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Universality in the brain while listening to music

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The human brain, which is one of the most complex organic systems, involves billions of interacting physiological and chemical processes that give rise to experimentally observed neuroelectrical activity, which is called an electroencephalogram (EEG). The presence of non-stationarity and intermittency render standard available methods unsuitable for detecting hidden dynamical patterns in the EEG. In this paper, a method that is suitable for non-stationary signals and preserving the phase characteristics and that combines wavelet and Hilbert transforms was applied to multivariate EEG signals from human subjects at rest as well as in different cognitive states: listening to music, listening to text and performing spatial imagination. It was found that, if suitably rescaled, the gamma band EEG over distributed brain areas while listening to music can be described by a universal and homogeneous scaling, whereas this homogeneity in scale is reduced at resting conditions and also during listening to text and performing spatial imagination. The degree of universality is characterized by a Kullback–Leibler divergence measure. By statistical surrogate analysis, nonlinear phase interaction was found to play an important role in exhibiting universality among multiple cortical regions.

Keywords: EEG; gamma band; wavelet; nonlinearity; universality; cognitive functioning

1. INTRODUCTION

An electroencephalogram (EEG) represents complex irregular signals that may provide information about underlying neuronal activities in the brain. Traditionally, an EEG is modelled as a linear stochastic Gaussian process (Niedermeyer & Lopes da Silva 1993). However, the brain is intrinsically a nonlinear system, so theoretically a more accurate approach would be to formulate the problem in a nonlinear framework. The application of concepts from the theory of nonlinear dynamics (Kantz & Schreiber 1997) to EEG signals has already provided a number of interesting attempts (Lehnertz & Elger 1998; Galka 2000). However, the success of this kind of analysis has mostly been confined to the prediction and characterization of seizures. The question of whether or not the underlying system is deterministic chaos is still an open one. The presence of different kinds of noise (measurement noise as well as dynamic noise), the requirement of huge numbers of data and the inherent non-stationarity of the signal (Kawabata 1973) make the task of the detection of low-dimensional chaos in an EEG nearly insurmountable (Rapp 1993). Therefore, new approaches in the domain of brain signal analysis are needed, that can handle the problems of nonlinearity and non-stationarity in a more efficient way.

Recently, there has been considerable interest (Stanley *et al*. 1996, 1999) in the application of statistical physics to physiological signal analysis in attempts to find an explanation for the macroscopic phenomena resulting from the microscopic interactions among innumerous individual components. Physiological systems such as the brain are not in equilibrium, since they are driven by nonlinear and complex (deterministic as well as stochastic) interactions of many external and internal degrees of freedom. Efforts have been made (Ingber 1982, 1991; Nunez 2000) for such systems, which exhibit various phenomena arising at different spatio-temporal scales, to study macroscopic neocortical phenomena such as EEGs by using a chain of methods dealing with overlapping microscopic and mesoscopic scales. The two most interesting properties that are relevant in this context are universality and scaling (Stanley 1971). Universality means that different systems behave in a very similar way near their critical points. A critical point is a type of singular point that is associated with an abrupt change of qualitative behaviour. Examples are the melting process (where an ordered phase, such as ice, changes into a disordered phase, such as water) or the disappearance of ferromagnetism above the critical Curie temperature. An example of universality is the lattice gas analogy between the behaviour of a single axis ferromagnet and a simple fluid: their critical exponents are identical near their respective critical points (Stanley 1999). Scaling implies that the correlation function obeys a power law (the correlation $C(l)$ between subunits separated by distance l follows $C(l) \sim l^{-\xi}$, where ξ is the critical exponent). Systems exhibiting the power law are free from any characteristic length scale, e.g. to some degree they are invariant under transformations of scale. Many physical systems exhibiting universal properties are characterized by fluctuations described by $1/f$ noise or pink noise, i.e. the power spectral density is inversely proportional to the frequency. The presence of this kind of power law correlation is widespread among diverse complex systems, such as healthy human heartbeat intervals (Ivanov *et al*. 1996), atmospheric variability (Bunde *et al*. 1998), DNA sequences (Li *et al*. 1994), landforms (Turcotte & Newman 1996) and fossil records (Sole *et al*. 1997). It has been shown (Georgelin *et al*. 1999) that a power law relationship exists in the pattern of alpha bursts in an EEG when the eyes are open. $1/f$ power spectra were also observed in the alpha band when the eyes were closed for magnetoencephalogram signals (Chen *et al*. 1998), whereas a different scaling was found for EEG data in

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similar frequency ranges (Pritchard 1992). However, finding a power law relationship is not sufficient for characterizing underlying dynamics since power spectrum-based approaches do not carry the information hidden in the Fourier phases, which is crucial in determining nonlinear characteristics.

It is well known that, for cognitive functioning of the human brain, even if several cortical areas do perform unique elementary functions, any complex function requires concerted actions of multiple cortical areas that are distributed over the entire brain (Bressler 1995). During cognition, multiple cortical areas may not only become coactive but also functionally connected; these functional connections between the cortical areas are manifested in the EEG in the form of interareal correlation or synchronization. Thus, the detection of this hidden correlation or synchrony between distant cortical areas remains an important issue in cognitive neuroscience (Engel & Singer 2001).

In order to address these problems and to search for a hidden universality in brain functions, a newly developed approach called 'cumulative variation amplitude analysis' (Ivanov *et al*. 1996) is employed for analysing spontaneous EEGs recorded during several cognitive tasks, such as listening to music, listening to text and spatial imagery. This method is a combination of the wavelet and Hilbert transforms and is suitable for the analysis of non-stationary signals. To the best of the authors' knowledge, this study is the first to yield results demonstrating universality and scaling in the brain in higher cognitive functioning.

2. MATERIAL AND METHODS

(a) *Wavelet transform*

It has been pointed out that EEG signals exhibit non-stationary and extremely complex behaviour. Traditional methods, such as short-term Fourier transform and Gabor transform, are not suitable for localizing the transient and patchy features of EEG signals. The following method was therefore used for circumventing this problem. First, wavelet transform is applied to the raw EEG signal; this is a method of signal decomposition onto a set of basis functions that are obtained by dilations, contractions and translations of a unique function called the mother wavelet. Given the input signal $x(t)$, the continuous wavelet transform (Kaiser 1994) is defined as

$$X_{\mathrm{CWT}}(a,b) = \int_{-\infty}^{\infty} x(t)\psi^*_{a,b}(\lambda)\mathrm{d}\lambda, \tag{2.1}$$

where the asterisk denotes complex conjugation, a is a scaling factor and b is time. The $\psi_{a,b}(t)$ term is obtained by scaling the mother wavelet $\Psi(t)$ at time b and with scaling factor a, i.e.

