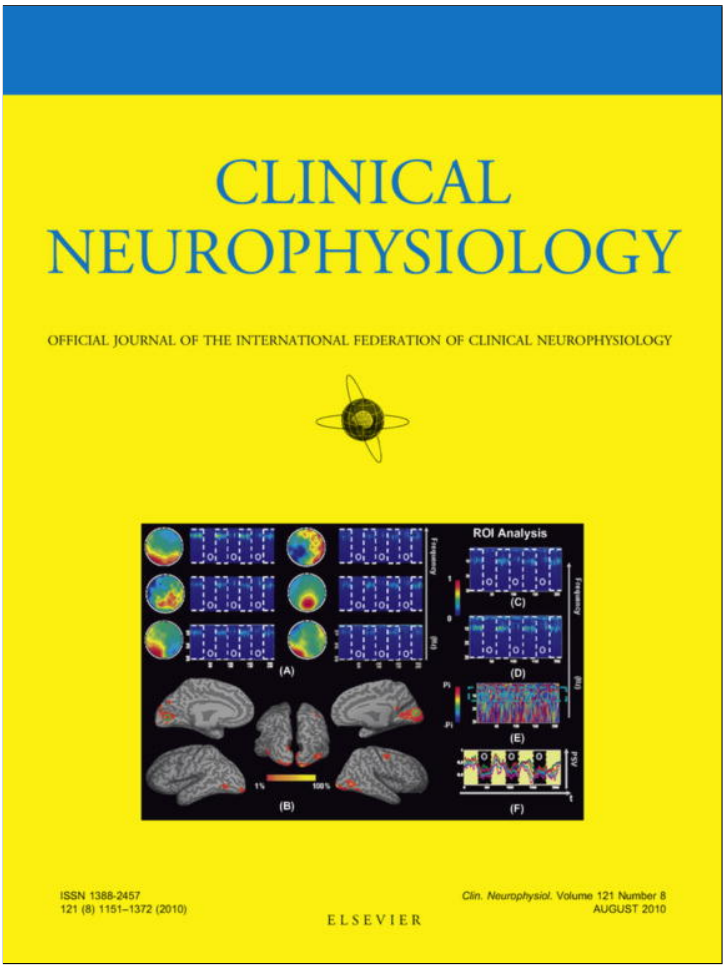

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Human EEG shows long-range temporal correlations of oscillation amplitude in Theta, Alpha and Beta bands across a wide age range

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ABSTRACT

Objective: Long-range temporal correlations (LRTC) of EEG amplitude fluctuations in adults reveal power-law statistics and have been interpreted within the framework of self-organized criticality (SOC). In physical systems states of self-organized criticality showing power-law statistics take time to develop. In this paper we have sought evidence for the idea that brain development tends towards SOC through examining the hypothesis that during normal human development a power law behaviour of EEG oscillations is approached with increasing chronological age.
Methods: We examined EEGs from central and parietal electrodes in 36 subjects aged between 0 and 660 months during performance of a steady wrist extension task with their dominant hand and applied spectral and detrended fluctuation analysis in 36 subjects to assess long-range temporal correlations of oscillation amplitude in the Theta, Alpha and Beta frequency bands.
Results: Our data indicate that at all subject ages power-law statistics dominate the records at Alpha, Beta and Theta frequencies. Small consistent effects of chronological age were detected for amplitude fluctuations at Theta and Beta frequencies.
Conclusions: The data suggest that the scale-free nature of EEG LRTCs is a feature from early childhood through to maturity but that there are changes in the magnitude of these effects with age.
Significance: This study is the first to have explored long-range temporal correlations over a wide range of chronological age.

1. Introduction

Neural oscillations at various frequencies are a defining characteristic of the EEG. Recent studies have shown that EEG oscillations are log–log linearly correlated over a wide range of temporal scales (Linkenkaer-Hansen et al., 2001, 2004, 2005, 2007; Nikulin and Brismar 2004, 2005). Different frequencies of EEG and MEG (Theta, Alpha, Beta and Gamma) have been associated with different neural functions and behaviours (Buzsáki, 2006). EEG oscillations are typically characterized using the power spectral density function (PSD) and the linear approach to analysis of EEG/MEG and other signals e.g., intra-areal EEG–EEG/MEG–MEG and EEG/MEG–EMG emphasizes spatio-temporal correlation as an organizing principle of the nervous system (see for review Salenius and Hari, 2003). Linear interactions between different areas of the brain and between brain and muscle may be characterized using time and frequency domain correlational techniques especially coherence-based techniques. However, the underlying generators of EEG are highly non-linear with oscillations arising from the correlated activity of a number of complex non-linear interactions (Friston, 2000; Linkenkaer-Hansen et al., 2001).

Analysis of raw EEG data indicates that even in the resting state the amplitude of oscillations at different frequencies undergoes marked and seemingly random changes. Furthermore, short-range (EEG–EEG) and long-range EEG–EMG synchrony as shown by coherence also fluctuates in strength over time even though task parameters are unchanged (e.g., Farmer et al., unpublished; Halliday et al., unpublished). Correlated amplitude fluctuations reveal information about the temporal structure of the EEG (Linkenkaer-Hansen et al., 2001). Power-law statistics of EEG oscillation amplitude fluctuations allow for 'memory affects' i.e. events in the past influence the future dynamics of the oscillations and may facilitate information transfer. Power-law statistics are one feature of systems that display self-organized criticality (SOC) (Bak et al., 1987, 1988). Correlation of amplitude fluctuations over a wide range of temporal scales differentiates EEG and MEG signals

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from filtered white noise. In the pioneering studies of Linkenkaer-Hansen et al. (2001) power law relations with estimated Hurst exponents in the range 0.5–1.0 were detected for amplitude fluctuations of Alpha band (8–13 Hz) and Beta band (15–25 Hz) oscillations in MEG and EEG recorded during resting state with eyes open and eyes closed. The magnitude of the derived EEG exponent is affected by afferent stimulation (Linkenkaer-Hansen et al., 2004) and provides a measure of the LRTC within the EEG which itself may yield information about how close the EEG is to a critical state.

The existence of LRTCs does not necessarily imply the presence of SOC and more generally the existence of critical states in neural activity has not been firmly established (Bédard et al., 2006). However, recent experimental results in cortex slice cultures (Shew et al., 2009) and results from the analysis of human EEG and MEG signals (Linkenkaer-Hansen, 2002; Thatcher et al., 2008, 2009) support the concept of the brain as a self-organizing non-linear system with emergent structures and dynamics, which reflect its developmental history. In species with large brains, mature brain dynamics are characterized by a high degree of integrity as shown by power laws. It may be postulated that these emerge during the processes of brain maturation. It has been suggested that during maturation in order to enter a SOC state the system (brain) must have developed for a long time relative to its size because correlations develop slowly and the system is only truly critical when fully correlated according to statistical power law (Linkenkaer-Hansen, 2002). In the present study we have tested this hypothesis directly through cross-sectional analysis of human EEG recordings over a large age range (range 0–660 months). We hypothesized that if self-organized criticality (SOC) develops as a feature of brain maturation then age related effects will be detected in EEG data analyzed using the methodology of Linkenkaer-Hansen et al. (2001), indicating convergence to a critical state with increasing age. The methodology we have used is based on spectral and DFA (Peng et al., 1995), analysis of human EEG data recorded from central and parietal electrodes. We have focused on long-range temporal correlations of oscillation amplitude in the Alpha, Beta and Theta frequency ranges.

