RECOVERY OF EMG SIGNALS FROM THE MIXTURE OF ECG-EMG SIGNALS USING NON-STATIONARY HARMONIC MODELING

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ABSTRACT

An approach for removal of the presence of ECG in electromyographic signals by means of time-variant harmonic modeling of the cardiac artifact. The amplitude and frequency time variations in heart rate and QRS complex variability of the electrocardiograms 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 signal component 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 result suggests that the proposed method outperforms in terms of the EMG preservation at low frequencies.

Keywords -- ECG, EMG, QRS Complex, Artifacts, WICA

I. INTRODUCTION

Electromyography (EMG) is a technique used to evaluate the activity of the muscles. For extracting accurate information, it is required to record a clean and undistorted electromyography (EMG) signal. There are many artifacts that could affect EMG signals, such as crosstalk, which can be avoided or minimized by a correct placement of the surface electrodes on the skin. However, when the EMG signal is recorded on some specific muscles (e.g. the trunk's muscles), it is often contaminated by the ECG signal and significantly increasing the power of the EMG signal. This artifact can hardly be avoided; therefore, to extract valid information of the EMG signal, it is necessary to process the EMG signal to remove the ECG signal. There are many different methods to remove the ECG components from the 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. The main problem of this method is that an important part of the EMG signal concerning the changes of negative afterpotentials is removed as well. It is known that the negative afterpotentials 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 techniques are required the recording of additional signals. Some of those techniques were based on adaptive filtering which needed an external reference ECG signal as well as the EMG signals. Another method required the recording of several EMG signals to remove the ECG signals using independent component analysis (ICA). Another form of adaptive filtering 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.

In this paper, there is an approach that addresses the issue of explicit non stationary harmonic modeling of the ECG signal component. This approach arose from audio signal processing. Although, 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. Accordingly, the overall ECG model is a linear system of equations, which can be efficiently solved by any linear solver, e.g., least squares. Once the model parameters (polynomial coefficients) are estimated, the ECG signal component is generated and subtracted from the mixture in order to obtain the EMG signal component estimation.

II. EXISTING METHODOLOGY

2.1 EXISTING SYSTEMS

There are different methods to remove the ECG components from the EMG signal "Elimination of electrocardiogram contamination from electromyogram signal: 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.

- Filter Method
- Wavelet Independent Component Analysis (WICA) Method

The simplest method consists of high-pass filtering EMG signal with a fourth order Butterworth filter at a cut-off frequency of 30Hz [6]. The main problem of this 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 [7], [8] 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 [10]. 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 authors developed techniques that required the recording of additional signals. Some of those techniques were based on adaptive filtering [11], [13] which an external reference ECG needed signal as well as the EMG signals. Other methods required the recording of several EMG signals to remove the ECG signals using independent component analysis (ICA) [14]. Another form of adaptive filtering was the wavelet-based approach [15], [16] which performed without external reference signals. However, the selection of an appropriate wavelet shape and corresponding decision thresholding are major drawbacks from the user's point of view. Let us also mention a recent approach [17] which uses a nonlinear scaled wavelet decomposition followed by ECG–EMG pattern separation by means of frequency domain ICA.

III. PROPOSED METHODOLOGY

3.1 PROPOSED SYSTEM

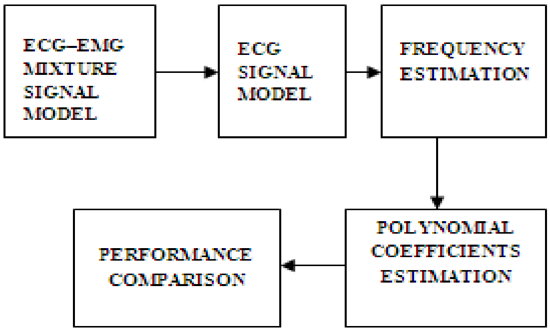

Fig: 3.1 Block Diagram of Proposed System

3.2 MODULES

- ECG signal generation
- EMG-ECG mixture
- Sine/Cosine approximation
- Polynomial coefficients estimation

3.3 ECG SIGNAL GENERATIONS

The ECG signal can by 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 multiples of fundamental frequency.

The general Fourier series expression can be given as

$$f(x) = \left(\frac{a_0}{2}\right) + \sum a_n \cos\left(\frac{n\pi x}{l}\right) + \sum b_n \sin\left(\frac{n\pi x}{l}\right) \quad (1)$$

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

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

$n = 1, 2, 3, ...$

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

$n = 1, 2, 3, ...$

Let's take QRS waveform as the centre one and all shifting takes place with respect to this part of the signal.

