

EEG responses to long-term audio–visual stimulation

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Abstract

In this study, linear and nonlinear electroencephalogram (EEG) changes due to long-term audio–visual stimulation (AVS) were investigated. In the course of 2 months, 25 repetitions of a 20-min AVS program with stimulation frequencies in the range 2–18 Hz were applied to six healthy volunteers. EEG data were recorded from six head locations during relaxed wakefulness prior to AVS. Then linear spectral measures (total power, frequency band powers, spectral edge frequency, and spectral entropy), nonlinear measures of complexity (histogram-based entropy and correlation dimension), interdependency measures (linear correlation coefficient, mutual information, and coherence), and measures of subjective assessment were estimated. Evolution of these measures during the whole experiment period was analyzed with respect to the significance of their linear regression. Our results confirm that repetitive training with audio–visual stimulation does induce changes in the electro-cortical activity of the brain. Long-term AVS significantly increased power in theta-1, theta-2, and alpha-1 bands in the frontal and central cortex locations. Total power increased in the right central region. Interhemispheric coherence in alpha-1 band displayed a significant increase between frontal parts in contrast to the decrease of both linear correlation and mutual information. Correlation dimension significantly decreased in some locations while entropy displayed an ascending trend.

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1. Introduction

AVS is a simple method for external influence on the brain. The source of rhythmic stimulation such as light and sound synthesizers delivers the AVS signal to the brain through peripheral nerves. Headphones and glasses with light-emitting diodes are usually utilized. Transmission from space can also be used.

During AVS, adaptation of dominant EEG frequency to external stimuli may be observed (Walter and Walter, 1949). This kind of resonant phenomenon is known as entrainment of brain waves. AVS primarily activates brain centers of visual and sound processing. Several studies have suggested that the photic driving response has a more diffuse character on cortical EEG, not limited only to occipital regions. Duration of induced rhythms is usually limited; mostly

direct and transient effects were observed (Brauchli et al., 1995; Timmermann et al., 1999).

Since the early 1930s, a number of studies have been devoted to the effects of external stimulation on the cortical EEG (Adrian and Matthews, 1934; Walter and Walter, 1949; Townsend et al., 1975; Pigeau and Frame, 1992). Audio–visual stimulation has been reported to influence sleep and learning disorders, neurological disorders, addictions, tension, anxiety, premenstrual syndrome, migraine headaches, etc. (Morse, 1993; Dieter and Weinstein, 1995; Solomon, 1985; Anderson, 1989; Anderson et al., 1997; Carter and Russell, 1993; Montgomery et al., 1994; Russell, 1997; Lubar, 1989; Serman, 1996; Tansey, 1985). AVS has become popular mainly for assumed induction of relaxing effects and altered states of consciousness. Relaxation can be generally regarded as attenuation of some bodily functions from tension, and is a manifestation of integrated response of the parasympathetic system. When interested in resting EEG data processing, one usually scans alpha and theta power increase, right hemispheric activation, alpha

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synchronization, and some other signs (Graham, 1977; Brauchli et al., 1995; Cantero et al., 1999). Evidently, to detect the effects of the AVS devices, spectral characteristics of the human EEG are mostly studied. For instance, alpha oscillations (8–12 Hz) spontaneously appearing in relaxed wakefulness with eyes closed have been treated as one of the fundamental electrophysiological phenomena.

However, some findings concerning the rhythmic brain activity seem to be inconsistent. Brauchli et al. (1995) used rhythmic audio–visual stimulation programs with different intensity of stimuli: decrease of contribution of the alpha band and higher activation of the right hemisphere during all programs were interpreted as an indication that AVS induced changes in the brain, such as those found in altered states of consciousness. Timmermann et al. (1999) found that the overall effects of AVS in the alpha range did not have a significant effect on the corresponding alpha activity of the cortex. Investigations made by Walach and Käseberg (1998) showed no specific state of relaxation compared to rest state without AVS impact, but they reported that AVS seems to alter the state of consciousness. Kawaguchi et al. (1993) reported that one-half of their subjects did not produce a photic driving response within the alpha band pass to stroboscopic flashes ranging from 5 to 16 Hz. In experiments conducted by Rosenfeld et al. (1997), one group of subjects did not produce a photic driving response within the alpha band, whereas low-baseline alpha participants showed transient AVS effects.

The main purpose of this study was to investigate the effects of AVS on the EEG on the long-term basis. Up to now, most of the EEG research on AVS has focused on direct and short-term effects of AVS (during and shortly after the stimulation). To our knowledge, this is the first study dealing with EEG features under repetitive stimulation sessions during a longer time period.

Moreover, we have utilized both linear and nonlinear approaches for analyses of the AVS effects.

