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Variability analysis of visual evoked potentials in humans by pattern recognition in phase domain

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Abstract. A novel approach to single trial visually evoked potentials (VEP) variability analysis based on a new model of post-stimulus brain electrical activity is presented. The convolution model introduced by the author is experimentally verified by the analysis of flash stimulus effects on EEG amplitude and phase spectra. Pattern recognition in the signal phase domain is proposed for detection of any time locked transient signals. This is illustrated by an application of a clustering algorithm in two-dimensional unwrapped phase of EEG Fourier transform space for occipitally recorded VEPs in human subjects.

Key words: evoked potentials dynamics, single trials, pattern recognition, phase spectrum, perception

INTRODUCTION

The time variability or dynamics of brain processes manifested by the time variability of electrical potentials evoked by series of identical stimuli has been recently recognized as a possible source of information about the neural processes underlying functioning of the central nervous system (Basar 1990). However the effective methods for analysis of this variability are not currently available due to the inherent limitation of mathematical models of the processes under study.

This so called "trial to trial", within subject variability is widely used in psychophysiological studies concerning selective attention and perception (Natanen 1975, Chapman 1979). It refers to the late evoked response components with the latency of 300 or more milliseconds. However, it has been also observed that the evoked potential components of shorter latencies, recognised as specific to sensory pathways, reveal a natural variability which cannot be attributed to the spontaneous EEG (electroencephalogram) activity alone (John 1973, Copolla 1978).

Analysis of this variability can be essential for diagnostic purposes, as it has been found to change with age and can even be treated as a maturation index of the brain (Callaway and Holiday 1973). Increased visual response variability was also revealed in subjects with behavioural disturbances as determined for schizophrenic patients (Kopell 1969, Callaway 1970, Donchin 1970, Shagass 1979). Even in normal subjects, experimental modification of attention can lead to different average potentials (Garcia-Austt et al. 1964, Haider 1967, Shagass 1979).

The synchronous averaging technique, introduced by Dowson (Dowson 1951) is the most commonly used evoked potential measurement technique. This signal estimation-extraction method introduces implicitly an additive model of the signal. It is often forgotten that for its proper and effective use, specific conditions must be satisfied. The basic condition is that the evoked response should be identical for each one of a series of identical stimuli delivered to the subject and does not depend on the EEG before or at the time when the stimulus was applied. EEG, which is usually treated as additive noise, should be an uncorrelated random process with zero mean. However, these assumptions are very rarely fulfilled, if experimentally verified at all, especially concerning the deterministic and stationary character of evoked potentials (Aunon et al. 1981).

Several attempts have been made to improve the popular averaging method, for example the method of corrected latency averaging (Woody 1967) or the method of selective averaging by cross-varying (Gasser et al. 1983). Digital filtration methods have been also used to enhance the quality of the evoked response estimate in the form of the average (for a review see Nagelkerke et al. 1983). These approaches are based mainly on the Wiener filter theory, but proved to be inefficient, since the application of this theory is based on the unjustified assumption that spontaneous and evoked activities occupy separate frequency bands. Even the most sophisticated parametric methods (Cerutti et al. 1988), including Kalman filtering (Spreckelsen and Bromm 1988), proposed recently for analysis of trial to trial variability, do not go beyond the traditional additive model. The introduction of a more realistic model of the signal than the additive one seems to be desirable for when the response variability is of primary interest (Piątkowski and Achimowicz 1983, Wróbel et al. 1995). The model should explain, for example, the experimental results of Sayers et al. (Sayers and Beagley 1974, Sayers et al. 1974, 1979) which indicate that the evoked response to auditory stimuli can result from a reordering of EEG signal phases without any additive component. An experiment performed by Jervis (Jervis et al. 1983) did not provide any convincing arguments in favour of additive or phase reordering mechanism of evoked response generation and the contribution of both mechanisms in the formation of evoked response requires further investigation. The assessment of trial to trial evoked response variability requires application of a new signal feature extraction techniques. The wavelet representation of the signal may be very adequate for this purposes as recently proposed (Bartnik et al. 1992, Blinowska 1994).

The aim of the current study is to present a new convolution model of post-stimulus brain electrical activity, more appropriate for studying the dynamics of evoked response. The method for studying the trial-to-trial variability of Event Related Potentials (ERP) derived from this model is also described in detail. This method has already been verified experimentally (Achimowicz 1988) and was used to reveal the deterministic (discrete) character of ERP dynamics in the visual (Achimowicz 1991) and somatosensory (Wróbel et al. 1995) cortex.

METHODS

Convolution model and pattern recognition in phase domain

In the traditional additive model, widely used in ERP studies, the post-stimulus signal is treated as the sum of spontaneous and evoked brain electrical activities. In terms of system theory this is equivalent to the assumption that the cortex is a linear system in which the superposition principle is satisfied. However it is also commonly accepted that when the neural substrates involved in the generation of these electrical signals are analysed a substantial nonlinearity of relevant processes is found. At the level of single units the non-linear dependence of firing rate on a neural membrane potential at the triggering zone was revealed (Purpura et al. 1964). The non-linear properties of spontaneous EEG signal recorded not only from scalp but also from subdural and intracranial electrodes in humans (Achimowicz and Bullock 1993) and of evoked activity (Bullock and Achimowicz 1995) also indicated the possibility of non-linear (multiplicative) interaction of postsynaptic potentials. It was postulated a long time ago that the postsynaptic potentials and hence their extracellural equivalents should be nonlinearily related. For example, the contributions from dendritic and somatic synapses are quite different as shown by Rall (Rall 1970). Rall also suggests that dendritic elements, which provide the greatest contribution to the field potentials, are capable of performing the operations of spatio-temporal integration, differentiation and even more complex transformations of electrical signals generated by firing neurones. It is also a well established fact that the amplitudes of EEG and evoked potential waveforms, recorded from micro electrodes, reveal an impressively high correlation with spike probability (Frost and Elazar 1968, Fox 1970). It may be justified to assume that in this situation the non-linear "summation" of postsynaptic potentials will in consequence result in a non-linear, e.g., multiplicative, interaction of the spontaneous and evoked field potentials resulting in the compound field recorded at the extracellular electrode.

