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Non-Stationary Harmonic Modelling For ECG Removal In surface EMG Signal

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Abstract - *In general electromyography (EMG) is used to find the activity of muscles to extract accurate information, it is required to record a clean and undistorted electromyography (EMG) signal. However, when EMG is recorded of some specific muscles, it is often contaminated by ECG signal, hereby significantly increasing the power of EMG signal. This artifact can hardly be avoided; therefore, to extract valid information it is necessary to process EMG signal to remove ECG signal. The variations of the ECG in terms of amplitude and frequency time are evaluated by using the Heart rate and QRS complex; the respective variations are simultaneously captured by a set of third-order constant-coefficient polynomials modulating a stationary harmonic basis in the analysis window. The novelty of the proposed method is allows to suppress the ECG signal content at low frequencies and the resulting model is linear in parameters and the least-squares solution to the corresponding linear system of equations efficiently provides model parameter estimates. The comparative results suggest that the proposed method outperforms two reference methods in terms of the EMG preservation at low frequencies.*

Keywords: ECG, EMG, Amplitude, Low Frequency.

1. INTRODUCTION

Surface electromyography is a noninvasive technique used to evaluate the activity of the muscles [1]. When EMG is recorded of some specific muscles, it is often contaminated by ECG signal, hereby significantly increasing the power of EMG signal. This artifact can hardly be avoided; therefore, to extract valid information, various research done and schemes proposed by the various authors [2] to remove ECG signal from EMG signal. The simplest method consists of high-pass filtering EMG signal with a fourth order Butterworth filter at a cut-off frequency of 30Hz [3]. The main problem of this method ([4]-[7]) is that an important part of the EMG signals concerning the changes of negative after potentials is removed as well. It is known that the negative after potentials increase during fatigue, and these changes could affect the amplitude of the EMG signal significantly.

In addition, it is found that these changes are reflected in the EMG spectrum within a frequency range below 10 Hz. Therefore, by filtering the EMG signal using a high-pass filter of 30Hz, valuable information of the EMG signal is removed when fatigue is analyzed. Other researchers developed techniques that required the recording of additional signals. Some of those techniques were based on adaptive filtering, which an external reference ECG needed signal as well as the EMG signals [8]. Other methods required the recording of several EMG signals to remove the ECG signals using independent component analysis (ICA). Another form of adaptive filtering [9] was the wavelet-based approach, which performed without external reference signals. However, the selection of an appropriate wavelet shapes and corresponding decision thresholding are major drawbacks from the user's point of view. Let us also mention a recent approach which uses a nonlinear scaled wavelet decomposition followed by ECG–EMG pattern separation by means of frequency domain ICA.

In this paper, we present an approach that addresses the issue of explicit non-stationary harmonic modeling of the ECG signal component. The motivation behind this approach arose from audio signal processing, where a similar scenario featuring a mixture of a quasi-harmonic signal component and a stochastic perturbation is often dealt. Herein, we model simultaneously both amplitude and frequency changes in the ECG signal component by means of a time-variant harmonic structure whose mean fundamental frequency is kept constant in the analysis window. It is shown that the time changes in an ECG harmonic are correctly captured by two constant-coefficients cubic polynomials each modulating a sine and a cosine function, respectively.

2. PROPOSED METHOD

2.1 ECG–EMG Mixture Signal Model:

We assume that the mixture signal S (t) can be represented as a superposition of the ECG and EMG components and the measurement noise e (t)

$$S(t) = S_{ECG}(t) + S_{EMG}(t) + e(t) \quad (1)$$

The EMG component is a random signal usually modeled as a Gaussian white noise whose power spectral density is modified by a time-variant filter.

The $S_{EMG}(t)$ and e (t) are often treated as a single component because they can be distinguished only if adequate noise models are known prior (which is usually not the case). The

$S_{ECG}(t)$ is a deterministic component whose signal model we will describe thoroughly in the following subsection.

