1-1-2011

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10.1109/HONET.2011.6149770

Adaptive Noise Canceller for Magnetocardiography

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***Abstract*—This paper discusses the use of adaptive noise cancellation in magnetocardiography system within unshielded environment using three algorithms: Least-Mean Squared (LMS) algorithm; normalized LMS (nLMS) algorithm and Genetic Algorithms (GA). Simulation results show that for low signal-to-noise ratio (SNR) values, the GA algorithm outperforms the other algorithms, displaying an improvement in SNR of 51.155 dB and completely suppressing the noise sources at 60Hz and at low frequencies. However, the convergence time of the GA algorithm is longer due to the high computational complexity.**

***Index Terms*— Telehealth; Magnetocardiography; Adaptive noise cancellation; Least-Mean Squared algorithms; Genetic algorithms.**

I. INTRODUCTION

Telehealth is a health care program where the patient and the medical practitioner are in different geographic locations. Recently, Telehealth has become a part of research and development in social healthcare systems. The undeniable important application of Telehealth is where a continuous monitoring of specific parameters (health indicators) is needed, such as for chronic disease that can be only controlled but not cured. Telehealth technology is a combination of: (i) a telecommunication system that provides communication between distant locations, (ii) a user control interface which includes audio/video devices and (iii) specific peripheral medical devices for sensing the health parameters. Among various health parameters required to be obtained from medical services, such as blood pressure, the heart beat rate is known as an important indicator to many heart diseases. A typical example is the fetal heart rate monitoring, which provides useful information on the wellbeing of a pregnancy and allowing early diagnosis of fetal distress and a prompt intervention in case of adverse events.

The human heart is characterized by a conductive tissue that produces both an electric field and a magnetic field according to its electrical activity. The electrical field can be detected by placing electrodes on the surface of the human body while the electromagnetic field surrounding the body can be sensed by a magnetometer. Because this magnetic field is very low, about 100pT for adults and few picotesla for a fetus, it requires a high sensitivity magnetometer to be captured. Furthermore, the environment magnetic noise is much higher than the heart magnetic field, resulting in a low signal to noise ratio that requires improvement in by electromagnetic shielding or by applying noise cancellation techniques. Most of the conventional magnetocardiographic systems perform the measurements inside a magnetically shielded room to reduce the effect of the environment magnetic noise. Thus the systems cannot be portable and are not suitable for integrating in telehealth programs. Cardio-magnetic systems do not support portability because they use Superconducting Quantum Interference Device (SQUID) magnetometers that have a typical sensitivity in the order of $fT/\sqrt{Hz}$ [1] but must work at very low temperatures, about 4K, so they need a cryostat containing liquid helium for cooling. The solution to this problem is the use of optical magnetometry. This method has been demonstrated to have sensitivity comparable to SQUID [2] and offers the best potential for miniaturization [3].

The main problem of a magnetocardiography system is the high electromagnetic noise generated by the power supply and electronic devices, which entails the magnetometers to operate inside a magnetic shielded room. This problem could be solved by measuring the magnetic field gradient, instead of the absolute magnetic field, through an array configuration of magnetometers or by using techniques for noise reduction or noise cancellation. The performance of a multichannel system based on SQUID magnetometry into an unshielded environment has been demonstrated to be comparable with measurements performed inside a shielded room [4]. This implies that the application of an efficient noise canceller system based on adaptive signal processing can be used to improve the measurement of magnetocardiographic signals in an unshielded environment.

This paper will discuss the use of adaptive noise cancellation in magnetocardiography system within unshielded environment through the comparison of three techniques:

- Least-Mean Squared (LMS) algorithm;
- normalized LMS (nLMS) algorithm and
- Genetic Algorithms (GA).

LMS and GA have been largely used for noise removal in electrocardiographic signals [5-6]. The aim of this paper is to demonstrate that these techniques can be applied also in magnetocardiography where the noise is at least 100 times higher than the noise in electrocardiography (ECG).

II. ADAPTIVE NOISE CANCELLER

A noise canceller based on adaptive filtering requires very little or no prior knowledge of the signal of interest. Noise cancellation technique uses a reference input derived from one or more sensors placed where the noise is higher than the signal to cancel noise from the primary input. Fig. 1 shows a block diagram of an adaptive noise canceller. The primary input to the canceller, denoted *d(k),* is formed by the signal of interest *s(k)* and the noise *n(k)* uncorrelated with it. The reference input of the system is the signal *x(k)=n1(k)* that is uncorrelated with *s(k)* but correlated in some unknown way with noise *n(k)*. The noise *n1(k)* is adaptively filtered to produce a replica of the noise *n(k)* that can be subtracted from the primary input to produce the system output *e(k)*. The objective of the noise canceller is to minimize the mean-squared error between the system output and the desired signal [7].

