ANALYSIS OF VISUAL EVOKED POTENTIALS THROUGH WIENER FILTERING APPLIED TO A SMALL NUMBER OF SWEEPS

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ABSTRACT

We introduce a method for processing visual evoked potentials, on the basis of a Wiener filter algorithm applied to a small number of consecutive responses. The transfer function of the filter is obtained by taking into account both the average of 99 sweeps (as an estimate of the true signal) and the EEG signal just before the stimulus onset (as an estimate of the noise superimposed on each individual response). The process acts as a sweep-by-sweep filter (in the sense of the mean square error) which considers the possible non-stationarities of the EEG signal during a complete clinical procedure. The average of a small number of consecutive filtered sweeps reveals variations in the morphology of the evoked responses which produce a change in the principal latencies. Applications are foreseen in neurophysiological studies of visual evoked potential responses, and in the clinic, where it is important to evaluate adaptive mechanisms, dynamic changes in single groups of visual evoked potentials and cognitive responses.

Keywords: Signal processing, EEG, visual evoked potential, parametric identification, Wiener filtering, neuroscience

INTRODUCTION

Because it is possible to select for measurement only a few parameters (basically amplitudes and latencies of the main peaks of the response) which have precise neurophysiological and clinical relevance, in recent years there has been an increasing interest in cerebral stimuli (visual, acoustic or somatosensory) and event-related responses[1–4,23]. The analysis of the assumed stationary EEG activity, which is strongly influenced by quasi-random oscillations, is unable to provide, with the same precision, a quantitative index of the behaviour of those neural pathways along which an electrical stimulus is propagated. Unfortunately, as Gevins[4] and others have recently pointed out, even such deterministic responses show, in varying degree, some sweep-by-sweep changes due to both casual modifications of the structure of the neural network involved, and to systematically different evoked response patterns during the entire clinical examination which may last from a few minutes to an hour or more; a time which reflects the fact that in order to improve the signal-to-noise ratio, responses are averaged after many repetitive and identical stimuli. Some hypotheses must be satisfied and these will be described in the next section. Therefore, there is an intrinsic conflict between the need for many responses, in order to improve the S/N ratio, and the ever increasing demand for a single sweep (or at least a small number of consecutive sweeps) analysis.

This last approach will be considered here; it employs an optimal digital filter (in the mean square error sense), i.e. a Wiener filter which is capable of obtaining single sweep responses with a considerable increase in S/N ratio. The method is based on recent results reported in the literature[5,6] with the difference that the contribution of noise in this case is taken from the EEG before the stimulus onset, thus assuming that EEG statistical properties (estimated by autoregressive modelling) do not change substantially either before or after the stimulus. Future development will take into account changes in the basal EEG, with or without the activity of the selective cerebral nuclei stimulated by the visual pattern reversal used in the present research.

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PROCESSING OF EVOKED POTENTIALS

The main problem in processing evoked potentials (EP) is the presence in the recorded data of noise which is not simply superimposed on the useful signal, as would be the case for muscle artefacts, thermal nose and dielectric phenomena, but also corrupted by an 'intrinsic' noise: the background EEG, whose source is the same cortical neurons which are responsible for the generation of event-related cerebral processes, although in a more circumscribed and synchronized way in both the temporal and spatial sense.

This particular situation leads to some important consequences. First, the usual simplified hypothesis in signal processing of noise additively superimposed and uncorrelated with the signal is more difficult to justify, due to the relationship between the two sources; in fact a complex and probably non-linear interaction exists between the two signals. For example, recent studies[7] tend to enhance the phenomenon of phase ordering in the

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EEG, related to the stimulus. It seems likely that both the recruitment of silent populations of neurons, and some type of 'reset' of other neurons still active, are involved in the evoked response, possibly with a different relative importance with respect to the variable state of this complex system on the arrival of a stimulus.

It is not easy either to understand the actual effect of this behaviour, if it is true, on the evoked potential itself as recorded from the surface of the scalp, or to evaluate how well the additive model describes the actual situation, at least for the more common clinical applications. It would be easy to define the evoked response as the difference between the recorded activity and the background EEG, but unfortunately the EEG is also a non-deterministic signal[8] and certainly less deterministic than the EP. Thus, this process of addition must be assumed to act in a stochastic way, and possibly be tested *a posteriori* on that hypothesis. However, the result is not easy to verify, because the reference signal is unknown[4]. It is the well known problem of the 'gold standard' so important in biological data processing: the absence of an exact *a priori* knowledge of the true signal (or the true noise) leads to problems of increasing difficulty in detection and in comparing the results from different approaches.

In spite of all these theoretical problems, evoked potentials have been successfully employed for many years in psychology, sensory physiology and clinical medicine[2,25], although generally in confirmation of a diagnosis obtained from other investigations rather than as a primary diagnosis[4].

The classical method used to extract the evoked response from the background EEG is the synchronized average of many successive responses to the same repetitive stimulus (≈ 100 in the visual case)[1,9,10,24].

This is performed on the hypothesis of additive superposition of the two signals: EP [$s(t)$] and the background EEG, viewed as a noise [$n(t)$]. The recorded electrical activity, $y(t)$, related to the stimulus may be modelled as follows:

$$y(t) = s(t) + n(t).$$

By supposing also that:

(i) the EP is stationary over the successive trials, i.e. the response to the same stimulus is always the same for the whole recording;

(ii) the background EEG is a zero-mean random signal;

(iii) it is uncorrelated with the EP and

(iv) the background EEG recordings are uncorrelated with one another;

then the averaging technique allows us to improve the signal-to-noise ratio by a factor N, equal to the number of repetitions. In reality, the resultant pattern may be only a rough estimate of the average of the many responses involved, because all the hypotheses are not necessarily justified: it is well known[4] that the morphology of event related-processes is not exactly the same for different trials.

To avoid the assumption that the evoked response is a purely deterministic signal, it would be useful to perform a single-sweep analysis of the evoked potential[11]. It is necessary then, to have an alternative method for improving the signal to noise ratio, which is so unfavourable that it is quite impossible to detect an event-related pattern in the absence of difficult assumptions concerning the nature of the generating model of the recorded signal.