2. Methods

2.1. Subjects

Recordings were obtained, with local ethical approval (St Mary's Hospital, London) adhering to standards set out in the Declaration of Helsinki, from 50 subjects (24 males and 26 females) aged from 0 to 55 years. Handedness was tested above the age of 2 years and all subjects were right-handed. Verbal and written consent was obtained from the subjects and in the case of children their parents. The subjects were recruited from the patient population and from a pool of volunteer subjects. The subjects taken from the patient population had been referred for clinical neurophysiological evaluation and their EEGs and EMGs were recorded simultaneously. The patient subjects whose data comprise this study were being investigated for brief episodes of loss of, or altered, awareness. The ultimate diagnosis was either syncope or unexplained. None of the subjects whose data are included in the present study were known to be suffering from neurological or neuro-developmental problems. Their EEG data had been passed as normal by a consultant clinical neurophysiologist.

2.2. EEG recordings

EEG was acquired (sampling rate 512 Hz) and stored digitally using a PC-based system built by Viasys Healthcare Oxford Instruments, Medical systems divisions, Old Woking, Surrey, UK. We recorded EEG using band pass filtering between 4–256 Hz. The recorded EEG was then re-referenced to the common average. The head was measured and distances in millimetres between scalp electrodes were recorded in order to determine accurately the electrodes' position relative to anatomical landmarks and to each other. EEG was obtained from 22–24 Ag/AgCl electrodes (Viasys healthcare Oxford Medical Instruments) positioned on the scalp in accordance with the modified Maudsley system of electrode placement (Pampiglione, 1956; Margerison et al., 1970, see Fig. 1). These data have been previously analyzed in an experiment looking at the effects of age on ~20 Hz EEG–EMG coherence. Therefore during the EEG recordings subjects had eyes open and were activating their dominant wrist extensor muscles. For cooperative subjects, this was at 10–20% MVC (maximal voluntary contraction) maintained through visual feedback (see James et al., 2008, for description).

2.3. Data analysis

In order to be able to compute age statistics regarding the presence of long-range temporal correlations across age/subjects, it was necessary to obtain data from records of similar lengths across all ages/subjects. Experimental difficulties linked to the age of the subjects meant that artifact-free data records lengths varied from 19 to 125 s. Following rigorous artifact rejection 64 records from 36 subjects were included for analysis (see below). Our basic criterion was to examine contiguous records of 40 s duration. However in 6/64 records the records length was slightly shorter (33–37 s).

Following these procedures the number of subjects included for analysis was 36.

2.3.1. Artefact rejection

Visual inspection using the EEGLAB data scroll viewer (Delorme and Makeig, 2004) was used to recognize EMG (e.g., jaw clenching or yawns) and eye blink artifacts affecting the electrodes of interest. The contaminated region was manually removed and only contiguous segments >~40 s were kept for further processing. Independent component analysis (ICA) was used to decompose the data into maximally independent components. Those components that showed the spectral and spatial characteristics of low-frequency artefacts such as eye movements, blinks, heartbeat, or breathing, were projected out of the data (Jung et al., 2000). Where multiple records of 40 s could be obtained from a single subject (either because of the above, or by chunking longer intact records, e.g.,>100 s-long segments as in $n = 5$ adults), analysis was performed on each chunk separately and then averaged per subject before being submitted to statistical analysis. This was the case for 21 subjects.

2.3.2. Data filtering

To speed up computations, the data was decimated off-line to 128 Hz by filtering the data with an 8th order Chebyshev Type 1 low pass filter with cutoff frequency ~50 Hz, before resampling. This decimation does not affect the temporal structure of the oscillations in the band of interest and has also been used by other authors (e.g., Linkenkaer-Hansen et al., 2004).

For each record, the amplitude envelope (instantaneous amplitude) of the signal in the three bands of interests (Theta, Alpha, Beta) was extracted using band-pass finite impulse response filtering (FIR) and the Hilbert transform. A similar approach has been used in a number of recent studies (e.g., Linkenkaer-Hansen et al., 2001,2004,2005,2007; Nikulin and Brismar, 2004, 2005). Definition of the frequency bands Theta, Alpha and Beta followed Gasser et al. (1988). The order of the FIR filters was chosen so that it included three cycles of the low-frequency component of the band

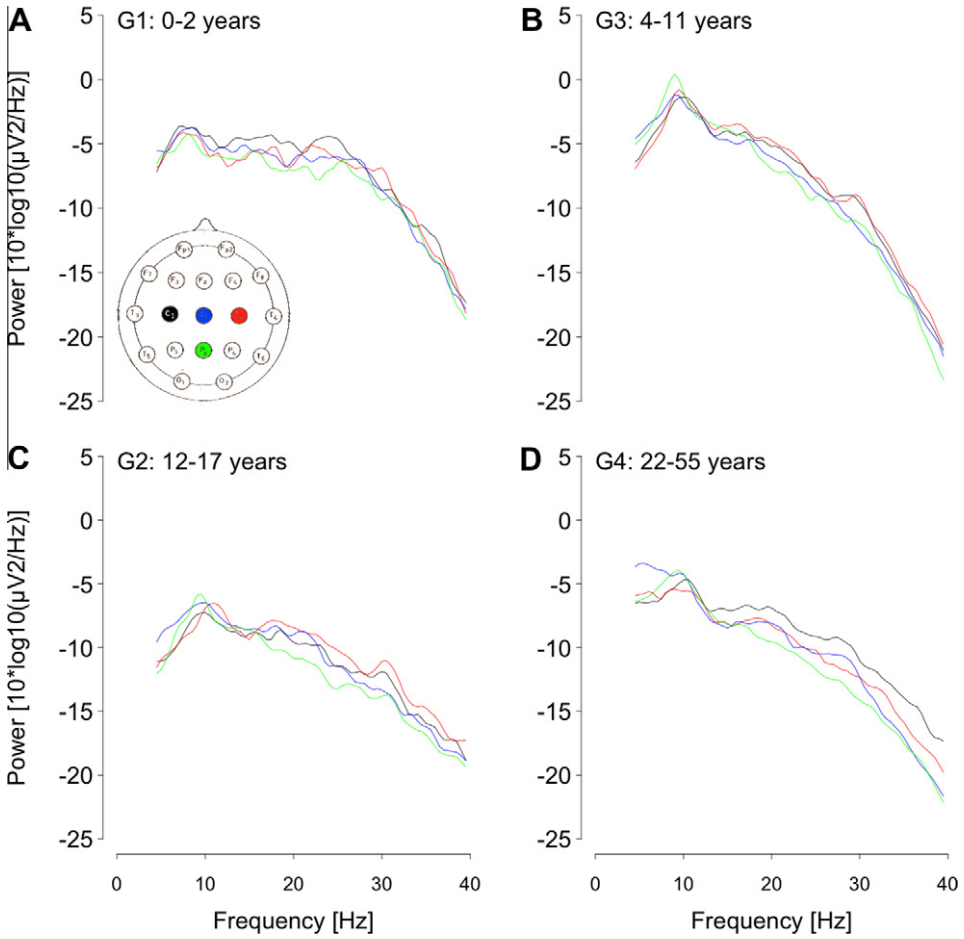

Fig. 1. Pooled power spectra (in range 4–40 Hz) for each electrode (C3,C4,Cz,Pz) for each age group: 0–2 years (A); 4–11 years (B); 12–17 years (C); 22–55 years (D). The insert (A) shows the position of the electrodes in the Maudsley system. The colored electrodes correspond to the spectra from C3, C4, Cz and Pz. The spectra reveal a slight developmental shift in the peak Alpha frequency, from 7.5 Hz in G1 (0–2 years) to 10 Hz in G4 (22–55 years). However, this shift is compatible with the choice of 8–13 Hz for extracting the Alpha component of the signal. There are no significant differences in power between age groups. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

considered: 96 for Theta (4–6 Hz), 48 for Alpha (8–13 Hz) and 32 for Beta (16–24 Hz).

