Dynamics of Spontaneous Transitions Between Global Brain States

Junji Ito,* Andrey R. Nikolaev, and Cees van Leeuwen

Laboratory for Perceptual Dynamics, Brain Science Institute, RIKEN, Wako-shi, Saitama, Japan

Abstract: Phase patterns of human scalp alpha EEG activity show spontaneous transitions between different globally phase-synchronized states. We studied the dynamical properties of these transitions using the method of symbolic dynamics. We found greater predictability (deterministic) and heterogeneity in the dynamics than what was expected from corresponding surrogate series in which linear correlations are retained. A possible explanation of these observations within the framework of chaotic itinerancy is discussed. *Hum Brain Mapp* 28:904–913, 2007. © 2007 Wiley-Liss, Inc.

Key words: EEG; alpha activity; resting state; phase pattern; spontaneous dynamics; chaotic itinerancy

INTRODUCTION

The electroencephalogram (EEG) has contributed greatly to our understanding of human brain activity. While most research has been focused on event-related EEG activity, our present study is concerned with the ongoing dynamical properties of spontaneous EEG activity in the resting state.

The most robust component of spontaneous EEG is the 8–13 Hz oscillatory activity known as alpha rhythm. Though the functional role of this activity is largely unknown, one hypothesis is that it mediates long-range interactions between distant cortical areas [Nunez et al., 2001; von Stein and Sarnthein, 2000]. This implies that the global patterns of alpha activity are of particular interest. A fundamental concern about these patterns would be: do they vary randomly or do they possess a certain dynamic regularity?

Pioneering work by Lehmann and coworkers demonstrated that global patterns of alpha activity in resting state

EEG are far from random: certain patterns in the spatial distribution of the potential across the scalp are systematically preferred [Lehmann et al., 1987]. The authors discovered typical concentric potential distributions around two extrema (maximum and minimum), which remained stationary for some time, and then suddenly jumped to new locations. They considered each segment of the data within which the positions of the extrema were relatively stationary as reflecting the type and content of information which was momentarily processed in the brain. They called these segments “brain microstates”.

Though their analysis enabled a compact and comprehensive description of global brain states, it has considerable shortcomings. One is that their description is crucially dependent on the existence of potential extrema. In fact, in their analysis, EEG episodes in which there are no extrema were discarded in an early stage of data processing. However, important processes, such as phase synchronization between EEG signals or travelling waves in EEG potentials, are not necessarily accompanied by potential extrema. Phase synchrony of EEG has been considered to reflect long-range neural integration [Varela et al., 2001], and has widely been used as a measure of global interaction in the brain [Breakspear et al., 2004; Freeman and Rogers, 2002; Nakatani et al., 2005]. Travelling waves in EEG potentials have been considered as possible means of communication between distant brain areas [Burkitt et al., 2000; Ito et al., 2005; Rodriguez et al., 1999; Thatcher et al., 1986]. These phenomena, therefore, cannot be neglected if we are to consider the alpha activity as a medium of long-

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*Correspondence to: Junji Ito, Laboratory for Perceptual Dynamics, Brain Science Institute, RIKEN, 2-1 Hirosawa, Wako-shi, Saitama, 351-0198 Japan. E-mail: j-ito@brain.riken.jp

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range interaction. To take them into account, the microstate approach needs to be amended.

Another shortcoming of the microstate approach is that it is only concerned with statistical description of classes of microstates; it lacks a characterization of their temporal evolution. This aspect of brain activity has recently been emphasized as an essential property for effective and integrated brain functioning [Freeman, 2004a,b, 2005, 2006; Friston, 2000a,b,c; Kaplan et al. 2005; Tsuda, 2001]. Our analysis, therefore, will consider brain activity in a dynamical perspective.

In the present study, we assess the temporal evolution of alpha activity on the scalp during the resting state, in particular of its phase pattern. Phase patterns are chosen as the target of our study because they serve as a convenient way to represent instantaneous relationships between signals, measured at multiple scalp positions, within a single map. While previous studies have focused on the statistical description of phase-synchronized states in spontaneous EEG [Breakspear et al., 2004; Gong et al., 2003; Ito et al., 2005; Kaplan et al., 2005], the present study emphasizes the dynamics of the transitions between these states. The aim of our study is to analyze the global spatiotemporal patterns of alpha phase during the resting state and to characterize the dynamics of their transitions in a quantitative manner.

