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A normalized data-reusing least-mean-square algorithm of noise cancellation for magnetocardiography*

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An adaptive filter based on Data-Reusing Least-Mean-Square algorithm has been proposed and applied in magnetocardiography (MCG) to suppress ambient noise. Numerical simulation studies indicate that the adaptive filter is a powerful noise suppresser for correlated interferences, especially for those with amplitude changing and time delay. Also the filter has a wide frequency bandwidth. With this filter, the signal-to-noise ratio of an MCG is improved to the intrinsic noise level. The periodic average method for further improvement of the noise level in MCG is also discussed.

Keywords: magnetocardiography, noise suppression
PACC: 0755, 0650D

1. Introduction

The retrieving of signals buried in an environmental noise is one of the fundamental purposes of signal processing in telecommunication and detection systems. In recent years, due to the success of digital techniques, more and more attention has been paid to the use of digital data processing in those systems. For many applications information data are now most conveniently recorded, stored and transmitted in digital form. As a result, digital signal processing is becoming an important modern tool. In general, the category for signal processing includes estimation and characterization of signal parameters, elimination or reduction of unwanted interference, and transformation of a signal from one form into another more informative form in a certain sense.[1,2]

A category of digital processing known as adaptive filtering is a relatively new algorithm area in which researches and applications are being rapidly extended. The essential and distinguishing features of an adaptive filter system are its time-varying, self-adjusting property, etc.[3]

A filter, in general, can be used in different situations. However, if certain conditions of the environment for our measurement are known, they would be worthy to be used in design of a filter. The main idea of adaptive filtering is to retrieve the original information to some extent by reducing the environmental noise under the noise conditions.

Up to now, many algorithms have been developed for adaptive filters used in different situations, such as Least-Mean-Square (LMS) and Recursive Least Square (RLS) algorithms. They have advantages but also disadvantages. The LMS algorithm is the simplest and not sensitive to the rounding error. Furthermore, in a wide range of step-sizes of μ, it is steadily convergent even when the precision has stepped down to 8-bits. But the convergence speed in LMS algorithm is not so high as in RLS one. In addition, RLS algorithm has fast tracking ability. Nevertheless, it is sensitive to the rounding error, and needs to be equipped with very high (higher than 24 bits) precision.[4–6]

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In this paper, we report an application of an adaptive filter to the cancellation of environmental interference in the signals of magnetocardiography (MCG). With a normalized data-reusing LMS algorithm the environmental interference noise can be suppressed down to a level comparable with the intrinsic noise of equipped SQUIDs.

2. Normalized data-reusing LMS algorithm

2.1. Adaptive filter with LMS algorithm

The block diagram of our adaptive noise canceller is shown in Fig.1.[3] It has two input channels, signal input $d(k)$ and reference input $X(k)$. Here $d(k)$ includes an information-bearing part and a residual part regarded as a noise. $X(k)$ is mainly the noise correlated or uncorrelated with the residual part of $d(k)$. The number k is time sequence.

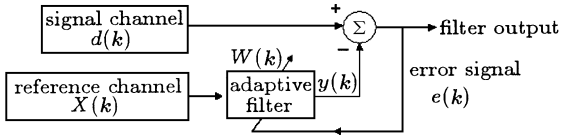


Fig.1. Block diagram of the adaptive noise canceller.

In the normalized LMS (NLMS) algorithm, the processing formulas of an adaptive filter can be expressed as

