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**LAPSES IN ALERTNESS:  
COHERENCE OF FLUCTUATIONS IN PERFORMANCE  
AND EEG SPECTRUM**

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*Report No. 91-39*

**93-24122**



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## Lapses in alertness: coherence of fluctuations in performance and EEG spectrum \*

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(Accepted for publication: 9 September 1992)

**Summary** Thirteen subjects detected noise burst targets presented in a white noise background at a mean rate of 10/min. Within each session, local error rate, defined as the fraction of targets detected in a 33 sec moving window, fluctuated widely. Mean coherence between slow mean variations in EEG power and in local error rate was computed for each EEG frequency and performance cycle length, and was shown by a Monte Carlo procedure to be significant for many EEG frequencies and performance cycle lengths, particularly in 4 well-defined EEG frequency bands, near 3, 10, 13, and 19 Hz, and at higher frequencies in two cycle length ranges, one longer than 4 min and the other near 90 sec/cycle. The coherence phase plane contained a prominent phase reversal near 6 Hz. Sorting individual spectra by local error rate confirmed the close relation between performance and EEG power and its relative within-subject stability. These results show that attempts to maintain alertness in an auditory detection task result in concurrent minute and multi-minute scale fluctuations in performance and the EEG power spectrum.

**Key words:** EEG spectrum; Coherence; Sleep; Alertness; Vigilance; Sonar

Since the landmark investigations of Mackworth (1948), studies of alertness have confirmed that, despite sincere intentions, few watchstanders remain “unwaveringly” vigilant while engaged in monotonous monitoring tasks. Detection rates in laboratory tests begin to degrade after only 2–3 min, eventually reaching a plateau during which, on average, only 70–80% of targets are detected (Davies and Parasuraman 1982). Most vigilance research has only studied mean trends in performance across subjects, and ignored dynamics of performance within individual sessions. However, there is evidence that performance on target detection and other tasks actually tends to fluctuate with cycle lengths ranging from a few seconds to several minutes (Seashore and Kent 1905; Wertheimer 1953; Stroud 1966; Stebel and Sinz 1971; Warner 1979; Treisman 1984; Makeig 1985). Unfortunately, most vigilance ex-

periments designed to simulate actual work environments have used target presentation rates too low to observe minute-scale performance dynamics.

Profound changes in the appearance and spectrum of the EEG with sleep and drowsiness have been noted since the first investigations of Loomis et al. (1937), and EEG power band measures have been shown to correlate with visually defined sleep stages (Rechtschaffen and Kales 1968). Matoušek and Petersén (1983), using a linear combination of over 30 band and band-ratio amplitude measures, were able to reproduce the classification of EEG epochs into awake and stage I sleep states by visual inspection, and Penzel and Petzold (1989) observed that hand-scored EEG vigilance estimates of sleep onset periods could be predicted reliably using measures of the cumulative power spectral distribution. The link between EEG and arousal is well enough accepted that many studies of vigilance simply define vigilance using electroencephalographic (EEG) and electrooculographic (EOG) criteria (Fruhstorfer and Bergstrom 1969). However, detailed studies of the appearance of the EEG in drowsiness have noted that in different subjects the EEG can take a variety of routes from wakefulness to sleep (Santamaria and Chiappa 1987).

Most studies correlating task performance and the EEG spectrum have computed measures on one or more EEG spectral bands defined a priori (Williams et al. 1962), rather than computing full-spectrum correla-

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\* Research supported by the Office of Naval Technology (RS34H21). The views expressed in this paper are those of the authors and do not reflect the official policy or position of the Department of the Navy, Department of Defense, or the U.S. Government.

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tions between performance and behavior. These reports have generally found that the correlation between EEG band amplitudes and performance varies depending on performance measure, task, subject state, and electrode site. For example, Beatty et al. (1974) reported that periods of lowered performance on a visual task were predicted by lowered electrocortical activation as indexed by a simple measure of occipital theta band EEG amplitude, and Townsend and Johnson (1979) showed that errors of omission in sleep-deprived subjects were correlated with changes in the EEG spectrum, although the structure of this relationship varied across subjects.