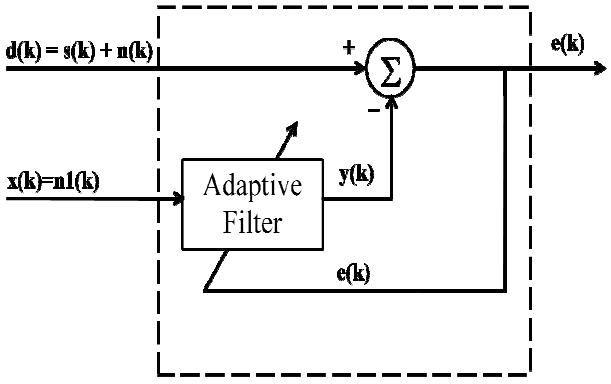

Fig. 1: Adaptive Noise Canceller block diagram.

The output signal is defined as:

$$e(k) = d(k) - y(k) = s(k) + n(k) - y(k) \quad (1)$$

Squaring and taking expectations of both sides of (1):

$$E\{e^2(k)\} = E\{s^2(k)\} + E\left\{\left(n(k) - y(k)\right)^2\right\} + 2E\left\{s(k)\left(n(k) - y(k)\right)\right\} \quad (2)$$

s(k) is assumed uncorrelated with *n(k)* and *y(k)*, therefore, the last term in (2) is zero, yielding:

$$E\{e^2(k)\} = E\{s^2(k)\} + E\left\{\left(n(k) - y(k)\right)^2\right\} \quad (3)$$

From (3) we can see that the mean-squared error is minimized when *n(k)=y(k)* and consequently the output of the system *e(k)* is equal to the desired signal *s(k)*.

a) LMS based algorithms

The LMS algorithm is based on the steepest descend algorithm that aims to minimize the mean-squared error. The steepest descend algorithm updates the filter parameters based on the gradient of the mean-squared error ε, calculated from the transfer function of the filter, governed by:

$$f_i^{(k+1)} = f_i^{(k)} - \mu\nabla(\varepsilon) = f_i^{(k)} - \mu\frac{\delta E\{e^2(k)\}}{\delta f(k)} \quad (4)$$

where μ is the adaption rate.

The steepest descend algorithm assumes the complete knowledge of the gradient, but generally this is not always possible. The LMS algorithm replaces it with an estimation given by the punctual derivative of the squared error:

$$\widehat{\nabla}(\varepsilon) = \frac{\delta e^2(k)}{\delta f(k)} \quad (5)$$

Assuming that the adaptive filter is an FIR filter of order *M* (Fig. 2), then (1) becomes:

$$e(k) = d(k) - \sum_{i=0}^{M-1} b_i x[k-i] \quad (6)$$

The updating procedure is applied on coefficients b_i following the above rule [8]:

$$b_i^{(k+1)} = b_i^{(k)} + 2\mu e(k)x(k-i) \quad (7)$$

where

$$k = 0,1,\dots,M-1$$

and μ is the step size.

The step size μ usually is included in the range *(0,1]*; the condition to assure convergence and stability is given by [8]:

$$0 < \mu < \frac{2}{ME\{x^2(k)\}} \quad (8)$$

With the filter length *M*, the LMS algorithm has computational complexity of *O(M)*.

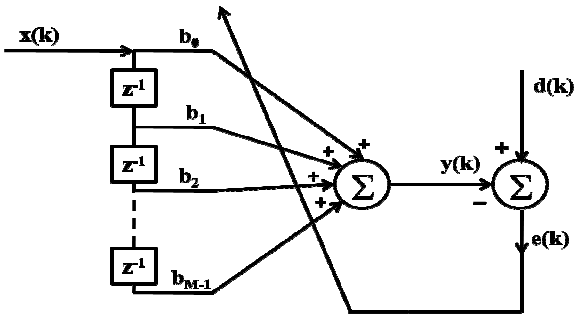

Fig. 2: LMS FIR filter coefficients updating

The LMS algorithm can have high convergence time especially if the noise to be removed is much larger than the signal. To increase the convergence speed, a variable adaption rate can be used. This is a variant of the LMS algorithm called normalized LMS. Equation (7) now can be written [8]:

$$b_i^{(k+1)} = b_i^{(k)} + 2\mu_k e(k)x(k-i) \quad (9)$$

where

$$\mu_k = \frac{\mu_n}{\|x(k)\|^2}, \qquad 0 < \mu_n < 2 \quad (10)$$

The normalization of the LMS step size by $\|x(k)\|^2$ will reduce the convergence time.

