MEAN FREQUENCY ESTIMATION OF SURFACE EMG SIGNALS USING FILTERBANK METHODS

Stephen R. Alty & Apostolos Georgakis

King's College London,
Centre for Digital Signal Processing Research,
London WC2R 2LS, U.K.

ABSTRACT

This paper focusses on the accurate estimation of the Mean Frequency of surface electromyogram (EMG) signals during voluntary isometric contractions. This particular type of analysis is commonly used by kinesiologists to gain important information relating to muscle fatigue. These EMG signals are typically processed to extract the Mean Frequency (MNF) and studies often follow how these parameters evolve through time. Traditional approaches to estimate the MNF variables are based on the periodogram or Burg's autoregressive approach, but these methods suffer from a high degree of variability due to the choice of window size and/or significant bias in frequency estimation due to other inherent limitations. In this paper we propose the use of a data-adaptive filterbank spectral analysis technique, namely the Power Spectrum Capon (PSC) to overcome the problems associated with the traditional methods. This new method is shown to provide significant reductions in MNF parameter bias and variability over a wide range of data window sizes. Experiments are performed on simulated data with known spectral characteristics in order to compare the relative performance of the different techniques. This paper follows on from previous work by the authors showing that the filterbank methods outperform currently used methods in terms of consistency on real patient data.

1. INTRODUCTION

During sustained contractions, muscles progressively become less able to perform as well as at the beginning of the application of the force, a phenomenon referred to as muscle fatigue. It is possible to quantify this process in a non-invasive way by monitoring the associated neuromuscular activation which is manifested in the surface electromyography(EMG) signal [1, 2]. Indeed, the spectrum of the EMG undergoes a compression-like change during the course of a muscle contraction and this behaviour can be measured by introducing appropriate descriptors of the alteration. To this end, spectral variables are typically used to track the spectral shift against time. The mean (MNF) and median (MDF) spectral frequencies have been the most popular such variables both in academic studies and in clinical practice owing to their relevance to underlying physiological processes that control fatigue. For example, the initial value of MDF has been associated with the distribution of the muscle fibre type recruited, while its rate of change has been linked to the fatigability properties of the active motor units [3].

Since EMG is a random signal, its power spectral density (PSD) should be estimated prior to calculating the time-course of the spectral variables. There are a number of different approaches commonly employed for spectral estimation, broadly classified in two categories: the classical methods, e.g. periodogram or Blackman-Tukey estimators, and the parametric model methods such as the autoregressive (AR), moving average (MA), and autoregressive moving average (ARMA) estimators. Each of these spectral estimation methods has its own strengths and weaknesses and it is important to assess and compare their performance before adopting one for subsequent analysis of the EMG data.

A number of additional factors such as the shape and size of the analysis window (epoch), or the order of the parametric spectral estimator can also potentially affect the results. Of course, since both MNF and MDF are global spectral descriptors one expects that minor differences in the estimated spectra might not have a severe effect on the values of these variables. This appears to be the case regarding, for example, the window shape but on the other hand it has also been observed that the selection of the spectral estimation method does affect the computation of the spectral variables. For instance, an extensive experimental study between the periodogram and the Burg's AR method was conducted in [4] which showed that the latter approach provided a more accurate basis for the study of fatigue from the surface EMG during isometric contractions.

In this paper, we introduce the use of high-resolution filterbank-based methods, namely the Power Spectrum Capon [5] as spectral estimators which have characteristics especially suited for the EMG. We have shown previously [6] using real EMG data that filterbank methods suffer from less variability than the periodogram method for different windows lengths. In this work we present new results based on simulated data of known spectra which show by means of comparison that the PSC method outperforms both the periodogram and Burg's AR method by increasing the accuracy of MNF estimation. Specifically, that the new method of estimating the MNF EMG variables suffer from less bias and variance than their periodogram or autoregressive based counterparts.

