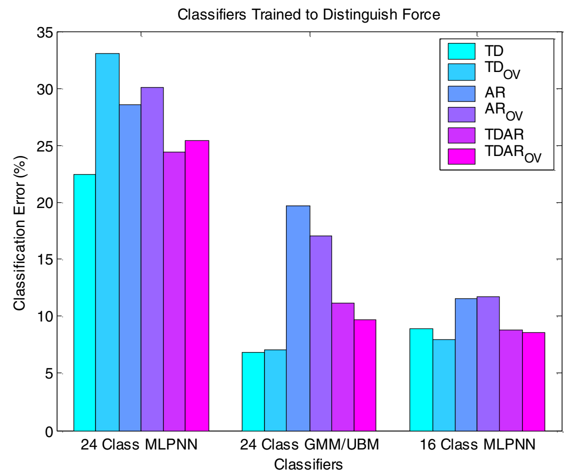


Fig. 3. Above are the classification errors for three classifiers (averaged across five participants) trained to distinguish the force with which a motion is executed. The first two (3 force MLPNN and GMM/UBM) are trained to recognize each force level as a separate class, and the last (2 force MLPNN) is trained to force proportional targets and recognizes two force levels.

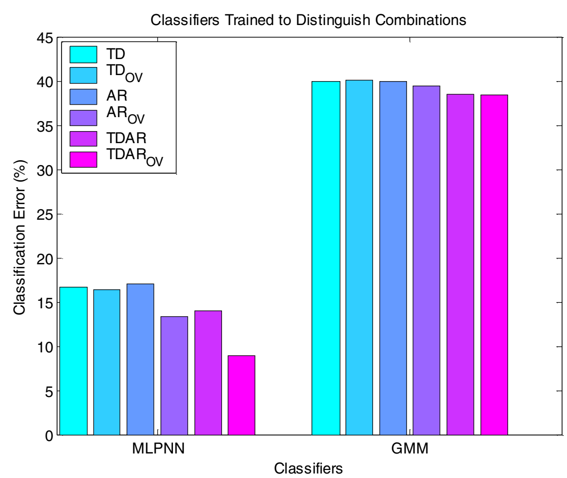


Fig. 4. Above are the classification errors for two classifiers which recognize combined motion data as combinations of two single classes. The MLPNN is specially trained to distinguish combinations in this manner, while the GMM/UBM is not.

Fig. 4 illustrates the classification error of both the MLPNN and the GMM/UBM on the artificial combination data. In the case of the MLPNN the network is trained to targets which on combination data are equal to one half for each of the two motions involved in the combination, and zero otherwise. The trained MLPNN is capable of determining which input patterns are combinations and which are not by examining the outputs. The GMM/UBM are not trained to any specific targets and are not trained on combination data, rather they examine the outputs and attempt to make class and combination decisions based on which outputs are high, and whether two outputs are high simultaneously (as would be the case in a combination). The MLPNN controller can recognize combinations in this manner with a mean classification error of 8% on the best feature set. The GMM/UMB performs poorly in comparison, with an average classification error of approximately 38% on the best feature set.

On all models the TDAR features consistently outperform the AR features, with a slight improvement being noted with the addition of overlapped data. Although there is no significant difference between the TD and TDAR feature sets, TD features tend to perform slightly better with force distinguishment problems, and TDAR features perform slightly better on combined motion problems. There is little difference in classification accuracy using overlapped and non-overlapped data.

V. Conclusion

As shown, feature selection and classifier design play an important role in the accuracy of a classification system. While the MLPNN is not well suited to classifying a large number of separate motions, it can consistently discern two force levels of eight classes of motion by using force proportional outputs. It can reliably detect combinations by the same method. The GMM/UBM pairs perform well on data containing a large number of classes, but are not adept at detecting combinations which are not defined as separate classes. TD and TDAR features show the best results for classification of myoelectric signals from the shoulder, with TD features offering a slight advantage over TDAR features for force determination problems, and TDAR features offering the advantage for combined data problems. AR features perform poorly in general.

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