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Removing harmonic power line interference from biopotential signals in low cost acquisition systems

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ABSTRACT

This paper presents a new proposal of a very low cost and highly efficient interference canceller to be applied to biomedical signals. The power line reference is obtained from analog to digital conversion while higher harmonics are mathematically estimated by means of trigonometric relations. These signals are processed by an adaptive algorithm in order to suppress harmonic interference. Biomedical acquisition systems that incorporate a conventional adaptive canceller, whose reference signal is sampled from power line, can be easily modified to improve interference suppression without hardware modifications. Real application examples are supplied in order to demonstrate its usefulness in electroencephalographic, electrocardiographic and auditory evoked potential signals.

1. Introduction

Clinical interpretation of bioelectrical signals plays an important role in the diagnostic of human being diseases. Important information is frequently carried by small amplitude bioelectric signals. Thus, several contamination sources can conceal critical information [1]. Typical examples are baseline wander caused by varying electrode-skin impedance [2] and additive electromiographic (EMG) signals. The most common and important external interferences associated with bioelectric signals are, however, those originated from the power line source [3]. Such additive disturbances are usually modelled by: (1) a fixed frequency sinusoid with random phase and amplitude (electrical field interference), and (2) higher order harmonics due to magnetic fields originated from nonlinear characteristics of the propagation path (e.g. main power transformer) [1] or due to other equipments like fluorescent lamp reactors.

Several techniques have been developed to suppress power line interference (60 Hz or 50 Hz) and its higher harmonics from bioelectric signals [4,5]. Physical solutions such as shielding, grounding and careful amplifier printed circuit board design are usually employed [6]. Typically, such solutions are insufficient to provide the required signal quality level. Conventional low-pass analog filtering tends to severely attenuate signal components above its cut off frequency, which limits the system's frequency range. Such a limitation cannot be tolerated in applications such as high-resolution electrocardiography [7]. Fixed notch filters have been widely used for interference suppression and a variety of design techniques are available in the specialized literature [8]. However, the efficiency of highly selective fixed notch filters is compromised by power line frequency variability [1,9].

Adaptive filtering is an alternative solution to power line interference cancellation. The adaptive noise[2] canceller (ANC) developed by Widrow [10] has been shown to lead to significant interference suppression in bioelectric signals. Its high selectivity, frequency tracking capability, low distortion and low computational cost characteristics are very attractive for bioelectric acquisition systems. Many modern commercial systems incorporate adaptive (active) noise cancelling techniques. Despite its excellent performance in 60 Hz (50 Hz) cancellation, the linear filtering structure of the ANC leads to a poor performance when higher harmonics cancellation is necessary.

Nowadays, microprocessor-based systems find widespread use in bioelectric signal acquisition. They offer higher resolution and better quality and flexibility when compared to conventional analog instruments [11]. Several digital signal processing methods are currently applied to bioelectric signals to enhance clinical information and to suppress interference. Nevertheless, the high computational cost of many signal processing algorithms, the need for sharing the available computational resources among different tasks, which must be

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[2] In this context, the word "noise" is used as an equivalent to "interference".

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executed at the system's sampling rate, and the need for multichannel systems increase the demand for low computational cost processing strategies.

This paper proposes an improvement on the conventional ANC described in [10], which provides harmonic suppression with a minimal computational complexity increase. Moreover, it requires no hardware modifications in systems that already embed a conventional ANC (assuming the availability of an analog to digital converter to sample the power line signal). The proposed algorithm is an attractive solution for the implementation of low cost and high quality bioelectric commercial acquisition systems.

This paper is organized as follows: Section 2 reviews the conventional ANC. The harmonic cancelling problem is defined in Section 3. Section 4 presents the new algorithm. Sections 5 and 6 present comparisons between the new strategy and the conventional ANC. Section 7 presents the conclusions of this work.

2. The conventional ANC

The structure of the conventional ANC [10] is shown in Fig. 1. Here, $x(n)$ is the reference signal at time index n (power line samples obtained by an analog to digital converter). $z(n)$ is the bioelectrical signal of interest and $d(n)$ is its contaminated version. $y(n)$ is the interference cancelling signal produced by the adaptive filter and $e(n)$ is the output signal. Ideally, $e(n)$ converges to the interference-free bioelectrical signal $z(n)$. $H(n)$ represents a time-variant nonlinear system responsible for the power line contamination.

The least mean square (LMS) update equation for the (single frequency) ANC is given by [10]:

$$\mathbf{w}(n+1)=\mathbf{w}(n)+\mu e(n)\mathbf{x}(n) \quad (1)$$

where $\mathbf{w}(n)=[w_1(n)\ w_2(n)]^T$ is the adaptive weight vector and $\mathbf{x}(n)=[x_F(n)\ x_Q(n)]^T$ is the reference input signal, which consists of the in-phase ($x_F(n)$) and quadrature ($x_Q(n)$) components of the power line source. Signals $x_F(n)$ and $x_Q(n)$ are obtained through a delay line with length depending on the relation between the power line frequency (60 Hz or 50 Hz) and the sampling rate of the acquisition system. The parameter μ is called step size and is responsible for the performance of the cancelling process. The identifier **A** in Fig. 1 refers to the model for the contamination of the bioelectric signal. Block **B** contains the canceller structure.