We have applied a minimum mean-square error filter to the signal in the frequency domain, a process well known in stochastic signal processing as the Wiener filter[12]. This approach is not free from *a priori* hypotheses: the signal and the noise are always supposed to be additively superimposed and uncorrelated, and the need for a theoretically exact repetition of the same EP is removed, but for the Wiener filter spectral models for the signal and the noise are now required separately.

The first approach of this type was to filter the average[5,13]: a kind of post processing which leads to a selective improvement in the S/N ratio, different at different frequencies of the spectrum, provided that models for the spectrum of the signal and of the noise can in some way be estimated.

Usually, the spectrum of the signal plus $1/N$ times the noise is assumed to be the spectrum of the average, according to the improvement in the S/N ratio obtained in the theoretical case, for which the hypotheses are fully satisfied.

The noise spectrum is estimated in different ways by different authors.

(i) An exact repetition of the same EP sweep leads to an average with polarity reversed on alternate sweeps, with the aim of eliminating the signal, keeping only the noise.

(ii) The additive superposition hypothesis for the EP and the background EEG suggests the subtraction of the average from the post-stimulus, and then the average of the residuals is computed to obtain an estimate of the noise.

(iii) A third approach[5] is to estimate the noise spectrum by subtracting the spectrum of the average from the average of the spectra of all sweeps; in this case the additive superposition is in some sense supposed for the powers too, which implies an absence of correlation between the signal and the noise.

Some improvements have been introduced to avoid the intrinsic problem of applying an inherently time-invariant method, such as the Wiener filter, to a transient signal – the EP. The time varying Wiener filter proposed by de Weerd[14] is a bank of filters with time varying gain, while Yu and McGillem[15] extract the fluctuations in several hypothesized components in the time domain. All the approaches reported are both interesting and useful; they imply that the average of many sweeps is being considered, thereby rendering impossible an evaluation of the variability of event-related processes from one trial to another.

It is therefore desirable to attempt an analysis of single sweep responses instead of averaging many trials[16]. In this single sweep approach, the synchronized average may still be used for an *a priori* estimation of the signal spectrum. The estimation of the noise spectrum is instead made on the pre-stimulus EEG of each sweep[17]: under the hypothesis of additive superposition of the signal and the noise, necessary for the application of the Wiener filter, the background EEG is assumed to have the same statistical, and therefore spectral, characteristics both before and after the stimulus, a total duration of 1 s.

This is in agreement with the classical analysis of the statistical properties of the background EEG, which aims at evaluating its wide sense stationarity, i.e. the stationarity of the first and second order statistical moments, for periods of finite length. We have chosen a 2 s period which is in a wide sense stationary, a period which is the duration adopted for the autoregressive analysis of the background EEG by Bodestein and Praetorius[18] and ourselves[19] with satisfactory results.

THE PROPOSED METHOD: WIENER FILTERING OF EP WITH NOISE ESTIMATION FROM THE PRESTIMULUS

The Wiener filter[12] allows one to estimate the 'optimal' form of a signal, corrupted by an additive stochastic noise, by minimizing the mean square error. In the frequency domain the Wiener filter is characterized by the transfer function:

$$\mathcal{H}(\omega) = \frac{\phi_{ss}(\omega)}{\phi_{ss}(\omega) + \phi_{nn}(\omega)}$$

where $\phi_{ss}(\omega)$ is the power spectral density (PSD) of the signal and $\phi_{nn}(\omega)$ is the PSD of the noise.

This transfer function weighs the spectral components of the input signal (corrupted by noise) at each frequency; the maximum attenuation is obtained at those frequencies where the noise is most powerful with respect to the signal, as will readily be seen from the analytical expression of the transfer function.

However, to determine this transfer function it is necessary to have an *a priori* knowledge of both the signal and the noise spectrum or, at least to have an estimate of them. In particular, the application of the filter to a single evoked potential trial suggests that one should obtain an estimate of the noise which strictly correlates with the process under analysis.

The single sweep signal $x_i(t)$, recorded simultaneously with the stimulus triggered at $t = 0$, is modelled as

$$x_i(t) = \begin{cases} n_i(t) & = x_i^-(t) \quad t \leqslant 0 \\ s_i(t) + n_i(t) & = x_i^+(t) \quad t > 0 \end{cases}$$

where the evoked response $s_i(t)$ is zero before the stimulus, according to the definition of causality in the time domain of the process under analysis[20], i.e. no response is supposed to exist before the stimulus itself. This kind of model implies the previously discussed hypothesis of additive superposition of the signal and the noise $n_i(t)$ as represented by the background EEG. Now if this hypothesis is accepted, it is easy to assume that the noise $n_i(t)$ has the same stochastic properties before and after the stimulus, for a total period of 1 s. In fact, all the data on the background EEG reported in the previous section agree that this signal may be considered as wide sense stationary for a few seconds.

The natural consequence of this reasoning is to assume the PSD of the prestimulus EEG [$n_i(t)$ for $t \leqslant 0$] as a useful estimate for the post-stimulus noise $n_i(t)$ for $t > 0$; results will confirm or possibly reject this simplification. However, it is important to point out that the main hypothesis implied in this approach is the summation of the two components, postulated in the literature but impossible to prove for lack of a reference signal. One possible inadequacy of this model may be attributed to the non-linear effects of the arrival of the stimulus on the EEG; effects which have been analysed by Perry and Childers[1] who conclude that although the additive superposition is a simplified model, it is a good approximation in practical applications.

Less critical is the choice of an estimate for the spectrum of the signal. In our approach, we take the classical synchronized average as the first estimate of the evoked response. Thus, the PSD obtained from the average is taken as an estimate of the PSD of the signal.

This need for preprocessing the data in order to obtain the average implies an off-line analysis from a recording of the whole period. This step may in future be avoided by using a parametric model of the EP as a reference estimation, its parameters being related to the actual condition of the patient.

