TIME-FREQUENCY CLASSIFICATION OF THE TRANSIENT MECHANOMYOGRAM

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ABSTRACT

Muscle vibrations, known as the mechanomyogram (MMG), have been used in a limited manner to control upper-limb prostheses. MMG is dependent on the recruitment and firing rates of muscle motor units during contraction. It was thus hypothesized that MMG signals would reflect the distinctive patterns of muscle activation during the grasp of differently shaped objects. This study investigates this hypothesis, specifically focusing on forearm muscles. MMG patterns originating from grasps were classified. The classification performance was evaluated for a number of combinations of feature-sets and sensor sites. With seven able-bodied participants, MMG signal transients from three sites could be differentiated among three classes of forearm muscle activity with 78.6 ± 13% accuracy using wavelet packet-derived features and a linear classifier. These results suggest that, with additional research, MMG may indeed become a usable control signal for multifunction prostheses.

INTRODUCTION

The incidence of amputation in most developed countries is about 1.55 per 1000, 8.3% of which are upper-limb amputees [1]. Up to 70% of upper-limb amputees are fitted with a prosthesis [2]; however, over 35% eventually abandon their prosthesis [3], citing poor functionality and discomfort as the primary reasons for dissatisfaction [4].

Existing commercial prostheses provide a reduced set of manipulative abilities as compared to the human hand. Most upper-limb prostheses are controlled by surface electromyogram (EMG) signals, and are merely capable of providing two functions: hand open and close. The primary cause for the deficiency in functionality is the limited number of available control muscles [5]. However, advances in pattern recognition of EMG signals have provided greater potential for discriminating among multiple muscle states from a limited number of muscle sites [6, 7].

An alternative strategy for the control of upper-limb prostheses is the surface mechanomyogram (MMG) [8, 9]. Like EMG, surface MMG is an indicator of underlying muscle activity [5]. In addition to sharing many of the characteristics of EMG, such as the linear relationship between the amplitude of the signal and the strength of muscle contraction [10, 11], MMG sensors may be used with soft sockets [8], thus providing the user with added comfort. Moreover, because MMG signals are measured by microphones, accelerometers or laser distance sensors [5], skin problems associated with electrode gel sensitivities, a reported reason for prosthesis rejection [4], are not a factor for MMG driven prostheses.

The goal of this paper is to distinguish among patterns of transient MMG signals associated with the grasp of six differently shaped objects. During object grasp, a coordinated activation of forearm muscles is required to shape the hand in relation to the physical properties of the object. Studies have shown that there are distinctive and reproducible patterns of muscle activation during the grasp of differently shaped objects [12]. Since the MMG provides information about the number and firing rates of recruited motor units during voluntary isometric contraction [5], it is expected that patterns of muscle activity will be reflected in MMG signals. If complex MMG patterns are sufficiently consistent in between recordings to allow differentiation among several classes of muscle activity, MMG may be used as a control signal in multi-function prosthesis.

EXPERIMENTAL METHOD

Signal Measurement

Seven able-bodied subjects participated in the study. Six classes of MMG activity were recorded: pinch, palmar, lateral, hook, spherical, and cylindrical, as defined by Schlesinger [13]. Three MMG sensors were placed at bellies of the extensor digitorum, flexor digitorum and flexor pollicis longus muscle groups. Three additional sensors were placed at the distal end of the same muscles. The MMG signals were sampled at 1kHz and low-pass filtered (50Hz). Starting from a neutral position, participants picked an object, grasped it with constant force, and then returned to the neutral position. Each participant performed this sequence of grip and rest 68 times for each type of grip.

Signal Isolation

We define the transient signal as the portion of the signal associated with hand and finger movements while a grasp is being stabilized. The transient lasts for approximately 600±300ms[1]. In designing a function controller for powered upper-limb prosthesis, 300ms is generally accepted as the maximum allowable response delay between function initiation and actuation [14]. Therefore, it is impractical to wait until the MMG signal has reached a steady state to make classification decisions. Pattern recognition of transient rather than steady-state MMG signals may be the preferred implementation for a practical prosthesis controller.

MMG data recording was synchronized with video recording, and the segments of MMG data associated with transient grip were isolated from the data stream using the methods described in [15].

Signal Pre-processing

The isolated transients were low frequency signals with a duration of 600±300ms. The long duration and variations in duration posed two issues:

1. The prosthesis response time requirement of 300ms cannot be met if the entire transient is classified; and
2. Although the duration of the transients varied, visual inspection showed similar structures in the transient signal for some classes. Structural features would be lost if the transient signals were trimmed.

