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Application of Wiener Filtering Techniques for Extraction of Evoked Potential

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Abstract:

In the present study, the performances of two well-known linear filtering techniques are compared for extraction of auditory Evoked Potential (EP) from a relatively small number of sweeps. Both experimental and simulated data are filtered. Our filtering method consists of Wiener filtering (WF) applications, where conventional WF and Coherence Weighted WF (CWWF)) have been assessed in combination with the Subspace Method (SM). The application of the SM before filtering improves the performance of WF where the CWWF works better than the conventional WF in that case. In conclusion, most of the linear filters show definitely better performance compared to EA. WF effectively reduces the experimental time (to half of that required by EA). The SM that has recently been revealed in EP estimation is found to be a meaningful pre-filter as it significantly reduces the noise level of raw data.

1. Introduction

The auditory nervous system refers to neural systems that start at the inner ear and extend through several stages up to the auditory cortex of the brain. It is considered the most complex neural system when compared to the other sensory systems. The Auditory Brainstem Response (ABR) is a reliable signal that can be used to objectively evaluate the function of the auditory system. In current clinical practice, the ABR is recorded when the auditory system is stimulated with an artificial sound such as a click, tone burst, or an amplitude modulated tone. More recently, the ABR generated by a speech stimulus (speech ABR) has been investigated because speech is of primary importance in human acoustic communication. In particular, speech ABR has been proposed as a marker of defects in central auditory processing in children with learning problems, and has also been proposed to study degradation in auditory processing in the aging auditory system. Since ABR is recorded non-invasively using electrodes placed on the surface of the scalp, the signal-to-noise (SNR) ratio of the ABR signal is generally very low. This low SNR has limited the application of speech ABR in the clinic because the conventional approach of coherently averaging the responses over multiple presentations of the relatively long duration speech stimulus requires an exceedingly long recording time that ranges from several minutes to tens of minutes with a single speech sample.

2. Methods

The EP signals and the ongoing electro encephalogram sequence z are assumed to be additive in the consecutive noisy measurements of x. Mathematically, this basic assumption is expressed by an additive signal model in the for

$x_i(n) = s + z_i(n)$ (1)

Here, n is time index and i is trial number, and n = 1. . . N, i = 1. . . L. For the empirical data, the total average is considered as the template EP:

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

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

$X = S + Z.$ (3)

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

2.1 Ensemble Averaging

In statistical mechanics, the **ensemble average** is defined as the mean of a quantity that is a function of the microstate of a system (the ensemble of possible states), according to the distribution of the system on its micro-states in this ensemble.

Since the ensemble average is dependent on the ensemble chosen, its mathematical expression varies from ensemble to ensemble. However, the mean obtained for a given physical quantity doesn't depend on the ensemble chosen at the thermodynamic limit. Grand canonical ensemble is an example of open system.

Following are the steps followed to obtain Ensemble average of a signal

- Collect multiple signals over the same time or wavelength (for example) domain
- Calculate the mean signal at each point in the domain
- Re-plot the averaged signal
- Since noise is random (some +/ some -), this helps reduce the overall noise by cancellation.

2.2 Wiener filter

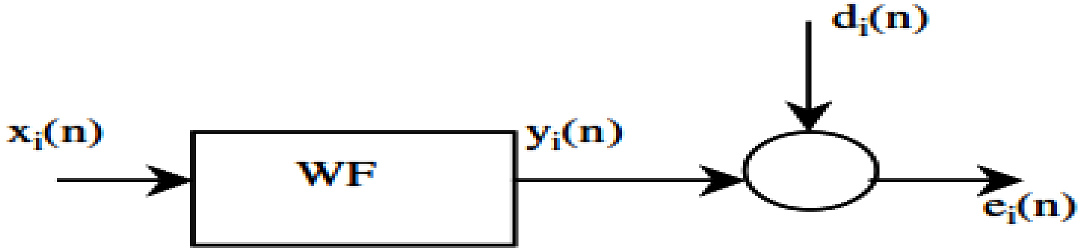

Figure 1: Wiener filtering model

In the evoked potential field, there have been some attempts to build an optimal filter in the least mean-squared sense, i.e., the WF, under the assumptions of additivity and independence of signal and noise. For processing the average event related potential, the Wiener filter becomes

$$H(\omega) = \frac{S_s(\omega)}{S_s(\omega)+S_n(\omega)} \qquad (4)$$

Where Ss(ω) is the spectral density of the signal and Sn(ω) is the spectral density of the noise defined as

$$S_s(\omega) = \frac{N}{N-1} S_{\bar{x}}(\omega) - S_x(\omega) \qquad (5)$$

$$S_n(\omega) = \frac{N}{N-1} [S_x(\omega) - S_{\bar{x}}(\omega)] \qquad (6)$$

Where $S_{\bar{x}}(\omega)$is spectral density of ensemble average $\bar{x}$(n).

