A Novel Approach to Denoise Visual Evoked Potentials Using Higher Order Statistics

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Abstract

Evoked Potentials (EPs) are time varying signals buried in large background noise. In order to detect and extract Visual Evoked Potentials (VEP) in real time, we use the fourth order cumulant of the observed noisy signal in an adaptive filter. The noisy signal is passed through a Finite Impulse Response (FIR) filter whose impulse response is matched with the shape of the noise-free signal. The impulse response of the said filter is estimated using the fourth order cumulant of the input signal. We also use a method to recursively utilize fourth order cumulants of the input signal for updating the coefficients of the adaptive FIR filter. This enables us to extract the VEP signal in real time. We show that the fourth order cumulant based method provides better results in comparison to the conventional third order cumulant based method and both yield better results as compared to the widely used autocorrelation function.

Key Words— **Visual Evoked Potentials, Higher-Order-Statistics, Adaptive Methods, Colored Gaussian Noise, Fourth-Order Cumulants.**

1. Introduction

VISUAL evoked potentials (VEPs) represent the gross electrical activity of a specific region of the brain usually resulting from a visual stimulation. Like other types of evoked potentials, the raw VEP is corrupted by noise as a result of the on-going activity of the brain cells. Signal-to-Noise Ratios (SNRs) of the raw VEPs are often less than 0.0 dB [4]-[8]. Ensemble averaging and weighted ensemble averaging have been widely used to extract evoked potentials from a noisy background [5]-[6],[8]. It has been shown that evoked potentials are non-stationary and therefore have characteristics that vary across stimuli [5],[7]. Thus, averaging methods fail to track dynamic changes that take place both in the latency and in the amplitude of the evoked potentials. Furthermore, averaging methods need a large number of records to obtain a suitable estimate of the EP. Classical filtering with known and fixed bandwidths is not usable for SNR enhancement of VEPs, as the spectrum of VEPs and the EEG overlap [5].

Adaptive filters have been extensively used for estimation of evoked potentials [1]-[3],[6]-[10]. They can track dynamic variations of EPs and reduce the noise that is uncorrelated with the underlying signal. The performance of an adaptive filter greatly depends on its reference signal, several of which have been used to extract evoked potentials. Vaz and Thakor [1] used a finite number of sine and cosine functions as the reference in the time domain. Laguna et al. [2] set the reference input as a unit impulse sequence; the onset of each is synchronized with the beginning of a corresponding epoch. This is based on the fact that EPs are responses that are time-locked to the stimulus. In order to establish the validity of results, one should use a known reference and show that the outcome (i.e., the constructed reference signal) closely matches the signal of interest. Furthermore, such filters are effective when noise is additive white Gaussian (AWGN). However, if noise is colored, the adaptive filter's impulse response is affected by the cross-correlation of the signal and colored noise, and its output contains noise as well as the signal [9]-[10].

In order to do this, during the past decade various methods have been developed in which higher-order-statistics (HOS or cumulants) are used for signal detection in Gaussian noise. The main advantage of using higher-order statistics is their insensitivity to the colored Gaussian noise. This is because higher-order-statistics of the Gaussian noise (white or colored) are identically zero [11]-[18]. Such approaches have been

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developed for harmonic retrieval [13], spectral estimation [14], [17], and line enhancement [15]. Gharieb et al. in [18] estimated the impulse response of the FIR matched filter by using a selected slice of the third order correlation of the input noisy signal. In [19] we presented a framework for using higher-order statistics for detection of transient signals embedded in Gaussian noise. Here, we apply the same to extract VEPs to demonstrate the usefulness and applicability of our approach.

In this paper we use a selected slice of the fourth order cumulant of the noisy signal to estimate the impulse response of the FIR matched filter, instead of using the third order correlation in [18]. We will show that the fourth order cumulant based method yields better results compared to the second and the third order correlation based methods. The results are clearly better than that of [18]. We also use a method to recursively utilize higher-order statistics of the input signal for updating the coefficients of an adaptive FIR filter. This enables us to extract the signal in real time, and improves the SNR at the output of the filter as compared to the use of third order correlation in [18]. Simulation and experimental results show that the proposed method is effective in real time tracking of VEPs and their variations.

