DENOISING OF AUDITORY EVOKED POTENTIALS

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Abstract—Thepurpose of this study is to reduce the number of sweeps in extracting the auditory evoked potential (AEP) from ongoing electroencephalography (EEG) to minimize the time of diagnosis. In noisy environments, when conventional ensemble averaging of waveforms is used, recording must continue for excessively long time in order to accurately detect the ABR signal. This leads to problem when subject under test is infants, children, or others who may not be cooperative. Only partial data may be collected and a follow on appointment must be arranged to complete the test adding to costs and inconvenience for all concerned. So using basic estimation techniques in estimating the AEP with less number of sweeps compared to traditional Ensemble average (EA) is aim of this study. Signal to noise ratio (SNR) is parameter used to compare performance of different filter outputs against EA. For this purpose, basic estimation techniques are categorized into two groups. Group A includes Wiener filter (WF), combination of subspace method (SM) and wiener filter, Coherence weighted wiener filter (CWWF).Group B consists of standard adaptive filtering techniques like Least mean square (LMS), Recursive least square (RLS),one-step Kalman filter. Performance of above techniques is checked for both simulated and experimental data. In simulation Gaussian noise is added to known template AEP to create noisy sweeps.

Keywords—Auditory Evoked Potential, Adaptive filtering, Subspace method, EEG

I. INTRODUCTION

The brain electrical activity, that occurs in association with an external stimulus (auditory, visual or somatosensory), is called Evoked Potential (EP). In general, EPs or Event Related Potentials (ERPs) are not recognizable by visual inspection because they are buried in spontaneous Electroencephalogram (EEG) with signal-to-noise ratio (SNR) as low as −10 dB considering stimulus-independent background EEG as the noise in the measurements. The auditory evoked potentials (AEPs) help to evaluate the auditory nerve pathways from the ears through the brainstem.

The AEP amplitude and frequency range is 0.5-10μVolts, 10Hz-3000Hzrespectively [1]. EPs are interpreted in terms of the wave components such as amplitude and latencies. EPs have no special characteristics like ECG signals. Their components changes depending on type of stimulus, psychophysiological factors for a given individual .

The auditory brainstem response (ABR) is a subclass of AEPs. ABR is the brain wave activity starting in the inner ear that travels through the auditory nerve and to the auditory nuclei of the brain stem. It does not affected by the mental state of the subject and has very small amplitudes, ranging from 0.001 to 2 μVolt. The typical ABR waveform is shown in Fig.1 [2].

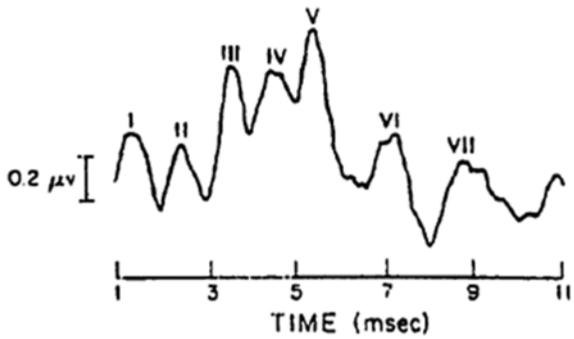

Fig.1. Typical ABR with seven general response categories.

The ultimate goal in the field of EP research is to recover the response to each stimulus. Traditionally, a large number of repetitive measurements are ensemble-averaged to suppress the background noise and find a template EP signal, assuming the stimulus-inducedchanges in the EEG are small. This approach is based on an additive model to describe the background EEG noise and an uncorrelated EP signal.The use of EA is impractical, however in cases where there are relatively tight constraints related to the available recording time or cooperativity of the subject. This has led to the development of the alternative SNR improvement methods based on the additive model.

All methods in both groups are implemented with the following two assumptions: 1) the EP and background EEG noise are uncorrelated; and 2) the background EEG noise is independent of the stimulus. Thus we adopt the well-known additive signal model to perform the linear filtering algorithms for auditory brain activities.