2.3 Subspace method

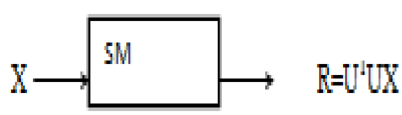

Figure 2 :Subspace model

When, a small number of noisy observations(X) are considered as a real-valued noisy matrix that is summation of uncorrelated matrix and real signal matrix in equation (1), linear independent basis vectors are chosen by dominant left eigenvectors of X [7]. So, the projected version of X can be written in the form

$$R=U^TUX \qquad (7)$$

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

$$\mathrm{SVD}(X) = [U\ \bar{U}]\ [\lambda_1\ \lambda_2\ \ldots\ \lambda_L]\ [V\ V] \qquad (8)$$

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

In this paper we have used this as pre-filter.

2.4 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 calculated 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 γxy of two stationary time sequences x(k) and y(k) is defined as [2]

$$\gamma_{xy} = \frac{Sxy(\omega)}{[sxx(\omega)Syy(\omega)]^{1/2}} \qquad (9)$$

Where S xx (ω) and S yy (ω) are the Autopower spectra of the signals x(k) and y(k) and S xy (ω) is the cross spectrum between x(k) and y(k). Degree of correlation between different frequency components of two sequences are represented by coherence. 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 the ith ensemble becomes [2]

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

$$S_{\bar{n}}(\omega,i) == \frac{i-1}{i} S_{\bar{n}}(\omega, i) + \frac{1}{i}(1-\gamma(\omega,i))\, S_x(\omega,i) \qquad (11)$$

Where γ(ω, i) is the spectral coherence computed for the recent member S x (ω, i) and the previous average $S\bar{x}$ (ω,i -1).

At each iteration, the filter is constructed using

$$H(\omega, i) = \frac{S_{\bar{x}}(\omega,i)}{S_{\bar{x}}(\omega,i) + S_{\bar{n}}(\omega,i)} \qquad (12)$$

The filter function is obtained as the IDFT of H(ω,i).

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:

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

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

Here 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 e□ect of the number of sweeps for a specified input SNR, the output SNR improvements are calculated after each additional sweep.

During the experiments, the subject was sleeping on a bed . The stimuli were 10. 35 dB hearing Level intensity and 1Hz tones of 100 µs duration, presented with inter stimulus interval of 100ms sec. 513 single sweeps were acquired with the sampling rate of 30samples/sec. The epoch length obtained was 20msec of post stimulus part .The SNR of single sweep (with respect to grand average of count of 1800 sweeps) was found to be about -10 dB.

4. RESULTS

The filter parameters are chosen for actual data as

- Order of filter N=50
- Step size μ=2.7205(LMS)
- Forgetting factor λ=0.995(RLS)
- Value to initialize P(0) δ=3.6016e-06 (RLS and Kalman)
- Process noise variance qp=0.00001
- Measurement noise variance q_m= 0.01
- Value to initialize state vector k_0=3.6016e-06 (Kalman)