The convolution model of the post-stimulus signal recorded from intact scalp, proposed by the author (see Appendix) seems to be a possible alternative to a classical additive model. The basic experimental fact used in the derivation of this model is the well documented similarity of spontaneous activity power spectra and the shape of the transfer function of the visual cortex measured by the steady state method introduced by Regan (Regan 1966). Now we can make more specific assumptions concerning the character of EEG and VEP signal variability and try to predict the consequences of the convolution model proposed by the author. The main consequences of this model in the frequency domain are the additivity of phases and multiplicativity of amplitudes of corresponding Fourier transforms.

It was found the post-stimulus activity reveals long lasting components of deterministic character, which were not specific to the visual system (Ciganek 1969). This so called "after discharge" or "triggered alpha rhythm" (Walter 1963, Peacock 1969) does not average to zero even if the number of stimuli repetitions is increased. This is due to the fact that this transient signal is phase locked to a stimulus onset and the corresponding Fourier transform phases are deterministic. Let us assume for simplicity that the evoked response has also deterministic (constant) amplitude wave shape but it can assume two different latencies. In this case these waveforms will differ only by small and constant time shift (delay) along the time axis. This time delay will manifest itself only in the two possible phase values of corresponding evoked response Fourier transforms. This effect may result e.g., from two different propagation times of stimulus related activity in neural networks of visual pathways. Of course to be more realistic the small latency jitter for the proposed two response templates should be additionally introduced. In the frequency domain it will manifest itself as a phase noise of small amplitude. When the stimuli are applied randomly in time, the pre-stimulus signal Fourier transform phase should be totally random (i.e., uniform). At the same time the post-stimulus segments, (see equation (10) in Appendix), should reveal aggregation around two modal values corresponding to two types of evoked responses. These values will be shifted by the additive constant factor related to phase locked post-stimulus EEG.

We can also assume that the only effect of stimuli on the spontaneous activity may be phase locking, as observed for triggered alpha activity. If we analyse short time segments of EEG signal as in the case of sensory responses, the quasi-stationarity of EEG provides the stability of its amplitude. In other words, the amplitudes of post-stimulus EEG harmonics may be approximated by the amplitudes of the relevant pre-stimulus data segment. Then the linear correlation should be found between pre- and post- stimulus signal harmonics amplitudes (see equation (9) in Appendix). If a clustering of single evoked responses in Fourier transform phase domain occurs, it seems natural to classify the post-stimulus segments according to their phase features. This should allow for the detection of any stimulus locked transient signal in spite of its amplitude variability which seems to be of lesser biological importance. Amplitude variability may be due only to temporal fluctuations of the number of synchronously firing cortical neurones, triggered by the afferent spike trains. To verify the presented approach the experiment was performed on a group of healthy human subjects using light flash stimulation.

Application of the model

The study was performed on 30 healthy, male subjects with an average age of 30. The brain electrical activity was recorded in an environment standard for evoked response studies. The subjects were placed seated in a soundproof, dimly illuminated Faraday chamber and the visual flash light stimulation was used. The light flashes with energy of 0.3 J were triggered randomly by the computer in time intervals ranging from 3 to 5 s, with uniform time distribution. Bioelectrical signals were recorded from four Ag/AgCl occipitally placed electrodes in monopolar montage with linked ear electrodes serving as the reference. Two of active electrodes corresponded to O_1 and O_2 derivation, according to the International 10-20 System, and two additional electrodes were positioned in the same line, symmetrically 4 cm outside the former ones. The signals were amplified by a polyphysiograph with 0.6 dB cut-off frequency at 250 Hz and fed into the computer-controlled data acquisition system. The 500 ms long segments of signals, before and after stimuli application, were digitised to 12 bits at 500 Hz sampling frequency. The series of 32 to 64 responses to identical stimuli were saved on disk for off-line processing. The raw data were visually inspected for eye movements, muscle potentials or instrumentation artefacts. To control the acquisition process the average visual potential was calculated, with the pre-stimulus signal average serving as the baseline. The typical, single evoked response data segments for four channels and corresponding grand average responses are shown in Fig. 1 in the upper and lower portion respectively. The channels denoted K-2 and K-3 correspond to O_1 and O_2 derivations while K-1 and K-4 to the two additional ones.

As the early components of visually evoked potentials, specific to visual pathways, were of main interest in this study, only 250 ms of the signal before and after the stimulus application (marked by vertical lines in Fig.1) were taken for the subsequent analysis. The relevant segments were padded with zeros to obtain the 1 Hz resolution of

