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Phase Cone Detection Optimization in EEG Data

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Abstract - **Signals measured by electroencephalogram (EEG) arrays were decomposed using Hilbert Transformations to produce the spatial amplitude and phase modulation (AM and PM) patterns. Spatial PM patterns intermittently exhibit synchronization-desynchronization transitions. During desynchronization, the spatial PM patterns intermittently conform to conic shapes. These phase cones mark the onset of emergent AM patterns, which carry cognitive content. In this work, various temporal band pass filters were applied to study the frequency dependence of phase cones in the beta-gamma range (10-40 Hz). The results are interpreted in the context of the cognitive cycle of knowledge generation.**

I. Introduction

Identification of spatio-temporal spontaneous and input induced synchronization-desynchronization events in cortical populations poses a difficult problem due to the noisy and transient character of the processes involved [1], [2]. We propose to use optimized band-pass filtering and dynamic logic-based neural networks for this identification task. Dynamic Logic (DL) neural network is based on expectation maximization algorithm to optimally select model parameters [3], [4].

In this paper we utilize the DL-based learning method for analyzing spatially distributed EEG distributions. EEG signals are highly nonlinear and various advanced methods have been developed to characterize them [5]. First, we apply spatio-temporal filtering to the rabbit EEG dataset [6] to remove any extraneous noise from the signal. Then we utilize the corresponding DL equations applicable to the case of time varying EEG [7], [8]. We describe the algorithm to solve these equations and estimate the model parameters [9]. We analyze in detail the frequency-dependence of the phase cones. We interpret the obtained results in the context of the cognitive cycle [10], [11]. Our results indicate that phase cones are relevant to the synchronization-desynchronization transitions in EEG patterns manifesting the conversion of sensory information into meaningful knowledge during cognitive processing.

II. METHODOLOGY

In order to reveal successive spatial patterns within EEG waves, an optimal temporal band pass filter must be designed. In prior studies the ultimate criterion for choosing the upper and lower cut-off frequencies was optimization of the classification of spatial patterns of amplitude modulation of brief epochs of gamma oscillations (AM patterns) with respect to conditioned stimuli [6] [12].

Temporal band pass filtering, preceded by spatial low pass filtering, enabled phase cone detection. Analysis of rabbit EEG data with implanted arrays of 64 electrodes indicated that processing the EEG data in 0.2 seconds provided the most consistent set of phase cone display over the time series [6]. The distributions of phase gradients were bimodal, i.e., on average across all sets about half had phase lead ('explosion') and half had phase lag ('implosion') [13]. Pre- and post-stimulus time intervals showed higher than average probabilities of cones.

A. Phase Transitions and their Relation to Phase Cones

Widespread synchrony in oscillations in background brain activity is seen within the beta-gamma frequency range. Temporally the synchrony was interrupted but then re-established in phase jumps. Each jump lasted only a few ms and recurred at irregular intervals, yet successive jumps were nearly simultaneous, even over long distances. The olfactory bulb and neocortical areas were found to generate spatial patterns of amplitude modulation (AM) during oscillations in the beta and gamma ranges. Phase cones are manifestations of state transitions in the mesoscopic dynamics of sensory cortices, by which intermittent AM patterns are formed [13]. Each AM pattern expressed a state of the cortex, which formed by an abrupt change in the cortical dynamics known as a phase transition. Each phase transition had four steps. The very rapid spread of re-initialization of the phase of the beta-gamma activity was followed by re-synchronization, then by the stabilization of a pattern, and an increase in amplitude of the AM pattern. These phase-locked spatial patterns in the EEG revealed organizations of cortical activity that were termed "wave packets" [14], [15], [16]. Successive AM wave packets resembled frames in a cinema with successive spatial patterns held briefly [11]. The AM patterns observed in sensory areas were statistically related to conditioned stimuli, not so much to the features of the stimuli as to the categories of the stimuli that provided for the meanings of the stimuli for the animals [17], [18].

From the standpoint of modeling, the cone is significant as a potential marker for the occurrence of phase transitions in cortical dynamics [11], [19]. In a distributed system a phase transition is unlikely to occur everywhere at the same instant. It begins at one point called a site of nucleation and spreads radially across the system [13], just as a snowflake or a

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raindrop enlarges with radial symmetry. When a new cortical state appears that is expressed in a shared oscillatory waveform, the delay in onset imposes a radially symmetric gradient in the phase that is defined at the peak frequency of the dominant component.

