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Full Length Research Paper

Power Spectral Density Estimation of EMG Signals Using Parametric and Non-Parametric Approach

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Abstract 05 April 2013

EMG is classified on the basis of RMS amplitude values and frequency analysis by using non-parametric and parametric approach. The variation of EMG spectra is used to compare the estimation methods in terms of frequency resolution as well as in determining the spectral components. Spectral analysis of EMG signals are done on four major lower limb muscles during isometric contraction using three methods i.e. Welch, Yule walker and Burg. Yule walker showed superior performance among the three methods as it performs well for long continuous signals.

Keywords: Spectral Estimation, Power Spectral Density, Parametric Approach, Non- Parametric Approach, Frequency Resolution, RMS value, Amplitude.

INTRODUCTION

The purpose of this paper is to focus on the issue of EMG amplitude and spectral estimation with algorithms based on parametric and nonparametric approach at different conditions, compare them and outline the advantages and drawbacks of each. Though many studies have focused on the comparison of different methods for information extraction from surface EMG signals under different conditions, a complete comparison is not available. The algorithms for estimation of amplitude variables of the surface EMG signal detected during voluntary contractions were used in different areas for the non invasive assessment of muscle functions (Dario and Roberto, 2000 ; Karlsson and Yu, 2000). The surface EMG signal detected during voluntary muscle contraction is a non-stationary stochastic process due to which the spectra changes during contraction. It can be quantified by the measurement of amplitude and spectral variables. Different approaches needs to be discussed for time and spectral description of the EMG signal (Carlo JL, 1997).

METHODOLOGY

Amplitude features and their estimators

Root-mean-squared (RMS) value is preferred to average rectified value for measuring and processing the EMG signals during voluntarily elicited contractions in the time domain, and it also represents the signal power. It is usually computed by the following equation,

$$RMS\ value = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2} \quad (1)$$

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It is necessary to process an EMG signal and limit the analysis to an isometric epoch of the record by interpreting the analysis based on the results.

Power Spectral Density features and their estimators

Power spectral density describes how the power density of a signal or time series is distributed with frequency. It detects periodicities in data by observing peaks at frequencies corresponding to those particular periodicities.
The performance of various power spectral density estimation techniques; Non-parametric methods and parametric methods are compared for different epoch lengths in case of real signal.

Non-parametric methods

The simple and easy non-parametric methods do not assume a fixed structure of a model. It can expand to accommodate the complexity of data. It is based on fewer assumptions like wide sense stationarity hence their applicability is much wider than parametric methods.

Welch method

It is the average modified periodogram that was never a consistent estimate of true power density spectrum due to its low resolution and distorted estimate for spectrum of the signal.
In Welch's method, (Ahmet and Kemal, 2006; Bronzino and Joseph, YEAR; Proakis and Manolakis, 1996) the original signal is split into L data segments of length M, overlapping by D points. The overlapping data segments are defined as

$$x_m(n) = x(n + mD), \qquad n = 0, 1, \dots, L-1$$
$$m = 0, 1, \dots, K-1$$

Where D is the size of the segments and D≠L. The data segments are then windowed prior to the periodogram computation,

$$P_{PER}^{(m)}(f) = \frac{1}{LU}\left|\sum_{n=0}^{L-1} x_m(n)w(n)\exp(-j2\pi fn)\right|^2 \quad (2)$$

where

$$U = \frac{1}{M}\sum_{n=0}^{M-1} w^2(n) \quad (3)$$

Finally, the Welch spectrum estimate is the average of these modified periodograms,

$$P_w(f) = \frac{1}{K}\sum_{m=0}^{K-1} P_{PER}^{(m)}(f) \quad (4)$$

But, a long set of data is required to obtain a good resolution and due to windowing, these methods also suffer leakage thus making it difficult to find the weak signals in the data. However, it is expected to be overcome by parametric approach.

