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On-line Detection of Perceptual Signatures in Multichannel ECoG

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***Abstract*— Neocortical ECoG studies have unveiled the presence of active states - spatial patterns of amplitude modulation- in the beta- gamma ranges in the presence of conditioned stimuli that resemble cinematographic frames. These sequences of active frames emerge with abrupt phase resettings, followed by resynchronization and stabilization over channels, and magnified intensity. An online pattern recognizer that captures the spatial and spectral characteristics of the active frames is presented. The results of detection are confirmed via high occurrences of pragmatic information, defined by the ratio of pattern intensity to pattern stability.**

I. Introduction

NEUROPHYSIOLOGIC studies have revealed the generation of active state sequences in cortical activity during an act of perception evoked by the presentation of conditioned stimuli [1,3-6]. These active states observed in the beta (12-30 Hz) and gamma (30-80 Hz) ranges were described by Sacks as 'cinematographic' [9], and can be conceived as *frames* of spatial patterns [6,7] related to perception of stimuli. Each frame begins with sudden sharp phase resettings, followed by resynchronization, spatial pattern stabilization and increase in intensity to a brief maximum lasting about 3-5 cycles of the carrier wave [3,7]. These stable spatial amplitude modulations occur aperiodically, but in synchrony amongst different channels.

The ratio of pattern intensity to rate of pattern change, referred to as *pragmatic information* in [4,6,7] shows incidences of high values shortly after arrivals of conditioned stimulus. This measure has been used not only in the detection of beta-gamma frames, but also in classification of different types of conditioned stimuli (visual, auditory, somatosensory) [6]. However, the estimation of pragmatic information requires block computation, which is not suitable for online applications.

The aim of this study is to employ multichannel pattern recognizers based on the observed properties of active frames, such as their frequency ranges, duration and amplitude characteristics and compare the results with those gathered via pragmatic information. Such temporal pattern recognizing schemes have been previously employed in sleep analysis studies in which phasic events called *spindles* [2,10] resemble the temporal structure of the filtered ECoG (electrocorticography) during frames. Our motivation is therefore to suggest methodologies for on-line detection of frames.

This paper is organized as follows. The methods of detection of beta-gamma frames via pragmatic information and pattern recognizers are presented in the following section along with a brief description of the data sets. Section III gives the results of the two algorithms and their comparisons. Finally concluding remarks are given in Section IV.

II. Detection of Beta-Gamma Frames in ECoG

A. Pragmatic Information

Pragmatic information, H_e, given by the ratio of the instantaneous temporal pattern intensity to the rate of spatial pattern change, was demonstrated to detect frames of beta and gamma activity related to behavior [6]. Analytic signals from each channel were computed via the Hilbert transform to calculate pattern intensity. Let $x_i(t)$ represent the signal measured at channel i and let $H\{x_i(t)\}$ denote its Hilbert transform. Then (1) represents the analytic signal of channel i:

$$X_i(t) = x_i(t) + j \cdot H\{x_i(t)\}, \; i = 1,..,N, \qquad (1)$$

where N is the total number of recorded channels [5]. The analytic amplitude is defined as the magnitude of (1). The mean square of the analytic amplitudes over all channels yields the pattern intensity and the rate of pattern change over the array is estimated from the difference of temporal pattern intensities, i.e. the difference between pattern intensities at time t and t-1. Hence the pragmatic information is given by:

$$H_e(t) = \frac{1}{N}\sum_{i=1}^{N} \frac{\|X_i(t)\|^2}{\|X_i(t) - X_i(t-1)\|} \, . \qquad (2)$$

High values of H_e corresponds to low rate of pattern change and high pattern intensities which are common in active states [7]. Low rate of changes in pattern suggests stability of the brain activity which is related to perception of a stimulus.

Although pragmatic information is a promising measure for the detection and classification of active states, calculating discrete-time Hilbert transforms requires long windows of data and results in distortions at both ends of signals. This in turn implies that pragmatic information may not be suitable for online applications such as real-time data transmission and processing. Moreover, Hilbert

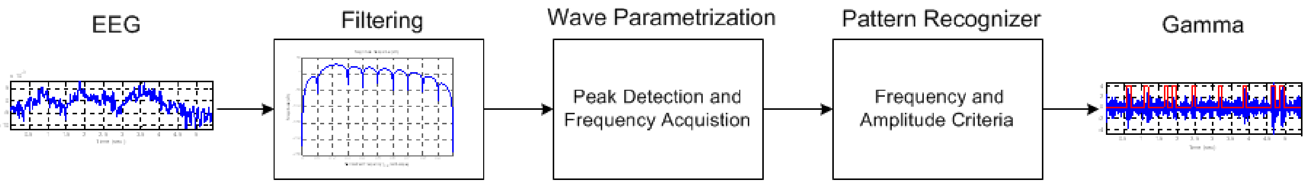

Figure 1. Block diagram of frame detection scheme.

