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Dynamic process of information transmission complexity in human brains

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Abstract. Based on a complexity analysis of mutual information transmission of EEG developed by us [Xu J, Liu Z, Liu R, Yang Q (1997) Physica D 106: 363–374], dynamic processes of the complexity of mutual information transmission in human brains were studied. To diminish possible problems due to coarse graining preprocessing, some new measures of complexity were used. The results show that, just before and after generalized seizures, the complexities of almost all information transmission between different brain areas drop significantly; there is also a temporary decrease of complexity when subjects shift their attention. The above facts suggest that there is a transient decrease of information transmission complexity when brain state changes occur suddenly. Mental arithmetic tasks activate the left temporal lobe to exchange more information with other brain areas. The results hint that the methods used here might be an approach to observe quick processes in the living brain.

1 Introduction

Brain imaging technologies such as positron emission tomography (PET) and functional magnetic resonance imaging (fMRI) have been developing quickly in the recent years (Posner and Raichle 1998). These technologies allow the visualization of functional activities in living brains for the first time with improving spatial resolution. However, because these technologies are primarily based on measuring metabolism or blood flow differences, their temporal resolutions are slower than the electrical and chemical processes of brain neurons. Therefore, such technologies have limited utility in the study of fast processes in the brain such as thinking and attention shifting. Moreover, they may not distinguish an excitatory activity from an inhibitory one, as both activities can lead to an increase in metabolic rate or quantity of blood flow. In addition, equipment for such technologies is very expensive and this may also limit their application. On the other hand, the electroencephalogram (EEG) has high temporal resolution, it is a direct reflection of electric activities of neurons in the brain and the equipment is cheap, although its spatial resolution is not so high. Therefore, these different technologies may complement each other if they can be used properly.

The term EEG as we use it here only denotes the spontaneous brain electrical activity; we will not discuss evoked potentials or event-related potentials in this paper. Since the discovery of the EEG by Berger in 1929, it has always been difficult to extract useful information. Many efforts have been made to utilize various analytical methods, such as spectral analysis and EEG mapping. Many digital signal processing methods have also been used to extract frequency and time domain features of the EEG under different conditions (Nunez 1981; Yang and Gao 1989). However, most of the above analyses belong to the category of linear analysis. Its use is limited for complex phenomena such as EEG activity. From the 1980s, due to the quick development of nonlinear dynamics, many authors devoted themselves to studying the chaotic characteristics of the EEG, especially to estimate its fractal dimension or Lyapunov exponential under different conditions (Babloyantz et al. 1985; Babloyantz and Destexhe 1986; Dvorak et al. 1986; Varghese et al. 1987; Babloyantz and Destexhe 1988a,b; Xu and Xu 1988; Rapp 1989; Frank et al. 1990; Iasemidis and Sackellares 1991; Roschke and Aldenhoff 1991; Lutzenberger et al. 1992; Fell et al. 1993; Stam et al. 1994; Besthorn et al. 1995; Theiler 1995; Cerf et al. 1999). Nevertheless, the estimated fractal dimension or Lyapunov exponential values from different laboratories even under similar experiment conditions vary over a wide range (Basar 1990), and no generally acknowledged value exists. This is due to contradiction between the mathematical need for a long time series to obtain reliable estimations and the extreme instationarity of the EEG. More recently, studies using nonlinear dynamic analysis of the EEG have been more interested in

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characterizing its dynamics rather than arguing as to whether the EEG is chaotic or not (Rapp 1993; Stam et al. 1997) and some new approaches have been tried. Stam and his colleagues (1997, 1999) suggested the use of nonlinear forecasting methods to analyze EEG data. Wu and Xu (1991) suggested the use of a complexity measure, the Kolmogorov complexity (KC), defined by Lempel and Ziv (1976) to characterize EEG signals for different functional states of the brain. We will describe the definition of KC briefly in the next section. For calculating, KC only needs thousands of sampled points and it does not matter if the signal is chaotic or not; it therefore seems to be a good candidate for such analysis. Furthermore, Xu et al. (1997) suggested that, as the main function of the brain is in information processing, it is reasonable to study the information transmission among the various parts of the human cerebral cortex by the information theory of Vastano and Swinney (1988). To characterize the global feature of the information transmission process from one location to another, the mutual information transmission between a segment of the EEG at the source and segments of the EEG at the destination with the same length but different delays is calculated. Some complexity measures, including KC or C1, C2, defined by Xu et al. (1994), of the information transmission process are calculated. To visualize the result intuitively, Xu et al. (1994, 1997) proposed drawing a so-called information transmission matrix (ITM); we shall give a brief review of this in the next section. They showed a difference of ITMs between normal and abnormal subjects under different conditions. Their results showed that the ITM might provide an approach to distinguish different functional states of the brain.

In this paper, by taking the advantage of the higher temporal resolution of the EEG, we will examine dynamic changes of ITMs during performance of mental tasks, such as doing mental arithmetic or shifting one's attention to listen to soft music, and also during epileptic seizure. We try to use this method to observe objectively some functional dynamic process related to consciousness in the human brain.

2 Methods

2.1 Subjects

Thirty-one undergraduate students or graduate students, 19–30 years old, including 22 males and 9 females, participated in the experiments involving listening to music. Five subjects were asked to do mental arithmetic. Another 11 data sets for this task were generously provided by Prof. Q. Yang from her laboratory in Beijing University of Traditional Chinese Medicine, and the epileptic seizure data were kindly provided by Prof. K. Ouyan from the Capital University of Medicine.

2.2 EEG recording

The subject sat comfortably in a quiet electrically shielded room while the EEG was recorded with an EEG apparatus produced by ESAOTEBIOMEDICA (Galileo Vega 24W). The electrodes were placed at F1, F2, C3, C4, T3, T4, O1 and O2 according to the international 10–20 system (we shall label the above electrode positions as 1,2,...,7,8). An earlobe electrode was taken as the reference. The electrode resistance is less than 5 KΩ for all leads. The filter setting time constant was 0.3 s with a low-pass filter at 1500 Hz. The analog EEG signals of all channels were transferred by a cable to a personal computer for A/D conversion (1000-Hz sampling rate; 12-bit A/D precision.). Nearly 11 s of consecutive EEG were stored on hard disk for further analysis.