MATERIALS AND METHODS

Subjects and EEG Recording

Five male and six female subjects with a mean age of 23.3 years (SD = 3.1) participated in the experiment. Informed consent was obtained from all subjects. RIKEN BSI Institutional Board No. 2 (Research Ethics Committee) had approved this study. Subjects were seated in a comfortable armchair in a light-attenuated and electrically shielded room and asked to relax with their eyes closed during 8 min of EEG recording. A 256-channel Geodisc Sensor net (Electrical Geodiscs, Eugene, OR) was used for recording. All channels were referenced to the vertex electrode during recording. Impedances were kept below 50 k Ω . Data sampling rate was 250 Hz. All channels were preprocessed on-line using 0.1 Hz high-pass and 100 Hz low-pass filtering. Later, off-line, EEG segments with artifacts from muscle or eye movement were excluded by visual inspection. After that, a spatial average of the signals was calculated at each time moment and subtracted from all channels to obtain average-referenced data. To extract α -band components, a Fourier transform was applied to the entire episode (393.2 s for all subjects) of the average-referenced data and their 8–13 Hz components were inverse Fourier transformed into the time domain. To further eliminate possible contamination, we used the data only from the central 169 channels (covering almost the same area as the International 10–20 Electrode Placement System). Data from one subject (male, aged 26) was discarded because of absence of a peak in the alpha band.

Data Processing

The process of data analysis is outlined in Figure 1.

Phase pattern vector

For extracting phase information from the alpha component data, we use the Hilbert transform (HT) method. The HT of a signal $s(t)$ is obtained by convolution of $s(t)$ with $1/\pi t$ as follows:

$$\tilde{s}(t) = \pi^{-1} \text{PV} \int_{-\infty}^{\infty} \frac{s(\tau)}{t - \tau} d\tau \quad (1)$$

where PV indicates that a Cauchy principal value integral is used in order to avoid the singularity at $t = \tau$ [Pikovsky et al., 2001]. This convolution is identical to multiplying the Fourier transformed signal by $-i$ for the positive or i for the negative frequency component respectively and corresponds to a $-\pi/2$ phase shift of the signal performed in the frequency domain. Therefore, the analytic signal $\zeta(t)$ defined as

$$\zeta(t) = s(t) + i\tilde{s}(t) = A(t) e^{i\theta(t)} \quad (2)$$

uniquely gives the instantaneous amplitude $A(t)$ and instantaneous phase $\theta(t)$ of the original signal. Given the alpha component $X_i(t_n)$ at the i^{th} channel ($1 \leq i \leq N$, $N = 169$) at time t_n ($t_n \equiv n\Delta t$ where $n \in N$ and Δt is the inverse sampling rate), we can obtain the phase θ_i of X_i as

$$\theta_i(t_n) = \tan^{-1} \frac{X_i(t_n)}{X_i(t_n)} \quad (3)$$

where X_i is the HT of X_i . Narrow band filtering (8–13 Hz) and the presence of a peak in the power spectrum of this frequency band assure the reliability of phase estimation with the HT. The next step in our analysis involves the representation of phase patterns on the scalp as a vector in an N -dimensional phase space. To focus on transitions between states of global phase-synchrony (GPS), we adopt a definition of the phase pattern vector based on *relative* phase. Given an arbitrarily chosen phase-reference channel with index R , relative phase ϕ_i at the i^{th} channel and relative phase pattern vector $\mathbf{P}$ are defined as

$$\phi_i(t_n) = \theta_i(t_n) - \theta_R(t_n) \quad (4)$$

and

$$\mathbf{P}(t_n) = (\phi_1(t_n), \dots, \phi_N(t_n)), \quad (5)$$

respectively. This definition of $\mathbf{P}$ assigns an identical vector to phase patterns that differ by a fixed phase shift. During periods with GPS, $\mathbf{P}$ will show only small fluctuations, while the changes in phase pattern during

Step 1: Representation of phase patterns with relative phase

Multivariate phase values: $\theta_1(t_n), \theta_2(t_n), \dots, \theta_N(t_n)$

↓

Relative phase: $\phi_i(t_n) = \theta_i(t_n) - \theta_R(t_n)$

↓

Phase pattern vector: $\mathbf{P}(t_n) = (\phi_1(t_n), \phi_2(t_n), \dots, \phi_N(t_n))$

Step 2: Calculation of stability in phase pattern dynamics

Instantaneous instability index $I(t_n)$:
distance between $\mathbf{P}(t_n)$ and $\mathbf{P}(t_{n-1})$ (c.f. Eqns. (6) and (7))

Step 3: Detecting episodes of Global Phase Synchrony (GPS).

