# An Adaptive Filtering Approach to the Processing of Single Sweep Event Related Potentials Data

Adrien Decostre and Burak Arslan
TCTS Lab. Faculté Polytechnique de Mons

***Abstract*— We present an adaptive filtering method applied to the single sweep event related potentials data. The method is based on time-sequenced version of the typical adaptive signal enhancers. Two different signals are used at the reference input and the results are compared. The evaluation is made using both simulated and real measurement data. It is found that the use of a reference input composed of the eigenvectors of the desired target signals, improved the estimation error while minimizing the distortion for the non target sweeps. It also enables a better tracking of the sweep to sweep changes of the ERP waveform.**

***Keywords- EEG, ERP, adaptive filter, single sweep, principal eigenvector***

## I. INTRODUCTION

Event related potentials (ERPs) are the voltage fluctuations of the brain electrical activity that follow or precede the presence or omission of a stimulus which are generally of acoustical or visual nature. Since they have very low amplitude compared to the ongoing electroencephalographic (EEG) activity onto which they are superposed, they require special methods of signal extraction. The most commonly used technique for this purpose is the ensemble averaging of the sweeps obtained in response to stimuli. It takes advantage of the repeatability of the response, where signal (ERP) adds up while the noise (EEG) tends to cancel with increasing number of trials. One disadvantage of the ensemble averaging is that it is not suitable to reflect the changes that may occur in the response between trials. Several methods that consider such changes have been proposed [1], [2], [3].

In this study we present a time sequenced adaptive filtering method based on principal components of the ERP signal.

## II. METHODS

The alternative approach to the traditional ensemble averaging for detecting ERPs is to minimize the mean square error $mse$ between the signal and the output of a filter. The LMS adaptive filtering algorithm solves the $mse$ problem iteratively in a much simpler way than the optimum filtering approaches. It also has the advantage to follow the time varying characteristics of the signal. This is successfully used in many biomedical engineering problems. The basic adaptive filter structure has two inputs: the primary signal which is composed of the signal mixed with unknown noise and a reference signal that contains the signal to be detected with a higher SNR.

This work is supported by the DREAMS project financed by the Walloon Region in Belgium

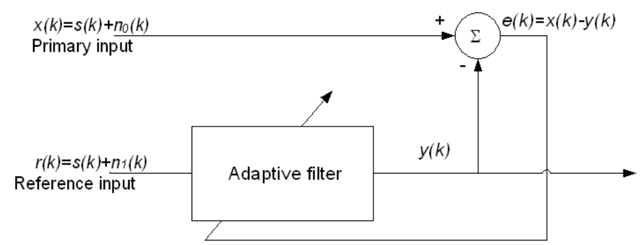


Fig. 1. Adaptive signal enhancer

The adaptive filters are capable of adjusting their parameters in order to minimize the $mse$. The model used in the detection of ERP or EP recordings is called the adaptive signal enhancer (ASE). Fig.1 shows an ASE where $x$ and $r$ are the two inputs to the adaptive filter. The filter tries to minimize the error by adjusting its weights. That means it makes the output $y$ resemble the signal $s$.

$$x(k) = s(k) + n_0(k) \tag{1}$$

$$r(k) = s(k) + n_1(k) \tag{2}$$

$$E[e^2(k)] = E[(s(k) - y(k))^2] + E[n_0^2(k)] \tag{3}$$

LMS algorithm uses the steepest descend method for the parameter adjustment:

$$\omega(k+1) = \omega(k) - \mu \cdot \nabla_{E[e^2(k)]}(k) \tag{4}$$

$$\omega(k+1) = \omega(k) + 2\mu \cdot e(k) \cdot R(k) \tag{5}$$

where $\mu$ controls the stability and the convergence rate.

The LMS adaptive filter is used by Thakor [4] for the estimation of evoked potentials. A problem occurs when the signal changes from trial to trial, because of the non-stationarity of the signal. The minimum value of the $mse$ changes in time and it becomes difficult for the adaptive filter to track these changes. It responds either in speed or error minimization. An alternative approach is to use the time-sequenced adaptive filter (TSAF) structure proposed by Ferrara and Widrow [5]. TSAF is designed to estimate a nonstationary signal $x$ by decomposing into segments $x_j$ in which it is assumed stationary (Fig.2).

