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MEG Adaptive Noise Suppression using Fast LMS

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***Abstract*-Magnetoencephalography (MEG) measures magnetic fields generated by electric currents in the brain, non-invasively and with millisecond temporal resolution. Typical signals are 10^{-13} T, so noise contamination due to external magnetic fields is a serious concern. Digital signal processing is typically required in addition to magnetic shielding. Using three reference channels, displaced from the head, to measure the noise, we apply adaptive filtering to subtract out estimates of the noise, via the Block Least-Mean-Square ("Fast LMS") method. The algorithm is tested by its effects on the number and distribution of channels which have statistically significant signals (distinguishable from background noise at a specified false-positive rate). We show that Fast LMS both increases the number significant channels and reduces the variance of false positives.**

I. Introduction

Magnetoencephalography (MEG) is a noninvasive tool that measures the magnetic activity of the brain, using extremely sensitive magnetometers based on Superconducting Quantum Interference Devices (SQUIDs). MEG has moderate spatial resolution (~ 1 cm) and extremely high temporal resolution (≤ 1 ms), thus complementing other techniques such as electroencephalography (EEG) and functional Magnetic Resonance Imaging (fMRI). Because the magnetic signals emitted by the brain are on the order of 10^{-13} T, shielding from external magnetic signals, including the Earth's magnetic field (~ 5×10^{-5} T), is necessary. Even with shielding, though, poor signal to noise ratio (SNR) is still a challenge.

To remove such noise, which is typically non stationary, we resort to adaptive filtering. Three reference channels, separated from the head, measure the noise alone, while 157 neuronal channels, arranged above the head surface, record brain activity. The filter coefficients that linearly map the noise in the reference channels to the noise in the observed signal are calculated using Least Mean Square method (LMS) [13], then the estimated noise in the observed neuronal signal is subtracted. A fast version of LMS is adopted for speed [7].

To test its validity and usefulness, we use significance tests devised in [12] that combine Rayleigh's phase coherence test and the F-test [10, 8, 11]. Comparison of the raw data with the filtered data shows substantial improvement in number of significant channels and a drop (and more consistency) in the false positives. Finally, we compare this method to the Continuously Adjusted Least-Squares Method (CALM) [5].

II. Methods

A. Stimuli and Data

Sinusoidally amplitude-modulated sounds of 2 s duration were presented 50 times each in a random order with inter-stimulus intervals uniformly distributed between 700 and 900 ms as described in [4]. A total of 20 stimuli were generated with five modulation frequencies (1.5 Hz, 3.5 Hz, 7.5 Hz 15.5 Hz and 31.5 Hz) and four different carriers (pure tone, 1/3 octave, 1 octave, and 5 octave pink noise all centered at 707 Hz). All stimuli were presented binaurally at approximately 70 dB SPL. 8 right handed subjects (5 female) were used and gave their written informed consent for the MEG study.

The magnetic signals were recorded using a 160-channel, whole-head axial gradiometer system (KIT, Kanazawa, Japan) housed in a magnetically shielded room. Its detection coils are in a uniform array on a helmet-shaped surface of the bottom of the dewar, with ~25 mm between the centers of two adjacent 15.5 mm diameter coils. Sensors are first order axial gradiometers with 50 mm baseline; their field sensitivities are 5 fT/√Hz or better in the white noise region. 3 of the 160 channels are magnetometers (25 cm apart from neuronal data sensors), used as reference channels. The magnetic signals were band-passed between 1 Hz and 200 Hz, notch filtered at 60 Hz, and sampled at the rate of 500 Hz.

Responses to each stimulus from 300 to 2300 ms post-stimulus were concatenated, resulting in 20 responses (2 ms resolution, 100 s duration) for each channel. Each response was discrete Fourier Transformed (DFT), resulting in 20 complex frequency responses (0.01 Hz resolution, 250 Hz bandwidth) for each channel. See Fig. 1 for the magnitude squared of the DFT of the response (periodogram) of a single channel to the 31.5 Hz amplitude modulated sinusoid tone. The SSR peak at 31.5 Hz is stereotypically narrow with a width of 0.01 Hz. Also as seen in Fig.1, the background responses became noisier with decreasing frequency.

