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Improved pattern recognition classification accuracy for surface myoelectric signals using spectral enhancement☆

Paul McCool[a,*], Lykourgos Petropoulakis[b,1], John J. Soraghan[b,1,2], Navin Chatlani[c]

[a] School of Engineering and Physical Sciences, Heriot-Watt University, Edinburgh EH14 4AS, UK
[b] Centre for Excellence in Signal and Image Processing, Department of Electronic and Electrical Engineering, University of Strathclyde, George Street, Glasgow G1 1XW, UK
[c] Intel, 1110 American Parkway NE, Allentown, PA 18109, United States

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ABSTRACT

In this paper, we demonstrate that spectral enhancement techniques can be configured to improve the classification accuracy of a pattern recognition-based myoelectric control system. This is based on the observation that, when the subject is at rest, the power in EMG recordings drops to levels characteristic of the noise. Two Minimum Statistics techniques, which were developed for speech processing, are compared against electromyographic (EMG) de-noising methods such as wavelets and Empirical Mode Decomposition. In the cases of simulated EMG signals contaminated with white noise and for real EMG signals with added and intrinsic noise the gesture classification accuracy was shown to increase. The mean improvement in the classification accuracy is greatest when Improved Minima-Controlled Recursive Averaging (IMCRA)-based spectral enhancement is applied, thus demonstrating the potential of spectral enhancement techniques for improving the performance of pattern recognition-based myoelectric control.

1. Introduction

Surface Electromyography (EMG) is a non-invasive measurement method of muscle activity that can be used for telehealth [1] and for prosthesis control [2,3]. The presence of noise [4–11] such as measurement noise [6,7], power line interference, quantisation noise, ECG and motion artefact [4,5] obscure the information content of the signal and reduce its usefulness for pattern recognition-based prosthetic control by causing a reduction in gesture classification accuracy.

Some types of noise can be preventatively reduced by careful hardware setup: for example, motion artefact can be reduced by minimising the sensor movement relative to the skin. Once digitised, band pass filtering is used to restrict the frequency content to the band within which most of the energy of the EMG resides. Notch filtering or adaptive filtering [5] blind rejection [8] or spectral interpolation [9] can also be performed to remove 50 Hz or 60 Hz power line interference. ECG can be removed by applying template methods or moving average filtering [10].

Noise detection and identification methods have been applied to EMG signals in order to mitigate the effects of noise that could not be preventatively removed. The methods were tested by artificially adding noise to EMG signals. ECG, motion artefact, Additive White Gaussian Noise (AWGN), amplifier saturation and power line interference were added to EMG in [4,5] to test the feasibility of pattern recognition. AWGN was used in [11] to assess the robustness of features and to assess noise reduction techniques such as wavelets in [12,13].

In this paper, we will demonstrate how two spectral enhancement techniques designed for speech signals can be configured for EMG to improve the classification accuracy of pattern recognition: Minimum Statistics Noise Estimation (MSNE) and Improved Minima Controlled Recursive Averaging (IMCRA). The techniques are tested with simulated EMG, real EMG that is artificially contaminated with AWGN and an intrinsically noisy EMG data set. To assess the effectiveness of the noise reduction, classification accuracy is used as a means of evaluating EMG signal quality: It is asserted here that if signal quality has been improved, then classification accuracy will increase. Three measurements for evaluating EMG signal

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* Corresponding author. Tel.: +44 781 629 7008.
E-mail addresses: p.mccool@hw.ac.uk (P. McCool), l.petropoulakis@strath.ac.uk (L. Petropoulakis), j.soraghan@strath.ac.uk (J.J. Soraghan), navin.chatlani@gmail.com (N. Chatlani).
[1] Tel.: +44 141 548 2935.
[2] Senior Member, IEEE.

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quality are first examined, which are assessed on the 'steady state' parts of the EMG. They are:

a. Maximum Drop in Power Density (DP ratio) is a measurement between the maximum and minimum energy content of FFT bins. The threshold value from [14] is 30 dB.
b. The SN ratio is a type of SNR in which the shape of the spectrum is taken into account. It is calculated based on the assumption that no EMG is present in the upper 20% of the frequency range. For our data sets, which will be discussed in Section 2.1.2, the upper 20% is 800–1000 Hz and 720–800 Hz. According to [15] surface EMG resides in the band 10–400 Hz so this assumption is valid. The threshold value for SN ratio from [14] is 15 dB.
c. The Ω ratio is an "index of spectral deformation" [14] used to detect "disturbances" in the EMG spectrum. The threshold value from [14] is 1.4.

The only prior instance of the application of spectral enhancement to EMG was spectral subtraction in [16], where the mean spectrum of the noise is calculated across several 'noise only' STFT windows to account for its variation. The mean noise spectrum is then subtracted across the STFT windows of the entire signal. However, the authors were unable to find any prior research in which spectral enhancement using minimum statistics was applied within the EMG frequency band as a means of noise identification or reduction.

