Power Line Interference Cancelling in EEG Inspection

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Abstract - This paper presents a FIR adaptive filter to cancelling interference due to 50 Hz power line in human electroencephalographic (EEG) inspection. An overview of EEG techniques to study brain activity will be outlined. Then, the problem of spurious signal rejection, in this particular handset, shows the meaningfull application of adaptive filter structure. Poles of filter are driven to find an optimum bandwidth to eliminate noise. Least-Mean-Square (LMS) algorithm is used for adaptive process. Effect of finite filter length and non-zero response time, and their effect on time response will be also showed.

I.Introduction

Normal brain activity consist of a superposing of four types of "characteristic waves" denoted from greek alphabetical letter α, β, γ, δ. During an EEG exam, that shows these waves superposing, a very low amplitude periodic signal due to power line interference could be observed. So, an extraction signal method is necessary to preserve interesting biopotential.

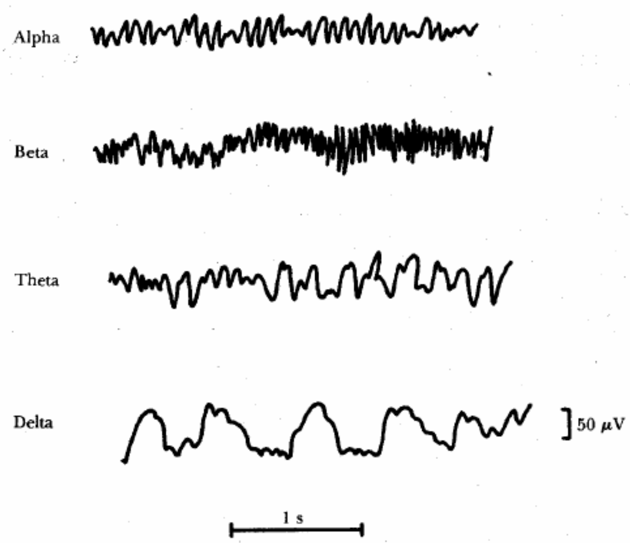


Figure 1: Characteristics brain waves

Due to low levels of these signals, a fully numerical implementation of a detector and a filter is necessary, thus an adaptive FIR filter has been designed and simulated with typical EEG signals corrupted from this periodic interference.

II. FIR system description

This kind of system needs a couple of input signal: EEG observation, and a noisless reference signal input, that represents 50 Hz power line signals. Neverthless, noiseless signal is the goal, so the scheme in figure summarizes a choice for reference input obtained from primary input signal by a delay.

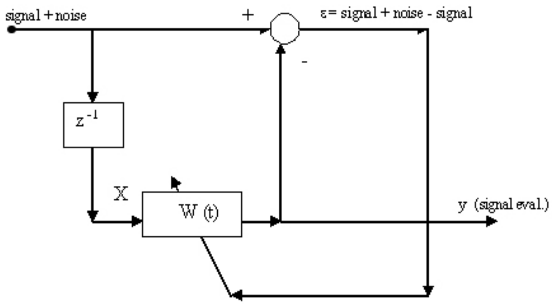
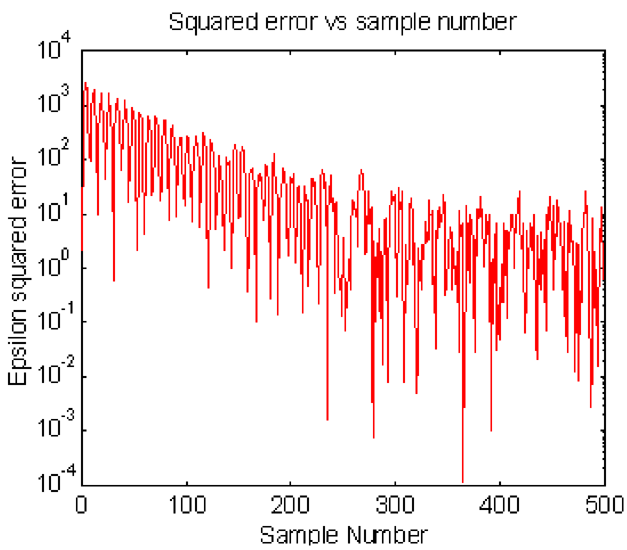


Figure 2: Adaptive digital filter

This delay allows a decorrelation between signal and periodic noise, so at the filter input there is only signal from electroencephalograph pre-amplifier.
So, the minimum error power will be

$$E_{\min}[\varepsilon^2] = E[n^2] + E_{\min}[(s-y)^2] \qquad (1)$$

For this application, mean squared error decreases, step by step, while system reaching the best set of weight vector.



