Event-Related Brain Dynamics in Continuous Sustained-Attention Tasks

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Abstract. Event-related brain dynamics of electroencephalographic (EEG) activity in a continuous compensatory tracking task (CTT) and in a continuous driving simulation were analyzed by independent component analysis (ICA) and time-frequency techniques. We showed that changes in the level of subject performance are accompanied by distinct changes in EEG spectrum of a class of bilateral posterior independent EEG components. During periods of high-error (drowsy) performance, tonic alpha band EEG power was significantly elevated, compared to that during periods of low-error (alert) performance. In addition, characteristic transient (phasic) alpha and other band increases and decreases followed critical task events, depending on current performance level. These performance-related and event-related spectral changes were consistently observed across subjects and sessions, and were remarkably similar across the two continuous sustained-attention tasks.

Keywords: EEG, ICA, brain dynamics, driving, drowsiness.

1 Introduction

In the real world, many tasks require sustained attention to maintain continuous performance. During the course of sustained-attention tasks, we usually receive continuous visual or auditory stimulus streams along with continuous performance feedback. Continuous efforts are required to resolve situations that last for less than a second to 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. Failure to respond to lane drifts could lead to catastrophic consequences.

Electroencephalographic (EEG) correlates of fluctuations in human performance and alertness have been demonstrated on time scales of one second to several minutes [1-8]. Event-related potentials (ERP) following sensory stimuli or events were often obtained by averaging time-domain EEG epochs precisely time-locked to stimulus onsets. In many ERP paradigms, participants respond to abrupt stimulus onset events

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with single and discrete button presses. This might not be the case in real-world working environments that often involve more or less continuous efforts to maintain appropriate performance, instead of occasional impulsive and discretely cued behavioral choices (e.g., selective button presses). Furthermore, both ERP time courses and scalp distributions, among other ERP features, may change with onsets of drowsiness [9]. These limitations make ERP measures inappropriate or insufficient for assessing event-related brain dynamics during continuous sustained-attention tasks accompanied by fluctuating alertness levels.

In this study, we investigated event-related brain dynamics in response to random perturbations in two different continuous attention-sustained tasks. First, in an hour-long continuous compensatory tracking task (CTT), participants attempted to use a trackball to keep a randomly drifting disc in a bulls-eye on the center of screen. Second, during hour-long continuous driving simulation, participants tried to steer a drifting vehicle at the center of the left lane with arrow keys. Independent component analysis (ICA) [10-12] and event-related spectral perturbation (ERSP) [13] methods were applied to continuous EEG data collected in each of the 1-hour sessions. Event-related spectral changes were consistently observed across subjects and sessions in both continuous sustained-attention tasks.

2 Methods

2.1 Participants and Tasks

Non-sleep-deprived healthy adults with normal or corrected to normal vision were paid to participate in the experiment. All subjects gave informed consent before participating in a protocol approved by UCSD Human Research Protections Program. All subjects had lunch about two hours before arriving at the lab around 2:00 PM, and EEG recordings began near 3:00 PM. Subjects sat on a comfortable office chair with armrests and watched stimuli on a 19-inch screen in an EEG booth in which lighting was dim. Each subject took part in more than one hour-long session of sustained-attention tasks on different days.

The compensatory tracking task (CTT) required subjects (n=6) to attempt to use a trackball to keep a drifting (‘wind-blown’) disc as near as possible to a bulls-eye which was continuously visible in the center of screen (Fig. 1a), by making frequent (~3/s) movements of the trackball in the direction of intended movement, producing (‘rocket-thrust’ like) bursts of directional disc acceleration [14]. The coordinates and dynamics of the drifting disc, and the trackball velocity vector were recorded about 14 times per second via a synchronous pulse marker train that was recorded in parallel by the EEG acquisition system for subsequent analysis.

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 (Fig. 1b). Subjects (n=11) 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.

In both tasks, subjects were instructed to maintain their best performance even if they began to feel drowsy. No intervention was made when subjects occasionally fell asleep and stopped responding.