2.2 ECG Signal Model:

We know that an ECG represents a non-stationary quasi-periodic time waveform. Due to quasi-periodicity, the time waveform will present some periodic (harmonic) components. Due to non-stationary, some amplitude and frequency time variations will appear superimposed to those periodic components. Those variations are usually classified as interbeat (RR-interval) and intrabeat (morphology) changes. The former accounts for instantaneous frequency variation, which can be provoked by a number of phenomena generally known as heart rate variability (HRV). The latter encompasses the instantaneous amplitude changes, which are often related to time variability of the QRS complex due to respiration. If we denote the instantaneous frequency and amplitude time variations by f(t) and a(t)respectively, then the following signal model completely characterizes the ECG component:

$$S_{ECG}(t) = \sum_{k=1}^{k} A_k(t)\sin[2\pi f_k(t)(t)] \tag{2}$$

Where K is the number of harmonics and θ_k are the initial harmonic phases. Due to harmonicity, the instantaneous frequency can be expressed as $f_k(t)=k\, f_0(t)$ where $f_0(t)$ is the instantaneous fundamental frequency. Determining $f_k(t)$ and $a_k(t)$ for each time instant might not be an easy task to perform, especially for a long-term analysis. However, if we assume that $f_k(t)$ and $a_k(t)$ vary slowly and continuously in a short analysis window, then (2) can be reformulated in a compact and efficient. Recalling Cos (x+y) = Cos x Cos y-Sin x Sin y, we can rewrite (1) as

$$S_{ECG}(n) = \sum_{k=1}^{k} A_k(t)\sin[2\pi f_k(t)(t)] + B_k(t)\cos[2\pi f_k(t)(t)] \tag{3}$$

$$A_K(t) = -a_t(t)\,\mathrm{Sin}\theta_k\,,\ B_k(t) = a_k(t)\,\mathrm{Cos}\theta_k \tag{4}$$

We will next assume that the amplitude and frequency parameters vary linearly in the analysis window of duration T:

$$A_k(t) = A_0^{(k)} + A_1^{(k)}t,\ Bk(t) = B_0^{(k)} + BA_1^{(k)} \tag{5}$$

$$f_0(t) = f_0 + f_1 t,\ (-T)/2 \le t \le T/2 \tag{6}$$

Accordingly, we can express $S_{ECG}(t)$ as

$$\begin{aligned} &S_{ECG}(t) \\ &= \sum_{k=1}^{k} \left(A_0^{(k)} + A_1^{(k)}t\right)\sin(2\pi k f_0 t)\cos(2\pi k f_1 t^2) \\ &+ \left(A_0^{(k)} + A_1^{(k)}t\right)\cos(2\pi k f_0 t)\sin(2\pi k f_1 t^2) \\ &+ \left(B_0^{(k)} + B_1^{(k)}t\right)\cos(2\pi k f_0 t)\cos(2\pi k f_1 t^2) \end{aligned} \tag{7}$$

In (7), the trigonometric terms of the nonlinear argument encompass the contribution to the HRV by instantaneous ECG frequency deviation f_1. This parameter depends on various phenomena that account for the changes in HVR spectra of short recordings (2–5 min) in high- frequency (HF), low frequency (LF), and very low frequency (VLF) bands. The HF band (0.15–0.4 Hz) accounts for the respiratory activity, while the lower bands (< 0.15 Hz) include physiologic oscillations associated with baro receptor reflexes (closely related to the Mayer waves). In the context of modeling instantaneous frequency by (6), it is clear that the most critical scenario corresponds to the HF band, which obviously gives rise to the largest f_1 . We shall next show that the herein proposed model can properly capture instantaneous frequency variations corresponding to the HF band; accordingly, the discussion below will implicitly encompass f_1 localized in lower bands. In the HF band, the most prominent effect related to f_1 is respiratory sinus arrhythmia. This phenomenon is originated in the breathing process and gives rise to periodic respiratory frequency modulations in the interbeat interval series (IBI). In most cases, the modulation rate of the IBI series is in the range 2.5–8.3 s (corresponding to the breathing frequencies in 0.12–0.4Hz), while the mean modulation extent is typically 100 ms . Accordingly, for the ECG mean frequency (MF) f_0 in the range 1–1.3 Hz (60–80 beats per minute), the frequency deviation f_1 is around 0.05 Hz/s. Accordingly, if the analysis window is short enough, then (7) can be enormously simplified by applying the trigonometric approximation of a small argument