When filter will become optimum for that specific EEG observation, $E[\varepsilon]$ will be minimized reaching minimum value on a L-dimensional Hyper-quadratic surface, with L taps for filter.
LMS (Normalized-Least Mean Square) algorithm is an easy way to descend the performance surface that uses a special estimate of the gradient, suitable for the adaptive FIR scheme described above. It does not require off-line surface gradient estimation, so it is simple to implemenmt in real- time applications. The transversal filter presentend in fig.1 with label *W(t)* may be rappresented as an Adaptive Linear Combiner

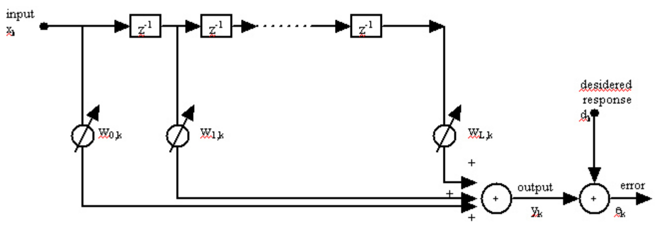


Fig. 1 The Adaptive Linear Combiner as a transversal filter

where the combiner output, y_k, is a linear combination of the input samples, so

$$\varepsilon_k = d_k - \underline{X}_k^T \underline{W}_k \qquad (3)$$

where $\underline{X}_k^T$ is the vector of input samples.
To develop an adaptive algorithm using the previous methods, we would estimate the gradient of $\xi_k = E[\varepsilon_k^2]$ with ε_k^2, taking itself as an estimate of ξ_k.
At each iteration in the adaptive process, the gradient estimation in performed like this

$$\nabla_k = \begin{bmatrix} \frac{\partial \varepsilon^2_k}{\partial w_0} \\ . \\ . \\ \frac{\partial \varepsilon^2_k}{\partial w_L} \end{bmatrix} = 2\varepsilon_k \begin{bmatrix} \frac{\partial \varepsilon_k}{\partial w_0} \\ . \\ . \\ \frac{\partial \varepsilon_k}{\partial w_L} \end{bmatrix} = -2\varepsilon_k \underline{X}_k \qquad (4)$$

with this simple esitimate of the gradient, we can now specify a steepest type of adaptive algorithm. In detail,

$$\underline{W}_{k+1} = \underline{W}_k - \frac{\mu}{\sigma^2} \nabla_k = \underline{W}_k - 2\frac{\mu}{\sigma^2} \varepsilon_k \underline{X}_k \qquad (5)$$

this is the N-LMS algorithm with μ as gain constant that regulates the speed and stability of adaption, and σ^2 is the input signal power.

A choice for μ is $\frac{1}{\lambda_{\max}} > \mu > 0$ that guarantes the convergence. If [R] is the input correlation matrix, $\lambda_{\max}$ cannot be greater than the trace of [R]; thus convergence of the weight-vector mean is assured by:

$$0 < \mu < \frac{1}{(L+1)\sigma^2} \qquad (6)$$

with $\lambda_{\max}$ the maximum eigenvalue of [R] and σ^2 is the input signal power.

III. Simulation results

Matlab® system simulation will be now presented.

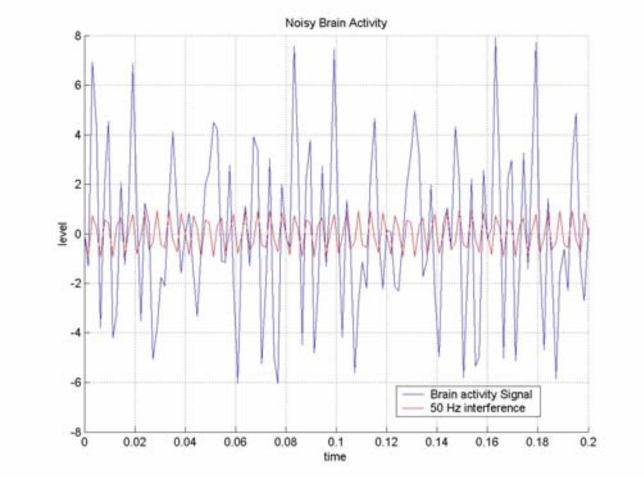


Figure 3: Noisy brain activity corrupted by 50 Hz power line interference

Low 50 Hz pseudo-amplitude modulation could be seen in figure 3. SNR, in this condition, reaches 2.5 dB. This appearance is due to interference that will be locked and suppressed by FIR filter presented.

After digital filter, SNR increases to 12.3 dB and low amplitude modulation effect in signals has been suppressed like interference.

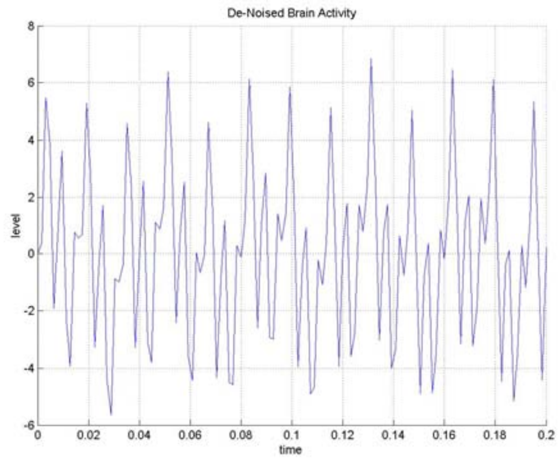


Figure 4: Denoised acquired brain signal

IV. Conclusion

Performance of implemented FIR filter could be considered acceptable in simulation test bed. A SNR gain of 9.8 dB bring to good consideration about adaptive interference searching and cancelling. A “bulk” implementation of this study will be computed to show different results about real system performance.

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