The adaptive canceller working principle is based on the fact that a sinusoidal signal can be expressed by its in-phase and quadrature components

$$x(t)=A\cos(\omega t+\phi)=A_1\cos(\omega t)+A_2\sin(\omega t) \quad (2)$$

where $A_1=A\cos(\phi)$ and $A_2=-A\sin(\phi)$ [12]. Assuming that $H(n)$ is linear and time invariant and that $x(n)$ is sampled at a sufficient rate, the adaptive weights $w_1(n)$ and $w_2(n)$ converge to the optimum values A_1 and A_2, respectively. In such a situation, the adaptive system output is equal to the interference-free bioelectric signal ($e(n)=z(n)$).

3. Harmonic contamination

Several works in the literature demonstrate the ability of the adaptive canceller in Fig. 1 to considerably reduce power line interference. However, obtaining high quality bioelectric signals requires also cancellation of power line harmonics. Harmonics are originated from nonlinearities in the propagation path (environment and electronic circuitry-block $H(n)$ in Fig. 1). Since harmonics are orthogonal signals, the adaptive canceller is unable to deal with this kind of contamination due to its linear filtering structure (Fig. 1, part B).

Many adaptive filter techniques can be used to cancel harmonics. However, they generally imply the need for unavailable computational resources and/or hardware requirements, especially in low cost acquisition systems. This is the case when the acquired reference signal $x(n)$ contains the main interference and its harmonics. Satisfactory cancelling performance, by the LMS algorithm, requires either a digital filter bank to separate desired harmonics, or a large number of adaptive coefficients (since it is not possible to obtain individual in-phase and quadrature components for each harmonic). If computational resources are not available, one possibility is the use of an extra acquisition channel for each harmonic. However, such a solution implies the use of additional electronic circuitry, such as analog filters for frequency separation. These alternatives imply an increase in computational and/or hardware complexity and, as a result, in the system's cost.

4. The proposed solution

The block diagram of the proposed algorithm is presented in Fig. 2. The proposed structure is similar to the conventional noise canceller presented in Fig. 1 but incorporates one block for harmonic estimation (Fig. 2, part **E**) and one extra canceller for each estimated harmonic (Fig. 2, parts $\mathbf{B}_i$, $i=1,2,\ldots,N$). In fact, it is a multichannel version of Widrow's ANC associated with sinusoid estimators (magnitude and phase) whose frequencies are synchronized multiples of the reference signal. As shown in Fig. 2 no extra external reference signals are used, and the hardware requirements are the same as those for the conventional adaptive canceller. Thus, existing biomedical acquisition systems can be modified with only a small change in software and a small increase in computational complexity.

The main problem to be overcome in such architecture is to obtain low cost and precise estimations of the power line

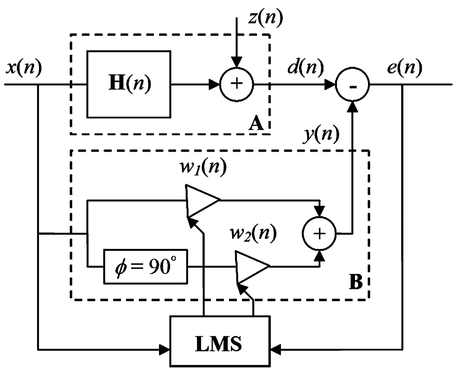

Fig. 1. Block diagram of the Widrow's conventional adaptive noise canceller [10].

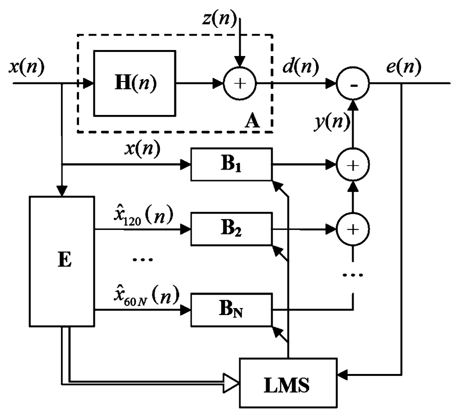

Fig. 2. Block diagram of the proposed adaptive noise canceller (60 Hz notation).

harmonics. Conventional estimators usually make use of spectrum analysis methods, whose computational complexities are not affordable in low cost processors. As stated in Section 3, direct acquisition of individual harmonics will require undesired extra hardware, while internal generation of reference signals would result in a performance similar to that of conventional notch filters [13] (due to deviations from the nominal main frequency [1,9]).

In this paper, the use of trigonometric relations applied to samples of the main power line signal to obtain synchronized estimations of the higher harmonics is proposed. The main advantages of this method, related to previous papers presented in the literature [1,2,4,5,8,10,13], are:

- no need for extra acquisition channels;
- no need for filter banks or spectrum analysis methods;
- the number of harmonics can be easily increased (or decreased) depending on the available microprocessor resources;
- tracking capacity (in case of frequency deviation);
- instantaneous, stable and reliable (high signal to noise ratio) estimations;
- low computational cost;
- conventional cancellers can be easily updated.