II.DENOISING METHODS

The EP signal sand the ongoing EEG sequence zare assumed to be additive in consecutive noisy measurements x. Mathematically, this basic assumption is expressed by an additive signal model as[3]

$$x_i\,(n) = s + z_i(n) \qquad (1)$$

Here, n is the time index and i denotes the trial number, where $n = 1, 2..N, i = 1, 2..L$. For empirical data, the grand average is taken as the template EP:

$$X_{ga} = \sum_{i=1}^{M} x_i(n), M \geq 512,\ M >> L \qquad (2)$$

The aim of this study is to estimate the clear EP from L number of records instead of M.We can write the raw data in matrix form as

$$X = S + Z \qquad (3)$$

The signal matrix S is estimated by linear filtering algorithms in the present work. The related methods are briefly presented in the following sections.

2. GROUP A

2.1.1Conventional wiener filter

Let $x_i$and d_i be the i^{th} noisy sweep and desired response respectively. Both of these are assumed to be jointly wide-sense stationary stochastic processes[3],[5].WF computes the optimum filter coefficients $w_{o\,i}$by minimizing mean square error (MSE) as below

$$J_i(n) = E|e_i(n)|^2 \qquad (4)$$

$$w_{oi} = R_i^{-1} p_i \qquad (5)$$

Where $R_i$is $N \times N$ correlation matrix of the i^{th}noisy input sequence, x_i and p_i is cross-correlation vector between desired response and input noisy sweep. Then the output of filter y_i is convolution of input noisy sequence x_i and filter coefficient w_{oi} given by

$$y_i(n) = \sum_{m=0}^{M} w_{oi}(m) x_i(n-m), \quad n = 1,2 \ldots .N$$
(6)

Where M is order of filter, w_{oi} is optimum weight vector for i^{th} input noisy sweep.

2.1.2 Subspace method

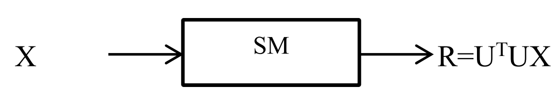

Fig.2 SM Block diagram

When, a small number of noisy observations(X) are considered as a real-valued noisy matrix that is summation of clear signal matrix(S) and uncorrelated noise matrix(Z) as formulated in equation (1), the dominant left eigenvectors of X can be chosen as linear independent basis vectors [3],[6]. So, the projected version of X can be written in the form

$$R=U^{T}UX \quad (6)$$

Where the matrix U is computed from singular-value-decomposition pairs of X such that

$$SVD(X) = [U\ \bar{U}]\ [\lambda 1\ \lambda 2\ \ldots \lambda L]\ [\bar{V}\ V] \quad (7)$$

If we assume that the EP signal is stationary, then only the first left singular vector spans the signal subspace of interest.

2.1.3 Coherence weighted wiener filter

The accuracy of the filtered output is increased if the filter is able to account for those frequency regions with a larger amount of background noise. To achieve this, the power spectrum is computed iteratively with the inclusion of each additional recording into the ensemble. With this procedure, the effect of outliers or other artifacts entering into the ensemble is reduced. The coherence function γ_{xy} of two stationary time sequences $x(k)$ and $y(k)$ is defined as [4]

$$\gamma_{xy} = \frac{Sxy(\omega)}{[sxx(\omega)Syy(\omega)]^{1/2}} \quad (8)$$

Where $S_{xx}(\omega)$ and $S_{yy}(\omega)$ are the Autopower spectra of the signals $x(k)$ and $y(k)$ and $S_{xy}(\omega)$ is the cross spectrum between $x(k)$and $y(k)$. The coherences represent the degree of correlation between the different frequency components of the two sequences. In the process of averaging, it is important to give more weighting to the frequencies that are highly correlated than the rest. This is accomplished by multiplying the power spectrum of each vector in the ensemble with coherence spectrum estimated between the new time sequence and the recent average. Additionally, the noise spectrum is weighted in a complementary fashion to reduce the influence of noise for those frequencies with lesser degree of correlation. Thus the ensemble averaging equations for thei^{th}ensemble becomes [4]

$$S_{\bar{x}}(\omega,i) = \frac{i-1}{i} S_{\bar{x}}(\omega,i-1) + \frac{1}{i}\gamma(\omega,i)S_x(\omega,i) \quad (9)$$

$$S_{\bar{n}}(\omega,i) = \frac{i-1}{i} S_{\bar{n}}(\omega,i) + \frac{1}{i}(1-\gamma(\omega,i))S_x(\omega,i) \quad (10)$$

Where $\gamma(\omega,i)$ is the spectral coherence computed for therecent member $S_x(\omega,i)$ and the previous average .i.e. $S_{\bar{x}}(\omega,i-1)$. At each iteration, the filter transfer function is constructed using

$$H(\omega,i) = \frac{S_{\bar{x}}(\omega,i)}{S_{\bar{x}}(\omega,i)+S_{\bar{n}}(\omega,i)} \quad (11)$$

The filter function is obtained as the IDFT of $H(\omega,i)$.