B. Phase Cone Organization

Phase cones are present at different frequencies. A theory is provided that discusses the manner in which phase cones are organized throughout an EEG time series. When viewed from the proper perspective, the seemingly chaotic environment becomes clear. The background EEG, especially at the scalp, reveals robust, structured dynamics which manifest the mechanics of self-organization that regulate the multiple brain systems adapting the brain and body to an ever-changing environment. A way to understand the phase patterns is to see cones as resembling avalanches. Their times and locations of onset are predictable not locally but only in the average. They overlap so that any grain of sand or neuron may participate in multiple cones or avalanches simultaneously. The sizes and durations of cones and avalanches give histograms that are fractal [11].

In the 2-dimensional spatial domain, a radially symmetric circular cone is displayed with respect to the gradient of a plane. Validation of choosing the cone as the spatial basis function comes from comparing the results of measurement with known anatomical, physiological and behavioral properties of the EEG. Measurements of the gradient of the cone give estimates of the phase velocity that fall within the known range of conduction velocities of axons running parallel to the pia [12], 13].

When the brain is in a relaxed state, the basal state activity of the mesoscopic organization of neurons is more uniform or “symmetric”. When sensory input is manifested in the brain, a phase transition is induced that breaks the symmetry [6]. The mechanism of destabilization is provided by the nonlinear gain function that governs the conversion of dendritic wave density to axonal pulse density at the trigger zones in populations of neurons [14]. The symmetry- breaking can be either by implosion or explosion, meaning lead or lag at the apex of the cone.

III. EXPERIMENTATION

Data has been obtained at rabbit chronically implanted with an 8x8 array of EEG sensors [6]. Preprocessing of the signal is conducted as follows:

- Starting with the raw EEG time series (Fig. 1), spatial low-pass filtering (across channels) and temporal (across time) band pass filtering is applied.
- Initial bandwidth activity is set between 20-80Hz.
- Entire data set is normalized to unit standard deviation.
- Hilbert transformation is applied to the pre-processed data:

$$X_j(t)= x_j(t)+x_j'(t) \qquad (1)$$

Here $x_j(t)$ and $x_j'(t)$ are the real and imaginary part, respectively, of the signal of the j-th channel, j=1,…, 64.

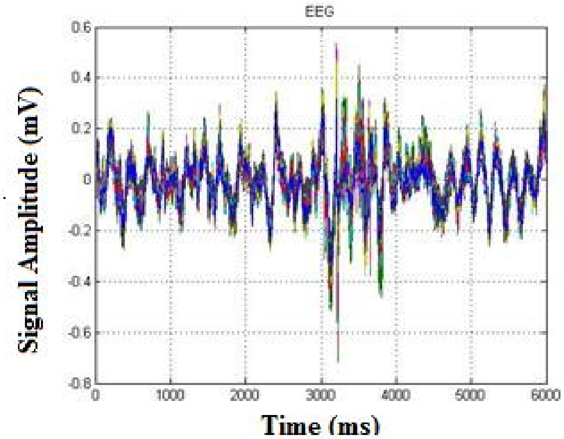

Figure 1. Raw visual EEG signals for all 64 channels; note the significant variation in the signals following the stimulus (light flash) at 3000 ms.

The Analytic Phase ($P_j(t)$) and Analytic Amplitude ($A_j(t)$) are given by the following formula:

$$\mathrm{X}j(t) = Aj(t)e^{ifPj(t)} \quad . \qquad (2)$$

The Analytic Phase (AP) is calculated for each channel. It is given by the arc tangent of the ratio of the imaginary and real part of the signal. The Analytic Amplitude (AA) is also calculated for each channel, and is given by the square root of the squares of the imaginary and real parts of the signal.

The Hilbert Transform is calculated for each channel in the 8x8 array. In this manner, we can find the frequency components of a signal buried in a noisy time domain signal and which part of the signal produces the strong peaks. The phase angles, in radians, are computed for each element of the complex array.