2.3.3. Temporal correlations

Long-range temporal correlations (LRTC), which are an important subclass of $1/f^{\alpha}$ noise (Gao et al., 2006), are typically characterized using a key scaling parameter, the Hurst parameter H. When $H = ½$, the process is said to be memoryless or with short-range correlation. For $½ < H < 1$, the process is said to have persistent correlations. There are three methods commonly used to estimate the Hurst parameter (spectral methods, rescaled range analysis and DFA). Keeping in mind that these methods only provide an estimate of the parameter, it is recommended practice (Gao et al., 2006) to check consistency of the results based on at least two different methods. In this study we calculated the DFA and cross-checked our results using the spectral method. Use of this methodology allowed us to compare our results to those of earlier published studies of EEG and MEG LRTC. Using DFA (α exponent) and spectral method (β exponent) the estimated exponents relate according to: $\beta = 2\alpha - 1$ in ideally long-range correlated signals (Rangarajan and Ding, 2000; Poupard et al., 2001). This theoretical equivalence allows for an assessment of the reliability of the measured exponents (Rangarajan and Ding, 2000; Gao et al., 2006). DFA was applied using 50 window sizes equidistantly placed on a logarithmic scale in the range 1–10 s. The largest size of window was set to 10s as a compromise between having a sufficiently high number of segments in each record (Hu et al., 2001) and maximizing the temporal range of correlations (here, 1–10 s). Using the spectral method we were able to compute both over 0.1–1 Hz (i.e., correlations in the range [1–10 s]), and the maximal frequency range allowed by the length of the data ~0.025–1 Hz (i.e., correlations in the range [1–40 s]). In addition to providing a measure of the reliability of the DFA-measured scaling exponent (over the 1–10 s time range), the regression of the spectral scaling exponents obtained from each range enabled us to examine to what extent the DFA and spectral scaling parameters that were obtained over the shorter time range 1–10 s could predict the scaling parameter over the longer time range of 1–40 s. The lowest window size of 1 s was also chosen to maximise the temporal range of correlations. In Nikulin and Brismar, 2004, the authors limit measurements to 5 s after suggesting that the exponents are being affected by temporal correlations produced by the extraction of the instantaneous amplitude of the oscillations at shorter time windows.

To provide a confidence value for the measured exponents, for each subject, 5000 new sequences preserving the amplitude distribution of the original data were generated by randomly shuffling the record. It should be noted that these realizations do not preserve the frequency spectrum of the original record. Shuffling by block would partially address the problem, however, the short length of the data makes it difficult to obtain an appropriate com-

promise between number of blocks and frequency range. Each sequence was filtered and Hilbert transformed as for the original EEG data, and its exponent was extracted. The resulting distribution of exponents was estimated by maximum-likelihood fitting of a normal distribution. Normality of the distribution was assessed by applying the Anderson–Darling test for the composite hypothesis of normality. This test makes use of the empirical distribution function in calculating critical values and provides a more sensitive test through giving more weight to the tails than does the Kolmogorov–Smirnov (K–S) test (Stephens, 1986). Using the estimated distribution parameters, one-sample tests were applied to provide statistical significance on a per-subject basis.

The estimated exponent derived from DFA was plotted against subject age both as continuous and categorical variable. In the continuous case, linear regression analysis was used to assess the presence of an effect of age. In the categorical case, subjects were grouped together according to age (James et al., 2008) into 4 age groups: 0–2 years ($n = 6$ subjects), 4–11 years ($n = 10$ subjects), 12–17 years ($n = 8$ subjects), 22–55 years ($n = 12$ subjects). Effect of age was assessed using a non-parametric form of ANOVA, and post hoc pair-wise comparisons were performed to identify significant differences between age groups.

3. Results

3.1. Power spectra

Power spectra were computed for all 4 electrodes in all subjects. The pooled power spectra for the 4 electrodes and the 4 age ranges are shown in Fig. 1A–D. A diagram showing the EEG recording set-up used for all subjects is inserted into Fig. 1A. The power spectra show a prominent Alpha frequency peak at 8–12 Hz. The spectral data show small peaks at Beta frequencies especially for the electrodes located over the sensori-motor cortex (C3 and C4). As discussed by Linkenkaer-Hansen et al. (2001) the presence of discrete spectral peaks at ~10 Hz (Alpha) frequencies indicates that the power spectra of the EEG data is not scale free but dominated by a particular (100 ms) time scale. This consideration applies to other EEG spectral components with additional segmentation at time scales relating to 1/frequency of discrete EEG oscillations.

3.2. Determination of the scaling exponents

Fig. 2 shows raw EEG data from a child aged 7 years and an adult aged 25 years. The processing steps used to derive scaling exponents for this data are shown. Fig. 2A shows a sample of raw EEG. Fig. 2B shows the sample data subjected to finite impulse response filtering between 8–13 Hz. The red line in the amplitude envelope for this data is computed from the modulus of the Hilbert transform (see Linkenkaer-Hansen et al., 2004). Fig. 2C shows the power spectra of the entire raw data record. Fig. 2D shows for the entire data record the power spectrum of the Hilbert transform for frequencies <1 Hz. Fig. 2E shows the results of detrended fluctuation analysis (DFA) on the entire data. Fig. 2F–I show the identical data analysis approach for the adult's EEG data. The spectral analysis of the amplitude fluctuations for the child's data revealed a β of 0.63, the analysis of the adult data showed a β of 0.43. The results of detrended fluctuation analysis for the child and adult were exponents α of 0.87 and 0.70, respectively (shuffling of these data – solid dots in Fig. 2E and J – produced exponents α of ~0.5). Note that the relationship $\beta = 2\alpha - 1$ valid in ideally long-range temporal correlations was approximately true in both cases.

The steps illustrated in Fig. 2 were repeated for Theta and Beta frequency ranges (4–6 Hz and 16–24 Hz), and for each of the 4 electrode sites (C3, C4, Cz and Pz).

3.3. Spectral exponent vs. DFA exponent

Fig. 3 A–C shows plots of the two exponents β (derived from spectral analysis) x-axis and α (derived from DFA) y-axis for Theta, Alpha and Beta frequencies. It can be seen that the two measures are correlated (R^2: 0.48–0.68). The slope coefficient in all three cases is lower than the theoretically expected value of 0.5. This could be explained by the finding that DFA can overestimate the Hurst exponent (see Gao et al., 2006 for example), however, exponent estimation from DFA is much more reliable than that from the PSD of the EEG amplitude envelope. The goodness of fit for DFA was 0.970 on average, in excess of values accepted in other studies. As discussed by Gao et al., (2006) the spectral method provides a useful confirmation of the DFA estimate and this is borne out by our analysis. Consequently, the remainder of the data analysis contains the results of DFA of EEG.

However, it is important to note that the method of extracting the spectral exponent does not have the same requirement in terms of computing it on a number of disjoint segments of data. Therefore we have compared the spectral exponents obtained when only focusing on the range 1–10 s to those of the entire length of the record 1–40 s. Fig. 3 D–F shows that the spectral exponent evaluated for the frequency range 1–10 s is a reasonable predictor of the spectral exponent for the longer time range 1–40 s, ($R^2 = 0.42$–55). This encourages us to believe that our necessarily short sections of data used for DFA provide an accurate reflection of LRTC at longer time scales.