B. Adaptive filter model

Background brain activity is always changing even if the area of interest responds to stimuli in a stationary fashion. External noise is also non-stationary since many of its sources are of random characteristics in space and time. We use an adaptive process, which automatically adjusts the filter parameters to minimize estimation error.

We implement a normalized LMS method for the 3 reference channels (Fig. 2), where the adaptation of tap weight is based on error estimation. We compute the filter coefficients that when convolved with the noise signal, capture the noise in

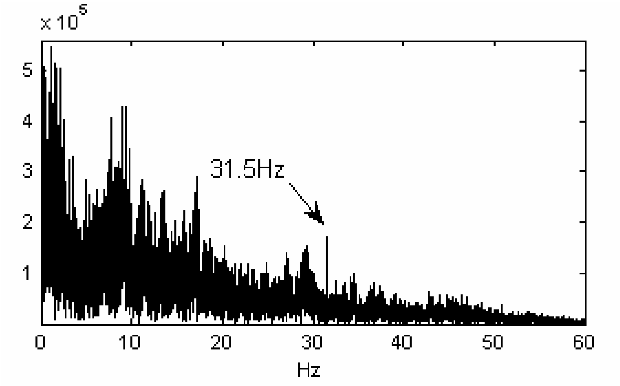

Fig. 1. (top panel) Periodogram of the Fourier transform of magnetic field response from one channel to a sinusoidal amplitude modulated tone with modulation frequency 31.5 Hz and carrier frequency 707 Hz.

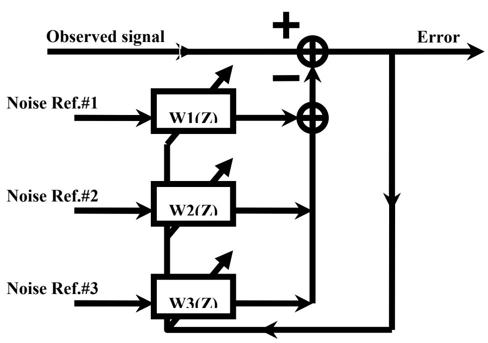

Fig.2. Three reference adaptive filter noise cancellation

the observed signal in a least mean square sense. With a block size of user-defined length (M), the improvement in execution time is the order of the Complexity ratio $= \left(5\log_2 M + 13\right)/M$ [7]. For example, block size M = 1024, fast LMS is 16 times faster than standard LMS algorithm in computational terms.

A summary of the implementation of Block LMS algorithm described in [6, 7], but modified for use with multi-reference channels is outlined in Table 1.

Dimensions:

r=0,…,R ; reference channels, e.g. R = 3.

M; block size (e.g. 1024 samples)

i=0,…,2M-1

Initialization:

$\hat{W}_r(0) = zeros(2M, R)$; *Filter coefficients initialized to zero*

$P_{i,r}(0) = \delta_i$; *average signal power per Reference channel, initialized to small positive constant* δ .

Computation: For each block of M input samples:

Filtering:

$$U_r(k) = diag\left\{FFT[u_r(kM-M),\ldots,u_r(kM-1),u_r(kM),\ldots,u_r(kM+M-1)]^T\right\}$$

$y_r^T(k) =$ *last M elements of* $IFFT[U_r(k)\hat{W}_r(k)]$

Error estimation:

$$e(k) = d(k) - \sum_{r=1}^{R} y_r(k)$$

$$E(k) = FFT\begin{bmatrix} 0 \\ e(k) \end{bmatrix}$$

Signal-power estimation:

$$P_{i,r}(k) = \gamma P_{i,r}(k-1) + (1-\gamma)\left|U_{i,r}(k)\right|^2$$

$$D(k) = diag[P_0^{-1}(k), P_1^{-1}(k), \ldots, P_{2M-1}^{-1}(k)]$$

Tap-weight adaptation:

