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On Neural Substrates of Cognition

Theory, Experiments and Application in Brain Computer Interfaces

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***Abstract*— Recent experiments with high-resolution brain imaging techniques provide an amazing view on the complex spatio-temporal dynamics of cortical processes. There is ample of evidence pointing to frequent transitions between periods of large-scale synchronization and intermittent desynchronization at alpha-theta rates (period length of 0.1 s to 0.25s). These observations have been interpreted based on the cinematic model of cognitive processing. In the corresponding mathematical theories, brains are perceived as open thermodynamic systems converting noisy sensory data into meaningful knowledge. We employ a graph-theoretic model called neuropercolation, which extends the concept of phase transitions to large interactive populations of nerve cells. We show that normal brains operate at the edge of criticality, where phase transitions are manifested via intermittent phase synchronization. Cortical phase transitions are viewed as neural correlates of cognition and serve as basis for non-invasive cognitive monitoring using novel brain-computer interfaces.**

Keywords—EEG, Phase Transition, Brain Computer Interface (BCI), High-density Array.

I. INTRODUCTION

Brain computer interfaces (BCIs) explore the possibility to establish a communication channel between brains and external devices such as computers. The potential benefits are enormous. In clinical setting BCIs can help to diagnose, predict, and treat cognitive diseases at an early stage; they can also drastically improve the quality of life of physically disabled people. These clinical methods are often invasive, i.e., they involve the placement of implants on brains by opening the scull (Yamakawa, 2012). In everyday life, noninvasive BCIs are increasingly popular, for example, the entertainment industry, and they have the potential to serve as personal assistants in physical training and exercises. BCIs are young and immature technologies, and they are still at the very early stage of their development. Clearly, a large number of technological challenges must be solved before BCIs widespread proliferation in broad segments of the society.

Here we focus on noninvasive devices, when the BCI electrodes are located on the scull far away from the cortical neurons. Extracting meaningful information from the signals of such electrodes may seem daunting. Indeed, significant exponents of the neuroscience community consider the obstacles impenetrable and the related activities outright foolish. The impossibility of the task has been compared to the burlesque assignment of Keystone Cops who try to eavesdrop on a single conservation from outside a giant football stadium (Marcus and Koch, 2014).

Or one may compare the situation to the case of a group of free men of fishing trade installing a dense array of flotation-sensors on the surface of a lake. They keep applying ever more sophisticated tools and models to their multi-channel bobbing-record. Methods, which can indeed catch some statistical signs of at least the movements of some of the creatures beneath the surface they are monitoring. These swirls and eddies, they proclaim, are the real secret of the piece of nature that is the lake. Keystone Cops and free fishermen illustrate the prevalent view concerning the apparent impossibility of brain monitoring using noninvasive devices. However, increasing experimental evidence indicates that, in spite of the difficulties, this task can be solved (Kozma and Freeman, 2014).

Noninvasive BCIs using EEG electrodes placed on the scalp provide a feasible method for measuring the brain electrical activity, for a review; see (Liao et al., 2012). In recent years, EEG sensors and sensing circuit designs have enabled the integration of sensors into portable multimodal acquisition devices to measure a wide variety of physiological signals. In this essay we describe the experimentally documented intermittent phase synchronization-desynchronization effects carrying cognitive content. Then we introduce neuropercolation as a mathematical approach to model the synchronization transitions. We conclude with the need for future developments of high-density scalp EEG arrays for building efficient BCI devices.

II. CINEMATIC THEORY OF COGNITION

Various brain imaging technologies can be used to monitor cognitive functions, including functional magnetic resonance imaging (fMRI), positron emission tomography (PET), electroencephalograms (EEGs), near-infrared spectroscopy (NIRS), and others (Mazaheri and Jensen, 2006).