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\Psi\left(\frac{t-b}{a}\right). \tag{2.2}$$

It is noteworthy that, when a becomes large, the basis function $\psi_{a,b}$ becomes a stretched version of the mother wavelet, which can be useful for analysis of the low-frequency components of the signal. On the other hand, when the scale factor is small, the basis function will be contracted, which is useful for capturing the high-frequency components of the signal. The normalization $(1/\sqrt{a})$ is performed for energy preservation. Thus, the dominant frequency of the wavelet-transformed signal depends on the choice of a. An EEG signal is generally a broad band signal, but is usually divided into five different frequency bands (the delta (<4 Hz), theta (4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz) and gamma (>30 Hz) bands) that reflect functionally different components of information processing, from sensory perception to memory operation (Petsche & Etlinger 1998). In this study most emphasis is put on the gamma band, since there is evidence that neuronal oscillations and synchronization in the 30–70 Hz range in multiple cortical areas provide a general framework for large-scale cognitive integration (Singer & Gray 1995; Rodriguez *et al*. 1999). In this study, the scale factor $a=2$ guarantees the signal $X_{\mathrm{CWT}}(a,b)$, which mostly contains gamma oscillation.

The Morlet wavelet (Kaiser 1994) is chosen as the mother wavelet, which consists of a plane wave modulated by a Gaussian, i.e.

$$\Psi(\theta) = \pi^{-0.25}\mathrm{e}^{i\omega_0\theta}\mathrm{e}^{-\theta^2/2}. \tag{2.3}$$

The term ω_0 is a numerical constant, which is particularly suitable for frequency characterization and offers a good compromise between frequency and time resolution. In this study $\omega_0 = 5.5$, which fulfils the admissibility condition (Kaiser 1994). Three important properties make wavelet transform suitable for EEG analysis: (i) it removes the local polynomial trend, (ii) it is suitable for non-stationary signals, and (iii) it preserves the Fourier phase information.

(b) *Hilbert transform*

Next, the envelope of the wavelet-transformed EEG signal is extracted through an analytic signal approach (Cohen 1995; Bendat & Piersol 2000), which does not require the condition of stationarity. The analytic signal is formed as follows:

$$X_{\mathrm{anl}}(t) = x_{\mathrm{CWT}}(t) + ix_{\mathrm{h}}(t) = x_{\mathrm{CWT}}(t) + i\frac{1}{\pi}\int_{-\infty}^{+\infty}\frac{x_{\mathrm{CWT}}(\tau)}{t-\tau}\mathrm{d}\tau, \tag{2.4}$$

where $x_{\mathrm{h}}(t)$ is the Hilbert transform of $x_{\mathrm{CWT}}(t)$ and the integral is summed up in the sense of its Cauchy principal value. Since the analytic signal is a complex quantity, it can be decomposed into a polar form, i.e. $X_{\mathrm{anl}}(t) = A(t)\mathrm{e}^{i\phi(t)}$ where $A(t)$ $(=\sqrt{x^2_{\mathrm{CWT}}(t) + x^2_{\mathrm{h}}(t)})$ is the instantaneous amplitude or envelope and $\phi(t)$ $(=\tan^{-1}(x_{\mathrm{h}}(t)/x_{\mathrm{CWT}}(t)))$ is the instantaneous phase.

Further, the probability distribution function (PDF) $P(y)$ of $A(t)$ is studied. The whole procedure is repeated for all of the 19 EEG channels used in this study and a set of 19 PDFs is finally obtained.

(c) *Universality*

In order to test the hypothesis that there is a hidden, possibly universal structure in these multivariate time-series obtained from different spatial locations over the scalp, each individual PDF is rescaled as follows: $P(y)$ by $P_{\max}$ and y by $1/P_{\max}$ where $P_{\max}$ is the maximum of $P(y)$. If there is hidden universality in the different brain areas, the 19 rescaled PDFs collapse into a single PDF and the whole set can be described by a single homogeneous scaling parameter. This kind of data collapsing of PDFs is also found in a wide class of physical systems with universal scaling properties. Thus, whenever different PDFs converge into a single PDF after being properly rescaled, the underlying hidden universality can be assumed. The collapse of PDFs is an important property of generalized homogeneous functions (GHFs) (Gel'fand & Shilov 1964). A function $f(x, y, \ldots)$ is called homogeneous of degree m if $f(\lambda x, \lambda y, \ldots) = \lambda^m f(x, y, \ldots)$ for any positive scalar multiplier λ. The same function can be called a GHF if we can find a set of numbers p, q, . . ., that are not all zero such that $f(\lambda^p x, \lambda^q y, \ldots) = \lambda f(x, y, \ldots)$. This type of function is typically investigated in the context of thermodynamic functions, static correlation functions, dynamic correlation functions and universality near the critical points of phase transitions (Stanley 1971). In the domain of physiological signal analysis, it has been found (Ivanov *et al.* 1996) that the heartbeat interval in healthy subjects can be described by a GHF reflecting universal scaling, whereas universality was destroyed for subjects with cardiopulmonary instability caused by sleep apnoea. In another study (Bhattacharya *et al.* 2000), the alpha waves of EEG signals were decomposed into regular and irregular components based on the presence of a dominant oscillation. A similar kind of universality was found for the regular components in the occipital area of healthy subjects, whereas subjects with seizure and mania failed to display this behaviour; no difference was found for the irregular components. Thus, it seems worth probing whether such universal scaling properties displayed by complex systems at the points of their phase transition can also be found in the brain while being involved in higher cognitive functioning.

(d) *Kullback–Leibler divergence*

Since we are dealing with real-life EEG signals, the probability of observing a perfect data collapsing phenomenon is low. In practical terms, for a case with strong data collapse the rescaled PDFs are similar and clustered together and for weaker data collapse the PDFs are more dissimilar and spread. The Kullback–Liebler divergence (Kullback 1997), which was originally proposed to measure the difference between two PDFs, is used to characterize the similarity (or dissimilarity) of the rescaled PDFs in order to assess the degree of universality. Let us say that P_i ($=\{p_i(k)\}$, where $k = 1, \ldots, M$, where M is the number of bins) and P_j ($=\{p_j(k)\}$) be the two different scaled PDFs associated with the ith and jth electrodes. Then the Kullback–Liebler divergence is defined as

$$K(i|j) = \sum_k p_i(k) \log_2 \frac{p_i(k)}{p_j(k)}. \qquad (2.5)$$

This measure can be considered as a kind of distance between the two PDFs, though it is not a real distance measure because it is not symmetrical (equality only holds when the two distributions are identical, leading to $K = 0$). The general interpretation of this measure is as follows: assume that P_i is the original distribution but that P_j is used for encoding; then $K(i|j)$ indicates the length of excess codes (measured in bits) over the shortest length of code (using the original distribution P_i) in the process of encoding. Similar analogous interpretation can be deduced for $K(j|i)$. In the present context, the lower the values of $K(i|j)$ or $K(j|i)$, the lower the difference between the two distributions and the higher the degree of correlation between associated electrode regions. Thus, the average value of $K(i|j, i|j)$ (where $j \neq i$ and $i, j = 1, \ldots, 19$) approximately quantifies the degree of the underlying universality: strong data collapsing produces low divergence and weak data collapse or spread PDFs leads to higher divergence. The Kullback–Liebler divergence measure has previously been used in clinical neurophysiology for classifying the level of anaesthesia (Gersch *et al.* 1979) and for the detection of seizures (Quiroga *et al.* 2000).