$$y(k) = W^{\mathrm{T}}(k)X(k), \tag{1}$$

$$e(k) = d(k) - y(k), \tag{2}$$

$$W(k+1) = W(k) + \mu(k)X(k)e(k), \tag{3}$$

$$\mu(k) = \frac{\alpha}{X^{\mathrm{T}}(k)X(k) + \gamma}, \tag{4}$$

where $X(k) = [x_{k-1}, x_{k-2}, \ldots, x_{k-M+1}]^{\mathrm{T}}$ is the reference vector, in which the superscript T stands for the transposition of the vector and M is the filter length which depends on the sampling frequency and the bandwidth of the signal to be dealt with. $W(k) = [w_k, w_{k-1}, \ldots, w_{k-M+1}]^{\mathrm{T}}$ is the filter weight vector, in which $w_{k-i} (i = 0, 1, \ldots, M-1)$ are the elements of the vector. μ(k) is a step-size of the adaptive filter at time k. In Eq.(4) α is a normalized adaptive constant and γ is a very small positive number, by which the divergence of Eq.(4) can be avoided when $X^{\mathrm{T}}(k)X(k) = 0$. Equation (3) shows that the updated value of filter weight $W(k+1)$ is determined by $W(k)$, $\mu(k)$, $e(k)$ and $X(k)$. The filter will not work well or even diverge if α and γ are not properly chosen.

Before operation of the algorithm, special attention has to be paid to two closely related issues: the choice of α and γ values for a suitable step-size parameter μ, and the selection of filter length M. It is important to have an appropriate μ, which controls the convergence speed of the LMS algorithm in finding the optimal solution. Generally, the larger the μ, the faster the convergence. However, too large a value of μ makes a steady noise worse or even may result in an unstable LMS algorithm. To ensure the stability, μ should be in a range $0 < \mu < 1/(10MP_x)$, where P_x is the input power of the reference, which can be approximately estimated by $P_x = r_{xx}(0)/(M+1)$, where $r_{xx}(0) =< x_k^2 >$ is an autocorrelation function of the reference sequence for zero lag. At the same time, the filter length M (i.e. the number of independently adjusted parameters in the filter) should be selected so that the filter models the regular features of a set of input data best. The minimum description length (MDL) criterion[3] has been brought forward for this issue. There is a value of M which can minimize MDL, representing the optimal length of the filter. In principle, if the above-mentioned parameters are properly selected, the value of the misadjustment will be very small, i.e. the deviation is small from the minimum mean error produced by the adaptive filter.

In MCG measurement, the magnetic signals from human hearts are extremely weak compared with ambient magnetic field variations. Thus rejection of ambient disturbances is of utmost importance. In this situation, the main issue is to make the misadjustment (steady error) as small as possible at all costs.[7] In the LMS algorithm, most likely the smallest possible steady misadjustment corresponds to a very small step-size. As a result, it makes the convergence speed of algorithms severely slow. Besides, the data acquisition time in MCG measurement must be limited to a relatively short period that patients may accept. If the sampling frequency is not high enough, the length of signal and reference sequences could be too small to meet the requirements for the adapting process. In order to solve this problem, we present a modified LMS algorithm—data-reusing method, which is feasible under the condition of the short-term steady characteristic of the environmental noise. Assuming that we have acquired an original data sequence u_k (k=1, 2, 3, ..., N) with a length N, we can always build a new sequence u_k (k=1, 2, 3, ..., $2N$) with a double length $2N$ simply by repeating the original sequence just once, namely u_{N+k}=u_k. Similarly, the size of the

original sequence will be increased by $(m+1)$ times if the value of u_{mN+k} is defined by u_k. In this way we can obtain a sequence with an arbitrary length from a finite one, which is subject to almost no variation of the iterated noise environment. With this scheme, a steady adaptive output can be obtained by taking a sufficiently large value of m in our experiments. In the next section, numerical simulations are used to explore some of the features of such an adaptive filter before applying it to the real MCG data.

2.2. Numerical simulation

Numerical simulation studies are carried out in order to demonstrate the feasibility of such an adaptive filter scheme, and to explore some of the characteristics of the filter.