3.4. Statistical significance of the exponents

Analysis of the shuffled data for each data set, i.e., for the 3 frequency ranges and 4 electrodes, revealed normal distributions of exponents centred at 0.485 ± 0.001 (NB: in finite length data, the theoretical value of the Hurst exponent, $H = 0.5$ is obtained asymptotically only) with standard deviation 0.061 ± 0.004 indicating that in contrast to the measured EEG, the shuffled EEG data show the temporal correlation signature of white noise. A significance value for each subject was obtained analytically using a 1-sample t-test with the empirical distribution resulting from the shuffled data. Table 1 shows for each frequency and age group the proportion of data records with DFA exponents significantly different from those expected from the shuffled distribution ($P < 0.05$). The table shows that for Beta frequencies subject groups 1–3 (i.e. not adults) had a higher proportion of records that did not differ from the shuffled distribution at the ($P < 0.05$) level. This method of computing significance suffers from the drawback that we may be rejecting exponents that express genuine LRTC in the data. In addition, as the shuffled data do not preserve the frequency spectrum of the original record, there is also an increased risk of false-positives (type-1 errors). As noted by Nikulin and Brismar (2004, 2005), even if exponents do not exceed the significance threshold, they can be still used as estimators of the dynamics of neuronal oscillations at a group level. Therefore, we have plotted across age summary statistics with all the data, irrespective of significance. Taken together, however, the tests revealed that in the Theta and Alpha ranges, DFA exponents are significantly greater than the exponent expected from the shuffled data. This gives statistical support to the idea that the DFA exponents at all age ranges are showing long-range temporal correlations. In the Beta range, it was found that the DFA exponents tend with age to become significantly greater than the exponent expected from the shuffled data.

3.5. Effect of frequency band on scaling exponents

Only 2 out of 36 subjects (1 in the youngest age group – electrode C3, 1 in the oldest age group – electrodes C3, C4 and Pz)

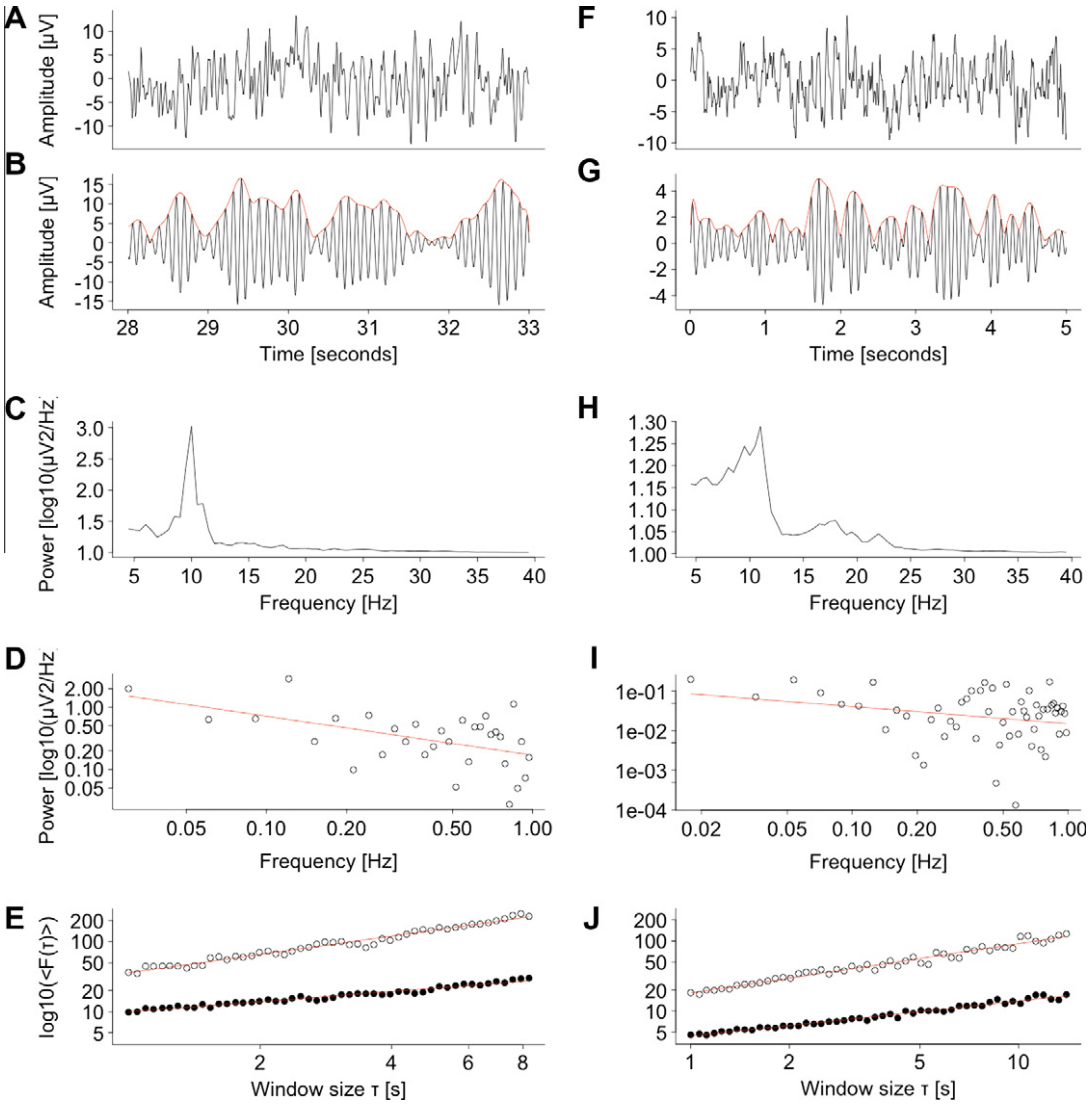

Fig. 2. Extraction of the spectral and DFA scaling exponents for a young child (left, 7-year old) and an adult (right, 25-year old). (A,F) 5s segment of raw EEG signal from the C3 electrode. (B,G) The signal shown in (A,F) has been band pass filtered (8–13 Hz) by FIR (black line) and its amplitude envelope (red line) computed using the Hilbert transform. (C,H) Power spectra of the entire records, samples of which are shown in (A,G). The spectra show a strong alpha component at ~10 Hz, especially in the young infant. The adult spectrum shows some Beta power in the range 17–23 Hz. (D,I) Power spectrum of the amplitude envelope of the oscillations at 10 Hz shown in the range <1 Hz (circles). The power law exponent β is the slope of the line fitted to the data points. (E,J) Average of the root-mean-square fluctuation of the entire integrated and detrended original signal (circles) and shuffled signal (solid dots) in the interval 1–10 s. The power law exponent α is the slope of the line fitted to the data points. In both E and J, the scaling exponent is ~0.5 for the shuffled data, showing a memoryless process. The scaling exponents are 0.87 in the young child and 0.70 in the adult. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

showed a DFA exponent for the Beta range in excess of Theta and Alpha. Therefore in ~95% subjects the highest DFA exponents were either at Alpha or Theta frequencies. Alpha and Theta were approximately equally well represented as the highest exponent value when viewed from the perspective of an individual subject.