2. FILTERBANK SPECTRAL ANALYSIS

There has recently been a renewed interest in *non-parametric* spectral estimators, due in part to their inherent robustness to model assumptions. Among the non-parametric approaches, the *data-dependent* filterbank spectral estimators have many promising properties, allowing for low bias, computationally efficient, high-resolution estimates (see, e.g., [5]). The *Power Spectrum Capon* estimator, i.e., the estimator obtained when using the classical Capon filter to estimate a sinusoidal component at the center frequency of the bandpass filter, can be

Please address all correspondence to steve.alty@kcl.ac.uk

seen as a *matched* filterbank method.

Matched filterbank spectral estimators are constructed from a set of data-adaptive, frequency dependent, L-tap FIR filters, $\mathbf{h}_\omega$, such that

$$\min_{\mathbf{h}_\omega} \mathbf{h}_\omega^* \mathbf{Q}_\omega \mathbf{h}_\omega \quad \text{subject to} \quad \mathbf{h}_\omega^* \mathbf{a}_\omega = 1 \tag{1}$$

where $\mathbf{Q}_\omega$ is the $L \times L$ covariance matrix of the signal consisting of all frequencies except ω, $(\cdot)^*$ denotes the conjugate transpose, and $\mathbf{a}_\omega$ is an L-tap Fourier vector, i.e.,

$$\mathbf{a}_\omega = \left[\begin{array}{cccc} 1 & e^{i\omega} & \ldots & e^{i\omega(L-1)} \end{array} \right]^T \tag{2}$$

The classical Capon filter is obtained by minimizing (1) using the covariance matrix of the measured data as an *estimate* of $\mathbf{Q}_\omega$, i.e.,

$$\mathbf{Q}_\omega = \mathbf{R}_x \equiv \mathscr{E}\{\mathbf{x}_t \mathbf{x}_t^*\} \tag{3}$$

where

$$\mathbf{x}_t = \left[\begin{array}{cccc} x(t) & x(t+1) & \ldots & x(t+L-1) \end{array} \right]^T \tag{4}$$

and our estimate of the covariance matrix

$$\hat{\mathbf{R}}_x = \frac{1}{M} \sum_{t=1}^{M} \mathbf{x}_t \mathbf{x}_t^* \tag{5}$$

Here, $M = N - L + 1$, where N is the length of the sample frame (or epoch) and L is the filter tap length. As is the case with autoregressive spectral estimators (such a Burg's method), the choice of L is a compromise between resolution and statistical stability. That is to say, the larger L, the better the resolution but the higher the variance. Furthermore, a larger L increases the dimension of $\hat{\mathbf{R}}_x$ and thus the computational burden of evaluating the spectral estimate. Previous work in the field by Merletti [7] based on Burg's method has shown that for the target application a filter order of around $L = 10$ is a good compromise, hence this was the value used for the Capon estimator too. The subsequent Capon spectral estimate is obtained as [5]

$$\hat{\phi}_x^{PSC}(\omega) = \frac{1}{\mathbf{a}_\omega^* \mathbf{Q}_\omega^{-1} \mathbf{a}_\omega} \tag{6}$$

It is worth noting though, that there are numerous computationally efficient methods in the literature presented in [8] to increase the speed of the calculations for fixed window sizes and in [9] for sliding window based implementations among others.

3. EMG BENCHMARK VARIABLES

The most commonly used spectral variables in EMG fatigue analysis studies are the Mean Frequency (MNF) and the Median Frequency (MDF). The MNF is the centroid frequency of the power spectrum and is defined as follows:

$$MNF = \frac{\sum_{i=1}^{M} f_i P_i}{\sum_{i=1}^{M} P_i} \tag{7}$$

where P_i is the ith line of the power spectrum; f_i is the frequency variable; and M is the highest harmonic considered (i.e. just below the Nyquist Frequency). Previously, we have shown [6] that the filterbank approach has, in general, lower variance than traditional methods (i.e. the Welch periodogram). In this study we shall focus attention on the MNF variable and the accuracy of its estimation through time. In general, the EMG signal is segmented into consecutive short time-windows and then PSD estimation takes place, using the traditional periodogram method, Burg's AR method or the new Capon method. This is then followed by computation of the spectral variable MNF for all three methods for different window (epoch) lengths. The initial value and the rate of change of the spectral variable are calculated by fitting a least-square regression line to the MNF time course. The resulting 'points of intercept' and 'slopes' serve as indices [4] of the fatiguing process. See Figures 1 and 2 (a), (b) and (c) which shows the estimate of MNF for sources A and B using the periodogram, Burg and PSC methods respectively. The (green) dotted line on each plot indicates the ideal time course for MNF. A good degree of agreement can be observed for each approach, however, the Capon method clearly shows a *truer* spectrum estimate, the details of the results will be discussed in the next section. As these indices are used by physicians as the basis for various diagnostic and therapeutic purposes [10], it is essential that they are as accurate as possible.