2.2 GROUP B: LMS, RLS and KF approach

LMS, RLS algorithms and KF are linear adaptive filtering algorithms, performed as introduced in literature[3],[7].

The filter output denoted by $y_i(n)$ is computed by,

$$y_i(n) = x_i(n) * w_i(n) \quad (12)$$

Here, $w_i(n)$ refers the estimated filter coefficients, where * denotes linear convolution.These are the well-known standardalgorithms so no description is given here.

The target of the adaptive filter, namely the desired signal,$d_i(n)$ is calculated from the average of L sweeps, excluding the input sequence of interest, as

$$d_i(n) = \frac{1}{L-1}\sum_{j=1, j\neq i}^{L} x_j(n) \quad (13)$$

Thus, the estimation error is

$$e_i(n) = d_i(n) - y_i(n) \quad (14)$$

The error is minimized by different estimation techniques in aiterative manner.

2.3 Performance evaluation

In this study, we use the SNR in evaluating the performance of the algorithms. The input and output SNRs are defined as follows:

$$\text{Input SNR} = 10\log_{10}\frac{\sum_{i=1}^{N} S(i)^2}{\sum_{i=1}^{N}[S(i)^2 - x(i)]^2} \quad (15)$$

$$\text{Output SNR} = 10\log_{10}\frac{\sum_{i=1}^{N} S(i)^2}{\sum_{i=1}^{N}[S(i)^2 - y(i)]^2} \quad (16)$$

Where s, x and y denote the signal, i.e., the grand average auditory EP (or known EP in simulations), input noisy sequence of the estimator and the output of the estimator, respectively.To understand the effect of the number of sweeps for a specified input SNR, the output SNR is calculated after each additional sweep.

III. RESULTS

3.1 Data collection

Experimental data was recorded by placing three gold cup electrodes. One electrodeis located at front polar(Fpz of 10-20 International system of EEG electrode placement) position, other two are placed over the left and right earlobes of (auricular A1,A2 of 10-20 international system of EEG electrode placement) subject, listening to binaurally delivered stimuli via earphones. The pass-band of the amplifier was 100–3000 Hz. During the experiments, the subject was sleeping on a bed .The stimuli were 10.1Hz tones of 100 µs duration and 70 dB hearing Level intensity, presented with an inter stimulus interval of 100ms sec. Fig 3shows grand averaged evoked potential which is ensemble average of 1818 sweeps, one noisy sweep and their respective spectrum.

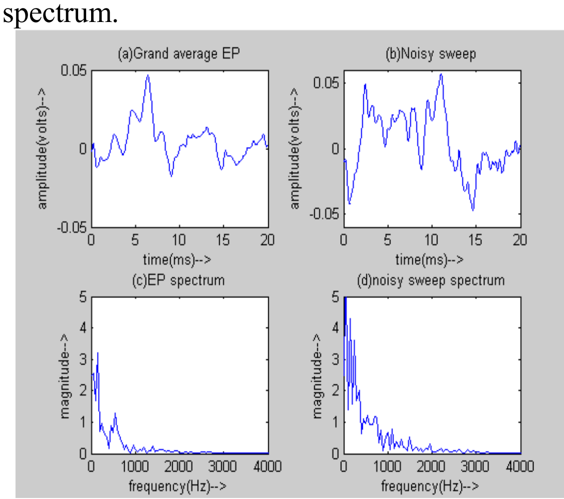

Fig.3 (a) Grand average EP, (b) Noisy actual sweep, (c) Grand average EP spectrum (d) Noisy sweep spectrum

3.2 Simulation

In simulations, ensemble average of 1818 actual auditory single epochs collected from healthy volunteer is assumed to be a template EP. To this EP template, normally distributed white noise sequences were added to create the simulated sweeps of specific SNR (In this study -10dB).Fig 4 shows simulated noisy sweep. Fig.5 shows reference ABR signal which is used as a reference to compute output SNR