Eq. (3) presents some well known trigonometric relations [12]. In order to preserve space, but without losing information, they are presented until the fourth order

$$\begin{cases} \cos^2(x) = 0.5\cos(2x) + 0.5 \\ \cos^3(x) = 0.25\cos(3x) + 0.75\cos(x) \\ \cos^4(x) = 0.125\cos(4x) + 0.5\cos(2x) + 0.375 \end{cases} \tag{3}$$

Rearranging the equations in (3) they result in

$$\begin{cases} \cos(2x) = 2\cos^2(x) - 1 \\ \cos(3x) = 4\cos^3(x) - 3\cos(x) \\ \cos(4x) = 8\cos^4(x) - 4\cos(2x) - 3 \end{cases} \tag{4}$$

Upon analyzing (4) it is easy to verify that higher harmonics estimations can be obtained from the instantaneous amplitude of the power line interference. This simple technique has not yet been exploited in adaptive interference cancellation.

As a result, at each discrete time instant n, higher harmonic sample estimations can be directly gotten from power line samples obtained by analog to digital conversion in the following way:

$$\begin{cases} \hat{x}_{F120}(n) = 2x^2(n) - 1 \\ \hat{x}_{F180}(n) = 4x^3(n) - 3x(n) \\ \hat{x}_{F240}(n) = 8x^4(n) - 4\hat{x}_{F120}(n) - 3 \end{cases} \tag{5}$$

where the subscript F means in-phase component and the following three numbers indicate the frequency of the estimated harmonic (in this case, for a 60 Hz power line: 120, 180 and 240 Hz). Quadrature components are obtained through a line delay whose length is determined by the following equation:

$$\hat{x}_{Qf}(n) = \hat{x}_{Ff}\left(n - round\left(\frac{f_{samp}}{4f}\right)\right) \tag{6}$$

where $round(\cdot)$ is the rounding operation, f refers to the desired harmonic (120 Hz, 180 Hz, ...) and f_{samp} is the sampling frequency of the acquisition system.

Eq. (6) determines that, for best performance, the sampling frequency should be chosen in such a way that $f_{samp}/(4f)$ is an integer for each harmonic. However, exhaustive tests have demonstrated that rough approximations can give very good results.

Intrinsic noise associated with the acquired power line signal, quantization errors and noninteger values of $f_{samp}/(4f)$ can result in base line wander of the obtained estimations. In order to correct this problem each estimated harmonic is processed by a one coefficient LMS adaptive algorithm. This adaptive filter has a constant input signal, being responsible for maintaining a zero continuous (DC) level.

The acquired reference signal is easily set to unit power since it is obtained from a power line transformer that supplies a stable waveform for the analog to digital converter. In general, the power line root mean square (RMS) value is approximately constant. However, surgical environments can present energy disturbances due to the switching of high loads, such as defibrillators and electrocauteries. In such cases, power fluctuations can be corrected through a normalization factor applied to each sample. This factor is an inverse estimate of the power line peak amplitude and is given by (see Appendix A for derivation)

$$k(n) = \frac{2P}{\pi\sum_{k=0}^{P-1}|x(n-k)| + \varepsilon} \tag{7}$$

where P is a multiple of $f_{samp}/60$ and ε is the regularization factor (to avoid division by zero and consequent overflow). The summation in the denominator of (7) can be recursively evaluated in order to minimize the computational cost. This procedure avoids the need for automatic gain control strategies [14]. A step by step description of the proposed algorithm can be found in Table 1.

5. Materials and methods

The proposed canceller was embedded in a low cost bioelectric acquisition system (Fig. 3) developed to study anaesthetic depth during surgery [15]. It allows the simultaneous acquisition of one electrocardiographic (ECG) derivation, two electroencephalographic (EEG) channels and power line reference. Auditory evoked potentials are obtained from one of the EEG channels at sampling frequency sufficient to perfectly depict midlatency auditory evoked potentials (MLAEP) and to detect the presence or absence of brainstem auditory evoked potentials (BAEP) [16].

This equipment consists of an acquisition module based on a low cost 16-bit microcontroller (Intel N87C196KD-20) and an external portable host microcomputer (Intel Pentium III—450 MHz). As the microcontroller carries out several concurrent processes, such as data conversion and data transfer to the host computer, only a small part of its computational capacity is available. The proposed canceller was implemented in the host computer, in a high-level programming language (C language), with four references (60, 120, 180 and 240 Hz), which provides real-time processed data for one ECG derivation and three EEG channels, one of them being used for obtaining auditory evoked potentials (MLAEP). The canceller can be turned on and off by the user.

Signals from six healthy volunteers and seven patients undergoing abdominal surgeries were acquired [17] in order to verify the performance of the proposed algorithm. The first group of signals was acquired at laboratory conditions. Four volunteers were male and two female (mean age of 25 years and an 8 year standard deviation). The second group of signals consisted of two male and five female (mean age of 50 years and an 18 year standard deviation) patients subjected to cholecystectomy surgeries.

