MULTI-SCALE EEG BRAIN DYNAMICS DURING SUSTAINED ATTENTION TASKS

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ABSTRACT

We present a novel experimental paradigm and data analysis methodology for studying brain dynamics during sustained-attention tasks. 256-channel EEG data were recorded while subjects participated in hour-long simulated driving sessions. Every few seconds, the vehicle drifted away from the center of the left lane, and subjects were instructed to steer back to the lane center. The error of each drifting event was measured by the maximum absolute distance from the vehicle's position at deviation onset. EEG data were analyzed using independent component analysis and time-frequency analysis [1]. An independent component with equivalent dipole sources located bilaterally in lateral occipital cortex exhibited multi-scale brain dynamics. Tonic (~20s) alpha-band power increased in high-error compared to low-error epochs, while phasic (~1s) alpha power was suppressed briefly after deviation onset, then increased strongly just before response offset. Other components also exhibited distinct tonic and/or phasic activity patterns relating to deviation onsets or response onsets.

***Index Terms*—** EEG, ICA, brain dynamics, tonic, phasic

1. INTRODUCTION

Sensory event-related potentials (ERP) index mean electroencephalographic (EEG) activities following onsets of visual or auditory stimuli. In many ERP paradigms, participants respond to stimulus events with single, discrete button presses. ERP averages are then obtained by averaging time-domain EEG epochs precisely time-locked to stimulus or response.

In real life, however, many tasks require sustained attention to maintain continuous performance. During the course of sustained attention paradigms, participants receive continuous visual or auditory stimulus streams along with continuous performance feedback. Continuous efforts, instead of discrete button responses, are required to resolve situations that last for a few seconds. For instance, one of the goals of driving safely on a highway is to stay in the center of a cruising lane by continuously controlling the steering wheel. Small changes in road curvature or uneven pavement may make the vehicle drift off the lane center. Sustained lapses of attention during such lane drifts could result in catastrophic accidents.

The ERP averaging technique is limited to tasks with sudden stimulus event boundaries. Further, both ERP waveforms as well as other EEG features may change with onset of drowsiness [2]. These limitations make ERP measures inappropriate or insufficient for assessing event-related brain dynamics during sustained attention tasks accompanied by fluctuating arousal states.

EEG correlates of fluctuations in human performance and alertness on time scales of one second to one minute have been demonstrated [3-10]. In this study, we applied independent component analysis (ICA) and event-related spectral perturbation (ERSP) methods to study brain dynamics following vehicle deviation in sustained attention tasks at multiple time scales [1, 3, 7, 11].

2. MATERIALS AND METHODS

2.1. Participants and Tasks

Eleven right-handed adults (5 males) with normal or corrected-to-normal vision were paid to participate in this experiment. Informed consent was obtained from all participants. All subjects except one participated in two one-hour sessions on different days. Subjects arrived after lunch and sat on an office chair with armrests in front of a 19-inch monitor in an EEG booth in which lighting was dim. A virtual-reality scene was constructed to simulate driving alone with cruise control on the left lane on a straight highway at night (Fig. 1). During the hour-long continuous driving simulation, every 3 to 7 seconds the car was linearly pulled towards the curb or into the opposite lane, with equal probability (Figs. 2, 3). Subjects were instructed to compensate for the drift by holding down an arrow key, and to release the key when the car returned to the center of the cruising lane. Subjects were instructed not to make small corrections for precise alignment after they returned to the lane center. Subjects were also instructed to put forth their best effort, even if they began to feel drowsy. No intervention was made when subjects occasionally fell asleep. Without prompt response, the car continued to drift until it hit the curb or ran into the opposite lane. After such nonresponsive periods subjects resumed task performance themselves, first steering the car back into the left lane.

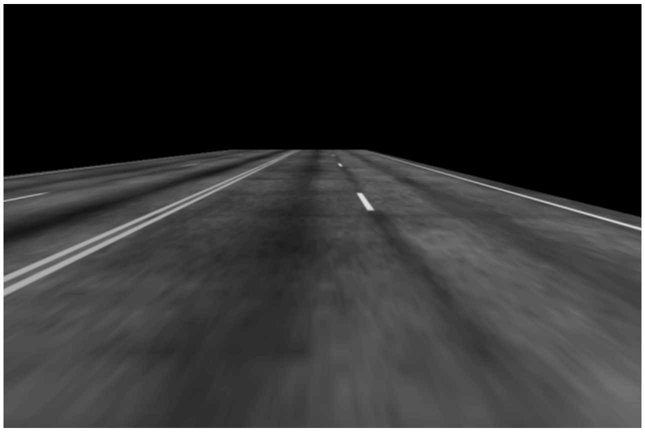

Fig. 1. A snapshot of the driving scene.