(e) *Nonlinearity*

Further, for exploring whether this scaling behaviour is indeed an intrinsic property of the brain dynamics associated with cognitive tasks, the method of surrogate data (Theiler *et al.* 1992; Schreiber & Schmitz 2000) is applied. The analysis with surrogate data involves a null hypothesis on which the surrogate generator is based. Here, the null hypothesis is that the signal has been generated by a linear, Gaussian, stochastic dynamical process. This process is observed through a measurement function that is instantaneous, invertible, static and time invariant. It may be noted that the system in this class is strictly speaking nonlinear (and non-Gaussian), but that the nonlinearity (and non-Gaussianity) is not in the true dynamics but in the observable process. These surrogates have the same mean, variance, auto-correlation and cross-correlation properties as the original signal (Prichard & Theiler 1994). First, a random series $\{r(k)\}$ of the same length as the original EEG signal $\{x(k)\}$ is sorted such that the numerical order of both the series agree. Then Fourier transform is taken on the reordered random series: the Fourier phases of the series are randomized while preserving the Fourier amplitude and the inverse Fourier transform is performed in order to obtain $\{r'(k)\}$. The same randomization is applied to the Fourier phases of all 19 signals in order to preserve the cross-correlation properties between EEG signals. The surrogate is finally obtained by reordering $\{x(k)\}$ so that the numerical ranks of its elements agree with those of $\{r'(k)\}$. In this study, 100 surrogates were generated for each channel and their PDFs of the instantaneous amplitude of the wavelet transform using the same scale (a) are compared with the corresponding PDFs of the original signal. If the PDF of the original data is significantly different from that of the surrogates, one can reject the associated null hypothesis of linearity.

(f) *Procedure*

In this study, 20 male subjects with a mean age of 25.5 years were chosen. They were instructed to listen to a piece of classical music (the Gigue of the French Suite Number 5 for harpsichord, by J. S. Bach) for several minutes using earphones and to a text of neutral content (a short story called *Versuendigung gegen die Nachwelt* by H. Weigel read by C. Hoerbiger over 2 min). In addition, the subjects were asked to perform a spatial imagination task, which involves mental rotation of figures (Shepard & Metzler 1971; Bhattacharya *et al.* 2001). Their EEG signals were recorded from 19 gold-cup electrodes that were equally distributed over the scalp according to the so-called 10–20 system (figure 1) with respect to the averaged signals from both ear lobes. The sampling frequency was 128 Hz. Periods of EEGs at rest (with eyes open and eyes closed) were recorded before, between and after each task. Their durations were the same as those of the tasks. The subjects' eyes were closed while listening to the music and text.

3. RESULTS

The span of the chosen segments of the EEGs for every task is 90 s. The EEG signal from electrode O2 (right occipital) from a subject (Vp. 632) listening to music and its wavelet transform are shown in figure 2*a*,*b*, respectively. The scale (a in equation (2.2)) is chosen as 2 so that it emphasizes the high-frequency components containing hidden dynamical patterns in the gamma band, which might be crucial for cognitive integration. The instantaneous amplitude or the envelope of the wavelet transform

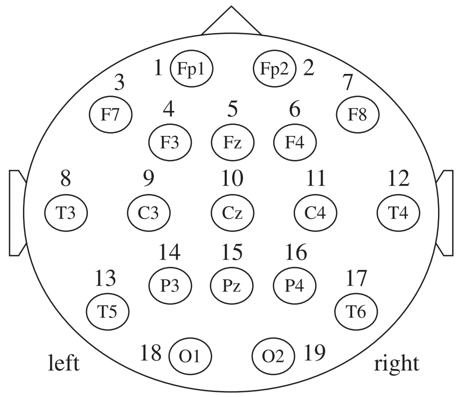

Figure 1. Location of the 19 electrodes and their designations according to the standard 10–20 electrodes placement system (Jasper 1958). The electrodes are numbered as 1–19.