b) Genetic Algorithms

The GA is a technique for solving optimization problems based on heuristic search that emulates the natural evolution process. The optimal solution is found through the minimization of a defined function, called the fitness functions. For our problem of noise cancellation, the objective of the optimization process is minimizing Mean-Squared Error (MSE), which is known as a GA's fitness function. Fig. 3 shows a flow diagram of the Genetic Algorithm.

The initialization process produces the initial population. This stage is significant because it strongly affects the convergence time and the success in finding the optimal solution. For each individual belonging to the population, the fitness function is evaluated to find its fitness value. If for a pre-established number of generations, the change of the lowest fitness value is lower than a defined threshold, it is considered as the optimum value and the iteration will be terminated. A few predefined end conditions are evaluated to avoid an infinite loop in case the optimum value cannot be found. If none predefined end conditions is verified, the algorithm proceeds with the reproduction. The individuals that better performed are chosen as parents to produce children either by mutation as making random changes to a single parent, or crossover by combining the vector entries of pair of parents. The current population is then replaced with the new generation and the iteration continues.

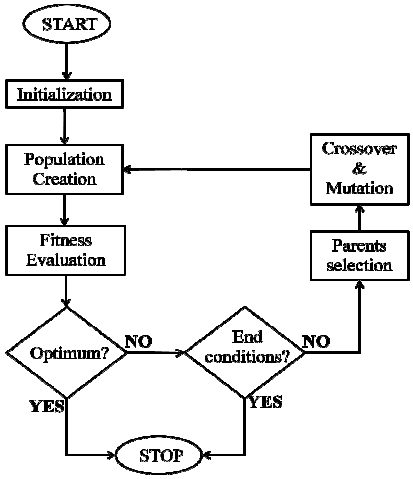

Fig. 3: Genetic Algorithm diagram flow

GA allows a parallel search that has less probability to fall in local minima than LMS family algorithm, but usually increases the computational complexity and the convergence time.

III. RESULTS AND DISCUSSION

a) Data set

The cardiac signal used was taken from the MIT-BIH Arrhythmia Database [9]. The recording is the 234.dat; it is digitized at 360 samples per second per channel with 11 bit resolution. This record contains ECG signals captured by electrodes placed on the surface of the patient chest. According to classic physics, the magnetic field and the electric field generated by human heart have similar waveforms but one is phase-shifted by 90 degrees with respect to the other [10]; then the recorded ECG signals were considered as MCG signals. For the selected ECG signal, the intensity was easily scaled to a corresponding cardiomagnetic signal intensity. Fig. 4 shows the cardiac signal and its spectrum, which is mainly spread over low frequencies.

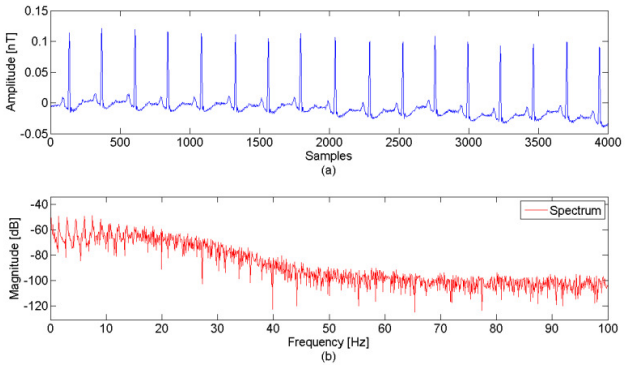

Fig. 4: (a) Original cardiac signal 234.dat and (b) cardiac signal spectrum.

The noise signal was simulated as the sum of two components, namely, a sinusoid of 60Hz frequency, which accounts for the power line interference, and a random noise with a standard uniform distribution, which account for white noise attributed to the noise generated by electronic devices and other wireless-related noise sources. This noise was linearly filtered to produce a correlated noise which was used as the reference signal input to the noise canceller.