IV. DETECTION METHODOLOGY

Numerous observations of the ECoG phase patterns lead to the hypothesis that the phase gradient starts at a single point, called apex [6], [19]. Following its initiation, the phase gradient propagates with constant lateral velocity through the cortex, resulting in a cone shaped pattern of phase differences. We assume that the height of the cone at the apex changes linearly with time. The parts of the cortex not affected by the propagating phase gradient of the cone maintain an unchanged phase. Our cone detection method is based on finding the best fit between the data and the mixture of one or several propagating cones. Let ξ and η denote the position on the cortical surface in Cartesian coordinates. According to the cone hypothesis, phase propagation $\hat{x}(\xi,\eta,t)$ in space and time is described as follows:

$$\hat{x}(\xi,\eta,t) = v_A\,(t - \rho(\xi,\eta)\,/v_R)\;, \qquad (3)$$

where v_A is the rate of phase change at the apex (deg/s), v_R is the lateral velocity of phase front in the cortex (m/s), $\rho(\xi,\eta)$ is the distance from apex (ξ_A,η_A), i.e., $\rho(\xi,\eta) = \mathrm{sqrt}((\xi-\xi_A)^2+(\eta-\eta_A)^2)$.

Following [9], a mixture model was designed to process a series of 8 by 8 frames and detect the occurrence of the cones over time. Given a set of H models that depend on a set of parameters $\boldsymbol{S}=\{\boldsymbol{S}_h, h=1..H\}$ and a set of data inputs $\boldsymbol{X}=\{x_n, n=1..N\}$, the maximum likelihood estimate of the parameters is obtained by maximizing the following objective function:

$$LL(\boldsymbol{X}|\boldsymbol{S})=\sum_{n=1}^{N} log \sum_{h=1}^{H} r_h(x_n|h), \quad (4)$$

with r_h denoting model mixture proportions, and each model expressed as a probability density function:

$$p(x_n|h)=pdf(x_n|S_h) \quad (5)$$

We will write G(x | m, C) to denote a Gaussian density with mean m and variance C. We use the notation $x(\xi,\eta)$ for the value of the data at the electrode (ξ,η). The cone model is then given as [15]:

$$p(x(\xi,\eta)\,|h)=G(x(\xi,\eta)\,|b-a\rho(\xi,\eta), C_h) \quad (6)$$

The unknown parameters of the cone model are the position of the apex, i.e., slope (a), height (b), and variance (C).

$$S_h=\{\xi_A,\eta_A,b,a,C_h\},\ h=1..H \quad (7)$$

Here H is the maximum number of cones in the data. The constant phase model has index H+1, and it is given as:

$$p(x(\xi,\eta)|H+1)=G(x(\xi,\eta)|m,C_n) \quad (8)$$

The unknown parameters are: $S_{H+1}=\{m,C_n\}$.

Both models assume that the errors between the model and the data follow Gaussian distribution. The objective function takes the following form:

$$LL(\boldsymbol{X}|\boldsymbol{S})=\sum_{\xi=1}^{8}\ \sum_{n=1}^{8} log\,[\sum_{h=1}^{H} p(x(\xi,\eta)|h+\ p(x(\xi,\eta)|H)\ +\ 1)] \quad (9)$$

The objective function is minimized in terms of error, using the following iterative procedure:

Association

$$f_{hn} = \frac{r_h p(x_n|h)}{\sum_{h_2=1}^{H} r_{h_2} p(x_n|h)}$$

Estimation $\quad S_h^{I+1} = S_h^{I+1} + \alpha \sum_{n=1}^{N} f_{hn} \frac{\partial \log p(x_n|h)}{\partial S_h} \quad (11)$

Here the notation was changed to x_n to show space, i.e., x_n is equivalent to $x(\xi,\eta)$ for some ξ and η. Procedure (11) is an iterative optimization algorithm that can be derived from the Expectation Maximization principle [4]. It is guaranteed to converge to a (possibly local) maximum of the objective function.

The algorithm is generic and can work with any number of cones (H). Here, the number H=4 was selected because the current data does not contain more cones. H can be put to be a larger number when the algorithm is applied to a larger array or to human EEG. The local maximum avoidance is accomplished by forcing the algorithm to follow the vague-to-crisp path of convergence as proposed in [2]. This approach has a long history of successful applications in the area of target detection and tracking [3]. Results of single frame processing are chained together by considering pairs of frames and by identifying cones with closely located apices.