In our experiments, we present simulated passive sonar targets at a more rapid rate (10/min) than has been used in most vigilance experiments. We are then able to define a measure of performance, local error rate, the fraction of targets detected in a moving time window, and use it to study the electrophysiological correlates of changes in performance. We examine the relationship of minute-scale and multi-minute-scale fluctuations in performance to concurrent changes in EEG spectrum using 3 methods of analysis — coherence, correlation, and error rate sorted spectra. The purpose of the experiments is 2-fold: first, to better understand the dynamics and electrophysiological correlates of lapses in detection performance, and second, to assess the information available in the EEG that might be used to perform automatic monitoring of operator readiness to detect and respond to auditory signals.

## Methods and materials

### Stimuli

Sound synthesis and data collection were controlled by a Concurrent Real-Time Unix 68030 computer system using 12-bit A/D and D/A converters sampling at 5 and 50 kHz respectively. Throughout each session, target and probe auditory stimuli were presented binaurally through headphones mounted in isolating cuffs in the presence of continuous white noise background at 62 dB nHL.

Task-irrelevant auditory probe tones of 568 and 1098 Hz were presented in random order at 72 dB nHL with stimulus onset asynchronies (SOAs) between 2 and 4 sec. The high tone was presented more frequently (80%) than the low tone (20%). Probe tones were 50 msec in duration with rise and fall times of 10 msec. Evoked responses to the probe tones in these experiments have been discussed elsewhere (Makeig et al. 1990).

Target noise bursts were 300 msec in duration with long rise and fall times of 150 and 110 msec respectively. Targets occurred pseudorandomly in 50% of the

inter-probe intervals, giving a mean target rate of 10/min. Temporal positions of the target onsets were also pseudorandom, but did not occur within 400 msec of the nearest probe tone. Target intensity was set at 6 dB above its relative threshold in the noise as determined by pre-testing on 10 normal-hearing laboratory workers. This intensity was high enough to allow near-perfect initial performance levels, but low enough not to startle subjects nor delay onset of decrements in alertness.

Steady-state click probe stimuli were also presented continuously throughout the experiment at a rate of 39.0625 Hz (an exact sub-multiple of the EEG and sound sampling rates) and an intensity of 63 dB nHL. Against the noise background, the click train was perceptible but not intrusive. The purpose of this stimulation was to evoke an auditory steady-state response (SSR) at the stimulus rate (Galambos et al. 1981; Makeig 1985).

### Subjects

A total of 13 males participated in a simulation of a passive sonar auditory target detection task. Of these, 9 were prospective students in the Navy sonar course, 3 were sonar instructors, and 1 was from the laboratory staff. Ages ranged from 18 to 34 years (mean 24). All had passed standard Navy hearing tests. Each subject participated in two simulated work sessions of 28 min.

### Procedure

Subjects sat in a comfortable chair with eyes closed, their right index finger resting on a response button. They were instructed to press the button as soon as possible each time they detected a target noise burst, and to ignore the probe tones. The instruction to keep eyes closed was used to increase the difficulty of remaining alert throughout the session.

### Data collection

Data from all sessions were continuously recorded to disk for off-line analysis. EEG and EOG signals were amplified 50 K times with a 0.1–100 Hz bandwidth through Grass EEG amplifiers, multiplexed with button press information and converted to 12-bit digital format at a sampling rate of 312.5 Hz/channel (exactly 8 times the steady-state probe repetition rate). EEG was collected from 13 scalp locations of the International 10–20 system (for locations see Fig. 5). An ECI Electro-Cap provided standardized placement of Ag/AgCl electrodes, all referred to the right mastoid. Electrical impedances at all electrode sites were less than 5 k $\Omega$ . Periocular electrodes were used to record electrical potentials generated by movements of the eyes during EEG recording, and to reject from analysis data epochs containing large eye movements.