The rest of the paper is organized as follows. In Section 2 we define the problem and briefly present the background material on HOS relevant to this work. In Section 3, we explain the algorithm. In Sections 4 and 5, we present simulation and experimental results, and the conclusions, respectively.

2. PROBLEM STATEMENT AND BACKGROUND MATERIALS

A. Problem Statement

We wish to extract a VEP signal *s(n)* from a noisy observation *x(n)*. The signal *s(n)* is modeled as sum of *P* exponentially damped sinusoids [18]-[21], and is contaminated by additive colored Gaussian noise *v(n)* of zero mean and unknown covariance, i.e.,

$$x(n) = s(n) + v(n) = \sum_{k=1}^{P} A_k e^{B_k n} + v(n)\,,\ 0 \le n \le N-1 \quad (1)$$

where *N* is the number of samples in *s(n)* and

$$A_k = \alpha_k e^{j\varphi_k}\ ,\ \ B_k = (\xi_k + j\omega_k)T \quad (2)$$

where α_k is the amplitude, ξ_k is the damping coefficient, ω_k is the frequency, and φ_k is the phase of the k^{th} sinusoid respectively, and *T* is the sampling time. We assume that P, α_k, φ_k, ξ_k and ω_k are unknown constants, and *v(n)* is a zero-mean additive noise statistically independent of *s(n)*. We further assume that *v(n)* is the output of a stable, linear time-invariant (LTI) filter driven by independent and identically distributed (i.i.d.) random variable with Gaussian distribution and bounded higher-order statistics. Given a finite data length, the problem is to extract *s(n)* from *x(n)*.

B. Fourth Order Cumulant

For ease of reference, we repeat some background material presented in [12] on the fourth order cumulant.

Cumulants may be defined as the coefficients in the Taylor series expansion of the log of the characteristics function of a random process, expanded about the origin. The fourth-order cumulants of a stationary zero-mean process $x(t)$ is

$$\begin{aligned} c_{4x}(\tau_1,\tau_2,\tau_3) = &\\ & E[x(t)x(t+\tau_1)x(t+\tau_2)x(t+\tau_3)] - \\ & - c_{2x}(\tau_1)c_{2x}(\tau_2-\tau_3) - \\ & - c_{2x}(\tau_2)c_{2x}(\tau_3-\tau_1) - \\ & - c_{2x}(\tau_3)c_{2x}(\tau_1-\tau_2) \end{aligned} \quad (3)$$

where $c_{kx}(\tau_1,...,\tau_{k-1})$ is the cumulant of the k^{th} order.

For a finite length deterministic signal *x(n)*, *n*=0,…*N*-1, the k^{th} order moment is

$$m_{kx}(\tau_1,...,\tau_{k-1}) \stackrel{\Delta}{=} \sum_{n=0}^{N-1} x(n)x(n+\tau_1)...x(n+\tau_{k-1}) \quad (4)$$

To obtain a consistent sample estimate of cumulants, we assume $\sum_{\tau_1,...,\tau_{k-1}} |c_{kx}(\tau_1,...,\tau_{k-1})| < \infty$ for *k* = 1, …, k_0, where k_0 is twice the value of the highest-order cumulant of interest. Given a sample sequence *x(n)*, *n*=0,…,*N*-1 for $k_0 = 8$, and as stated in [11], the estimate of fourth-order cumulant is

$$\begin{aligned} \hat{c}_{4x}(\tau_1,\tau_2,\tau_3) = & \frac{1}{N} m_{4x}(\tau_1,\tau_2,\tau_3) - \\ & - \frac{1}{N^2}[m_{2x}(\tau_1)m_{2x}(\tau_2-\tau_3) - \\ & - m_{2x}(\tau_2)m_{2x}(\tau_3-\tau_1) - m_{2x}(\tau_3)m_{2x}(\tau_1-\tau_2)] \end{aligned} \quad (5)$$

where $m_{kx}(.)$ is the deterministic k^{th} order moment of *x(n)*.