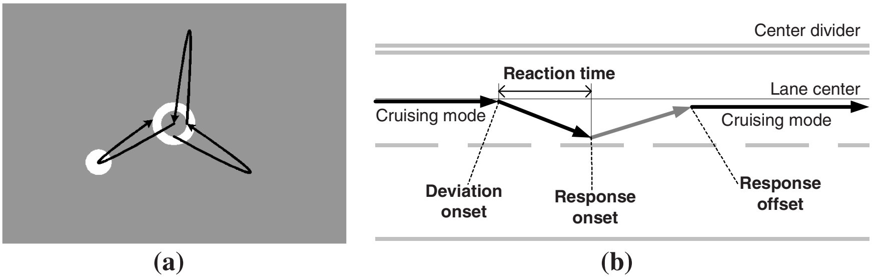

Fig. 1. Schematic plots of continuous sustained-attention tasks. (a) Compensatory tracking task. White ring: bulls-eye. Black curved arrows: trajectories of the drifting disc (white). (b) Driving simulation.

2.2 EEG Data Acquisition and Preprocessing

CTT. EEG activities were recorded from 70 scalp electrodes. Eye movements and blinks were recorded via two EOG electrodes placed below the right eye and at the left outer canthus, respectively. All electrodes used the right mastoid as reference. EEG and EOG activities were sampled at 250 Hz with an analog pass band of 0.01-100 Hz (SA Instrumentation, San Diego, CA).

Driving. 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.

All EEG data were digitally filtered with a linear 1-45 Hz FIR pass band filter 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.

2.3 Analysis of Behavioral Performance

CTT. The recorded time series of disc screen coordinates, x(t) and y(t), were converted into a disc error time series, d(t), defined as the radial distance between the disc and the screen center. Local minima of disc error, d(t), were identified as critical moments when the disc started to drift away from the bulls-eye (Fig. 1a). Each local minimum was defined as a time-locking event for a single trial in which participants had to attempt to use the trackball to return the disc back toward the central ring. Tracking performance was obtained by computing the root mean square (RMS) of d(t) in a moving time window centered at each local minimum. RMS disc error in a (4-s) short moving window indexed the subject's current ('local') CTT performance, whereas RMS disc error in a long (20-s) window was computed to index longer term ('global') changes in CTT performance (Fig. 2a,b).

Driving. In a representative hour-long driving session, 666 drift events (trials) were recorded (Fig. 2c,d). 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. 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. 2d), which was linearly correlated with reaction time, the interval between deviation onset and response onset (Fig. 1b). Shorter reaction times or lower errors generally indicated that the subject was more alert, and vice versa.