The subjects were informed in advance as to what they should do during the experiment. In the case of studying the shift in attention to soft classical music, the subjects were told to rest with their eyes closed before the music started and to focus their attention on their own abdomen. However, they were told to focus their attention on the music once it began. The music used in most of the experiments was Beethoven's "Für Elise". A pure tone was used as a control. In some experiments, the recording began 6 s before the music could be heard and lasted for 6 s; in others the music started at the beginning of the fourth second and lasted for 8 s. All the subjects knew the music, but on the experimental day did not hear it before the experiment. For the mental arithmetic task, the subjects were told to subtract 3 from 100, then subtract 3 from the product, and to repeat the subtraction of 3 until the end of the experiment.

2.3 ITM analysis

2.3.1 Information transmission matrix. Based on the mutual information theory (Vastino and Swinney 1988), for every EEG trail, m-dimension phase space could be reconstructed; the value m is taken to be 3 as Vastano and Swinney suggested. Taking a segment of EEG $[x_i(t_0), x_i(t_0+1), \ldots, x_i(t_0+1022), x_i(t_0+1023)]$ recorded at the ith position with a time window of 1024 ms beginning at the moment t_0, the probability of the vector $[x_i(t), x_i(t+1), x_i(t+2)]$ with its head locating at some sub-cube of the phase space can be estimated, and its entropy $H[X_i(t_0)]$ can thus be calculated. In a similar manner, another entropy $H[X_j(t_0+k\tau)]$ can also be calculated, and a joint entropy $H[X_i(t_0), X_j(t_0+k\tau)]$ too, where τ is 1 ms. Thus, the information transmission with a delay $k\tau$ from the ith location to the jth location can be determined as the following:

$$\mathrm{IT}_{i,j}(t_0, k\tau) = H[X_i(t_0)] + H[X_j(t_0+k\tau)] \\ - H[X_i(t_0), X_j(t_0+k\tau)] \ .$$

Fixing t_0 and taking different k values from 0 to 511, an information transmission time series is obtained. Calculating a complexity measure $C_{i,j}(t_0)$ of this time series, we obtain an index characterizing some activation degree of information transmission from the ith location to the jth location during a period $[t_0, t_0+511]$. Then, an array with $8 \times 8 = 64$ squares can be drawn, where the gray scale of the square at the ith row and the jth column is $C_{i,j}(t_0)$. Xu (Xu et al. 1997) called such an array an information transmission matrix or ITM. Thus, ITM is an intuitive representation of information transmission between different areas of the cerebral cortex. The ith row indicates the information transmitted from the ith position to other leads (including the ith lead itself), and the jth column means the information received by the jth lead from the other positions. Increasing the value t_0 by a step Δt (here we take $\Delta t = 0.5$ s) and repeating the above procedure again and again, a series of ITM is obtained which represents the dynamic process of the information transmission complexity in the brain.

2.3.2 Complexity. Several complexity measures such as KC, C1 and C2 were used for ITM analysis (Xu et al. 1994, 1996; Tong et al. 1996; Yang et al. 1996; Xu 1997), and similar results were obtained for these different measures. As we will not use C1 and C2 in this paper, we will give only a brief description of KC here; for a description of C1 and C2, see Xu et al. 1994, 1996; Tong et al. 1996; Yang et al. 1996; Xu 1997. KC can be defined as a measure to express the rate of new pattern occurrence with the length of a time series, the element of which is taken from a finite set. KC can be calculated as follows. For a given time series, the first element is taken as a sub-string and the complexity set to be 1. Then, the second element is taken and checked if it is the same as the first one; if it is not, the complexity is added by one; if it is, the complexity remains unchanged and a new element is appended to it to produce a new sub-string with two elements, and to see if the sub-string occurs in the string from the beginning to the element just before the latest appended new element. If it does not, then it means that a new pattern occurs, and the complexity should be increased by one. If it does, then no new pattern occurs, and the complexity remains unchanged. A new element should be appended to form a new sub-string with three elements and the above procedure should be repeated until a new pattern occurs so that the complexity is increased by one. The element just after the new pattern is taken and the above procedure repeated until the end of the series. It was proven that this complexity could be normalized to a number between 0 and 1. We call that number the Kolmogorov complexity (KC) here. If the time series is periodic, then KC will approach 0 with length; if it is completely random, it will approach 1 (Lempel and Ziv 1976). However, as the EEG signal is continuous, a coarse graining preprocessing was used to transform the original EEG data into a binary series. In general, a mean value of the original signal was calculated if the original value was greater than the mean. In this case it was set to 1, otherwise to 0. In the papers mentioned above, the complexity measures were measured for these {0,1} time series. However, such over-coarse graining preprocessing may lose some of the information of the original data. An improper coarse graining may even change the dynamic property of the original time series, for example, transferring a chaotic into a periodic time series, although such a possibility is small. To overcome

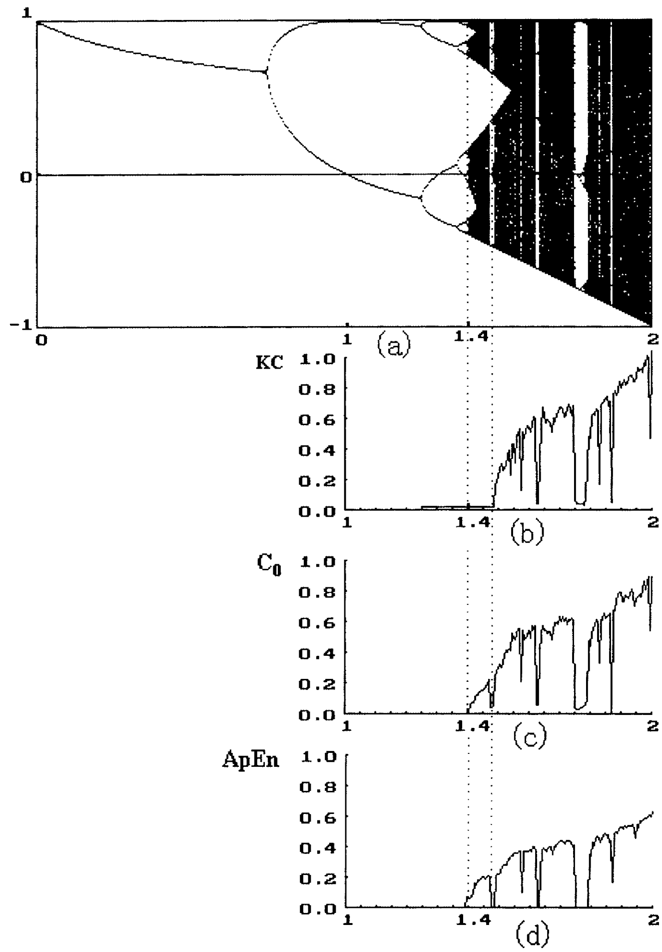


Fig. 1a–d. A comparison of Kolmogorov complexity (KC), C0 and the approximate entropy (ApEn). **a** A bifurcation diagram of logistic mapping; **b** coarse-grained KC - μ curve; **c** C0 - μ curve; **d** ApEn - μ curve