3.6. Effect of age on scaling exponents

The DFA scaling exponent from each individual subject was plotted against age for each of the 4 electrodes for the 3 frequency ranges. Linear regressions were calculated to assess the presence of an age effect for EEG electrodes C3, C4, Cz and Pz for Theta, Alpha and Beta frequencies. As shown by Table 2, there were no age effects in any band for electrodes C3, C4 and Cz. However, there were significant slopes between DFA scaling exponent of Pz and subject age in both Theta band (a decrease over age) and the Beta band (an increase over age). Fig. 4A–C shows the DFA scaling exponents for each subject's EEG plotted against the subject's age for Theta, Alpha and Beta frequencies (all electrodes included). The open circles represent data that were not significant with respect to the shuffled data. Fig. 4D shows that for electrode Pz, the ratio between the DFA scaling exponents in the Beta and Theta ranges showed a statistically significant slope, i.e., the DFA scaling exponent in Beta increasingly dominating relative to theta with increasing age. No age effects were detected for the Beta and Theta ranges for the C3, C4 and Cz electrodes (see Table 2).

The subjects were grouped according to the age ranges used for the paper of James et al., (2008). Fig. 5 summarises the DFA scaling exponent data for the Theta, Alpha and Beta frequencies from C3, C4, Cz and Pz electrodes. Mean ± SD exponents are plotted for the 4 age ranges of interest (G1: 0–2 years, G2: 4–11 years, G3: 12–17 years and G4: 22–55 years).

Because the assumptions of normality required for application of an ANOVA were not satisfied, the Kruskal–Wallis rank sum test,

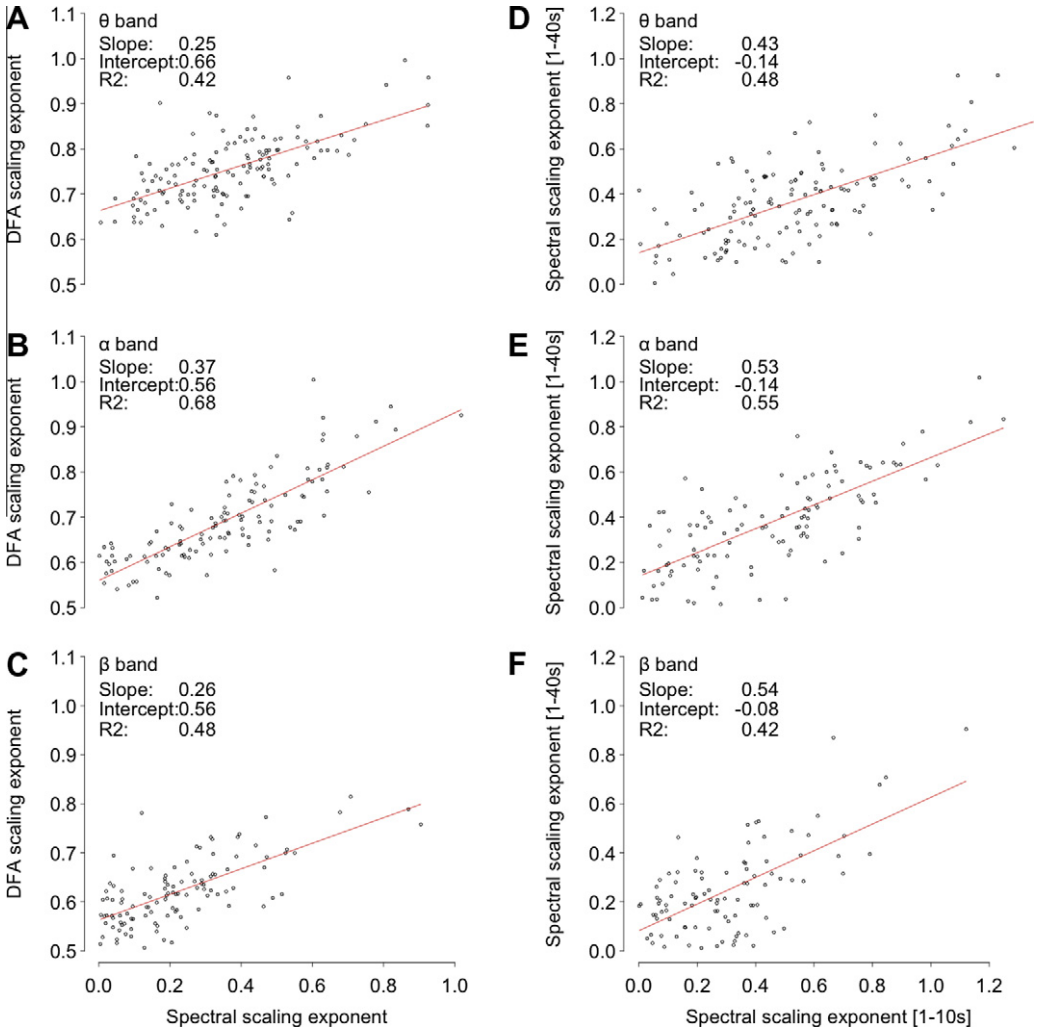

Fig. 3. Estimation of the reliability of exponent estimation between spectral and DFA methods (A–C), and between spectral methods in the [1–10 s] time scale vs. [1–40 s] time scale (D–F). In each band, scaling exponents obtained over all electrodes and all subjects from each method were plotted against one another and a linear regression was computed. Goodness of fit was assessed by R^2.

Table 1
Ratio of significant DFA scaling exponents with age (per subject), with significance at group level.

		G1 (n = 6)	G2 (n = 10)	G3 (n = 8)	G4 (n = 12)
θ	C3	6***	10***	7***	12***
	C4	6***	9***	8***	11***
	Cz	6***	10***	8***	12***
	Pz	6***	10***	8***	11***
α	C3	3	9***	7***	12***
	C4	4*	9***	6***	10***
	Cz	4**	5**	4	11***
	Pz	1	9**	5*	10***
β	C3	3*	3*	5*	8*
	C4	2*	4*	1	10*
	Cz	1	4*	1	7**
	Pz	1	4	2	10**

* $P < 0.05$.
** $P < 0.01$.
*** $P < 0.001$.

Table 2
Slopes (∗1e-5) of linear regressions of scaling DFA exponents over age.

	C3	C4	Cz	Pz
θ	1.6	−8.8	−1.0	−22.6*
α	11.2	−4.0	6.0	16.7
β	9.0	1.8	9.0	20.1***

* $P < 0.05$.
*** $P < 0.001$.

a non-parametric analogue, was used instead (Hollander and Wolfe, 1973). Table 3 reports the H statistics, along with the associated P value. DFA exponents for the Alpha and Theta frequency bands did not show a group age effect. A significant effect was found for electrode Pz in the Beta frequency range only. Pair-wise tests were performed to identify which between-group differences accounted for this effect. Significant differences ($P < 0.01$) were observed for G1–G4, G2–G4 and G3–G4. No differences were found for G1–G2 ($P = 0.329$) and G2–G3 ($P = 0.699$).