In contrast to the linear description (e.g., frequency analysis), it is natural to expect that the neuronal dynamics may behave in a nonlinear manner. The growing need for a better understanding of brain dynamics and the recent emergence of a physics of nonlinear systems have stimulated the development of more advanced data analysis techniques, often referred to as nonlinear methods. Traditional signal-processing procedures (e.g., Fourier analysis) reflect information about one-dimensional time series. On the other hand, the dynamical view suggests that a single time series may be seen as a manifestation of the whole dynamics of the system. Based on the embedding theorem (Takens, 1981), it is possible to reconstruct the behaviour of a dynamical system from a single variable like the single-channel EEG. Then, the reconstructed dynamics is analyzed with nonlinear methods. Although the applicability of these techniques to real systems has been questioned repeatedly, it is generally accepted that some nonlinear measures might be useful if used with care.

Complexity measures related to the concept of entropy rates estimation were reported by Rosipal (2001) to be useful for determining depth of anaesthesia. Results by Kobayashi et al. (2000) showed successful discrimination of sleep stages by measure of correlation dimension. AVS examined by Jin et al. (2002) had decreasing effects on EEG complexity, shown by the first positive Lyapunov exponent as one of nonlinear measures of complexity. These and similar findings indicate that nonlinear measures may be as good or even better in discrimination of brain states, compared to the existing, mainly spectrally based techniques. For comparison of an efficiency of linear and nonlinear approaches, we used both of them for EEG data analyses in this paper. Nonlinear measures were represented by histogram-based entropy, correlation dimension, and mutual information.

2. Materials and methods

2.1. Subjects

Six right-handed healthy subjects (two females and four males) volunteered for the AVS training. Participants ranged in age from 24 to 39 years, with a mean of 25.5 years (S.D. 5.1 years). They did not have any known neurological deficit and were not taking any drugs known to affect the EEG. The participants gave their written informed consent prior to their inclusion in the experiment.

2.2. Audio–visual stimulation

Overall training of each subject consisted of 25 AVS program sessions, each of 20-min length. Each person attended only one session per working day. Due to week-ends or other exceptional events, separation between stimulations could be prolonged to several days. During sessions, subjects were lying in a darkened, electrically shielded room. AVS was provided by commercially available Voyager XL light and sound synthesizer. The device consisted of headphones and glasses with red light-emitting diodes connected to a portable unit providing various programs for AVS stimulation. We chose a program described as suitable for AVS beginners to make acquaintance with different “mind states” according to their frequency profile performed. The program stimulated the brain at following frequencies: 18 Hz during the first 3 min; then 18–10–8 Hz at min 4–8; 8–5 Hz at min 8–9; 5–4 Hz at min 9–12; 4–2 Hz at min 13; 2 Hz at min 14–17; and 5, 9, and 15 Hz at min 18–19. Sound beats of a particular frequency were produced from three sine-wave pulses with close frequencies around 280 Hz. Visual stimulation was provided by rectangular red light pulses with a number of switches determining the stimulation frequency. This series was chosen to introduce a sequence of beta, alpha, theta, and delta frequency ranges to participants.

2.3. EEG recording

As we were interested in changes of resting EEG, data from the 3-min period were recorded before each AVS session. Subjects were instructed to keep their eyes closed and relax both physically and mentally. After initial EEG recording, headphones and glasses were placed over the electrode cap and the participants were instructed to stay relaxed and to follow the AVS. Participants adjusted brightness and loudness at the beginning of each AVS session to meet both their comfort and maintain effective stimulation. Subjects were provided with AVS or 20 min, with simultaneous EEG recording. After the stimulation, a post-session EEG during relaxed wakefulness with closed eyes was recorded for another 3 min (these data were not used for the purpose of this paper). The lying position during the EEG measurements was comfortable enough to avoid unwanted activities and to diminish the occurrence of some artifacts caused by feeble motion. On the other hand, the subjects sometimes fell asleep as a room was designed to be darkened and noiseless.

Monopolar EEG montage comprised eight channels with electrodes placed on F3, F4, C3, C4, P3, P4, O1, and O2 locations according to the International 10–20 system. The reference electrode was located at Cz and the ground electrode at the Fpz point (Fig. 1).

A standard cap system (Electro Cap, Inc.) with Ag–AgCl electrodes was employed. In order to prevent signal distortions, impedances at each electrode contact with the scalp were kept below 5 k Ω , and balanced within 1 k Ω of each other.

Our EEG recording unit was characterized by the following parameters: number of channels; amplifying gain: 402; sampling frequency: 500 Hz; A/D converter resolution: 16 bits; input resolution: 0.46 μ V; noise: max 4.1 μ V pp (0.07–234 Hz); lowpass filter: 234 Hz (–3 dB); highpass filter: 0.07 Hz (–3 dB). A digital highpass FIR filter with a cut-off at 0.75 Hz, a width of 3000 data points, and a Blackman window was utilized.

From the eight-channel signal between active electrodes and reference electrodes, six difference signals F3C3, F4C4, C3P3, C4P4, P3O1, and P4O2 were derived by off-line transformation in order to avoid undesirable effects of common reference electrode.