this potential risk, some new complexity measures were explored. In a previous paper (Chen et al. 1998), we defined a new complexity measure C0 as follows: calculating the power spectrum of the original time series with fast Fourier transform (FFT), a fast algorithm for calculating finite discrete Fourier transform proposed by Cooley and Tukey (1965), and calculating its mean value. Only those spectrum components are kept for which the amplitudes are greater than the mean; all the other spectral components are set to zero. Then, an inverse FFT for this new spectrum is taken to obtain a new time series. This is considered as the regular component of the original time series, and the difference between the original time series and its regular component is considered as the disorder component of the original. Then, a ratio of the area of the disorder component over the area of the original time series is considered as a complexity measure, which is denoted as C0. It is obvious that C0 for a periodic signal is zero, and for white noise is unit. No coarse graining preprocessing is needed for calculating C0.

Another alternative candidate for a complexity measure without the need for over-coarse graining prepro-

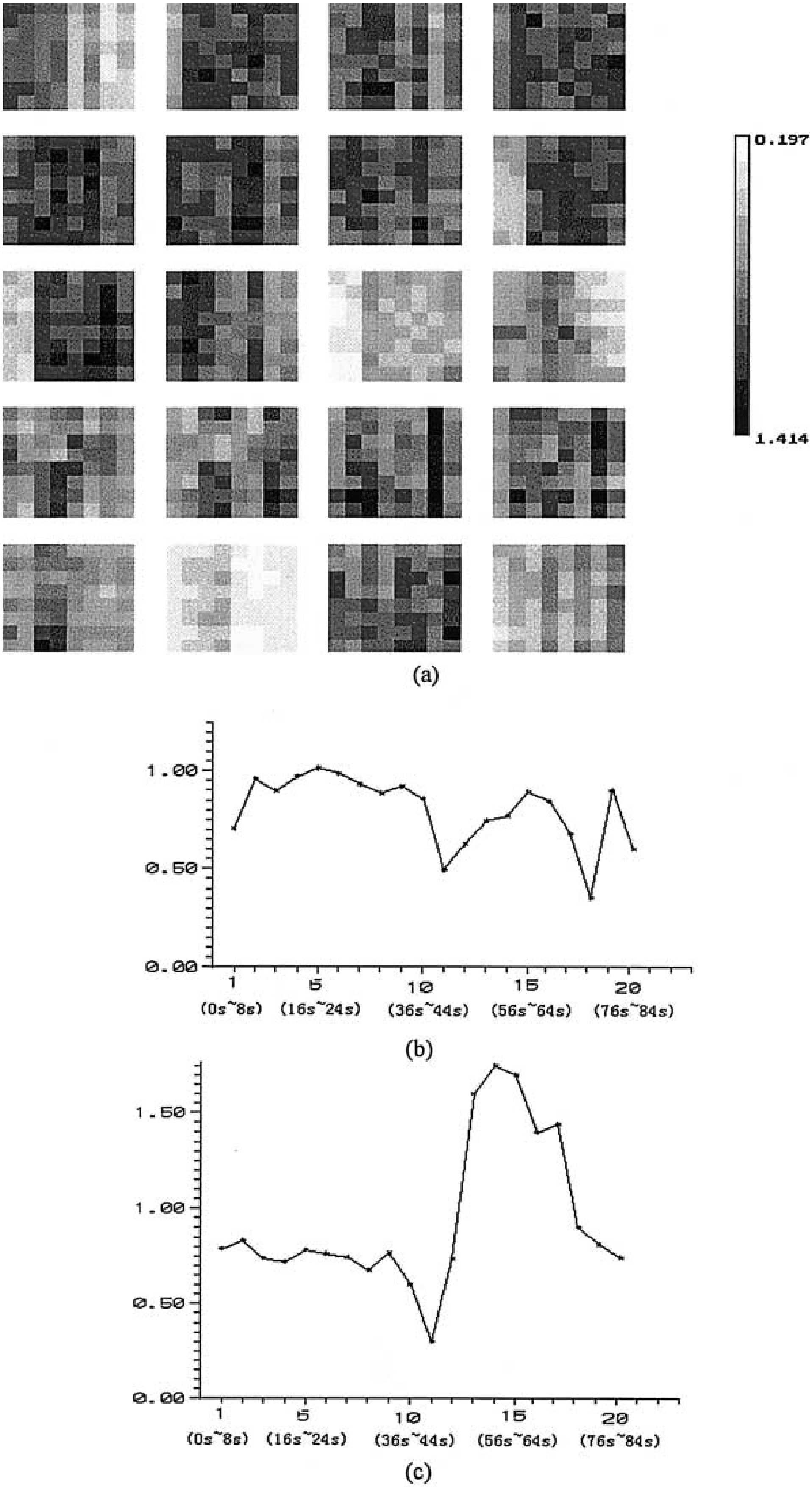
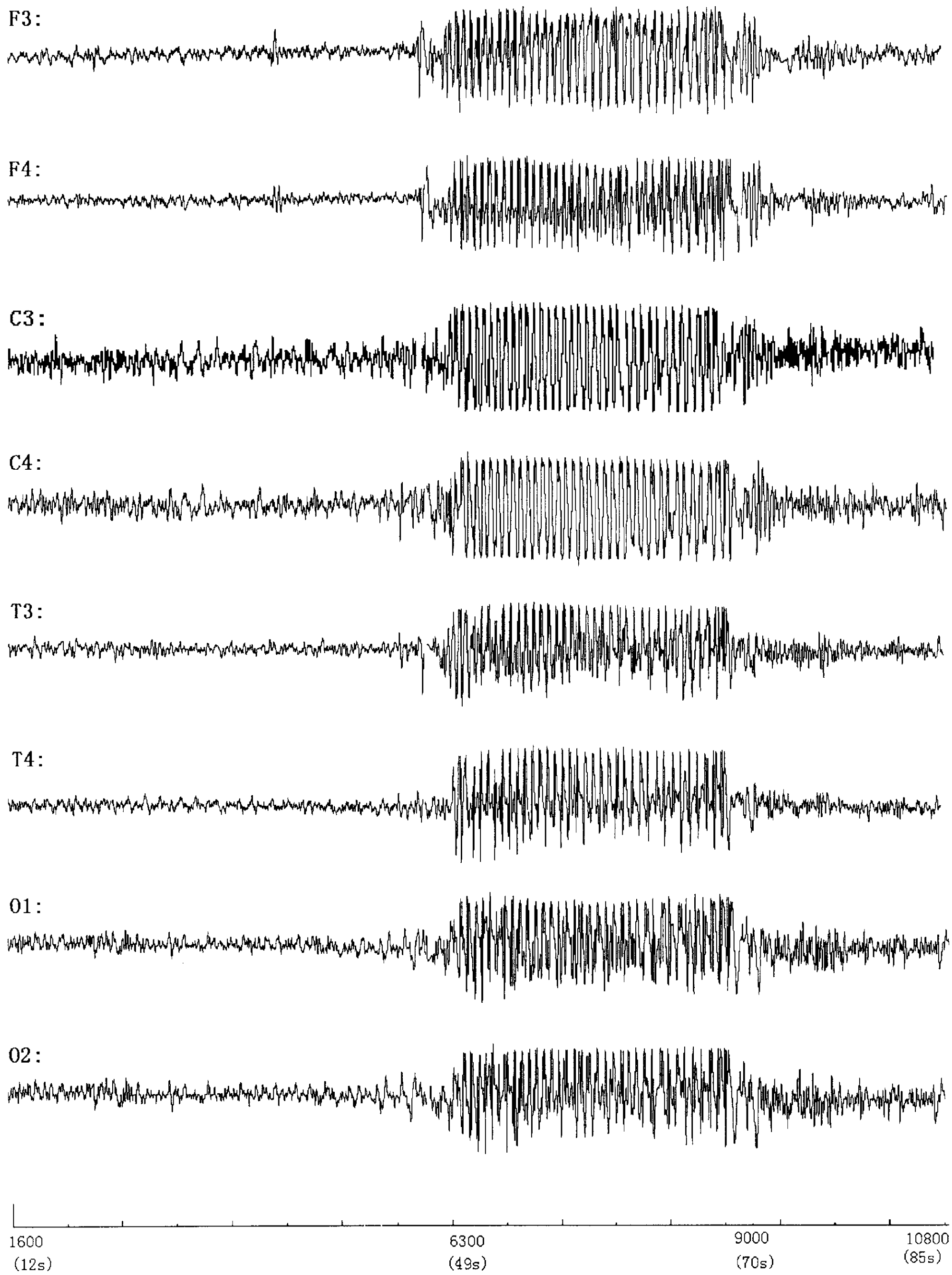