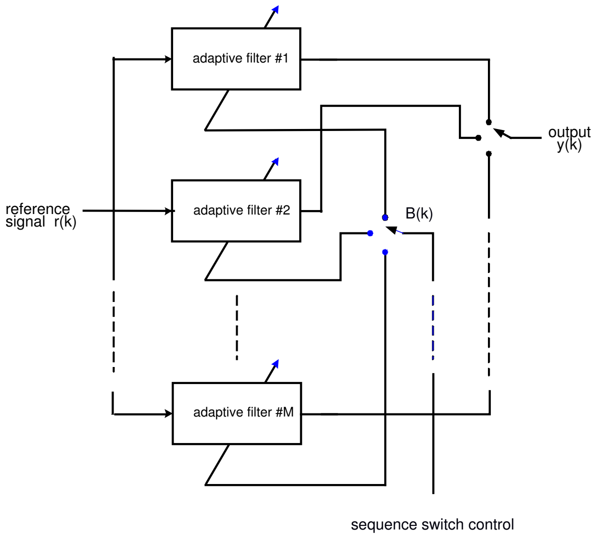


Fig. 2. Time sequenced version of the adaptive filtering block

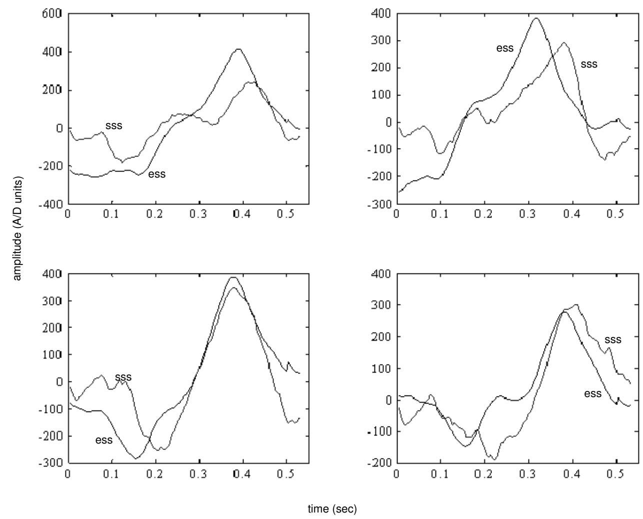


Fig. 4. Estimated single sweep signals from simulated data (SNR:-12 dB). sss : simulated single sweeps; ess : estimated single sweeps

$$x = \begin{cases} x_1(k) & k \in [k_0, k_1] \\ x_2(k) & k \in [k_1, k_2] \\ \dots & \\ x_M(k) & k \in [k_{M-1}, k_M] \end{cases}$$

This is a band of $M$ adaptive filters where each filter deals with only a segment of the data by adjusting its own coefficients. The discontinuities between segments are eliminated by convolving several points of two neighboring filters. Thus $y$ is estimated as a weighted average of the outputs of two filters.

$$y(k) = \alpha^j y^j(k) + \alpha^{j+1} y^{j+1}(k) \tag{6}$$

In order to evaluate the performance of the filter we first generated simulated ERP data of various SNR levels between 0 to -12 dB. Then real ERP data taken from a BCI experiment are used for calculations[1].

The sweep length for both simulation and real measurement data is 550 msecs with a sampling rate of 240 Hz. Each sweep is divided into 10 segments of equal length and then analyzed. The idea is that for the ERP signal, changes can be faster than the background EEG. Therefore at segments where the ERP appears, algorithm should be at a different pace than other portions of the data and still keep the error at minimum. The order of the LMS filter is chosen 2. The choice of reference is very important in adaptive filtering. To obtain a signal that can represent the ERP, first the average of a number $n$ of trials is used. Experimentally $n$ is chosen approximately 60 for the typical SNR values of an ERP.

In the second part of the study, another approach is used in order to better represent the ERP signal: the average waveform is decomposed into its orthogonal components and the reference signal is reconstructed from its $m$ principal eigenvectors (Fig.3). Thus the effects of noise in the desired signal are eliminated. A value of 3 for $m$ is found to be satisfactory for the filter performance. $\mu$ is chosen 0.01.

