Time Frequency Noise Canceller for an Optimized Separation of the ECG from low back sEMG recordings

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Abstract—This work describes a hybrid adaptive filtering technique, designed to optimize the removal of the electrocardiogram (ECG) from surface electromyography (sEMG) recordings. Using the adaptive noise cancellation technique (ANC), we minimize the error gradient based on combined Time-Frequency filtering enhancements. The validation on artificially prepared signals with a real data basis shows better frequency and time filtering performances in comparison to simulations with standard implementations.

I. INTRODUCTION

Surface electromyography (sEMG) is a powerful non-invasive technique with application prospects in many areas, of which muscle fatigue assessment to explain this physiological deficiency and give solutions for its relevant clinical problems (ANC), such as low back pain [1]. Indeed, the sEMG frequency information conveyed by its instantaneous median frequency (IMDF) and instantaneous mean frequency (IMFN) [2] is significantly associated with the clinical assessment of trunk muscles impairment in patients with low back pain (LBP), and these indicators have been shown indispensable to determine before any direct intervention through physical rehabilitation. The knowledge of temporal parameters such as the root mean square (RMS) values of the sEMG recordings is also useful, but it is not as precise to help diagnose LBP, where amplitude abnormality is the only symptom observed in the recordings. Hence, it can only complement the spectral parameters for improved global diagnosis [3].

Unfortunately, the recorded sEMG signal, from which the indicator values are derived is often subject to contaminating interferences that hamper the evaluation of the spectral and amplitude sEMG information. The electrocardiogram (ECG) signal is the most common and difficult to discard, especially when recording from the trunk muscles [4]. Therefore, many signal-processing techniques have been proposed to remove the ECG contamination over the last three decades. The early works proposed using high-pass filters with 30 Hz cutoff frequency [5] and the gating method [6]. However, useful sEMG information is also discarded by these techniques, due to the frequency and time overlapping between the sEMG and its ECG interference.

More sophisticated filtering approaches were also attempted in the hope of improved ECG rejection. Such is the case of the adaptive noise canceller (ANC), which employs a secondary sEMG channel recorded above the heart to guide the ECG removal process. The most popular algorithms used to implement the ANC are based on least mean-squares (LMS) [7] and recursive least squares (RLS) [8] error minimization. The focus on using ANC is due to its steadier performance in comparison to other recently-introduced techniques like independent component analysis (ICA) [4] or empirical mode decomposition (EMD) [9].

Recently, efficient algorithms, such as the DA-FBLMS filter [7], were introduced in order to obtain more precise spectral parameters for defining the type of LBP. However, although the DA-FBLMS offers good performance, it suffers from many factors to set or initialize.

This paper presents a hybrid filter, called Time-Frequency Block Least Mean Squares (TFBLMS) that performs filtering in both the time and frequency domains. More precisely, it can be seen as a composite transform filter based on the Stationary Wavelet Transform (SWT) and the Fast Fourier Transform (FFT), adapted with ANC error gradient minimization to obtain reliable sEMG spectral and temporal parameters. Our simulation results show that this new filtering structure offers better performance than the alternative filters used for comparison.

The balance of this paper is organized as follows: Section II summarizes the necessary theoretical background, while Section III shows the simulation results and demonstrates the gain obtained from the proposed method, Section IV draws the important conclusions of this research.

II. THEORETICAL BACKGROUND

A. Time-Frequency adaptive filter structure (TFBLMS)

The proposed method is summarized in Fig. 1. The aim is to design an efficient ANC filter for removal, by adaptive estimation, of an additive noise signal v[m] (ECG artifacts) that affects a desired signal s[m] (ECG-free sEMG), from a composite primary input z[m] ((ECG-contaminated sEMG) such that:

$$z[m] = s[m] + v[m]$$  \hspace{1cm} (1)

where m = 1,2,...,M, M being the number of samples. The coefficients of the FIR filter $W_k$ and $w_i$ are regularly updated to minimize the difference between $s[m]$ and its estimate $\hat{s}[m]$ at the ANC structure output.
and is distinguished by a tap weights matrix $W^k_k$ of size $(J+1)\times P$, where $J+1$ is the number of SWT decompositions and $P$ is the row length of $W^k_k$.

First, each of the $J+1$ components of the SWT is divided into data blocks (frames) of size $L$, where the $k^{th}$ block of the $j^{th}$ component is a vector:

$$r^{(j,k)} = [r^{(j,k)} ]_{1+(k-1)L}, r^{(j,k)} [2+(k-1)L], \ldots, r^{(j,k)} [kL]] \quad (2)$$

where $j=1,2,\ldots,J+1$ and $k=1,2,\ldots,\lfloor M/L \rfloor$. With $\lfloor \cdot \rfloor$ yielding the integer part.