Fig. 2. **a** Dynamic process of information transmission matrices (ITM) during an epileptic seizure; **b** the averages of $C_{i,j}(t_0)$ with time t_0; **c** the averages of mutual information transmission with time; **d** the original EEG data during the epileptic seizure (for details, see text)



(d)

Fig. 2. (Contd.)

cessing is approximate entropy or ApEn (Pincus 1991,1995; Yang and Liao 1997), which can be defined and calculated using the following algorithm for a given time series $x(1)$, $x(2)$, …, $x(N)$.

1. Construct a set of m-dimensional vectors:

$$X(i) = [x(i), x(i+1), \ldots, x(i+m-1)] \qquad i = 1, 2, \ldots, N-m+1$$

2. Define a distance $d[X(i),X(j)]$ between $X(i)$ and $X(j)$ as the maximum difference between their corresponding components, i.e.,

$$D[X(i), X(j)] = \max[|x(i+k) - x(j+k)|]$$

for all k values from 0 to $m-1$.
Then, calculate the distances for all possible pairs $[X(i),X(j)]$ if $i \neq j$.

3. Define a threshold r, and for every i value count the number of the case in which

$$D[X(i), X(j)] < r \ .$$

Calculate the ratio of this number over $N-m$, and denote it as $C_i^m(r)$.

4. Calculate the logarithm values of $C_i^m(r)$ for all possible i values, take their average and denote this as $\phi^m(r)$.

5. Increase m to $m + 1$; in a similar way as described in (1)–(4), $\phi^{m+1}(r)$ can be calculated.
6. In theory, the approximate entropy is defined as the limit of $\phi^m(r) - \phi^{m+1}(r)$, when N approaches infinity. It was proven that this limit exists with a probability of 1.

Therefore, intuitively, the ApEn can be taken as a measure of the probability of generating new patterns when m increases; thus, the bigger the ApEn value, the greater the probability of generating new patterns, and the more complex the time series (Yang and Liao 1997). In practice, N cannot be infinity; we can only estimate it if N is big enough. In addition, this value also depends on the values of m and r. According to his experience, Pincus (1995) suggested that it would be proper if $m = 2$ and $r = 0.1 - 0.2$ SD_x where SD_x is the standard deviation of the original data. It has been pointed out that for a robust estimation value ApEn, a shorter time series with only about 1000 data points is enough. Therefore, this measure is especially suitable for physiological signal analysis, where instationarity of such a signal is often strong.

We have used a segment of the time series generated by logistic mapping

$$x_{n+1} = 1 - \mu x_n^2, \quad \mu \in (0, 2), \quad x_n \in [-1, 1]$$

as a probe to test KC, C0 and ApEn (Chen 1999). The first 1000 points of the time series were abandoned to avoid the transient process, and the length of the time series was about the same as that used in the EEG analysis. A bifurcation diagram of logistic mapping, diagrams of KC, C0 and ApEn versus logistic mapping parameter μ were compared. It was shown that when the parameter μ varied within some ranges in (1.4, 1.48), although the original time series generated by the logistic mapping with such parameters should be chaotic as its bifurcation diagram showed, KC calculated from a coarse grained series was almost zero, but C0 and ApEn were not (Fig. 1). By observing the original time series, it is seen that they vary around the mean value periodically. However, the amplitude is in disorder; thus although the original series is chaotic globally, the coarse-grained series become periodic.

In the following, we will use C0 or ApEn as complexity measures instead of KC or C1 and C2.

3 Results

Figure 2a shows a dynamic process of ITM during an epileptic seizure, which is a complex partial seizure occurring in a patient who was monitored all day and night; the time order is from left to right, then from top to bottom. The time window for calculating is 8 s and the neighboring frames are separated by an interval of 4 s with 4 s overlap. In this experiment, the sampling rate is 128 Hz. In the ITMs (3rd row, 3rd column and 5th row, 2nd column), the complexities of almost all squares are much lower and they occur just before and just after the epileptic seizure. To demonstrate the dynamic process of this experiment more clearly, an average of $C_{i,j}(t_0)$ was calculated for every frame and plotted against t_0 (Fig. 2b). There is a significant drop of the averaged C_{ij} just before and just after epileptic seizure (comparing with the original EEG records shown in Fig. 2d).