Now we consider several properties of the cumulants. It is shown in [12] that for any Gaussian *v(n)* of unknown covariance, we have

$$c_{kv}(\tau_1,...,\tau_{k-1}) \equiv 0 \qquad \text{for all } k>2 \quad (6)$$

Cumulants are additive, so the cumulant of the sum is equal to the sum of the cumulants. This implies that if noise is added to the signal as in (1), we have

$$c_{kx}(\tau_1,...,\tau_{k-1}) = c_{ks}(\tau_1,...,\tau_{k-1}) + c_{kv}(\tau_1,...,\tau_{k-1}) \quad (7)$$

Furthermore, we use (6) to write

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$$c_{kx}(\tau_1,...,\tau_{k-1}) = c_{ks}(\tau_1,...,\tau_{k-1}) \quad (8)$$

and use (8) to improve the signal-to-noise ratio (SNR) when noise is additive Gaussian.

3. Method

In order to extract VEPs, we use a one-dimensional slice of the fourth order cumulant of the noisy signal to estimate the impulse response of an FIR matched filter. We show that the use of fourth-order cumulant yields a better SNR as compared to the widely used second-order correlation and also as compared to the third order cumulant in [18]. As in [22], we utilize a matched filter whose impulse response is

$$h(n) = s(N-1-n) \qquad 0 \le n \le N-1 \quad (9)$$

where N is the length of *s(n)*. Since *s(n)* is the unknown VEP, we obtain its estimate by utilizing the higher-order statistics of the noisy signal. We use a one-dimensional slice of the cumulants by setting $\tau_1 = \tau$ and $\tau_i = 0$ for $1 < i \le k-1$, and write

$$h(\tau) = \hat{c}_{ks}(\tau,0,...,0) \quad (10)$$

For convenience, we use the simple notation $\hat{c}_{ks}(\tau)$ to represent $\hat{c}_{ks}(\tau,0,...,0)$. Now, we compute the impulse response of the filter as

$$h(\tau) = \hat{c}_{kx}(|P-\tau|), \qquad \tau = 0,1,...,2P \quad (11)$$

where P is the order of the matched filter. Eq. (11) implies that the length of the impulse response is $2P+1$. To obtain the impulse response, we need to estimate $P+1$ samples of the cumulant using the estimator in (5). A symmetrical impulse response implies a causal filter.

For real time tracking of the signal, we use the following recursive algorithm to estimate the cumulant

$$\begin{aligned}\hat{c}_{kx}(\tau \mid n) &= \lambda \hat{c}_{kx}(\tau \mid n-1) \\ &+ (1-\lambda)|x(n)x(n+\tau)x(n)...x(n)|,\end{aligned} \quad (12)$$

where $\tau = 0,1,..,K$, and $0 \le \lambda < 1$ is the so-called forgetting factor. Small values of λ yield fast tracking but poor smoothing, and large values result in slow convergence but better smoothing. The absolute sign in (12) is to avoid negative values in higher order cumulants. Fig. 1 shows a block diagram of the open loop, cumulant based adaptive filter.

4. Results

A. Artificial VEP

To demonstrate the effectiveness of our proposed method, we use an artificial VEP constructed from (1). The *s(n)* in (1) is a noise free damped sinusoid as

$$s(n) = -.1 + 1.5(0.99)^{|n-612|}(0.1+\cos(2\pi(0.003n)) \quad (13)$$

the duration of which is 500 msec, and is sampled at the rate of 4 kHz, i.e. the sequence length N is 2000. Fig. 2(a) shows *s(n)* vs. time, and Fig. 2(b) shows its power spectrum. We also generate *v(n)* in (1) as

$$v(n) = z(n) + g(n) \quad (14)$$

where *z(n)* is the white Gaussian noise and *g(n)* is the colored Gaussian noise generated by passing the white Gaussian noise through a 6^{th} order band-pass Butterworth IIR filter with cutoff normalized frequencies of 0.04 and 0.08. Figs. 2(c) and 2(d) show *v(n)* vs. time and its power spectrum respectively. Figs. 2(e) and 2(f) show the noisy signal with SNR = -10 dB, and its corresponding power spectrum respectively.