The organisation of this paper is as follows: myoelectric signals and the data sets used in the work are introduced in Section 2, EMG filtering is described in Section 3, pattern recognition is described in Section 2.3, method in Section 3, results in Section 4, discussion in Section 5 and conclusions are given in Section 6.

2. Theory

2.1. Surface myoelectric signals

To move the forearm or hand, nerve impulses travel down the nerve to motoneurons, which interface with the muscles at motor units. When the motor units are activated, they fire and cause a potential difference. The activity from single motor unit action potentials (MUAPs) can be detected by invasive needle sensors, or EMG from a group of MUAPs can be sensed by an electrode on the skin's surface. When detected using the latter, the attenuated summation of MUAPs within range of the sensor is called the surface EMG, or sEMG, signal [17]:

$$y[n] = \sum_{i=1}^{R} \sum_{l=-\infty}^{+\infty} x_{il}[n - \Phi_{i,l}] + v[n] \tag{1}$$

$Y[n]$ is the measured SEMG signal, R is the number of active motor units, $x_{ik}[n]$ is lth motor unit action potential belonging to motor unit i, $\Phi_{i,l}$ is the occurrence time of $x_{il}[n]$ and $v[n]$ is additive noise [17]. The STFT of this is the summation of the STFT of the EMG and additive noise:

$$Y[f, t] = X[f, t] + V[f, t] \tag{2}$$

2.1.1. Simulated EMG

Simulated EMG has mathematical or structural properties similar in some useful way to real EMG. It is guaranteed to be clean, so it is suitable for assessing the performance of spectral noise estimators because the exact amount of additive noise can be controlled. The method from [18] was used, which is a phenomenological model [17] that we previously used in [4]. The following transfer function was used to generate simulated EMG [18]:

$$H_{\mathrm{EMG}}(f) = \frac{jKf_h^2 f}{(f_l + jf)(f_h + jf)^2} \tag{3}$$

The parameters f_l and f_h are used to adjust the shape of the EMG spectrum. In this work, the parameters were changed randomly for each simulated gesture, but kept constant during a gesture to simulate a static contraction. A simulated recording of a 'rest-gesture-rest' was generated of length 15 s that has a gesture of length 5 ± 0.5 s in duration starting between 5 and 10 s into the simulated recording. An onset and offset were generated by 100-sample 'ramps' at either side of the simulated steady-state contraction [19]. Finally, Additive White Gaussian Noise (AWGN) was added to the signal at the required SNR. Fig. 1 (left) shows a clean EMG gesture, which has AWGN added (Fig. 1 (centre)) to produce the signal shown in Fig. 1 (right).

The parameter f_l was chosen randomly from the frequency ranges from 30 to 60 Hz and f_h was randomly 30–100 Hz greater than f_l. The gain factor K was adjusted to make the EMG power unity.

2.1.2. Real EMG data sets

Two data sets of real EMG were used in this work. Data Set 1 consists of thirty subjects and six different gesture classes (plus rest) each for four sessions of six trials. Details can be found in [20]. There are eight bipolar channels, of which the seven lower-arm channels were used. The bandwidth of the amplifier was 1 Hz–1 kHz and the data set had been provided with a 60 Hz notch filter applied [20].

Data Set 2 is noisy 16-channel data from five subjects. There are two sessions for each subject, each consisting of a recording with 60 gestures. When used in the context of pattern recognition, one session was used for training and one for testing. There were twelve different gestures: all fingers flexion and extension (including thumb), as well as thumb opposition and antiopposition. Each gesture was initiated from rest and executed in random order.

2.2. EMG filtering

EMG can be measured using high-density sensor arrays [21]. Sensors that either degrade or do not contribute significantly to classification accuracy can be discarded through a process such as Sequential Forward Selection [21]. Such spatial filtering cannot be

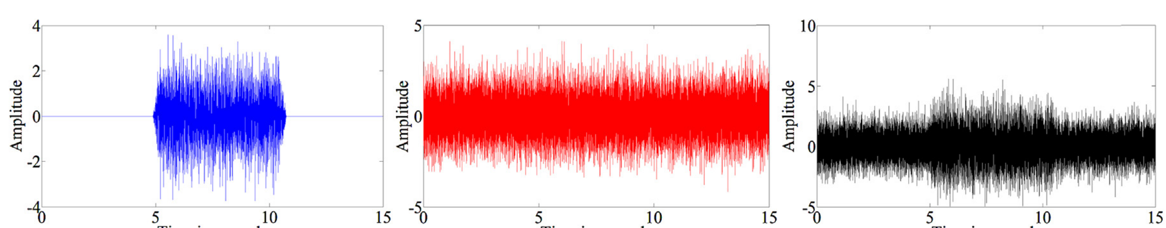

Fig. 1. The creation of simulated recording of an EMG corresponding to a gesture is created. The clean EMG, which has well-defined onset, steady-state and offset locations (left) has noise (centre) added to it (right). In this example, $f_l = 59$, $f_h = 129$, $f_s = 2000$, SNR = 0 dB. y-Axis units are arbitrary.