FILTERING STRATEGIES FOR ROBUST MYOELECTRIC PATTERN CLASSIFICATION

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ABSTRACT

Recent investigations into the use of real-time, pattern recognition based myoelectric control systems have shown excellent results in terms of classification accuracy and limb controllability under clinical supervision. Longer term, continuous use appears to be subject to deterioration in classification accuracy and usability due to factors including electrode displacement, electrode/skin interface impedance, and user variability. In this work, a simple filtering strategy for improved robustness to external noise is introduced. Recorded signals are digitally filtered to remove noise vulnerable frequencies while retaining discriminatory myoelectric information for classification.

INTRODUCTION

The surface myoelectric signal (MES) is an electrophysiological signal generated by muscular contractions which propagates along the length of skeletal muscle to detection points on the skin's surface. The MES measured from an amputee's residual limb can be used to determine the user's intent and act as a source of control information for powered prosthetic devices. Conventional control strategies usually map an amplitude estimate of the MES detected over independent control sites to degrees of freedom (DOF) of the prosthesis. This type of control system is limited by the number of appropriate independent control sites available [1].

Information extracted from signal patterns detected across multiple MES channels can also be used for control purposes [2]. Successful myoelectric pattern classification requires the user to make repeatable muscle contractions for each motion that is replaced. Recent investigations into the use of real-time, pattern recognition based myoelectric control systems have shown excellent short-term results under clinical supervision. Users are able to attain high classification accuracy and limb control when the system is trained and tested within a given session. Long term, continuous use appears to be subject to deterioration in classification accuracy and usability due to factors including electrode displacement, electrode/skin interface impedance, and user variability. While clinical measures can be taken to minimize some of these effects [3-4], a robust classification system is imperative.

This work consists of two experiments to investigate the classification accuracy of pattern recognition based myoelectric control in the presence of substantial power-line interference. In the first experiment, signals were collected in a low noise environment from normally limbed subjects. The signals were then artificially corrupted with 60 Hz, 120 Hz, and 180 Hz interference frequencies prior to classification. In the second experiment, data were collected from one amputee subject in a clinical setting which contained a large amount of power-line interference. It should be noted that these noisy data were not corrupted by intention, but rather, discovered after a testing session.

METHODOLOGY

Experimental 1 Protocol

MES data corresponding to eleven motion classes were collected from 10 normally-limbed subjects, in an experiment approved by the University of New Brunswick's Research Ethics Board.

Ten adhesive Duotrodes were placed on the proximal portion of the forearm as illustrated in Figure 2.

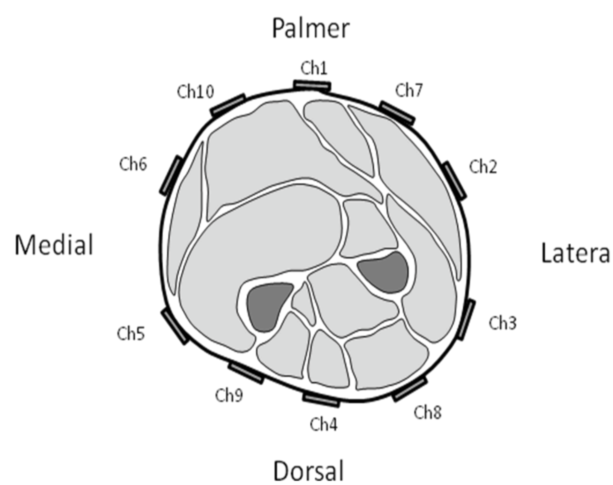

Figure 1: Cross-section of the upper-forearm showing electrode locations.

Twelve locations were marked at circumferentially equal lengths on the forearm, around the apex of the muscle bulge. The Duotrodes were placed at 10 of these markings, excluding the medial and lateral marking.

Experimental data were collected from subjects for 8 trials. Each trial consisted of 2 repetitions of the following 11 types of motion classes performed in sequential order: wrist pronation/supination, wrist flexion/extension, hand open, key grip, chuck grip, power grip, fine pinch grip, tool grip, and a rest class. The rest position was defined as one of the motion classes in this work, and the rest position for intact limbed subjects was 0 degrees flexion, with the palm of the hand perpendicular to the floor. The subject's elbow was allowed to rest on an armrest. The subjects were not restrained in any way during data collection and were given instructions to elicit repeatable, medium, constant force contractions to the best of their ability. Prior to data collection, subjects were allowed to practice making contractions for approximately 10 minutes. During this time, the MES was examined by the experimenter to ensure that good electrode/skin contact was maintained for all motions and that the gains of the amplifiers were appropriately set to avoid saturation. During all trials, subjects elicited the contraction from the rest position, held the contraction for 4 seconds and then returned to the rest position for a predetermined inter-motion class delay period. Trials 1-4 used inter-motion class delay periods of 3, 2, 1, and 0 seconds respectively. Note that a delay of 0 in trial 4 implies that the subjects instantaneously transitioned between the motion classes for this trial. Trials 5-8 used inter-motion class delay periods of 2 seconds. Each subject was given a brief rest period between trials to prevent fatigue. The entire experiment, including electrode placement took less than two hours to complete.