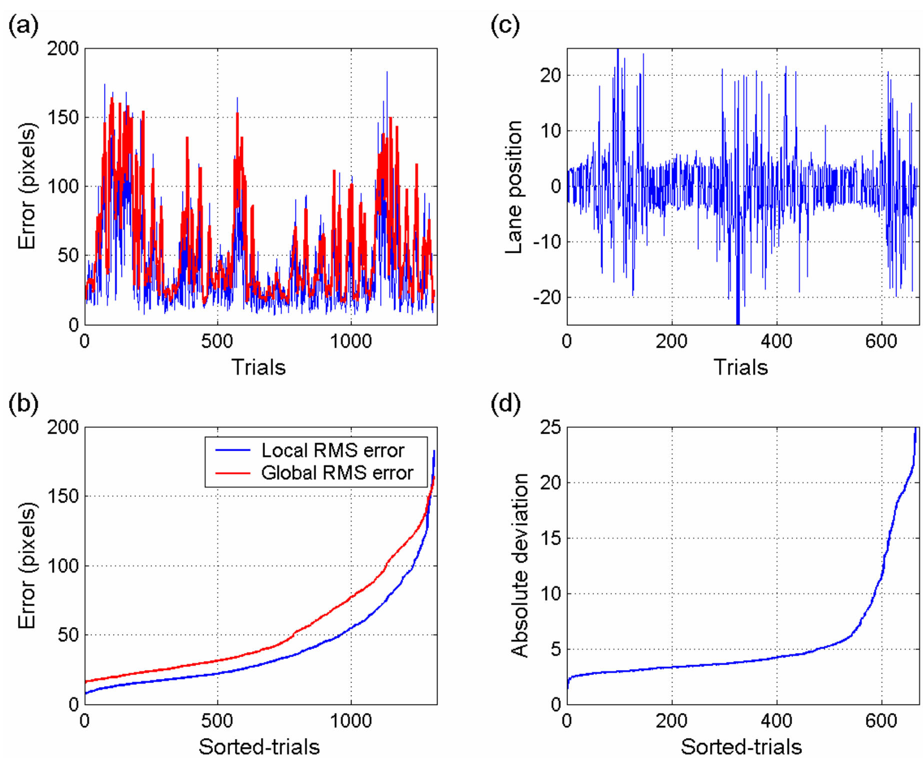

Fig. 2. Behavioral performance in hour-long sessions. (a) CTT. Local (blue) and global (red) RMS errors of trials in chronological order. (b) CTT. Trials sorted by local and global RMS errors. (c) Driving. Lane positions of trials in chronological order. (d) Driving. Trials sorted by absolute deviation.

2.4 Independent Component Analysis

Maximally independent EEG processes and their equivalent dipole source locations were obtained using the extended-infomax option of the *runica* algorithm and the DIPFIT tools in the EEGLAB toolbox (available for free download at http://sccn.ucsd.edu/eeglab) [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 (ICs). 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}. Some ICs were identified as accounting for blinks, other eye movements, or muscle artifacts [16]. Several non-artifact ICs showed event-related dynamics in various frequency bands that were time-locked to the lane drift or disc escape events. Below, we demonstrate time-frequency analysis of brain dynamics for a class of recovered ICs with equivalent dipole sources located bilaterally in lateral occipital cortex.

2.5 Time-Frequency Analysis

Epochs time-locked to drift events were extracted from the continuous IC time courses. In CTT sessions, each epoch contained data 1.5 s before and 3 s after each local minimum of disc error curve. In Driving task sessions, each epoch contained data 1 s before and 4 s after deviation onset (Fig. 1b). Epochs (trials) in each session were sorted by error, and then separated into five evenly spaced error-level groups. Here, we show results of time-frequency analysis on two groups of epochs, representing Alert (0-20%) and Drowsy (60-80%) performance in each session.

For each group of epochs, 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 linearly-spaced frequencies from 0.5 Hz to 50 Hz, and then were normalized by subtracting the log mean power spectrum in the baseline (pre-perturbation) periods for each group of epochs (Fig. 3). Event-related spectral perturbation (ERSP) images, were obtained by averaging n time-frequency matrices from the same group using:

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

ERSP images were constructed to show only statistically significant ($p<0.01$) spectral perturbations (log power differences) from the mean power spectral baseline (Fig. 3). Significance of deviations from power spectral baseline was assessed using a surrogate data permutation method [15]. In the resulting ERSP images, non-significant time/frequency points were colored green (Figs. 4 and 5).

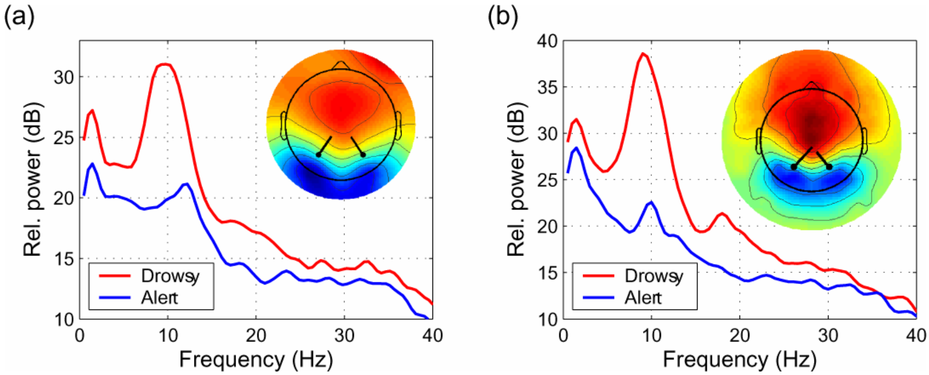

Fig. 3. Performance-related tonic increases in mean power spectra for independent components (ICs) with equivalent dipole sources located bilaterally in lateral occipital cortex, (a) from a CTT task session (70 channels), and (b) a Driving task session (256 channels). Insets: IC scalp maps and equivalent dipole source models.