$\Phi_r(k)$ = first M elements of $IFFT[D(k)U_r^H(k)E(k)]$

$$\hat{W}_r(k+1) = \hat{W}_r(k) + \alpha FFT\begin{bmatrix} \Phi(k) \\ 0 \end{bmatrix}$$

FFT : Fast Fourier Transform, IFFT: Inverse Fourier Transform,

α *: adaptation constant <1/2*

Table 1. Multi-reference Fast LMS

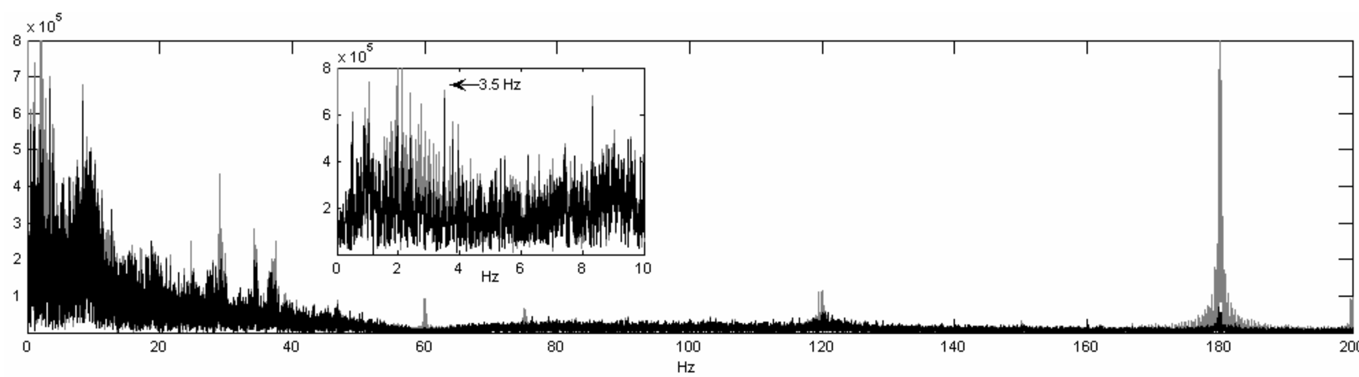

Fig. 3 Periodogram of raw data (gray) and filtered data (black) of 1 channel using Fast LMS, Block Size $M = 128$, adaptation constant $\alpha = 0.01$. Magnified spectrum (0-10Hz) shows the response at the stimulus frequency (3.5Hz) with suppressed noise in the vicinity.

C. *Significance tests*

In order to evaluate the performance of the adaptive noise suppression, we resort to a significance test developed in [12]. The test is a mixture of F-test and Phase coherence test [2], that uses both amplitude and phase information from both tests equally, while measuring the average false positive rate iteratively and explicitly.

III. Results

The comparative spectra for one neural channel, before and after adaptive filtering, in shown in Fig. 3. The SNR dropped substantially after applying the Block LMS (especially at the line noise frequency 180 Hz).

Fig. 4 shows the spectrum of a neural channel versus that of the reference channels. Fast LMS exploits the high correlation between the noise in the reference and neuronal channels. As well as suppressing noise near 180 Hz, it removed much of the noise in the vicinity of the (driven) frequency 3.5Hz. Additionally, Fast LMS excels at removing narrow band noise.

A. *Fast LMS and Significance*

Fig. 5a shows the complex field distribution at 3.5 Hz for a stimulus modulated at 3.5 Hz. Arrows represent the magnetic field response, at each of 157 channels, as phasors: the length of the arrow denotes amplitude and the orientation denotes phase. Circles mark those channels identified as significant by the joint balanced test ($p < 1/157$) [12]. Note that many of the channels strong in magnitude are not found to be significant. Fig. 5b, on the other hand shows the response at the same frequency (3.5 Hz) but after applying the noise suppression. It is clear how the number of significant channels is boosted, the structure of the background of the head map is established, and most of the strong signals over the temporal lobes (where robust signals are expected in response to auditory stimuli) are de-noised.