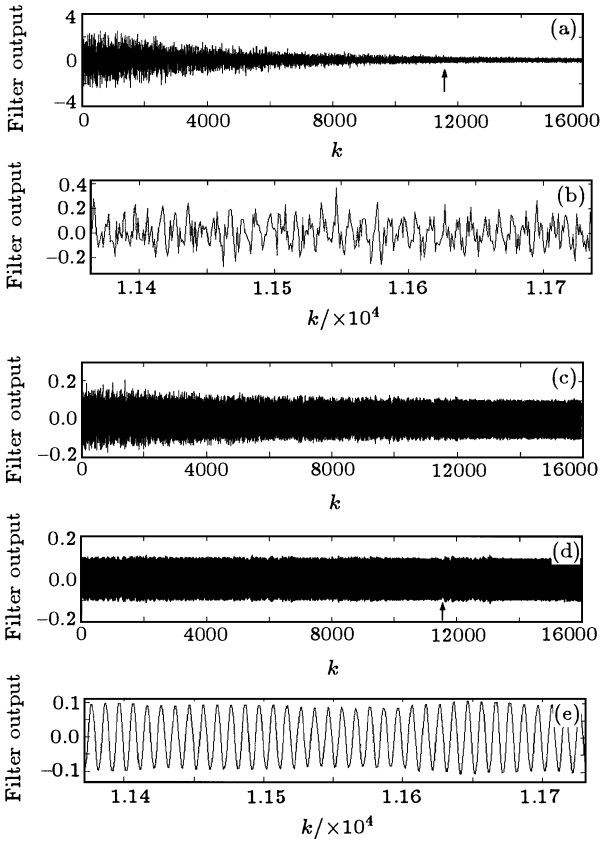


Fig.2. The output of the filter with the data reused different times: (a) without data reused, (b) magnified output signal in a section around the arrow in (a), (c) filter output with the data reused twice, (d) filter output with the data reused three times, (e) magnified filter output in a section around the arrow in (d). (The filter length is 64).

In our numerical simulation, we choose α=0.006 and γ=10^{-10}. In this case, the procedure will converge well. In the first simulation, the reference input $X(k)$ is a random white noise with a suitable normalized amplitude generated by computer, the signal input $d(k)$ is formed by a combination of $X(k)$ and a sinusoidal function with a frequency of 100Hz and an amplitude of 0.1. The filter length M is chosen to be 64. Figure 2 illustrates the result of data-reusing simulation. The result shows that the noise amplitude reduces rapidly at the beginning of the filtering, when data-reusing is performed more than three times, the amplitude of output noise level becomes almost constant. It can be clearly seen that the signal-to-noise ratio with data-reusing is much better than without data-reusing.

Next we investigate filtering with multiple weights. The noise in a reference channel is randomly generated by computer, the signal channel is linear combination of a sinusoidal function and three sequences of reference input with different amplitudes and time delays, which can be expressed as $d(k) = 0.1\sin(\pi k/5)+1.5X(k+17)+X(k+32)+0.5X(k+47)$. Figure 3 shows the result of multiple weight filtering. It can be seen that almost all the noises are well cancelled.

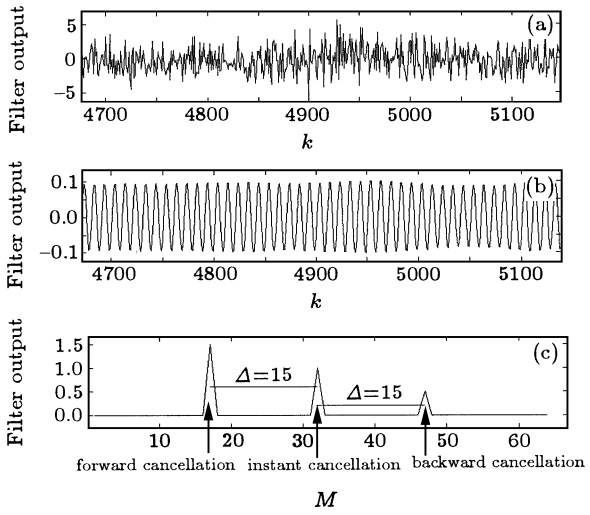


Fig.3. Multiple weights filtering: (a) signal input, (b) filter output (scaled up twelve times), (c) filter weights with different amplitudes and time delay.