$$sine\ x \sim x, \cos x \sim 1\ for\ x \to 0$$

to the sine/cosine terms of the nonlinear argument

$$\begin{aligned} S_{ECG}(t) = \textstyle\sum_{k=1}^{k}(A_0^{(k)} + A_1^{(K)}t) * [&Sin(2\pi k f_0 t) + \\ &2\pi k f_1 t^2 \cos((2\pi k f_0 t)] \end{aligned}$$

$$+(B_0^k + B_1^{(k)}t) * [\cos(2\pi k f_0 t)2\pi k f_1 t^2 \sin(2\pi k f_0 t)] \tag{8}$$

Reordering the last expression, we obtain the final ECG model

$$S_{ECG}(t)=\sum^{k}_{k=1}\alpha^{(k)}(t)\,\mathrm{Sin}(2\pi k f_0 t) + \beta^{(k)}(t)\,\mathrm{Cos}(2\pi k f_0 t) \quad (9)$$

$$\alpha^{(k)}(t)=\sum^{3}_{i=0}\alpha_i^{(k)}t^i = A_0^{(k)}+A_1^{(k)}t - 2\pi k f_1 B_0^{(k)}t^2 - 2\pi k f_1 B_1^{(k)}t^2 \quad (10)$$

$$\beta^{(k)}(t)=\sum_{i=0}^{3}\beta_i^{(k)}t^i = B_0^{(k)}+B_1^{(k)}t - 2\pi k f_1 A_0^{(K)}t^2 + 2\pi k f_1 A_1^{(K)}t^2 \quad (11)$$

The model (9) means the harmonic stationary f0 – basis modulated by the third-order time polynomials. Unlike (2), both amplitude and frequency time variations are compactly characterized by the polynomial coefficients in (10) and (11). As a result, (9) is linear in parameters, and can be easily estimated by solving a linear system of equations. In order to check the validity of the small-argument approximation in (9), we have evaluated the sine/cosine approximation quality as a function of T in the following way:

$$\varepsilon_s = \frac{\sum_n s_n^2}{\sum_n (s_n - x_n)^2} \qquad \varepsilon_c = \frac{\sum_n c_n^2}{\sum_n (c_n - 1)^2} \quad (12)$$

Where

$s_n = sin\,(x_n)$, $c_n = cos\,(x_n)$,

$x_n = 2\pi f_1 t_n^2$,

And t_n are uniformly distributed time instants in the range [– T/2, T/2]. The error terms $\varepsilon_s, \varepsilon_c$ (12), evaluated in decibels, are shown versus the duration of the analysis window T in Fig. 1. Both curves follow a descending trend because the longer the window the larger the sine/cosine argument. Very short windows (T < 0.4 s) provide extremely high-approximation quality of more than 100 dB. Such high quality, however, is not really necessary in clinical applications. In fact, for T = 2 s, the approximation quality is settled around 40 dB, which is still very good for the present application, as will be shown in the experimental section.

3. MODEL ESTIMATION

An implementation of (9) requires an estimation of the following parameters: f_0, $\alpha_i^{(k)}$and $\beta_i^{(k)}$ for i=0-3 and k=1,2…k. The estimation process has been performed in two steps: 1) the estimate f_0 is obtained, and 2) f_0 is inserted in (9) and the corresponding linear system is solved for $\alpha_i^{(k)}$and $\beta_i^{(k)}$.