V. RESULTS

Frequency band pass ranges change the occurrence of phase cones at a given instance, such as after stimulation has been applied after 3 seconds. Frequency band pass ranges provide different demarcations of phase jumps and the drop in analytic amplitude occurrences over time, seen in Figure 2. Figure 3 shows the formation of phase cones at the same instance per frequency band pass range. Since the phase of the signal is used to calculate phase cones, phase cone occurrences will be affected by band pass range selection.

The calculation of the likelihood of phase cones is discussed previously, but an additional evaluation must take place to determine whether the cones detected fit into the criteria of 'good' cones, i.e., cones generated via event related potentials of brain activity vs. background random noise. The following criterion is applied to separate signals in the presence of strong noise:

- Loglikelihood ratio to noise is less than threshold;
- Length of the cone is greater than threshold (6 ms);
- The apex or height of the cone is greater than a fixed threshold.

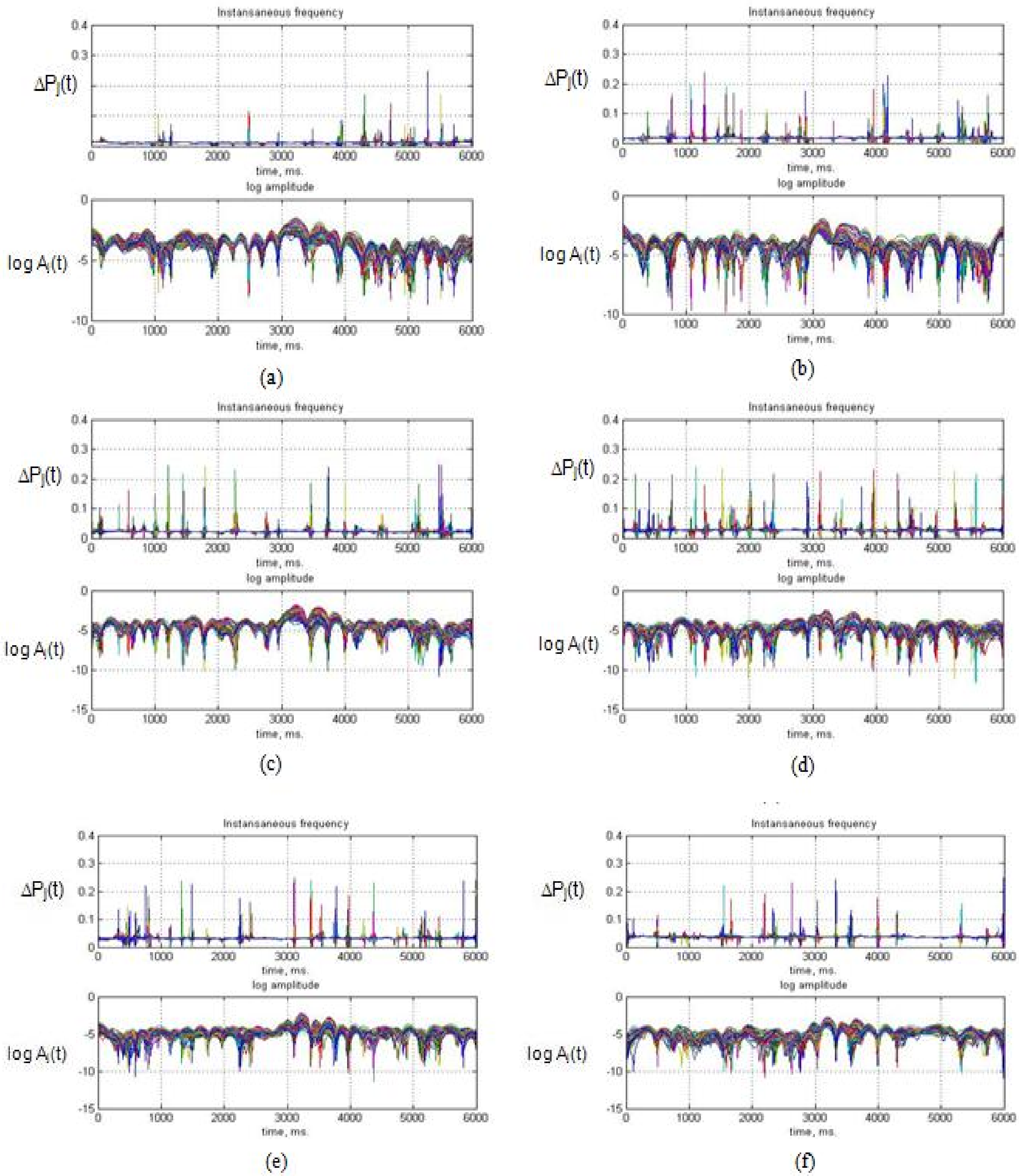

Figure 2. The instantaneous frequency (top displays) and the log amplitude (bottom displays) change per frequency band pass range (a) 10-15 Hz, (b) 15-20 Hz, (c) 20-25 Hz, (d) 25-30 Hz, (e) 30-35 Hz, and (f) 35-40 Hz.