4. Discussion

In this paper we have investigated the dynamics of EEG oscillation behaviour in the awake, behaving human brain across a wide range of chronological age. We have interpreted these results as set out in the papers of Linkenkaer-Hansen and colleagues (2001, 2004, 2005, 2007) as indicative of the scale-free nature of spontaneous EEG fluctuations. In the introduction we proposed that dur-

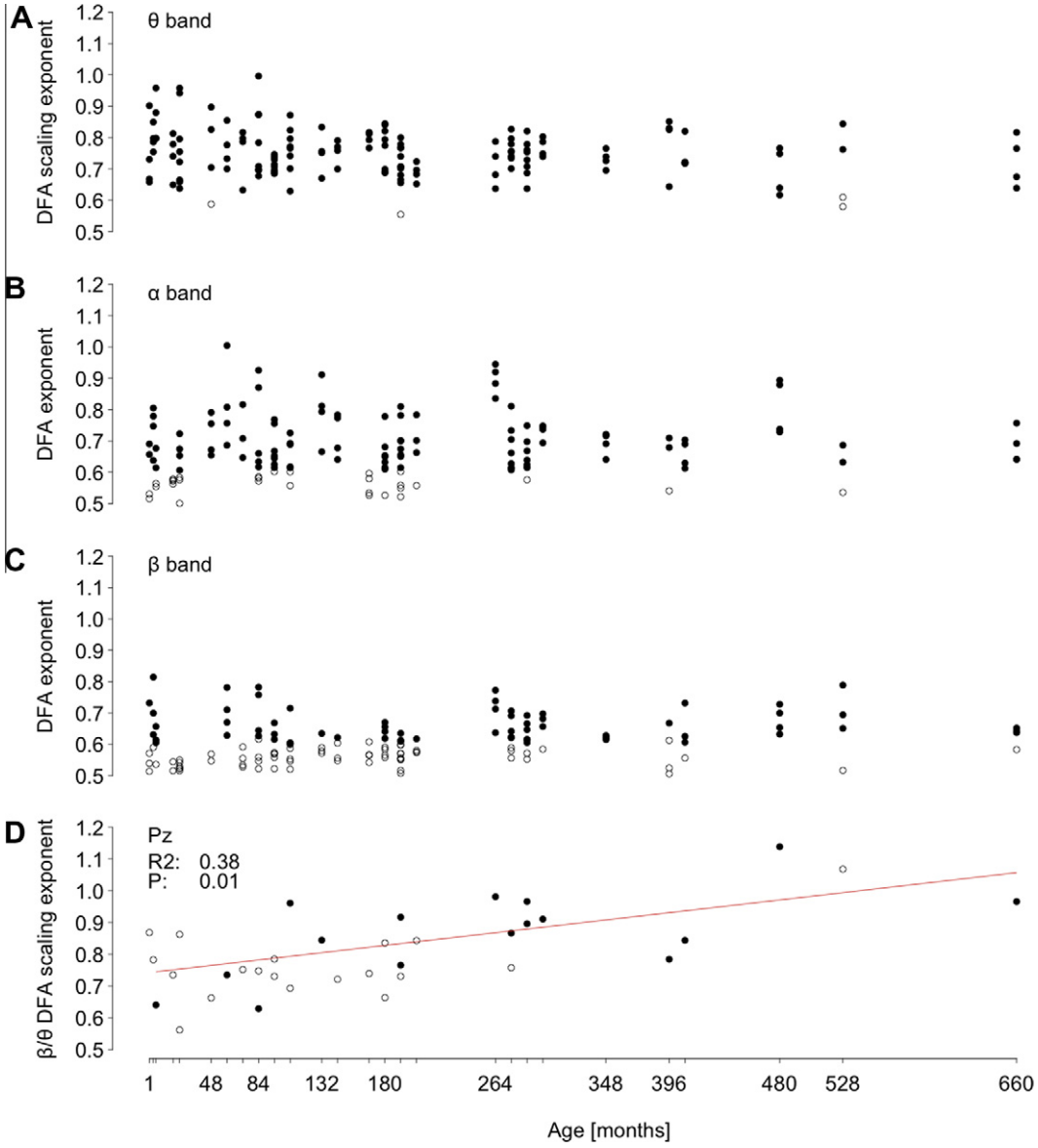

Fig. 4. Scatter plots of the DFA exponents from all subjects against age over all electrodes in the Theta (A), Alpha (B) and Beta (C) bands. Exponents that were statistically ($P < 0.05$) different from those expected from the shuffled data (i.e., data in which long-range temporal correlations were disrupted; see Methods) are shown in solid dots. Circles show exponents that are non-significant with respect to exponents derived from the same data when shuffled. There is no general effect of age as assessed by linear regressions. The plot of the ratio between scaling exponents obtained in the Beta and Theta range for electrode Pz (D) shows a significant ($P = 0.01$) positive slope. This slope is the result of a significant decrease with chronological age of the scaling exponent in the Theta band with a concomitant increase of the scaling exponent in the Beta band. Only Pz showed such a trend.

ing human development changes in brain age and dynamical complexity would be revealed as an increasing tendency to LRTC and therefore cross-sectional EEGs would show systematic differences in the scaling exponent indicating that LRTC and thus the potential for SOC is approached with increasing brain age. Our data, which show EEG oscillation amplitude long-range temporal correlations (LRTC) at different central and parietal electrode positions in Theta, Alpha and Beta frequency bands regardless of electrode position, EEG frequency and subject age, do not support this hypothesis but indicate that EEG amplitude scaling behaviour is present to a similar degree over a wide subject age range. Thus, these findings extend to a larger age distribution and support the findings of Nikulin and Brismar (2005) in which no consistent trends in Alpha rhythm LRTC between ages 20 and 65 years were detected. However, for EEG recorded from the Pz electrode we detected a consistent effect of subject age of the exponent value that defines EEG LRTC at Theta and Beta frequencies. The DFA exponent for the Theta range decreased with age (as continuous variable). The DFA exponent for the Beta range increased with age (both as continuous and categorical variable). The results extend our knowledge of EEG LRTC but raise important methodological and theoretical questions.

The exponent values obtained in the present study are within the range quoted by other researchers. Linkenkaer-Hansen et al. (2001) detected during resting eyes closed and eyes open paradigms MEG and EEG Alpha and Beta frequency DFA exponent values of ~0.7. During an eyes closed EEG paradigm Alpha rhythm DFA exponent values for C3 and C4 electrodes were 0.7 ± 0.08, in the same study Beta rhythm recorded from C3 and C4 the DFA exponent was 0.66 ± 0.09 (Linkenkaer-Hansen et al., 2007). Nikulin and Brismar, (2004) found DFA exponents for Alpha rhythm with eyes open of 0.65–0.675. For Beta rhythms with eyes open DFA