Fig. 6 illustrates the effect of Fast LMS on false positives by looking at responses at 15.5Hz, for a 31.5Hz modulated stimulus. In Fig. 6a, total of 13 False positives are identified, and after applying the de-noising algorithm, False positives drop to a total of 3 in Fig. 6b. Note that the test is designed so that there is, on average, one false positive for all responses in which there is no signal expected. Even so, the variance of the false positives among different response frequencies per each stimulus frequency is always reduced after applying Fast LMS, more evidence of the value of the noise suppression.

B. *Quantitative Measure*

We measured the ratio of power between observed neural responses and noise responses captured by reference channels, for both raw and filtered data (details in Table 2). Fast LMS preserved the signal at the stimulus frequency. In addition, it removed 1.4 dB of noise for frequencies below 10Hz, ~19 dB around 180Hz, and 1.8 dB for the whole spectrum.

C. *Fast LMS vs. CALM*

Continuously Adjusted Least Square Method (CALM), is a noise reduction procedure that eliminates correlations between the data and any of the 3 *unfiltered* reference magnetometers, by removing the detected covariance from the data MEG sensors [5]. This is performed, with a moving window of user-defined length.

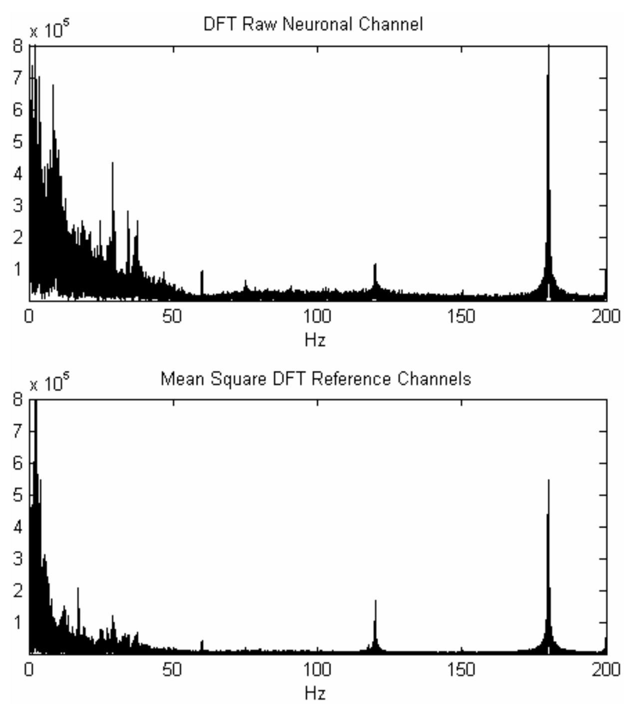

Fig. 4 (top) Periodogram of raw data. (bottom) Summed periodograms for the 3 reference noise channels.

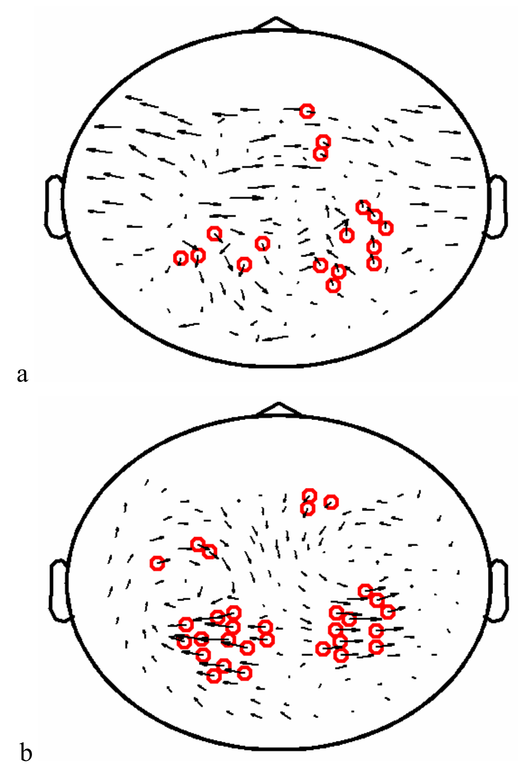

Fig. 5. (a) Response at 3.5 Hz for a 3.5 Hz modulated stimulus for raw data. Arrows represent amplitude and phase of signals at the stimulus frequency. The circles denote significant channels. (b) Same but for filtered data. Note the de-noising of strong channels on both head sides.

