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# Classification of EEG patterns using nonlinear dynamics and identifying chaotic phase transitions

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### Abstract

A dynamical classification method is introduced based on the principle of encoding sensory information in oscillating spatio-temporal patterns. The method is used for the evaluation of EEG signals measured by spatially distributed electrodes over sensory cortices of rabbits. Our analysis reveals two types of patterns in neocortex. One type occurs with short latency after stimulus arrival. This early pattern represents the direct impact of a discriminated stimulus on the receiving cortex. The other type is endogenous and occurs with variable latency in the subsequent  $\sim 1200$  ms. It represents the destabilization of the spatio-temporal dynamics of the cortices and consequent phase transitions. © 2002 Published by Elsevier Science B.V.

*Keywords:* Phase transitions; Cortical EEG; Spatio-temporal chaos

### 1. Introduction

Local areas of sensory cortex  $\sim 1$  cm in diameter generate broad-spectrum aperiodic waves of dendritic activity that have the same wave form [5]. This spatial coherence is shown by the similarity of the wave forms of EEGs that are recorded simultaneously from  $8 \times 8$  epidural electrode arrays giving 'windows'  $6 \times 6$  mm<sup>2</sup> in width onto the olfactory, visual, auditory and somatomotory cortices [1]. The spatial amplitude modulation (AM) of this coherent wave form in brief time segments gives a spatial pattern

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1 that is determined by the synaptic connectivity within each cortex. The connections  
and patterns change with training animals to identify significant stimuli.

3 Dynamical system theory has been used successfully by a number of authors to  
describe learning in neural systems [2,4,9,11]. In our approach, learning establishes an  
5 attractor landscape for each cortical area, in which the basins of attraction are shaped  
by experience [4] and each attractor in the landscape corresponds to a class of stimulus  
7 that the animals have learned to discriminate. Each attractor is accessed by the arrival  
of a learned stimulus of that class. Formation of a spatial pattern corresponding to  
9 the perception of a stimulus requires 5–6 ms, and the AM pattern lasts in the order  
of 50–100 ms before it slowly dissolves and is replaced by the next at intervals in  
11 the theta range (2–7 Hz). The microscopic neurons operate with point attractors; the  
chaotic oscillations are mesoscopic [5,7]. Accordingly, the pattern recognition requires  
13 distributed connectivity and mesoscopic state transitions involving all of the cortical  
neurons in local areas. Global state transitions are found in the spatial pattern of the  
15 phase values of the coherent oscillation with respect to the spatial ensemble average,  
which has the form of a cone [6]. The apices of these cones mark the sites of nucleation  
17 of the state transitions by which the AM patterns form. The present study uses a novel  
pattern recognition and classification method based on dynamical memory encoding  
19 [8]. The identified recognition process with relatively long latency (up to 1200 ms)  
supports the theory of chaotic self-organization and stimulus-induced phase transitions  
21 in cortical processes.

## 2. Pattern classification experiments using multi-variate statistics

23 Evidence for the theory of chaotic self-organization in cortices comes from the re-  
sults of classification of the spatial AM patterns. The EEG segments coming from a  
25 sensory area give clusters of points, each of which corresponds to a response to a  
sample of the class of stimulus that the animal has learned to identify. Discrimina-  
27 tion is learned by the animals under classical conditioning, in which one stimulus is  
reinforced (CS+) and the other is not (CS–). In order to establish a baseline level  
29 of classification, EEGs recorded from a sensory area are segmented by fixed-length  
windows stepped at fixed-length time intervals [1] into a matrix of spatial AM pattern  
31 vectors.

At each time step the data set is divided into a training set and a test set. The  
33 training set is used to identify centroids for the CS+ and CS– points. The test set is  
evaluated by determining which is the closest centroid to a given sample. In a more  
35 advanced algorithm, a series of four time-lagged centroids are used over a period of  
 $4 \times 32 \text{ ms} = 128 \text{ ms}$ . Classification results are consistently better with the shifting time  
37 window as compared to the frozen 128 ms window approach. Statistical hypothesis test  
is used to determine whether or not an observed level of classification is statistically  
39 significant. This method yields a sequence of probability values showing the times  
when the CS– and CS+ spatial AM patterns can and cannot be separated. Separation  
41 does not occur in the 3 s control period, and that it occurs just after the time of CS  
arrival and intermittently thereafter. Examples of the measured EEG patterns are given