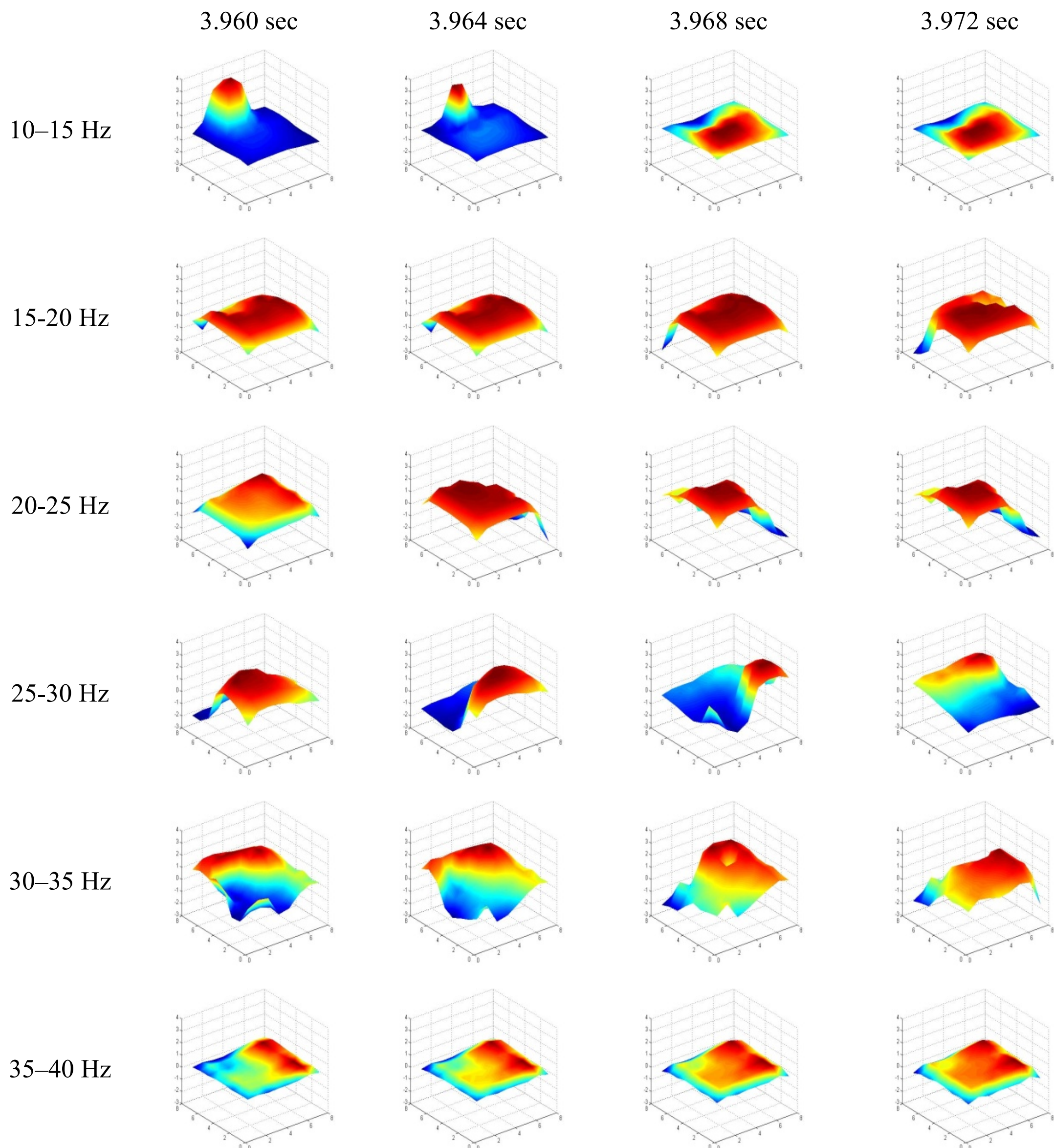

Figure 3. Illustration of phase cone formation; phase cones undergo significant changes as frequency band pass ranges change.

Phase cone detection using the above criteria will provide the likelihood of a cone as 1, otherwise, 0. Recordings of rabbit ECoG were calculated for the likelihood of phase cones per frequency band across the time series, after visual stimulation at time instant 3000 ms. The algorithm was applied to 8 data files recorded over the rabbit's visual cortex. The detections of cones are shown in Fig. 4, which displays the overall duration of all cones detected in that frequency band. The phase cones are cumulatively calculated over 500 ms time windows in Fig. 5. Phase cone cumulative duration varies widely in time and across frequencies without clear evolution pattern.

It is known that phase cone activity occurs even during the resting period, i.e. before a stimulus is applied. A decrease in cone activity has been observed at time around 500 ms after stimulation [9]. This effect has been described in large chaotic systems that reflect a build-up, preceding the 'avalanche-effect'. The neocortex is unique among cortices in maintaining a state at the edge of criticality, in which the critical order parameter is the global level of neural synaptic interaction that everywhere locally regulated by homeostasis [13]. In the next section we discuss on the relation between the cone activity and the frequencies from alpha trough gamma bands.