An episode of GPS:
a period during which $I(t_n)$ is below 50th percentile threshold

Step 4: Symbolization of GPS pattern vectors

$\mathbf{p}^j$ are classified into c clusters: $C_1, C_2, \dots, C_c$

GPS pattern vector $\mathbf{p}^j$: $\dots, \mathbf{p}^{n-1} \in C_2, \mathbf{p}^n \in C_5, \mathbf{p}^{n+1} \in C_3, \dots$

↓ Symbolization

Symbol sequence s^j : $\dots, s^{n-1} = 2, s^n = 5, s^{n+1} = 3, \dots$

s^j is analyzed with information-theoretic measures (c.f. *Information-theoretic measures* section)

Figure 1.

Outline of data analysis in the present study. See Text for the details.

such periods are mainly due to ongoing phase progression, which gives a fixed phase shift to every channel. On the other hand, $\mathbf{P}$ will fluctuate by a large amount whenever a transition between GPS states occurs, because the phase relationship between channels is largely disturbed by such a transition. Thus $\mathbf{P}$ can be used to detect GPS and their transitions.

To avoid the possibility that the results of our analysis depend on choice of the phase-reference channel, we prepare 6 data sets with different phase-reference channels, which are positioned evenly over the scalp (Channels 35, 71, 120, 174, 226, and the vertex channel in 256-Channel Geodesic Sensor Net). The average of the results from these 6 data sets is treated as the final outcome of our analysis.

Segmentation of phase pattern dynamics

Next, quantitative segmentation of the phase pattern dynamics into episodes of GPS is performed based on the *instantaneous instability index I* of the relative phase patterns. This index is defined as

$$I(t_n) = \sqrt{\sum_{i=1}^N d_i(t_n)^2}, \quad (6)$$

$$d_i(t_n) = \pi - |\pi - [(\phi_i(t_n) - \phi_i(t_{n-1})) \bmod 2\pi]|. \quad (7)$$

The index represents the distance between $\mathbf{P}(t_{n-1})$ and $\mathbf{P}(t_n)$ measured along an N -dimensional torus constructed by the cross products of N phase variables [Hutt et al., 2003]. It keeps small values during GPS states and assumes a large value whenever transitions between GPS states occur.

One episode of GPS is defined as a period during which the index I stays below a certain threshold value. While our results remain consistent with our conclusion for threshold values in a fairly wide range (roughly, from the 10th to the 60th percentile), throughout this study we use the 50th percentile of I values as the threshold. This value gives us approximately the largest number of GPS episodes across all subjects and therefore assures the reliability of statistical analyses.

We define a GPS pattern vector $\mathbf{p}^i$ as

$$\mathbf{p}^i = (\psi_1^i, \dots, \psi_N^i), \quad (8)$$

$$\psi_j^i = \tan^{-1} \frac{\sum_{t_n \in l^i} \sin \phi_j(t_n)}{\sum_{t_n \in l^i} \cos \phi_j(t_n)} \quad (9)$$

where l^i ($1 \leq i \leq N_l$, N_l : the number of GPS episodes) denotes the i^{th} GPS episode. This vector represents the average (relative) phase pattern during a single GPS episode. (A similar representation of phase-synchrony pattern is also used in [Hutt et al., 2003].)

Symbolization of phase pattern dynamics

To study the dynamical properties of vector series $\mathbf{p}^i$ ($\mathbf{p}^i$ ($1 \leq i \leq N_l$)), we use the method of symbolic dynamics. Symbolization of $\mathbf{p}^i$ is performed as follows. Let X represent the phase space in which vector $\mathbf{p}^i$ is defined. We prepare a partition $\mathbf{B} = \{B_1, \dots, B_c\}$ of phase space X , with c partition cells, which satisfies $\bigcup_{\mu=1}^c B_\mu = X$ and $B_\mu \cap B_\nu = \emptyset$ for $\mu \neq \nu$. With this partition, we define a symbol sequence s^i by associating s^i with $\mathbf{p}^i$ via the relationship $\mathbf{p}^i \in B_{s^i}$. The obtained symbol sequence is composed of an alphabet of c symbols, which are numbers representing the partition cells, and has a length N_l , the number of GPS episodes.