We consider a single VEP epoch embedded in colored Gaussian noise shown in Fig. 2(e), and use a non-adaptive matched filter (Eq. 11) that utilizes the second, the third and the fourth order cumulants of the input noisy signal. The results are shown in Fig. 3. We set the order of the matched-filter to P=28. Fig. 2(f) shows that the power of white noise in noisy signal is about -10 dB and the power of colored noise is about +10 dB.

Fig. 3(a) shows the enhanced signal vs. time using the conventional autocorrelation based method and Fig. 3(b) shows its corresponding power spectrum. In Figs. 3(c) and 3(d) the enhanced signal in the third-order cumulant based method and its corresponding power spectrum are shown. The output of the fourth order cumulant based filter and its corresponding power spectrum are shown in Figs. 3(e) and 3(f) respectively.

In autocorrelation based approach, we obtain about 10 dB attenuation in the power of white and colored noise. For the third order cumulant based method we obtain about 20 dB attenuation for the white noise and 15dB for the colored noise power. In the fourth order cumulant based method, 30 dB attenuation for the power of white noise and 20 dB attenuation for the power of colored noise is achieved.

Now we apply the autocorrelation based, the third order cumulant based and the fourth order cumulant based adaptive approaches to a quasi-periodic version

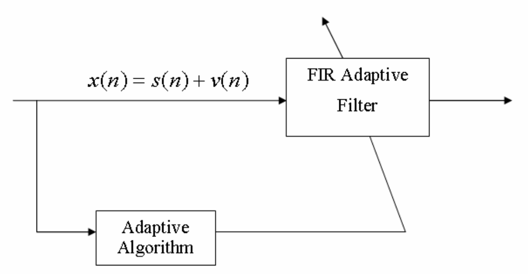

Fig. 1 - Block diagram of the adaptive filtering scheme

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of the noisy VEP in Fig. 2(e). The SNR for quasi-periodic noisy VEP at the input is –10 dB. The results are shown in Fig. 4 for two matched filters with orders P=32 and 64. Note that the fourth order cumulant based (adaptive) (Fig. 4) and non-adaptive (Fig. 3)) approaches yield better results as compared to the autocorrelation-based and to the third order cumulant methods. Furthermore, the fourth order cumluant based adaptive method enables us to extract the VEP in real time. It is evident from Fig. 4 that increasing the order of the matched-filter from 32 to 64 yields a better SNR.

B. Real VEP Acquisition and Processing

Now we apply our proposed method to extract the VEP from actual recording of human subjects. The subjects are males, between 19 and 23 years old, and without any visual disorders. We use Nicolet 1050 instrument for recording signals, and apply a simple grating pattern shown in Fig. 5 for stimulation, which has 100% contrast and 2 cpd (cycle per degree) spatial frequency. The VEP is recorded by using 3 electrodes that are placed on the scalp in visual cortex in 10-20 system (the active electrode on O_z, the ground electrode on C_z and the reference electrode on F_{P_z}) as in [23]. Fig. 6(a) shows the recorded VEP and Fig. 6(b) shows its corresponding power spectrum. Each epoch has 512 samples with duration of 250 msec and sampling frequency of $f_s = 2\,\text{kHz}$.

The results for the fixed matched-filter with P=40 are shown in Fig. 7. It is evident that the SNR in the fourth order cumulant based approach is improved compared to both the autocorrelation and the third order cumulant based methods, and the third order cumulant based method yields better results as compared to the autocorrelation based method.

Now, we apply our adaptive filter with P= 40 and $\lambda = .9995$. The results are shown in Fig. 8 for the autocorrelation, the third order cumulant, and the fourth order cumulnat based methods. It is evident that the results are improved as compared to the non-adaptive approaches in Fig. 8. It can also be seen that the higher order statistics based adaptive filtering achieves better results as compared to the autocorrelation based adaptive filtering. The results for the third order cumulant and the fourth order cumulant based methods are close to each other in this case.