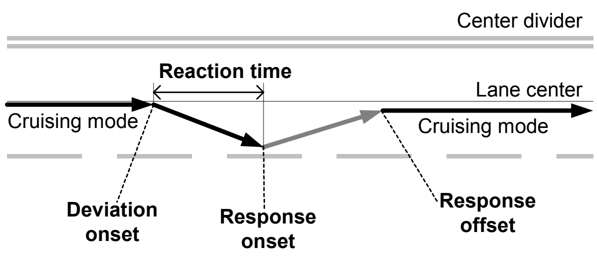

Fig. 2. A bird's eye view of a drifting event.

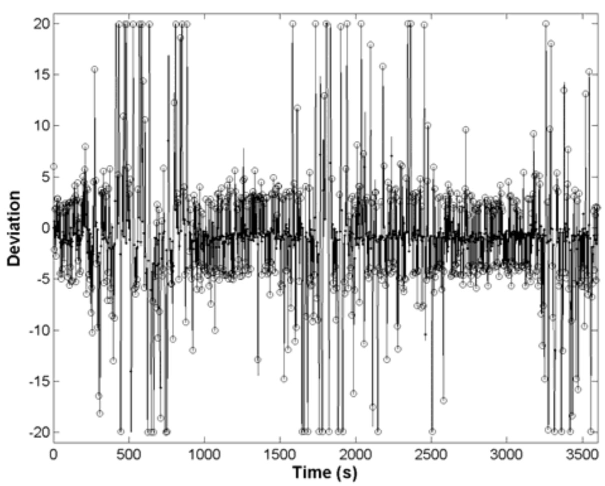

Fig. 3. Driving trajectory of a one-hour session. Dots: deviation onsets. Open circles: response onsets.

2.2. Analysis of Driving Performance

In a representative hour-long session (Fig. 3), 666 drifting events (trials) were recorded. The record of vehicle trajectory indicated that the subject became drowsy and hit the curb or drove into the opposite lane several times in this session. Similar to real-world driving experience, the vehicle did not always return to the same cruising position after each compensatory steering maneuver (Fig. 2). Therefore, during each drift/response trial, driving error was measured by maximum absolute deviation from the previous cruising position rather than by the absolute distance from lane center. Behavioral responses and corresponding EEG epochs were then sorted by this error measure (Fig. 4), which was linearly correlated with reaction time, the interval between deviation onset and response onset (Fig. 2). Shorter reaction times or lower errors generally indicated that the subject was more alert, and vice versa.

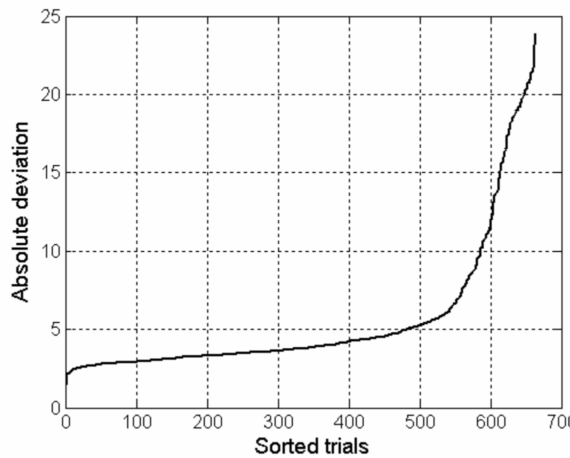

Fig. 4. Trials sorted by absolute deviation from the previous cruising position from which the drift began.

2.3. EEG Data Acquisition and Preprocessing

256-channel EEG/EOG/EKG signals were recorded at 256 Hz using a BioSemi system. The subject's behavior and driving trajectory were also recorded at 256 Hz, in sync with the EEG acquisition system. Data were digitally filtered with a linear FIR band pass filter (1-45 Hz) before further analysis. Due to poor skin contacts and bad electrodes, several channels showed large fluctuations during the entire experiment. These channels were rejected from further data analysis.