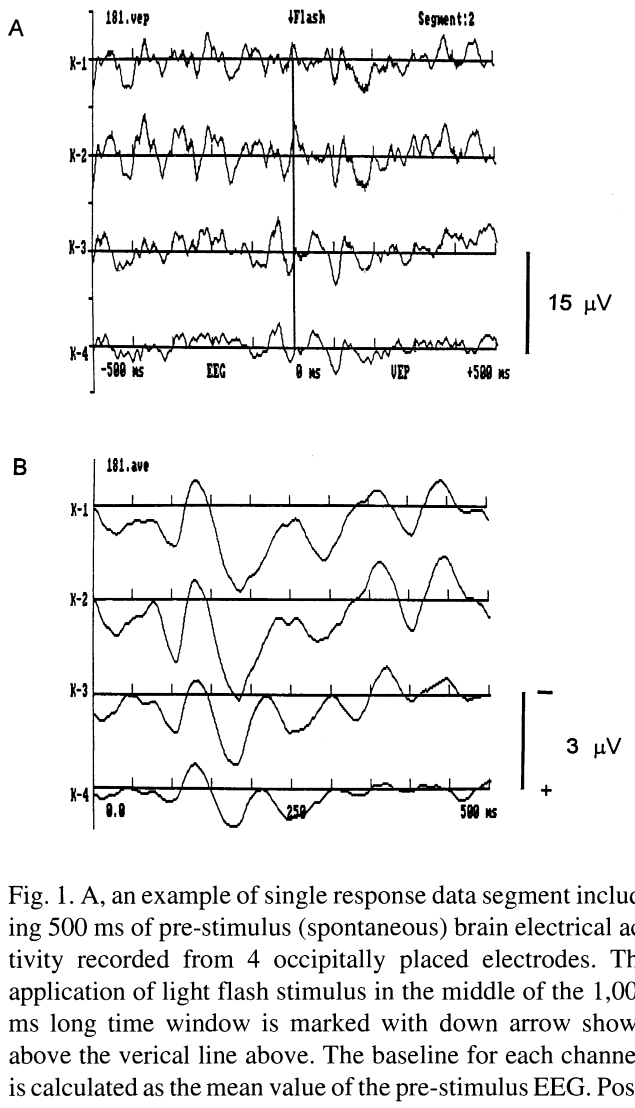

Fig. 1. A, an example of single response data segment including 500 ms of pre-stimulus (spontaneous) brain electrical activity recorded from 4 occipitally placed electrodes. The application of light flash stimulus in the middle of the 1,000 ms long time window is marked with down arrow shown above the verical line above. The baseline for each channell is calculated as the mean value of the pre-stimulus EEG. Positive values of the potentials are plotted below the zero line (negative up convention). B, the relevant classical average visual evoked potential for subject 181 (notice the difference in amplitude scales between A and B).

the corresponding discrete Fourier transforms computed by FFT algorithm. Then the effects of stimulation on amplitude and phase of subsequent EEG Fourier components (harmonics) were statistically analysed.

It is usually assumed that EEG segments represent the realisations of a gaussian random process. Due to the linear character of Fourier transform, its real and complex components should be gaussian random variables as well. In this case signal power density spectrum estimator at each frequency, in the form of a periodogram (squared transform module), is a random variable of χ^2 distribution with 2 degrees of freedom. Hence its square root, i.e., harmonic amplitude, should in this case have the Rayleigh distribution. To reduce spectrum estimator variance, averaging across all the stimulus repetitions was performed (Welsh 1976). For a number of stimuli used by the author (greater than or equal to 32), it can be assumed that power density estimator distribution is close to the normal one. Therefore to compare the power spectral densities in pre-stimulus and post-stimulus conditions a power spectrum equivalence test can be used (Bendat and Piersol 1976). The test statistics values-D were calculated as the sum of power spectrum estimators ratio logarithms, for all harmonics in the frequency band of interest, i.e., 1-31 Hz. The critical interval of this function value, which allows for acceptance of spectra equivalence hypothesis at significance level P=0.005, was equal to (-2.8 - +2.8).

Because the experimental distributions in many cases are different from the one corresponding to gaussian random process, to verify the hypothesis about the relation between pre- and post-stimulus signal harmonics amplitudes, the correlation coefficient was estimated not only with the Pearson parametric test but with the nonparametric ones as well. The Spearman correlation and Kendall rank correlation coefficients were calculated (Press et al. 1985). These nonparametric tests are more robust and their proper application does not require any specific type of the experimental distribution of the sample under study.

To detect the nonuniform distribution of harmonics phases, the Rayleigh circular variance test was used (Mardia 1965). The observed phase distributions, as revealed by experimental histograms, were usually multimodal. A split of peaks occurring for modal values close to +-π boundary may is superficial and results from the periodic character of the phase alone. So it is more adequate to use not the principal phase values but the absolute ones. Because the signal sampling frequency was taken high enough to trace the phase discontinuities at the +-π borders, a very simple "phase unwrapping" algorithm was used. At each discrete frequency the phase gradient was evaluated and compared with the one obtained by the modification of the subsequent phase sample by adding or subtracting of 2π value. Then this modified phase value which provided the smallest gradient was taken as the final one.

The observation of post-stimulus signal phase aggregation has led the author to the concept of the application of a certain classification procedure in the phase domain. The two dimensional "unwrapped phase" features space was chosen adaptively for each subject in the following way. For each data set of single evoked responses, the uniformity of phase distribution of subsequent harmonics was tested with Rayleigh test and the "spectral plot" of circular variance as the function of the frequency was constructed. The minima of these frequency functions (deeps) indicate the harmonics with the greatest deviation from random distribution. If the significance level of Rayleigh test at given deep was greater than 0.05, then the phases of these harmonics, usually corresponding to power spectrum peaks, were taken as the single evoked potentials features. The hierarchical deterministic clustering algorithm, based on the Euclidean distance similarity measure (Sobczak and Malina 1985), was used. The effectiveness of this approach was assessed by the comparison of single evoked responses from clusters revealed by a binary classification tree, shown in the form of a so called dendrogram, with the classical average VEP for each subject. No inter-subject comparisons, with the exception of data concerning the percentage fraction of observed trial to trial variability type, are discussed in this study.