5. CONCLUSION

We developed an adaptive filter in which we use higher order statistics to detect VEPs on line. The fact that our proposed method is capable of extracting VEPs on line is important in detecting VEP anomalies in each epoch, as compared to other methods that in effect average out the VEPs over the entire epochs.

We have shown that the SNR is also improved significantly as compared to other existing methods.

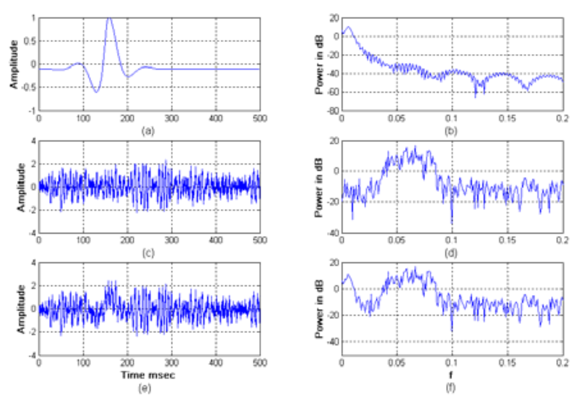

Figure 2- (a) The noise free signal; (b) The power spectrum of (a); (c) The additive noise; (d) The power spectrum of (c); (e) The input noisy signal; (f) The power spectrum of (e).

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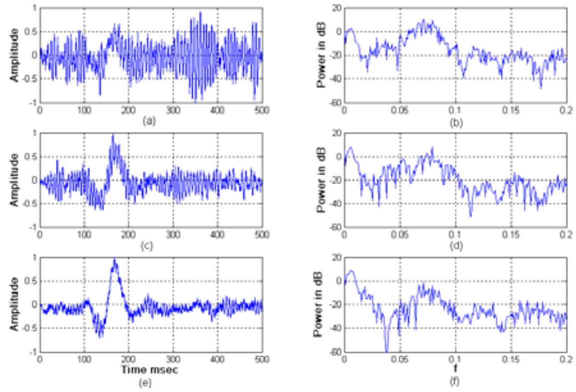

Figure 3- The output of the non-adaptive matched filter with the order *P=28*, (a) The output of the autocorrelation based filter; (b) The power spectrum of (a); (c) The output of the third order cumulant based filter; (d) The power spectrum of (c); (e) The output of the fourth order cumulant based filter; (f) The power spectrum of (e).

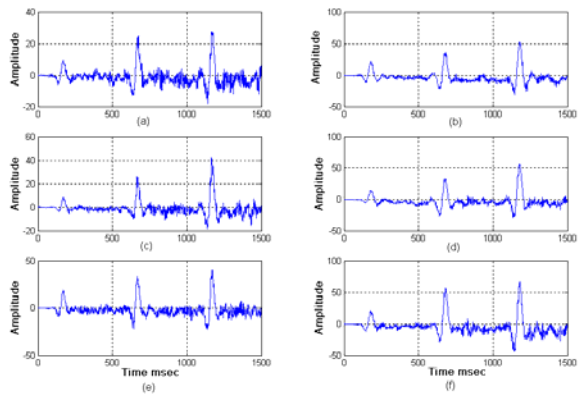

Figure 4- The output of the adaptive filter, (a) The output of the autocorrelation based adaptive filter for *P=32*; (b) The output of the autocorrelation based adaptive filter for *P=64*; (c) The output of the third order cumulant based adaptive filter for *P=32*; (d) The output of the third order cumulant based adaptive filter for *P=64*; (e) The output of the fourth order cumulant based adaptive filter for *P=32*; (f) The output of the fourth order cumulant based adaptive filter for *P=64*.