Parametric methods

The parametric spectrum estimation is based on assumption and a model of the data with prior knowledge. The frequency response of the model gives the estimate of power spectral density. They do not suffer leakage effects of windows and hence achieve better resolution than non-parametric methods. The most frequently used parametric approach is the Auto-regressive model that is one amongst the common models of random processes to predict natural phenomena (Djuric and Kay, 1999; Keith et al., 1993; Dhaparidze and Yaglom, 1983). The linear prediction formulae predict the output of a system based on previous input. The model assumes that the observed data have been generated by a system whose input output difference equation is given by,

$$x[n] = -\sum_{k=1}^{p} a_k x[n-k] + e[n] \quad (5)$$

where *x[n]* is the signal that is modeled, observed output of the system, a_k's are model coefficients, *e[n]* is a modeling error sequence. If the model order is correct, *e[n]* turns out to be white noise process with variance σ^2. The model is abbreviated as AR(p), *p* is the order of the system. The PSD of the process [10-13] is given by

$$PSD_{AR}(f) = \frac{\sigma^2}{\left|1 + \sum_{k=1}^{p} a_k \exp(-j2\pi fk)\right|^2} \quad (6)$$

Thus, in order to obtain the $PSD_{AR}(f)$, the estimates of AR coefficient a_k and error variance σ^2 needs to be estimated.
AR model is used most widely as it represents the spectra with narrow peaks. The two ways to estimate the coefficients form autocorrelation function are described below.

Yule Walker method

Multiplying *x*[n-k]* on both sides of equation 5 with $k \geq 0$, and taking their expectations, we get

$$r[k] = \begin{cases} -\sum_{l=1}^{p} a_l r[k-l] & k > 0 \\ -\sum_{l=1}^{p} a_l r[k-l] + \sigma^2 & k = 0 \end{cases} \quad (7)$$

The expressions in 7 give the Yule Walker equations. In order to estimate the p unknown AR coefficients, p equations are required as well as the estimates of appropriate autocorrelations. The set of equations that requires minimum number of correlation is

$$\hat{R}a = -\hat{r} \quad (8)$$

where R̂ is the p*p matrix

$$\hat{R} = \begin{bmatrix} \hat{r}(0) & \hat{r}(-1) & \dots & \hat{r}(-p+1) \\ \hat{r}(1) & \hat{r}(0) & \dots & \hat{r}(-p+2) \\ \vdots & \vdots & \vdots & \vdots \\ \hat{r}(p-1) & \cdots & \hat{r}(1) & \hat{r}(0) \end{bmatrix} \quad (9)$$

and $\hat{r} = [\hat{r}[1], \hat{r}[2], \dots \hat{r}[p]]^T \quad (10)$

the parameters a are estimated by

$$\hat{a} = -\hat{R}^{-1}\hat{r} \quad (11)$$

and noise variance is found from

$$\hat{\sigma}^2 = \hat{r}[0] + \sum_{k=1}^{p} a_k \hat{r}* [k] \quad (12)$$

The $PSD_{AR}(f)$ can be estimated by substituting equation 11 and 12 in 6.

Yule Walker method applies windows to the data and performs well for larger data records, i.e. continuous signal [7], along with good statistical consistency and smooth nature.

Burg method

The AR coefficients can directly be estimated from Burg method by minimizing the sum of squares of forward and backward prediction errors with respect to reflection coefficients for model stability, as in equation 13.

For data *x(n), n = 0, 1, ……N-1,*

The forward linear prediction estimates of order *m*, is

$$\hat{x}(n) = -\sum_{k=1}^{m} a_m(k)x(n-k)$$

$$\hat{x}(n-m) = -\sum_{k=1}^{m} a_m(k)\hat{x}(n+k-m)$$

where $a_m(k)$ are prediction coefficients with $0 \le k \le m-1$ *and m=1, 2, ….p.*

The corresponding forward and backward errors defined as

$f_m(n) = x(n) - \hat{x}(n),$

$b_m(n) = x(n-m) - \hat{x}(n-m)$

The least squares error is given by

$$\xi_m = \min \sum_{n=m}^{K-1} [|f_m(n)|^2 + |b_m(n)|^2] \quad (13)$$

The error is minimized by selecting the prediction coefficients

$$a_m(k) = a_{m-1}(k) + \lambda_m a_{m-1}^*(m-k) \quad 1 \le k \le m-1, 1 \le m \le$$

where $\lambda_m = a_m(m)$, is the m^{th} reflection coefficient. Minimizing the least square error ξ_m with respect to complex valued function λ_m, we obtain

$$\lambda_m = \frac{-\sum_{n=m}^{N-1} f_{m-1}(n)b_{m-1}^*(n)}{\left(\frac{1}{2}\right)\sum_{n=m}^{N-1} [|f_{m-1}(n)|^2 + |b_{m-1}(n)|^2]} \quad (14)$$

Since windows are not applied to the data, the AR estimates are assumed to be more accurate. It avoids calculating the autocorrelation function [14-16]. This method has a high resolution for short data records, producing a stable model. However, the frequencies belonging to prominent peaks are dependent on phases of sinusoids. It has certain limitations like exhibiting spectral line splitting at high SNR, gives spurious peaks for higher order models.