MES data recorded during trials 1-4, excluding the inter-motion class delays, were used to create a set of training data. MES data recorded during trials 5-8, excluding inter-motion class delays, were used as a test data set. All data were collected using a custom built pre-amplification system, a 16-bit DAQ and custom data acquisition software, sampled at 1 kHz per channel. The amplifier gains were set such that the detected myoelectric signal filled a dynamic range of 5 Vpp.

Experiment 2 Protocol

MES data corresponding to 9 motion classes were collected from 1 shoulder disarticulate amputee who had received targeted muscle reinnervation (TMR) surgery. Twelve stainless steel electrode pairs were placed over clinically used TMR control sites which were identified in high density electromyography experiments [5].

Experimental data were collected for 2 trials. Each trial consisted of 2 repetitions of the following 9 types of motion classes performed in sequential order: elbow flexion/extension, wrist pronation/supination, wrist flexion/extension, hand open, hand close, and a rest class. Each repetition lasted for 5 seconds with a 3 second inter-motion class delay between contractions. Trail 1 was used to train the pattern recognition system and trial 2 was used for testing. The subject was an experienced pattern recognition user and was provided a brief practice period during which the MES were inspected by the experimenter.

Signal Processing - Experiment 1

Simulated noise values were added to the data collected from experiment 1, but not experiment 2. Two different noise situations were simulated; 1) the training and test data were corrupted by the same noise amplitudes, and 2) training and test data were corrupted by different noise amplitudes. In both cases, the simulated noise frequencies were 60 Hz, 120 Hz, and 180 Hz, and simulated noise amplitudes were V_N (the baseline noise) $1/3V_N$ and $1/5V_N$ for each respective harmonic.. A number of different baseline noise amplitudes, V_N, were investigated; ranging from no added noise to 1V peak to peak.

The pattern recognition based myoelectric control system used for myoelectric signal classification consisted of time-domain feature extraction based on 150 ms analysis windows, followed by classification with a linear discriminant classifier. This control system has been described previously [2], and has been shown to effectively classify the motions under investigation for the intact limbed subjects [5] and the TMR amputee subject.

Classification accuracies were computed for two different filtering cases; with and without notch filtering to remove noise frequencies. The notch filters were 5 Hz Butterworth band-reject filters centered at 60, 120, and 180 Hz.

Signal Processing - Experiment 2

The same pattern recognition control system used to process experiment 1 was used to determine the classification accuracy for the TMR amputee with and without notch filtering. The notch filters were 5 Hz Butterworth band-reject filters centered at 60, 120, 180, 240, and 300 Hz. These frequencies were determined by visual inspection of the frequency spectrum of the raw signals.

RESULTS

Table 1 displays the results of experiment 1 without notch filtering. The results are averaged over the 10 subjects. The table diagonal represents situations where the training and test data have been corrupted by the same noise amplitudes while the off-diagonals represent situations where the training and test data have been corrupted by different noise amplitudes. Table 2 displays a similar table, except notch filters were used to remove the noisy frequency components.

		Test Noise Amplitude (V)				
		0	0.25	0.50	0.75	1.00
Train Noise Amplitude (V)	0	91.4	60.9	39.7	29.6	22.9
	.25	76.4	90.8	72.6	50.6	35.9
	.50	36.8	60.3	78.2	89.1	76.3
	.75	21.8	27.9	43.6	54.5	66.0
	1.00	14.6	18.1	24.4	29.3	37.39

Table 1: Classification accuracies, in percent, computed for a number of different noise corruptions without notch filtering.

		Test Noise Amplitude (V)				
		0	.25	.50	.75	1.00
Train Noise Amplitude (V)	0	91.6	91.6	91.5	91.2	90.7
	.25	91.7	91.7	91.6	91.4	91.1
	.50	91.8	91.8	91.8	91.7	91.7
	.75	91.7	91.7	91.6	91.7	91.7
	1.00	90.9	90.8	91.0	91.1	91.3

Table 2: Classification accuracies, in percent, computed for a number of different noise corruptions with notch filtering.

Figure 2 displays a plot of the frequency spectrum for a representative subject and channel in experiment 1. Figure 2a shows the spectrum of the raw signal, and figure 2b shows the result of the notch filtering after adding noise.

The average classification accuracy of the TMR amputee subject was found to be 54% without notch filtering, and 87% with notch filtering. Figure 3 displays a plot of the frequency spectrum with and without filtering.