Figure 3 shows a dynamic process of ITM for a mental arithmetic task. As mentioned above, the subjects were asked to subtract 3 from 100, then to subtract 3 from the product repeatedly. In the analysis, C0 was used as the complexity measure. The intensity is greater for the squares in the 5th row or 5th column during the process. There is a very intense "cross" at some moment. It suggests that, during the process, the left temporal lobe may be busy transmitting information to

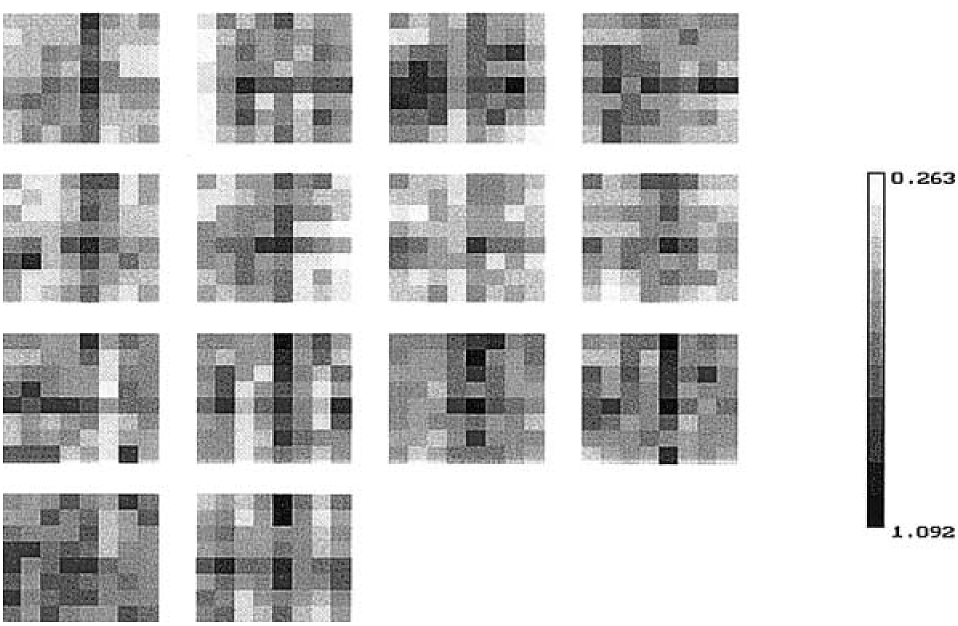


Fig. 3. Dynamic process of information transmission matrices (ITM) while performing mental arithmetic tasks. In the analysis, we used C0 as the complexity measure