During surgeries the experimental protocol consisted of the following procedures: skin previously cleaned with Nuprep™ abrasive paste; Ten20™ conductive paste was used for the contact between electrodes and scalp. Ag–AgCl pre-gel (Kendall 200 Meditrace™) ECG electrodes were placed at LA and RA (derivation I); conventional Ag–AgCl dry electrodes were placed at Cz-M1 (left mastoid) and Cz-M2 (right mastoid), with reference at Fpz, according to the 10–20 International System. The auditory stimulator was adjusted to generate clicks with 100 µs, 110 dB_{pe}SPL (peak-equivalent sound

Table 1
Proposed algorithm (60 Hz notation).

$x_{AC}(n) = x(n) - w_1(n)$	Input signal offset null
$w_1(n+1) = w_1(n) - \mu_1 x_{AC}(n)$	Offset null adaptive filter
$\mathbf{x}_{\mathbf{AC}} = x_{AC}(n) \cdots x_{AC}(n-p+1)^T$	Input vector
$x_{F60}(n) = \frac{2P}{\pi[\mathbf{x}_{\mathbf{AC}}^T(n)\mathbf{x}_{\mathbf{AC}}(n)+\varepsilon]}/x_{AC}(n)$	Input signal normalization
$\hat{x}_{F120}(n) = x_{F60}^2(n) - w_2(n)$	Second harmonic estimation
$w_2(n+1) = w_2(n) - \mu_2 \hat{x}_{F120}(n)$	Offset null adaptive filter
$\hat{x}_{F180}(n) = x_{F60}^3(n) - 0.75 x_{F60}(n)$	Third harmonic estimation
$w_3(n+1) = w_3(n) - \mu_2 \hat{x}_{F180}(n)$	Offset null adaptive filter
$\hat{x}_{F240}(n) = 2x_{F60}^4(n) - 2\hat{x}_{F120}(n) - w_4(n)$	Fourth harmonic estimation
$w_4(n+1) = w_4(n) - \mu_2 \hat{x}_{F240}(n)$	Offset null adaptive filter
$x_n = [x_{F60} x_{Q60}(n) 2\hat{x}_{F120}(n) 2\hat{x}_{Q120}(n) 4\hat{x}_{F120}(n) 4\hat{x}_{Q120}(n) 4\hat{x}_{F240}(n) 4\hat{x}_{Q240}(n)]^T$	Signal buffer
$e(n) = d(n) - \mathbf{w}^T(n)\mathbf{x}(n)$	Processed signal
$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu e(n)\mathbf{x}(n)$	LMS update equation

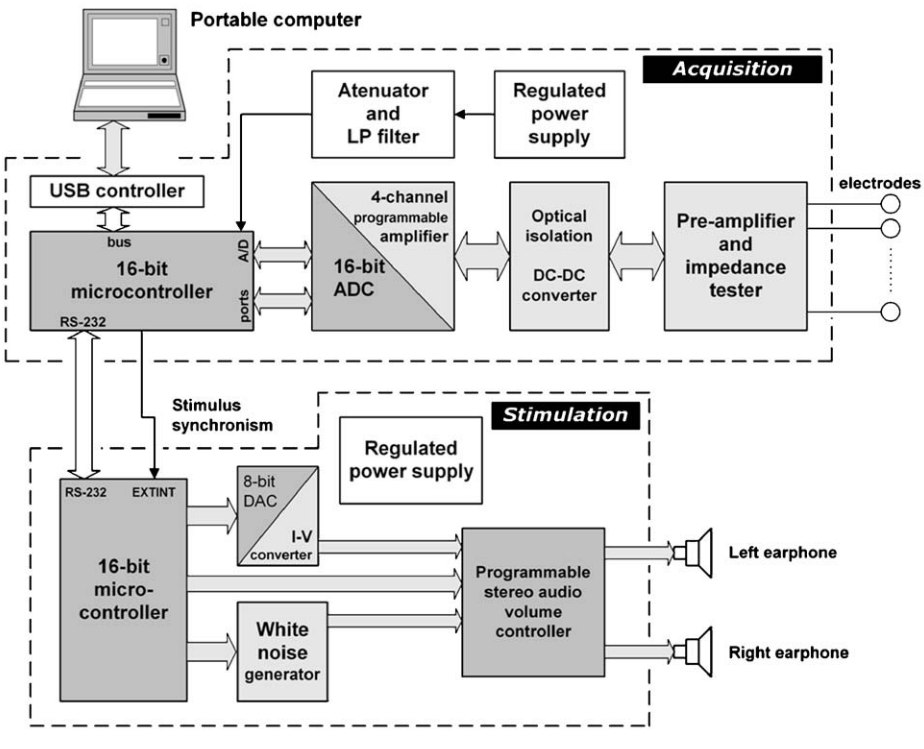

Fig. 3. Block diagram of the acquisition hardware [15].

pressure level) compressing polarity and 8.3 stimuli/s for both ears. The EEG-to-MLAEP channel gain was adjusted to a 200 μV full scale (± 100 μV). Band-pass filters were set to 0.5–100, 1–100 and 10–200 Hz for ECG, EEG and EEG-to-MLAEP channels, respectively. Each band-pass filter was made up of a first order high-pass and a second order low-pass. Sampling frequency was 1 kHz for ECG, EEG and power line signal, and 5 kHz for EEG-to-MLAEP. An interpolation routine on the external microcomputer was used to adapt the power line samples for EEG-to-MLAEP interference cancelling.