Continuous EEG data were segmented into 6-s epochs, 1 s preceding and 5 s following the deviation onsets. The driving task required frequent motor responses, sometimes accompanied by head or neck muscle twitch artifacts in the EEG data. In addition, subjects typically felt drowsy and yawned a few times during the sessions. These events caused severe artifacts across all the channels in some epochs. Epochs contain extreme values (fixed thresholds), abnormal trends (linear drifts), and abnormally distributed data (high kurtosis) were rejected using EEGLAB toolbox (available at sccn.ucsd.edu/eeglab) [1]. Epochs contaminated with other sources of artifacts (blinks, eye movements, heat beats, and head-muscle noise) were not rejected. However, these artifact sources could be separated from other

EEG processes using ICA as described below [12]. In total, the representative training dataset contained 562 6-s epochs of clean 240-channel EEG data.

2.4. Independent Component Analysis (ICA)

Maximally independent EEG processes and their dipole source locations were obtained using the extended-infomax option of the *runica* algorithm in the EEGLAB toolbox [1, 13, 14, 15]. ICA finds an 'unmixing' matrix, W, which decomposes or linearly unmixes the multichannel EEG data, x, into a sum of maximally temporally independent and spatially fixed components u, where $u = Wx$. The rows of the output data matrix, u, are time courses of activations of the independent components. The ICA unmixing matrix was trained separately for each session and subject. Initial learning rate was 10^{-4}; training was stopped when learning rate fell below 10^{-7}. To speedup the training processes, the 240-channel dataset was reduced to 100 dimensions using principal component analysis (PCA) before the training. 100 independent components were obtained. Some were identified as accounting for blinks, other eye movements, or muscle artifacts. Several non-artifact components showed event-related dynamics in various frequency bands that were time-locked to different phases of the drift events. Below, we demonstrate time-frequency analysis of multi-scale brain dynamics for a visual component with equivalent dipole sources located bilaterally in lateral occipital cortex (Fig. 5).

2.5. Event-Related Spectral Perturbations (ERSPs)

Fig. 5 shows averaged component power spectra when the subject made various levels of errors. 562 6-s epochs were first sorted by the absolute deviation from the previous cruising position (Fig. 4), and then divided into five evenly spaced groups between low-error (0%) and high-error (100%) epochs (Fig. 5). Time series in each epoch k were transformed into time-frequency matrix $F_k(f,t)$ using a 1-s moving-window fast Fourier transforms (FFTs). Log power spectra were estimated at 100 linear-spaced frequencies from 0.5 Hz to 50 Hz, and then were normalized by subtracting the log mean power spectrum in the baseline (pre-deviation) periods for each group of epochs (Fig. 5). Event-related spectral perturbation (ERSP) images (Fig. 6), were obtained by averaging n time-frequency matrices from the same group using:

$$ERSP(f,t) = \frac{1}{n}\sum_{k=1}^{n}\left|F_k(f,t)\right|^2 \quad (1)$$

ERSP images were constructed to show potentially significant spectral perturbations (log power differences) from the mean power spectral baseline ($p<0.01$, not corrected for multiple comparisons). Significance of deviations from power spectral baseline was assessed using a surrogate data permutation method [1]. In the resulting ERSP images, non-significant time/frequency points were colored green.

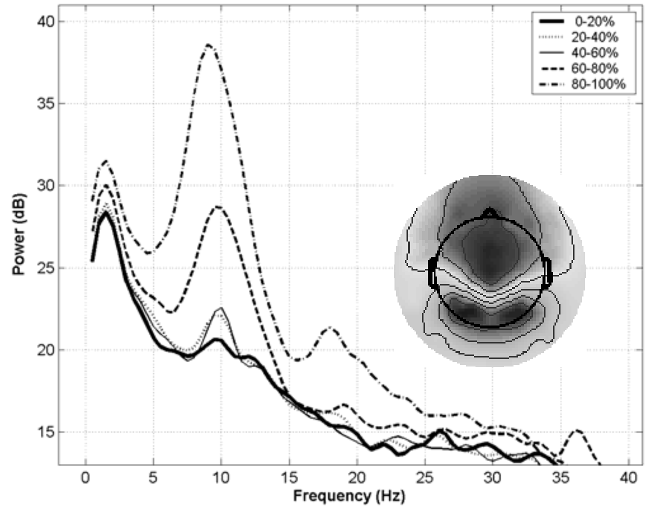

Fig. 5. Average power spectral baselines of five groups of epochs. Inset: scalp topographic map of the visual component.

3. RESULTS

3.1. Tonic Brain Dynamics at a Large Time Scale

The average power spectral baselines showed increased tonic changes, predominately in the alpha band, from low-error to high-error epochs (Fig. 5). Tonic brain activities in the occipital cortex have been shown to reflect fluctuations in drowsiness level on a time scale on the order of 20 s per cycle [5, 7, 9]. During high-error epochs (80-100%), the visual component showed broadband power increases in theta, alpha and beta bands, and the peak frequency of alpha band shifted slightly downwards (Fig. 5).