### Analysis

**Local error rate.** To test for linear relationships between alertness and the EEG power spectrum, a continuous estimate of performance at regularly spaced time intervals was necessary. Such a measure, the local error rate, was derived by computing the fraction of undetected targets within a time window with a constant width of 32.8 sec which was advanced through the data in steps of 1.64 sec. Targets were considered detected if the subject pressed the response button within a relatively wide time window of 200–4000 msec following stimulus onset. For the few instances in which no targets occurred within an error rate window, the value of the previous overlapping window was assigned to it. Averaged across all 26 sessions, the mean error rate followed the pattern typical in vigilance studies and the local error rate covaried linearly with mean reaction time (Makeig et al. 1990).

If the targets had been presented at evenly spaced intervals, computation of local error rate from the raw performance data would amount to low-pass filtering the performance data with a moving-average filter, a linear operation. But since the targets occurred at semi-random intervals, the local error rate was derived non-linearly and had spectral contents not found in the raw data. To assess the significance of the deviation of observed fluctuations from expected values, we compared the mean of the actual error rate spectra with a Monte Carlo distribution of spectra of synthesized local error rate time series derived from the real data by “shuffling” it, i.e., retaining the same target presentation times and performance level, but randomly permuting the order of the detected and undetected targets and then applying the same error rate algorithm as was applied to the actual data. This procedure was carried out 200 times and the results were averaged to determine the spectrum expected had the same responses and lapses been randomly ordered.

**Coherence.** To detect linear relationships between fluctuations in performance and changes in the EEG power spectrum, we estimated the coherence between the local error rate series and the corresponding EEG power spectrum series. Note that this coherence measure is very different from measures of coherence between EEG wave forms at different scalp sites (Rappelsberger and Petsche 1988). Here, coherence is used to measure the degree to which slow changes in EEG power at one site accompany slow changes in local error rate, a heuristic estimate of the current probability that a target will be detected. Our plots below show the square root of coherence amplitude or coherency (Brillinger 1981), and coherence phase. In our computations, each error rate time series consisted of 1024 points at 1.64 sec intervals. The EEG power spectrum time series consisted of 1024 power estimates for each

of 81 EEG frequencies spaced at 0.61 Hz intervals, from 0.61 to 49.41 Hz.<sup>1</sup>

**Significance level.** A non-parametric Monte Carlo procedure was used to assess the significance of the results. Statistical theory exists for assessing significance of coherency for gaussian time series (Brillinger 1981), but due to the frequent saturation of the local error rate series at 0.0 and 1.0 values and resulting non-normality, we instead determined the expected and critical values for coherency by estimating its distribution under the null hypothesis. To simulate statistical independence and destroy any expected linear relationship between local error rate and EEG power without altering their amplitude spectra, we randomly permuted the order of the error rate FFTs and computed the coherency of the mismatched pairs. This process was repeated 200 times and results averaged to generate expected coherency distributions.<sup>2</sup> From these the mean, standard deviation, skew, and kurtosis of coherency under the null hypothesis were computed for each cycle length and EEG frequency. Using these 4 statistics and the percentile function outlined in Ramberg et al. (1979), we then estimated the  $P = 0.01$  critical values for coherency at each cycle length and EEG frequency.

## Results

### Local error rate spectrum

Fig. 1 shows the fluctuations in error rate during the 26 test sessions sorted according to average error rate. The increase in mean error rate after the first 2–3 min is evident, but within individual runs numerous, apparently unpredictable fluctuations in performance occur. For example, in the trace above the asterisk (Fig. 1, center), the subject ceases to respond altogether for 3–4 min, but thereafter resumes responding with only

<sup>1</sup> These were computed from a total of 2.46 sec of artifact-free EEG data by averaging the spectra from five 50% overlapped, 0.82 sec, Hanning-windowed data segments zero-padded to 512 points. To derive the coherency estimate, each 1024-point error rate and EEG power series was segmented into 13 256-point blocks with 75% overlap. These were then Hanning-windowed and zero-padded to 1024 points and transformed to the frequency domain using FFTs. Since each of the 13 sessions contributed 13 FFTs, the average coherency was computed from a total of 169 FFTs.