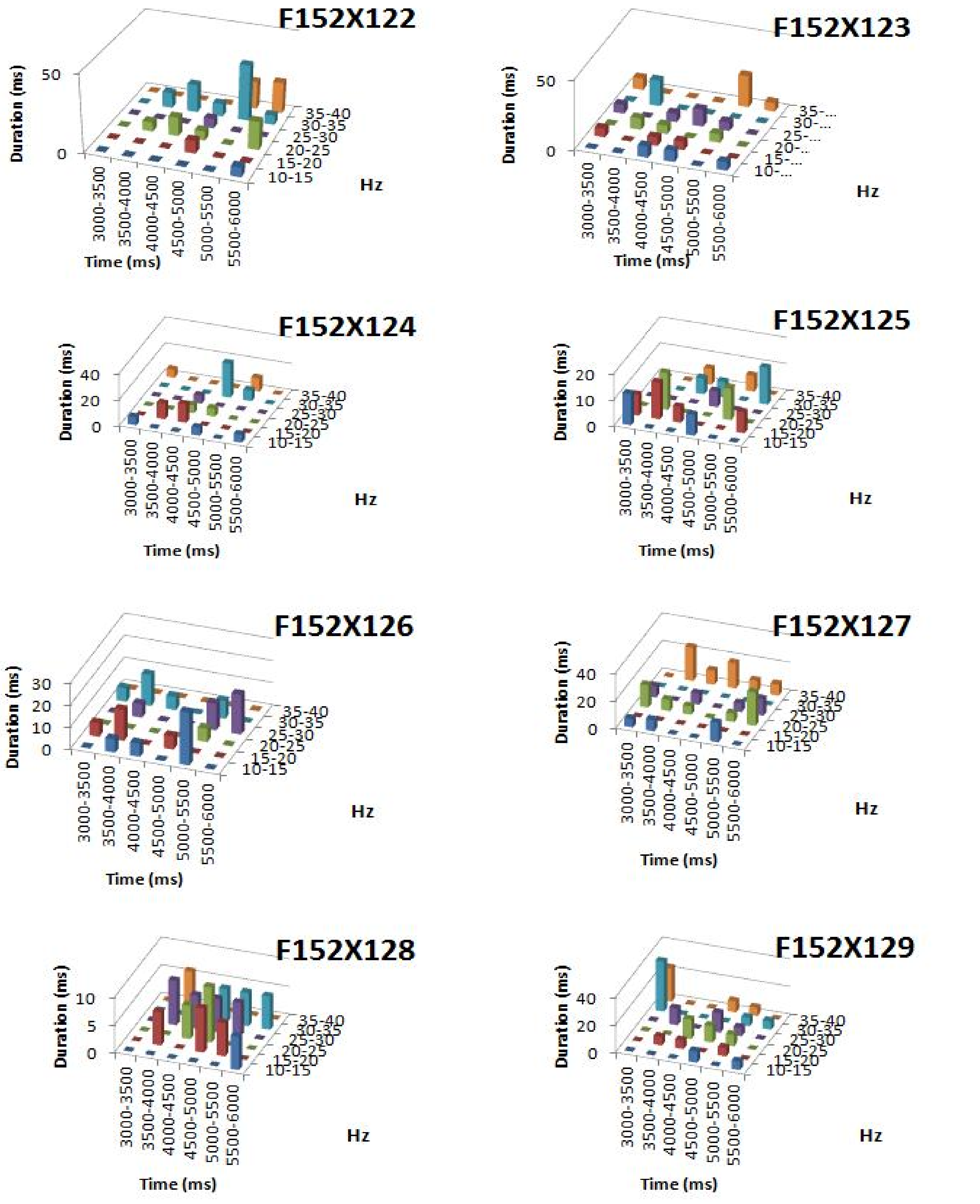

Fig. 4. Cumulative duration of all cones following visual stimulation (>3000 ms). Cone formations that last for more than 6 ms are depicted in each file instance, F152X122-F152X129. Durations are based on Log Likelihood calculations which provide the number of cone instances per frequency band pass range (a) 10-15 Hz-dark blue, (b) 15-20 Hz-magenta, (c) 20-25 Hz-green, (d) 25-30 Hz-purple, (e) 30-35 Hz-light blue, and (f) 35-40Hz -orange.

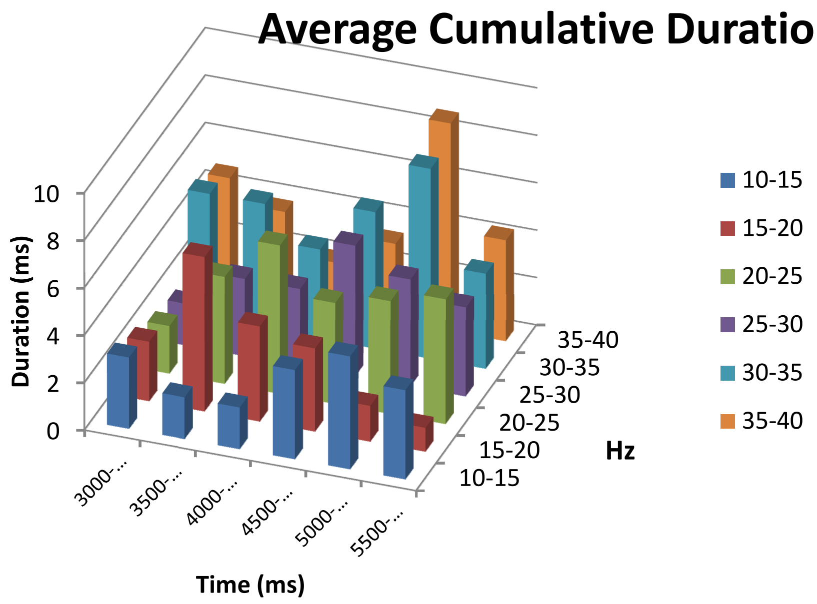

Fig. 5. Average cumulative cone durations across ten recordings in 500 ms windows per band-pass frequency intervals.

VI. DISCUSSION

In order to detect phase cones, temporal and spatial filtering must occur to mitigate noise effects and to reduce cross-frequency interference and aliasing. Temporal filtering facilitates proper cone detection, and it is likely to suit alternative electrode spacing configurations as well. Fundamentally, the application of temporal filtering will enable correlation of phase cone activity to cognitive activities after sensory stimulus is applied.