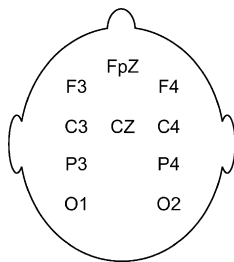


Fig. 1. EEG montage used in this study. Active electrodes are placed at F3, F4, C3, C4, P3, P4, O1, and O2, and reference and ground electrodes at Cz and Fpz points, respectively.

A total of 3200 electroencephalograms were analyzed first by online visual control of the ongoing EEG in eight channels and later by offline analysis. Sequences contaminated by either subject-related or technical artefact and obvious sleep occurrences were excluded by eye inspection and according to the subject's assessment. For the purpose of this study, about 1200 three-minute electroencephalograms recorded prior to AVS trainings were employed.

2.4. Measures

To uncover objective changes from our EEG data, we computed the following characteristics: (1) spectral measures: total power, frequency band powers, spectral edge frequency, and spectral entropy; (2) nonlinear complexity measures: histogram-based entropy and correlation dimension; and (3) interdependency measures: linear correlation coefficient, mutual information, and coherence.

The EEG measures were computed from the whole 3-min epochs recorded prior to AVS. As the raw EEG was digitized at 500 Hz, each 3-min series contained 90,000 data samples. By following digital filtering, the first and the last 1500 points were omitted and 87,000 data points remained. Instead of calculation from series that had to be omitted due to artefacts, the average of preceding and consecutive values of particular measure was used.

2.4.1. Spectral measures

Power spectrum was utilized by fast Fourier algorithm with a variation reduction factor of 10 and a frequency resolution of 0.06 Hz.

2.4.1.1. Total power. Total power was computed for the frequency range of 0.5–45 Hz.

2.4.1.2. Frequency band powers. Frequency spectrum was divided into nine bands: delta-1 (0.5–2 Hz), delta-2 (2–4 Hz), theta-1 (4–6 Hz), theta-2 (6–8 Hz), alpha-1 (8–10 Hz), alpha-2 (10–12 Hz), beta-1 (12–16 Hz), beta-2 (16–30 Hz), and gamma (30–45 Hz), and corresponding powers were computed.

2.4.1.3. Spectral edge frequency. Spectral edge frequency was set as a frequency below which 95% of the total power within the range 0.5–45 Hz lays.

2.4.1.4. Spectral entropy. Spectral entropy is a linear complexity measure in the spectral domain. Normalized distribution of power over frequency with respect to the total power spectrum yields a probability density function (PDF). According to Shannon channel entropy, an estimate of the spectral entropy can be computed as:

$$H_{sp} = - \sum_f p_f \ln(p_f) \quad (1)$$

where p_f is the PDF value at frequency f .

Spectral entropy was evaluated for the frequency range 0.5–45 Hz.

2.4.2. Nonlinear measures of complexity

Nonlinear complexity measures detect the degree of variability in the EEG signal concentrating on the dynamics of the process.

2.4.2.1. Histogram-based entropy. Histogram-based entropy estimators are related to the Shannon entropy concept that determines the degree of uncertainty or the rate of information acquisition from the given time series. Histogram is constructed from time series values and estimate is calculated as:

$$H_{\text{hb}} = - \sum_i n_i \ln(n_i) \quad (2)$$

where the summation runs through all bins and n_i is the histogram value of i th bin. We used this simple estimation and another estimation using further modifications (Modemeijer, 1989). For the latter, EEG data normalized by their standard deviation were employed, whereas for the former, data without normalization were used. All data points from minimal to maximal values were divided into 295 bins. The number of bins was set to be equal to the square root of the number of data points.

2.4.2.2. Correlation dimension. It has been mathematically established that, if we can measure any single variable of a dynamical system with sufficient accuracy, then it is possible to reconstruct the state portrait, topologically equivalent to the original system. For the reconstruction, a set of delay coordinates is a convenient choice (Takens, 1981). Then one state of the system is defined by a point $x_m(i) = (x_i, x_{i+\tau}, \dots, x_{i+(m-1)\tau})$ constructed from m samples taken at intervals of τ in a space of embedding dimension m . Under the assumption that the attractor of the system is a differentiable manifold of dimension D , the embedding with $m \geq 2D + 1$ saves a lot of important properties of the original attractor. The geometrical character of the attractor may provide important information about the system.

In this context, complexity of the system is often estimated by correlation dimension (CD). The CD may indicate chaos or identify low-dimensional determinism and estimate the minimum number of variables that must be considered in the description of the dynamics.