In order to address both issues, two versions of the original transient signal were considered:

1. Leading Transient (LT): The transient signal was trimmed to include the first 250ms of data. To simplify processing, the original signal recorded at 1kHz was downsampled to 128Hz to yield 32 data points.

2. Time-normalized Transient (NT): The entire transient was downsampled to frequencies ranging from 150 to 400Hz such that the resulting signal had 128 data points. Successful classification of the entire transient will prove that the transient has an inherent structure for object specific grasps.

Signal Representation

MMG signals were decomposed to their equivalent level 5 wavelet packet transform (WPT) using the Coiflet 4 wavelet. The Coiflet wavelet was arbitrarily chosen since its oscillatory nature is similar to that of MMG signals. Each signal was represented by their best basis as determined by the Local Discriminant Basis (LDB) algorithm using symmetric relative entropy as the discriminant measure. The discriminant power of each basis vector in the LDB was recorded. Ideally, parameters such as the wavelet and the discriminant measure should be chosen to maximize classification performance.

Feature extraction

Two methods of dimensionality reduction were compared:

1. Feature Selection (FS): A feature vector of five most discriminatory coefficients across all muscle sites was chosen to represent the grip. Higher dimensionality feature vectors would unnecessarily overwhelm the classifier.

2. Principal Components Analysis (PCA): Each grip was represented by 200 most discriminatory features reduced by PCA while retaining 90% of its variance. The resulting feature vector of 2 to 3 features was a combination of feature selection (using ranked LDB coefficients) and feature projection (using PCA).

a. Timing Information

In addition to WPT features, the duration of the transient signal, referred to as the time interval (τ), was considered as a feature for the time-normalized transient. Kruskal-Wallis tests for equal medians showed that time intervals were significantly different among grasps ($p<0.05$). Figure 1 shows an example of the distribution of the time intervals for each grasp.

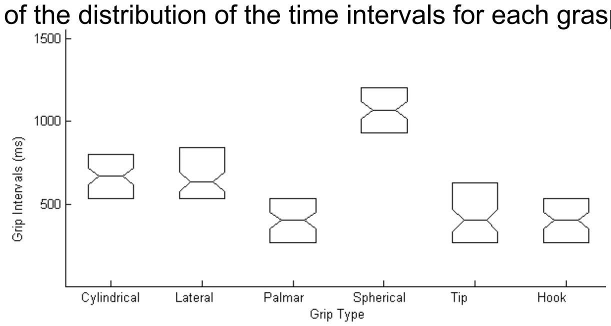

Figure 1. Distributions of durations of the transient signal for each grip (Participant A)

b. Muscle-Site Selection

In order to determine the effect of MMG signals from the three distal muscle sites[2] on grip recognition, two sources of MMG signals were compared: signals from three proximal sensors (referred to as 3-site); and signals from six sensors, 3 at proximal muscle sites and 3 at distal muscle sites (referred to as 6-site).

[1] Median ± inter-quartile range calculated from data recorded.

[2] Signal recorded distal to the muscle belly

Classification and Testing

Grip recognition performance was evaluated using 5-fold cross-validation. LDA classifiers and ANNs were trained in a supervised manner to distinguish among 3 to 6 grips. The classifier was tested for each feature set for all $\binom{6}{k}_{k=\{3\ldots6\}}$ combinations of grips. The best grip subset $\{\mathbf{g}^*_{k,f,s}\}$ for each participant and feature type was determined by the grip subset with minimum training error, where k is the number of target grips, f is the feature set, and s is the signal type (LT or NT). Classification test errors for each $\mathbf{g}^*_{k,f,s}$ were compared.

RESULTS

The performances of the feature sets, expressed in terms of their test set classification rates, were compared. Fairly low classification accuracies were obtained from the LT signals. This was likely because inherent discriminatory structures in the transient MMG were lost when the signal was truncated, resulting in poor classification accuracy.

To assess the performance of WPT features for classifying transient MMG signals, two types of feature set selection methods were compared: individually selected feature sets that minimized the median training error for each participant, and a single feature set that minimized the median training error for all participants.

The classification results are shown in Table 1. Rank-sum tests indicated that the performance of the two feature set selection methods was not significantly different (p = 0.05). Notice that the performance plummets when more than four types of grips are classified.

Table 1. Relative performance amongst feature set selection methods.

