Nonstationary Harmonic Modelling For ECG Removal In Surface EMG Signal

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***Abstract-* We present a compact approach for mitigating the presence of electrocardiograms (ECG) in surface electromyographic (EMG) signals by means of time-variant harmonic modeling of the cardiac artifact. Heart rate and QRS complex variability, which often account for amplitude and frequency time variations of the ECG, are simultaneously captured by a set of third-order constant-coefficient polynomials modulating a stationary harmonic basis in the analysis window. Such a characterization allows us to significantly suppress ECG from the mixture by preserving most of the EMG signal content at low frequencies (less than 20 Hz). Moreover, 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 signal, EMG signal, Noise.**

1. INTRODUCTION

There are different methods to remove the ECG components from the EMG signal “Elimination of electrocardiogram contamination from electromyogram signals: An evaluation of currently used removal technique’’. The simplest method consists of high-pass filtering EMG signal with a fourth order Butterworth filter at a cut-off frequency of 30Hz.

Existing Techniuqe

- FILTERS
- WICA

Disadvantages Of Existing System

- The selection of an appropriate wavelet shapes and corresponding decision thresholding are major drawbacks from the users
- The main problem with “Changes in the action potential and contraction of isolated frog muscle after repetitive stimulation,” method 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 EM

2. METHODOLOGIES

- **MODULE NAMES**

1.ECG SIGNAL GENERATION

Using an electrocardiogram (ECG) is an invaluable way to identify various physical ailments. To conduct an ECG, medical personnel place leads on a patient’s skin and measure the electrical activity of the heart over one beat cycle. The outputs of the leads are combined to create an ECG signal. Variations in the signal amplitude and timing provide indications of various ailments such as myocardial infarction, hypocalcaemia, and emphysema. Today there is a wide array of cardiac equipment that displays and interprets ECG signal patterns. Medical equipment designers need a flexible way to seamlessly generate accurate ECG signal patterns to verify and test their designs.

The ECG signal can be generated by the principle of Fourier series.

Any periodic functions which satisfy dirichlet’s condition can be expressed as a Series of scaled magnitudes of sine and cosine terms of frequencies which occur as a multiples of fundamental frequency.

The general Fourier series expression can be given as,

$$f(x) = \left(\frac{a_0}{2}\right) + \sum a_n \cos\left(\frac{n\pi x}{l}\right) + \sum b_n \sin\left(\frac{n\pi x}{l}\right)$$

$$a_0 = \left(\frac{1}{l}\right)\int f(x)\ dx$$

$$a_n = \left(\frac{1}{l}\right)\int f(x)\cos\left(\frac{n\pi x}{l}\right) dx, \qquad n = 1, 2, 3, \ldots.$$

$$b_n = \left(\frac{1}{l}\right)\int f(x)\sin\left(\frac{n\pi x}{l}\right) dx, \qquad n = 1, 2, 3, \ldots.$$

2.ECG - EMG MIXTURE WAVEFORM

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 length of the ECG component was 20000 samples (roughly 9.76 s). For the generation of an EMG component of the same length, we have followed a general approach, i.e., passing a zero-mean unitary-variance Gaussian white noise through an all-poles band pass filter whose spectral characteristics should closely match the ones of the real ECG-free surface EMG signals. This is typically achieved by calculating the filter coefficients in such a way that its frequency response fits the spectral envelope of the EMG signal.

The coefficients can be calculated in a number of ways, among which we have opted for linear predictive analysis (LPA) of order five. The LPA provided the following set of filter coefficients: [1, – 1.9408, 1.3108, –0.2965, –0.0037, and 0.0588], which yielded the EMG component whose bandwidth was roughly 72Hz.

The EMG contribution to the mixture was determined by the signal-to-noise ratio (SNR), which we defined as the energy ratio between the EMG and ECG component in the analysis time window. In this way, we could simulate any segment of an EMG burst by simply adjusting the corresponding SNR. For the sake of illustration, we calculated the spectrum of the 20000- sample-simulated mixture signal by means of the 80000-point fast Fourier transform for two scenarios: SNR = 0 dB and SNR = –30 dB.