The correlation dimension is defined as

$$D_2 = \lim_{\epsilon \rightarrow 0} \frac{\ln \sum_{i=1}^{N(\epsilon)} p_i^2}{\ln \epsilon} = \lim_{\epsilon \rightarrow 0} \frac{\ln C_2(\epsilon)}{\ln \epsilon} \quad (3)$$

where C_2 is the probability that a hypercube with a size ϵ contains two points of the attractor. It is approximately equal to the probability that the distance between two points of the attractor is less than ϵ . Then the correlation sum C_2 may be

estimated by the Grassberger–Procaccia algorithm (Grassberger and Procaccia, 1983):

$$C_2(\epsilon) = \frac{2}{N(N-1)} \sum_i^N \sum_{j>i}^N \Theta(\epsilon - \|\mathbf{x}_m(i) - \mathbf{x}_m(j)\|) \quad (4)$$

where N denotes the number of data points, Θ is Heaviside step function, and $\|\cdot\|$ usually represents the maximum norm.

In order to find the correlation dimension, we plot $\ln C_2(\epsilon)$ as a function of $\ln \epsilon$ and follow the slope $\nu(\epsilon) = \frac{d \ln C_2(\epsilon)}{d \ln \epsilon}$ of the obtained curve $\nu(\epsilon)$, which is called the correlation exponent, and its limit for vanishing ϵ represents the correlation dimension.

Reliable estimation of the CD requires sufficient amount of data points. Compromise has to be made between the requirements for a sufficiently long EEG window and stationarity. EEG window of tens of seconds in duration can be regarded as quasi-stationary, depending on the subject's behavioral state (da Silva, 1987).

Embedded vectors for CD estimate were constructed with a time lag $\tau = 10$, which corresponds to 5 ms. This value was chosen according to the first minimum of mutual information between the original signal and its shifted version, meaning that they are more independent with more information for utilization (Galka, 2000). Embedding dimension was chosen to be 1, 2, ..., 8. Another increase of ED is impossible as it was shown that in M -dimensional state space, about 10^M data points are needed for satisfactory dimension analyses (Krakovska, 1995; Nerenberg and Essex, 1990). Consequently, for a given data number, there is only a limited interval of possible choices for embedding dimension. This fact is often ignored in experimental applications of dimensional analyses. In our case, larger spaces were not needed as, for M above 5, the values of CD were saturating. However, obtained low estimates can arise from some linear features of data, as it is mentioned further.

2.4.3. Interdependency measures

In the study of EEG signals, synchronization phenomena have been increasingly recognized as a key feature for establishing the communication between different regions of the brain (Gray et al., 1989). A highly synchronized EEG means a high similarity in the wave shape occurring within a given point or period in time. The basic idea is that the similarity of the signal also means similarity in functioning. Interdependence can be evaluated by different measures possessing linear or nonlinear character.

Nonlinear interdependencies (e.g., mutual information) have the ability of being sensitive to every kind of interaction, either linear or nonlinear. Quiroga et al. (2002) reasoned that in EEG analysis, nonlinear synchronization measures might surpass traditional linear methods such as the crosscorrelation or the coherence function.

For investigation of the cooperation between hemispheres, we estimated linear correlation of paired signals from left and right hemispheres by linear correlation

coefficient (Pearson's correlation) and with respect to restriction to certain frequency bands by coherence. As a nonlinear measure with broader scope for evaluating interdependency, mutual information was estimated.

2.4.3.1. Linear correlation coefficient. For evaluating linear association between two finite time series, we used the well-known Pearson's correlation coefficient:

$$r = \frac{\sum_i (X_i - \bar{X})(Y_i - \bar{Y})}{\left[\sum_i (X_i - \bar{X})^2 \sum_i (Y_i - \bar{Y})^2 \right]^{1/2}} \quad (5)$$

where \bar{X} and \bar{Y} are the means of time series $X = \{X_i\}_{i=1}^N$ and $Y = \{Y_i\}_{i=1}^N$, respectively.

2.4.3.2. Coherence. EEG coherence estimates the degree of synchrony between the activities of two brain regions concentrating on a certain frequency band. For two time series X and Y , coherence is defined as a square of linear correlation of cumulative power spectra:

$$K_{XY}(f) = \frac{\text{cov}(P^X(f), P^Y(f))}{[\text{var}P^X(f)\text{var}P^Y(f)]^{1/2}} \quad (6)$$

where the nominator denotes the covariance $1/N \sum_i [P_i^X(f) - \bar{P}^X(f)][P_i^Y(f) - \bar{P}^Y(f)]$ and the denominator variances expressed as $1/N \sum_i [P_i^X(f) - \bar{P}^X(f)]^2$ for P^X occurs, and analogically for P^Y . $P_i^X(f)$ denotes spectral power of frequency band f from time series X computed from i th data sequence and $\bar{P}^X(f)$ is a mean in respect to i . The value of coherence ranges from 0 to 1. Coherence 1 means that the corresponding frequency components of both signals are identical and only amplitude and phase characteristics may differ. Coherence 0 means that the corresponding frequency components of both signals are completely uncorrelated (Rappelsberger, 2000).

Coherence was counted from the same frequency bands as frequency band powers. FFT was estimated from 40 overlapping windows of 8-s duration and with Hanning windowing utilization.