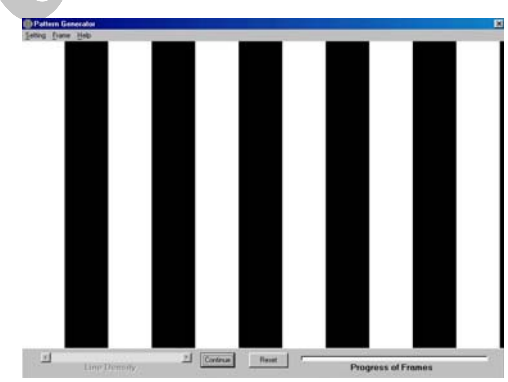

Figure 5- Grating stimulation pattern used for generating the VEPs.

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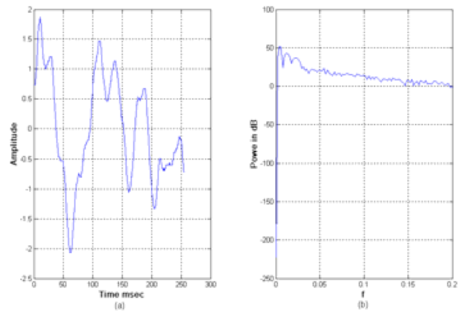

Figure 6- (a) Recorded VEP; (b) The power spectrum of (a).

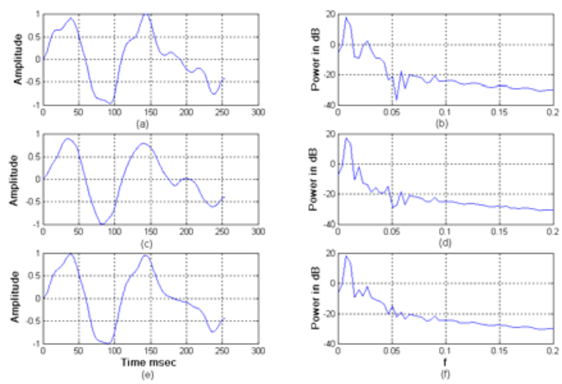

Figure7- The output of the non-adaptive filter with the order *P=40* for real VEP data, (a) The output of the autocorrelation based filter; (b) The power spectrum of (a); (c) The output of the third order cumulant based filter; (d) The power spectrum of (c); (e) The output of the fourth order cumulant based filter; (f) The power spectrum of (e).

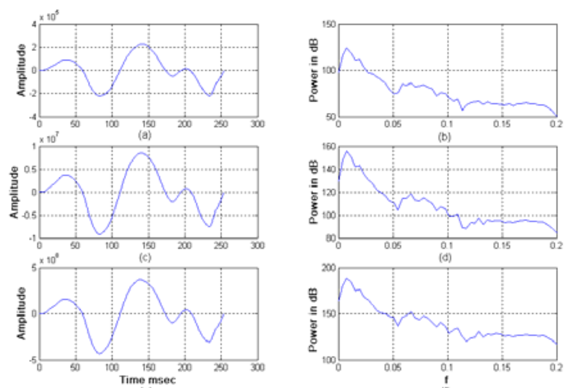

Figure 8- The output of the adaptive filter for *P=40* and $\lambda = .9995$, (a) The output of the autocorrelation based adaptive filter; (b) The power spectrum of (a); (c) The output of the third order cumulant based adaptive filter; (d) The power spectrum of (c); (e) The output of the fourth order cumulant based adaptive filter; (f) The power spectrum of (e).

REFERENCES

1- C. A. Vaz and N. V. Thakor, "Adaptive Fourier estimation of time-varying evoked potentials," *IEEE Trans. Biomed. Eng.*, vol. 36, pp. 448-455, April 1989.

2- P. Laguna, *et al.*, "Adaptive filter for event-related bioelectric signals using an impulse correlated reference input: comparison with signal averaging techniques," *IEEE Trans. Biomed. Eng.*, vol. 39, pp. 1032-1044, Oct. 1992.