Then we test the frequency bandwidth and noise suppression property. In magnetocardiography measurements, we are often interested in a frequency window from 0.1Hz to 300Hz. The response of the filtering is constantly accurate to a sinusoidal signal at a frequency within the range of this frequency window as shown in Fig.4. From the figure we note that the noise suppression at a lower frequency does not seem to be so good as at a higher frequency, which is possibly due to overcorrection in adjusting the weight parameters. More detailed investigation on noise suppression

at a low frequency is carried out for different signal-to-noise ratios. Figure 5 is the result of noise suppression property at 0.1Hz. Horizontal axis x stands for the input signal-to-noise ratio, the vertical axis y stands for the ratio of input noise to output noise (noise suppression factor). A straight line in the figure fits with the experimental data well, showing that a constant signal-to-noise ration can be obtained in the filtering output. It can be seen that the filter has a very good noise suppression property.

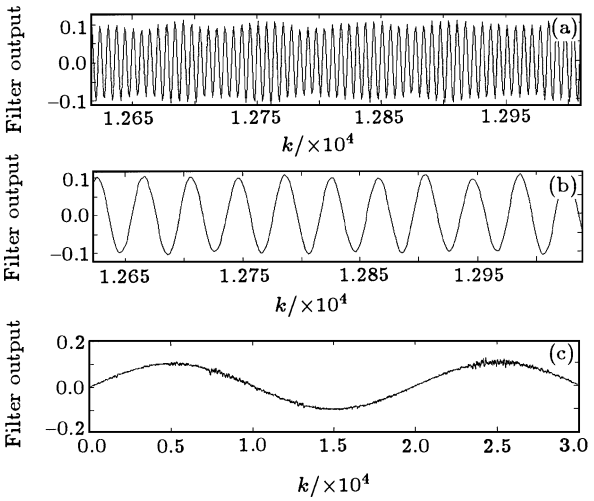


Fig.4. Frequency bandwidth testing: filter response to a signal at (a) 300Hz, (b) 80Hz and (c) 0.1Hz respectively.

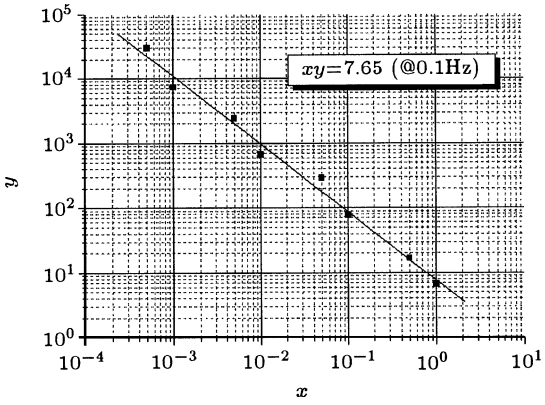


Fig.5. Noise suppression property of the filter tested at 0.1Hz.

One issue should be mentioned here is that in our numerical simulation, the noise part of two channels is completely correlated, but in fact this is impossible in realistic experiments due to the intrinsic noises in both electric circuits and sensors. We will have a further discussion on that issue in the following section.

3. Magnetocardiography experiments and results

Magnetocardiography (MCG) experiments are made in a magnetically shielded room that can attenuate the earth's steady field by a factor of 10^{-4}, i.e. to nT level and the environmental magnetic field interference down to about 30pT at the main power frequency (50Hz). We use a vertical axial gradiometer comprising two DC-SQUID sensors, a pickup SQUID and compensation one, which are immersed in liquid nitrogen (77K). In MCG measurement, rejection of outside disturbances is of great importance, and it can be done using either adaptive filter or gradiometer schemes. In order to achieve a higher signal-to-noise ratio, the pickup SQUID, which is fixed at the bottom inside a liquid nitrogen dewar, should be as close as possible to the subject's chest during data acquisition for the both schemes. The sensitivity of the measuring system to an external magnetic noise can be highly reduced by properly adjusting the distance between the two sensors. In a gradiometer operation regime, the distance should be not too large in order to reject the external disturbances, but on the other hand it should be not too small to obtain a higher signal resulting from simple subtraction of the data from the two channels. It has been reported that with a distance of 3–8cm, comparable with the size of signal source (human heart), a better signal-to-noise ratio can be obtained.[8] Another option of rejecting the disturbance is to use an adaptive filter as described before, which has at least two advantages over gradiometer. First, an adaptive filter has a 'study process' and its parameters are accessible each step to reach an optimal output, while the gradiometer only has one fixed coefficient, which may be determined by testing many times. Second, for the correlated environmental noise part in the input channels, it can be well cancelled by both adaptive filter and gradiometer. However, for the uncorrelated part it is another story. In dealing with uncorrelated noises, even with a proper coefficient, the resulting noise of a gradiometer will be larger than any of the two noises in primary input channels. However when an adaptive filter is used, the system output will have a noise level only as large as that in signal channel.

