ON THE DETECTION OF STEADY-STATE VISUALLY EVOKED POTENTIALS

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Abstract – **In this paper we develop a new method, based on the periodogram of a time-series, for the detection of steady-state VEPs. The method tests the data for the presence of hidden periodic components, which correspond to steady-state VEPs.**

I. INTRODUCTION

The objective perimetry is based on the analysis of visual evoked responses. In the ophthalmologic diagnostics, well-defined light stimuli are used for stimulating the visual system. These stimuli elicit responses in the visual cortex, which are acquired as VEPs, whose shape is sinusoidal. The detection problem then is reduced to find this a priori known periodic component in the spontaneous EEG [1]. In the sequel we develop a new method for the detection of steady-state VEPs (ssVEPs), based on the periodogram of a time-series. We denote stochastic quantities by bold letters.

II. METHODS

A. Periodogram

If $\{\mathbf{y}(n),\, n=1,\ldots,N\}$, are samples of a stationary time-series, then periodogram ordinates

$$\mathbf{I}_y(\omega_k) = \frac{1}{N}\left|\sum_{n=1}^{N} \mathbf{y}(n)e^{-j\omega_k n}\right|^2, \tag{1}$$

where $\omega_k = \frac{2\pi k}{N}$, $k=1,\ldots,N$, are asymptotically independent exponential random variables with mean $S_y(\omega_k)$, where $S_y(\omega)$ is the power spectral density (psd) of $\{\mathbf{y}(n)\}$ [2]. Equivalently, we can say that the random variable $\mathbf{I}_y(\omega_k)/S_y(\omega_k)$ is distributed according to the $\chi^2(2)/2$ distribution, i.e.,

$$\frac{\mathbf{I}_y(\omega_k)}{S_y(\omega_k)} \sim \frac{1}{2}\chi^2(2). \tag{2}$$

In the sequel we assume that N is large enough such that we may *regard periodogram ordinates as independent exponential random variables.*

B. Data Models

The VEPs are generated by a sequence of green bright LED flashes with frequency 8Hz ($L = 20\ldots40 * 10^4$ cd/m^2; $\lambda = 560nm$). To elicit visually evoked responses, the EEG is recorded using sixteen electrodes placed over the visual cortex. We process the data derived from the channel Oz-AVO. We derive one time-series, for each stimulated eye position, after time averaging over 16 realizations. Each time-series is composed of:

- 1000 samples pure EEG data, recorded just before the stimulation begun (pre-stimulus signal).
- 1000 samples EEG plus stimulation response data, recorded just after stimulation begun (post-stimulus signal).

The data models for the pre- and post-stimulus signals are

$$\mathbf{x}_{pre}(n) = \mathbf{y}_{pre}(n), \tag{3}$$

$$\mathbf{x}_{post}(n) = \sum_{i=1}^{m} A_i \cos(i\omega_0 n) + \mathbf{y}_{post}(n), \tag{4}$$

where m is the number of harmonics we are trying to detect, A_i, $i=1,\ldots,m$, are non-random numbers, and ω_0 is the basic stimulation frequency. The time-series $\mathbf{y}_{pre}(n)$ and $\mathbf{y}_{post}(n)$ represent the pure EEG signal in the pre- and post-stimulus data, respectively. If the EEG is assumed to be a stationary signal, then these time-series can be considered as parts of the same stationary process, implying that their psd's, denoted by $S_{ypre}(\omega)$ and $S_{ypost}(\omega)$, respectively, coincide. In the sequel we make a less restrictive assumption, which gives us the ability to handle a special type of EEG nonstationarity. More specifically, we assume that $S_{ypre}(\omega)$ and $S_{ypost}(\omega)$ are connected via a scaling factor, i.e.,

$$S_{ypost}(\omega) = \sigma S_{ypre}(\omega). \tag{5}$$

It is well known that the EEG signal is nonstationary, especially over certain frequency ranges (for example, over the α-band). However, at frequencies higher than the α-band we do not expect wild non-stationarities. Thus, the assumption of the aforementioned special type of nonstationarity (which includes stationarity), over this frequency range, appears to be quite reasonable.

C. Test for the presence of hidden periodicities

Based on the post-stimulus data model given in (4), we define the null and the alternative hypotheses as

$$H_0 : A_i = 0 \quad \text{for all} \quad i.$$
$$H_1 : H_0 \quad \text{is} \quad \text{false}.$$

Under H_0, $\mathbf{x}_{post}(n) = \mathbf{y}_{post}(n)$, which means that $\mathbf{I}_{xpost}(\omega) = \mathbf{I}_{ypost}(\omega)$. Using this observation and (2), we obtain that under H_0

$$\frac{\mathbf{I}_{xpost}(\omega_k)}{S_{ypost}(\omega_k)} \sim \frac{1}{2}\chi^2(2). \qquad (6)$$