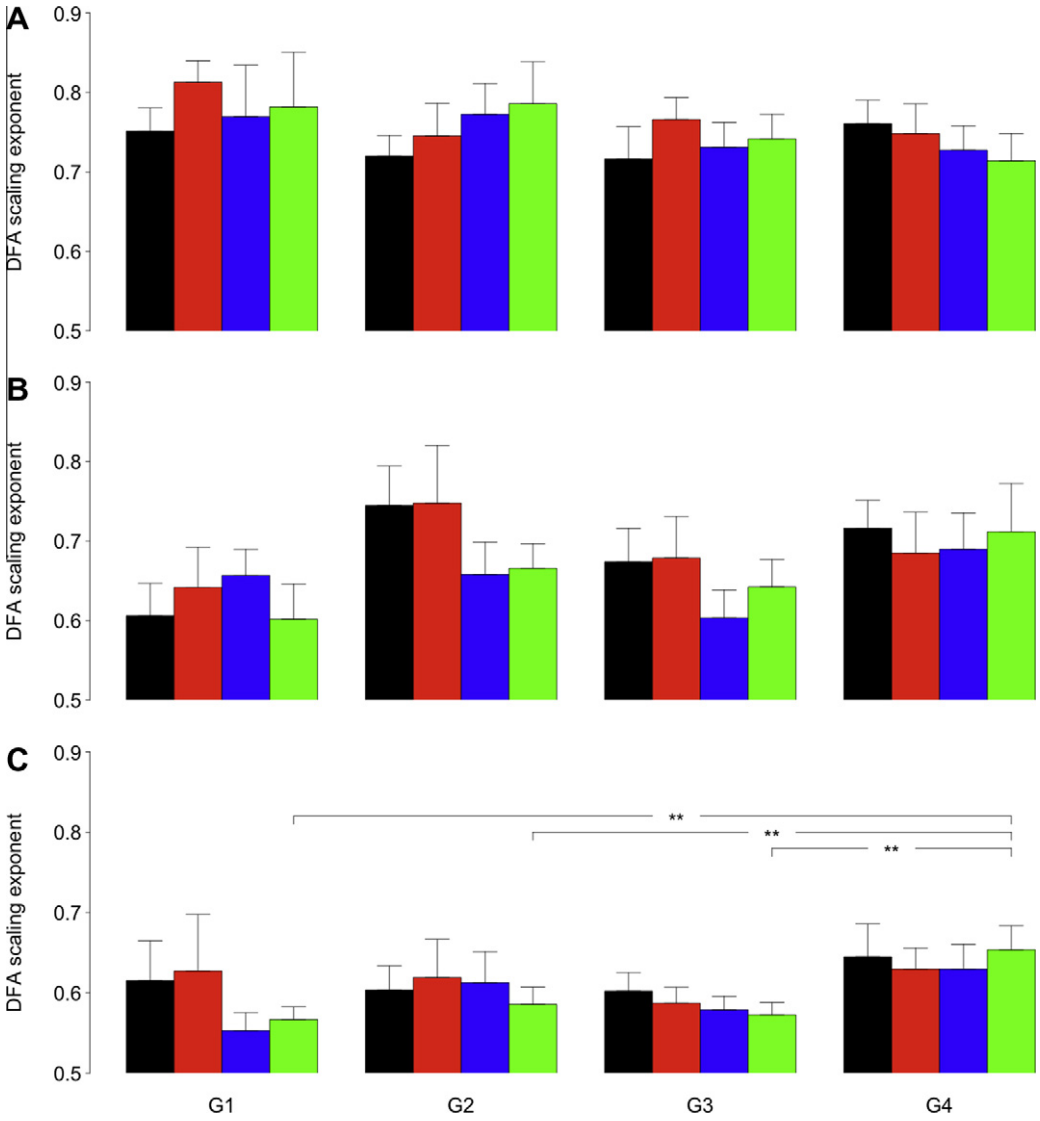

Fig. 5. Summary statistics of the DFA scaling exponents in the Theta (A), Alpha (B) and Beta (C) bands when pooling subjects into four age groups: 0–2 years (G1); 4–11 years (G2); 12–17 years (G3); 22–55 years (G4). Each histogram shows the average and standard deviation of the scaling exponents for each electrode (C3, C4, Cz, and PZ, from left to right). In line with the findings of Fig. 4, there is no effect general effect of age on the exponents, but in the Beta band for electrode Pz. Significant ($P < 0.05$) pair-wise differences are found between G4 and G1, G2 and G3.

Table 3
H statistics for non-parametric analysis of variance of DFA scaling exponents with age groups (df = 3; G1, 0–2 years; G2, 4–11 years; G3, 12–17 years; G4, 22–55 years) and post hoc pair-wise comparisons.

	C3	C4	Cz	Pz
θ	3.93	3.46	1.76	2.90
α	7.79	3.07	5.15	6.57
β	2.12	2.53	6.86	14.55**

** $P < 0.01$; significant ($P < 0.05$) post hoc pair-wise comparisons for β in Pz: G1–G4, G2–G4, G3–G4.

values were slightly lower at ~0.65. In the same study with eyes closed both Alpha and Beta frequency DFA exponent values were ~0.7. In a second study using an eye closed paradigm median exponent values of 0.75 and 0.68 were detected in the Alpha band for men and women, respectively. For the Beta band median exponent values for males and females were 0.7 and 0.65 (Nikulin and Brismar, 2005). In our study the exponent values were in this range. Across all age ranges the Beta band exponents we measured were almost always lower than the other frequency ranges (95% of the subjects). As discussed below an important difference between our experimental paradigm and those of other researches is that our subjects were performing a wrist extension activating forearm extensor muscles with the eyes open (see below).

4.1. Methodological considerations

4.1.1. Validation of DFA results and data duration

We calculated the exponent values using spectral and DFA methodology. The results were broadly similar. We utilized the spectral approach to validate the DFA data (see Gao et al., 2006). The correlation between DFA and spectral methods was reasonable (R^2: 0.42–0.68). Following other researchers we have used DFA methodology as the prime measure of EEG LRTC. One drawback of data in the present study is the short data lengths we were forced to use because of some of the subjects' young age and level of co-operation and the fact that lower frequency theta oscillations may have been affected by high-pass filtering the EEG at 4 Hz. Linkenkaer-Hansen et al., (2004) used data of duration 1200 s.

Because of the difficulties of obtaining continuous artifact-free data in young children our data was necessarily shorter (35–120 s, leading to DFA scaling exponents characterising shorter-range temporal correlations). Linkenkaer-Hansen et al., (2007), however, obtained similar exponent values with short data sections (240 s sections of EEG data) giving LTCs over ~20 s. Kantelhardt et al. (2001) showed improved performance with short records when using their modified DFA method. In this paper, we used the spectral method to test the degree to which the scaling exponents from shorter data sections (10 s) were representative of longer records (40 s). The correlation between shorter data segments giving spectral range of 0.01–1 Hz and longer segments giving a spectral range of 0.025–1 Hz gave R^2 values of 0.42–0.55. When comparing DFA to the spectral method and when looking at the widest spectral range possible in our data the strongest correlation (0.68 and 0.55, respectively) was for Alpha frequencies. The weaker correlations for Theta and Beta ranges might reflect stronger task and age effects in the Theta and Beta ranges (see below). Finally, it is important to note that within a subject there is variability of exponent values with a test–retest correlation of exponent $R = \sim 0.8$ (Nikulin and Brismar, 2004). For our data, the average standard deviation in exponent between multiple records of a single subject was ~0.05.