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3- N. V. Thakor, *et al.*, "Orthonormal (Fourier and Walsh) models of time varying evoked potentials in neurological injury," *IEEE Trans. Biomed. Eng.*, vol. 40, pp. 213-221, March 1993.
4- O. Rompelman and H. H. Ross, "Coherent averaging technique: A tutorial review part I: noise reduction and the equivalent filter, part 2: trigger filter, overlapping response and non periodic stimulation," *J. Biomed. Eng.*, vol. 8, pp. 24-35, 1988.
5- E. Niedermeyer and F. Lopez da Silva, *Elecroencephalography*, Urban & Schwarzenberg, 2nd edition 1987.
6- M. Akay, *Biomedical Signal Processing*, Academic Press Inc., 1994.
7- J. P. C. De Weerd and J. I. Kap, "Spectro-Temporal representation and time-varying spectra of evoked potentials," *Biol. Cybern.*, vol. 41, pp. 101-117, 1981.
8- J. P. C. De Weerd, "A posterior time-varying filtering of averaged evoked potentials, mathematical and computational aspects," *Biol. Cybern.*, vol. 41, pp. 223-234, 1981.
9- B. Widrow and S. D. Stearn, *Adaptive Signal Processing*, Prentice Hall, 1985.
10- N. V. Thakor, "Adaptive filtering of evoked potentials," *IEEE Trans. Biomed. Eng.,* vol. BME-34, pp. 6-12, 1987.
11- B. M. Sadler, G. B. Giannakis, and Keh-Shin Lii, "Estimation and Detection in NonGaussian Noise Using Higher Order Statistics," *IEEE Trans. Signal Processing*, vol. 42, No. 10, pp. 2729-2741, 1994.
12- J. M. Mendel, "Tutorial on higher-order statistics (spectra): theoretical results and some application," *Proc. IEEE*, vol. 70, pp. 278-305, 1991.
13- J. M. Anderson, G. B. Giannakis, and A. Swami, "Harmonic retrieval using higher order statistics: A deterministic formulation," *IEEE Trans. Signal Processing*, vol. 43, No. 8, pp. 1880-1889, 1995.
14- J. Muthuswamy, D. L. Sherman, and N. V. Thakor, "Higher order spectral analysis of burst pattern in EEG," *IEEE Trans. Biomed. Eng.*, vol. 46, pp. 92-99, January 1999.
15- H. M. Ibrahim, R. R. Gharieb, and M. M. Hassan, "A higher order Statistics based adaptive algorithm for line enhancement," *IEEE Trans. Signal Processing*, vol. 47, pp. 527-531, Feb. 1999.
16- G. B. Giannakis and M. K. Tsatsanis, "Signal detection and classification using matched filtering and higher order statistics," *IEEE Trans. Acoust. Speech and Signal Proc.*, vol. 38, No. 7, July 1990.
17- C. L. Nikias and A. P. Petropulu, *Higher Order Spectral Analysis: A Nonlinear Signal Processing Framework*, Prentice-Hall, 1993.
18- R. R. Gharieb and A. Cichocki, "Noise reduction in brain evoked potentials based on third-order correlations," *IEEE Trans. Biomed. Eng.*, vol. 48, pp. 501-512, May 2001.
19- A.R. Sharafat and H. Daneshvar, "Extraction of transient signals in Gaussian colored noise: recursive application of higher-order-statistics in adaptive filters," *Proceedings of IST 2003*, August 16-18, 2003, Isfahan, Iran, pp. 529-533, 2003.
20- T. Demiralp, A. Ademoglue, Y. Istefanopulos, and H. O. Gulcur, "Analysis of event-related potentials (ERP) by damped sinusoids," *Biol. Cybern.*, vol. 78, pp. 487-493, 1998.
21- R. Kumaresan and D. Tufts, "Estimating the parameters of exponentially damped sinusoids and pole-zero modeling in noise," *IEEE Trans. on Acoust. Speech Signal Processing,* vol. ASSP-30, pp. 833-840, Dec. 1982.
22- S. V. Vaseghi, *Advanced Signal Processing and Digital Noise Reduction*, Wiley & Teubner, 1996.
23- H. Jasper, "The ten twenty electrode system of the International Federation," *Electroencephalography and Clinical Neurophysiology*, vol. 10, pp. 371-375, 1958.

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