Duration of P, Q, R, S, and T waves are

- P-R interval 0.16s
- S-T interval 0.18s
- P interval 0.09s

- QRS interval 0.11s

$$f(x) = \sum_{n=1}^{\infty} \frac{(\sin((\pi/2b)*(b-2n)))}{(b-2n)+\frac{(\sin(\pi/2b)*(b+2n))}{(b+2n)}} * \left(\frac{2}{\pi}\right) * \cos\left(\frac{n\pi x}{l}\right) \quad (2)$$

$$f(x) = \sum_{n=1}^{\infty} a_n \cos\left(\frac{n\pi x}{l}\right) \quad (3)$$

$$a_n = (2ba/i^2\pi^2)\left(1 - \cos\left(\frac{n\pi}{b}\right)\right) \cos\left(\frac{n\pi x}{l}\right)$$

The amplitude of the QRS wave is 1.6 mv. This QRS wave can be estimated by using this expression

$$f(x) = \left(\frac{a_0}{2}\right) + \sum_{n=1}^{\infty} a_n \cos\left(\frac{n\pi x}{l}\right) \quad (4)$$

$$a_0 = \left(\frac{a}{b}\right)(2-b)$$

$$a_n = (2ba/i^2\pi^2)\left(1 - \cos\left(\frac{n\pi}{b}\right)\right)$$

The amplitude of the T wave is 0.35 mv. This T wave can be estimated by using this expression

$$f(x) = \sum_{n=1}^{\infty} \frac{(\sin((\pi/2b)(b-2n)))}{(b-2n)+\frac{(\sin(\pi/2b)(b+2n))}{(b+2n)}} \left(\left(\frac{2}{\pi}\right) \cos\left(\frac{n\pi x}{l}\right)\right) \quad (5)$$

3.4 ECG - EMG MIXTURE SIGNAL

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.

3.5 SINE/COSINE APPROXIMATION

$$s_{ECG}(t) = \sum_{k=1}^{K} \alpha^{(k)}(t)\sin(2\pi k f_0 t) + \beta^{(k)}(t)\cos(2\pi k f_0 t) \quad (6)$$

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

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.

3.6 POLYNOMIAL COEFFICIENT ESTIMATION

$$\alpha^{(k)}(t) = \sum_{i=0}^{3} \alpha_i^{(k)} t^i = A_0^{(k)} + A_1^{(k)} t - 2\pi k f_1 B_0^{(k)} t^2 - 2\pi k f_1 B_1^{(k)} t^3 \quad (7)$$

$$\beta^{(k)}(t) = \sum_{i=0}^{3} \beta_i^{(k)} t^i = B_0^{(k)} + B_1^{(k)} t - 2\pi k f_1 A_0^{(k)} t^2 - 2\pi k f_1 A_1^{(k)} t^3 \quad (8)$$

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,

$$s = M\lambda + \varepsilon \quad (9)$$

Where λ is the coefficient Vector.

3.7 DATA FLOW DIAGRAM

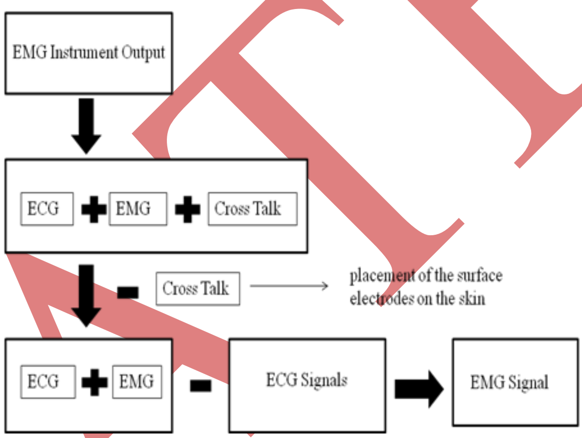

Fig: 3.2 Data Flow Diagram

IV. SIMULATION RESULTS

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.

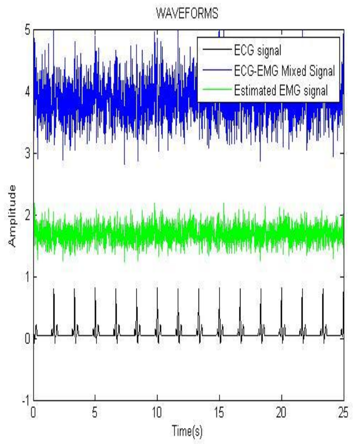

Fig: 4.1 Estimated EMG Signal

Accordingly, the overall ECG model is conceived as a linear system of equations, which can be efficiently solved by any linear solver, e.g., least squares. Once the model parameters (polynomial coefficients) are estimated, the ECG signal component is generated and subtracted from the mixture in order to obtain the EMG signal component estimation. The MATLAB simulation results are shown here.