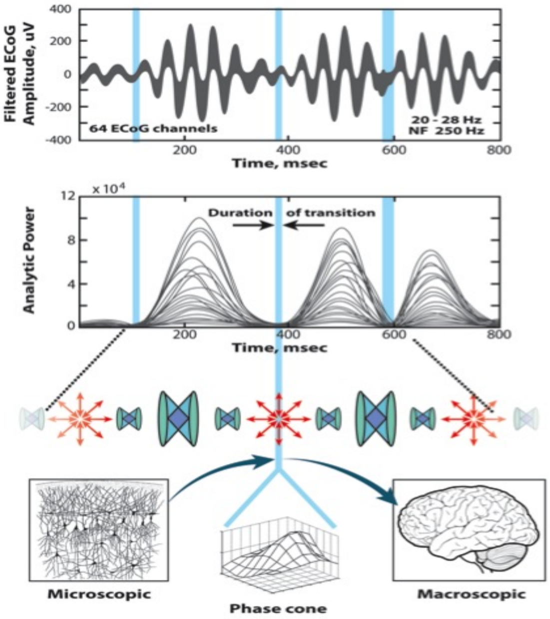

Figure 1. Illustration of the cognitive cycle, according to the cinematic theory of cognition. Top: 64 superimposed band-pass filtered ECoG signals. The 64 analytic amplitudes show drastic reduction during an intermittent singularity (blue bars). These are the null spikes (within the vertical blue bars), which are spatially and temporally localized. Bottom: During the singularity, phase cones convey the transition from microscopic disorder to macroscopic order. The amplitudes are high between the blue bars, and they correspond to the metastable AM patterns carrying the cognitive content.

During the past years, strong evidence has emerged in the literature about the existence of sudden jumps in measured cortical activities. Lehmann identifies microstates in brain activity and jumps between them (Lehman, 1998). Rapid switches in EEG activity have been described by (Freeman et al., 2003, Stam, 2003). A comprehensive overview of stability, metastability, and transitions in brain activity is given in (Le Van Quyen 2001; Werner 2007). Mathematical theory of heteroclinic channels in winnerless competition is a powerful approach of modeling sudden switches in cognitive behavior (Rabinovich et al., 2012). Chaotic itinerancy is a mathematical theory that describes the trajectory of a dynamical system, which intermittently visits "attractor ruins" as it traverses across the landscape (Tsuda, 2001).

Here we summarize the cinematic theory of cognition based on experimental studies of sudden transitions in brain dynamics using electrocorticograms (ECoGs). ECoGs indicate the presence of spatio-temporal dynamics over the cortical surface in the form of amplitude modulation (AM) patterns, which intermittently collapse at the theta rates and give rise to rapidly propagating phase modulated (PM) patterns. The observed dynamics has been shown to be of cognitive relevance carrying useful information on the meaning of sensory information perceived by the subject.

In the terminology of cinematic theory, the metastable AM patters are the frames and the sudden transitions through singularity represent the shutter, see Fig. 1. This result is based on a 64-channel intracranial experiment, where the analytic amplitudes (AA) and analytic phases (AP) are obtained following Hilbert transformation of the beta-gamma filtered ECoG signals. Intensive work has been conducted to describe dynamic transitions in cognitive processing as part of the action-perception (Freeman and Quiroga, 2013). Recent scalp EEG studies evidence that AM and PM patterns are observable by non-intrusive experimental techniques as well (Ruiz et al., 2010).

III. NEURPERCOLATION MODEL OF PHASE TRANSITION

Neuropercolation is a family of probabilistic models based on the mathematical theory of probabilistic cellular automata on lattices and random graphs. Neuropercolation is motivated by the structural and dynamical properties of large-scale neural populations. Neuropercolation extends the concept of phase transitions to interactive neural populations exhibiting frequent sudden transitions in their spatio-temporal dynamics. Neuropercolation develops equations for the probability distributions of macroscopic state variables using percolation theory as an alternative to models based on differential equations (Kozma et al., 2005; Puljic and Kozma, 2008).

Neuropercolation is a natural domain for modeling collective properties of brain networks, especially near critical states, when the behavior of the system changes abruptly with the variation of some parameter. Neuropercolation incorporates the following major generalizations based on the features of the neuropil, the filamentous neural tissue in the cortex.

- Noisy interaction: The dynamics of the interacting neural populations is inherently non-deterministic due to dendritic noise and other random effects in the nervous tissue and external noise acting on the population. Neuropercolation includes a small random component, which can act as a control parameter.
- Long axonal effects: In neural populations, most of the connections are short, but there are a relatively few long-range connections mediated by long axons. The effect of long-range axons is similar to small-world phenomena.
- Inhibition: The cortex contains excitatory and inhibitory connections. Inhibition contributes to the emergence of sustained narrow-band oscillations in the neural tissue. Inhibition is modeled by the interaction of excitatory and inhibitory populations in neuropercolation models.