Some laboratory acquisitions made use of intentional high impedance electrode coupling and an approximate 30 kΩ imbalance between differential amplifier inputs in order to raise the power line contamination in the bioelectric signals. The aim of such condition was to verify the effectiveness of the new canceller under high interference levels. The parameters of the adaptive canceller were set to $\mu = 0.05$ and $\varepsilon = 10^{-6}$.

Comparisons between the performance of the conventional canceller and the proposed algorithm were obtained for ECG, EEG and MLAEP signals. The presented results in Section 6 are representative of a wide set of experiments.

6. Results and discussion

In order to permit comparisons between raw and processed data, only off-line processing results are presented in this section (since the acquisition system is unable to store both signals). No significant

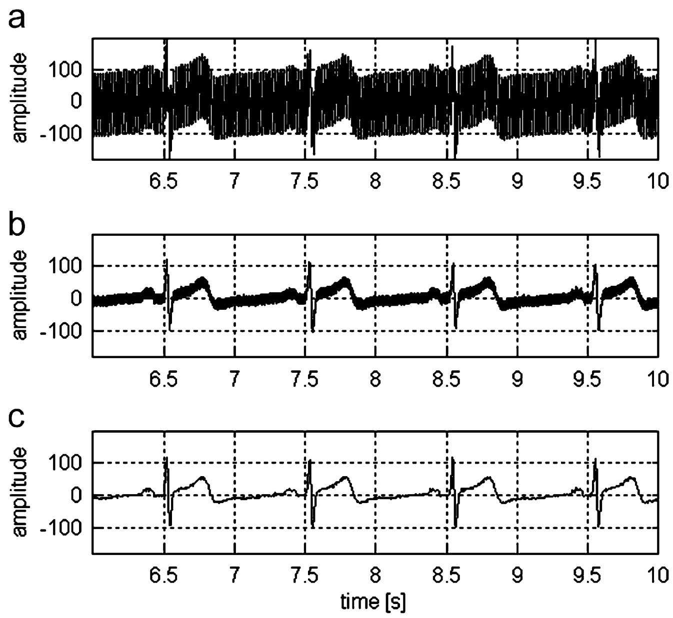

Fig. 4. Time evolution of the: (a) acquired ECG signal; (b) ECG signal processed by the conventional canceller [10]; (c) ECG signal processed by the proposed algorithm.

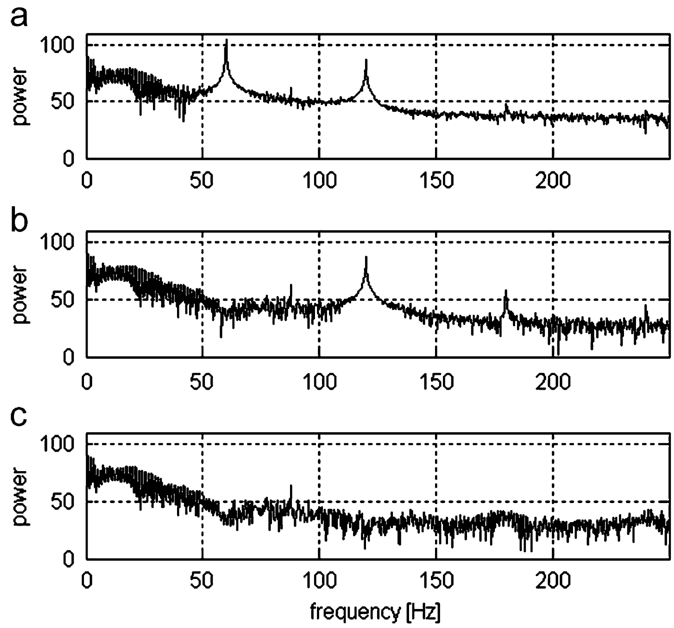

Fig. 5. Power spectrum of the: (a) acquired ECG signal; (b) ECG signal processed by the conventional canceller [10]; (c) ECG signal processed by the proposed algorithm.

differences were found in relation to on-line processing, once all mathematical operations were performed in floating point format.

Fig. 4 shows results of the proposed canceller applied to ECG signal acquired from a healthy volunteer with high impedance electrode coupling and high imbalance between differential amplifier inputs. Fig. 4a shows the contaminated raw ECG signal, Fig. 4b shows the ECG signal processed by the conventional canceller (Fig. 1) and Fig. 4c shows the result obtained by using the proposed canceller (Fig. 2). Clearly, Fig. 4c presents an ECG signal of higher quality when compared with Fig. 4a and b. The significant increase in the signal-to-interference ratio (SIR) is due to the harmonic suppression capability of the new algorithm. Fig. 5 presents the power spectrum of ECG signals presented in Fig. 4. The new canceller can reduce not only the main interference but also higher harmonics (120, 180 and 240 Hz).