The block diagram of the data acquisition in our adaptive filter system is shown in Fig.6, with which we collect the signal (MCG) from the first SQUID sensor close to the subject's chest, reference (noise) from the second one at a vertical distance of 10cm above the first and an additional electrocardiogram (ECG) signal synchronous with heart beating from an ECG electronics at the same time, as indicated with S1, S2,

and S3 respectively. The data of three channels are acquired by a 16-bit data-acquiring (DAQ) card, including a programmable multi-gate array (PGA), three parallel sampling/holding (S/H) circuits, an analogue switch, an analogue-to-digital (A/D) converter, a static random-access memory (SRAM), transmitted by a data BUS and finally saved in a personal computer (PC).

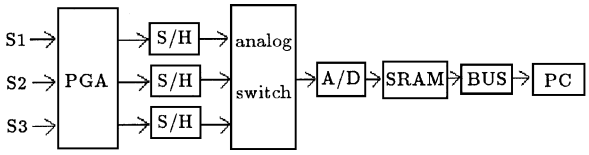


Fig.6. A block diagram of the data acquisition.

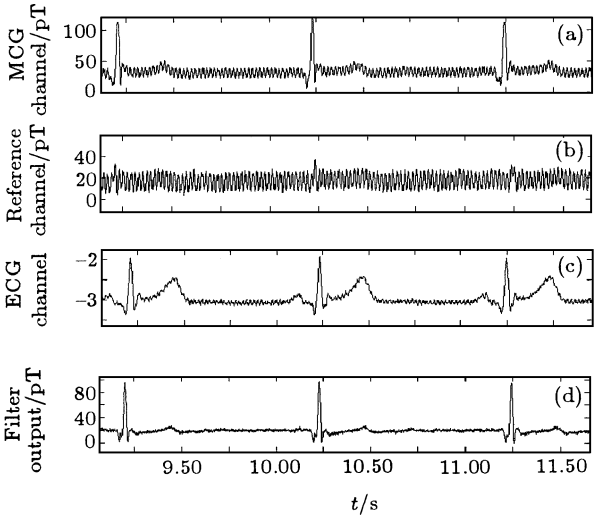


Fig.7. MCG experimental results: (a) magnetic field signal input (MCG), (b) magnetic field reference input, (c) ECG input data, (d) magnetic field signal (MCG) at the filter output.

In our MCG measurements, the sampling frequency is 2kHz, and the interesting bandwidth is below 500Hz, therefore the filter length M of the adaptive system should be larger than or equal to 4. Here we choose M=7. We take data-reusing five times in this processing. Figure 7 illustrates the original data sequence and output signal after adaptive filtering with the data reused five times. The MCG signal is quasi-periodic. It can be seen that the disturbance of the two channels is mainly from the main power at the frequency of 50Hz and with almost equal amplitude. From Fig.7 (d) we can see that the MCG signal is well retrieved by adaptive filtering and the signal-to-noise ratio is improved by 2–3 times. There is still some weak MCG signal in the reference channel as we notice in Fig.7 (b). It causes the amplitude of the output MCG signal to be weakened a little. Also there is some disturbance in the filter output due to the intrinsic noise of detection, which comes from the SQUID sensor and its electronics. We will discuss that in the next section.