In this sense, an approach to a black-box model of the EP was proposed[21]. In all cases, it is necessary to point out that our use of the average in this paper is quite different from the application of a Wiener filter to the average reported above. In that application, the average was the input of the filter, while here the average is the reference for the

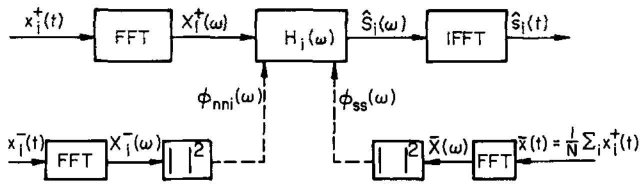

Figure 1 The proposed procedure of Wiener filtering relative to the single sweep x_i

signal in the transfer function, and the input is the single-sweep post-stimulus.

The diagram of the whole filtering procedure is shown in *Figure 1* for the single sweep $x_i(t)$: the input $x_i^+(t)$ is the single post-stimulus of the ith trial: the transfer function is defined[12] as

$$\mathcal{H}_i(\omega) = \frac{\phi_{ss}(\omega)}{\phi_{ss}(\omega) + \phi_{nni}(\omega)}$$

where $\phi_{ss}(\omega)$ and $\phi_{nni}(\omega)$ are respectively the PSD's of $s(t)$ and of $n_i(t)$. $\mathcal{H}_i(\omega)$ is different from one sweep to another as a consequence of the term $\phi_{nni}(\omega)$ estimated on the corresponding prestimulus signal.

The filter is defined in the frequency domain. Then, the FFT of the post-stimulus is taken as the input of the Wiener filter (*Figure 1*), the output of the filter being the inverse-FFT which allows one to obtain the filtered signal $s_i(t)$ in the time-domain.

In some cases the result is not sufficient to enhance the evoked response because of the unfavourable S/N ratio: it is therefore possible to make a partial average of some consecutive filtered response $s_i(t)$. By using a smaller number of sweeps than in the usual averaging method, it will be possible to reach a good compromise between the improvement of the S/N ratio which comes from the averaging procedure and the need of measuring the variability of the evoked response in the usual protocol of progressive trials.

SIMULATION TESTS

Two types of test were developed to evaluate the performance of the filter under conditions similar to those of the actual model of a quasi-deterministic signal (the evoked response) superimposed on a stochastic process (the background EEG). The stochastic process $n(k)$ is always simulated in these tests by means of white noise having a zero mean value and variance λ^2, for simplicity $[n(k) \approx \mathrm{WN}(0, \lambda^2)]$.

The signal $s(k)$ is simulated first by a narrow-band signal (a sinusoid of 6 Hz) in the principal spectral region of the evoked potential, and then by a wide-band transient of the form $[s(k) = A\ \alpha\ k \exp(-\ \alpha k)]$ (with $\alpha = 0.25$), also proposed by de Weerd[5].

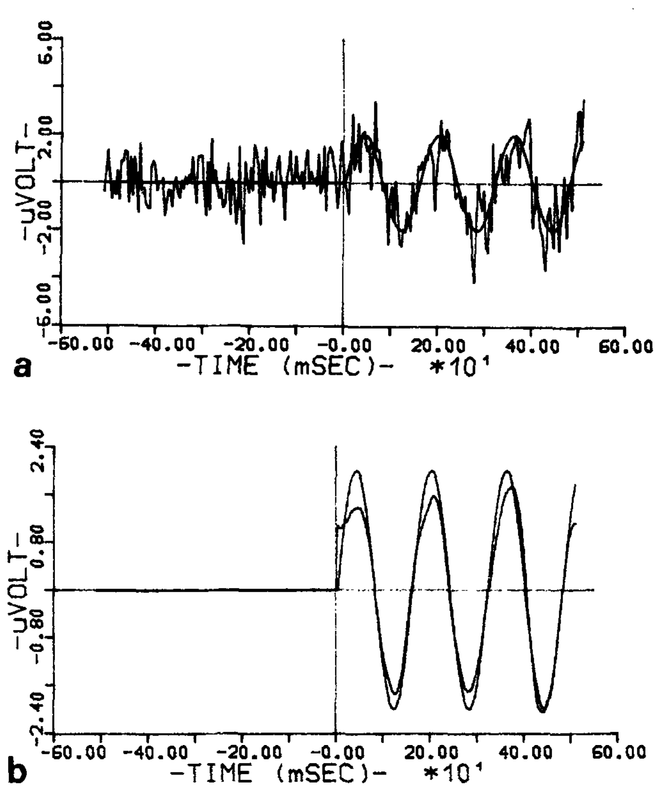

Figure 2 Test with a sinusoid in additive white noise (S/N=+6 dB): **a**, sinusoidal reference signal (for t>0), and corrupted signal (white noise for t<0, sum of the sinusoid and the white noise for t>0). **b**, Same sinuoid as in **a** (the scale of the plot is different) and the result of Wiener filtering on the corrupted signal

A discrete-time series $x(k)$ of 256 samples $(-127 \leqslant k \leqslant 128)$ is the simulation of a sweep having a duration of 1.024 s with the stimulus occurring at $k = 0$, sampled at 250 Hz rate. Thus

$$x(k) = \begin{cases} n(k) & -127 \leqslant k \leqslant 0 \\ s(k) + n(k) & 1 \leqslant k \leqslant 128 \end{cases}$$

The transfer function of the filter is computed as described above where ϕ_{ss} and ϕ_{nn} are now known *a priori*, having been computed from the simulated signals.

In *Figure 2a* the sinusoid $s(k)$ for $k > 0$ and signal $x(k)$ are shown on the same graph; the x-axis is in milliseconds and the simulated arrival of the stimulus occurs at zero time (corresponding to $k = 0$). The signal to noise ratio is in this case 6 dB.