The cumulative duration of cones was between 6 ms and 26 ms in Fig. 4. Note that we set the lower threshold for cone detection at 6 ms, to eliminate cones of small duration, thus simplifying the procedure. Overall, no clear patterns were identified regarding phase cone emergence in time and regarding the frequency bands, Fig. 5. One of the reasons of this inconclusive result could be the relatively crude time resolution (0.5s) of the preceding analysis. Therefore, next we introduce some results with higher temporal resolution of 0.006s.

Previous results indicated a decrease in the cone density during the poststimulus period [9]. This may be interpreted as an increased synchronization as part of the cognitive cycle manifesting the construction of meaning from the input sensory data: the "aha" effect. Based on information-theoretical measures, various frequency ranges were identified in studying synchronization behavior [16], [17]. The results summarized as follows. The post-stimulus segment of the time series is characterized using the knowledge cycle:

- Stage I: "Awe" moment: Initial direct impression of stimuli (3-3.1s).
- Stage II: "Chaotic Exploration" of memory traces with highly distributed and desynchronized patterns (3.1-3.3s).
- Stage III: "Aha" moment: Recognition/identification of the searched clue/decision (3.3 - 3.45 s).
- Stage IV: "Integration" of the new knowledge in a chaotic dynamic brain process (3.45 – 3.6 s).
- Stage V: "Return to Background" via a dramatic drop in the indices toward the end of the post-stimulus brain activity demonstrating the return to normal base level (3.6 - 3.9 s).

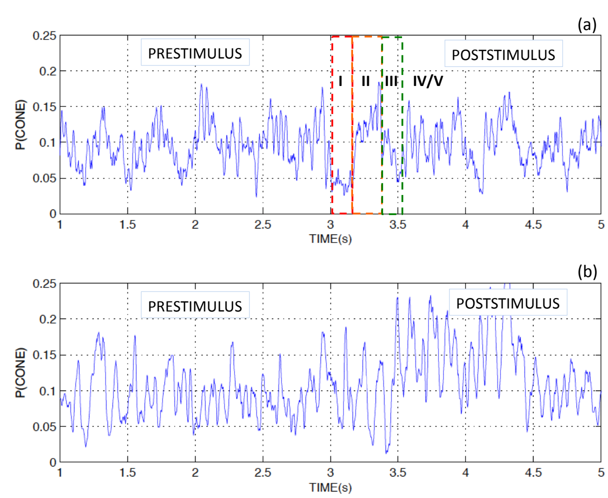

Figure 6. Probability of cones occurrence measured during the experiments at frequencies (a) 25-30Hz (low gamma), (b) 5-10Hz (theta-alpha). In gamma-band, behavior consistent with the anticipated cognitive cycle has been identified, denoted as stages I to V. Data smoothed with a 20 ms sliding window.

Figure 6 shows examples of the evolution of cone probability during the experiments. In the case of gamma-band on Fig. 6a, indications of stages I (awe), II (exploration), and III (aha) are seen. Cones are less probable at stage I, drastically increase at II, and drop again at III; no clear distinction is seen between IV and V. For theta-alpha band in Fig. 6b, the stages are less clear. There seems a more protracted drop until ~3.5s, and an extended increase well beyond 4s. Clearly, detailed additional studies are needed to confirm and quantitatively characterize any possible effect of cognitive relevance.

VII. CONCLUSIONS

In this work, phase cones are identification to characterize changes in EEG signals with potential cognitive relevance. For ideal phase cone detection algorithm, band pass ranges must be automatically optimized. Here, we use band-pass filters with variable upper and lower limits as parameters of the identification process. Parameterization is vital to improve the signal to noise ratio for the detection of phase cones linked to cognitive events.

We have shown that different frequency bands produce different frequency and different duration of the cones depending on the cognitive process in the poststimulus period. As various frequency bands have different cognitive functions, thus it is expected that different frequencies play different roles in cones formation as the cognitive cycle evolves.

Detailed evaluation revealed phase cone patterns consistent with the anticipated cognitive cycle in response to sensory stimuli, in particular in the gamma band. Further studies will be conducted with increased temporal resolution over all frequencies. Eventually, ideal band-pass ranges will need to correspond to neural activity frequency related to cognitive processing.

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