2.4.3.3. Mutual information. The concept of mutual information was firstly established in the field of communications theory (Shannon and Weaver, 1949). It was adopted to EEG analysis for evaluating certain nonlinear correlation between two time series (Callaway and Harris, 1974). In fact, mutual information measures the amount of information shared between two signals (Gel'Fand and Yaglom, 1959). It is defined as:

$$MI(X, Y) = \sum_{x_i, y_j} P_{XY}(X_i, Y_j) \log_2 \left[\frac{P_{XY}(X_i, Y_j)}{P_X(X_i)P_Y(Y_j)} \right] \quad (7)$$

where $P_X(X_i)$, $P_Y(Y_j)$ denote the normalized histograms of the distributions of observed values X_i , Y_j in the time series X , Y , and $P_{XY}(X_i, Y_j)$ is the joint distribution of both series (Abarbanel et al., 1996). For independent time series, MI is

0; otherwise, it will take positive values with a maximum value in case of identical signals.

2.4.4. Subjective assessment

A volunteer's subjective perception of the training process was monitored to set objective changes into the frame of the subjects' experience. Before each day procedure, subjects evaluated their general well-being by answering a question "How do you currently feel?" After 3-min relaxation prior to AVS session, subjects evaluated their general release accomplished during the relaxation; the task was formulated as "Assess a level of your relief accomplished during the prestimulation period." Both measures were rated on seven-point bipolar scale. Although subjects might interpret these questions slightly differently, relative movements on the scale are supposed to indicate changes of subjects' states. At the beginning and at the end of the whole experiment, participants rated their skills regarding ability to relax and expressed their attitude towards effectiveness of AVS machines, specifically whether they think AVS training may improve person's relaxation abilities.

2.5. Statistics

Our aim was to uncover statistically significant trends in examined measures. Evolutions of test group averages during the course of the AVS training were calculated for each individual measure. For these 25 data point time series, linear regression model $Y = a + bX + e$ was derived, and its significance was tested by an ANOVA F -test. The significance criterion was $p \leq 0.05$ (testing for $H_0: b = 0$ against $H_1: b \neq 0$). For consistency at a personal level, we have added another criterion for considering any trend as significant: Maximally one of the subjects could have an opposite trend compared to significant group-average trend. For significant trends, distribution of residuals from regression model was checked by Shapiro–Wilk test for normality.

3. Results

3.1. Spectral measures

To uncover spectral changes during relaxed wakefulness before stimulation, we estimated *total power*, *frequency band powers*, and *spectral edge frequency*.

We discovered significant trends especially in the contribution of lower frequencies and in the measure of right hemisphere activation.

Significant increase of power in theta-1, theta-2, and alpha-1 bands was observed in frontal and central regions. While theta-1 and theta-2 displayed significant increase in F3C3 ($F(1,23)$ for all, $p < 0.04$ and $p < 0.0004$), C3P3 ($p < 0.002$ and $p < 0.008$), and C4P4 ($p < 0.024$ and $p < 0.0002$) locations, alpha-1 showed increases in all four

areas F3C3 ($p < 10^{-5}$), F4C4 ($p < 2 \times 10^{-5}$), C3P3 ($p < 0.0004$), and C4P4 ($p < 5 \times 10^{-5}$) (Fig. 3). Other significant trends were decrease of delta-1 power (C3P3), increase of alpha-2 (F3C3 and C3P3), increase of beta-2 (C3P3 and C4P4), increase of gamma (C4P4), and decrease of gamma (P3O1); however, these changes were not generally so extensive as changes in ranges mentioned above. An example of spectral density shift in various frequency bands is presented in Fig. 2.

In spite of the fact that we did not detect a rise of lower frequencies in parieto-occipital regions, the spectral edge significantly decreased in P3O1 ($p < 0.0006$) and P4O2 ($p < 3 \times 10^{-5}$) locations of the cortex (both approximately from 22.5 to 19 Hz) (Fig. 3).

The increase of lower frequency bands (4–10 Hz) may correspond to findings on physiological rest during meditation obtained by Aftanas and Golocheikine (2001), which reflects emotionally positive state and internalized attention. According to Basar et al. (2001), theta and alpha rhythms might reflect fundamentally different functional operations. A concept of ‘selectively distributed theta system’ was proposed by him, covering structures located in different brain areas able to produce theta activity spontaneously or as a reaction on external or internal stimulus. Theta might deal with integrative cognition and association functions, and in frontal cortex also with response-controlling function: increased theta power implies decreased reaction of the cortex to sensory stimulation (Basar et al., 2001). Increase of alpha rhythms might be functionally correlated to several types of cognitive, sensory, and motor behaviors (Schurmann and Basar, 2001).

In order to find out whether any long-term effect depending on relative alpha strength occurred, we divided participants into high- and low-baseline alpha group according to initial values of their alpha band power ratio. In contrast to Rosenfeld et al. (1997), participants from the low-baseline alpha group did not change their alpha band power ratio distinctly from participants from the high-baseline alpha group.