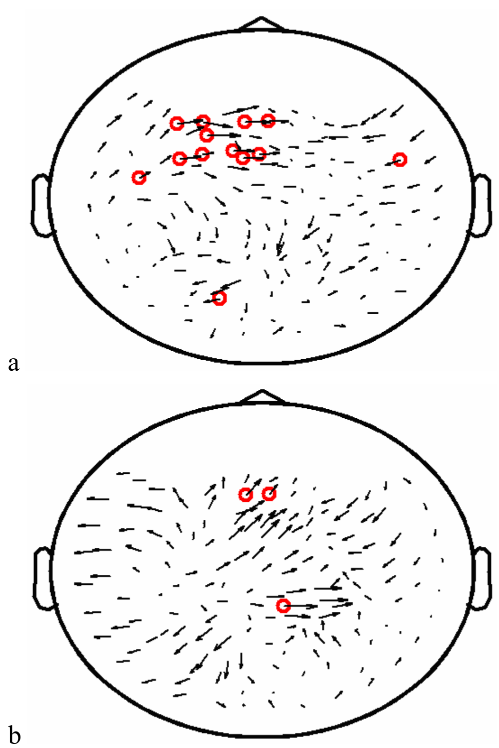

Fig. 6. (a) Response at 15.5 Hz for a 31.5 Hz modulated stimulus for raw data, as in Fig. 5. Total of 13 false positives (b) Same as above for filtered data. Number of False positives is reduced to 3.

	Raw data	F-LMS Filter	CALM Filter
3.5Hz	11.8 db	11.5 db	10.0 db
1-10Hz	5.9 db	4.5 db	3.9 db
175-185Hz	6.3 db	-13.6 db	2.0 db
1-500Hz	6.7 db	4.9 db	4.9db

Table 2. SNR measurements for raw and filtered data.

CALM is not efficient at removing multiple sources of narrow band noise, and it is less effective at frequencies above 10Hz (see Fig. 7). On the other hand, it is much faster than Block LMS (which is slowed by the time intensive DFT computations, and takes on the order of data acquisition time). But Block LMS is a whole spectrum de-noising algorithm. It does an excellent job for narrow band noise suppression. Table 2 compares quantitative measures for both methods.

IV. Conclusion

Adaptive noise suppression is critical in noise suppression for MEG responses. It improved SNR, increased number of significant neuronal channels, and suppressed and regularized false positives. Although the algorithm exploits a block structure, the method is slower than other non adaptive filtering methods because of DFT computations.

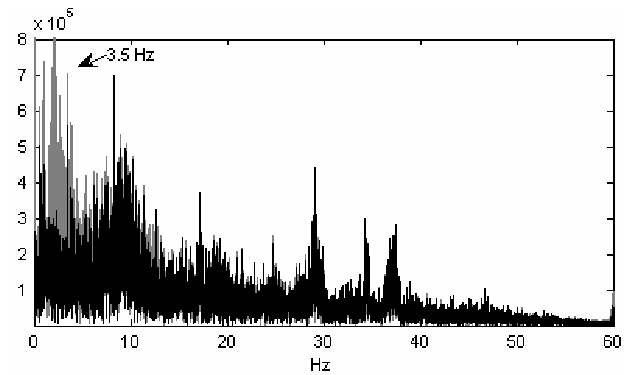

Fig. 7. Periodogram of raw data (gray) and data filtered with CALM (black). One channel. Stimulus frequency is 3.5 Hz.

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