Fig. 6 presents the power spectrum of an EEG epoch (Cz-M1) acquired under the same conditions as described in Fig. 4. Fig. 6a corresponds to the original signal, Fig. 6b to the signal processed by the conventional canceller and Fig. 6c to the result provided by the new proposal. As in Fig. 5 (ECG case) the new canceller is able to suppress higher harmonics and provide a better signal quality.

The conventional way for extracting MLAEPs is the synchronous average of EEG samples under auditory stimuli [18,19]. A number between 256 and 4096 of 100 ms EEG epochs (average of 1000) is usually needed to improve the usual $2\,\mu V/100\,mV$ signal-to-noise ratio so that clinical analysis can be performed [16]. Such amount of averaging, needed to minimize the background EEG influence (considered noise in this case), suffices to minimize some external interferences such as the main power line and its harmonics when fractional stimuli are used (e.g. 8.3 stimuli/s). However, large amplitude and high correlated muscular activity, such as eyeblinks and movements from noncolaborative patients (i.e. children), significantly deteriorate the averaged MLAEP, especially in small ensemble applications (like in anaesthesiology monitoring). In order to avoid such influence, evoked potential systems include artifact rejection routines that reject any EEG epoch containing a voltage value exceeding a previously established threshold [20,21]. In clinical trials, when the number of rejected epochs exceeds more than 10% of the epochs available to evaluate one MLAEP, the entire ensemble should

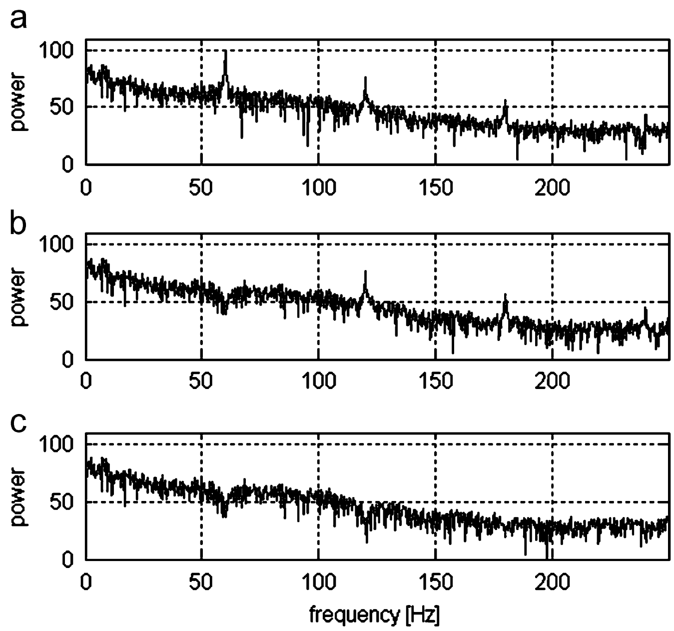

Fig. 6. Power spectrum of the: (a) acquired EEG signal; (b) EEG signal processed by the conventional canceller [10]; (c) EEG signal processed by the proposed algorithm.

be rejected [22]. In surgical monitoring, rejecting full ensembles is not desired due to the lack of information on the patient's anaesthetic state. Extensive analysis of the available database has demonstrated that the majority of large amplitude signals are due to power line (and harmonic) contamination instead of being of solely physiological nature. Since averaging is a very robust estimation procedure to power line influence, artifact rejection routines directly applied to raw EEG will reject many useful epochs. In this context it is essential to improve the EEG quality prior to averaging.

The rejection threshold usually is described as a voltage value or a fraction (percentage) of the full-scale range. A review of the

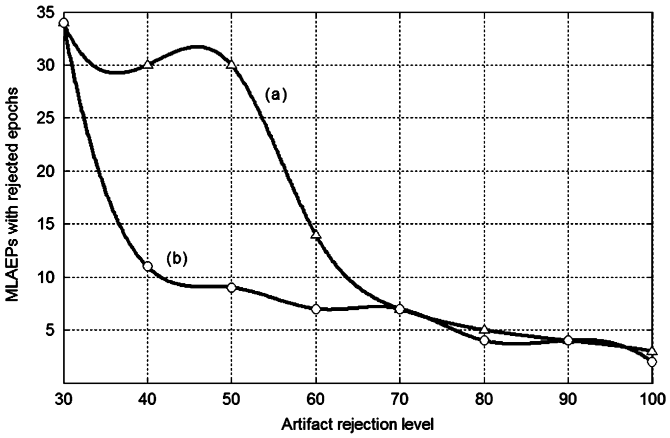

Fig. 7. Number of MLAEP (out of a 46 total) with rejected epochs, for patient 2, according to the artifact rejection level (defined as a percentage of the full-scale range): (a) conventional canceller; (b) proposed algorithm.