4.1.2. Motor task

The most important difference when comparing this data to that of other studies is the fact that the subjects were asked to perform a steady motor task (contraction of the right forearm extensor muscle) during a wrist extension. Beta frequencies of EEG and local field potentials are strongly associated with voluntary muscle activation (Murthy and Fetz, 1992; Pfurtscheller and Lopes da Silva, 1999; Conway et al., 1995). The DFA scaling exponents for Beta frequencies were lower than those for Alpha and Theta frequencies. However, the DFA exponent values of >0.5 indicate that Beta frequencies remain scale free and this was observed for all subject ages. This result may be explained by the fact that muscle contraction lowers the DFA exponent yet because in our experiments the contraction was continuous (steady state) the Beta frequency LRTC remains, albeit at a reduced level. Sensory perturbation lowers EEG LRTC and the DFA and spectral exponents measured show disruption but not destruction of long duration amplitude correlations (Linkenkaer-Hansen et al., 2004). Our previous study (James et al., 2008) showed that from age 24 months and above the motor task was performed in a similar way. Children below the age of 24 months have greater difficulty in maintaining steady muscle contraction whilst neonates and babies activate forearm muscles using the grasp reflex. This is shown as an increase in low frequency power in the EMG spectra (James et al., 2008). The reduced persistence of the muscle contraction in the youngest children could act as a perturbation that would have the affect of reducing exponent values in the younger children. This would lead to the prediction that exponent differences especially at Beta frequencies would differ between the youngest subjects and the older subjects and that these differences would be most marked for the C3 electrode situated over primary sensori-motor cortex contralateral to the activated muscle. Interestingly, DFA exponent values in the Beta frequency band did show detectable increases with age and the ratio of DFA exponents for Beta over Theta increased with age. However, these were only significant for the Pz electrode i.e., the electrode most distant from sensori-motor cortex. The DFA exponent values from the electrode contralateral to the activated muscle (C3 electrode) did not show systematic age related changes. Furthermore, there were no differences in exponent value between the C3 electrode contralateral to the contracted forearm extensor muscle and the C4 electrode situated over the sensori-motor cortex ipsilateral to the activated forearm muscles (the ratio of exponent values for C3/C4 was ~1). Whilst we cannot exclude more global effects of muscle activity variability, scalp topology argues against muscle activation variability as the primary cause of exponent change with age. In contrast to the EEG data, the EMG data from young children in the present study did not contain sufficiently long segments of continuous ~10–20% MVC EMG to allow calculation of the DFA exponent for EMG. It is important to note that even when motor task is not an experimental requirement, studies in awake young children especially babies will involve frequent motor activation. Sleep studies in which there is minimal motor activation would be possible but at the expense of losing interesting data from the alert waking EEG. A systematic study of the effects on LRTC of motor activation would be of interest and future studies may address LRTC of EMG with change in age using DFA methodology. Furthermore, the relation of EMG amplitude fluctuation to EEG LRTC and EEG–EMG coherence LRTC would be of great interest.

In studies of adult EEG–EMG correlation the electrode situated over the contralateral sensori-motor cortex shows maximal Beta range EEG–EMG coherence which reflect EEG–EMG synchronization mediated via fast-conducting corticospinal tract pathways (Halliday et al., 1998; Mima and Hallett, 1999; Farmer et al., 2004). Spontaneous fluctuations in the magnitude of the correlation have not been systematically investigated. Future studies will examine if the fluctuation of correlations (coherence and phase) between EEG and EMG and EMG and EMG show LRTC and evidence of scaling behaviour.

4.1.3. EEG spectral components

The generators and functional significance of Alpha (8–13 Hz), Beta (16–25 Hz) and Theta (4–6 Hz) EEG oscillations have been extensively studied in humans and animal (see Buzsáki, 2006). Previous studies of EEG development have focused on these frequency ranges and have described PSD amplitude changes with age (Gasser et al. 1988; Clarke et al., 2001). The pooled EEG spectra in the present study revealed subtle changes in PSD peak frequency with the lowest peak for Alpha frequency being in the 0–2 years age group. In our data the Alpha peaks, though at lower frequency in the younger subjects, were still maximal within 8–13 Hz range of analysis (see Fig. 1). In Theta and Beta ranges discrete peaks were less apparent in the PSD functions. The PSD amplitude of Alpha and Beta frequencies show age related increases relative to PSD amplitude of Theta frequencies (Clarke et al., 2001). We did not examine relative power amplitude systematically with age but our pooled data did not show consistent changes in amplitude and frequency of Theta and Beta rhythms. The spectral peaks within the PSD are a poor guide to the associated DFA exponent value for that range of frequencies for as shown by Linkenkaer-Hansen et al. (2007) there is no correlation between the power spectra amplitude and the DFA exponent value. Using frequency ranges derived from the literature (see Gasser et al., 1988), for the spectral and DFA analysis opens up the criticism that we are making assumptions about the similarity of the underlying generators over chronological age. For example, is the generator of the Alpha rhythm in a child the same as that of an adult and do subtle differences in frequency and power indicate fundamental differences in underlying dynamics? Spectral and DFA analysis when uniformly applied across the age ranges allowed us to make the general statement that notwithstanding subtle EEG frequency and amplitude changes with age, scaling behaviour is present in EEG from age 0 months to age 660 months. Inevitably cross-sectional data has limitations and our data may have missed subtle developmental trends in EEG spectral peak amplitude and frequency and DFA exponent values that would be detectable in a longitudinal analysis (see for example, Campbell and Feinberg (2009)'s longitudinal study of Delta and Theta EEG activity during sleep).

4.2. General considerations

To the best of our knowledge this study is the first to have applied spectral and DFA analyses to human EEG time series across a wide range of subjects encompassing neonates, infants, children, adolescents, young and middle-aged adults. The data provide support for the concept that the scale-free nature of EEG LRTC reflects a form of dynamical organization that is present from early childhood. We have demonstrated that at all ages the EEG at Alpha, Beta and Theta frequencies shows significant scaling behaviour and we have differentiated this from uncorrelated white noise obtained from shuffled EEG data in each subject. There is much interest in Theta, Beta and Gamma oscillation emergence in early mammalian development (Lahtinen et al., 2002; Gireesh and Plenz, 2008; Yang et al., 2009) and its role in organizing emerging neural circuitry. Although our primary result is that LRTC is detectable across a wide age range, the findings provide an early indication that over a wide range of chronological age there may be subtle effects on the magnitude of DFA exponents in that for the Pz electrode they decrease with age at Theta frequencies and increase with age for Beta frequencies. These age effects are as yet unexplained. We speculate that they may represent a shift in the functional significance of oscillation frequency with adults being more reliant on longer range temporal correlations within faster rhythms. Future studies will be needed to explore the extremes of age, especially neonates and premature but healthy babies in order to see if there is an age at which EEG LRTC becomes manifest. Longitudinal data studies will be particularly important and given that from our data the emergence of EEG LRTC must occur rapidly and very early in life such longitudinal studies would be feasible. Data from altricial species show that the immature cerebral cortex self-organizes into local neuronal clusters before it is activated by patterned sensory inputs (Katz and Crowley, 2002) and that within 1 week of birth the cortical network switches from a gap-junction driven syncytium to a synaptic network able to generate synchronous oscillatory activity and this activity may act as a template for the formation of cortical columnar architecture (Dupont et al., 2006). DFA exponents >0.5 are a signature of a system that is poised between a random and a completely synchronized state and are evidence that human EEG dynamics have self-organizing properties. Synchronous EEG oscillations with LRTC we suggest are an early feature of normal human development and potentially have an important role in guiding the development and organization of cortical circuitry in motor, sensory and cognitive systems. The emergence of LRTC may be very early in human life and the transition point (if there is one) when EEG oscillations develop LRTC and thus one important signature of SOC, might only be found in the EEGs of premature babies or neonates.

Recent work by Stewart and Plenz (2008) has revealed that cortical slice neuro-physiological data from newborn rats show critical state dynamics; our data provide the first evidence in humans for the early emergence of such dynamics in the human brain.

There is a growing body of evidence that disorders such as depression, Alzheimer disease, schizophrenia, and epilepsy are associated with changes in long-range temporal correlations as shown by DFA (Linkenkaer-Hansen et al., 2005; Montez et al., 2009; Parish et al., 2004). Schizophrenia and epilepsy often manifest during times of significant brain structure development characterized by synaptic and neuronal pruning and increased myelination. A systematic longitudinal study of healthy subjects would be needed to establish age, developmental status, IQ, sex and handedness matched ranges of DFA exponent values. The precise details of the 'normality' of such data would require further detailed and extensive analysis in a greater number of subjects as such details could not be extracted from our data set. We believe that such studies would be highly worthwhile and these may ultimately pave the way to simple non-invasive EEG-based measures of patients at risk of neurological and psychiatric illness facilitating the early detection of deviations from a normal developmental course that may allow for early therapeutic intervention.

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