Data acquisition and protocol

The Biometrics Data LINK (DLK900) is a general purpose data capture system with real time display and analysis that collects signals from a wide range of EMG sensors. The Bipolar surface electrodes, SX230 EMG sensor are affixed on the subject with normally functioning limbs at the most dominant middle portion of the muscle belly for best selectivity and in parallel to muscle fiber direction with the help of adhesive tape. The Earthing strap R206 has a convenient elasticized wrist band for attachment at the ankle. The subject unit has 8 different channels to connect the sensors for different muscles, programmable instrumentation amplifiers and power supply for energizing the sensors, sampling and converting SEMG signal inputs into digital signals. The raw EMG signals containing baseline noise and artifacts are filtered using a band pass filter with lower cut-off frequency 20 Hz and upper cut-off frequency 450 Hz. The base unit acts as an interface between subject unit and PC interface, through a RS-422 cable.

Five sets of data are recorded for three different positions of individuals. The subject is asked to perform isometric contraction at different positions. The electrodes pick up the EMG signals from the muscles and transmit them to the standard EMG signal acquisition system via connecting cables. A continuous stream of EMG signals from the muscle sites, are recorded by the analysis software after proper filtering, as in figure 2. The filtered EMG signals are then amplified and rectified using the standard analysis software provided with EMG acquisition device.

Epochs are taken from the sampled data and spectrum analysis is done to compare the four muscles at various positions. The figure below presents the data link base unit, DLK 900, Earthing strap R206 with elastic wrist band and SX230 EMG sensor.

Figure 1. (a) Data LINK, DLK 900 base unit and subject unit respectively **(**b) Earthing strap R206 with elastic wrist band (c) SX230 EMG sensor

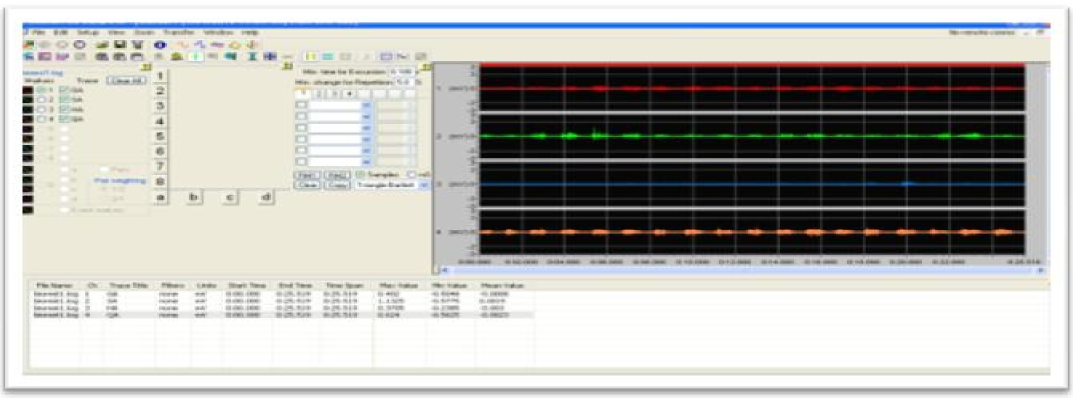
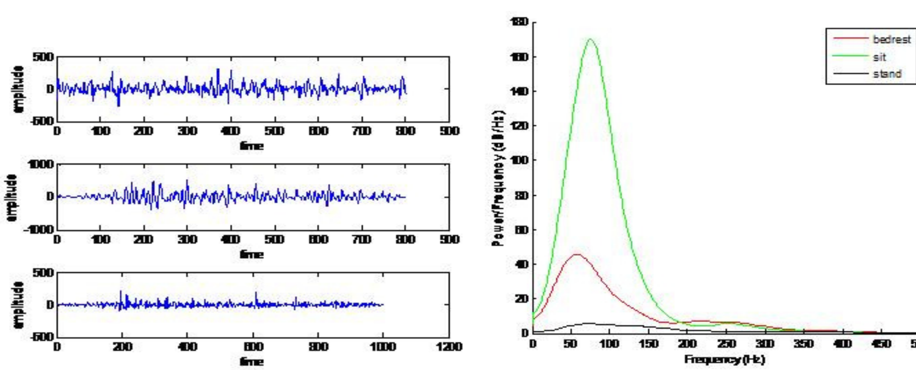