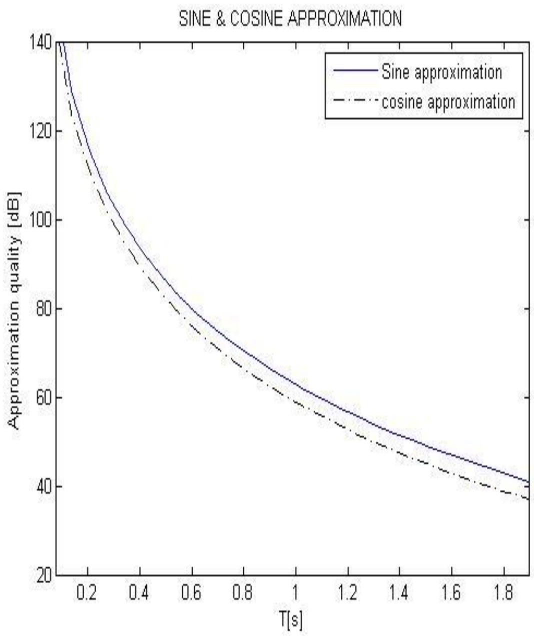

Fig: 4.2 Quality of the small-argument approximation

In Fig: 4.2, 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.

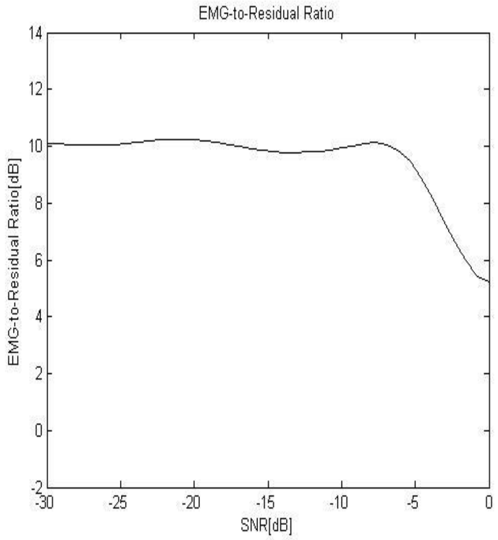

Fig: 4.3 EMGRR in the frequency band 0–20 Hz. [1]

We observe very different EMGRR trends for the proposed and WICA methods on one hand, and the filter method on the other [1]. In particular, the filter method seems to be almost insensitive to SNR variations. This phenomenon is easy to explain if we recall that the filter method suppresses almost completely the frequency content up to 30 Hz. Therefore, the estimation error in the analysis bandwidth 0–20 Hz will be practically independent of the SNR. The other two methods, however, provide a more sophisticated performance, which gives rise to the EMGRR dependent on the SNR. The descending EMGRR trend is due to the fact that for increasing SNR the estimation error becomes more significant, as the EMG energy vanishes.

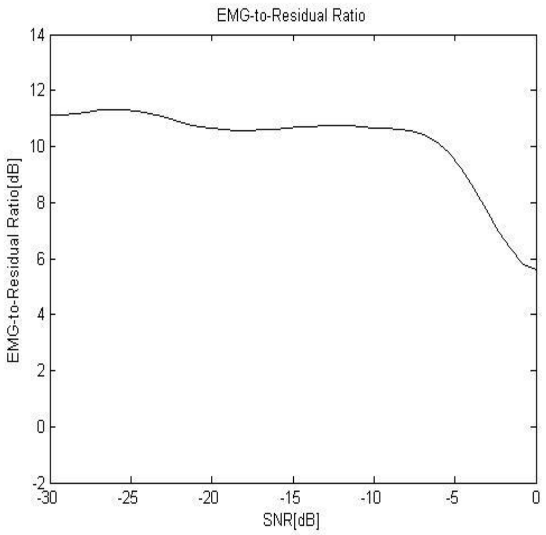

Fig: 4.4 EMGRR in the frequency Band 0–20 Hz (Proposed Method).

Here in this proposed method the EMGRR in fig 4.4 is significantly improved as compared with EMGRR in fig 4.3.

V. CONCLUSION

This paper has 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 Sine 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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