The phase space partition is performed by applying k-means clustering [Anderberg, 1973] to the entire series of $\mathbf{p}^i$ of an individual subject. K-means clustering is an optimization, via adaptive adjustment of clustering, of the total variance $J(c)$ defined as $J(c) = \sum_{i=1}^c \sum_{\mathbf{x}_j \in C_i} |\mathbf{x}_j - \mathbf{v}_i|^2$, where $\mathbf{x}_j$ is the element to be classified (represented in vector form), C_i is the i -th cluster, $\mathbf{v}_i$ is the centroid vector of C_i and c is the number of clusters.¹ The obtained clustering is used as our phase space partition.

The cluster-centroid vectors $\mathbf{v}_i$ represent the average (relative) phase patterns exhibited during the GPS states belonging to the corresponding clusters. Their corresponding phase maps are shown in Figure 4, for the case of a phase space partition into 6 partition cells. This number of cells is uniformly used in the analyses shown below; the results of the analyses are qualitatively unchanged unless the value of c becomes too small.²

Information-Theoretic Measures

We apply information-theoretic measures to the symbol sequences in order to study their underlying dynamics. We use two measures, i.e. *entropy reduction rate* and *instantaneous entropy*, to study the dynamics on two different time scales; the former is on the dynamics of stepwise transitions and the latter is on longer term dynamics, in the order of several seconds.

Entropy reduction rate

Entropy H of a symbol sequence s^i is defined as

$$H = - \sum_{\mu=1}^c P(\mu) \log P(\mu) \quad (10)$$

where $P(\mu)$ is the probability of occurrence of symbol μ ($1 \leq \mu \leq c$). As widely known, entropy measures the

¹The same clustering method has been used for EEG data analysis in Hutt et al. [2003] and Schack [2004]. The authors used it to extract prototypical patterns from their data, while we use it in order to describe pattern dynamics.

²In our case, analyses with 5-9 clusters gave results that are consistent with our conclusion. The upper bound would depend on the number of samples (laminar intervals), as sufficient sample size for reliable statistics in our analysis increases in proportion to c^2 .

degree of uncertainty in stochastic processes. Conditional entropy H^μ is defined as

$$H_\mu = - \sum_{v=1}^c P(v|\mu) \log P(v|\mu) \quad (11)$$

where $P(v|\mu)$ is the probability of the occurrence of symbol v immediately after the occurrence of symbol μ ($\sum_v P(v|\mu) = 1$). This measure represents the uncertainty *not* resolved by the occurrence of the preceding symbol. Entropy reduction rate h_{red} defined as

$$h_{\text{red}} = \frac{H - \sum_{\mu=1}^c P(\mu) H_\mu}{H} \quad (12)$$

represents how large a portion of the uncertainty about the next symbol on average is resolved by the occurrence of the preceding symbol [Schack, 2004]. This measure can be used to assess the (stepwise) predictability of the symbol sequence.

Instantaneous entropy

For the study of the dynamics in a larger time scale, we consider instantaneous probability $\rho_\mu(t_n)$ ($1 \leq \mu \leq c$) to find the system state in partition cell μ defined as

$$\rho_\mu(t_n) = \frac{\sum_{l^i \in \left[t_n - \frac{w}{2}, t_n + \frac{w}{2} \right]} \delta_{\mu, s^i} \tau^i}{\sum_{l^i \in \left[t_n - \frac{w}{2}, t_n + \frac{w}{2} \right]} \tau^i} \quad (13)$$

where τ^i is the duration of laminar interval l^i and parameter w is the width of the time window within which the probability is calculated. We set the value of w at 5 s, having numerically confirmed that the results do not strongly depend on this specific choice as long as w is on the order of several seconds.

The instantaneous entropy $H_{\text{ins}}(t_n)$ related to $\rho_\mu(t_n)$ is defined as

$$H_{\text{ins}}(t_n) = - \sum_{\mu=1}^c \rho_\mu(t_n) \log \rho_\mu(t_n). \quad (14)$$

This represents the (time-varying) uncertainty of the phase pattern dynamics around time point t_n .