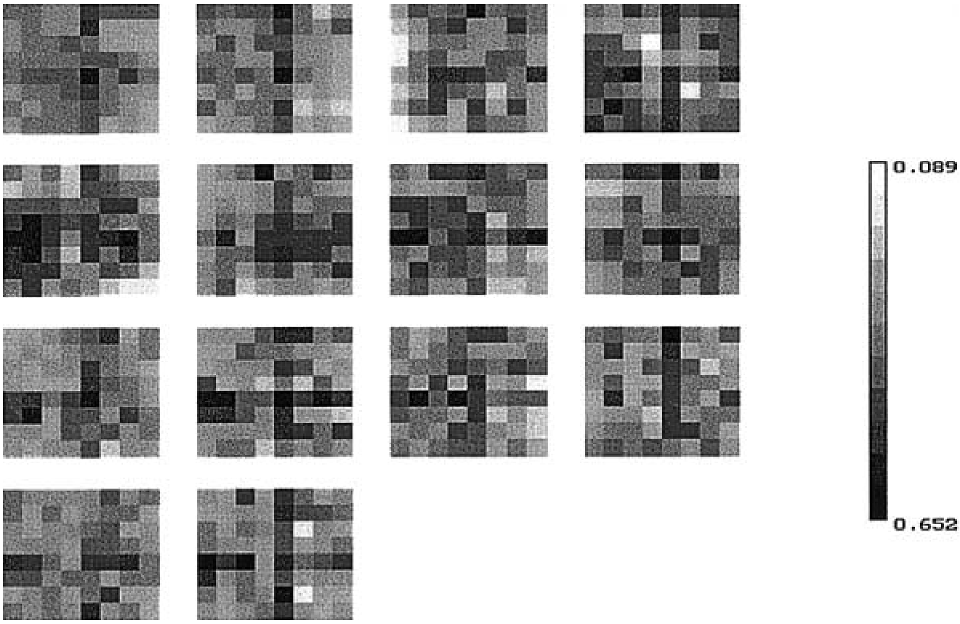


Fig. 4. Using KC as the complexity measure to analyze the same data as in Fig. 3

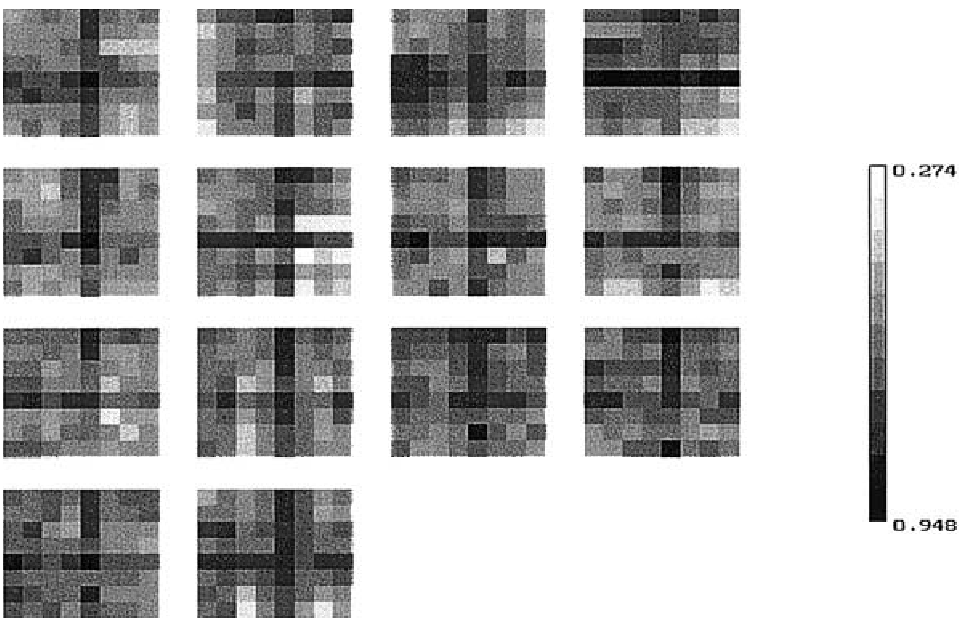


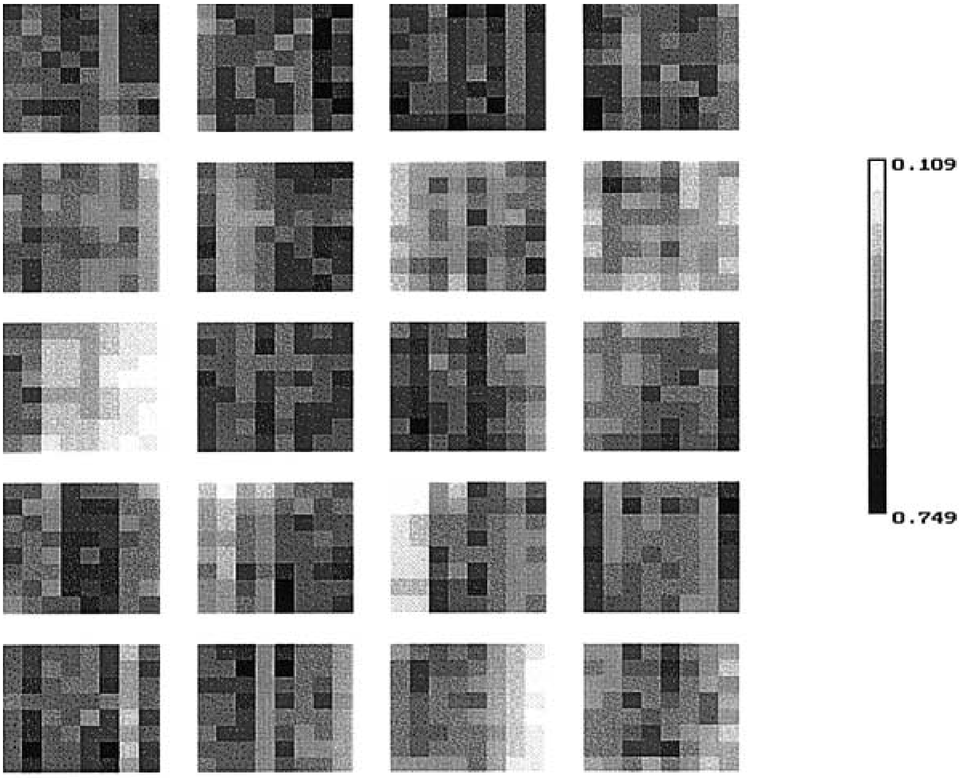
Fig. 5. Using ApEn as the complexity measure to analyze the same data as in Fig. 3

or receiving information from other areas, or doing both. In Fig. 4, we used KC as the complexity measure to analyze the same data and, in Fig. 5, ApEn was taken as the complexity measure. The results were similar.

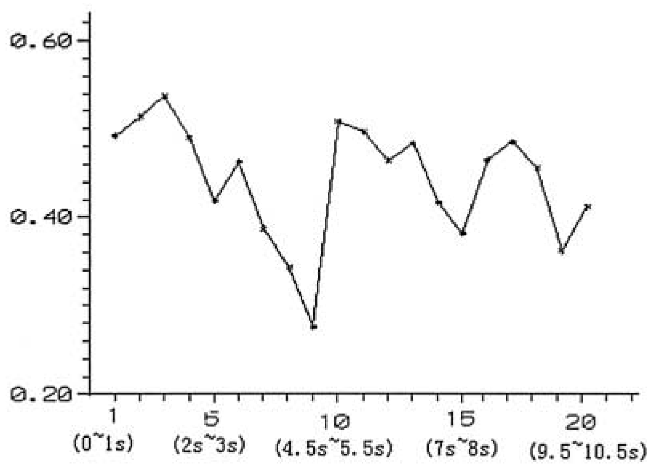
Figure 6 shows an example of the dynamic process of ITM when the subject rests with eyes closed and focused on his own abdomen in a quiet environment for the first 3 s. Then the music started and the piece was played to the end. C0 was the complexity measure. There was a temporary decrease in complexity after the music started (Fig. 6). About 80% of the subjects show such a decrease in complexity. However, there was no such clear drop if the subject listened to the same music again immediately after the experiment (Fig. 7). Figure 8 shows a result when an acoustic stimulus lasted for the first 5 s, then stopped and silence ensued for another 5 s. There was also a significant decrease in information transmission complexity during such state transferring.

4 Discussion

Tononi and Edelman (1998) defined a quantity "neural complexity" to measure the differentiation degree of the brain which is some average of mutual information between every possible subset and the rest of the brain. They hoped that this index could characterize consciousness in some way. However, due to the combina-