For negative time, corresponding to $k < 0$, only the white noise $n(k)$ is present in the signal $x(k)$; for positive time, the nonsinusoidal signal $x(k)$ is the superposition of the sinusoid and the white noise. In this particular example the sinusoidal signal may be clearly distinguished from the noise by visual inspection. However, it is interesting to evaluate on this simulated signal the same parameters as would be used in clinical applications: first the latencies, defined as the temporal delay of each maximum or minimum with respect to the stimulus, and second the amplitude of the peaks.

It is evident from an inspection of *Figure 2a* that it is necessary to choose a proper threshold in the automatic recognition of the 'true' peaks to avoid the spurious detection. Moreover the values of the temporal occurrence of maxima and minima on the simulated signal are far from the 'true' values of the reference sinusoid.

The filtered signal $\hat{s}(k)$ obtained from $x(k)$ is shown in *Figure 2b* together with the reference signal $s(k)$. The values of the temporal occurrence of maxima and minima are now easy to obtain, as expected for every band-pass filter; these values in the estimated signal are very close to those in the reference. On the other hand, the amplitudes of most peaks are significantly different from the actual value. This difference is always in the sense of a reduction in the amplitude of the filtered signal $\hat{s}(k)$ with respect to the reference signal $s(k)$, because of the superposition of the signal and the noise in the same frequency bands. In fact, the gain of the filter is always $\leqslant 1$ for all frequencies, and tends to 1 only in the absence of noise.

In *Figure 3a* the same simulation is repeated, changing the signal to noise ratio to S/N = −10 dB, which is closer to the normal situation in evoked potential processing. Now, it is quite impossible to detect the latencies in the signal $x(k)$. The estimated signal $\hat{s}(k)$ plotted in *Figure 3b* shows a performance that is comparable to that in *Figure 2b* as regards the temporal occurrence of maxima and