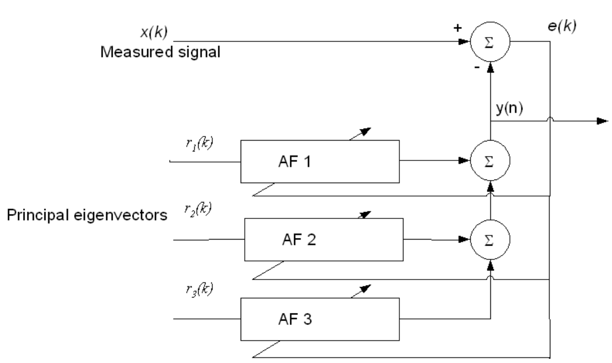


Fig. 3. Eigenvector based adaptive filter

## III. RESULTS

The estimated signals for the simulated data are shown in Fig.4. The SNR of the simulated data is -12 dB. The noise free signal is plotted with the corresponding estimation. The plots for four random sweeps show that the adaptive filter is able to estimate the signal in real ERP conditions.

Table 1 summarizes the performance of the two different reference approaches applied to the TSAF. Principal eigenvector based adaptive filter performs better and more accurately.

[1] $2^nd$ Wadsworth BCI dataset (P300 evoked potentials) Data were acquired using P3 speller paradigm

TABLE I

ADAPTIVE FILTER WITH DIFFERENT REFERENCE SIGNALS

| | averaged response | principal eigenvectors |
|---|---|---|
| Estimation error | 1.1166 | 0.9941 |
| Error st.dev | 0.4232 | 0.1426 |

Finally Fig.5 shows the output of the proposed adaptive filter for the real measurement data. Since the single sweep original is not available for the measurement, the average ERP waveform is plotted against the single sweep estimate. Here again plots for four random sweeps show the ability of the filter to extract target waveform in a real ERP experiment.

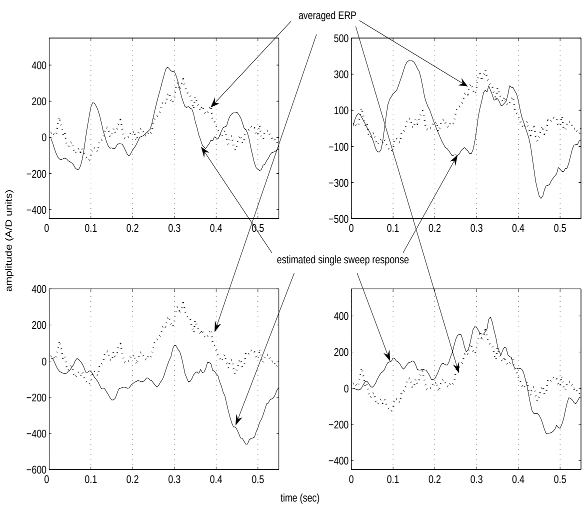


Fig. 5. Single sweep estimated signals from real measurement data

## IV. CONCLUSIONS

We proposed an adaptive filtering method for the estimation of single sweep ERP data. The first technique uses the time-sequencing approach to improve the minimization of the estimation error. The results show that it is successful in extracting the ERP waveform. The use of three principal eigenvectors obtained from an averaged signal as the reference to the filter further improves the results. It also enables better tracking of time varying latency changes of trials. There are several issues open to further investigation. Simpler LMS method was chosen for an adaptation to real time processing. Other algorithms may provide subject to future studies. Time sequencing was kept at constant intervals but an adaptive scheme that uses the a priori information about the possible interval of an ERP response would improve its efficiency. Finally, the principal eigenvector based approach which shows less distortion of nontarget sweeps can be exploited for the single sweep ERP detection that can be used in applications such as BCI.

## REFERENCES

[1] F.H.Y. Chan, W. Qiu F.K. Lam P.WF. Poon, Evoked potential estimation using modified time-sequenced adaptive filter, *Med.Biol.Eng.Comp*, vol. 36, 1998, pp 407-414.

[2] X.Kong and T.Qiu, Latency change estimation for evoked potentials; a comparison of algorithms, *Med.Biol.Eng.Comp*, vol. 39, 2001, pp 208-224.

[3] P.Karjalainen, J.Kaipio, A.Koistinen and M.Vauhkonen, Subspace regularization method for the single trial estimation of evoked potentials, *IEEE Trans on BME*, vol. 46, 1999, pp 849-860.

[4] N. Thakor, Adaptive filtering of evoked potentials, *IEEE Trans on BME*, vol. 34, No.1 1987, pp 6 11.

[5] E.R.Ferrara and B.Widrow The time-sequenced adaptive filter, *IEEE Trans on Circuits and Systems*, vol. 28, No.6 1981, pp 519-525.