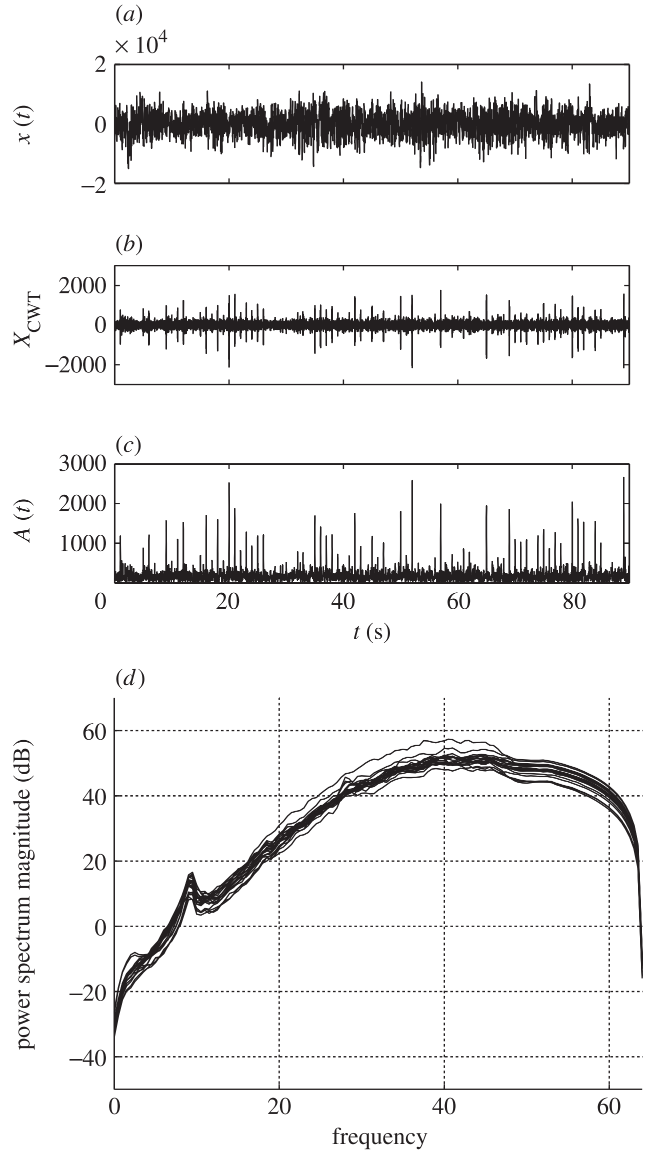

Figure 2. (*a*) Plot of 90 s of EEG obtained from the right occipital electrode (O2) from a subject (Vp. 632) while listening to music. Non-stationary segments can be found on close inspection of the signal. (*b*) Wavelet transform (with scale $a=2$) of the signal in (*a*). (*c*) The instantaneous amplitude of the wavelet-transformed signal in (*b*). (*d*) Power spectral densities of the wavelet-transformed signal for 19 electrodes. Although the power is mostly confined to the gamma band due to the choice of low value of scale, lower frequency components in the alpha range are still visible.

is displayed in figure 2*c*. This envelope measures the cumulative variations in the EEG signal over an interval proportional to the scale *a*. The power spectra of the wavelet-transformed signal for the 19 electrodes are plotted in figure 2*d*. As expected, the dominant spectral power is found in the gamma band at 30–50 Hz where peaks are found at around 40 Hz. Interestingly, a small peak in the alpha band is still present even for this chosen scale. Similar profiles of the gamma band power spectra are obtained for the other two cognitive tasks: listening to text and performing spatial imagination.

(a) *Data collapse*

Next, we studied the distributions ($P(y)$) of the instantaneous amplitudes of the wavelet-transformed (with scale $a=2$) EEG signals, that were recorded simultaneously from the different spatial positions that were equally distributed over the scalp. Figure 3*a*–*c* shows sets of PDFs for the same subject that were obtained during listening to music, listening to text and spatial imagination, respectively. At first inspection, the distribution functions of the 19 electrodes reveal marked differences in all three tasks. Apparently, these differences reflect different ongoing activities in various cortical regions in the gamma frequency range during each task. In order to explore hidden universal features, each individual PDF is rescaled as described in § 2c. This rescaling is done while normalizing the area to unity. The data points collapse into a single curve or cluster together (figure 3*d*). This kind of data collapsing behaviour is seen in diverse complex systems with universal scaling properties. On the other hand, during spatial imagination, the set of PDFs fails to collapse into a single curve even after being suitably rescaled (figure 3*f*). The collapsing of PDFs while listening to text is in between these two tasks. Thus, a common scaling function exists in the gamma frequency range over the entire cortex while listening to music, but there is a wide variation in scaling values within brain areas during spatial imagination.

In order to determine whether this property of universality and scaling has anything to do with listening to music, a similar study has also been performed for EEGs at rest (eyes open and eyes closed). No strong data collapse or dense clustering of PDFs was found for resting states. Thus, this provides the first hint that some cognitive tasks involving higher information processing, for example, listening to music, are associated with a universal behaviour even among distant brain areas.

(b) *Degree of universality*

In order to quantify the degree of collapsing of PDFs that approximately characterizes the degree of universality, the Kullback–Leibler divergence measure is calculated for the set of 19 rescaled PDFs. Figure 4 shows the profiles of the Kullback–Leibler divergences in the gamma frequency range averaged over the 20 subjects and over all possible combinations of each electrode for each position for the cognitive states, i.e. listening to music (solid line), listening to text (open diamonds) and

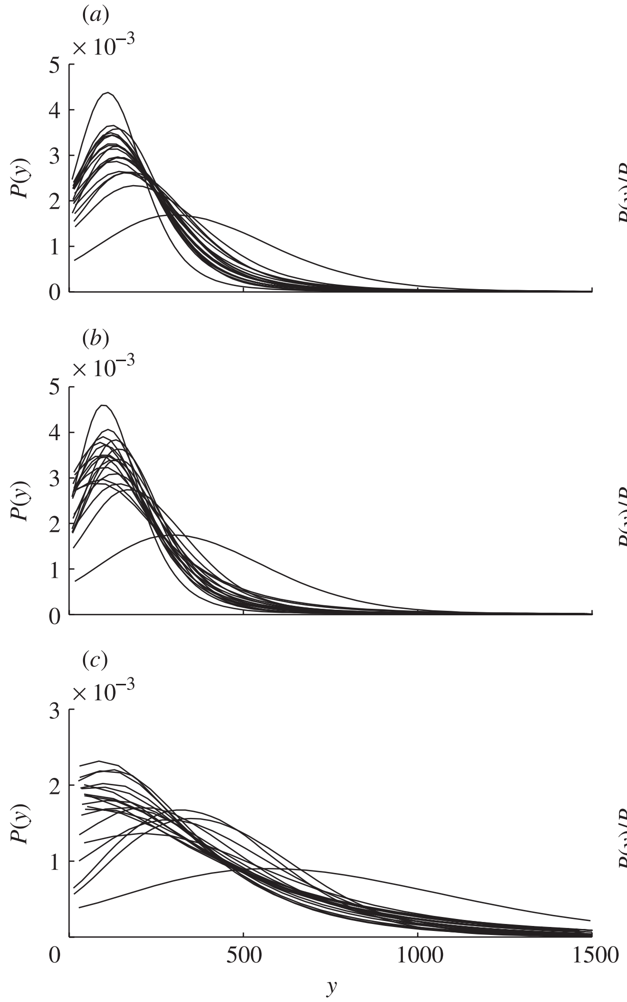

Figure 3. (*a*–*c*) The probability distributions $P(y)$ of the instantaneous amplitudes of the gamma band for all 19 electrodes that were obtained while listening to music, listening to text and performing the task of spatial imagination, respectively, for the same subject as in figure 2. Differences between individual PDFs are evident in the first two moments (mean and standard deviation) of these distributions. (*d*–*f*) Similar sets of PDFs as in (*a*–*c*) but after rescaling each distribution as follows: the ordinate by $P(y)/P_{\max}$ and the abscissa by $yP_{\max}$, where $P_{\max}$ is the maximum of $P(y)$. The strongest collapse of the 19 PDFs is found in (*d*) while listening to music. No data collapse is found during spatial imagination.