Total power (0.5–45 Hz) increased significantly in central region C4P4 ($p < 0.03$). Also in all other areas

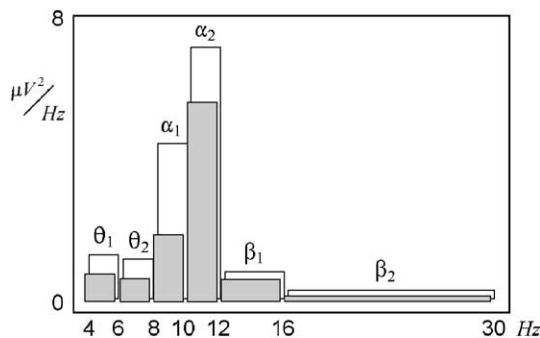


Fig. 2. Spectral density in C4P4 location after the whole experiment (white) compared to initial values (grey). The most expressive increase was observed in alpha-1 band.

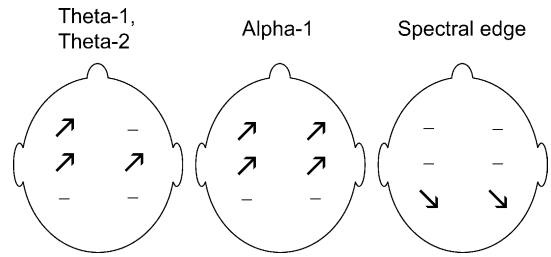


Fig. 3. Illustration of significant trends in spectral measures across cortex regions.

power increased (Fig. 4), which resembles findings of general increase of total power during sleep onset observed by Ogilvie et al. (1991). We detected left–right asymmetry of total power distribution in central cortex locations as well. Moreover, its dynamics during the whole course of the experiment displayed a shift from the left to the right hemisphere (Fig. 4). The phenomenon of enhancing the right hemisphere activation was reported to be state effect linked to altered states of consciousness (Graham, 1977). A more detailed view on the frequency bands uncovered that the same power shift was apparent in central cortex regions in theta-2 and alpha-1 bands: During the training weeks, the dominant activity of dipole sources in frequency interval 6–10 Hz moved from the left side to the right side of the cortex. Our final values correspond with the results of Pereda et al. (1999) who found interhemispheric differences during waking in the alpha band: values from the right hemisphere were higher than those from the left one.

Spectral entropy as a linear complexity measure significantly increased in C3P3 ($p < 0.005$) during the training period.

3.2. Nonlinear complexity measures

Increase in both histogram-based entropy estimators was obtained in F3C3 location ($p < 0.048$) (Fig. 5). Topographically, wider changes occurred in the correlation dimension that decreased in all six locations, significantly in three of them: F3C3 ($p < 0.0007$), F4C4 ($p < 3 \times 10^{-5}$) (Fig. 6), and C4P4 ($p < 0.0007$) (Fig. 5).

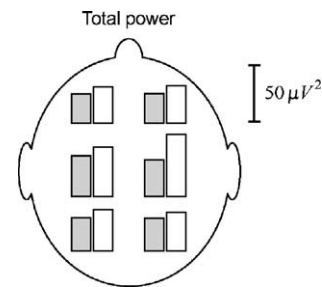


Fig. 4. Progress of the total power (from grey to white). The shift from the left to the right side activation during the course of the experiment in the central region is apparent.

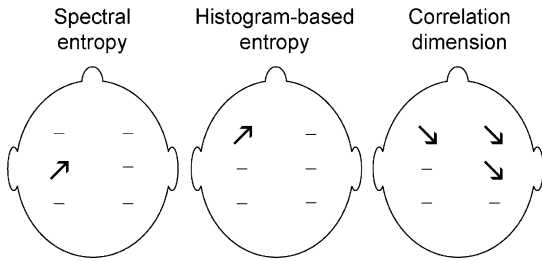


Fig. 5. Illustration of significant trends in complexity measures across cortex regions.

These decreasing trends correspond to some previous findings. Some authors reported decreasing values of CD with deepening of the level of sleep and the level of anaesthesia (Rosipal, 2001; Kobayashi et al., 2000). Aftanas and Golocheikine (2002) found a decrease in dimensional complexity estimate over midline frontal and central regions during meditation. Elbert et al. (1994) found reduced CD in those areas in which networks became actively engaged.

In contrast, Jeong (2004) interprets reduced EEG complexity in connection with Alzheimer’s disease as diminished information processing of the cortex due to the inactivation of previously active networks or a loss of dynamical brain responsiveness to external stimuli.

Anyhow, claims of low-dimensional dynamics in brain behaviour have to be taken with very much skepticism. In spite of the fact that most estimates of low dimension from complex experimental data seem to be artefacts (most often artefacts due to small data set), estimated CD is expected to provide a valuable relative, generic measure of the dynamical complexity of a signal. In this study, we tried to avoid problems with small data set size (we used 87,000 points) and with the effect of lowpass filtering (our measuring device fully covered frequency band from 1 to 100 Hz). As a result, a significant indication of relatively low values of CD of about 3–6 was found.