The three techniques, namely, LMS and nLMS and GA, were investigated and compared to one another on the basis of:

- Signal to Noise Ratio (SNR) improvement;
- 60Hz noise cancellation;
- Convergence speed;
- Ability to detect peaks.

For SNR improvement three SNR values were considered: (i) -9.2913dB, which is the typical value used in ECG noise cancellation, (ii) -29.291 and (iii) -49.291, which are SNR values compatible with MCG applications.

b) Simulation Results

In our simulations we used 4000 samples to represent the cardiac signal and the noise. The order of the FIR filter used was 7; the step size was 0.001 for LMS and 1 for nLMS.

The performances of the algorithms were firstly compared on the basis of SNR. The difference between the SNR calculated before the noise canceller and the SNR calculated after noise cancellation was considered as the improvement factor that results from the noise canceller. This improvement factor varied depending on the techniques used for filter coefficients adaption.

Table 1: Improvements in SNR for each algorithm

SNR before NC	-9.2913 dB		-29.291 dB		-49.291 dB	
	SNR[dB] after NC	Impr [dB]	SNR[dB] after NC	Impr [dB]	SNR[dB] after NC	Impr [dB]
LMS	26.808	36.099	6.7933	36.084	-13.209	36.081
nLMS	26.336	35.627	6.7342	36.025	-13.267	36.023
GA	10.905	20.196	10.586	39.877	1.8645	51.155

Table 1 shows the SNR after filtering for each algorithm calculated for three different input SNR values. For a starting input SNR of -9.29 dB, LMS and nLMS achieved improvement factors of 36.099dB and 35.627 respectively, whereas the GA resulted in an improvement factor of 20.196dB. As the noise increased the improvement factors of the LMS and nLMS algorithms dropped, while the GA algorithm attained better improvement factor. For a starting SNR value of -49.291 dB, the LMS and nLMS algorithms provided negative SNR values after filtering however, the improvement factor was around 36dB for both algorithms, whereas the GA exhibited an improvement factor of 51.155dB with the SNR of 1.8645dB after filtering.

Fig. 5-(a) shows the spectrum of the cardiac signal corrupted with noise with a SNR of -49.291 dB; the added noise component at 60Hz is clearly visible. Fig. 5-(b), (c) and (d) show the spectra of signals after noise cancellation using the LMS, nLMS and GA techniques respectively. Comparing these signal spectra with the signal spectrum in Fig. 4-(b) we see that the component at 60Hz was not completely suppressed by either the LMS algorithm or nLMS algorithm but it was suppressed by the GA algorithm, which provided the best performance for removing the noise sources at 60Hz and at low frequencies.

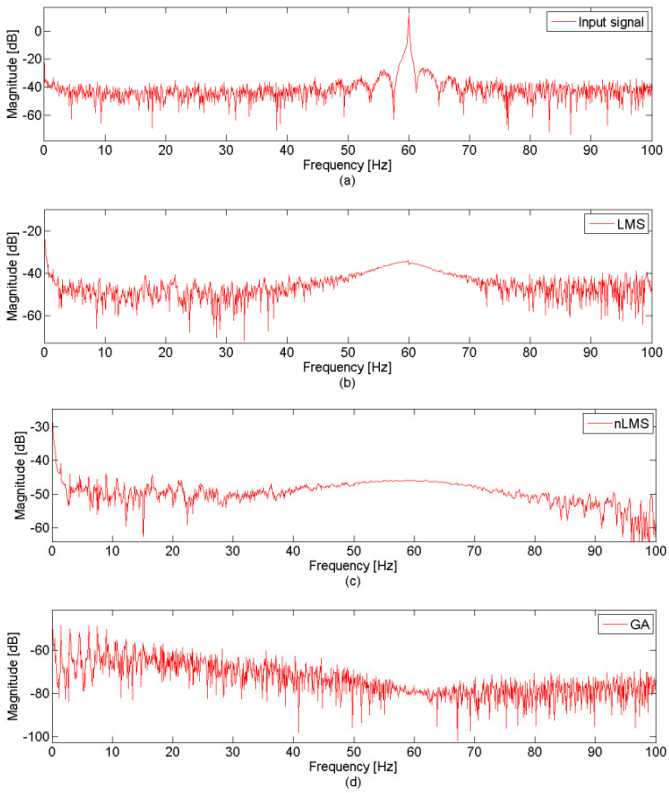

Fig. 5: Spectrum of corrupted signal before filtering (a), spectra of signals after filtering based on LMS (b), nLMS (c) and GA (d).