3.2. Phasic Brain Dynamics at a Small Time Scale

EEG dynamics on a smaller time scale (on the order of 1 s) were also observed (Fig. 6). Alpha power was suppressed briefly after deviation onset, then increased strongly (~10 dB) just before the subject released the key. This transient (1.5-3 s) alpha rebound activity was consistently observed during all single events, regardless of alertness level. The latency of alpha rebound was linearly correlated with reaction time (first response onset) in the first four trial groups (0-80%). During high-error trials (80-100%), a prolonged suppression in alpha power was observed before response onset, followed by an alpha rebound that lasted for a few seconds (not shown).

3.3. Deviation-sorted Alpha Power Image

Fig. 7 shows a deviation-sorted alpha power image generated by the erpimage( ) function of the EEGLAB toolbox. This image also shows tonic increase in alpha power in the pre-deviation period from low-error to high-error epochs (cf. Fig. 5). Alpha power was suppressed near response onset and increased again just before response offset.

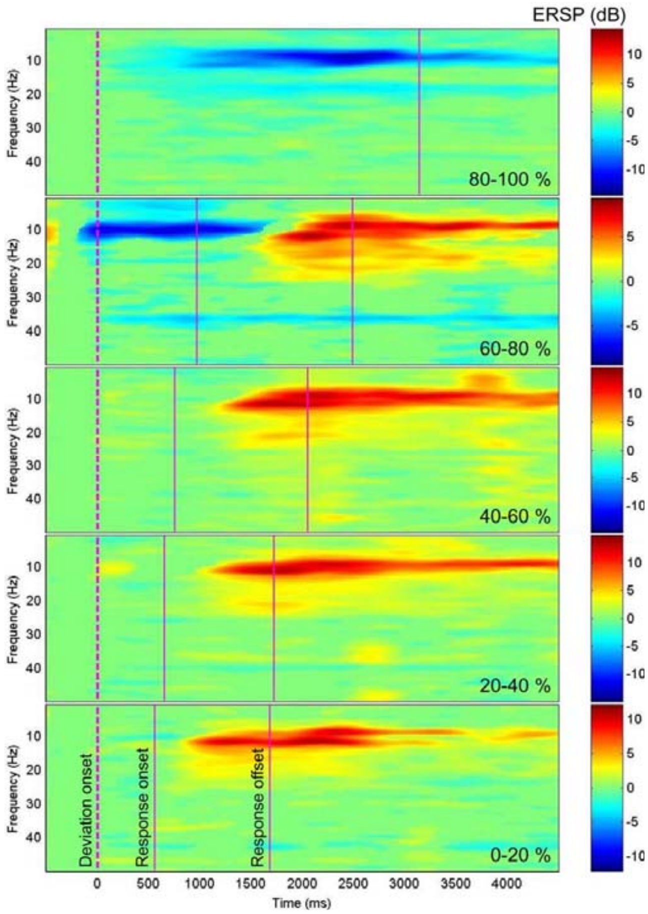

Fig. 6. ERSP images of five groups of epochs.

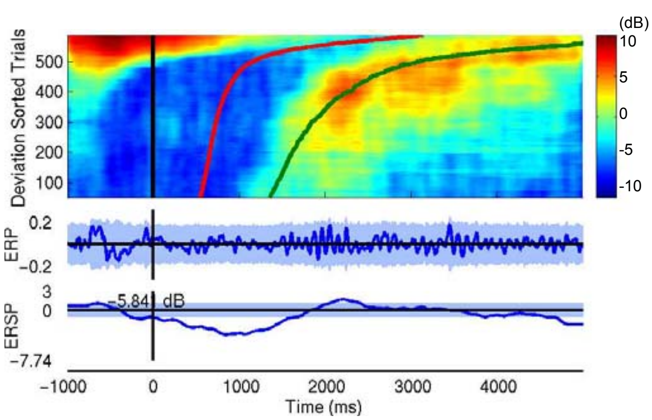

Fig. 7. Deviation-sorted alpha power image. Black line: deviation onset; red curve: response onset; green curve: response offset.

4. CONCLUSIONS

Novel experimental design and data analysis procedures were demonstrated for studying multi-scale brain dynamics in near-realistic sustained attention tasks. Our results show that ICA and time-frequency analysis can detect and model multi-scale (tonic and phasic) event-related EEG brain dynamics in a behavioral task required sustained attention and responses.

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