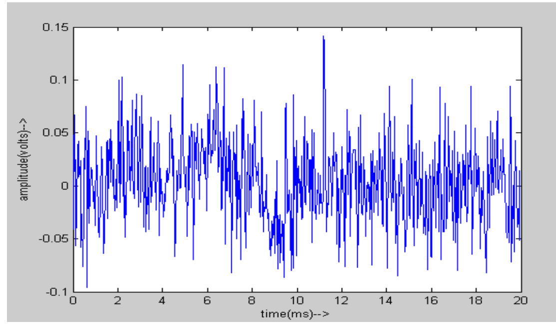

Fig.4 Simulated noisy sweep

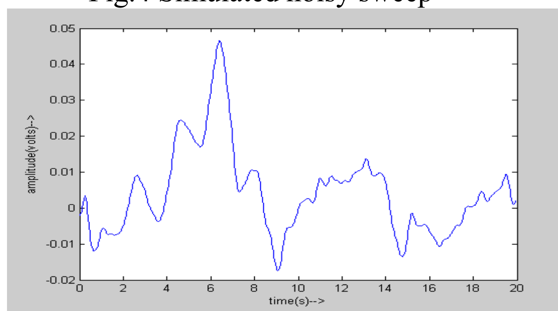

Fig.5 Reference ABR signal

3.3 Results for GROUP A

Fig.6 shows output SNR changes for incremental number of sweeps used in simulation study. It is observed that SMWF performed superior compared to EA, SMCWWF and WF.SMCWWF provides marginal improvement over EA. Pre-filtering (subspace method) has increased output SNR of WF drastically. For 40 sweeps there is a difference of 3dB between EA and SMWF. No SNR improvement observed for CWWF alone thus result is not shown in figure. There is a small increment in output SNR on addition of each sweep.. Fig.7 shows estimated ABR of 512 sweeps with input SNR -10dB respectively, it is seen that estimated ABR of SMWF is less noisy compared to other methods from Group A.

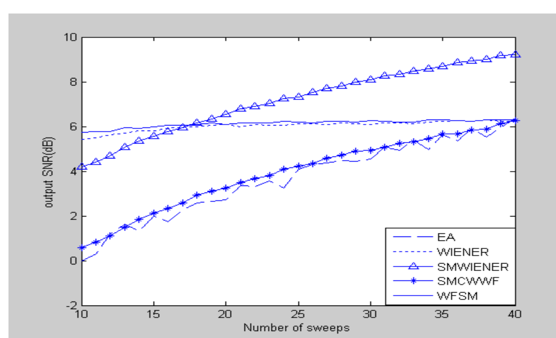

Fig.6 Output SNR for Group A versus the number of simulated sweeps for input SNR=-10dB

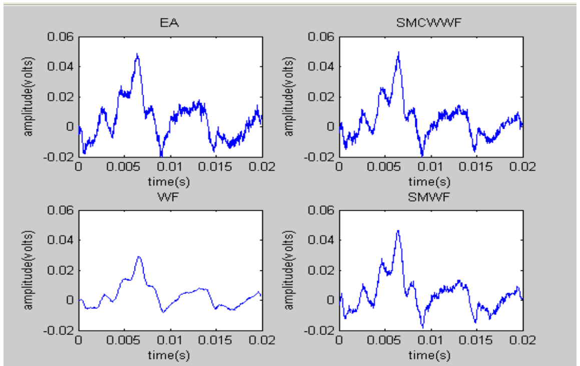

Fig.7 GROUP A estimated ABR of 512 simulated sweeps with input SNR -10dB

Fig.8 shows the output SNR versus number of actual sweeps. It is observed that SMWF performed superior to other methods. There is a 2dB SNR difference between EA and SMWF at 40 sweeps. Fig 9 shows estimated ABR for 512 actual sweeps with input SNR -10dB.It is observed that estimated signal for SMWF over the duration from 10ms to 20ms is smoother compared to EA and also peaks are well defined. Some peaks of ABR are merged in estimated signal of SMCWWF.