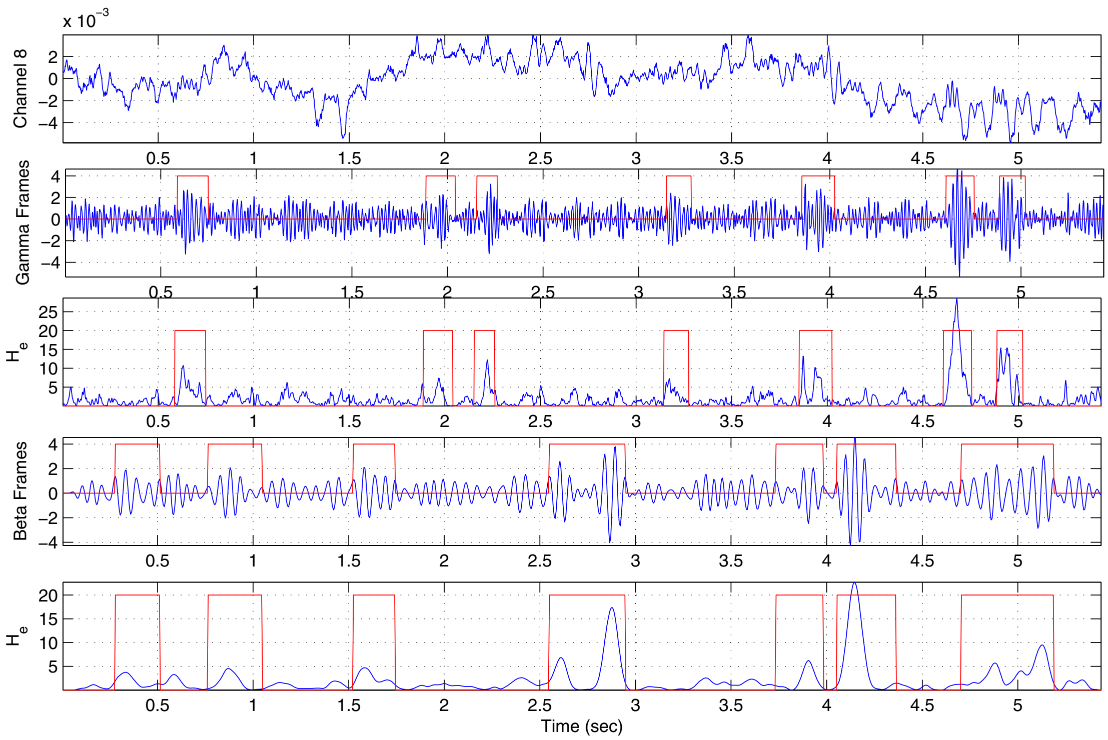

Figure 2. (a) A single channel of simulated ECoG, (b) the detected frames in the gamma range, (c) comparison of pragmatic information with the pattern recognizer, (d) the detected frames in the beta range, (e) comparison of pragmatic information with the pattern recognizer. The extracted frames correspond to high values and durations of pragmatic information.

transformation requires signals to be narrowband and thus high order filtering which may distort the important temporal characteristics of the frames. If the waveform is not narrowband, spurious phase initializations that do not correspond to perception are detected by the Hilbert transform [7].

B. Frame Detection via Pattern Recognizers

In sleep analysis, frames of active states have been widely referred to as "spindles" due to the shape resemblance [2,10,11]. The spindle detection method proposed by Smith et al. [2] utilizes a linear phase bandpass filter, a peak detector and a pattern recognizer. The block diagram is presented in Figure 1. A digital implementation of this method is used for our study. The linear phase FIR filters employed are specially designed for this application [8]. They are low order (20-30) and broadband, in order to avoid distorting the waveforms of interest [8], with a passband of 10-30 Hz for the beta range and 25-75 Hz for the gamma range. The peak detectors employ an amplitude thresholding scheme which discards low amplitude high frequency peaks that are riding on slow waveforms. The time difference between two successive peaks yields the full-cycle period of the individual wave that lies in between. The frequency of the wave is then defined as the inverse of its full-cycle period.