4. RESULTS AND DISCUSSION

The EMG data analysed in this paper was obtained from the SENIAM [11] cohort of synthetic EMG signals so that their parameters were known *a priori* which was necessary to facilitate testing and comparison. The sampling rate used to generate the signals was $1024Hz$ as this is commonly used in practice. There are two synthetic signals under test in this work, and they are labelled Sources A & B. Both sources comprise 20480 samples each having a duration of $20s$ and are formed by passing a noise source through a time-varying shaped filter. Source A has a mean frequency of $80Hz$ initially and finishes at $60Hz$ at its end, whilst Source B has a mean frequency of $80Hz$ initially and finishes at $40Hz$ at its end. Hence, *ideally* we would expect to measure $80Hz$ as a point of intercept for both sources and a slope (rate of descent in frequency over time) of exactly $-1.0Hz.s^{-1}$ and $-2.0Hz.s^{-1}$ for Sources A & B respectively. For each signal the point of intercept and slope was calculated for various window sizes on a block basis with no overlap (i.e. values of $N = 256, 512, 768, 1024, 1280, 1536, 1792, 2048$). Further, the *variation* (i.e. the ratio of their standard deviations divided by their means, Coefficient of Variation (CoV) $= \sigma/\mu$) in these parameters was determined and used as a measure of consistency (see Table 1).

Figures 1 and 2 show the estimate of the MNF for a constant and commonly used window size of $N = 256$ (i.e. $250ms$) for each method; Welch periodogram, Burg's method and the Capon method. It can be seen that for both sources the new method gives a truer estimate of the point of intercept and either equal best (Source A) or the best (Source B) estimate of the slope. Lack of space precludes including all the plots for all eight windows sizes, but our experimentation shows that this result is consistent across all eight window sizes and this is borne out in the averaged error shown in Figure 3.

Table 1 shows the variability of the point of intercept and slope in estimating the Mean Frequency across eight different window sizes using the three methods; Welch peri-

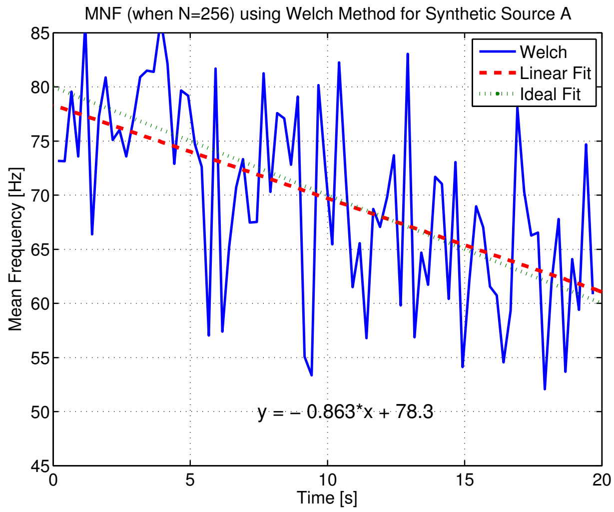

Fig. 1. (a)