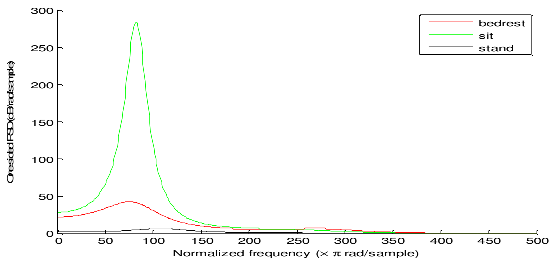
Figure 2. Analysis software through Datalink DLK900

Table 1. Mean amplitude of EMG signals for different muscles at various positions

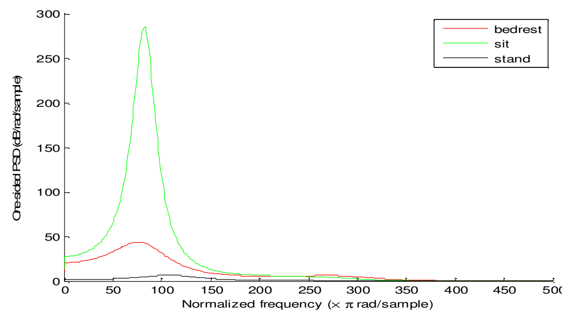
Muscles	Rest(mV)	Sit(mV)	Stand(mV)
GA	0.0367	0.0352	0.0375
SA	0.0585	0.0622	0.012
HA	0.0412	0.0862	0.0105
QA	0.093	0.0202	0.0525



(a) **(b)**



(c)



(d)

Figure 3. (a) Raw EMG signals from soleus muscle (b)Welch method applied to soleus muscle with 25% overlap (c) Fourth order Yule Walker method applied to soleus muscle (d) Fourth order Burg method applied to soleus muscle

RESULTS

The SEMG data for RMS values of amplitude is analyzed and tabulated in table 1. It can be observed that the RMS value of signal amplitude tends to vary from 0 to 1 for four different muscles.

The EMG signals are also analyzed using parametric and non-parametric spectral analysis methods. Welch (a non-parametric approach), Yule Walker and Burg method (parametric approachs) are used to obtain the PSD of EMG signals. In order to get an idea on the performance of the methods, results of the spectra of these methods are represented below and compared to each other along with the sample results.

MATLAB is the tool used for spectral analysis of the four muscles. The raw EMG signals, Welch method, Yule Walker method and Burg method for soleus, gastronemius, hamstring and quadriceps are observed. From among them the spectral feature of the soleus muscle was found to be the most distinct and hence was taken up for further analysis. On examining the frequency spectrum of Welch method in figure 3(b), it is seen that there are broader peaks at lower frequency. On the other hand, when Yule walker and Burg methods PSDs are analyzed from figure 3(c) and 3(d), the most clear and sharp peaks are seen at Yule walker method. PSD of EMG signals are recorded. The spectra are examined across same frequency bands, and noted that Welch spectrum has got broaden and misleading peaks than AR spectrum, and Yule walker methods have got sharp and clear peaks. However for AR model of higher orders, redundant peaks are noticed, so a lower order model is selected. Order 4 gives a PSD which have better agreement with results obtained using other spectral estimation techniques.

CONCLUSION

The PSDs of EMG signals are calculated by using parametric (Yule Walker and Burg) and nonparametric (Welch) spectral estimation methods. EMG spectra are used to compare the applied estimation methods in terms of frequency resolution as well as the effects in determining the spectral components. The variation in shape of EMG spectra is examined. The performance of proposed methods is evaluated through visual inspection of PSDs. The graphs comparing the performance of proposed methods are given. The peak in the spectrum produced by the Welch method is found to be the least pronounced, hence the performance of Yule Walker and Burg methods is better than Welch method. Also it is found out that the Burg method gave better performance for shorter data records while Yule Walker method showed better performance for longer data records. Since EMG signals are a long continuous signal, the results demonstrate superior performance of Yule walker methods over Welch and Burg methods.

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