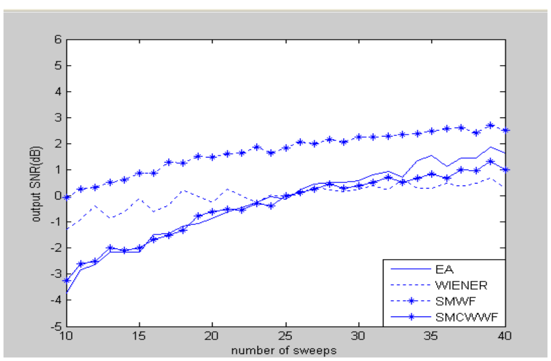

Fig.8 Output SNR for Group A versus the number of actual sweeps for input SNR=-10dB

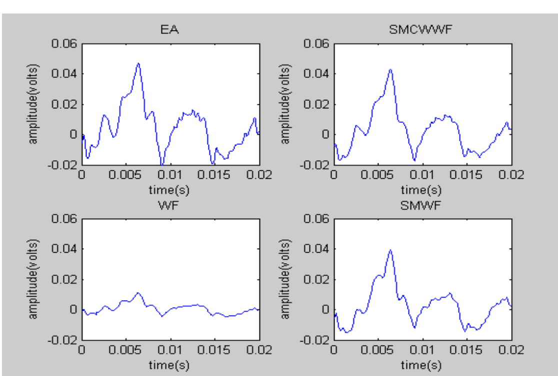

Fig.9GROUP AestimatedABR of 512 actual sweeps with input SNR-10dB

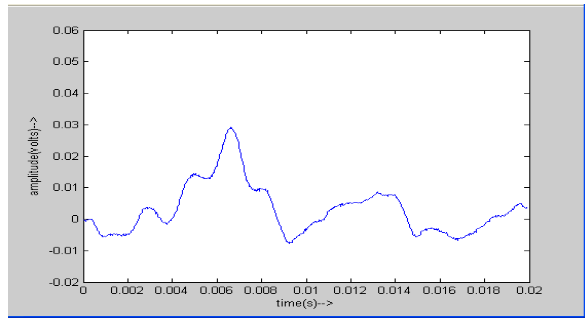

Fig.10 Wiener filter ouptput for 512 simulated sweeps with input SNR -10dB (Output SNR=6.48 dB)

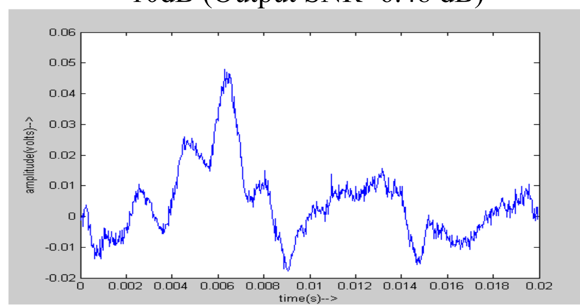

Fig.11 SMWF output for 512 simulated sweeps considering one dominant Eigen vector (Output SNR=17.02 dB)

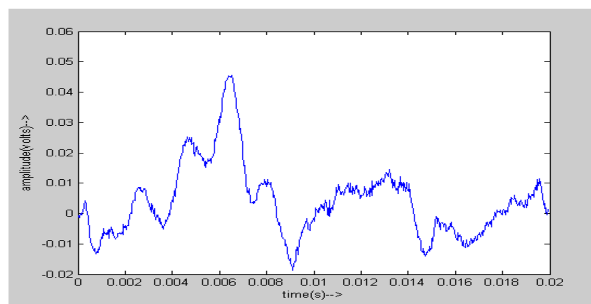

Fig.12 SMWF output for 512 simulated sweeps considering two dominant Eigen vectors (Output SNR=18.7 dB)

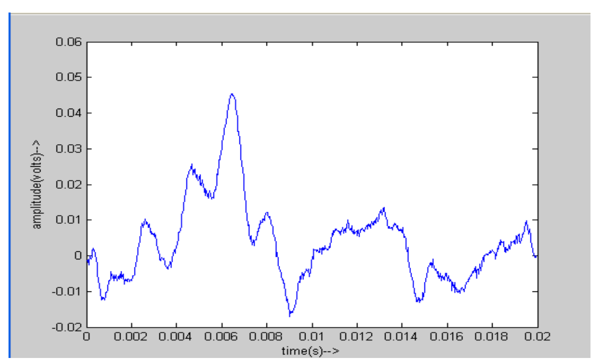

Fig.13 SMWF output for 512 simulated sweeps considering three dominant Eigen vectors (Output SNR=19.17 dB)