Each one of the $J+1$ blocks obtained for the $k^{th}$ frame is convolved with its corresponding row vector in $W^k_k$ of the same row index $j$, as described in (3) where $*$ is the convolutional operator. The resulting row vector $b^{(j,k)}$ is of $(L+P-1)$ size, but only its $L$ first elements are used to construct $c^{(j,k)}$:

$$b^{(j,k)} = r^{(j,k)} * w^{(j,k)} \text{ with } w^{(j,0)} = 0 \quad (3)$$

Finally, the sum (or SWT reconstruction) of the $J+1$ blocks of $\hat{c}^k$ is computed in (4):

$$c^k = \sum_{j=1}^{j=J+1} c^{(j,k)} \quad (4)$$

c) Spectral filtering process (FBLMS)

In this step, we concatenate the current block $\hat{c}^k$ with the previous one $\hat{c}^{k-1}$. Then, the resulting double-block is transformed into the frequency domain by FFT (5):

$$c^f_j = \text{FFT}\left[ c^{k-1} \hat{c}^k \right] \quad (5)$$

The spectral filtering process through an element-by-element multiplication ($\otimes$) with a frequency tap weights vector $w^k_f$ of length $2L$:

$$\hat{v}^f_j = c^f_j \otimes w^k_f \quad (6)$$

The estimated ECG artifact $\hat{e}^k$ of size $L$ is the last (second) block of the temporal double-block $\hat{y}^k$, obtained by inverse FFT of the result of (6):

$$\hat{y}^k = \text{IFFT}\left[ \hat{v}^f_j \right], \text{dim}(\hat{y}^k) = 2L \times 1 \quad (7)$$

$$\hat{s}^k = \left[ \hat{y}^k_{L+1}, \hat{y}^k_{L+2}, \ldots, \hat{y}^k_{2L} \right] \quad (8)$$

The $k^{th}$ block vector of the estimated sEMG $\hat{s}^k$ is computed as:

$$\hat{e}^k = \hat{s}^k - \hat{v}^k = (\hat{s}^k + \hat{v}^k) - \hat{v}^k \quad (9)$$

where $\hat{s}^k$ is the $k^{th}$ data block of the primary input, generated the same way as $r^{(j,k)}$ in (2) but with $J$ set to zero.
2) Error back propagation:
   a) Spectral adaptation (FBLMS)

   First, we insert \( L \) elements of zero values (null vector, noted \( 0_L \)) at the beginning of \( e^k \) and we transform the result into the spectral domain (10). Afterward, we multiply it with \( c_f^k \) element-by-element. Then, we transform it back into the temporal domain (11), using the inverse Fourier transform (IFFT):
   \[
   e^k = \text{FFT}\left(\left[0_L, e^k\right]\right) \quad (10)
   \]
   \[
   \Delta w^k = \text{IFFT}\left(\left[e^k \otimes c_f^k\right]\right) \quad (11)
   \]

   Now, we set the last block (second) of \( \Delta w^k \) to \( L \) elements of zero values \( 0_L \), and we transform the result into to the spectral domain (12).
   \[
   \Delta w_f^k = \text{FFT}\left(\left[\Delta w^k_1, \Delta w^k_2, \ldots, \Delta w^k_L, 0_L\right]\right) \quad (12)
   \]

   Finally, the spectral tap weights update equation follows
   \[
   w_f^{k+1} = w_f^k + \mu_2 \frac{\Delta w_f^k}{p_f^k} \quad (13)
   \]

   The power estimation \( p_f^k \) of the input blocks, computed in (14) is used to normalise the adaptive step-size \( \mu_2 \).
   \[
   p_f^{k+1} = \beta p_f^k + (1 - \beta) \left( c_f^k \right)^2 \quad \text{with} \quad p_f^0 = 0_{2L} \quad (14)
   \]

   where \( \beta \) is the amnesia factor.

   b) temporal adaptation (MxLMS)

   In order to update the MxLMS tap weights, we compute the relevant error by back-propagating \( e^k \):
   \[
   g^k = \text{IFFT}\left( e^k \otimes w_x^k \right) \quad (15)
   \]

   We take the last block of \( g^k \), noted \( q^k \):
   \[
   q^k = [q_{1,k+1}^k, q_{2,k+2}^k, \ldots, q_{2L}^k] \quad (16)
   \]

   We pad a null vector \( 0_{P-1} \) of \( (P-1) \) length to the beginning of each of the \( J+1 \) input blocks \( r^{(j,k)} \), and we obtain a Hankel trajectory matrix \( \left( L \times P \right) \) for each block as
   \[
   H^{(j,k)} = \begin{bmatrix}
   0 & 0 & \ldots & 0 & r^{(j,k)}_1 \\
   0 & 0 & \ldots & 0 & r^{(j,k)}_2 \\
   \vdots & \vdots & \ddots & \vdots \\
   r^{(j,k)}_{L-1-P+1} & r^{(j,k)}_{L-1-P+2} & \ldots & r^{(j,k)}_{L-1} & r^{(j,k)}_L 
   \end{bmatrix} \quad (17)
   \]

   Then, the MxLMS matrix tap weights rows are updated as follows:
   \[
   w_t^{(j,k+1)} = w_t^{(j,k)} + \mu_1 \left( q^k \mathbf{H}^{(j,k)} \right) \quad (18)
   \]

   where \( \mu \) is the update step size.