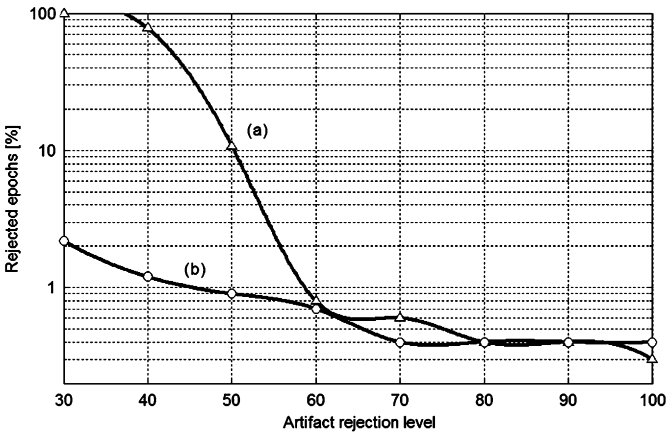

Fig. 8. Rejected epochs in the most contaminated MLAEP of a patient under surgery: (a) conventional canceller and (b) proposed algorithm.

literature shows that this threshold is in between $\pm 30\,\mu V$ (30%) and $\pm 60\,\mu V$ (60%) for a full-scale of $\pm 100\,\mu V$ (100%) [23–25].

Fig. 7 presents the number of MLAEPs with rejected epochs for patient 2 during surgery, along a 92.37 min interval and a 1000 epoch averaging for each MLAEP. A comparison between results obtained from the signal processed by the conventional canceller and by the proposed algorithm demonstrates the significant decrease of the number of MLAEPs with rejected epochs for thresholds between 30% and 70%. For thresholds below 30% both algorithms present approximately the same number of rejections due to the background EEG. Fig. 8 presents comparative results between the two techniques for epochs belonging to the most contaminated MLAEP of patient 2. Here the influence of higher harmonics over the rejection routine when using small thresholds can be seen. For thresholds below 50% the epochs obtained from the conventional canceller were entirely rejected (the number of rejected epochs is over 10% of the epochs available to evaluate one MLAEP) while the new algorithm rejected less than 2% of the total number of epochs providing a high quality MLAEP.

Fig. 9 shows the number of rejected epochs for the entire ensemble for both the conventional and new canceller as a function of the artifact rejection level. The use of the new canceller permits the attainment of high quality signals without rejecting useful epochs (threshold less than 40%).

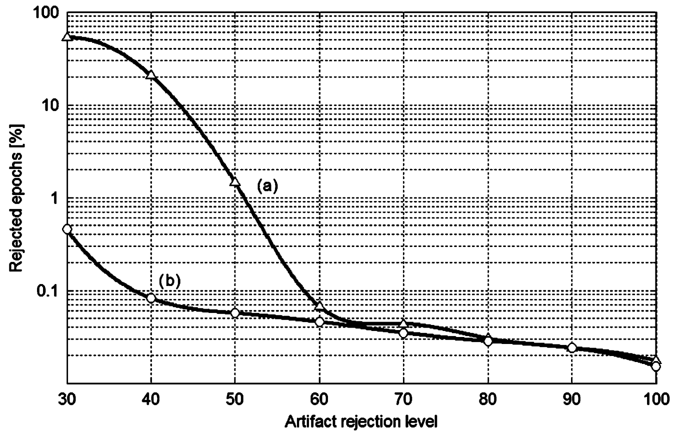

Fig. 9. Rejected epochs of a patient during surgery for all 46 obtained MLAEPs: (a) conventional canceller and (b) proposed algorithm.

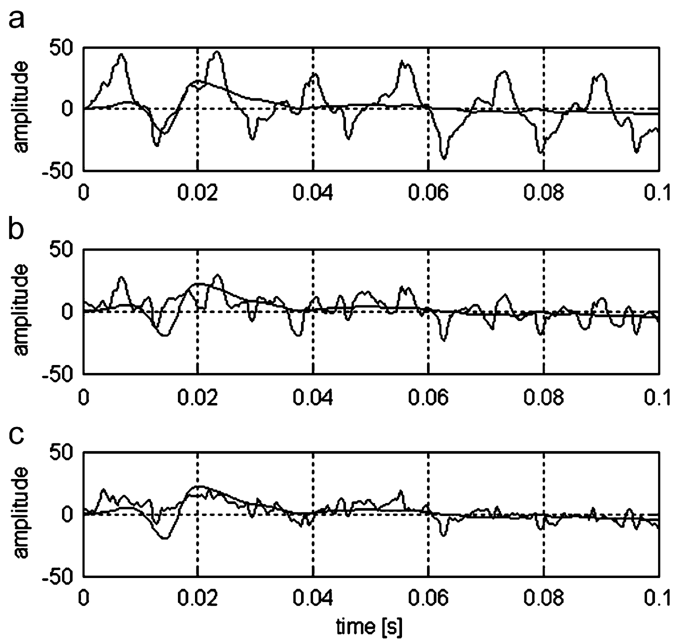

Fig. 10. Time evolution of the: (a) EEG signal; (b) EEG signal processed by the conventional canceller; (c) EEG signal processed by the proposed algorithm. A scaled version of the averaged MLAEP (1000 epochs, scale factor of 7) is synchronously superimposed with all plots (smoothed line).