<sup>2</sup> Initially, two shuffling procedures were compared, one in which the coherence of shuffled error rate data was computed against randomly selected epochs from the same subject's EEG data, and another in which shuffled error rates were compared with EEG epochs selected randomly from all sessions. The resulting significance planes were nearly indistinguishable, and the second method was chosen.

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occasional lapses, while in the trace below the asterisk, local error rate fluctuates throughout the session. In order to maximize the variance of the error rate data, 13 sessions with highest error rates were selected from the original 26 sessions for intensive analysis. These 13 sessions each included at least 40 lapses and involved a total of 10 subjects — for 3 subjects 2 sessions were analyzed, while for another 7 subjects, 1 session met the minimum lapse criterion and was used in the analysis.

Fig. 2 shows the mean spectrum of the fluctuations in local error rate, averaged across the 10 subjects, for the latter 21 min of each run, a period during which mean error rate was approximately constant. The expected mean error rate spectrum, derived as explained above by permuting the order of detected and undetected targets, is also shown with 2 S.D. bands above and below it. The lower part of the figure plots the difference between the actual and expected spectral power. The lower trace shows that cycle lengths of 4 min and longer dominated the performance records more than could be expected by chance alone, but give no evidence for rhythmicity at any particular cycle length. A similar analysis of fluctuations in EEG power also failed to reveal peak periodicities in this range.

Fig. 3 gives an example from a single 28 min session of variation in the EEG spectrum (normalized by dividing by the mean spectrum during the first 2 min of the session and plotted on a log scale). During this session, local error rate (shown in black on the left side of the spectral plane) increased irregularly, reaching 100% at

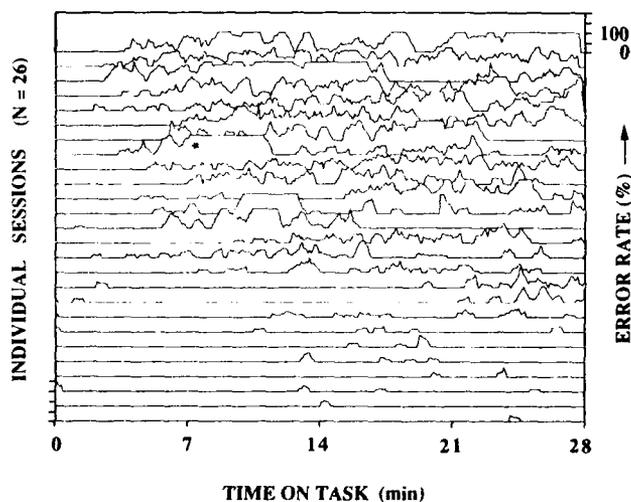


Fig. 1. Local error rates during twenty-six 0.5 h test sessions (2 sessions from each of 13 subjects). Adjacent traces are not necessarily from the same subject; rather, sessions are arranged from top to bottom of the figure by decreasing mean error rate. Error rates are computed using a moving 33 sec wide window. Note the wide fluctuations in error rate, including the complete absence of responding for several minutes in the run marked with an asterisk. After this session, the subject did not recall the episode.

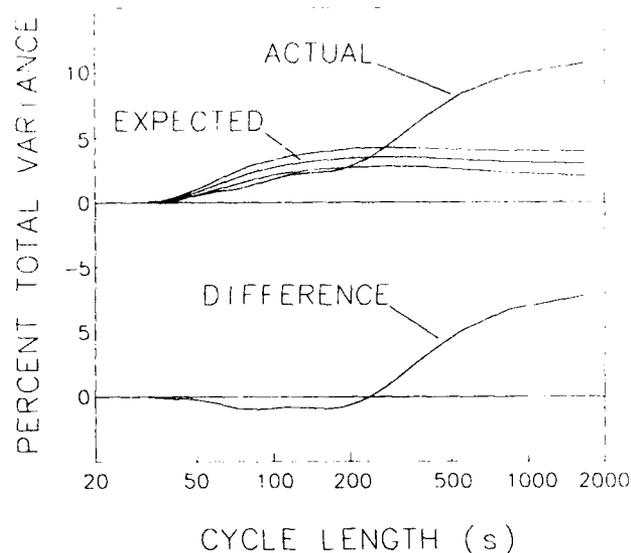


Fig. 2. Mean spectrum of fluctuations in local error rate, with the spectrum expected from Monte Carlo simulation and 2 S.D. bands. Lower trace. The difference between the actual and expected error rate spectra, with larger values than by chance occurring at cycle lengths longer than about 4 min/cycle.