   Then, we concatenate the \( J+1 \) results vertically to obtain the new MxLMS matrix tap weights \( W_f^{k+1} \) as
   \[
   W^{k+1}_f = \left[ w_t^{(1,k+1)}; w_t^{(2,k+1)}; \ldots; w_t^{(J+1,k+1)} \right] \quad (19)
   \]

III. SIMULATION RESULTS

To evaluate the efficiency of the proposed ECG filter, we compared it with other conventional algorithms like BLMS (temporal filtering) and FBLMS (spectral filtering).

Since a precise evaluation of our method is impossible with real signals, since \( s[m] \) is not known a priori. The semi-artificial signals prepared in [7] from real signals are used. Only the linear case is used in this study at 35 dB of SNR, which is the closest to the real signals. We conducted 100 simulations using a random beat rate between [60, 100] beats/min and randomly fluctuating QRS amplitudes and R-R intervals by up to 10% in every realization.

The simulation parameters shown in Table I were selected empirically. All the algorithms have the same block length \( L \). The length of the tap weights, noted \( P \) characterise the MxLMS and BLMS. The convergence step sizes are \( \mu \) for both BLMS and FBLMS.

<table>
<thead>
<tr>
<th>Parameter Values of Compared Algorithms</th>
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<tbody>
<tr>
<td>Time-Frequency-ANC (TFBLMS)</td>
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<td>Time-Frequency-ANC (TFBLMS)</td>
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<td>( \mu_1 )</td>
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<td>( \mu_2 )</td>
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The performances evaluation and comparison of these algorithms are done in two ways: in the spectral and temporal domains, respectively.

1) Spectral filtering evaluation

The coherence function between \( s[m] \) and its estimation at the output of the ANC structure \( \hat{s}[m] \) is defined in (20).

\[
\text{Coh}[u] = \frac{\left| P_{w_s}[u] \right|^2}{P_{w_s}[u] P_{w_i}[u]} \quad (20)
\]

where \( P_{w_s}[u] \), \( P_{w_i}[u] \), and \( P_{w_i}[u] \) are respectively the cross-spectral density and the auto-spectral densities of \( s[m] \) and \( \hat{s}[m] \), and \( u = 0, 2, 4, \ldots, 500 \text{Hz} \) represents the frequency range used in analysis. The closer the coherence value is to 1, the closer the filtering process is to perfection.

Fig. 2 shows the boxplots of the obtained frequency coherence distribution and its median value (line in the middle). We can observe, using zoom, the increase of coherence median value when combining the time and frequency filtering (TFBLMS), in comparison to temporal filtering (BLMS) or spectral filtering (FBLMS) alone.
The numerical comparisons are summarized in Table II, where, \( \overline{\text{Coh}} \), the mean coherence values across all frequencies “\( u \)” defined as:

\[
\overline{\text{Coh}} = \frac{1}{u_{\text{Max}}} \sum_{u=0}^{u_{\text{Max}}} \text{Coh}[u] \quad (21)
\]

With \( \text{Coh}[u] \) being the coherence function defined in (20), and \( u_{\text{Max}} \) the maximum frequency used, 500 Hz in our case.

Table II provides also the relative mean coherence \( \overline{\text{Coh}_r} \) defined in (22), and the relevant standard deviations \( \sigma \) of the 100 different ECG artifact simulations.

\[
\overline{\text{Coh}_r} = \frac{\overline{\text{Coh}} - \overline{\text{Coh}_{\text{No-Filting}}}}{1 - \overline{\text{Coh}_{\text{No-Filting}}}} \times 100 \quad (22)
\]

Table III. Temporal Evaluation For Different Algorithms.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>( \overline{\text{Coh}} )</th>
<th>( \sigma )</th>
<th>( \overline{\text{Coh}_r} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>TFBLMS</td>
<td>0.9781</td>
<td>± 0.0133</td>
<td>82.52 %</td>
</tr>
<tr>
<td>BLMS</td>
<td>0.9359</td>
<td>± 0.0088</td>
<td>48.26 %</td>
</tr>
<tr>
<td>FBLMS</td>
<td>0.9678</td>
<td>± 0.0107</td>
<td>74.01 %</td>
</tr>
<tr>
<td>No-Filting</td>
<td>0.8761</td>
<td>± 0.0118</td>
<td>0 %</td>
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As shown by the obtained results, the filtering performance of TFBLMS is substantially higher than that of FBLMS and slightly higher than that of BLMS. This improvement was the result of input ortho-normalization by the stationary wavelet transform (SWT), followed by temporal filtering (MxLMS), for cleaner sEMG in the end.

IV. CONCLUSION

In conclusion, a time-frequency block least mean squares based adaptive noise cancelation filter to enhance the spectral and temporal removal of ECG contamination affecting electromyography signals was introduced. Better performance is demonstrated in comparison to the standard algorithms like BLMS and FBLMS. Its efficiency was proved for 100 realizations of different ECG signals according to Monte Carlo simulations.

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REFERENCES