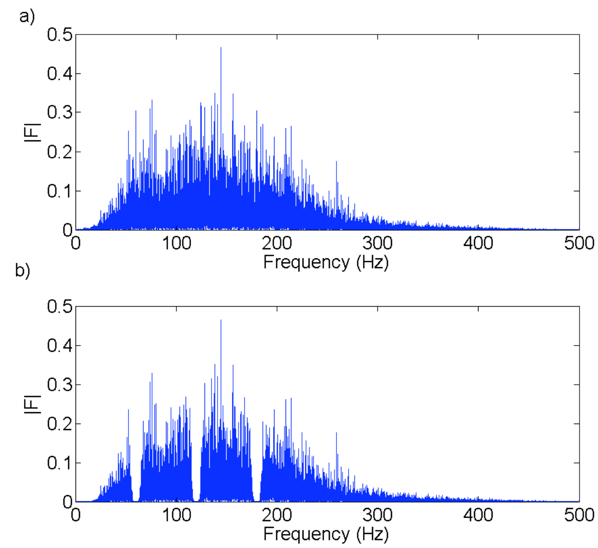

Figure 2: Frequency Spectrum of representative MES from simulation experiment (a) before filtering, and (b) after filtering.

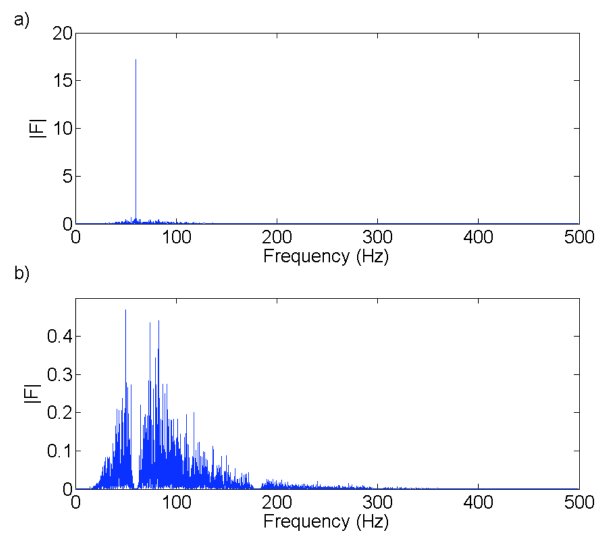

Figure 3: Frequency Spectrum of representative MES from TMR amputee (a) before filtering, and (b) after filtering.

DISCUSSION

The dataset collected in experiment 1 was used as a control data set to investigate how amplitude varying power-line interference affects classification accuracy. It is evident from table 1 that classification accuracy decreases dramatically if noise levels differ between training and test data; however, degradation is less pronounced when similar noise is added to both training and test sets. It appears that the classification system still yields high classification accuracy if a small amount of noise (<0.25 Vpp) is added to both the training and test data.

It is evident from table 2 that notch filtering the training and test data restores classification accuracy to a high level. The average classification accuracy for the noise free data was found to be 91.4% and actually increased slightly to 91.6% after notch filtering. This is most likely because the experimental data contained a small amount of 60 Hz noise despite efforts to collect noise free data. Figure 2 displays the section of the spectrum removed by notch filtering. The results of this experiment suggest that even though considerable power is removed in the notches, it is not required for motion discrimination.

While it may seem trivial to add noise only to filter it using notch filters; the authors wish to illustrate that the portions of the spectrum which tend to be corrupted by powerline interference are not critical for motion discrimination. Furthermore, leaving this portion of the spectrum in the signal could lead to a catastrophic system failure if the user moved from a low-noise to a high noise environment.

The data collected in experiment 2 contained much more noise (see Figure 3) than the data collected in experiment 1. There are several likely reasons for this including; 1) the subject's MES were of a much smaller amplitude than the normally limbed subjects and consequently required a much larger amplification factor, 2) the electrode mismatches of the non-gelled stainless steel electrodes were likely higher than the electrode mismatch of the Duotrodes; 3) the environment in which the measurements were taken was different and contained a different amount of interference, and 4) a smaller ground electrode was attached in experiment 2. It should be noted that the measurements were taken from the TMR patient while wearing their socket normally worn while operating their prosthesis. The classification accuracy of the data prior to notch filtering was 54%, rendering the controller unresponsive and leading to the collection session being considered a clinical failure. After notch filtering the accuracy was improved to 87% which compared well to previous data collection sessions performed using gelled electrodes.

CONCLUSIONS

This work demonstrates that notch filtering the MES at power-line interference frequencies can increase robustness in a pattern recognition based myoelectric control system. Simulations have shown that extraneous noise can greatly degrade classification performance, particularly when varied with respect to training levels. Using notch filtering, problematic frequencies were selectively removed, without losing discriminatory MES information, returning classification levels to 'noise free' levels. Amputee data, collected during a session which was deemed to be a clinical failure, was shown to yield good classification accuracies when notch filtered.

ACKNOWLEDGEMENTS

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