session end. Concomitant drops in alpha, increases in low theta and delta, and moderate increases in sigma band power can be seen in the figure. In the upper left portion of the figure, 4 sec segments of raw EEG data are shown. These segments come from periods marked A and B in the figure. They illustrate the reduction of 10 Hz and the emergence of 4 Hz EEG activity when error rate becomes high. To assess and quantify these relationships between EEG and performance, a coherence analysis was performed on data from the same 13 relatively high error rate sessions.

### Coherence

The sample coherence between local error rate and time-varying power in each of 81 different EEG frequencies was computed across 13 sessions from 10 subjects for a range of 36 cycle lengths. Results are depicted for site Cz in Fig. 4 which plots coherence (square root of coherence amplitude) and phase for all points at which the coherence value exceeds the  $P = 0.01$  critical value determined by the Monte Carlo procedure.<sup>3</sup> Locations at which coherence is below the

<sup>3</sup> Note that this Monte Carlo method of determining the statistical significance of the coherence amplitude estimates was unaffected by the fact that 2 sessions each from 3 subjects were used in the computations. The validity of the Monte Carlo procedure depends only on how accurately the shuffling employed simulated the null hypothesis of no linear relationship between the respective pairs of DFTs, not upon the fact that each pair is derived from a different individual. We explore individual subject differences using 3 other methods (Figs. 6-8).