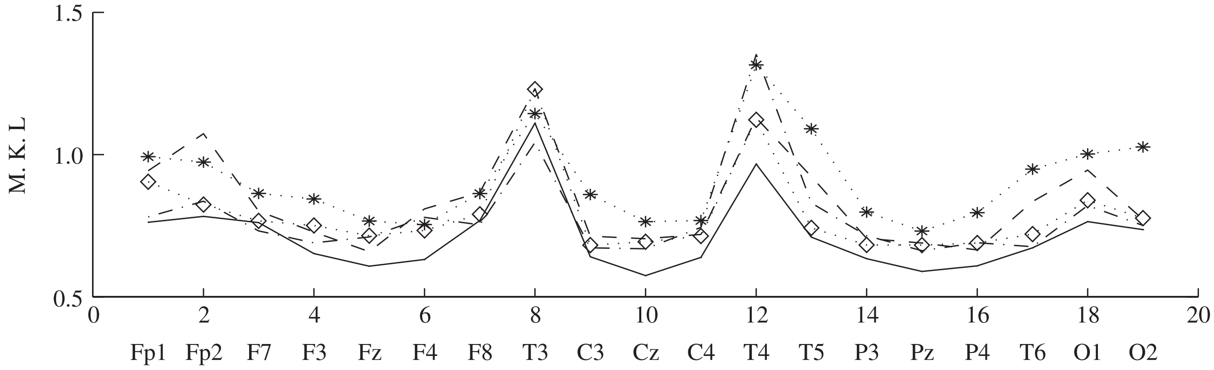

Figure 4. Degree of data collapsing in the gamma band as measured by the mean Kullback–Leibler divergences (M.K.L.) in different states: eyes closed (dashed–dotted line), eyes opened (dashed line), listening to music (solid line), listening to text (open diamonds) and performing spatial imagination (asterisks). The results are averaged over 20 subjects and for all possible combinations for each electrode. Data collapsing (low values of the mean Kullback–Leibler divergence) is strongest while listening to music in the cortical regions associated with the midline electrodes. The temporal electrodes (T3 and T4) produce the highest divergence, which is most probably due to electromyographic contamination.

performing spatial imagination (asterisks) and the resting states, i.e. with eyes opened (dashed line) and with eyes closed (dashed-dotted line). The two peaks, which are associated with temporal electrodes T3 and T4, represent the highest divergence from other electrode regions; this is most probably due to interference of muscle activities with the gamma band. The lowest profile with the lowest degree of divergence or the strongest degree of data collapsing is

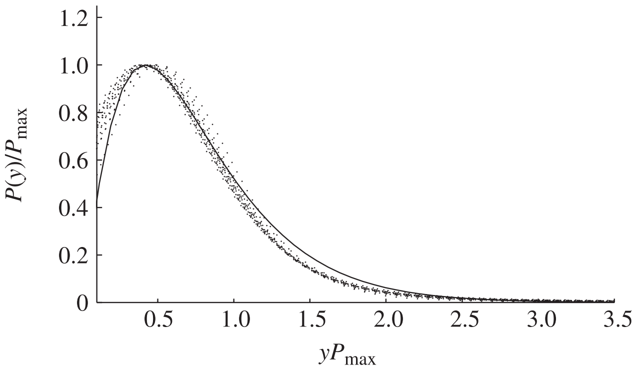

Figure 5. Numerical fit (solid line) of the rescaled PDFs of the amplitudes of the analytic signal of the wavelet transform in the gamma frequency range with the Γ-function ($\sigma = 1.25$) for the same subject as in figure 2 while listening to music. Dotted lines represent the rescaled PDFs of the 19 electrodes.

found while listening to music. The midline electrode regions showed the strongest correlations with other electrode regions. Data collapsing is weakest while performing spatial imagination. Table 1 lists the values of significance (paired Wilcoxon test) obtained through comparison between the cognitive tasks and resting states and also between pairs of cognitive tasks. The midline electrode regions (Fz, Cz and Pz) and their close bilateral neighbours are found to be significant while listening to music as compared with the eyes closed condition. On the other hand, listening to text does not show any significant increase in collapsing with respect to the resting state. Since the subjects' eyes were opened during spatial imagination, it is compared with the respective resting state, i.e. eyes open; data collapsing was reduced in the frontal regions (F7, F3 and Fz) during this task. If the Kullback–Leibler measures while listening to music are compared with the Kullback–Leibler measures while listening to text or during spatial imagination, the multiple electrode regions show a highly significant increase in data collapsing behaviour for the former task. Thus, universality while listening to music as represented by the strongest data collapse is the highest among all tasks chosen in this study.

(c) *Fit of GHF*

Next, these PDFs are described by a GHF of the form (Ivanov *et al.* 1996; Kaipio & Karajalainen 1997)

$$P(y,z) = z^{\sigma+1} y^{\nu} \mathrm{e}^{-yz} / \Gamma(\sigma + 1), \tag{3.1}$$

where $z = \nu / y_{\max}$ is the position of the maximum value of P, $\Gamma(\sigma+1)$ is the gamma function and σ is the fitting parameter. P is also a GHF for $p = -1$ and $q = 1$ (see § 2c for details). The family of curves obtained for this kind of function for different values of z falls into a single curve after rescaling as $P(\mu) \equiv P(y,z)/z$, where $\mu \equiv yz$; this