Surrogate Data

We use surrogate data to test the statistical significance of the results of our analysis. The null hypothesis postulated here is that *the observed spatiotemporal dynamics are produced by (linearly) correlated stationary stochastic processes*. The surrogate data are generated by randomizing the phase of $X_i(\omega_n)$, i.e. the Fourier transform of $X_i(t_n)$, and

applying the inverse Fourier transform to it. To preserve cross-correlations between the components of X_i , the same random number sequence is used for the phase-randomization of every component [Prichard and Theiler, 1994].

RESULTS

The temporal evolution of alpha phase patterns is illustrated in Figure 2 as a series of snapshots of a phase map projected on the scalp. We observe a fronto-occipital propagation of an isophase domain along the mid-line in the upper rows until time point **a**. The (quasi-)stability of the phase propagation and the spatial extent of the propagation pattern, which is on the scale of the whole scalp, allows us to consider it as a manifestation of global phase-synchrony (GPS). Between time points **a** and **b**, however, the propagation has disappeared and disordered patterns prevail. From time point **b**, a different GPS state, which is exhibited as a lateral (left-to-right) phase propagation, appears. Such transitions between different GPS states are observed during the entire episode of recording.

The transitions are captured by our calculation of the instantaneous instability index I . This index takes small values during periods with a stable (relative) phase pattern and large values during transitions between different phase patterns. A typical time series of I in Figure 3 (a) shows the intermittent character of the phase pattern dynamics: seemingly stable intervals representing GPS states, alternated with sudden changes. Figure 3b shows longer time series of I for real and surrogate data. Both these series show similar intermittent dynamics.

Through the segmentation and symbolization of the phase pattern dynamics, each of the GPS periods is picked up from the phase pattern time series in a quantitative manner and assigned a GPS pattern vector. This vector represents the average relative phase pattern exhibited during the corresponding GPS period. The whole set of GPS pattern vectors are classified into 6 clusters by using the k-means clustering method. In Figure 4, the cluster-centroid vectors, each of which represents average relative phase pattern for each of the clusters, are shown in the form of corresponding scalp phase maps. Symbolization of the phase pattern dynamics is performed by associating each GPS period with the number of the cluster to which the corresponding GPS pattern vector belongs.

The obtained series of numbers is a symbolic expression of the phase pattern dynamics. By applying information-theoretic measures to this series, we can assess the underlying dynamics. We studied short and long term dynamics with two different measures.

Short term dynamics are studied with entropy reduction rate h_{red} . This measure takes a value between 0 and 1; larger values indicate higher (stepwise) predictability. In Table I, h_{red} values for all subjects are shown together with the average h_{red} values calculated from 1000 sets of surrogate data. Five out of 10 subjects showed significantly ($P < 0.05$) larger h_{red} values than the surrogate data average. Of

Figure 2.

Typical phase map time series, containing snapshots of the phase pattern at every 12 ms (data from Subject 3 in Tables I and II). Time proceeds from left to right, from top to bottom. Each map shows a phase pattern of alpha activity on the scalp viewed from above (top is front, bottom is back), color-coded according to

the color bar at the bottom. The letters **a** and **b** indicate the time points at which global phase-synchrony pattern shows changes. Phase values measured at 169 points on the scalp were linearly interpolated to obtain spatially continuous images.

the remaining subjects, one showed significantly smaller h_{red} values than the surrogate average. The transitions between GPS states are more predictable than expected from linearly correlated surrogate series in half of our subjects. High predictability in a symbol sequence implies that there exist deterministic processes in the underlying dynamics. However, the fact that only half of the subjects showed significantly high predictability and one subject even showed significantly lower predictability implies that the dynamics possess, besides deterministic, a large stochastic component as well.

Next, we move to the study of the long term dynamics. To smoothen the short term stochastic fluctuation, instantaneous probability ρ_μ of occurrence of the GPS pattern belonging to cluster μ is calculated for a sliding window of 5-s width. Figure 5 shows the time series of ρ_μ for a representative subject. The upper and lower panels show ρ_μ calculated from the real data and typical surrogate data, respectively. The probability distribution ρ_μ for the real data shows larger deviations from the uniform distribution than the surrogate data; certain clusters have a particularly high probability of occurrence during some time intervals. These deviations are quantified by the instantaneous entropy H_{ins} . The temporal evolution of H_{ins} normalized by its theoretical maximum, i.e. $\log c$, is shown for a representative subject in Figure 6, together with that of typical surrogate data. Although the surrogate data show only modest fluctuations, large reductions in H_{ins} value frequently occur for the real data. These drops correctly reflect the

occasional rises of ρ_μ for one particular cluster seen in Figure 5. Thus H_{ins} reflects deviations of ρ_μ from the uniform distribution. To test the statistical significance of the differ-

Figure 3.