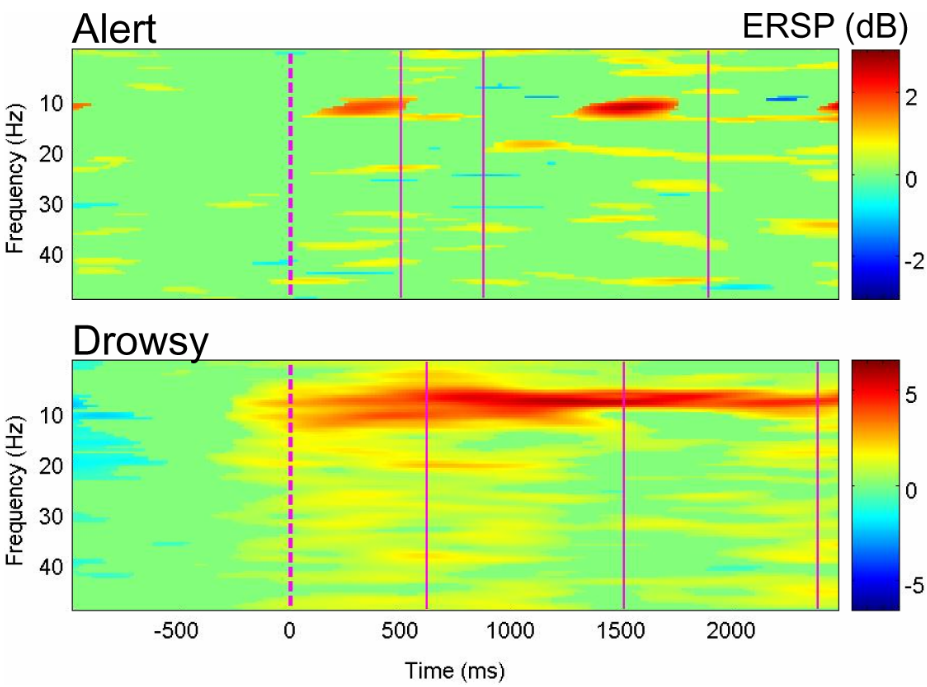

Fig. 4. Time-frequency images of event-related spectral perturbations (ERSPs) for the same IC in a CTT session (see Fig. 3). Dashed magenta line at time 0 marks a local error minimum in the disc trajectory. Solid magenta lines show median times of: 1) next subject response onset, 2) next local disc error maximum, 3) next disc error minimum.

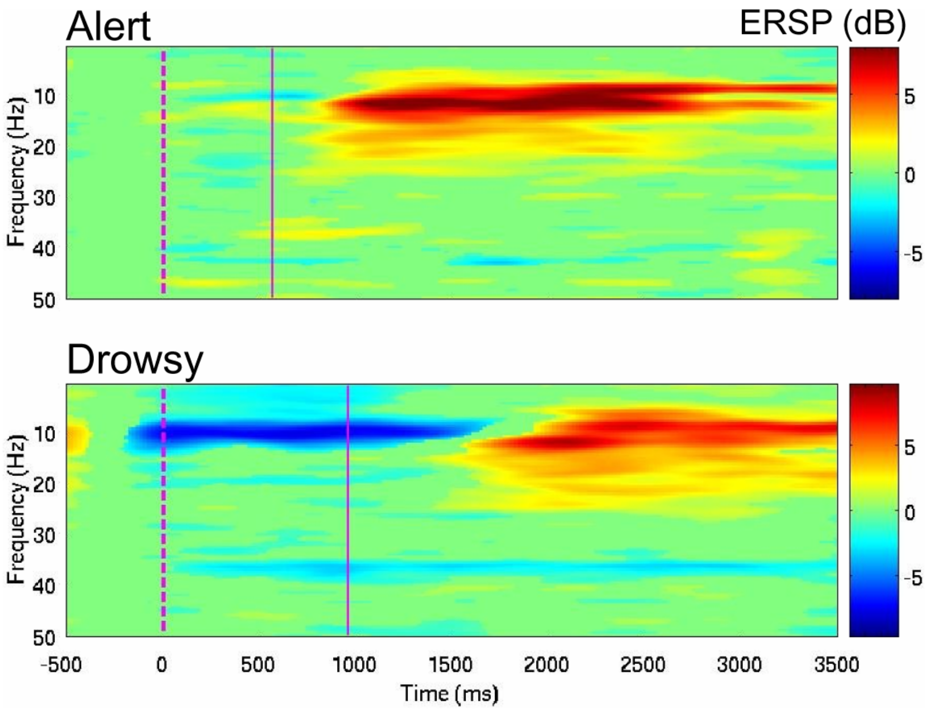

Fig. 5. Time-frequency images of event-related spectral perturbations (ERSPs) for the same IC in a Driving task session (see Fig. 3). Dash magenta lines: deviation onsets. Solid magenta lines: response onsets. Note that the initial alpha baseline power (not shown) was higher during Drowsy than during Alert performance (Fig. 3b).