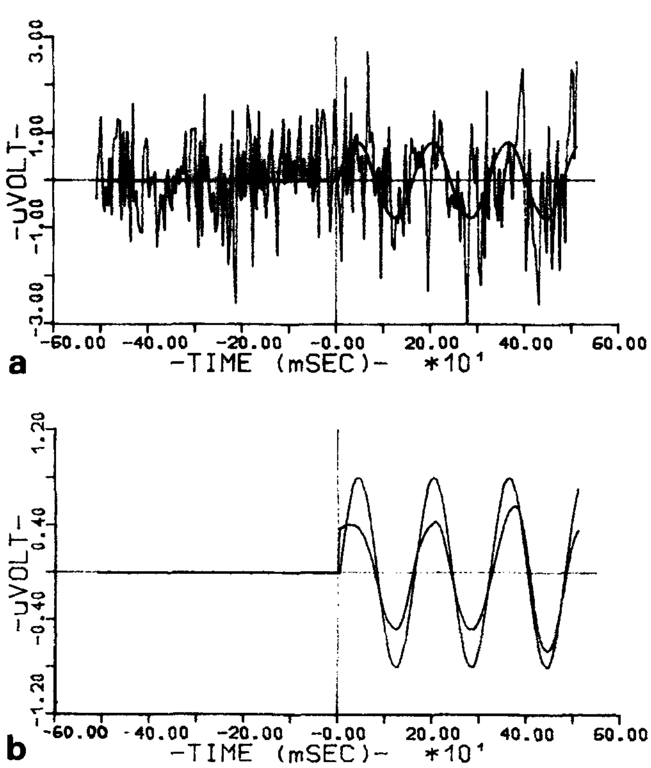

Figure 3 The same test as in *Figure 2,* but with S/N=−10 dB

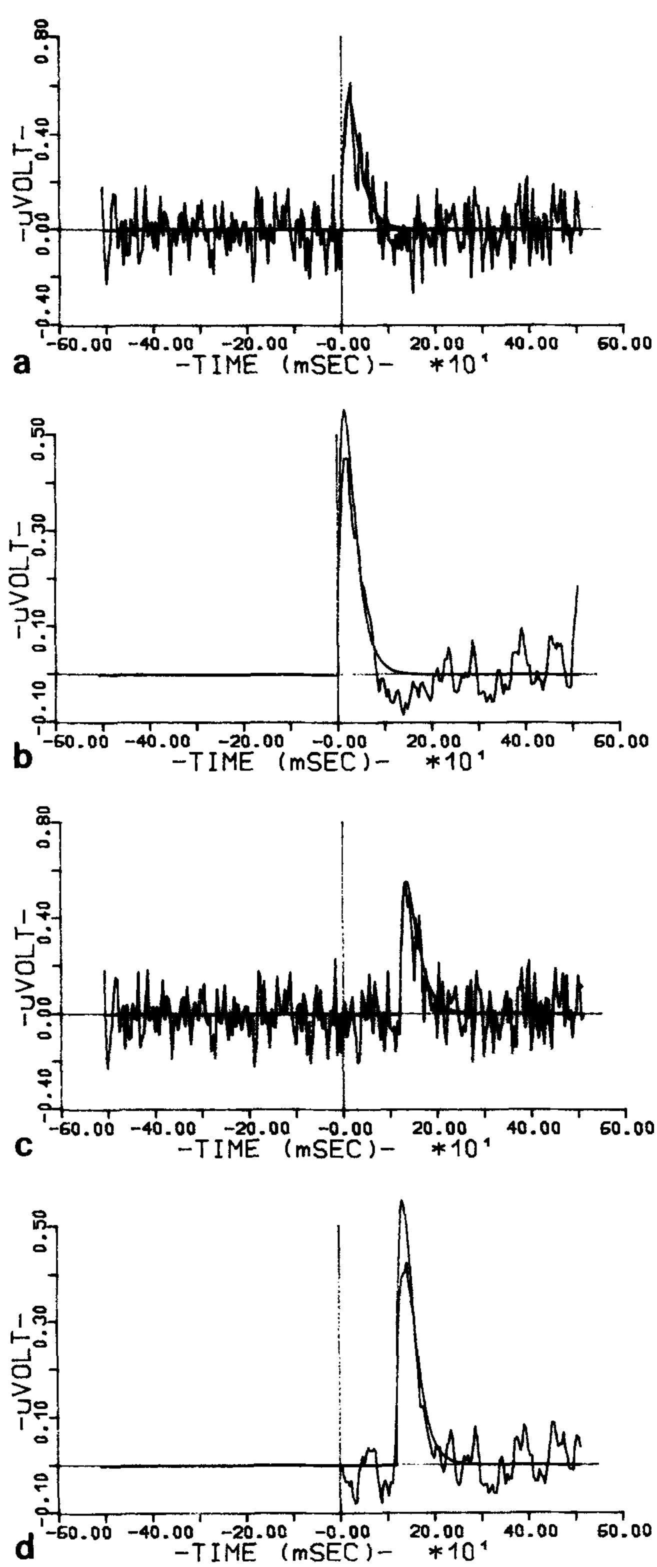

Figure 4 The reference signal is the transient described in the text. a, Reference signal and corrupted signal by additive white noise. b, Reference signal and result of filtering the corrupted signal. c As in a, but the reference signal is delayed. d Result of the filtering with the delayed reference

minima, while the amplitudes are more attenuated.

From these results, it is possible to conclude that the Wiener filter works well in finding the temporal values of a narrow-band signal independently of the signal to noise ratio in the analysed range, while the amplitude is as much underestimated as the S/N is low.

In *Figure 4a* the reference signal is the transient $s(k) = A\alpha k \exp(-\alpha k)$, whose estimate $\hat{s}(k)$, obtained by means of the Wiener filter, is shown in *Figure 4b* with the reference $s(k)$.

Now, the band of the signal is extended to frequencies below 10 Hz. Thus, such low frequencies are less attenuated in the filter and then part of the noise in this range of frequencies is present also in the estimate $\hat{s}(k)$, as can be seen in the deflections from the baseline after 100 ms (see *Figure 4b*). In all cases, the time of occurrence of the peak is still well estimated, even when the reference is displaced in the time, as shown in *Figures 4c* and *d*. In this case, the filter is exactly the same as in the previous trial, as it is phase and time independent: the time-locking is performed only on the input signal.

EXPERIMENTAL PROTOCOL

The analysis is performed on a set of visual evoked potentials (VEP) recorded in the Department of Informatics, Systems and Telematics, University of Genova, from eight healthy subjects, under a cooperative research project funded by the Italian Ministry of Education.

The shape of the stimulus is a circularly symmetric difference of two bidimensional gaussian functions, with geometric centres superimposed. The ratio of the standard deviation values of the two gaussian functions is 3. The stimulus is a pattern reversal with randomized period in the range 1.5 to 2.5 s.

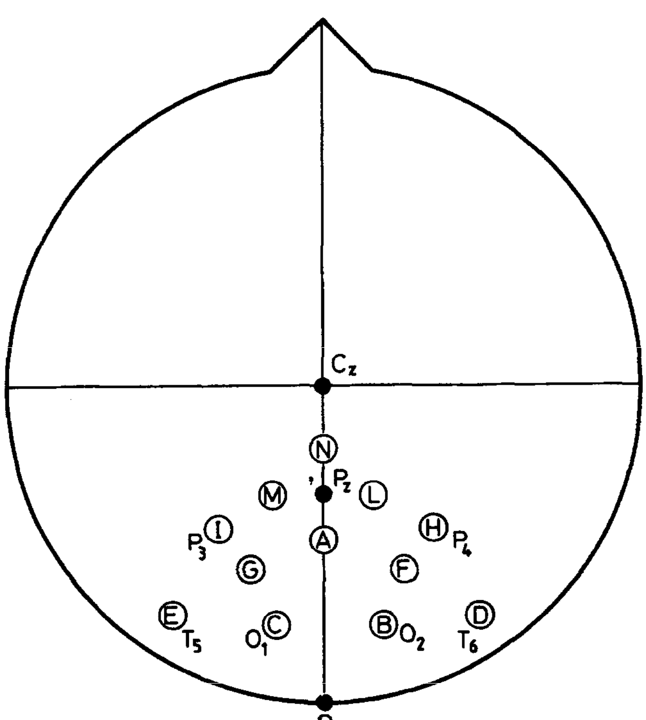

Figure 5 Map of the electrodes (circled letters) on the skull (top view). The letters outside the circles indicate the standard 10–20 system leads

Visual stimulation is carried out in a partially darkened room, the stimulus being presented on a TV screen. In the visual field, it is centred over the vertical meridian, at 8° eccentricity.

The VEP's are detected on 12 channels, whose leads are placed on the parietal and occipital regions of the skull — the location of the electrodes is shown in *Figure 5*, by means of letters inside circles. The leads of the international 10–20 system in this region are also plotted as spatial reference. A fixed duration of 512 ms is recorded before (prestimulus) and after the stimulus (post-stimulus) for a total of 1.024 s each sweep. The sampling is performed at 250 Hz rate on a 10 bit A/D converter DEC AR 11 whose complete range of 10 V is exploited by proper pre-amplification.

Before, and at the end of, the recording session a 10 Hz sine wave is sampled on all the channels. The amplitude of the sine wave (100 μV peak to peak) is used to check the gain of the recording apparatus, to convert the experimental data to microvolt values. Further details on the acquisition and preprocessing of VEP tracings may be found in reference 22.

The sampled data relative to an entire protocol of 99 sweeps on a single patient are stored on a magnetic tape in a file where the samples from the 12 channels are multiplexed, after a record of general information, as the identification of the patient, the code of stimulation, the sampling rate, the number of channels and the gain for each channel.

The set of programs for the Wiener filter are implemented in Fortran 77 language under VMS operating system on the DEC VAX 750 at the Computer Center of the Polytechnic of Milan Graphic outputs are obtained on the CALCOMP 1038 and M84 plotters.