Accuracies are reported as median ± inter-quartile range

No. of Targets	Signal Type	Individual best feature set	Single best feature set for all participants	
		Accuracy (%)	*Feature set (Classifier)*	*Accuracy (%)*
3	NT-τ	78.6 ± 13	6-PCA(LDA)	76.9 ± 13
	NT	69.2 ± 11	3-FS (ANN)	61.5 ± 4
	LT	69.2 ± 4	3-FS (ANN)	69.2 ± 14
4	NT-τ	70.3 ± 13	6-PCA(LDA)	61.5 ± 14
	NT	53.6 ± 3	3-FS (ANN)	51.9 ± 7
	LT	54.2 ± 5	3-FS (ANN)	51.9 ± 8
5	NT-τ	50.0 ± 14	6-PCA(LDA)	50.0 ± 9
	NT	42.9 ± 7	3-FS (ANN)	38.5 ± 6
	LT	42.9 ± 7	3-FS (ANN)	38.5 ± 5
6	NT-τ	43.6 ± 11	6-PCA(LDA)	38.5 ± 12
	NT	34.5 ± 2	3-FS (ANN)	32.1 ± 12
	LT	33.2 ± 7	3-FS (ANN)	26.8 ± 10

3-site=proximal sensors only; 6-site= proximal and distal sensors; LT=leading transient; NT=normalized transient; τ=duration of transient; FS=feature selection; PCA=principal components analysis; LDA=Linear discriminant analysis classifier; ANN=Artificial Neural Network classifier.

Effect of location of sensors

The features chosen for each of the feature sets were the five most discriminatory wavelet coefficients ranked across all muscle sites. Sixty percent of the discriminatory features were extracted from signals recorded at distal muscle sites. This suggests that distal signals have discriminatory information.

DISCUSSION

The WPT and LDB algorithm have complexities of O(NlogN) [7, 16]. Being computationally inexpensive, the processing time does not represent a significant source of delay in prosthesis response time. However, because MMG signals have low frequency, a long record length (>200ms[3]) is required to capture the time evolving structure of transient MMG signals. Classification of the first 250ms of the transient may meet the response time requirement of 300ms; however, this method did not yield promising classification performance. Conversely, classifying the entire transient will result in a perceivable delay in prosthesis response time.

The highest classification accuracy was obtained by classifying time-normalized transient signals with transient durations as an additional feature. This method attained a median accuracy of 78.6% for distinguishing among three classes of grips. In comparison, accuracies of more than 95% have been reported for classifying four classes of hand motion from transient EMG signals using WPT feature extraction methods [7]. The possible causes for the low recognition rates of the MMG classification system are discussed in the following sections.

[3] Visually observed

Subtle signal changes

Unlike works on multi-function classification of EMG signals, which have primarily classified hand and wrist motions with more obtuse superficial forearm muscle activity [6, 7], the functional grips classified in this experiment involved small changes in digit activity primarily controlled by deep forearm muscles. It is possible that the MMG sensors were not placed in optimal locations for capturing forearm muscle activity underlying grips.

Temporal Shifts

A fundamental drawback of the wavelet packet transform is that it lacks shift invariance. If the transient signal is not well aligned but is temporally shifted by even a small amount, the wavelet transform coefficients are modified in a complex manner [17]. Transforms that are less susceptible to temporal shifts, such as the continuous wavelet transform, although computationally complex, may yield better features for classifying signals that are subject to temporal translation. Further, other feature extraction methods that could provide better classification performance, such as the Fourier transforms and time-domain analysis, were not investigated in this experiment.

Inconsistent MMG patterns

When fingers move, an important part of muscle movement is not involved in finger motion but in compensating for the interaction torques between the different finger segments [12]. Minor difference in the posture of the hand could alter these interaction torques and result in profound changes in muscle activity, and hence the MMG. Moreover, muscle activity is effected by small differences in contact between the fingers and the object being grasped. Since functional grip is extremely susceptible to variations in muscle activity patterns, it is likely that other motions, such as wrist flexions and extensions, could yield more promising results.

CONCLUSION

A wavelet-based method for classifying transient MMG signals has been proposed. Classification accuracies of 78.6% were obtained for identifying three types of functional grip, indicating that some discernable patterns exist in transient MMG signals. Classification decisions of the transient MMG could serve as an initial cue about the intent of the prosthesis user that could be verified by subsequent classification of steady-state MMG signals. To this end, optimum sensor placement, better feature extraction methods, and classification of hand movements that can generate more consistent MMG patterns will be the focus of future work on multi-function MMG classification.

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