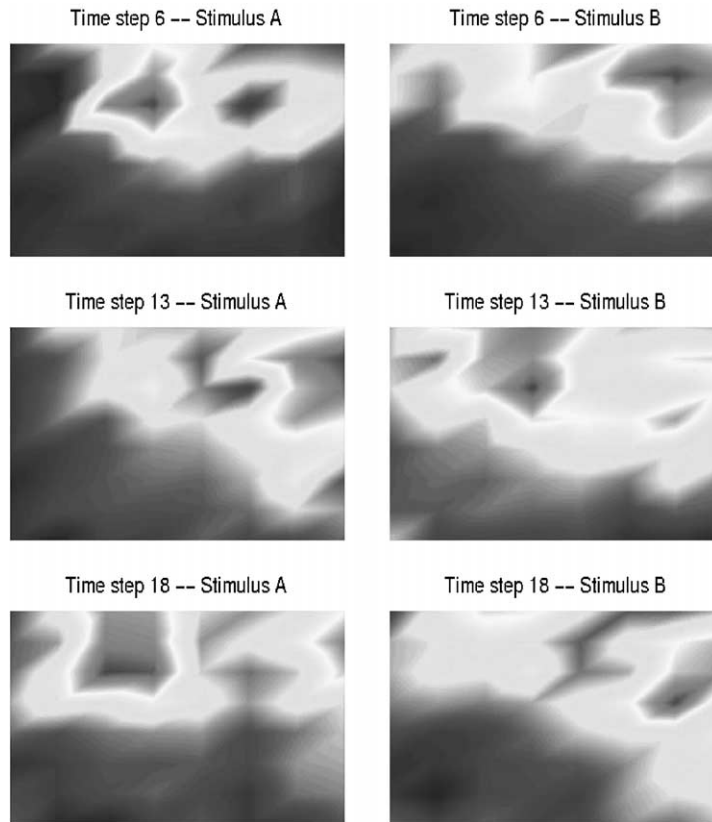


Fig. 1. Illustration of spatial EEG patterns measured on the rabbit visual cortex for stimuli A and B (CS+ and CS-). Different time frames correspond to various temporal instances. A low-frequency periodicity is observed in the sequence of EEG patterns, with a frequency of 3–4 Hz.

1 in Fig. 1, which indicates the variability of EEG patterns and shows the presence of  
 2 the underlying low-frequency oscillations in the theta band.

### 3 3. Results of identification of EEG memory patterns in the rabbit's visual cortex

4 The KIII network has been used for classification of spatial AM patterns from EEG  
 5 oscillations. KIII has multi-layer architecture and it is used as a general-purpose pat-  
 6 tern recognition device having excellent classification performance [8]. The multi-layer  
 7 KIII model consists of various subunits. Of special interest are the KII units, which  
 8 have limit cycle attractors in an autonomous operation regime. In KIII with coupled  
 9 KII sets with massive feedforward and feedback connections across layers, aperiodic  
 10 (chaotic) oscillations arise. The KIII network is trained using continuous (incremental)  
 11 habituation and Hebbian associative learning. The learning converges in < 10 iterations.

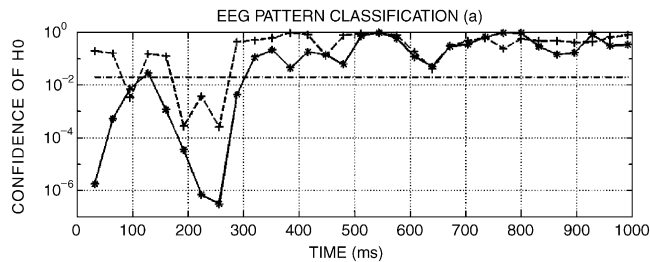


Fig. 2. Probability of correct classification of visual EEG patterns by chance at fixed time steps of 32 ms; (solid line): case of statistical discrimination without KIII model; (dashed line): discrimination with KIII.