RESULTS

The effect of stimulation with light flash on the power spectrum of occipitally recorded brain electrical activity was analysed. The power spectrum density (PSD) estimators, obtained by averaging of 32 periodograms, were evaluated for pre- and post-stimulus signals and compared by the previously described equivalence test. The flashes of 0.3 Joule energy applied binocularly did not change the average spectrum in the analysed frequency range up to 32 Hz in 75% of the subjects tested. For the rest of the subjects a slight increase of the low and high (20 Hz) frequency components amplitudes was observed but was not statistically significant. The typical results for two subjects are shown in Fig. 2 with the PSD curves normalized to their maximum values. The curves on the left and the right side

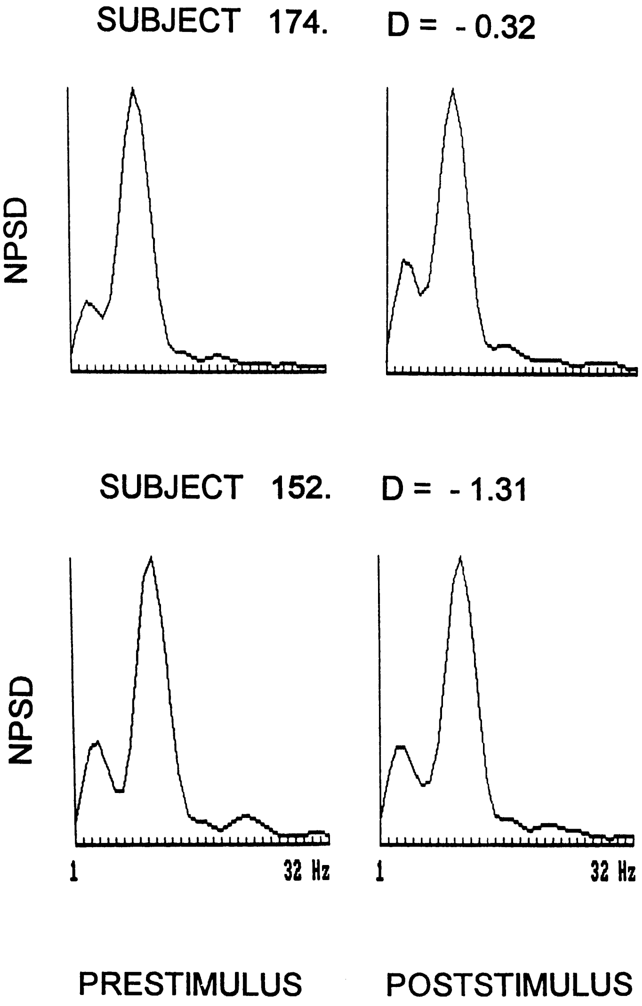

Fig. 2. The comparison of pre- and post-stimulus EEG normalized power spectrum densities (NPSD), on the left and the right side correspondingly for two subjects (174 and 152). The spectra are normalized to their maximal values to show the relative contribution of lower and higher frequency bands to signal variance. The values of D statistics indicate the absence of significant effect of light flash stimulus on EEG signal energy.

correspond to pre-stimulus and post-stimulus signal respectively. The extreme values, together with the D statistics values, are shown, indicating that the power (amplitude) spectra do not change significantly (P=0.005) as the result of visual simulation.

Because the applied power spectra equivalence test is based on the statistic function which evaluates the joint effect of spectrum changes at all frequencies, certain subtle effects, for example the increase of power in one frequency band and decrease in the other, can be undetected. So the author had tested also the stimulus effect on each of the signal Fourier transform harmonics separately and no statistically significant changes due to visual stimula-

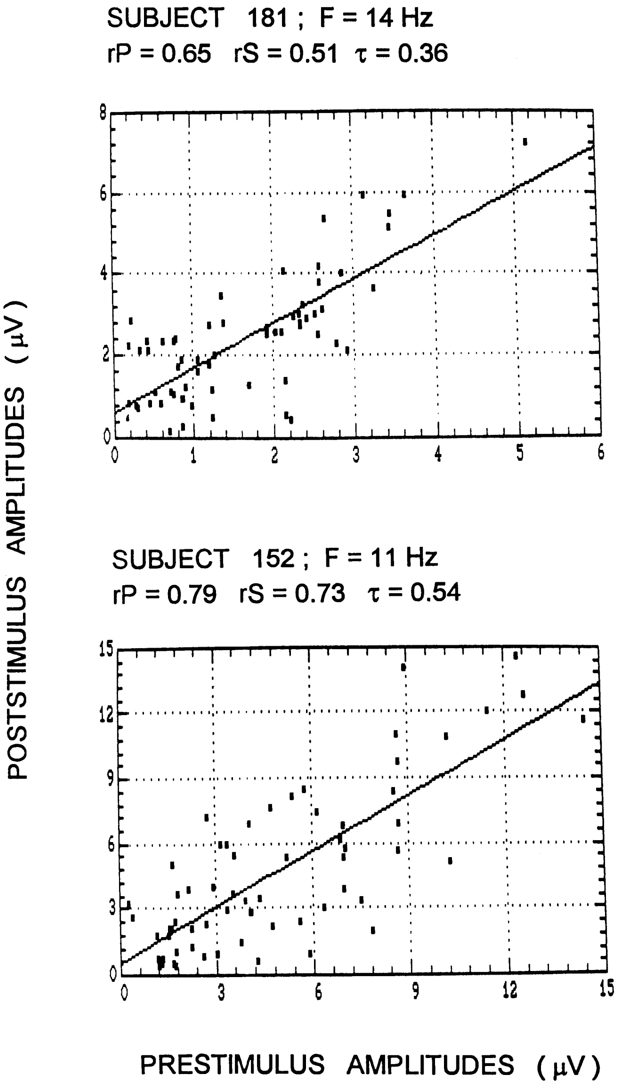

Fig. 3. Scatterplots of post- and pre-stimulus EEG Fourier transform amplitudes for a series of 24 light flashes for two subjecta (181 and 152) illustrating the significant positive correlation between these signals. The linear regression curves and correlation coefficients values are also indicated for harmonics with frequencies of 14 Hz and 11 Hz in the upper and lower portion respectively. Pearson, Spearman and Kendall correlation measures are denoted as rP, rS and τ respectively.