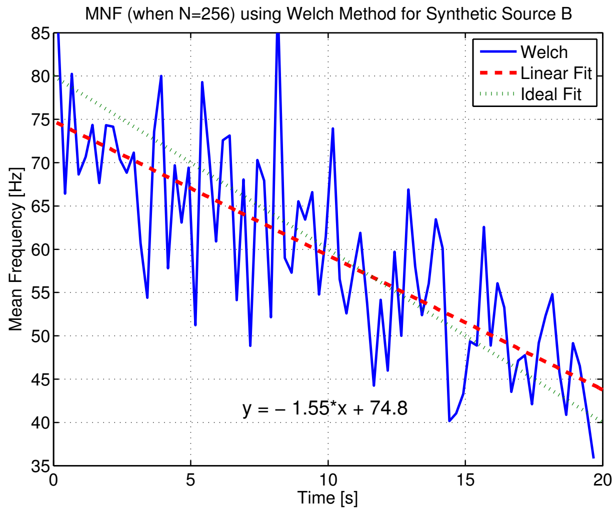

Fig. 2. (a)

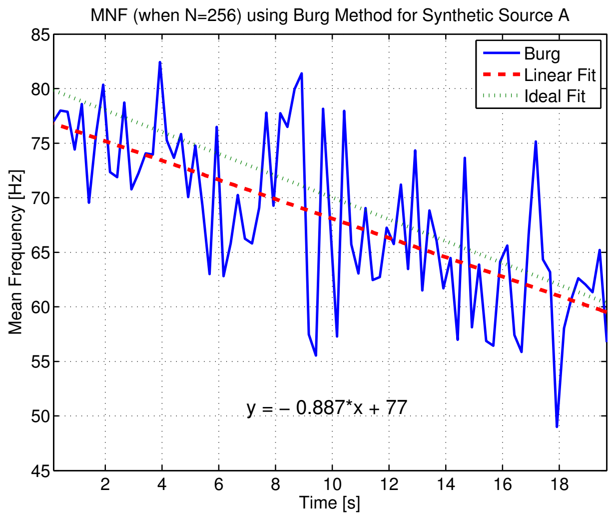

Fig. 1. (b)

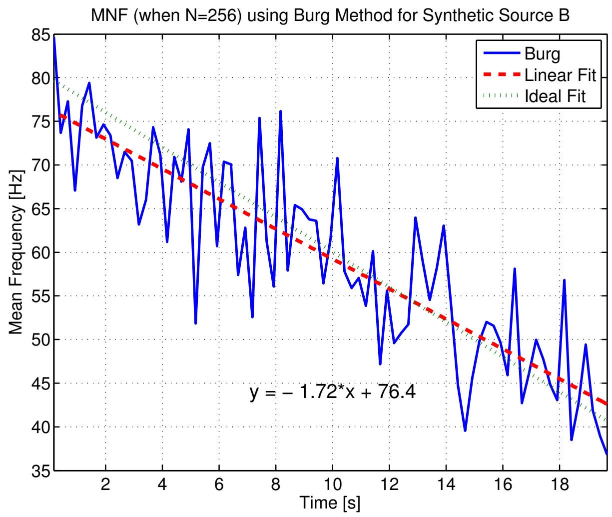

Fig. 2. (b)

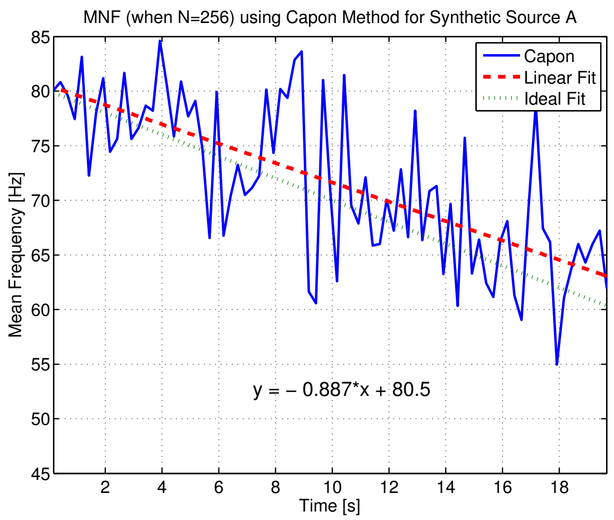

Fig. 1. (c)