3 Results

3.1 Performance-Related Tonic Spectral Changes

Fig. 3 shows scalp topographies and power spectral baselines for an IC appearing in separate decompositions of data recorded from the same subject during the two sustained-attention tasks. DIPFIT2 routines from EEGLAB were used to fit equivalent dipole source models to the IC scalp maps using a four-shell spherical head model [15, 17]. Results showed the equivalent dipole sources for this IC to be located in bilateral occipital cortex.

Wideband tonic increases were observed in the mean IC power spectra from low-error (Alert) to high-error (Drowsy) epochs, predominately in the alpha band (Fig. 3). Tonic brain activities in the occipital cortex have been shown to correlate with fluctuations of performance [3, 7]. Figure 3 shows that performance-related tonic spectral changes for equivalent ICs were very similar in two different sustained-attention tasks. ICs with quite similar scalp maps and tonic power spectral activities were consistently observed across sessions and subjects of both tasks (not shown because of space constraints).

3.2 Event-Related Phasic Spectral Changes

Event-related spectral perturbation (ERSP) images for the same IC in the CTT and Driving task sessions are shown in Figs. 4 and 5. In CTT sessions (Fig. 4) during periods of both alert (good) and most drowsy (poor) performance, significant phasic increases in alpha band power were observed following local disc error minima. This increase was larger (note scales) and was significant for longer during and following slower responses during drowsy performance (lower panel).

In Driving task sessions (Fig. 5), during periods of alert performance, baseline alpha band power was suppressed at deviation onset, then increased strongly (~10 dB) just before the subject released the key (at about 1500 ms). This transient (1.5-3 s) alpha rebound was consistently observed during single trials, regardless of the subjects' (alert or drowsy) performance status. During Drowsy performance, no alpha decrease from (higher) baseline alpha power level occurred during lane deviations.

4 Discussion

Here, we demonstrate some results of analysis of tonic and phasic changes in EEG spectral dynamics during continuous sustained-attention tasks combining independent component analysis (ICA), time-frequency analysis, and nonparametric permutation-based statistics. Clean separation of EEG data into functionally and anatomically distinct processes has traditionally been difficult or impossible, making it difficult to identify the brain origins of distinct EEG sources or to relate distinct EEG patterns originating in specific brain areas to behavior or pathology. In this study, we used ICA to blindly separate multi-channel data sets into statistically maximally independent components arising from distinct or overlapping brain and extra-brain networks. Time-frequency analysis could then be applied to the activations of the separated EEG source signals as opposed to the scalp-recorded mixtures of EEG activities, minimizing potential confounds arising from volume conduction and summation of source signals at the scalp sensors.

In two sustained-attention tasks, independent components (ICs) with equivalent dipole sources located in bilateral occipital cortex exhibited similar tonic and phasic performance-related power spectra changes. Tonic alpha-band power increased during periods of poor (high-error) compared to good (low-error) performance, while phasic alpha power increased following the drift events regardless of performance level.

The tonic increases in power spectra from alert to drowsy epochs were consistently observed across subjects and sessions, and were remarkably similar across two different sustained-attention tasks. The phasic power increases following lane-deviation events were very stable across subjects in the Driving experiments, possibly indexing subjects' visual relaxation of attention following each return to lane center. The phasic spectral perturbations were more variable for some subjects in the CTT experiments, possibly arising from our too uncritical selection of disc-escape moments to minor events to which subjects' brain activity might not have reacted strongly.

In real-world working environments, many tasks require sustained attention and responding to maintain continuous performance. It is critical for performers to detect significant events during continuous tasks, such as lane drifts during driving. In this study, we showed event-related phasic brain dynamic responses to events embedded in two tasks requiring continuous attention. These phasic event-related brain activities could be useful markers for measuring changes in the operator's awareness during tasks requiring continuous monitoring of information in their natural or machine environment.

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