Frequency and amplitude criteria represented by **N/M/m** and **N/a** are applied on the data set to detect the beta and gamma frames. The pattern recognizer selects a window of data within which **N** consecutive full-cycle waves lies. The in-band frequency range for beta and gamma are selected to be 15-25 Hz and 30-50 Hz, respectively. **M** is the minimum required number of consecutive in-band waves and **m** is the minimum number of in-band waves to sustain detection [2,11]. For the gamma range, a window of 6 consecutive full-period waves are selected, 5 of which have to be in the range. Once such a waveform is detected, the successive sliding windows must have at least 4 in-band waves to be the continuation of the frame. Hence, the selected pattern is

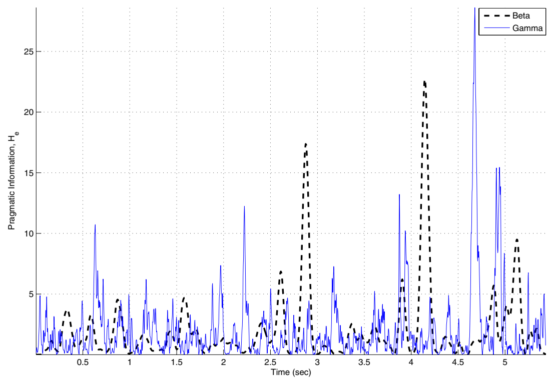

Figure 3. Superimposition of pragmatic information of beta-gamma ranges illustrates the tendency for the peaks to alternate in the simulated data.

represented as 6/5/4. An additional restriction, average window frequency, constrains the average frequency of windowed waveform (6 full-cycle waves) to be in the narrower range of 40-55 Hz, which increases the measurement accuracy. Moreover, during an active state, amplitude patterns emerge, stabilize, and reach a maximum and then decay [4]. The peaks that lie around the center of the spindle, thus, have larger amplitudes compared to those at the initial and final stages of the transient. Based on this observation, an amplitude threshold is applied to the window to ensure the presence of high amplitudes (around the center of the frame) and low amplitudes (initially and towards the end). **N/a**: 6/3 represents that at least 3 out of the 6 peaks in the window should be greater in amplitude than a fixed threshold. The patterns for the beta range are 4/3/3 for frequency and 4/2 for amplitude.

C. Simulated and In vivo Data

This study analyzes two types of data: simulated ECoG and experimental data collected from incranial visual, auditory and somatosensory cortex of rabbits [1].

The simulated data replicates the aperiodic characteristics, Gaussian amplitude histogram, $1/f^2$ temporal and spatial power spectral densities of ECoG acquired from neocortices of rabbits [7]. Stable episodic active states that last 3-4 cycles of beta and 4-5 cycles of gamma waveform were generated alternately by adding highly correlated segments and removing the uncorrelated background. For further details, refer to [7].

The experimental incranial recordings from rabbits were acquired by 8x8 electrode arrays with 0.79mm spacing. Signals with analog bandpass of 0.1-100 Hz were amplified, sampled at 500 Hz with 12 bit ADC. Further details of the experimental procedures can be found in [1].

III. Results

An example of simulated data with sampling frequency of 500 Hz is given in Figure 2. For analysis in the beta range, the signal is resampled to 200 Hz. The waveform is bandpass filtered with the following linear-phase FIR filters of orders 24 and 30 in the gamma and beta ranges in order to extract the frames:

$$\begin{aligned} H_\gamma(z) &= (1+z^{-10})(z^{-2}-0.618z^{-1}+1)(z^{-2}+0.618z^{-1}+1)(z^{-2}+1.618z^{-1}+1)(z^{-2}-1)^4 \\ H_\beta(z) &= (1+z^{-10})(z^{-2}-0.618z^{-1}+1)(z^{-2}+0.618z^{-1}+1)(z^{-2}+1.618z^{-1}+1)(z^{-2}-1)^4(z^{-1}+1)^6 \end{aligned} \tag{3}$$

which yield center frequencies of 50 Hz and 20 Hz, and bandwidths of 25 Hz and 10 Hz, respectively. Indeed, the amplitude modulation patterns with high intensities are easy to detect for human scorers [2]. The detected gamma and beta frames for the simulated data are also presented in Figure 2. The pattern recognizer is able to capture frames of amplitude modulation in both ranges. Moreover, the detected frames correspond to temporal states in which the pragmatic information was found to be of high intensity and long duration.

In addition, the alternating nature of the embedded active states (from beta to gamma, back to beta) is captured with the pattern recognizer, as well as pragmatic information. Figure 3 illustrates the superimposition of pragmatic information from both ranges.