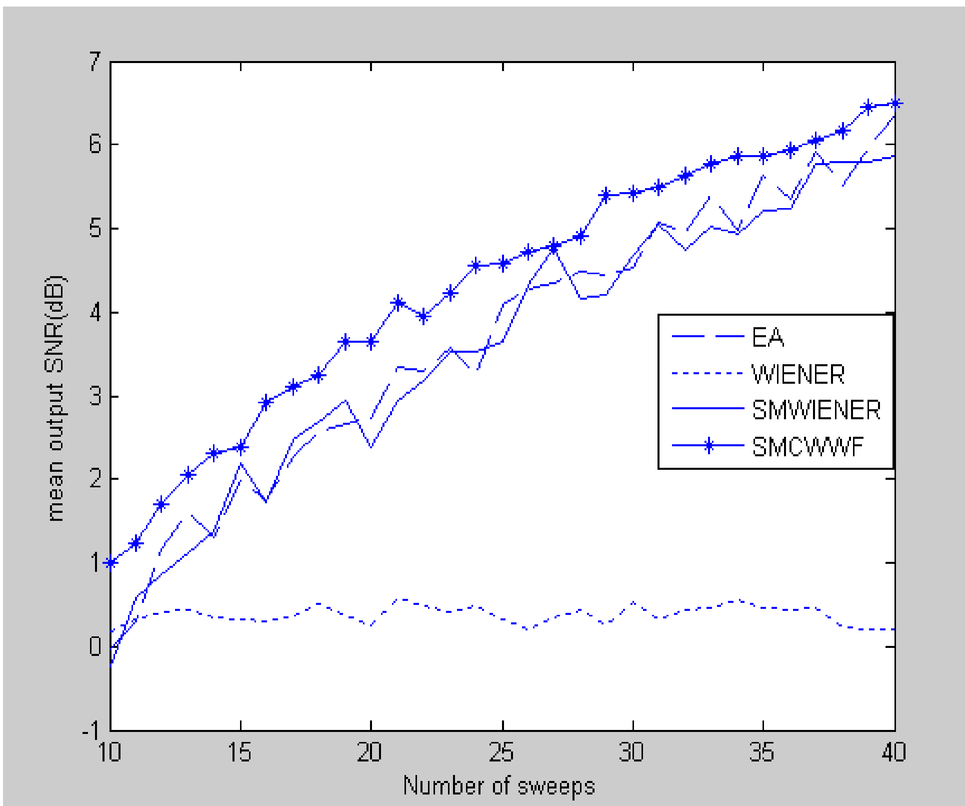

Figure 3: Output SNR for Group A versus the number of simulated sweeps for input SNR=-10dB

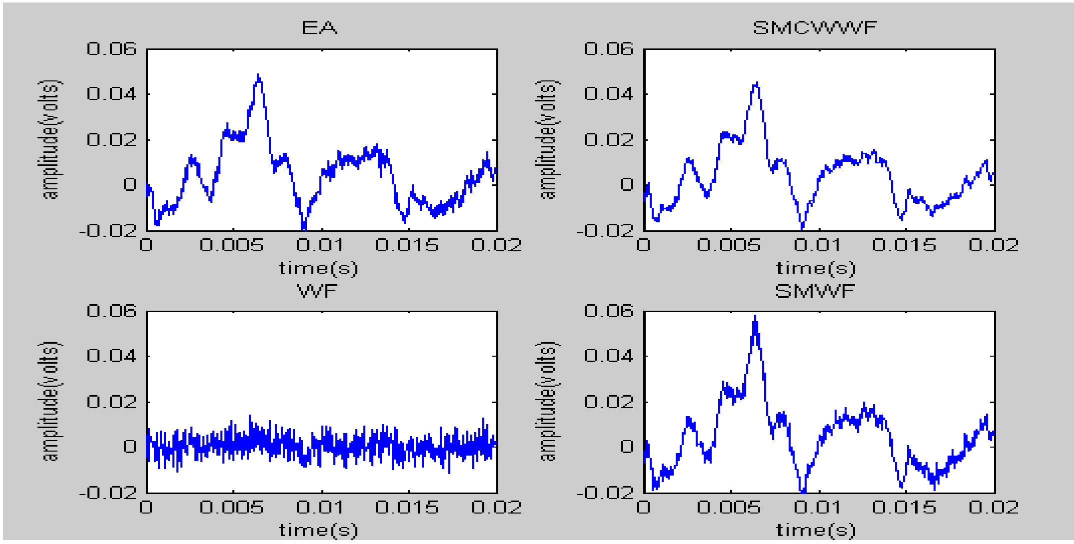

Figure 4: GROUP A Estimated ABR of 512 simulated sweeps with input SNR=-10dB

5. Conclusion

150 ABRs with 64 repetitions are used for this work. Results show that, the SM can remove a large amount of EEG noise. As per the results SMCWWF was found to be better for all data(simulated and experimental). Though EA and Wiener filters are better to some extent SMCWWF simulates the best result among various the static filtering techniques. Compared to Wavelet Analysis and Bayesian Network that were used in previous papers this method improves 3% of overall accuracy.

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