EXPERIMENTAL RESULTS

Results are presented which are relative to the data recorded from channel A of one patient. In *Figure 6* the first 5 sweeps of the total of 99 are plotted

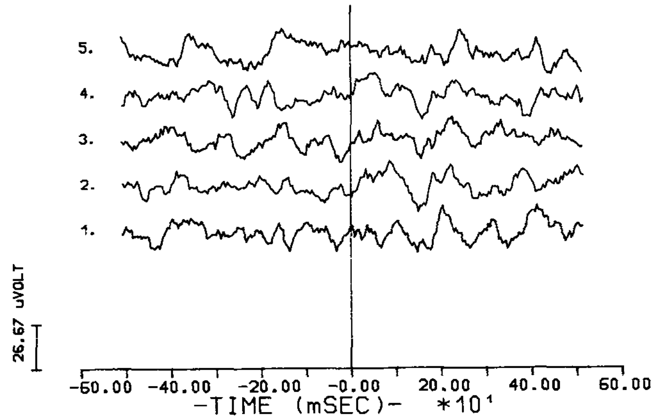

Figure 6 Plot of the first 5 sweeps for channel A. The arrival of the stimulus, at zero time, is marked by the vertical bar

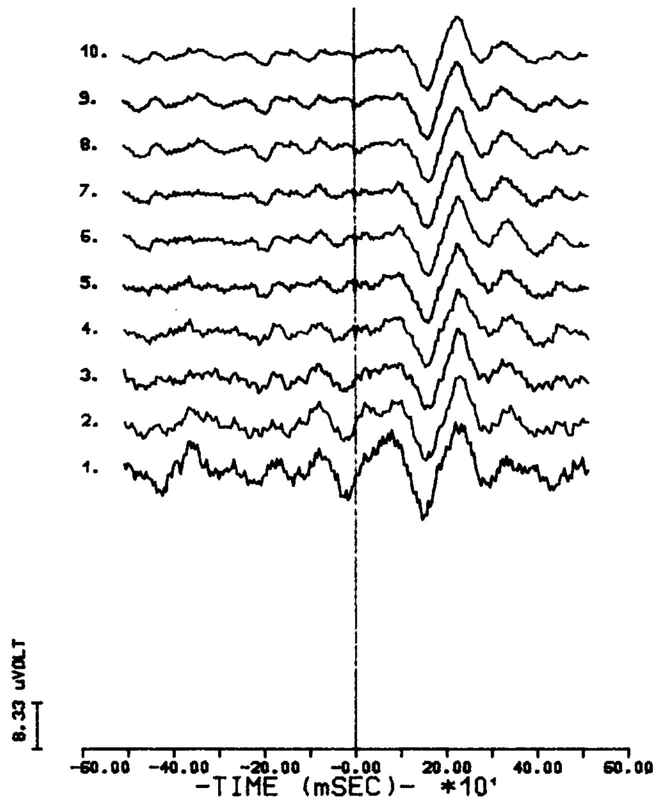

Figure 7 Features of the traditional synchronized averaging. From the bottom to the top, the number of averaged sweeps increases by 10 at each line. The top trace is the total average of 99 sweeps

without processing. The vertical line at zero time marks the arrival of the stimulus. On the left (negative time) the prestimulus EEG is plotted. The evoked potential of the previous sweep is assumed to have ended: the minimum interval between the two trials is 1.5 s, thus the beginning of the actual prestimulus starts at least 1 s after the previous stimulus. On the right (positive time) the post-stimulus is plotted. No evidence is visible of the expected evoked potential, because of the fact that the background EEG has more power with respect to the hidden signal.

The performances of the classical synchronized average are visible in *Figure 7*. The bottom trace (1) is the average of the first 10 sweeps, trace 2 is the cumulative average of the first 20 sweeps, and so on: the upper trace (10) is the average of all 99 sweeps. From bottom to top, it is evident that only the components of the signal which are persistent for the whole recording period are maintained in the average, as is evident from the biphasic wave between 150 and 300 ms of latency, which is enhanced with respect to the single sweeps in *Figure 6*.

A problem arises when the random components, which tend to zero as the average progresses, are completely related to the noise, instead of being associated with different features of the signal, which changes significantly in the different trials.

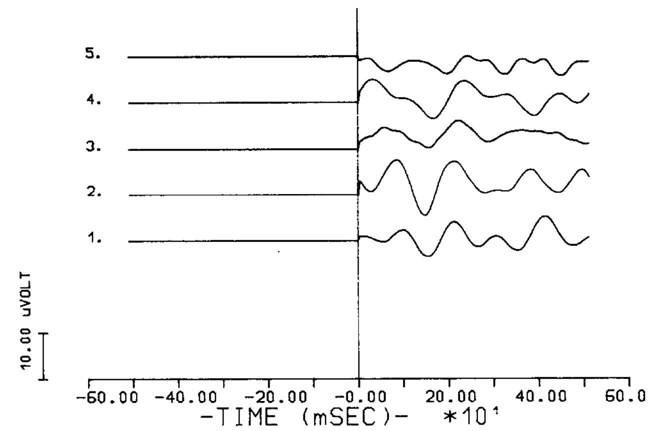

Figure 8 The 5 sweeps of *Figure 6* after Wiener filtering

The randomized protocol of stimuli sequences tends to minimize systematic events in this kind of physiological phenomenon, but it is not able to eliminate it completely.

The result of Wiener filtering of the same five sweeps shown in *Figure 6* is plotted in *Figure 8*. Here the prestimulus is set to zero by hypothesis; no response is supposed to be evoked before the stimulus.

The comparison of the post-stimulus with the original signal enhances a pattern with slow deflections from the baseline, where the latencies are more easily detected than in *Figure 6*. This is partially due to a low-pass filter effect of the Wiener filter: on the other hand, this kind of filter tends to enhance the pattern relative to the evoked response, even in the same band of the noise, as it is possible to see in a comparison with the total average in the upper trace of *Figure 7*. The main biphasic wave is clearly visible particularly in trace 2 of *Figure 8*. Also traces 1, 3, 4 show negative–positive deflections in this range of latencies, but less marked than in trace 2.