Theiler (1986) and other authors have shown that changes in some spectral properties of data, especially in correlations, may lead to spuriously low estimates of dimension. In accordance with these findings, we suppose that the observed decreasing trends in correlation dimension behaviour relate to the increase of power in alpha and theta bands.

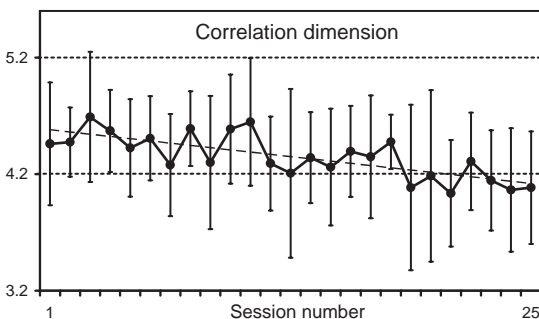


Fig. 6. Evolution of correlation dimension estimates in F4C4 location (standard deviation depicted by bars).

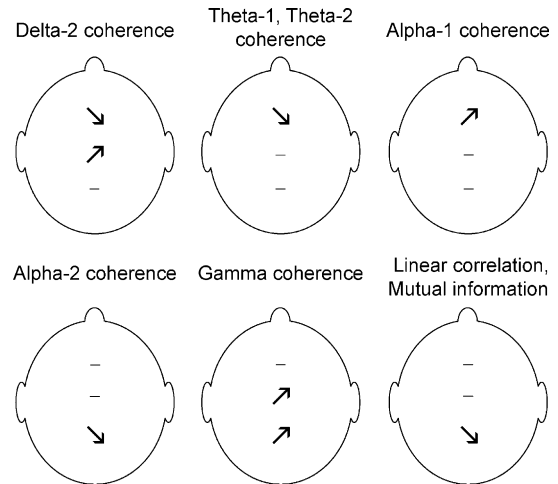


Fig. 7. Illustration of significant trends in interdependency measures across cortex regions.

Consequently, we treat CD not as an indicator of low-dimensional dynamics but only as a relative measure of changes in the course of the experiment.

3.3. Interdependency measures

Interhemispheric interdependency measures, namely linear correlation coefficient, mutual information, and coherence, were evaluated between fronto-central (F3C3–F4C4), centro-parietal (C3P3–C4P4), and parieto-occipital (P3O1–P4O1) locations. Both linear correlation coefficient and mutual information significantly decreased in parieto-occipital parts ($p < 0.006$ and $p < 0.007$) (Fig. 7). Mutual information appeared to be almost two times more sensitive in relative change from initial values than linear correlation (28% vs. 16% decrease).

Principal match of both trends confirms that interhemispheric relationship was mostly of linear type. This is in agreement with findings of Pereda et al. (2001) and Breakspear and Terry (2002), stating that nonlinear interdependency occurs infrequently in normal human EEG.

Coherence analysis revealed significantly increased coherence in the alpha-1 band in frontal regions ($p < 0.027$)

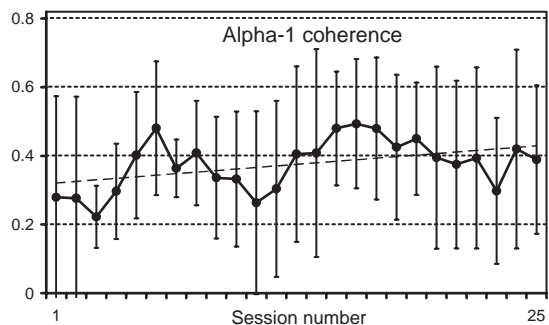


Fig. 8. Evolution of frontal interhemispheric coherence in alpha-1 band (standard deviation depicted by bars).

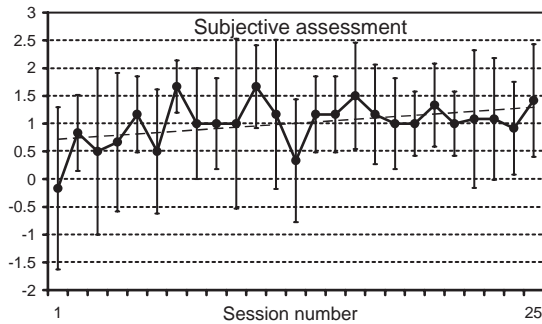


Fig. 9. Evolution of subjective assessment of the relief accomplished during relaxation (standard deviation depicted by bars).

(Fig. 8), while theta-1 and theta-2 coherences displayed opposite trends in this region ($p < 0.0003$ and $p < 0.036$) (Fig. 7). In other ranges, delta-1 coherence increased in parieto-occipital area ($p < 0.049$), delta-2 coherence decreased in fronto-central ($p < 7 \times 10^{-6}$) and increased in centro-parietal ($p < 0.014$) area, alpha-2 coherence decreased in parieto-occipital ($p < 0.01$), and gamma coherence increased in centro-parietal ($p < 0.01$) and parieto-occipital ($p < 0.024$) regions.