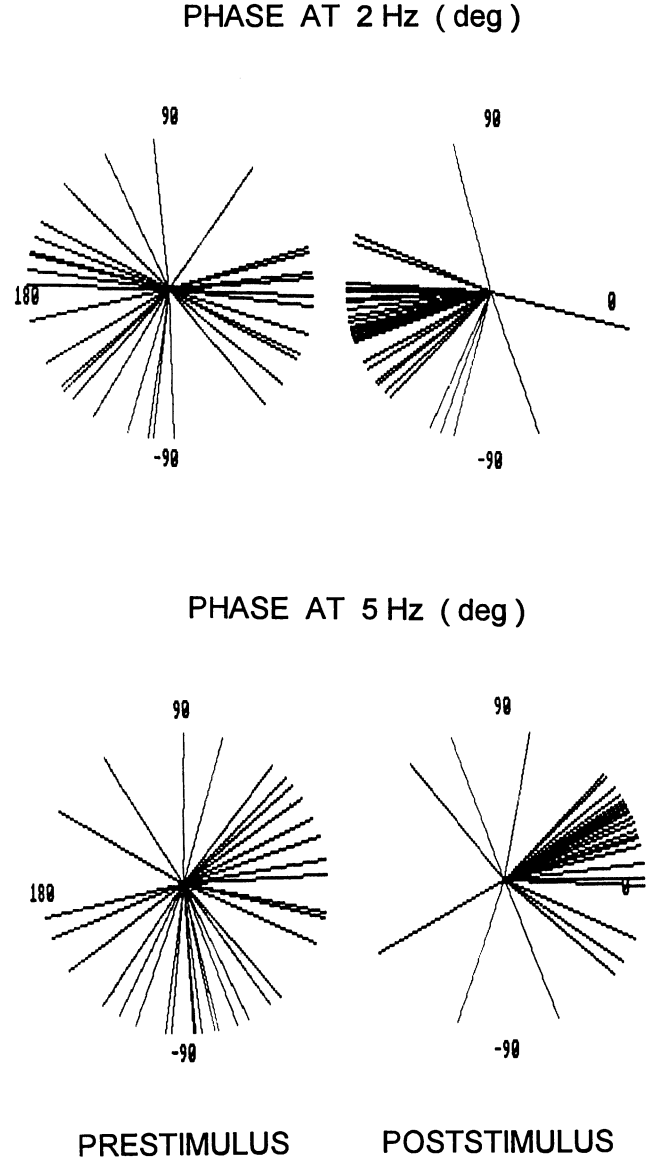

Fig. 4. The effects of light flash on phase distributions of two harmonics (2 Hz in the upper and 5 Hz in lower part of the figure respectively) of EEG segments Fourier transforms for the same subject 124 shown in the form of vector (polar) plots. The pre- and post-stimulus signals phase values data are shown on the left and right side correspondingly.

tion were found as reported elsewhere (Achimowicz 1988). Then the correlation between the harmonics amplitudes of pre- and post- stimulus signal was tested. In 60% of tested subjects a statistically significant ($P<0.005$) positive correlation was found for frequencies corresponding to spectral peaks. Correlation coefficients were the greatest for alpha band waves as shown for two subjects in Fig. 3.

As it has been mentioned before, in some cases the harmonics amplitudes distributions revealed a significant deviation from the normal one and hence more robust, nonparametric correlation measures were also used. The scatter plots, with best fitted linear regression curves (in mean square error sense), together with Pearson (rP), Spearman (rS) and Kendall (τ) rank correlation coefficient values, significant at $P=0.005$ level, are presented on the right side of the Fig. 3 for the 14 Hz and 11 Hz harmonic respectively.

In contrast to the amplitude spectrum, the phase component turned out to be affected by the visual stimulation. In all cases studied, comparison of the pre-stimulus and post-stimulus signal phases revealed the aggregation of phases after the stimuli as shown on polar plots in Fig. 4 for two subjects. Each equal length vector represents the phase of selected harmonic for each single pre- or post-stimulus signal segment, on the left and right side of the figure respectively, for the 32 stimuli test run. The uniform distribution of pre-stimulus and nonuniform distribution of post-stimulus signals phases was confirmed by the Rayleigh circular variance test for harmonics corresponding to the spectral peaks. The effect was stronger for the theta band than for the alpha one. In certain subjects the non uniformity of phase distribution at higher frequencies, e.g., at 17 Hz, was additionally found.

In half of the subjects examined, in the phase features space, a single cluster, containing most of the single responses, was found with a small number of randomly scattered responses as shown in the upper part of Fig. 5. Below the scatter plot the result of corresponding single responses classification with clustering algorithm is shown in the form of a dendrogram. On its left side the position of each single response in the dendrogram is denoted by the stimulus number. For clarity, only the first 24 classified responses are shown. The abscissa variable corresponds to the normalized Euclidean distance in the two dimensional absolute phase space.

The determination of the number of response classes (templates) can be performed by selecting a

