Nonparametric, Low Bias, and Low Variance Time-Frequency Analysis of Myoelectric Signals

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Abstract. We apply Thomson's multiple window method to myoelectric signal time-frequency analysis for the first time. We extend Thomson's spectral estimation methodology for stationary signals to a time-frequency analysis tool, which we call the short-time Thomson transform. We compare this time-frequency analysis approach with the short-time Fourier transform.

Introduction. The myoelectric signal is, in general, non-stationary during all phases of force production. In a steady-state contraction, the non-stationarity is due to physiological variations such as blood flow and build-up of chemical byproducts of the muscle contraction process which affect action potential conduction velocity. During the initiation of a motion, the force and motion-dependent motor unit recruitment and firing rate modulation contributes non-stationarity [1].

Consequently, joint time-frequency methods, where we estimate the signal's spectrum locally at time intervals, appear well-suited to myoelectric signal analysis. Here, we compare two time-frequency methods suitable for piece-wise stationary signals in this work: one based on the well-known periodogram and one based on the newer Thomson's multiple window method (MWM) [2].

Methods. Hannaford and Lehman [3] first used short-time Fourier transforms (STFTs) to analyze the myoelectric signals recorded during rapid head and wrist movements. They used a Hamming-windowed STFT to compute the spectrogram

$$\hat{P}_{hp}(f, m) = \left| \sum_{n=0}^{N-1} w[m-n]x[n]e^{-j2\pi f n} \right|^2, \quad (1)$$

where $x[n]$ is the myoelectric signal of length greater than the window length N , $w[n]$ is the Hamming window, n is the time index inside the window, m is the frequency-localization variable, and f is frequency. They reported consistent patterns in the spectrograms of rapid movements in terms of mean frequency drift. This convinced us to try Hamming STFTs to compute motion classification features in a myoelectric control system [4]; however, the STFT's high variance resulted in unsatisfactory classification performance and led us to seek a lower variance time-frequency method.

Thomson's MWM provides a lower variance kernel. The short-time Thomson transform (STTT), introduced in [4] and [5], is:

$$\hat{P}_{mwm}(f, m) = \frac{1}{2NW} \sum_{k=0}^{2NW-1} \frac{1}{\lambda_k} |x_k(f, m)|^2, \quad (2)$$

where $x_k(f)$ are the eigenspectra

$$|x_k(f, m)|^2 = \left| \sum_{n=0}^{N-1} x[n]v_k[m-n]e^{-j2\pi f n} \right|^2. \quad (3)$$

$v_k[n]$ is the k th discrete prolate spheroidal sequence window and λ_k is its corresponding eigenvalue [2]. W is the resolution of the estimate. There are two versions of the STTT; these equations and results are for the cruder (and hence lower computation) version.

Results and Discussion. Figure 1 compares the Hamming-windowed STFT with the crude STTT ($NW=2$) for a surface-measured Abductor Pollicis Longus and Extensor Pollicis Brevis monopolar myoelectric signal (6mm recessed wet electrodes, bandpass filtered 3-300 Hz, sampled at 1000 Hz). The STTT shows behavior closer to what our understanding of the muscle physiology leads us to expect: progressively more activity in the lower spectrum (below 75 Hz) as more motor units are recruited to meet increasing force demands, coupled with upper spectrum activity from their action potentials, modulo tissue filtering [1].

Figure 2 shows a 3-dimensional view of the two approaches. Figure 3 superimposes 5 spectral time slices (10 ms apart) from the STFT and the STTT, covering a 50 ms interval just after the motion's start. We expect some change in the myoelectric spectra with increasing force demands; however, the STFT shows much greater changes over the same time interval than the STTT. The difference is the STFT's greater inherent variance.

Conclusions. The STTT results show much less time-smearing and variance than the STFT results. They suggest that the myoelectric spectrum may be more stationary than the STFT results indicate.

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Figure 1: A sample thumb abduction myoelectric signal (top) and its STFT (middle) and STTT (bottom). The thumb motion becomes measurable at 0.15 sec.

Figure 2: Three-dimensional views of the same signal's STFT (top) and STTT (bottom), showing the difference in variance and bias.

Figure 3: Five 64 ms time slices (spaced 10 ms apart) from the sample signal's STFT (left) and STTT (right), covering 50 ms just after motion start, superimposed.