It is not easy to quantify the performances of the filter, e.g. with the usual criterion of the mean square error, possibly modified to take into account the difference in amplitude from one trial to another. The absence of a reference signal is a problem, since the total average is only an approximate estimation of the behaviour of the stimulated system in all the trials of the protocol: it would not be valid to compare, in the sense of the mean square error, the results from a method which tends to enhance individual behaviour, with respect to the average, when increasing the number of the sweeps.

The qualitative result of the Wiener filtering is thus an improvement of the signal to noise ratio in the useful band. On the other hand, in order to obtain a better estimation of EP it is advisable to make an average on a very small number of consecutive filtered sweeps. Although this operation still presents the problems described above, the procedure is less critical due to the low number of averaging operations, 10 instead of 99.

It is therefore possible to avoid the effects of the average of those variations in the EP which are related to changing conditions in the system and which are related to relatively long term intervals, of the order of tenths of second. But by employing this procedure it is impossible to enhance the intrinsic differences which may exist between one trial and another.

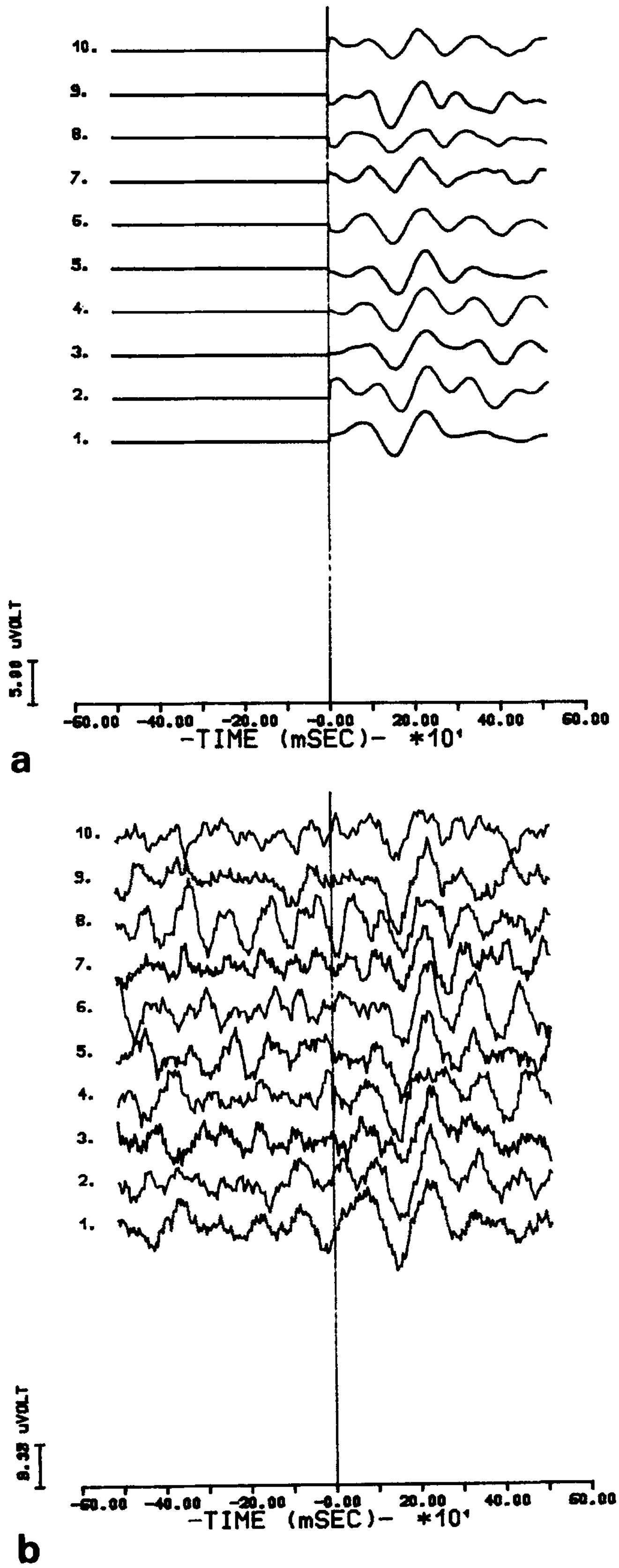

Figure 9 Partial averages of groups of 10 consecutive sweeps for channel A. a After Wiener filtering b without Wiener filtering

The results of partial averaging of 10 filtered sweeps are shown in *Figure 9a,* where the bottom trace (1) is relative to the first 10 sweeps, the trace 2 is the average of the filtered sweeps from 11 to 20, and so on, to the top trace which represents the last 10 sweeps. In *Figure 9b* the average of the corresponding unfiltered sweeps is presented as a reference, in order to show the degree of improvement from the filtering. The method provides a good estimate of the EP in almost all the analysed cases and from an average of only ten responses it is possible to obtain the typical parameters of the EP, i.e. peaks and their latencies. In *Table 1* the calculated latencies of the larger positive and negative peaks are presented. They are quite stable around the values of the same latencies in the average, also reported in *Table 1*.

The peak-to-peak amplitude is, however, different for the partial averages of filtered responses with respect to the total average: this characteristic of attenuation was also found in the simulated trials. The final estimate using Wiener filtering will

Table 1 Channel A. Latencies of the main two peaks, and peak to peak amplitude for the partial averages of 10 filtered sweeps plotted in *Figure 9a*

Partial average (sweeps from . . to)	Latency of positive peak (ms)	Latency of negative peak (ms)	Peak to peak amplitude (μV)
1(1 . . 10)	220	148	5.54
2(10 . . 19)	228	164	5.59
3(20 . . 29)	236	152	4.57
4(30 . . 39)	224	160	5.27
5(40 . . 49)	224	160	5.45
6(50 . . 59)	220	152	4.15
7(60 . . 69)	216	160	4.24
8(70 . . 79)	232	148	2.87
9(80 . . 89)	228	152	5.53
10(90 . . 99)	212	148	3.35
Total average	228	160	13.07

Table 2 Channel A. Powers in μV^2 of the relevant unfiltered and filtered partial averages of 10 sweeps plotted in *Figure 9*

Partial average	Unfiltered sweeps (AVE) [μV^2]	Filtered sweeps (AWI) [μV^2]
1	13.773	2.635
2	10.446	2.716
3	5.378	3.263
4	11.435	2.561
5	15.318	2.836
6	9.296	2.733
7	10.726	3.396
8	26.836	4.424
9	9.097	3.019
10	7.807	3.827
Mean	12.015	3.143
Standard deviation	5.926	.598

probably result in an underestimation of the amplitude of the desired signal.