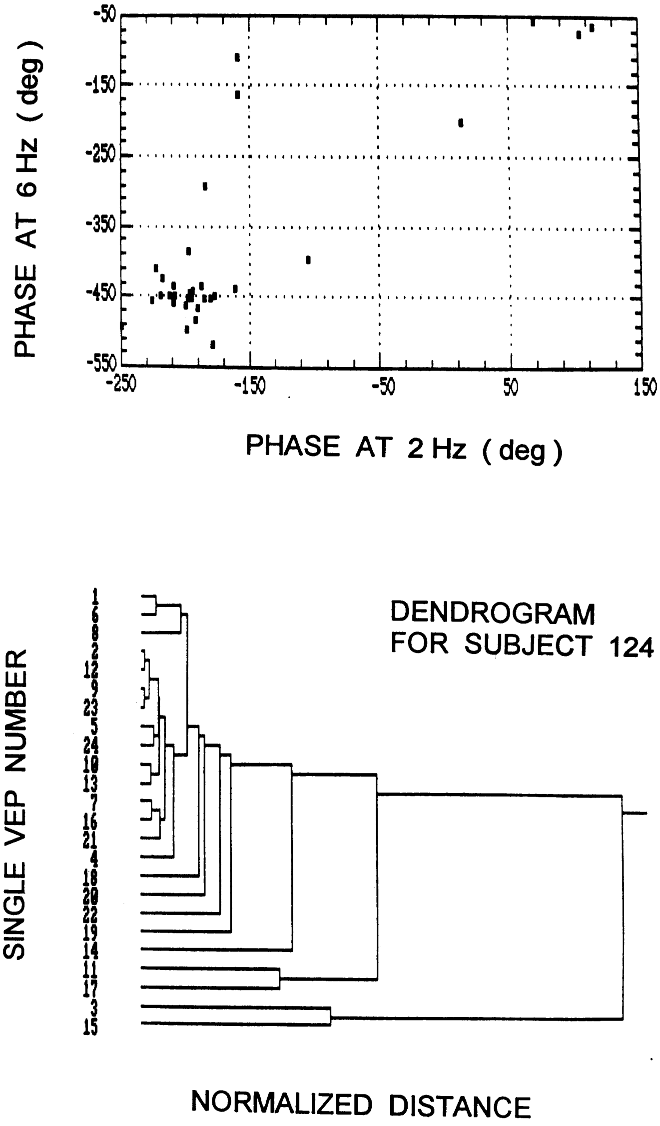

Fig. 5. Single trial responses phase scatterplot for 2 Hz and 8 Hz harmonic (at the top) with corresponding dendrogram (at the bottom) generated for subject 124 by clustering algorithm typical for so called "homogenous responders" (Gasser et al. 1983). The single VEP reproducibility is reflected by low normalized distance for majority of responses. The numbers of responses in given stimuli sequence are marked on the left side of the binary classification tree (dendrogram).

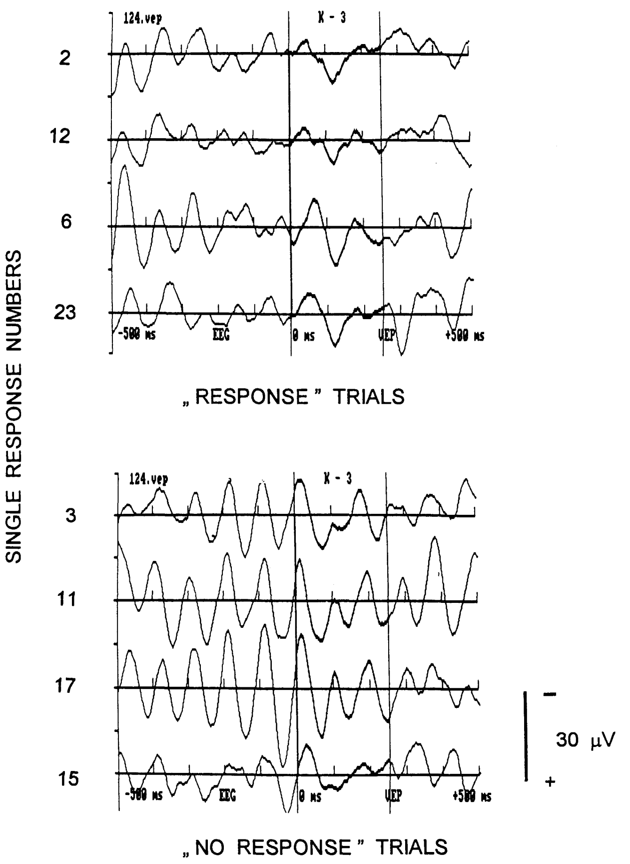

Fig. 6. The frequent (upper portion) and infrequent (lower portion of the figure) single trial evoked responses corresponding to main cluster members and outliers in phase space presented in Fig. 5. The portions of the signal used for that classification are plotted in bold line. The response numbers, printed on the left side of the baselines are the same as the corresponding numbers in Fig. 5.

certain threshold value of this distance which can be treated as the response similarity measure. The binary classification diagram provides an excellent tool for evaluation of the homogeneity or variability of a given set of single responses.

When single responses corresponding to the main cluster centre are compared with the outliers, a striking phenomenon is observed as shown in Fig. 6. Single responses from the main cluster can be described as the deterministic ones, as far as the localisation of these transient signals extremes on the time axis is concerned. The response amplitude variability is discarded by the phase pattern recognition approach used by the author.

These responses are presented in the upper portion of Fig.6 and labelled "response trials". The full raw data segment including pre-stimulus EEG is shown with the response number in the upper right hand corner, which helps to identify them in the classification tree in Fig. 5. Only the portion of each signal in the range 0-250 ms after the stimuli onset, plotted in a bold line, was used in the classification procedure. In the lower portion of the figure the single responses found as the furthest from the main cluster are shown. They are labelled "no response trials" because the effect of stimuli on EEG is negligible. It is no surprise that these responses oc-