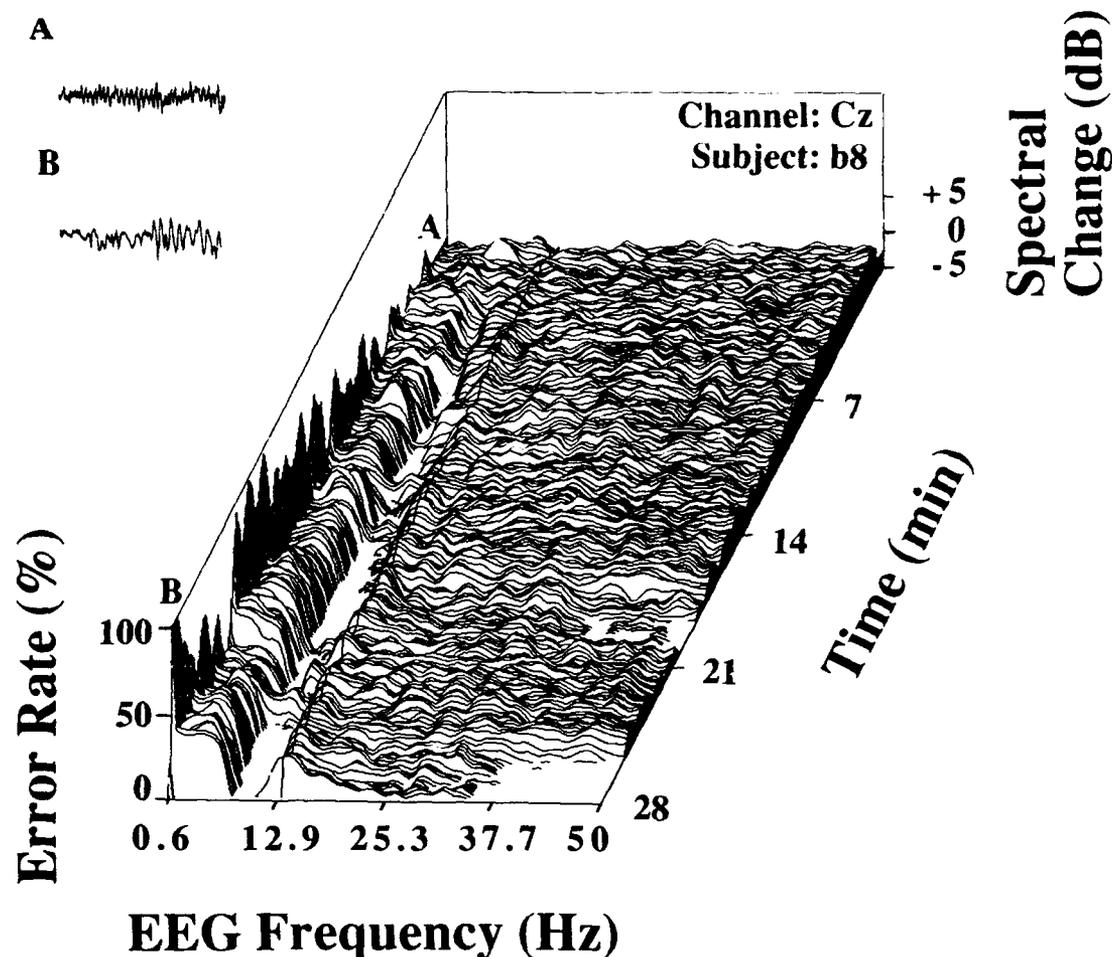


Fig. 3. Error rate and EEG spectral power (normalized by converting to dB and subtracting the mean log spectrum for the first 2 min) during a 28 min session for one subject (b8). The gradually increasing fluctuations in local error rate are plotted to the left of the spectral plane. Note the relationship between changes in the EEG spectrum and changes in local error rate. These are illustrated by two 4 sec EEG segments (upper left) taken from moments in the session marked A and B in the figure. These excerpts demonstrate a contrast between dominant near 10 Hz activity when error rate is low (A), and near 4 Hz activity when error rate is high (B).

critical value are indicated by baseline coherency and coherence phase planes (plotted as critical coherency and  $-270^\circ$  phase respectively).

Several features of these coherence planes merit comment: there is strong evidence for a linear relationship between the fluctuations in EEG power and performance at all cycle lengths and almost all EEG frequencies. Three relatively narrow EEG spectral bands, with maxima near to 3, 10 and 13 Hz, dominate the coherency plane at Cz. At the longest cycle lengths, coherency is non-significant in two narrow EEG bands near 7 and 12 Hz, the null-near 7 Hz extending across all cycle lengths. The corresponding phase plane shows that this coherency trough accompanies a reversal in coherence phase from near  $0$  to  $180^\circ$  (left side of Fig. 4b). That is, fluctuations in EEG power below 6 Hz are in phase (and positively correlated) with error rate fluctuations, while fluctuations above 7 Hz are near  $180^\circ$  out of phase (and negatively correlated) with error

rate fluctuations. At almost all EEG frequencies, the flatness of the coherence phase plane with respect to cycle length indicates there is no appreciable time lag between changes in error rate and EEG power. That is, changes in performance tend to be accompanied by nearly simultaneous shifts in EEG spectral power.<sup>4</sup>

A second region in coherence phase occurs for EEG frequencies near 13 Hz, where, at longer error rate cycle lengths, rise in error rate is accompanied by an increase in 13 Hz EEG spectral power. However, for these same frequencies at shorter cycle lengths (as for all other EEG frequencies above 7 Hz), rise in spectral power is correlated with a decrease in local error rate. Note also that between 10 and 20 Hz, significant coherence extends to the shortest cycle length shown (35

<sup>4</sup> Note that simultaneity is measured in terms of fraction of a performance cycle, i.e., in seconds rather than milliseconds.

sec), indicating that power at these EEG frequencies reliably tracks even comparatively rapid error rate fluctuations.<sup>5</sup>

Details of the coherency plane suggest that fluctuations in error rate with different cycle lengths may have different EEG concomitants. As cycle length decreases from 28 min to near 1 min/cycle, the locus of maximum coherency appears to seesaw above and below an EEG frequency fulcrum at about 20 Hz. At the longest cycle lengths, EEG frequencies below 15 Hz dominate the coherency plane, while in the range 15–39 Hz, coherency is insignificant. At 3–4 min/cycle, at high EEG frequencies coherency is maximum, while at low frequencies, coherency reaches relative minima. Near 2 min/cycle, there are local peaks in the 3 low-frequency EEG bands and a null in coherency above 20 Hz, while below 60 sec/cycle, for high EEG frequencies, coherency again becomes insignificant, but modest peaks are present in the 3 and 10 Hz bands. While the significance of these cycle length regions is not known, they appear to be distinguishable, since time scale structure is not visible in the Monte Carlo coherency plane simulations.