(a) Time series of the instantaneous instability index I of a relative-phase pattern (data from the subject in Fig. 2). The threshold used to determine laminar intervals for this subject is shown with a dotted horizontal line. The horizontal bar around 130.5 s indicates the time interval shown in Figure 2. The cross-points A and B of the threshold and I correspond to time points a and b in Figure 2. (b) Time series of I for the real and typical surrogate data are shown with red and green lines, respectively.

Figure 4.

The centroid vectors of the partition cells obtained from the data of Subject 3 in Tables I and II with a case of the phase space partition into 6 cells. Each vector is shown in the form of the corresponding phase map. Colors indicate phase values relative to the phase at the vertex, according to the color bar at the bottom. Each map represents the average relative phase pattern in the corresponding partition cell.

ence between real and surrogate data, we consider the temporal average of H_{ins} , denoted by $\overline{H_{\text{ins}}}$. It roughly estimates the degree of fluctuation in H_{ins} : a smaller $\overline{H_{\text{ins}}}$ value indicates stronger H_{ins} fluctuation, i.e. larger and more frequent deviations of ρ_{μ} from the uniform distribution. In Table II, $\overline{H_{\text{ins}}}$ values for all subjects are shown together with the average $\overline{H_{\text{ins}}}$ values calculated from 1,000 surrogate data sets. Eight out of 10 subjects showed significantly ($P < 0.05$) smaller $\overline{H_{\text{ins}}}$ values than the surrogate data average. This result suggests that the transitions between GPS states contain more heterogeneity than expected from linearly correlated surrogate series. The majority of subjects showed significantly more heterogeneity, in spite of the stochasticity in the short term dynamics. This indicates that this heterogeneity is a fundamental property of the transitions between GPS states.

DISCUSSION

We studied the phase pattern dynamics of alpha activity in human EEG during the resting state. Alpha activity was characterized by a series of globally phase-synchronized states exhibited as quasi-stable relative-phase patterns on

TABLE I. Entropy reduction rate

Sbj.	Real	Surrogate
1	0.15	0.158 (± 0.005)
2	0.10	0.098 (± 0.005)
3	0.24*	0.186 (± 0.006)
4	0.14*	0.123 (± 0.005)
5	0.098*	0.081 (± 0.005)
6	0.097*	0.087 (± 0.004)
7	0.099**	0.113 (± 0.005)
8	0.091	0.098 (± 0.004)
9	0.12	0.120 (± 0.004)
10	0.099*	0.064 (± 0.004)

Entropy reduction rate h_{red} calculated from the real and 1000 sets of surrogate data. For the surrogate data, the average h_{red} value and its standard deviation are shown. The real h_{red} values that are significantly ($P < 0.05$) larger or smaller than the surrogates according to Monte-Carlo significance tests are indicated with an asterisk or double asterisk, respectively.

Figure 5.

Temporal evolution of the instantaneous probability $\rho_{\mu}(t_n)$ of finding the system state in partition cell μ ($1 \leq \mu \leq 6$), color-coded according to the color bar at the bottom. Partition cells are those shown in Figure 4. (top) $\rho_{\mu}(t_n)$ obtained from real data (Subject 3). (bottom) $\rho_{\mu}(t_n)$ obtained from typical corresponding surrogate data.

the scalp. The transitions between these states were analyzed with information-theoretic measures, which characterize short- and long-term behavior. We compared these measures to ones derived from surrogate data, in which linear properties of the real data are retained but nonlinear structure is removed by randomization. Our analyses indicated weak deterministic in the short-term dynamics and strong heterogeneity in the long-term dynamics.

Breakspear [2002] studied transient synchrony in 4.096-s segments of bivariate EEG signals. In this and other studies by the same author on short-term EEG dynamics [Breakspear and Terry, 2002a,b], only a small fraction of the data showed nonlinear characteristics. Our result on short-term dynamics, which showed only weak determinism, seems to be consistent with their result.

The most salient feature of the phase pattern dynamics revealed in this study is the heterogeneity in long-term dynamics. Figures 5 and 6 allow us to conclude that this long-term heterogeneity is realized by selective enhancement of the frequency of certain states of global phase-synchrony (GPS) during certain episodes. The identity of these pre-

Figure 6.