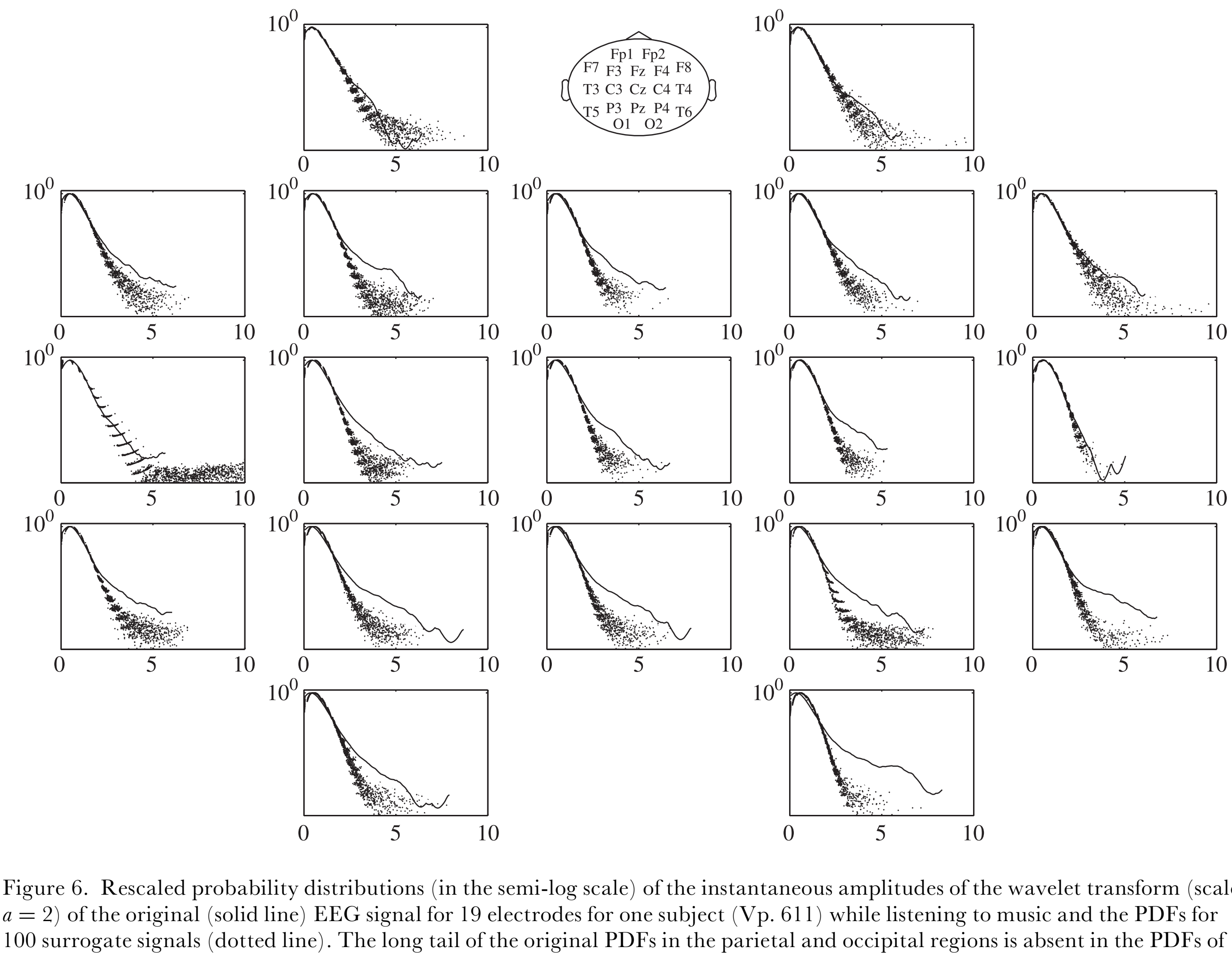

Figure 6. Rescaled probability distributions (in the semi-log scale) of the instantaneous amplitudes of the wavelet transform (scale $a = 2$) of the original (solid line) EEG signal for 19 electrodes for one subject (Vp. 611) while listening to music and the PDFs for 100 surrogate signals (dotted line). The long tail of the original PDFs in the parietal and occipital regions is absent in the PDFs of their surrogates, indicating significant non-random phase correlations. The electrodes' locations are shown at the top of the figure.

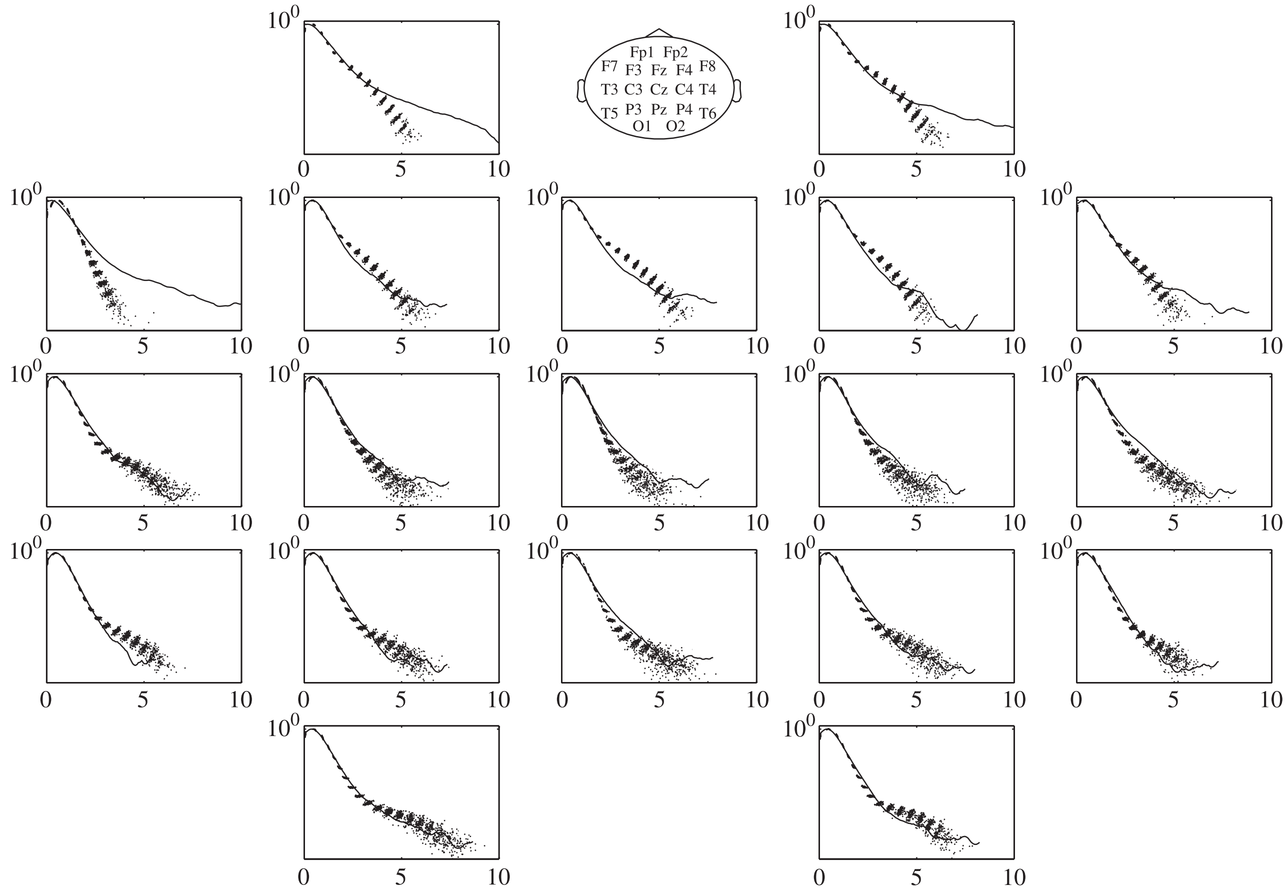

Figure 7. Rescaled probability distributions (in the semi-log scale) of the instantaneous amplitudes of the wavelet transform (scale $a = 2$) of the original (solid line) EEG signal for 19 electrodes for one subject (Vp. 611) during spatial imagination and the PDFs for 100 surrogate signals (dotted line). The frontopolar and frontal regions show PDFs significantly different from those of their surrogates, indicating significant non-random phase correlations.

phenomenon, which is known as data collapse, is mentioned earlier (see § 2c). If data collapse is found, the family of distribution functions can be represented by a single scaling function $P(\mu)$, which characterizes the entire brain. Figure 5 shows the analytic fit of the PDF while listening to music with the above GHF function for the same subject (Vp. 632). Another measure for quantifying the collapsing of PDFs in different tasks can be the sum of the absolute differences between individual PDFs and the analytical fit. The higher the value of this index, the greater the spread of the overall distribution for the associated task. This index has been found to be lowest while listening to music.