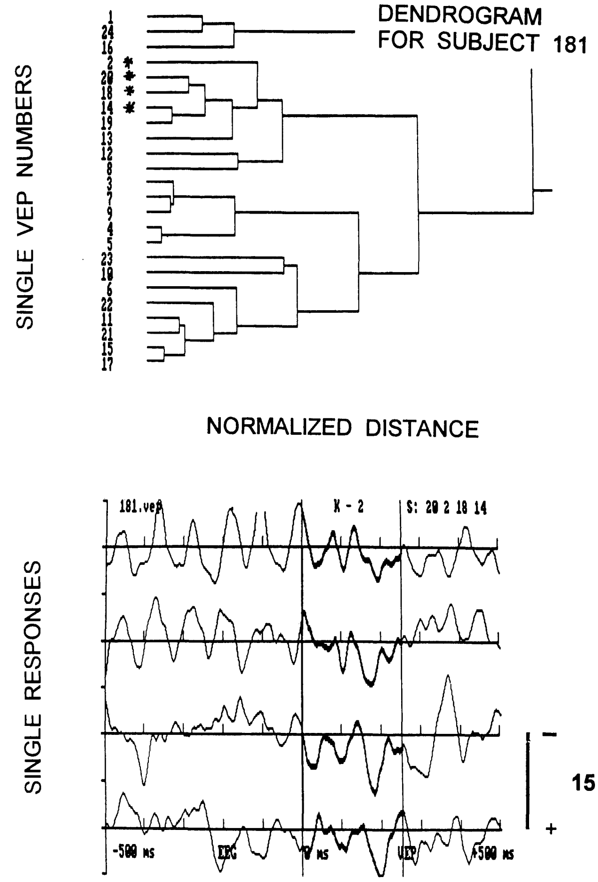

Fig. 7. Two dimensional signal phase features space (at 5 Hz and 13 Hz frequencies) derived dendrogram for typical subject (181) with high trial to trial response variability is shown in the upper part. Several deterministic single evoked potentials were found by inspection of the cluster content and are shown below. The asterisks in the upper left side of the dendrogram indicate the location of these responses in the classification diagram.

curred when the stimuli had been applied during the "spindle"-like EEG activity. The data presented above are typical for subjects with the ability to respond regularly to the stimuli. They are often called in the literature "homogeneous responders" (Gasser et al. 1983). Usually the response dynamics is much more complex as shown for another subject. In this case the phases of the 5 Hz and 13 Hz harmonics revealed the greatest non uniformity and were taken as the single response features. Single evoked responses classification is illustrated by the dendrogram in the upper part of Fig. 7. Several classes of responses with comparable response variability can be determined.

However the inspection of the clusters content revealed a small number of deterministic single evoked potentials as shown in the lower portion of Fig. 7. Their localization in the classification scheme is denoted by asterisks close to the response numbers in given stimuli sequence, in the upper left part of the figure. When these single responses are compared with the classical average, shown for this test run in Fig. 1, it turns out that these infrequent responses determine the average waveform morphology. Moreover, single responses of deterministic character as seen in Fig. 7 had amplitudes comparable with that of the background activity. The amplitudes of positive polarity component with 100 ms latency were in that case of the order of 6 μV, whereas the corresponding grand average value is about 3 μV, i.e., two times lower. This may serve as a good example of the limitation of the classical averaging method, in case of high trial to trial evoked response variability.

DISCUSSION

The dynamics of brain processes as reflected in trial to trial evoked response variability can give deeper insight into its functioning mechanisms. The possibility of its analysis is of prime importance in neurocognitive experiments when varying stimuli are used. The method proposed by the author is based on a new, convolution model of post-stimulus bioelectrical signals. When trying to verify the signal model, several empirical facts were observed, often with direct practical consequences. The experimentally discovered lack of significant effects of light flash stimulation on EEG power spectrum density can serve as the explanation of the small effectiveness of Wiener filter theory based approach to the enhancement of average potential estimate. Due to a substantial overlap of signal and noise spectra, such an estimator can be strongly biased and the use of sophisticated filter techniques (Heinze and Kunkel 1981) seems to be irrelevant.

The correlation of pre- and post-stimulus signal harmonics amplitudes can be interpreted in terms of short time EEG signal stationarity. A positive correlation was observed whereas other researches indicate an inversely proportional relationship (Basar 1980). Basar suggested that the greater the neural pool involved in synchronous spontaneous activity the smaller the ability to fire synchronously in response to afferent pathways activation. This discrepancy may be due to the fact that the "enhancement factor" introduced by Basar is more related to the after-discharge activity then to the stimuli specific sensory responses with shorter latencies studied by the author.

The variability of visual evoked response Fourier components for latencies shorter than 250 ms, corresponding to frequencies dominating in the power spectrum, suggests that the generating neural network reveals a phase modulation effect. The spontaneous neural activity synchronized by subcortical systems can be desynchronized by the impulses from the visual tract. This phase synchronization is observed as the stimuli induced "phase ordering" measured by non uniformity of harmonics phase distributions.

Experimental data obtained by the author for visual stimulation are similar to the results of Sayers reported for acoustic stimulation (Sayers et al. 1974). The author suggests that stimulus induced phase locking is a cortical mechanism of a more universal character. The absolute phase values patterns revealed evident clustering and allowed for the application of classification procedures avoiding the ambiguities related to periodic character of the phase observable. Single trial responses, in the simplest case, can be separated into two classes: the first corresponding to transient signals precisely time locked to stimuli and the second comprising responses dominated by a spontaneous activity. The classical average evoked potentials amplitude data have to be treated with great caution in cases of high response variability as it was shown that only a small fraction of reproducible responses can determine the average response wave shape. Furthermore, two methods for response template selection can be suggested. Firstly, in the case of good separation of clusters, the cluster averages may serve as the response type templates. Secondly, in the case of multimodal phase distribution with sharp peaks, the single responses corresponding to modal phase values can be used as the templates.

The experimental data obtained by the author so far provide partial confirmation of the new convolution model of the signal. What is more important, however, is that they show the possibility of replacing the classical canon of "evoked response extraction" by "the deterministic signal recognition" approach in the studies of event related brain potentials as already suggested by Gevins (Gevins et al. 1986). The development of sophisticated "extraction methods" seems to be unjustified as they can not be objectively verified due to the lack of any a priori knowledge of the signal under study, e.g. visual evoked response waveforms which reveal high within subject variability. This also refers to the attempt to extract the evoked response by the deconvolution procedures (Piątkowski and Achimowicz 1983).

Starting from the estimation of EEG amplitude from pre-stimulus segments and averaging of post--stimulus signal phases one can try to reconstruct the single evoked potential by taking the inverse Fourier transform. This approach is equivalent to the "whitening" of the post-stimulus signal spectrum due to its similarity with the pre-stimulus one and no additional information about the evoked response can be extracted in this way. Also the phase averaging is not a straightforward procedure and involves series methodological problems (Rabiner and Gold 1975).