Differences in amplitude inside the single partial averages are interesting: with one exception, the amplitude of the peaks tend to decrease in the second half of the experiment. The ratio between the highest peak to peak amplitude (first partial average) and the lowest, No. 8, is close to 2. This fact seems to confirm the phenomenon of adaptation in the response, which is not completely avoided by the randomized protocol. Moreover, important changes are revealed in *Figure 6* by comparing the first 150 ms of each trace. The total average, (upper trace in *Figure 7*), shows a quite flat pattern in this interval of latencies: the possible information may be lost in the average when changing from one sweep to another.

The averages of 10 filtered sweeps in *Figure 9a* show quite a different pattern between the various traces and, of course, different with respect to the total average. This kind of behaviour is also seen at higher latencies, over 300 ms.

We would argue that the evoked response is varying along the total protocol of 99 sweeps and that the Wiener filter seems able to capture these changes.

The power variability between the different averages of each 10 successive sweeps is also reduced by applying the Wiener filter. In *Table 2* the values are shown for the power of the post-stimulus averages of 10 unfiltered sweeps compared with the power of the same average of filtered sweeps. In the first case, the mean of the powers is about 12 μV^2, with a standard deviation of nearly 6 μV^2, which is about 50% of the mean value. For the partial averages of the 10 filtered responses the mean of the powers is instead 3.143 μV^2, with a standard deviation of 0.598 μV^2, which is less than 20% of the mean value.

This is significant because the high variability in power is correlated with a strong presence of noise, whose amplitude varies considerably, as can be seen by examining the power of single-sweeps in the pre- and post-stimulus epochs. The greater stability in the power of the filtered averages is then a sign of a lower component of noise in these estimates, compared with the corresponding averages of the unfiltered responses.

Analyses performed on other channels confirm these results, but not so strongly: channel A was the nearest to the cortical area directly involved in the processing of the visual stimulus employed. Other leads will be affected by a still less favourable signal to noise ratio because of the weak power of the evoked response in the peripheral occipital region. For example, in *Figure 10* the partial averages of 10 filtered postimulus are shown as in *Figure 9a*, but relative to the data recorded from channel E, which is at the extreme periphery of the region with which we are concerned. In this case the single-sweep analysis is much more difficult, and the partial average of the filtered responses shows a very little enhancement of the EP.

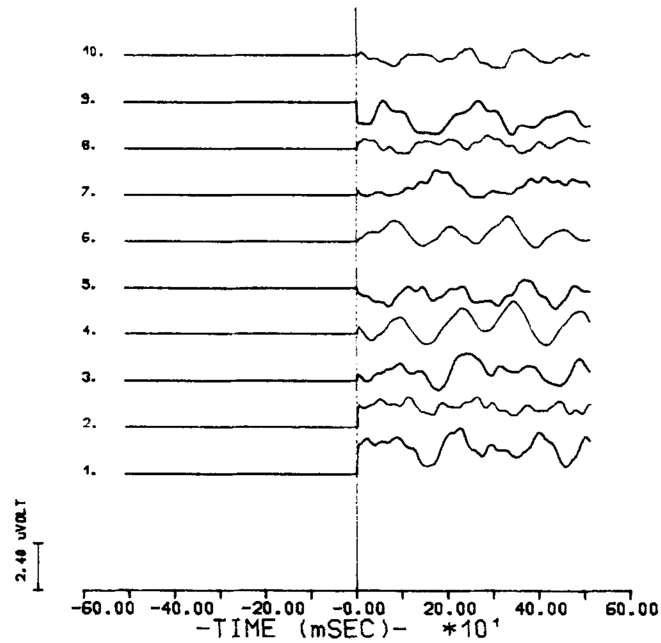

Figure 10 Partial averages of groups of 10 consecutive filtered sweeps for channel E

CONCLUSION

We propose a Wiener filtering algorithm which may be applied to a single-sweep, or a small number of sweeps, evoked response from the brain following a visual stimulus: other papers in the literature apply the same filter to the average of all the responses.

It is a new approach which requires, as a reference signal, an estimate of the true signal, which is obtained from the normal EP average. The estimation of the 'noise' is peculiar to our approach: the EEG in the prestimulus period is assumed to be the best estimate (in respect of the frequency distribution of the power) of the unknown background EEG upon which the evoked response is superimposed. The result of this approach is an improvement of the signal-to-noise ratio, which is however insufficient in most cases to detect the signal response resulting from a single stimulus; but an average of ten filtered responses does show an enhancement in the signal-to-noise ratio comparable with the improvement obtained by averaging 100 sweeps in the traditional way.

The technique makes it possible to follow the dynamics of the evoked potential on a few consecutive sweeps. Such a possibility would become increasingly important in an application to the event related potentials (ERP) elicited, for example, by neurocognitive tasks, where the learning phenomena and the high number of noncontrollable variables could be responsible for important differences between trials.

Moreover, the ability to carry out an analysis from a reduced number of sweeps is important in order to decrease the total time necessary for the examination. In this case, it is necessary to substitute the average in the estimation of the signal spectrum with a pre-defined 'standard' evoked potential.

The reduction of the number of sweeps by a factor 1:10 is important especially for those stimuli which, using traditional procedures, require an average of a great number of trials, acoustic EP's for example. A fast method for obtaining a clinically interpretable evoked response in only a few sweeps would be important in monitoring the integrity of some neural pathway during neurosurgical procedures which could damage the neurons involved in the investigated pathway. The implementation of a real time processing of the EP for monitoring possible pathologies of perturbations in the brain may avoid more serious injuries caused by peroperative procedures.

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