(d) *Nonlinearity*

Figure 6 shows a comparison with surrogates for the 19 EEG signals of another subject (Vp. 611) while listening to music; the same comparison is displayed in figure 7 for spatial imagination. If the long tail of the distribution of the original signal cannot be reproduced by the surrogates, then the phase correlations in the original signal can be claimed to be non-stochastic. This temporal correlation in the Fourier phase sequence is a sign of nonlinear coupling in associated cortical areas. Several electrodes in the posterior regions of the scalp (Cz, P3, Pz, T6, O1 and O2) show significant differences from their surrogates. During spatial imagination, these electrode regions do not show any significant difference from their surrogates, whereas the frontopolar and frontal regions (Fp1, Fp2, F7, F4 and F8) do. After repeating the study for all 20 subjects, it has been found that the posterior regions show consistently significant nonlinear characteristics while listening to music, whereas during spatial imagination the frontopolar regions present significant nonlinear characteristics. Thus, through this procedure, by preserving the linear properties of the original signal, one is able to trace the nonlinear signature hidden in the collective phase properties of the gamma band, which otherwise would pass unnoticed in the conventional analysis based on Fourier power spectrum.

(e) *Other frequency bands*

Universality and data collapsing were also studied for other frequency bands, i.e. the theta, alpha and beta bands, with scaling parameters (a in equation (2.2)) of 18, 8 and 5, respectively. The centre frequencies of the dominant bands in these ranges are 20.8, 10 and 6 Hz, respectively. Figure 8 shows the mean Kullback–Leibler divergence measures for individual electrodes for the three cognitive tasks. Several points are noteworthy. First, the Kullback–Leibler divergence measure is lower for higher frequencies, thus there might exist some correlation between the degree of data collapsing and frequency. Second, the topographical profiles for listening to music

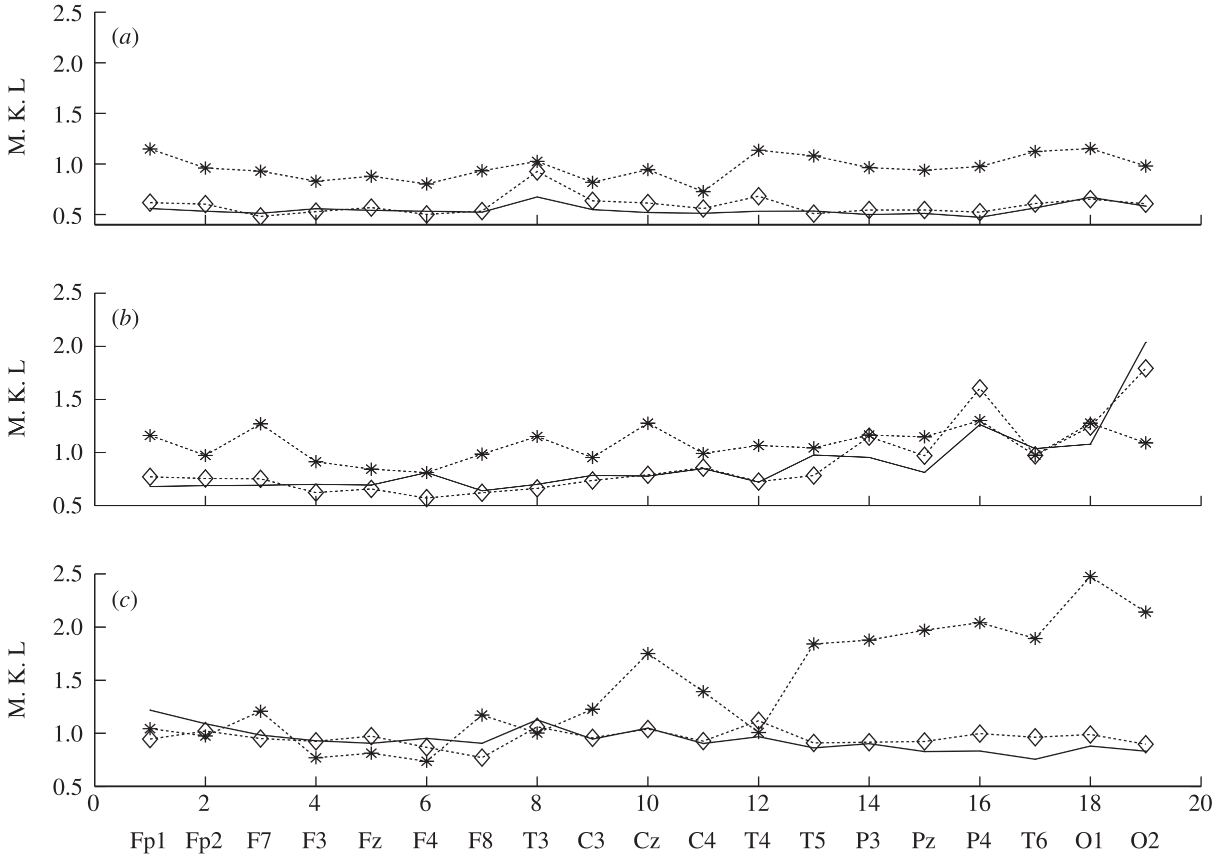

Figure 8. Degree of data collapsing as measured by the mean Kullback–Leibler divergence measure (M. K. L.) in the (*a*) beta, (*b*) alpha and (*c*) theta bands. Three cognitive tasks are considered: listening to music (solid line), listening to text (open diamonds) and performing spatial imagination (asterisks). The results are averaged over 20 subjects and for all possible combinations for each electrode. The data collapsing in the beta band is higher (lower values of mean Kullback–Leibler divergence) while listening to music than while listening to text, but the differences between the two listening tasks are not evident in the other frequency bands.

Table 1. Electrodes at which a significant decrease in the Kullback–Leibler divergence measure between the cognitive tasks and resting conditions as well as between different cognitive tasks can be observed in the gamma band.