1 The KIII model has been used to generate encoding of input vectors in the form of  
 spatio-temporal oscillations over a typical grid of  $8 \times 8$  nodes.  
 3 Results of classification are compared with and without using the KIII network. Two  
 data sets are applied. In one set the time window is stepped at fixed intervals from  
 5 the stimulus onset, and AM patterns are classified at the same time latency across  
 every trial. In the other set, a search is made for the nearest phase cone before or  
 7 after that step on every trial, and the AM patterns in those time windows are aligned  
 and compared [6]. The correct classification rate with the KIII network is shown by  
 9 the solid curve, and without KIII, see dashed curve in Fig. 2. While the classification  
 is evident with and without KIII pre-processing in the first 300 ms after the input  
 11 stimulus onset, the KIII network substantially improves the performance over direct  
 classification.

#### 13 4. Discussions on the physiological significance of phase transitions

The objective of this research is introducing a novel classification and pattern recog-  
 15 nition method and applying it to the characterization of two functionally distinct  
 memory processes identified in spatio-temporal EEG patterns. The crucial test of the  
 17 physiological significance of phase cones is provided by locating AM pattern segments  
 demarcated by the locations of stable phase cones for classification (Fig. 3) instead of  
 19 taking EEG segments at arbitrarily fixed times across all trials. This latter treatment  
 essentially ignores the variability in times of the onset of endogenous cortical events  
 21 during perception. Fig. 4 (solid curve) shows the classification rate of AM patterns  
 selected by the detection of phase cones. As expected [10] the classification rate is  
 23 lowered in the first 300 ms, where chaotic self-organization plays no substantial role.  
 There is, however, an increase in the classification rate later in the trials, provided that  
 25 KIII pre-processing is used.

Phase cones therefore serve as markers by which to locate emergent AM patterns  
 27 at varying latencies over sequential trials in which either of two discriminated stimuli  
 are presented, one reinforced and the other not. Our analysis reveals two types of AM  
 29 pattern in neocortex; see Table 1. One type occurs with short latency immediately after  
 stimulus arrival within the first 250 ms. This early AM pattern represents the impact

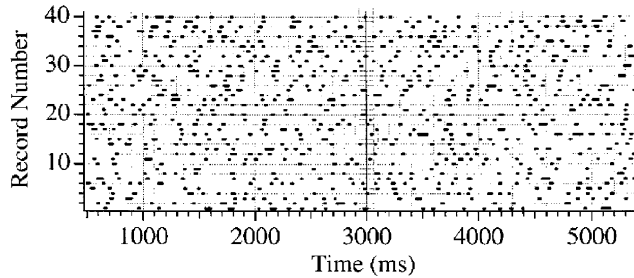


Fig. 3. Line segments of the times of occurrence of phase cones during 40 trials by one rabbit in one session. Data are from visual cortex; the cones were fitted in planar coordinates. Each trial lasted 6 s (the display is truncated at 400 and 5600 ms by temporal filtering), with the stimulus arriving at the middle (3000 ms). The phase cones occur equally often in the control and test periods, as expected in self-organizing cortical dynamics; see [6].

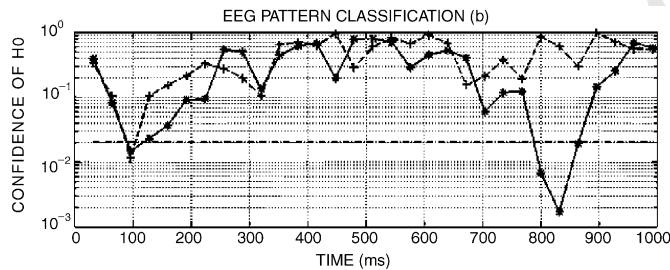


Fig. 4. Probability of correct classification by chance at times determined by phase cones; (solid line): without KIII; (dashed line): with KIII.

Table 1  
Space-time structure of post-stimulus response

Response type	Timing	Space structure	Origin	Interpretation
Type I	Short latency within 250 ms	Topographic specificity (mapping)	Externally driven by input stimuli	Direct impact of discriminated stimuli
Type II	Variable latency within 1200 ms	Convergent-divergent transformation	Self-organized	Destabilization of cortices by sensory stimuli

- 1 of a discriminated stimulus on the activity of the receiving cortex. The other type is
- endogenous and occurs with variable latency in the subsequent 1200 ms. Its location
- 3 in time is revealed by a phase cone at the center frequency of the gamma oscillation, as given by Freeman and Barrie (2000).

1 **5. Uncited references**

[3]

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