On the other hand, under H_1, $\mathbf{I}_{xpost}(i\omega_0)$ is expected to be larger than $\mathbf{I}_{ypost}(i\omega_0)$, due to the power of the superimposed sinusoids. Thus, under H_1, we expect that for $1 \leq i \leq m$,

$$\frac{\mathbf{I}_{xpost}(i\omega_0)}{S_{ypost}(i\omega_0)} \succ \frac{1}{2}\chi^2(2), \qquad (7)$$

with "$\succ$" meaning that the random variable at the left-hand side takes, with high enough probability, larger values than a $\chi^2(2)/2$ distributed random variable takes. In order to develop a statistical test based on relations (6) and (7), we must compute $\mathbf{I}_{xpost}(\omega_k)$ and $S_{ypost}(\omega_k)$. We can easily compute $\mathbf{I}_{xpost}(\omega_k)$ via (1). The most natural estimate of $S_{ypost}(\omega_k)$ can be computed through the post-stimulus data. However, our post-stimulus data contain both EEG and stimulation response. Consequently, its psd around the harmonics of the basic stimulation frequency, $i\omega_0$, $1 \leq i \leq m$, differs from $S_{ypost}(\omega)$. Thus, we should estimate $S_{ypost}(\omega)$, around these harmonics, using some interpolation technique. An alternative solution would be to estimate $S_{ypost}(\omega_k)$ using $\mathbf{x}_{pre}(n)$. In this way we compute $S_{ypre}(\omega_k)$ which, as we have already assumed in (5), is connected with $S_{ypost}(\omega_k)$ via the scaling factor σ. We select the smoothed periodogram as a robust and reliable way to construct a consistent estimate of $S_{ypre}(\omega_k)$ [3]. Thus, we reject the hypothesis H_0 in favour of H_1 if $\sum_{i=1}^{m} \mathbf{I}_{xpost}(i\omega_0)/S_{ypre}(i\omega_0)$ is sufficiently large. To determine how large, we observe, recalling the (assumed) independence of the periodogram ordinates, (2), (5) and well known formulas for the sum and the ratio of independent χ^2 random variables [4], that under H_0

$$\mathcal{A}_1 = \sum_{i=1}^{m} \mathbf{I}_{xpost}(i\omega_0)/S_{ypre}(i\omega_0) \sim \frac{\sigma}{2}\chi^2(2m), \qquad (8)$$

$$\mathcal{A}_2 = \sum_{\substack{k=1 \\ \omega_k \neq i\omega_0, i=1,\ldots,m}}^{N/2} \mathbf{I}_{xpost}(\omega_k)/S_{ypre}(\omega_k) \sim \frac{\sigma}{2}\chi^2(N-2m), \qquad (9)$$

and

$$\mathcal{A} = \frac{\mathcal{A}_1/2m}{\mathcal{A}_2/(N-2m)} \sim F(2m, N-2m). \qquad (10)$$

Consequently, we reject H_0 in favour of H_1 at level a if

$$\mathcal{A} > F_{1-a}(2m, N-2m). \qquad (11)$$

Remark 1. From a Signal Processing point of view $\mathbf{I}_{xpost}(\omega_k)/S_{ypre}(\omega_k)$, is the (approximate) periodogram of the pre-whitened post-stimulus data, using for pre-whitening the pre-stimulus data. From a Statistics point of view division of $\mathbf{I}_{xpost}(\omega_k)$ by $S_{ypre}(\omega_k)$ is an effort for transformation of the random sequence $\mathbf{I}_{xpost}(\omega_k)$ to a sequence of $\frac{\sigma}{2}\chi^2(2)$-distributed random variables.

Remark 2. In order to be able to detect stimulation response we must detect peaks in the sequence $\mathbf{I}_{xpost}(\omega_k)/S_{ypre}(\omega_k)$. This sequence expresses in a way the "change" of the signal psd between the post- and pre-stimulus parts. Thus, our requirement for stimulation response detection may be translated to "*larger mean increase (smaller mean decrease) of the post-stimulus over the pre-stimulus psd's at specified harmonic frequencies, compared with the corresponding mean increase (decrease) over the neighbouring frequencies*".

Remark 3. We use the independence and the special type of nonstationarity assumptions in order to be able to derive closed form expressions for the pdf's of the various quantities of interest. We may drop both assumptions and compute the pdf of $\mathcal{A}$, under H_0, experimentally. We must note that we found a striking resemblance between the experimental estimates computed using pure EEG data and the theoretical quantities derived from the aforementioned assumptions.

III. Results

In Figure 1 we present an application of the statistical test to real data. We are looking for sinusoidal terms with frequencies 8, 16, 24, and 32 Hz, since the basic stimulation frequency in our experiment was 8Hz. Observing the "normalized" or "pre-whitened" post-stimulus periodogram we see large peaks at the harmonics of 8Hz. In this case $\mathcal{A} = 10.08$ and consequently we reject H_0 in favour of H_1 at level 10^{-16}.

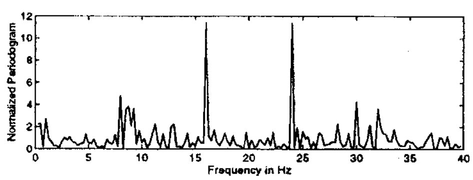

Fig. 1. Pre-whitened Post-stimulus Periodogram

References

[1] G. Henning, O. Hoenecke, P. Husar, K. Schellhorn, U. Trautwein, "Time-Frequency Analysis of Flicker-Burst Visual Evoked Respones", *Proceedings of IEEE Engineering in Medicine and Biology*, 1995.

[2] P. Brockwell and R. Davis, "*Time-Series: Theory and Methods*", Springer-Verlag, 1991.

[3] L. Ljung, "*System Identification - Theory for the User*", Prentice Hall, Englewood Cliffs, NJ, 1987.

[4] A. Papoulis, "*Probability and Statistics*", Prentice Hall, Englewood Cliffs, NJ, 1990.