Multi-layer neuropercolation models have been built for implementing hierarchical models of cortical populations (Freeman 2001; Kozma and Puljic, 2013). The results indicate that multi-layer neuropercolation reproduces intermittent phase transitions observed in brains. Long axons communicating across mesoscopic cortical distances control the rapid switching from one pattern to another. The functional advantage of a network structure with overlapping hubs, similar to the observed "Rich Club" has been analyzed based on the pioneer neurons concept.

IV. HIGH-DENSITY SCALP EEG ARRAY FOR MEASURING SPACE-TIME DISCONTINUITIES

The human scalp EEG contains massive information that is correlated with higher cognitive functions. Samples taken from arrays of electrodes show that the information is in the form of spatiotemporal patterns of briefly stationary bursts of electric potential differences (Freeman and Quiroga, 2013). The bursts are generated by masses of cortical neurons located 10-30 mm below the scalp surface. They are signals that are contaminated by electrical noise from scalp muscles located 2-5 mm beneath the scalp surface.

Theoretical considerations indicate the need for a high-density array with spatial resolution in the range of 3-5 mm. In order to produce robust spatial power spectral densities, it is required to have a linear array of 64 electrodes. The spacing requirement is based on analyses of the spatial frequencies imposed on the scalp EEG by the gyri and sulci of the cortex (Ramon et al., 2009); the typical width and length of gyri are on the order of 10 and 30 cm, giving a spatial Nyquist frequency of 0.2 cycles/mm. The temporal Nyquist frequency of 2000 Hz is based on the need for temporal precision in measurements of the phase of signals in the high gamma and epsilon ranges, respectively 30-80 Hz and 80-200 Hz.

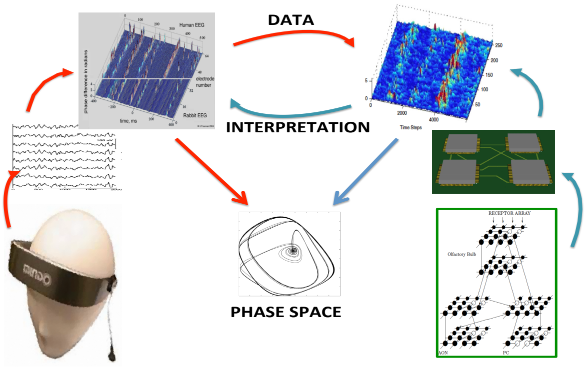

Figure 2. Illustration of the high-density EEG array combined with model studies using hierarchical neuropercolation model exhibiting repeated phase transitions. The required massive simulations and hypothesis generation is best performed using a dedicated FPGA chip device. The experimental device is a headband of length about 25-30 cm, placed along the forehead. Both approaches lead to temporal-spatial patterns (insets), which can be described as trajectories in a phase space. This approach allows direct comparison between experiment and model, generating and testing several hypotheses about the relevance of phase transitions in complex neurodynamic systems for explaining cognitive state changes. The approach is a generalization based on ECoG experiments on learning and strategy change in gerbils (Ohl et al., 2001).

Previous studies have shown that the PSDt of the EEG is f^A, where the exponent is $2<A<4$, while on average the EMG PSDt conforms to f^B, where $B = 0$ (Freeman et al., 2003). Therefore the EMG imposes a plateau onto the combined PSDt, with an inflection at a high frequency, f_H, on transit from f^A to f^B above f_H. Subjects can be trained by biofeedback, on seeing the PSDt, to minimize EMG and reveal the signals in the upper gamma ranges.

V. CONCLUSIONS

BCI technology is developed based on noninvasive scalp electroencephalogram (EEG). Main conclusions are as follows:

- The proposed approach is based on the monitoring of the experimentally documented intermittent phase synchronization-desynchronization effects, which carry the cognitive content.
- We introduce an integrated experimental and modeling approach using neuropercolation. The neuropercolation model is used to interpret the experimental data in real time using massive parallel computing on a chip.
- The information extracted from high-density EEG array manifests neural correlates of higher cognitive behaviors.

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