3.1 Frequency Estimation:

The mixture (1) is similar to voiced speech it means that it contains a deterministic quasi-harmonic component corrupted by noise. In voiced speech the deterministic component represents the vocal tract excitation and its fundamental frequency is usually called pitch. If we associate the concept of pitch to the ECG fundamental frequency f_0, we can obtain f_0 by means of some pitch estimation algorithm. The approach based on difference function is very popular due to its simplicity and computational efficiency. It aims to detect regular dip patterns in the cumulative mean normalized difference function of a windowed signal segment. Then, the corresponding pitch is estimated as a distance between the contiguous dips. Formally, the cumulative mean normalized difference function $D_t(T)$ is defined as

$$D_t(\mathrm{T}) = \begin{cases} 1, & T = 0 \\ \frac{D_t(\mathrm{T})}{\sum_{m=1}^{T} d_t(m)}, & otherwise \end{cases} \quad (13)$$

With $D_t(T)$ is an ordinary difference equation:

$$D_t(\mathrm{T}) = \sum_{m=t+1}^{t+T}[s(m) - s(m+T)] \quad (14)$$

The function $D_t(T)$ efficiently compensates for imperfect periodicity. EMG component is usually energy-dominant over the ECG component during the experiment. Consequently, it can happen that some noise- induced high-order dip in (13) gets more pronounced than the period dip. This gives rise to a wrong f0 estimate and accordingly the model (9) is degraded. Fortunately, most of the EMG energy is clustered out of the typical ECG frequency band up to 50–60 Hz. Therefore, a simple low-pass filter will reinforce the ECG and weaken the EMG component. A linear-phase 20th-order finite-impulse response filter with the 20-Hz cut-off frequency proved to be an adequate tool for simultaneously preserving the quasi-periodicity in the ECG component and reducing the interference level from the EMG component. Once is low-pass filtered, f_0 is estimated by (13).

3.2 Polynomial Coefficients Estimation:

The coefficients $\alpha_i^{(k)}$and $\beta_i^{(k)}$ from (10) and (11) are efficiently estimated by means of the linear least-squares (LS) algorithm applied to (9) in the matrix form

$$S = M\lambda + \varepsilon \quad (15)$$

where λ is the coefficient vector given as (16)

$$\lambda = \left(\lambda^{(1)}\ \lambda^{(2)}\ \dots\ \lambda^{(K)}\right)^T \quad (16)$$

$$\lambda^{(K)} = \left(\alpha_0^{(k)}\ \alpha_1^{(k)}\ \alpha_2^{(k)}\ \alpha_3^{(k)}\ \beta_0^{(k)}\ \beta_1^{(k)}\ \beta_2^{(k)}\ \beta_3^{(k)}\right)^T \quad (17)$$

M is the signal model matrix which can be written as

$$M = M_s^{(1)}\ M_c^{(1)}\ M_s^{(2)}\ M_c^{(2)}\ \dots\dots M_s^{(K)}\ M_c^{(K)} \quad (18)$$

$$M_S^K = \begin{pmatrix} \sin(2\pi k f_0 t_1 \sin(2\pi k f_0 t_2) .. \sin(2\pi k f_0 t_N) \\ t_1 \sin(2\pi k f_0 t_1) t_2 \sin(2\pi k f_0 t_2) .. t_N \sin(2\pi k f_0 t_N) \\ t_1^2 \sin(2\pi k f_0 t_1) t_2^2 \sin(2\pi k f_0 t_2) .. t_N^2 \sin(2\pi k f_0 t_N \\ t_1^3 \sin(2\pi k f_0 t_1) t_2^3 \sin(2\pi k f_0 t_2) .. t_N^3 \sin(2\pi k f_0 t_N \end{pmatrix} \text{^T} \quad (19)$$

$$M_c^{(K)} = \begin{pmatrix} \cos(2\pi k f_0 t_1) \cos(2\pi k f_0 t_2) .. \cos(2\pi k f_0 t_N) \\ t_1 \cos(2\pi k f_0 t_1) t_2 \cos(2\pi k f_0 t_2) .. t_N \cos(2\pi k f_0 t_N) \\ t_1^2 \cos(2\pi k f_0 t_1) t_2^2 \cos(2\pi k f_0 t_2) .. t_N^2 \cos(2\pi k f_0 t_N) \\ t_1^3 \cos(2\pi k f_0 t_1) t_2^3 \cos(2\pi k f_0 t_2) .. t_N^3 \cos(2\pi k f_0 t_N) \end{pmatrix}^T \quad (20)$$