Time series of the instantaneous entropy H_{ins} related to the probability distribution ρ_{μ} , obtained from the real and surrogate data in Figure 5. H_{ins} is normalized by its theoretical maximum $\log b$ ($b = 6$ in the present case). Red and green lines show the real and surrogate series, respectively.

TABLE II. Temporal average of instantaneous entropy

Sbj.	Real	Surrogate
1	2.18*	2.22 (± 0.02)
2	2.12*	2.19 (± 0.02)
3	1.86*	2.21 (± 0.01)
4	2.08*	2.26 (± 0.01)
5	2.15*	2.25 (± 0.02)
6	2.19*	2.24 (± 0.02)
7	2.25	2.27 (± 0.02)
8	2.30	2.30 (± 0.01)
9	2.28*	2.33 (± 0.01)
10	2.18*	2.27 (± 0.02)

$\overline{H_{\text{ins}}}$, the temporal average of $\overline{H_{\text{ins}}}$, calculated from the real and 1000 sets of surrogate data (unit: bits). For the surrogate data, the average $\overline{H_{\text{ins}}}$ value and its standard deviation are shown. The real $\overline{H_{\text{ins}}}$ values that are significantly ($P < 0.05$) smaller than the surrogates according to Monte-Carlo significance tests are indicated with an asterisk.

ferred states varies over time. This implies two dynamical properties of the transition between GPS states: (1) there is a preference for the system to dwell, during GPS states, in a particular area (or a partition cell); (2) this preference shows changes on a time scale of several to ten seconds. What is noteworthy is that the time scale of the change in preference for a pattern is much larger than that of the underlying dynamics of alpha activity, which is on the order of 0.1 s. This implies that each preferred pattern has a certain degree of stability. However, the fact that preference does change in time shows that it also has unstable aspects.

To reconcile these seemingly contradictory observations, we may think of the preferred areas (or partition cells) in the phase space as containing weakly destabilized attractors. In dynamical systems theory, such structures are called *attractor ruins*. The dynamics of a system in a landscape populated by these structures is characterized by wandering among these attractor ruins. This behavior is called *chaotic itinerancy* [Kaneko and Tsuda, 2001; Tsuda, 2001]. The concept of chaotic itinerancy offers a theoretical basis for the transient character of brain dynamics, which has been observed in many studies besides the present one [Breakspear et al., 2004; Freeman et al., 2003; Schack, 2004; Stam et al., 2003] and raised as a property essential for effective and integrated brain functioning [Freeman, 2004a,b, 2005, 2006; Friston, 2000a,b,c; Kaplan et al., 2005; Tsuda, 2001].³

So far, transient dynamics in spontaneous EEG has mainly been assessed for short-term dynamics whereas long term

dynamical properties have largely been ignored. Lehmann et al. [1987] assessed long term behavior of spontaneous alpha activity. Their microstate approach, however, was concerned only with statistical description of classes of microstates. Our study reaches beyond this goal: besides revealing a long-term heterogeneity in state preference, a quantitative characterization of long-term dynamics is provided.

Previous studies reported on a relatively small number of EEG recording channels. Breakspear and Terry [2002b] studied the topological organization of nonlinear interdependence on the spatial scale of the whole scalp using only 4 channels. A notable exception is a series of studies by Kaplan and coworkers, in which 16 or 60 channels were used to assess nonstationary synchronization and desynchronization in EEG (for a review, see [Kaplan et al., 2005]). The authors reported quasi-stable global synchronization structures in brain activity and their noncontinuous changes under various experimental conditions. However, their way of surrogate generation by independent time shift of each channel destroys linear correlations between the channels and, therefore, appears inadequate for studying nonlinear and nonstationary properties of EEG (as it will be discussed below). Our current study visualized scalp topography of global phase synchrony in a much more detailed fashion than previous methods, by using a large number of channels and a phase map representation.

The use of phase maps enables us to interpret synchronized states in terms of travelling waves on the scalp. As shown in Figure 4, different classes of phase patterns are characterized by different configurations of phase gradients, which can be considered manifestations of travelling waves. If we interpret travelling waves as means of communication between distant brain areas [Burkitt et al., 2000; Ito et al., 2005; Rodriguez et al., 1999; Thatcher et al., 1986], the long-term heterogeneity may indicate transient changes in the modes of global interaction within the brain on a time scale of several seconds.