3.SINE/COSINE APPROXIMATION

$$s_{ECG}(t) = \sum_{k=1}^{K} \alpha^{(k)}(t) \sin(2\pi k f_0 t) + \beta^{(k)}(t) \cos(2\pi k f_0 t)$$

The harmonic stationary *f*0 -basis modulated by the third-order time polynomials. Both amplitude and frequency time variations are compactly characterized by the polynomial coefficients. As a result, the above equation 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, we have evaluated the sine/cosine approximation quality as a function of *T* in the following way:

$$\varepsilon_s = \frac{\sum_n s_n^2}{\sum_n (s_n - x_n)^2}$$

$$\varepsilon_c = \frac{\sum_n c_n^2}{\sum_n (c_n - 1)^2}$$

Where

$s_n = sin\,(x_n)$,

$c_n = cos\,(x_n)$,

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

t_n are uniformly distributed time instants in the range [–*T*/2, *T*/2]. The error terms ε_s and ε_c are evaluated in decibels.

4.POLYNOMIAL COEFFICIENTS ESTIMATION

$$\alpha^{(k)}(t) = \sum_{i=0}^{3} \alpha_i^{(k)} t^i = A_o^{(k)} + A_1^{(k)} t - 2\pi k f_1 B_o^{(k)} t^2 - 2\pi k f_1 B_1^{(k)} t^3$$

$$\beta^{(k)}(t) = \sum_{i=0}^{3} \beta_i^{(k)} t^i = B_o^{(k)} + B_1^{(k)} t - 2\pi k f_1 A_o^{(k)} t^2 - 2\pi k f_1 A_1^{(k)} t^3$$

The coefficients $\alpha_i(k)$ and $\beta_i(k)$ are efficiently estimated by means of the linear least-squares (LS) algorithm applied to above equation in the matrix form,

$$s = M\lambda + \varepsilon$$

Where λ is the coefficient vector

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

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

M is the signal model matrix which can be written as

$$M = M_s^{(1)}\, M_c^{(1)}\, M_s^{(2)}\, M_c^{(2)} \ldots\ldots M_s^{(K)}\, M_c^{(K)}$$

$$M_s^{(K)} = \begin{pmatrix} sin(2\pi k f_0 t_1) & sin(2\pi k f_0 t_2) & \ldots & sin(2\pi k f_0 t_N) \\ t_1 sin(2\pi k f_0 t_1) & t_2 sin(2\pi k f_0 t_2) & \ldots & t_N sin(2\pi k f_0 t_N) \\ t_1^2 sin(2\pi k f_0 t_1) & t_2^2 sin(2\pi k f_0 t_2) & \ldots & t_N^2 sin(2\pi k f_0 t_N) \\ t_1^3 sin(2\pi k f_0 t_1) & t_2^3 sin(2\pi k f_0 t_2) & \ldots & t_N^3 sin(2\pi k f_0 t_N) \end{pmatrix}^T$$