Artifact rejection procedures are essential in order to obtain high quality MLAEPs, once high level background activity and ocular movements can severely deteriorate the estimated MLAEPs. The use of the new canceller permits a better decision as to whether epochs should be rejected or accepted during MLAEP extraction procedures, resulting in a large number of valid epochs and consequent high quality signals.

Fig. 10 presents a comparison between a high SIR single MLAEP and its ensemble average over 1000 epochs. Three cases are presented: raw data, data processed by the conventional canceller and data processed by the proposed algorithm. Fig. 10c shows the use of the new canceller approximates the shapes of single and averaged MLAEPs. This example demonstrates the capability of the new algorithm in minimizing the influence of power line harmonic interference and its potential use in association with single trial MLAEP techniques [26].

Possible effects on changes in amplitude and latency of MLAEPs due to the application of the proposed canceller were investigated in signals from five surgical patients. Visual inspection of MLAEPS from all patients demonstrated no clinical significant differences between processed and nonprocessed signals.

The complete proposed canceller requires only 27 sums, 31 multiplications and 1 division (corresponding to 16 multiplications [27]) in the case of the three harmonics presented case (60, 120, 180 and 240 Hz).[3] Such computational cost is compatible with some commercial 16-bit microcontrollers (Texas MSP430F2XXX, Freescale 68HC16Z1). Extra references and channels could be obtained by the use of digital signal controllers with multiply-accumulate hardware units [28] (Freescale MC56F80XX, Texas TMS320F28XX). The unitary cost of these processors is less than U$20 in very small quantities.

7. Conclusion

This paper presented a very effective and low computational cost strategy for power line harmonic suppression in biomedical signals. The power line reference is obtained from analog to digital conversion while higher harmonics are mathematically estimated through trigonometric relations. These samples and estimates make up a set of reference signals to be processed by a multichannel LMS adaptive canceller. Performance comparison with the conventional adaptive canceller in ECG and EEG demonstrates the new algorithm can improve the signal to interference ratio of such bioelectric signals due to suppression of power line and harmonic interference. The proposed canceller is also very useful as a pre-processing step prior to artifact rejection routines in evoked potentials averaging. Use in intraoperative monitoring resulted in high quality MLAEP signals, permitting continuous monitoring, even during intense harmonic interference periods. Laboratory and surgery data, obtained with a low cost biomedical acquisition system demonstrate the positive performance of the proposed strategy. This technique is of special interest for low cost high quality acquisition systems that incorporate a conventional adaptive canceller, as no hardware modifications are needed.

Conflict of interest statement

None declared.

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Appendix A.

A simple estimator for the peak value of a discrete sinusoid $x(n) = A(n)\sin(\Omega n+\Phi)$—where $\Omega = 2\pi f/f_{samp} = 2\pi/P$, $A(n)$ is the peak value (assumed slowly varying), P (integer) is a multiple of the period, f is the sinusoid frequency (in this case 60 Hz or 50 Hz), f_{samp} is the sampling frequency and Φ is the phase—can be built using estimates of the mean absolute value, given by

$$\eta(n) = \frac{1}{P}\sum_{k=0}^{P-1}|x(n-k)| \tag{A.1}$$

Using trigonometric relations in (A.1) and disregarding phase information (since P is a multiple of the sinusoid period) (A.1) turns to

$$\eta(n) = \frac{|A(n)|}{P}\left[j\sum_{k=0}^{P/2-1} e^{-j\Omega k} - j\sum_{k=0}^{P/2-1} e^{j\Omega k}\right] \tag{A.2}$$

Eq. (A.2) can be presented in closed form as

$$\eta(n) = \frac{|A(n)|}{P}\left[j\frac{1-e^{-j(\Omega P/2)}}{1-e^{-j\Omega}} - j\frac{1-e^{j(\Omega P/2)}}{1-e^{j\Omega}}\right] \tag{A.3}$$

Since $e^{j\Omega P}/2 = -1$, after some manipulation (A.3) results in

$$\eta(n) = \frac{2|A(n)|}{P}\frac{\sin(\Omega)}{1-\cos(\Omega)} \tag{A.4}$$

Using (A.1) in (A.4) then $k(n)$ is defined as

$$k(n) = \frac{1}{|A(n)|} = \frac{2\dfrac{\sin(\Omega)}{(1-\cos(\Omega))}}{\sum_{k=0}^{P-1}|x(n-k)|} \tag{A.5}$$

Taking for granted $P > 30$ then $\sin(\Omega)/(1-\cos(\Omega)) \cong P/\pi$, resulting in Eq. (7). Since $k(n)$ is an approximation to the instantaneous sinusoid peak value, then $x(n)/k(n)$ has approximately a unitary peak amplitude. This strategy avoids squaring the data $x(n-k)$.

[3] Matlab routines, real data and application examples are freely available at http://eel.ufsc.br/~costa/Research/HarmonicCanceller.html.

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