Similar results are obtained with rabbit neocortical data, which are demonstrated in Figure 4. The same pattern recognizers were employed, however, due to noisy high frequency components, the filter orders needed to be increased for better performance (to orders of 30 for gamma and 44 for beta) by adding zeros at $z = -1$. The bandpass filtered signals are also plotted in Figure 4. The detected frames once again are highly correlated with high values of pragmatic information. For this data, it can be observed that the active states reside mainly in the gamma range. Similar results are observed over the remaining 63 channels suggesting spatial synchrony.

IV. Concluding Remarks

A real-time multichannel pattern recognizing scheme for the detection of frames of active states in the beta and gamma ranges is presented. The ranges of interest were extracted via broadband linear phase filters. The methodology is able to detect spatiotemporal frames of beta-gamma activity in ECoG data related to the presence of conditioned stimuli. Thus, the located frames contain organized neural activity associated with perception and recall. The results are confirmed by high intensity and long durations of pragmatic information within the frames. Hence, the detected patterns not only lie in the frequency range of interest, but are stable states with high pattern intensities.

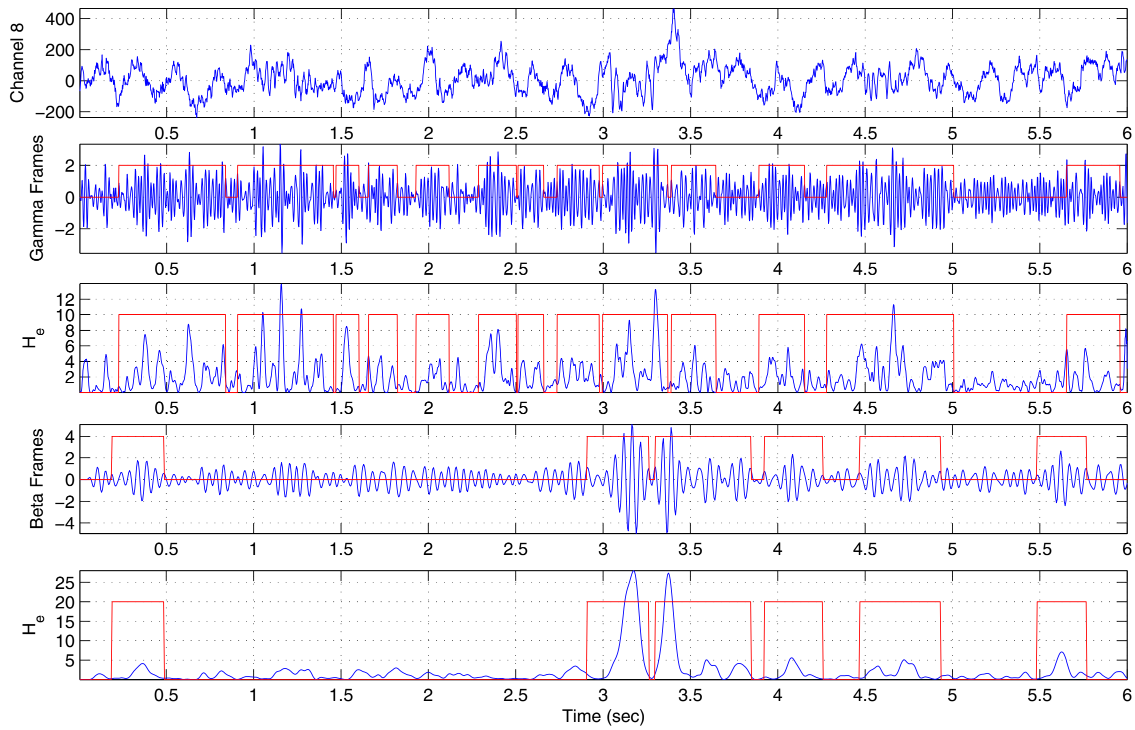

Figure 4. (a) A single channel of neocortical rabbit ECOG, (b) the detected frames in the gamma range, (c) comparison of pragmatic information with the pattern recognizer, (d) the detected frames in the beta range, (e) comparison of pragmatic information with the pattern recognizer. The extracted frames once again correspond to high values and durations of pragmatic information.

The pattern recognizer only requires 4-6 cycles of carrier waves in order to recognize an active frame. This would be quite advantageous for real time applications. However, the phasic event detector requires tuning of parameters (such as in-band frequency ranges), which may depend from patient to patient (or from species to species).

The fact that the pattern recognizer proved to capture the beta-gamma frames in real data as well as for simulated active states indicates that further development of the pattern scheme could yield improved results and applications to other species. Future research will analyze a larger data set associated with perception not only in the rabbits but also in humans.

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