The vectors s and ε contain the signal samples and stochastic perturbation, respectively. The solution to the LS problem is a vector of the sought model parameters:

$$\lambda = M^+ S \quad (21)$$

where M⁺ is the pseudo inverse matrix of M. The expression (21) can be evaluated in many different ways, among which we used the QR factorization of the over determined linear system M. Once the parameters λ are estimated, the EMG signal component is easily obtained as

$$S_{EMG} = S - M\lambda \quad (22)$$

4. SIMULATION RESULTS

Simulation results of this paper is shown in bellow Figs.1 to 9.

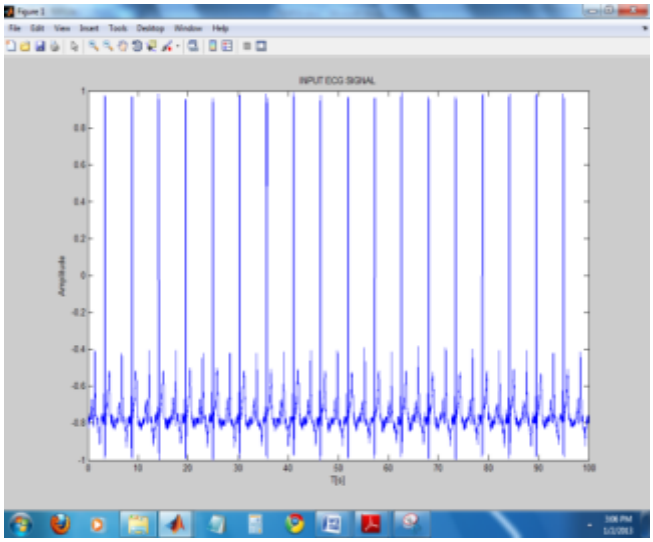

Fig -1: Input Image

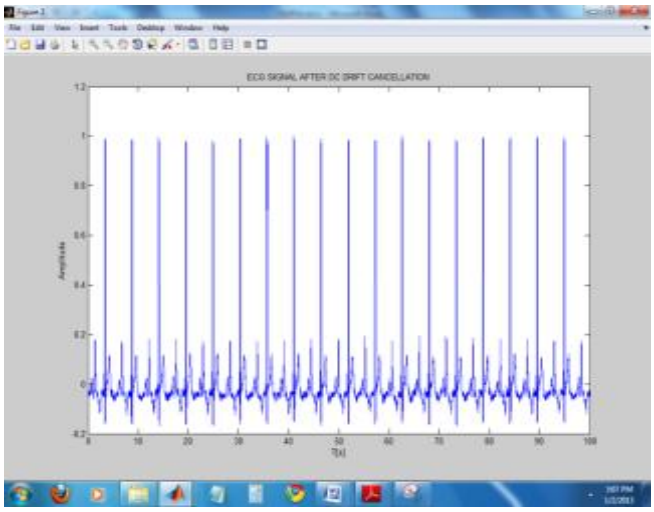

Fig -2: ECG Signal After DC Drift Cancellation