Sophisticated deconvolution procedures by iterative reconstruction may be effective for handling the latency jitter problem (Pomalaza-Raez et al. 1986) but are not adequate for the extraction purposes. The intention of the author is not to introduce a new method of extraction of evoked potential but to provide a tool for analysis of the time locked response variability. It is an open question if it is possible to discriminate between the phase synchronized contribution from the sensory specific cortical generators and non-specific subcortical ones on the basis of single lead EEG recording alone. The effectiveness of the phase pattern recognition approach in transient signals classification results from the well known importance of the signal phase (Oppenheim et al. 1968, Oppenheim and Lim 1981). The phase component of the Fourier transform contrasted with the amplitude one is not invariant with respect to small shifts along the time axis. Due to this fact, the phase of the signal contains almost all the information about the localization of events on the time axis including extreme locations, that is the waveform peak latencies. So if the latency of the waveform is of primary interest, its phase parametrisation is optimal for classification purposes.

The pattern recognition in phase domain is no doubt a very effective approach to detection of any brain activity time locked to the external stimuli. This approach was revealed to be effective for studying the effect of subject's functional state modification on sensory responses (Achimowicz 1990, 1991) and may be also useful in neurocognitive electrophysiological studies. The discrete character of VEP variability observed by the author, which contradicts the common understanding of a random latency jitter, may be interpreted as the brain functional state related switching between afferent pathways due to activation or inhibition of certain portions of neuronal circuits resulting in the deterministic change of evoked potential waveform pattern (Wróbel et al. 1995).

APPENDIX

Convolution model of VEP generation

The new model of brain electrical activity can be derived starting from certain well known experimental data related to the analysis of the so called steady state response method introduced by Regan (Regan 1965). In that approach the visual system is treated as a linear time shift-invariant system described by a transfer function. This function can be determined by analysis of the brain electrical response to sinusoidally modulated light delivered at different frequencies. It has been observed that transfer function peaks coincide with the spectral maxima of the spontaneous activity. Similar results were obtained by Sato (Sato et al. 1961) and revealed the similarity of both functions with accuracy to the multiplicative constant.

The linear system output signal Y(t) and its power spectrum density $G_{YY}(f)$ are related to a transfer function module H(f) and input signal X(t) power spectrum $G_{XX}(f)$ by the basic equation:

$$G_{yy}(f) = |H(f)|^2 \cdot G_{xx}(f) \tag{1}$$

Let us assume that EEG ,which is a band limited signal, results from low pass filtering action of the cortex imposed on wide band excitation from afferent pathways. If this input signal has a relatively flat spectrum with a cut-off frequency greater than the frequency bandwidth of the EEG, treated as the output of a cortical system, then within a certain approximation the following relations hold in the frequency range of interest:

$$G_{xx}(f) = C \tag{2}$$

$$G_{EEG}(f) = C \cdot |H(f)|^2 \tag{3}$$

in agreement with experimental data discussed above, where C is a constant related to the mean energy of the input signal. The temporal changes of EEG power spectrum can then be interpreted as resulting from time varying filtering properties of the cortex as already proposed by Knott (Knott 1960). Let us make an assumption that after stimulus application we measure a certain signal V(t) which is the filtered version of the unknown signal under consideration i.e., visually evoked response (VEP). By analogy to equation (1) one can introduce relation for the corresponding spectral functions:

$$G_{VV}(f) = |H(f)|^2 \cdot G_{VEP}(f) \tag{4}$$

and using the approximate relation (3)

$$G_{VV}(f) = 1/C \cdot G_{EEG}(f) \cdot G_{VEP}(f) \tag{5}$$

It is obvious that the above relation is fulfilled if we assume for the post-stimulus brain activity the convolution model expressed in time domain by a folding integral of the following form:

$$V(t) = \int_{-\infty}^{+\infty} C \cdot EEG(\tau) \cdot VEP(t-\tau) \cdot d\tau \tag{6}$$

This integral describes the behaviour of linear systems with "memory " meaning that system output depends not only on the instantaneous values of input signal but also on the values of EEG(t) at earlier time (signal history). In this model the post--stimulus EEG can be interpreted as the cortical impulse response function. This relation can also hold for quasi-stationary processes and/or systems which can, in short time periods, be described as linear. Its parameters may change in time, slowly in comparison with short time signal variability. Keeping in mind that convolution in time domain leads to multiplication in the frequency domain, for the sequence of single responses $VEP_i(t)$ and i=1..N, we can have for a finite length T time window signal segments $V_i(t)$ the relation:

$$V_i(t) = \int_0^T VEP_i(\tau) \cdot EEG_i(t-\tau) d\tau \tag{7}$$

and for their corresponding complex Fourier transforms F{ }:

$$F\{V_i\} = F\{VEP_i\} \cdot F\{EEG_i\} \tag{8}$$

Using a polar representation for the Fourier transforms in the form of the product: $A_i(f)*\exp(-jF_i(f))$, we obtain the following relations for amplitude - $A_i(f)$ and phase - $F_i(f)$ components of the considered signals:

$$A_{Vi}(f) = A_{EEGi}(f) \cdot A_{VEPi}(f) \tag{9}$$

$$\Phi_{Vi}(f) = \Phi_{EEGi}(f) + \Phi_{VEPi}(f) \qquad (10)$$

where A_{Vi}, A_{EEGi} and A_{VEPi} denote the amplitudes and F_{Vi}, F_{EEGi} and F_{VEPi} the corresponding phases of measured signal V, VEP and EEG Fourier transforms, recorded after the i-th from the series of N identical stimuli correspondingly. The same equations are valid for discrete representation of continuous functions as long as the sampling frequency is taken high enough to prevent spectral aliasing.

In this way the convolution model of bioelectrical signals following stimuli implies a multiplicative relation for amplitudes of Fourier harmonics of spontaneous and evoked activity and an additive one for the corresponding phases.

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