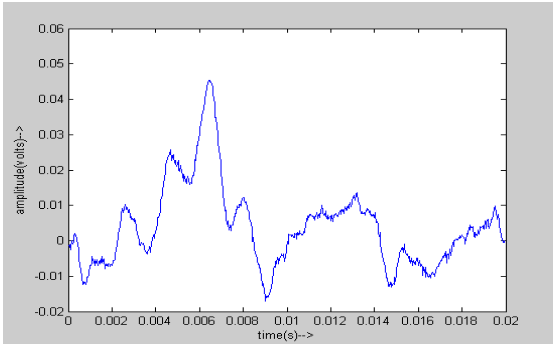

Fig.14 SMWF output for 512 simulated sweeps considering four dominant Eigen vectors (Output SNR=18.45 dB)

In equation 6 and 7, when considered only one dominant Eigen vector (Eigen vector corresponding to matrix decomposition of small number of noisy observations) SNR is increased by large amount. When considered two dominant basis vectors output SNR increased by small value, whereas for number of Eigen vectors beyond three output SNR starts decreasing. Fig.15shows output SNR versus number of Eigen vectors.Observed thatbeyond three Eigen vectors output SNR is exponentially decaying.Fig.16shows that output SNR is maximum at 3.

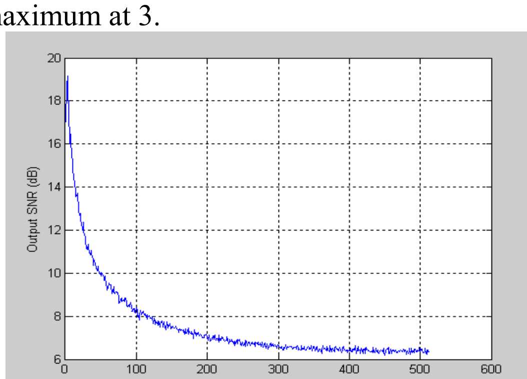

Fig.15 Output SNR v/s Number of Eigen vectors for 512 simulated sweeps using SMWF

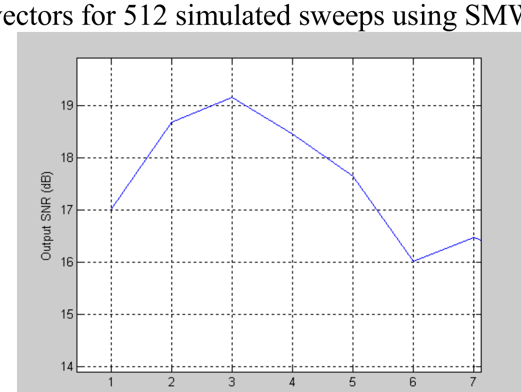

Fig.16Peak output SNR for three dominant Eigen vectors.

3.4 Results for GROUP B

The filter parameters are chosen for actual data as

TableI Filter parameters for adaptive filters

Filter parameters	μ	λ	Δ	q_p	q_m	k_0
Values	2.7205	0.995	0.1	0.0001	0.01	0.1

Where N is order of filter, μ is step size in LMS algorithm, λ is forgetting factor and δ is small positive constant to initialize input correlation matrix of RLS algorithm,$q_p$is process noise variance and $q_m$is measurement noise variance of Kalman filter, k_0 is value to initialize the state error correlation matrix of Kalman filter.

Fig.17 shows output SNR versus number of simulated sweeps with input SNR -10dB.It is observed that SMKF preforms better compared to other filters beyond 32 sweeps. LMS performs poorer compared to EA. But pre-filtering improved the SNR drastically. RLS performed better compared to LMS. SMRLS performance is in between SMLMS and SMKF. SMLMS, SMRLS and SMKF shows better performance compared to EA. There is a 4 dB difference in output SNR between SMKF and EA. Fig.18 shows the estimated ABR for 512 simulated sweeps with input SNR -10dB respectively. Estimated ABR of SMKF is less noisy and peaks more prominent compared to others. There are little differences between estimated ABR of SMKF and SMLMS because SNR difference between them is less which can be noticed from Fig.17. There is a small increment in output SNR for LMS filter on addition of each sweep; hence output SNR is almost straight line.