Fig. 6 shows the learning curves that represent the rate of change in the MSE versus the number of iterations used.

The MSE for the nLMS algorithm started from a lower level in comparison to the MSE for the LMS algorithm, and converged quickly to a mimimum value. For the LMS algorithm a large number of iterations was needed before convergence to a minimum value. Generally, this convergence time increases when the SNR deteriorates.

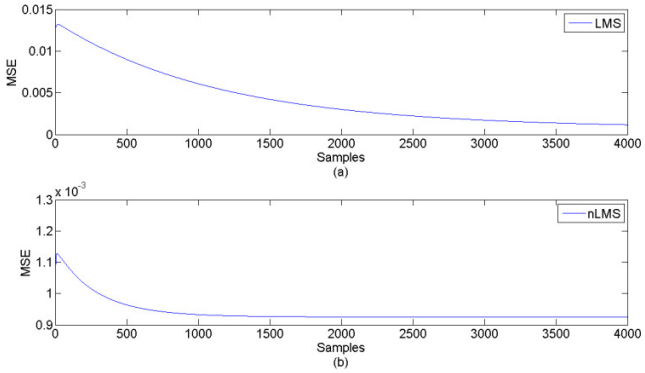

Fig. 6: Predicted learning curve of LMS (a) and nLMS (b) algorithms.

Fig. 7 shows the learning curve for the GA algorithm, i.e. the change in MSE versus the number of generations. Each iteraction corresponds to the creation of a new generation and does not depends on the number of samples. The blue dots represent the average MSE of the population while the black dots represent the minimum MSE for each population. It is clear that for the GA algorithm, the convergence speed is low because a high number of generations are needed to attain the mimimum MSE.

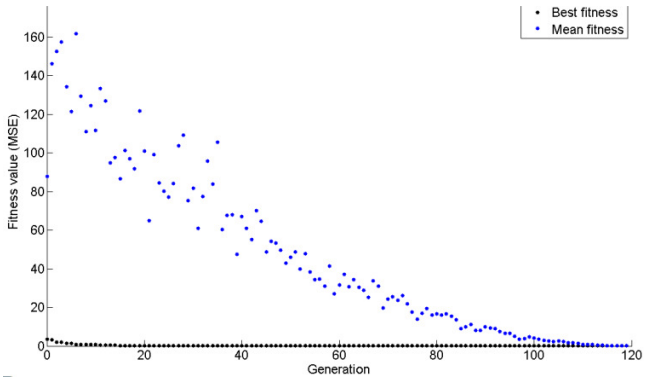

Fig. 7: Learning curve for GA

Fig. 8 shows the signals recovered using the noise canceller for all adaptive techniques. It is obviuos that the LMS algorithm is not suitable for peak detection, whereas both the nLMS and GA algorithms can recover the signal peaks, and hence they can perform peak detection which allows accurate calculation of the heart rate.

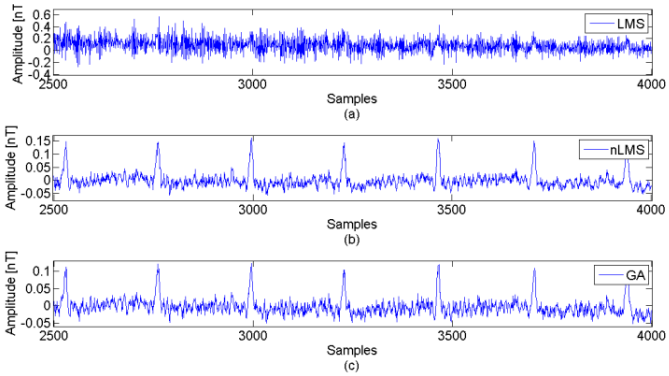

Fig. 8: De-noised signals by LMS (a), nLMS (b) and GA (c).

IV. CONCLUSION

In this paper, techniques of adaptive noise canceller based on the Least-Mean Squared, normalized Least-Mean Squared and genetic algorithms have been investigated to demonstrate their applicability to magnetocardiography. Simulation results have shown that for low SNR values, the GA technique outperforms the other techniques in noise cancellation; however, its convergence time is longer. Techniques that are based on optimal search have the potential for noise cancellation in applications where the signal to noise ratio is much lower than unity.

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