The increase of alpha-1 coherence might be related to findings of Cantero et al. (1999) concerning significantly higher alpha coherence in the frontal area compared to central and occipital locations during relaxation period.

3.4. Subjective assessment

At the beginning of our long-term training, only two out of six volunteers were optimistic about the possible impact of the AVS training on their relaxation abilities. One of them had neutral opinion, and three persons did not expect any progress of relaxation abilities for the future.

Perception of the training process showed the following results. While general well-being before each day of relaxation period displayed no significant trend, subjective measure that evaluated general release accomplished during the relaxation interval showed significantly increasing trend ($p < 0.037$) (Fig. 9) towards better performance. In spite of the fact that, from subjective results, certain progress of relaxing effects is apparent, spontaneous relaxation abilities evaluated at the end of the whole experiment were perceived as unchanged.

4. Discussion

To our knowledge, this study represents the first attempt to systematically test the hypothesis that long-term use of varying audio–visual input can have extended effects on electro-cortical activity. We detected several significant changes in EEG during the weeks of regular use of AVS. An important question is whether these changes are indicators of improved relaxation capacity.

In the literature, however, there is no clear definition of EEG descriptors of relaxation. One of the useful information sources appears to be the research on meditation, where various types of meditation can be considered as procedures with a relaxation effect (Banquet, 1973; Aftanas and Golocheikine, 2001; Travis, 2001). With increase of meditation condition, increase of depth of relaxation usually appears, confirmed by subjective and other physiological parameters, such as respiratory rate, skin conductance, and plasma lactate.

Neurophysiological indicators for a state of sensorimotor and mental rest are usually considered to be the increase of alpha and theta frequencies (Banquet, 1973; Brown, 1970) and interhemispheric synchronization, especially frontal alpha coherence (Travis, 2001). In our study, the power increase was not detected in alpha range (8–12 Hz), but more significantly in a rather shifted frequency range (4–10 Hz) merging the theta-1, theta-2, and alpha-1 ranges. The rise of coherence in alpha-1 band in the frontal area was observed as well, although general synchronization did not occur (i.e., both linear correlation and mutual information in the frontal region did not display an increase).

Our results show that regular training with AVS does induce changes in cortex functioning, such as those commonly reported to be features specific to relaxation or altered states of consciousness.

As a contribution to linear characteristics, we found significant trends in the behaviour of some nonlinear measures. Changes in mutual information exactly follow changes in linear correlation. Actually, mutual information appeared to be more sensitive than linear correlation.

However, trends of spectral entropy do not match changes in nonlinear complexity measures. This may be an example of a case when nonlinear complexity measures might represent new possible indicators of dynamical changes of resting EEG, or these changes might be indexed better by a combination of linear and nonlinear EEG variables.

Another relationship between nonlinear and linear measures may be given by possible connection between the spectral features of data and dimensional estimates. It is possible that the decreasing trends of CD and increasing trend of theta and alpha band powers are reflections of the same spectral changes of EEG signals.

In spite of the fact that we did not employ a fully acceptable control group, we engaged in the same measurement procedure two other volunteers. Instead of AVS, they listened to relaxation music. The significant results of the test group were compared with results obtained from this small control group. The control group did not display consistent agreement with most of the significant trends from the test group.

Thus, it seems that AVS training could be more effective in inducing long-continuing changes of EEG than regular 20-min listening to relaxation music. However, we must stress again that this fact was not supported by strong

statistical evidence because our control and test groups could not be properly compared.

We can not exclude a possibility that certain contributions to increased relaxation effects could come from repetitive relaxation training itself, regardless of the use of AVS. Subjects might adapt gradually to experimental conditions and develop some progress reflected in trends of studied measures.

Despite our findings about the measurable influence of AVS, we are very skeptical regarding the declarations found in various manuals of popular AVS machines claiming that, after some training (minimally 30 repetitions), one may learn to distinguish among beta, alpha, theta, and delta "states," and even to induce these states voluntarily when desired.

The present study was conducted to fill a gap in the knowledge of brain functioning during long-term AVS training. Gathered evidence in a form of trends of certain linear and nonlinear measures indicates that AVS training may serve as a useful tool for evoking long-term changes in resting EEG and in the improvement of relaxation abilities.

However, further research is needed to support extensive clinical applications of AVS technology. For future studies, we suggest an investigation of long-term AVS with simultaneous recording of other relevant physiological parameters (e.g., electrodermal resistance, respiratory rate) for determination purposes, and postmeasurements after longer time periods from completion of long-term AVS experiment.

In this study, we have evaluated data from rest sessions prior to stimulation. Further analyses of data recorded during and after audio–visual stimulation should directly display brain waves entrainment process and decide whether any transient effects occurred.

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