Fig.19 shows output SNR versus number of actual number of sweeps. It is observed that SMKF is superior compared to other methods. Although RLS filter looks better compared to EA, its SNRis almost constant (≈ 2.5 dB) on addition of new sweeps. Hence at 512 sweeps the output SNR of RLS filter is still at the same value. Fig.20 shows estimated ABR for 512 sweeps with input SNR -10dB.Observe that SMKF output resembles like a template ABR.

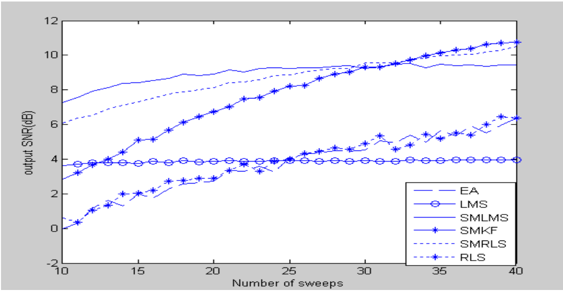

Fig.17Output SNR for Group B versus the number of simulated sweeps.

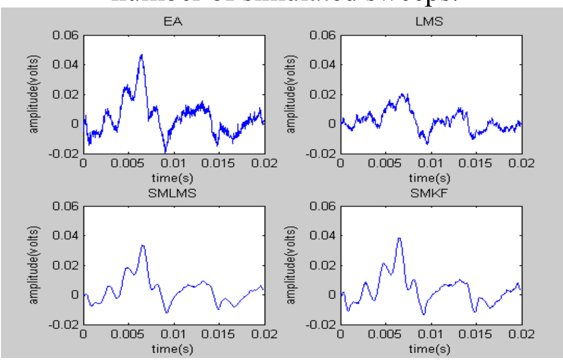

Fig.18 GROUP B estimated ABR of 512 simulated sweeps with input SNR-10dB

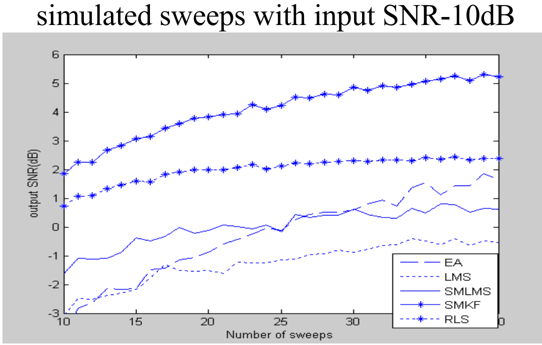

Fig.19 Output SNR for Group B versus the number of actual sweeps with input SNR=-10dB

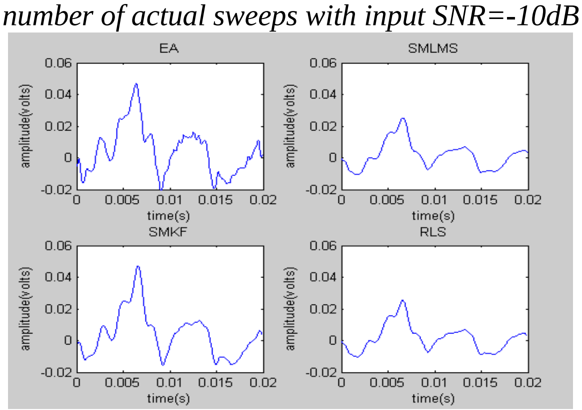

Fig.20GROUP B estimated ABR of 512 actual sweeps with input SNR -10dB

IV. CONCLUSIONS

The results show thatusing the SMas a pre-filter can remove a large amount of EEG noise. In addition, the characteristic of the EEG noise remaining on the projections renders white noise.The SMWF was found to be better for all data in Group A.

In the Group B, SMKF is better compared to EA. The SMKF provides the highest performance in both simulation and experimental studies.

The LMS filter performance depends on 1) the number of sweeps, 2) the step size parameter, 3) the filter length, and 4)the input SNR of single sweeps. The selection of step size parameter was assumed to be the crucial factor in the performance. To obtain a better performance with the LMS filtering the optimum value was determined empirically considering the filter length, input signal variance and the desired signal [8].

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