(A dash indicates that the value is non-significant. Non-parametric Wilcoxon test for matched pairs, $^{*}0.01<p<0.05$, $^{**}0.001<p<0.01$, $^{***}p<0.001$. A minus (−) sign preceding an asterisk mark indicates a significant increase in the Kullback–Leibler divergence measure.)

	cognitive tasks versus resting states		between cognitive tasks		
electrodes	music versus eyes closed	text versus eyes closed	spatial imagination versus eyes opened	music versus text	music versus spatial imagination
Fp1	—	—	—	—	***
Fp2	—	—	—	—	***
F7	—	—	−***	—	***
F3	—	—	−***	**	***
Fz	**	—	−**	***	***
F4	***	—	—	***	***
F8	—	—	**	*	***
T3	—	—	—	*	—
C3	—	—	−**	*	***
Cz	**	—	—	***	***
C4	**	—	—	**	*
T4	—	—	—	—	—
T5	***	—	—	*	***
P3	**	—	−*	—	**
Pz	**	—	—	***	**
P4	**	—	—	***	**
T6	—	−**	—	*	***
O1	—	—	—	*	—

and for listening to text are similar (Pearson's correlation coefficient, $r = 0.779 \pm 0.08$) in different frequency bands. Third, listening to music does not produce the lowest degree of data collapsing among the chosen cognitive tasks in other frequency bands. Finally, during spatial imagination, a steep increase in divergence measure is found in the posterior electrodes in the theta band. Long-range interaction between occipital and prefrontal electrodes has been reported while performing spatial tasks (Sarnthein *et al.* 1998); whether this fact has anything to do with this strong increase in the divergence measure demands further attention.

4. DISCUSSION

The results obtained here by methods of modern statistical mechanics for understanding complex cognitive information processing in the brain seem to be promising. First, the applied method, which acts as a 'mathematical microscope' (Ivanov *et al.* 1996), is suitable for the analysis of non-stationary signals. Second, it detects the hidden universality and scaling features. It has been found that, while listening to music, different brain areas, albeit physically far apart, possess a universal and homogeneous scaling. It has also been shown that the degree of universality is strongest in the high-frequency gamma band while listening to music. The role of the gamma band in cognitive processing is a matter of intense interest within the conceptual framework of temporal coding theory and the binding hypothesis (Singer 1993; Tallon-Baudry & Bertrand 1999). System-level studies have revealed that the different features of stimuli are signalled in separate sets of primary afferent fibres and that the resulting neuronal activity is expressed in spatially separate areas of the cortex that are linked to large-scale distributed systems. This distributed representation hypothesis requires processes for linking the separate nodes of activity, thereby allowing identification of the object as a whole. It has been proposed by many researchers (Crick & Koch 1990; Singer & Gray 1995; Von der Malsburg 1995) that the linking mechanism is the oscillations in the gamma band and synchronization of neurons in distributed populations. The existence of long-range correlation in the gamma band between multiple cortical areas reflected by the presence of universality and data collapsing phenomena while listening to music supports the putative role of the gamma band in higher cognitive functioning.

The most important information for different systems belonging to the same universal class does not depend on the details of their microscopic interactions, but rather on the nature of the paths along which a hidden order is distributed between different distant subunits. This behaviour is reminiscent of the characteristics of physical systems at their critical points of phase transition. Cortical areas possessing significant nonlinear phase correlations can be identified with the help of statistical analysis based on surrogate data.

The beauty of universality is that the underlying system is poised at its critical point and the interactions across even distant subunits propagate extensively throughout the entire system, out of which long-range correlation emerges. It is argued (Stanley *et al.* 1996) that, although the correlations decay exponentially along each path, the number of such paths also increases exponentially. Power law scaling appears primarily out of this competition from the multiplicity of interaction paths connecting neural assemblies in higher dimensions. In the resting state, when there is no apparent information processing involved, the absence of universality implies a lack of coordination among several cortical areas. It can be conjectured that, while listening to music, because of the way in which correlation among even distant neural assemblies spreads and the competition between them becomes stronger in order to accomplish the cognitive task, the entire system is pushed to the brink of the critical point where 'everything depends on everything else' (Edelman & Tononi 2000, p. 113).

There are a few more points that need further discussion.

(i) Among the classical frequency bands, the gamma band is most prone to muscle activities, but this contamination only has a major affect at temporal electrodes (T3 and T4), whereas no significant differences are found at these electrodes (see table 1), yet several other electrode regions produced significant differences while listening to music. Thus, the possible contribution of muscle activity to our results of universality in the gamma band while listening to music can be ruled out.

(ii) In this paper, we restricted ourselves to studying the instantaneous amplitude variations in different frequency bands, whereas the information in instantaneous phase coupling was not considered. In a parallel study, we have already shown that the degree of long-range gamma band synchrony was found to be significantly higher in musicians than non-musicians while listening to music, but not while listening to text (Bhattacharya & Petsche 2001).

(iii) Although the method of surrogate data has been used here for indicating significant temporal phase correlation, there can be some problems associated with the surrogate data, which need further attention (Schreiber & Schmitz 2000; Timmer 2000).

(iv) One may ask whether the data collapsing as shown here can be detected by some simpler methods instead of using a combination of wavelet and Hilbert transformations. However, we found that direct analysis of a band pass-filtered EEG signal histogram does not lead to data collapse, nor can the direct application of the Hilbert transformation of the original signal reproduce a hidden universality. Thus, the crucial role of the combined methods for extracting hidden dynamical properties embedded in the EEG signal is justified.

(v) In this paper, the importance of the underlying universality has only been addressed qualitatively. Theoretically, universality can be produced by the trajectories of two systems, the local manifolds of which have similar Jacobians near their critical points, and an important issue is how close the two systems are to their respective critical points. Although we have tried to quantify the degree of data collapsing phenomena (a characteristic of universality) by the Kullback–Leibler divergence measure, the direct proof of the closeness to the critical point is beyond our scope because scalp recordings do not allow the active neural source to be directly localized, so we cannot be sure whether the gamma band activity at any specific electrode region is generated exclusively within the underlying cortical area.

Thus, in the application of an EEG as an instrument in cognitive research these results give rise to at least two inferences: (i) whenever studying thinking processes by means of an EEG, it has to be considered that any local findings should not be interpreted as only being due to the underlying local morphological and functional properties, but have to be seen as the involvement of the global brain in this act of thinking, and (ii) that differentiating between linear and nonlinear characteristics of the system 'brain' may yield new insights into the electrical nature of thinking processes and, thus, assist in the interpretation and understanding of higher cognitive acts.

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