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

3.RESULTS AND DISCUSSION

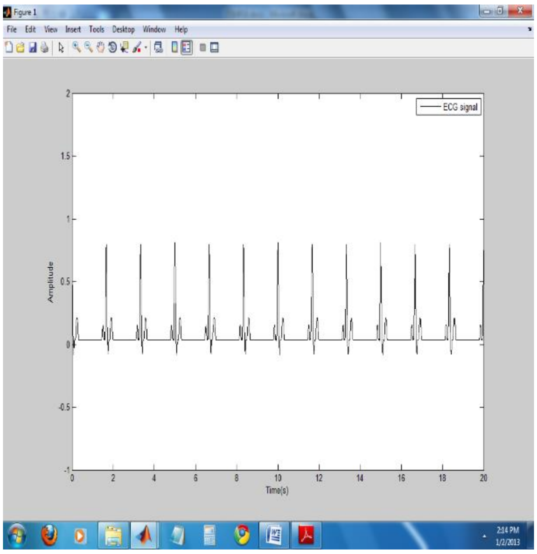

Fig1:GENERATED ECG SIGNAL

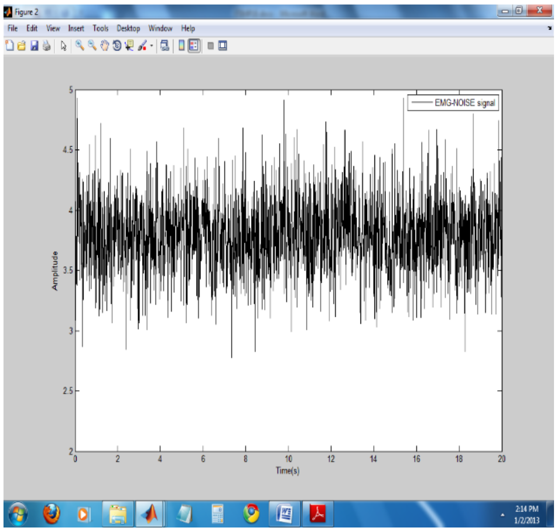

fig2: EMG Signal with Noise

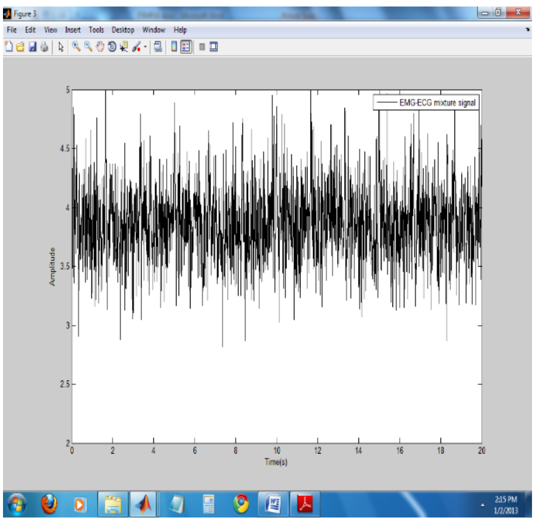

Fig3: ECG-EMG MIXTURE SIGNAL

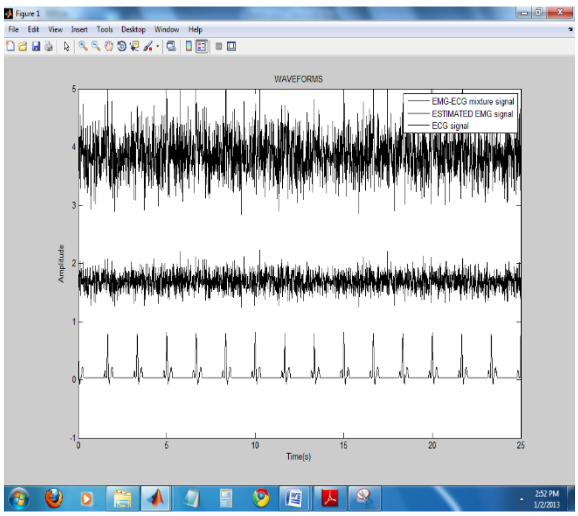

fig4:ESTIMATED EMG

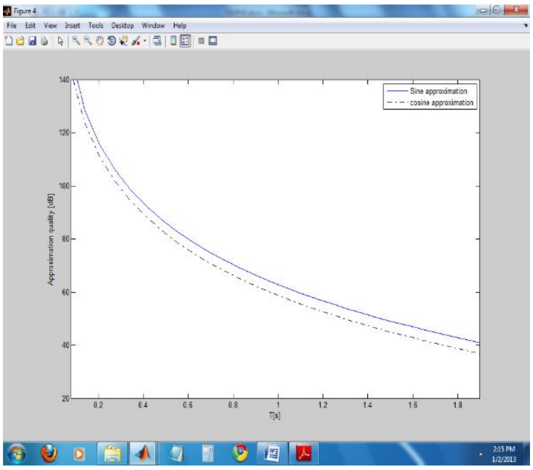

Fig5: SINE/COSINE APPROXIMATION

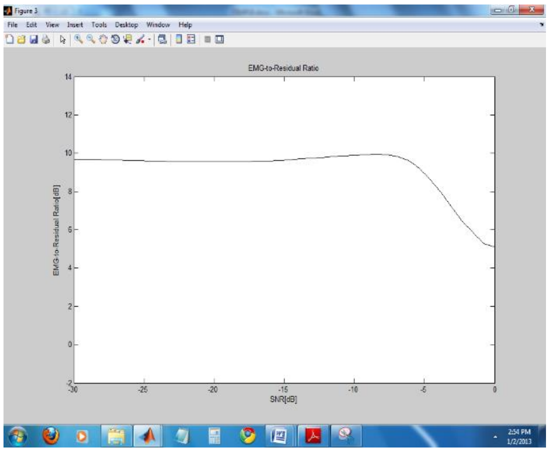

fig6: EMG- TO – RESIDUAL RATIO

4. CONCLUSION

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.

The proposed method has been compared to two reference methods based on high-pass filtering and combined independent component analysis and wavelet transform, respectively. The

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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