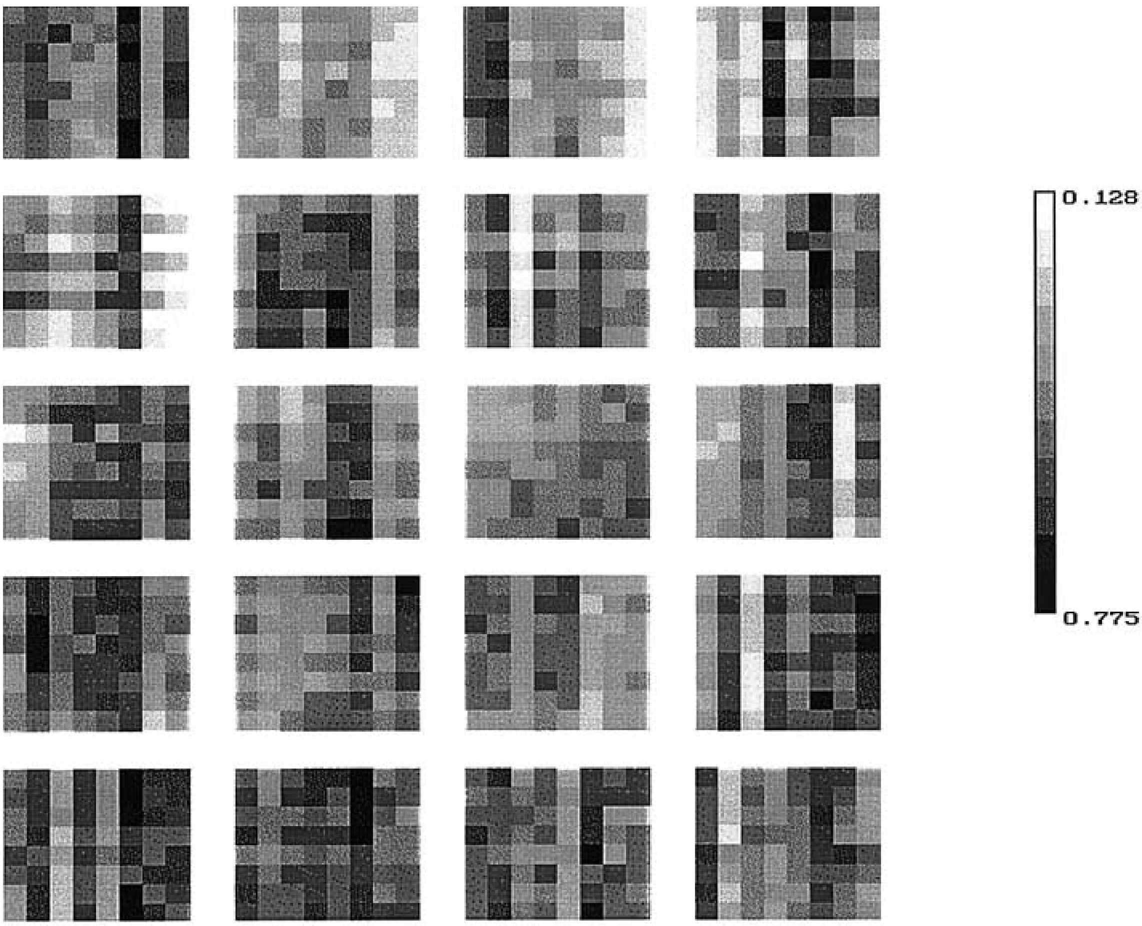
(a)



(b)

Fig. 6. Dynamic process of ITM when the subject rests with eyes closed and concentrate on his/her abdomen in a quiet environment for the first 3 s, then the music "Für Else" started and played to the end. The subject was asked to focus his/her attention on listening to the music once the music started. C0 was taken as the complexity measure

tory explosion, to calculate such neural complexity for bio-signal data we need a very powerful computer. Although the approach suggested in this paper is based only on the mutual information between pairs of locations on the scalp, it could still give us a quantitative and objective measure of differentiation of the brain in some way since the complexity of all pairs of locations was calculated. Its calculation time is short, and can be used on-line; and it seems to be able to provide an intuitive picture of dynamic processes in the living brain related to higher function. It is very interesting that there is a temporal decrease when the subject shifts his/her attention, or an epileptic seizure starts or stops, although the waveforms of the EEG signals for these different cases are quite different. For the former case, the non-stationary state is not obvious, at least with the naked eye while, for the latter case, the non-stationary state is outstanding. These facts suggest that the temporal drop in information transmission complexity may be a general outstanding index to note the change of brain states. Surely such a change should be implied in the original signal itself related to its non-stationary state



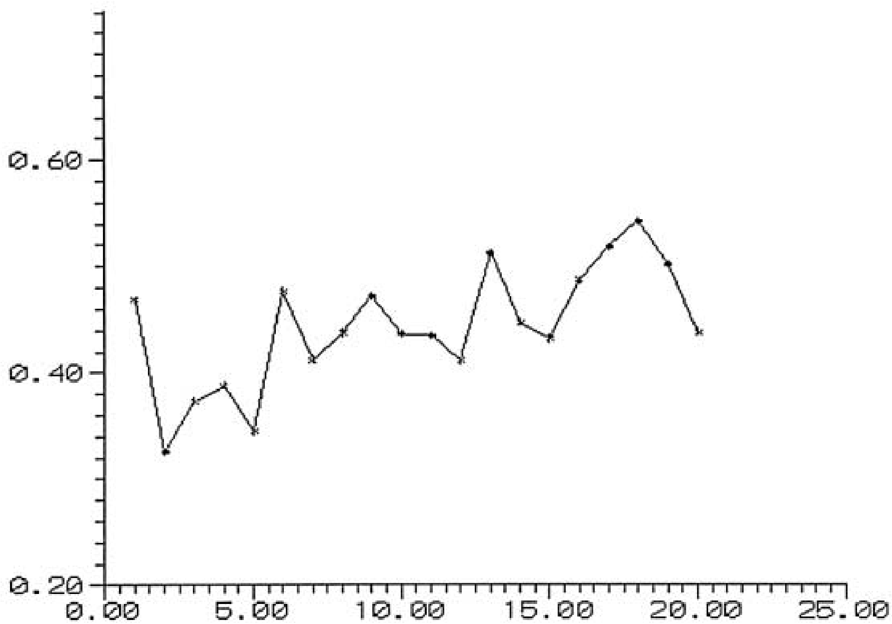


Fig. 7. The same as in Fig. 6, except that the subject listens to the same music a second time just after he/she finishes the experiment described in Fig. 6

during such changes in the state of the brain. However, as mentioned above, in some cases, such as the case of attention shifting, the change in the original EEG signal could not be clearly detected by the naked eye. Thus, it might be reasonable to propose a hypothesis here to explain the meaning of such a drop in signal, that is, the brain might have to deactivate its information transmission temporally in preparation for re-organization of its activities to change to a new state. To be sure, to separate such a drop from the non-stationary original