4. Discussion and conclusion

It has been mentioned that the noise parts in two channels of the adaptive filter are entirely correlated in numerical simulation, but they are partly correlated in MCG experiments due to the irrelevance of intrinsic noises of two SQUID sensors. A group of data shown in Figs.8(a) and 8(b) is obtained in a fairly well shielded environment, a shielded room that is enclosed by eight layers of metallic plate with high susceptibility and one layer of aluminum plate. The data in both input channels recorded by the two SQUIDs may be regarded as intrinsic noises that are completely uncorrelated. Figures 8(c) and 8(d) give the noise data resulting respectively from the adaptive filtering and the difference between the signals from the two channels (i.e. direct subtraction of the signal of one channel from that of another channel). It can be seen that the amplitudes of input noises are 5pT and 7.5pT respectively for signal and reference channels, while the amplitudes of the output noises are about 8pT and still nearly 5pT for direct subtraction and adaptive filtering respectively, which is consistent with the above analysis.

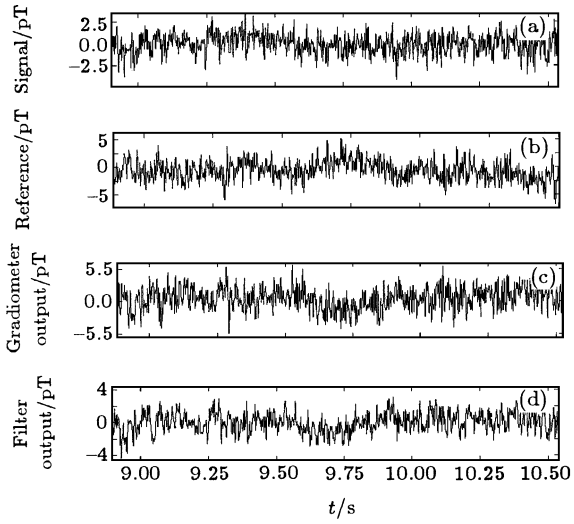


Fig.8. Comparison between responses to intrinsic noises in two SQUID sensors located between the adaptive filter and the gradiometer: (a) signal input (intrinsic noise in sensor 1), (b) reference input (intrinsic noise in sensor 2), (c) the gradiometer output (difference of signals from the two channels), (d) the output of adaptive filtering.

For a still better signal-to-noise ratio, periodic average is usually performed. For a certain application,

such as in the registration of normal magnetocardiography data, averaged curves recorded in one period section of cardiac activity for particular persons are required. Practically, the data taken from anybody's heart beating is not exactly periodical, thus, an averaged single-period graph cannot be obtained simply by roughly cutting the data sequence into single-period sectors and then averaging them. Any rough cutting will more or less cause the signal to be smeared-out. An exact single-periodic average can be obtained by means of a synchronous ECG signal taken simultaneously with the MCG signal for exactly periodic timing and proper data sequence cutting. By averaging the data in n periods the noise amplitude can be reduced by a factor of $\sqrt{n}$. Moreover, the average is effective on any kind of noise.

References

[1] Oppenheim Alan S and Willsky Alan S 1997 *Signal and System* Second Edition (Xi'an: Xi'an Jiaotong University Publishing House and Prentice Hall) p30 (in Chinese)

[2] Zhang X D 1995 *Modern Signal Processing* (Beijing: Tinghua University Publishing Company) p45 (in Chinese)

[3] Simon Haykin 2002 *Adaptive Filter Theory* Fourth Edition (Beijing: Publishing House of Electronic Industry) p67

[4] Dirk T M Slock 1993 *IEEE Transactions on Signal Processing* **41** 2811

[5] Wei Paul C, Han Jun, James R Zeidler and Walter H Ku 2002 *IEEE Trans. Signal Process.* **50** 1602

[6] So C F, Ng S C and Leung S H 2003 *Signal Process.* **83** 1163

[7] Cohen D 1967 *Science* **156** 652

[8] Vrba J 1997 *Proc. 19th Annual Int. Conf. IEEE-EMBS* Chicago, IL. USA, p1240