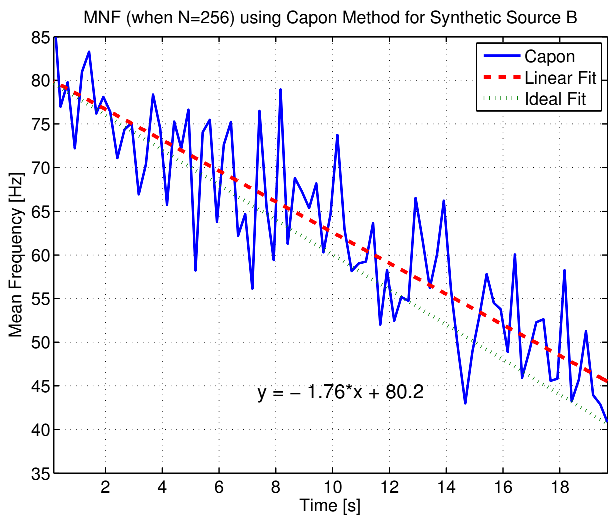

Fig. 2. (c)

Figure 1: MNF Estimation using (a) Welch, (b) Burg, (c) Capon methods for window size $N = 256$ for source A.

Figure 2: MNF Estimation using (a) Welch, (b) Burg, (c) Capon methods for window size $N = 256$ for source B.

	Source A		Source B	
	PoI	**Slope**	**PoI**	**Slope**
Welch Method	0.0152	0.1120	0.0187	0.0607
Burg Method	**0.0022**	0.0202	0.0037	0.0176
Capon Method	0.0034	**0.0191**	**0.0032**	**0.0137**

Table 1: CoV for Point of Intercept and Slope for MNF Estimation using three different methods for the two sources

odogram, Burg's AR and finally using Capon approach for the two synthetic sources as before. The 'best' results are highlighted in bold type. It can be seen that the Capon method provides lower variability than the Welch method for both features and sources and improves upon the Burg method in all but one measure.

5. COMPUTATIONAL CONSIDERATIONS

Finally, standard batch type algorithms were used to calculate the filterbank based variables and they required somewhat more processing time than those for the periodogram or Burg based methods. An Intel Quad Core $2.33GHz$ processor based PC environment using Matlab© $2007b$ was used to run the various algorithms. The periodogram method took $0.11s$ to complete all the calculations, whereas the Burg method took $0.41s$ and the Capon method took $1.54s$ to finish. Clearly, then the Capon method is noticeably more computationally burdensome than the traditional approaches. Although, considering that each timed run required each source to be analysed eight times over (effectively constituting $160s$ of data), all methods could be easily evaluated in real-time if necessary.

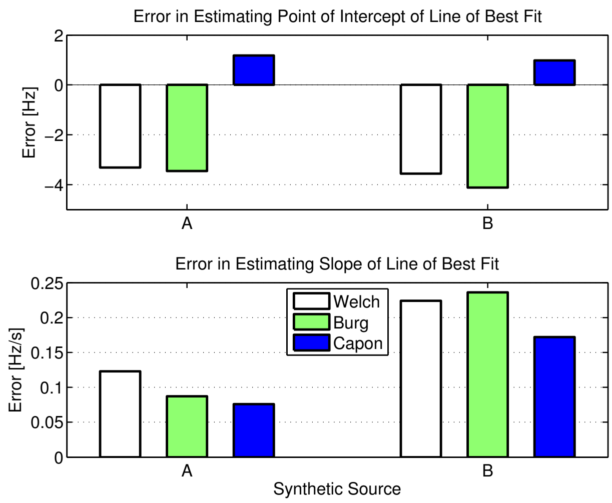

Figure 3: Estimation error for both Point of Intercept and Slope of line of best fit for three methods and both synthetic sources A & B averaged over the eight different window sizes.

6. CONCLUSIONS AND FUTURE WORK

This paper presents new results on the application of a filterbank based spectral analysis technique applied to the estimation of fundamental variables derived from EMG data. These new approaches give rise to more consistent and, in particular, more *accurate* estimates of the variables which can be used by physicians to quantify the effects of muscle fatigue. This work is ongoing and it is envisaged that further experimentation incorporating an extended cohort of real subject data will be used to extend and deepen this work in the future.

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