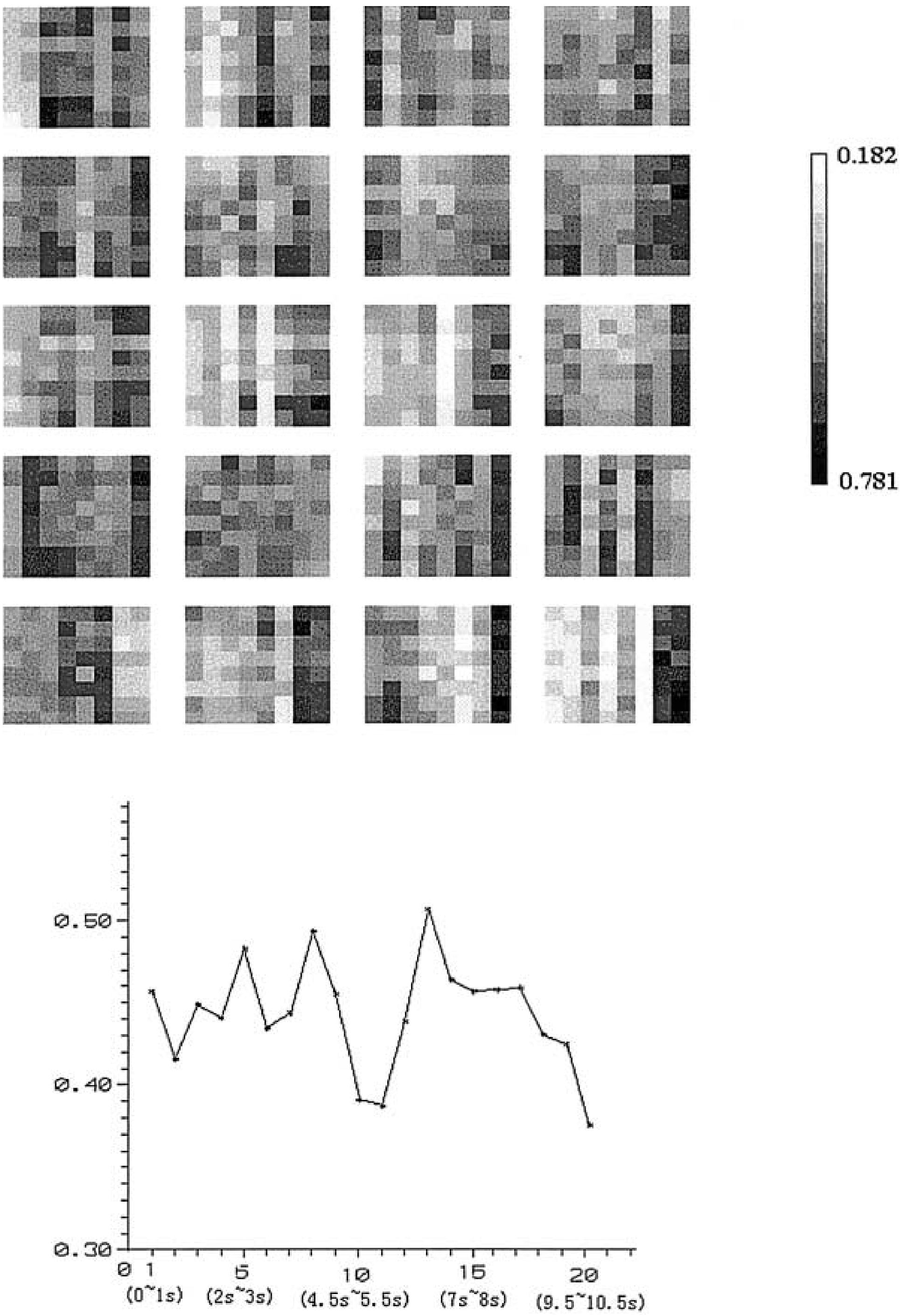


Fig. 8. Dynamic process of ITM when the subject focused on an acoustic stimulus for the first 5 s, then the sound stimulus was stopped and silence ensued for a further 5 s

EEG data is absolutely impossible. More experiments and signal analysis will be needed to test this hypothesis further.

Complexity is a very complex term; no generally accepted definition is available. In this paper, we chose not to provide a general review of all possible definitions of complexity. It should, however, be noted that the complexity measure we used in this paper is a measure of the degree of disorder of a time series, whereas Tononi and Edelman (1998) defined the differentiation of a system. However, we applied our complexity measures not to one channel of the EEG signal, but to the mutual information transmission of pairs of locations distributed over the whole scalp. Thus, our ITM also provides the possibility of measuring the differentiation of the brain. We have used KC, C0 and ApEn as our complexity measures to process all the data mentioned above. For most of the cases, no significant difference could be observed in the results. In this paper, we only show the results obtained by using some complexity, say, C0, and the results using other measures are similar to each other. The only exception is to calculate the dynamic process of information transmission complexity during epileptic seizure bursting. When we use KC as the complexity measure, KC is below the normal level during the whole bursting process; when we use C0 or ApEn as the complexity measure, it drops significantly at the beginning, then recovers to its normal level gradually during the bursting, then drops again significantly when the epileptic seizure stops. Careful examination of the mutual information transmission time series shows that it has slow drift with higher amplitude at the sampled time window; therefore the over-coarse graining for calculating the KC may lead to the wrong conclusions. Therefore, although for most cases KC can be used as the complexity measure effectively, there is still a potential risk owing to its need for over-coarse graining preprocessing.

What is the meaning of our complexity of mutual information transmission? According to the definitions of the complexity measures we used in this paper, they are functions of the degrees of disorder of a time series; thus they also have the meaning of information. However, the time series here is not the EEG signal itself, but the information transmission between two leads. Thus, we cannot imply that the complexity of the information transmission is simply a measure to express how much information is transmitted from the source to the destination. It is a quantity to describe the complexity of variation of the information transmission pattern with time. It can only be explained roughly as a measure of the activation degree of the information transmission process between the two areas. As information is a non-dimensional quantity, information about some information is still information. However, it is not information in the ordinary sense; it is "second-order information". To explain this intuitively, we can imagine a conservation between a sender and a receiver. If the conservation sent is constructed from artificially synthesized words one by one, although its speed can be very fast so that the information transmitted per second is very large, it may be difficult to understand and the receiver may not be able to detect the underlying meaning implied through intonation, change of speed, or a pause, used in natural conservations. The complexity of the information transmission may be a measure of such implied information, or some second-order information. We have used an average of mutual information transmission within the same time window to calculate the complexity of mutual information transmission and to draw ITM with the same data as we used in the results reported above, which we could consider as a measure of "first-order information". The results show that, in many cases, such as performing mental arithmetic tasks, the former is similar to the latter, although the averaged mutual information transmission does not distinguish different brain functional states as clearly as ITMs do (Chen 1999). To our surprise, calculating the average mutual information transmission for the epileptic seizure data mentioned above, we found it to increase greatly during an epileptic seizure (Fig. 2c). Therefore, it seems that it is not the mutual information transmission itself which represents the degree of consciousness which some may expect. Brain activities are so complicated that no single quantity can describe every aspect of the activity. Our approach is only one of the ways to address this problem; other approaches should also be considered so that we obtain a clearer picture of brain activities. In conclusion, the results reported in this paper show that our methods might provide an approach for observing quick processes related to consciousness in living brains.

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