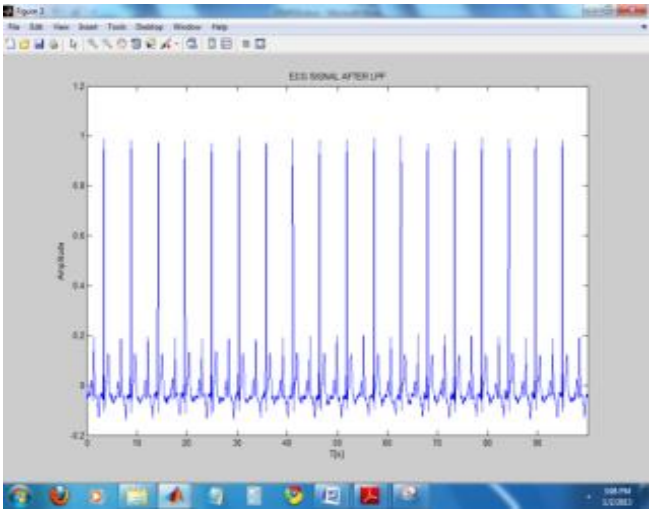

Fig -3: ECG Signal After LPF

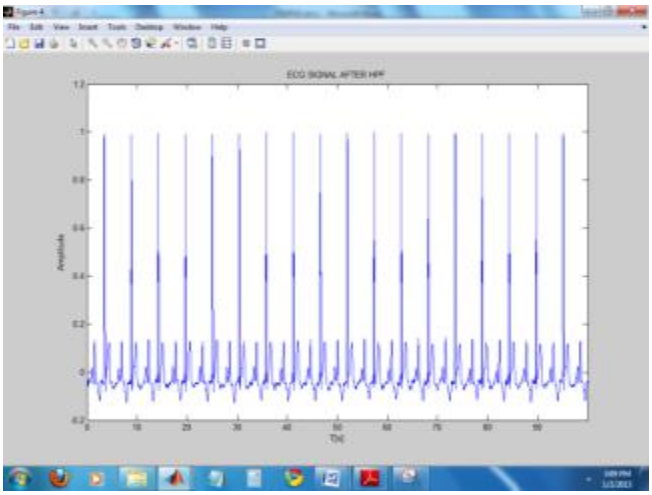

Fig -4: ECG Signal After HPF

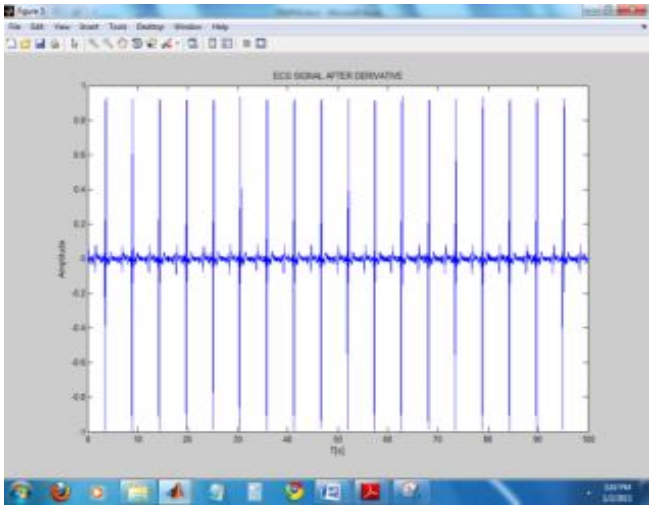

Fig -5: ECG Signal After Derivative

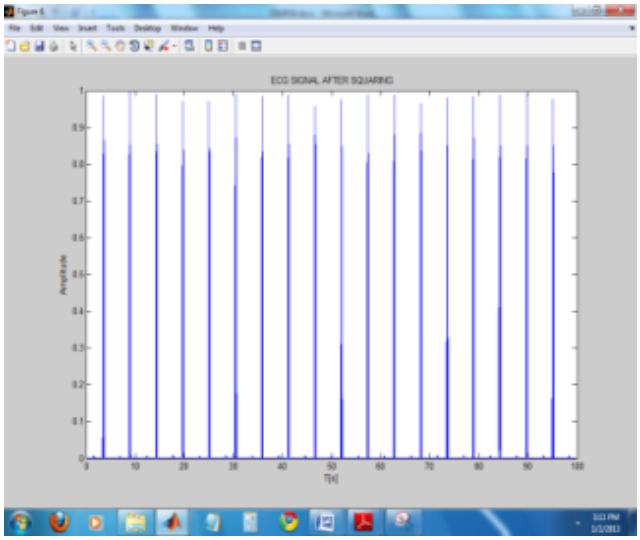

Fig -6: ECG Signal After Squaring

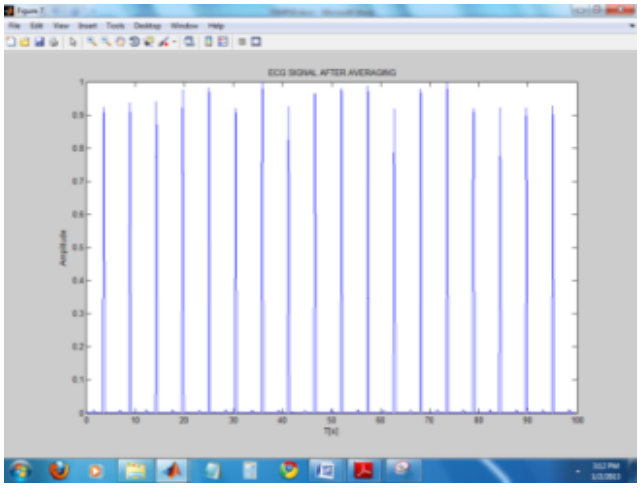

Fig -7: ECG Signal After Averaging

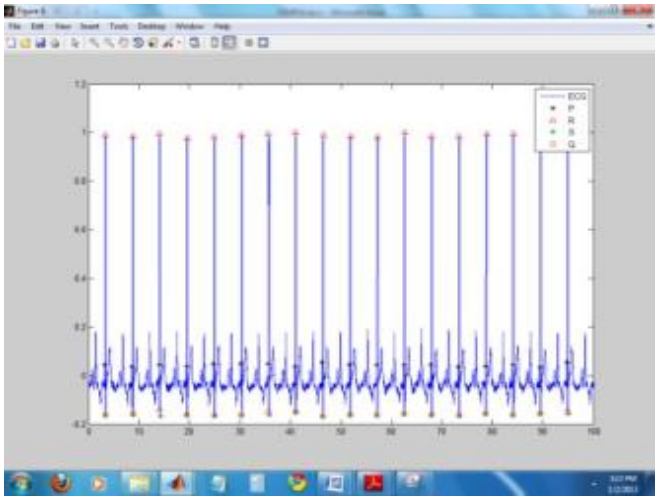

Fig -8: QRS Detection

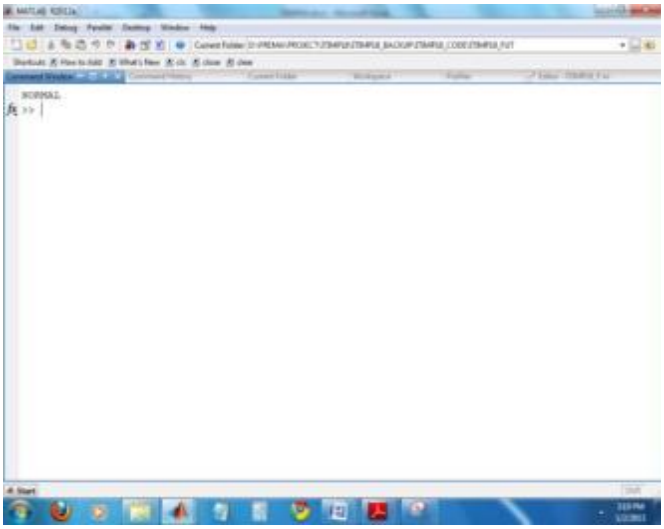

Fig -9: CASE

5. CONCLUSIONS

We have shown that explicit modeling of ECG as a time variant harmonic signal component is an adequate tool for removing cardiac artifacts in surface EMG signals. The strength of the proposed approach is founded in a correct characterization of instantaneous amplitude and frequency changes in the ECG, typically due to HRV and QRS complex time modulation.

It was shown that in a short analysis window, the ECG can be described by a simple analytical formulation containing low-order polynomials and harmonically related stationary Sins and cosines. The ECG model parameters are efficiently estimated from a linear system of equations by means of QR factorization.

Experimental comparison results, regarding both artificial and real-world signals, show that in the analysis bandwidth 0–20 Hz, the proposed method outperforms the reference methods, as it introduces the smallest distortion in the EMG signal component.

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