Shortcomings of our current method are: (1) amplitude information is ignored; (2) EEG epochs with partial synchrony are discarded. Novel analysis methods that include these aspects and integrate them into our current method would be desirable.

The use of surrogate data in the present as well as previous studies on spontaneous and transient brain dynamics [Breakspear, 2002; Breakspear and Terry, 2002a,b; Lachaux et al., 1999; Pritchard et al., 1995; Rombouts et al., 1995] remains a contested issue. Significant differences from surrogate data do not automatically mean nonlinearity in the real data. The null hypothesis underlying this kind of analysis is assuming linear correlation between signals and stationarity; rejection of the null hypothesis may, besides nonlinearity, be due to nonstationarity in the real data [Timmer, 1998]. The concept of chaotic itinerancy makes the situation even more complicated. Itinerant dynamics among attractor ruins is observed as a nonstationary process if measurement time is not sufficiently long. To argue stationarity of an itinerant process, in principle, an

³Whereas self-organized criticality (SOC) is widely conceived as a general mechanism for generating transient dynamics, we do not use this concept here. We consider it unsuitable for the description of the dynamics of patterns. SOC is only concerned with the distribution of a single measure, in which information in the temporal dimension is collapsed. For the present purpose this is considered too large a reduction of information in patterns and their dynamics. See, however, Gong et al. [2003] in which SOC based analyses of spontaneous alpha EEG activity are discussed.

epoch of measurement should be long enough to permit the system to enter (and leave) all the attractor ruins in the phase space for a sufficiently large number of times. In our case, where dwelling time within an attractor ruin is sometimes longer than ten seconds, such a long measurement period is not feasible. Several authors have proposed that brain dynamics involves a combination of nonstationarity and nonlinearity [Breakspear, 2002; Friston, 2000a,b,c; Paluís, 1996]. These arguments suggest that an absolute distinction between nonlinearity and nonstationarity is practically impossible based on surrogate data analyses, and may be inappropriate for understanding brain functioning.

On the other hand, it may be possible to tease apart the issues of nonlinearity and nonstationarity through experimentation. A recent study by Gonçalves et al. has reported spontaneous variability in the properties of alpha activity within and between subjects [Gonçalves et al., 2006]. They related this variety to the changes in “the external and internal stimuli to which the subject is submitted” and “the amount of memory load, attention, and spontaneous cognitive processes” (p. 211) during the resting state. Systematic control of these factors may allow us to selectively modify the nonlinearity and nonstationary properties of transient brain dynamics. In an effort to relate brain microstates to mental content, Lehmann et al. [1998] asked subjects to report, after a prompt, “what went through his mind just before the prompt occurred” (p. 3). Their reports were classified by blind raters into “visual imagery” or “abstract thought.” Microstates were found to be slightly but significantly different between these categories. An interesting question would be how our present methods would distinguish these conditions. Experiments in which subjects are instructed to actively maintain alternative mental contents (such as “visual imagery” vs. “abstract thought”) during episodes of EEG recording may enable us to assess the corresponding properties of transient brain dynamics. Even though results presented in this paper could be placed as the reference point for comparing between experimental conditions, further characterization of dynamical properties would be necessary for understanding the role of transient brain activity. For this purpose, development of new methods to assess dynamical properties of brain activity is strongly desired. We believe our present study provides a good starting point for this direction and application of our method to other frequency bands or other experimental conditions gives more insight into understanding brain functioning.

Although global synchronization has been observed as a typical feature of transient brain activity both in the rest EEG [Breakspear et al., 2004; Freeman et al., 2003; Lehmann et al., 1987] and in task conditions [Kaplan et al., 2005; Schack, 2004], getting caught in synchrony may lead to deterioration in task performance [Silberstein, 2006]. Nonlinear chaotic dynamics has been proposed as a possible mechanism for fast escape from synchronized states [Tsuda, 2001]. The concept of chaotic itinerancy brings to-

gether the properties of synchrony and transience. Our present study illustrated that transient dynamics in spontaneous EEG is expressed as a series of noncontinuous transitions between quasi-stable globally synchronized states. Its strong long-term heterogeneity is a notable property of chaotic itinerancy. Chaotic Itinerancy may therefore be the dynamic principle that provides the brain with the flexibility required for efficiency of performance.

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