Finally, the small peak at the steady-state response rate, 39 Hz, in the coherency plane (Fig. 4a) implies that some portion of the EEG at 39 Hz in this experiment, most likely the auditory SSR driven in these experiments by the 39 Hz click train, is independently correlated with fluctuations in performance. This may be due to the influence of central brain systems modulating the output (Galambos and Makeig 1988; Steriade and Biesold 1990) of the primary generator of the SSR in the auditory cortex (Romani et al. 1983; Mäkelä and Hari 1987).

#### Scalp topography

In these experiments, significant coherency between EEG and performance was not confined to a single scalp site. Fig. 5 displays coherency at all 13 EEG recording sites in topographic arrangement. The overall shape and extent of regions of significant coherency are similar at all scalp locations, but close inspection reveals between-site differences; note the 13 Hz peak in coherency for long cycle lengths at central sites, and the 19 Hz peak at posterior sites. The relatively small but well-defined coherency peak at 39 Hz seen most clearly at site Fz is largest at fronto-central sites, where

the SSR is also largest (Galambos et al. 1981), and coherency at 10 Hz appears stronger at the right temporal (T4) than at the left temporal (T3) site. Note also that the zone of significant coherency near 90 sec/cycle is present at all sites for EEG frequencies above 25 Hz.

#### Correlation

Since coherence analysis reveals no significant lags between performance and EEG, correlation can also be used to measure the linear relation between the two time series. Since most spectral variance in the error rate time series occurred for cycle lengths greater than 4 min, the EEG and error rate series were smoothed using a 2 min moving-average filter to eliminate variance at cycle lengths shorter than about 3 min. Then

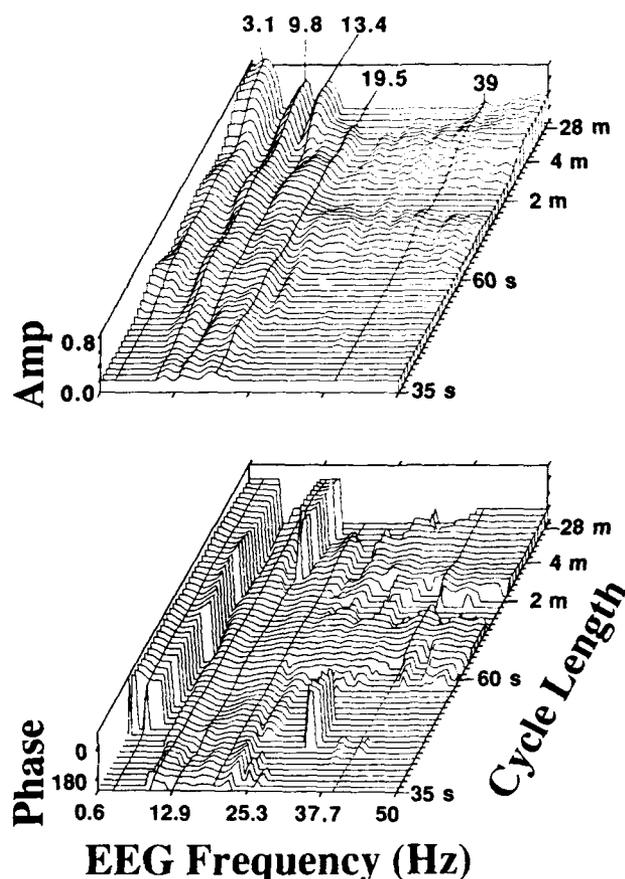
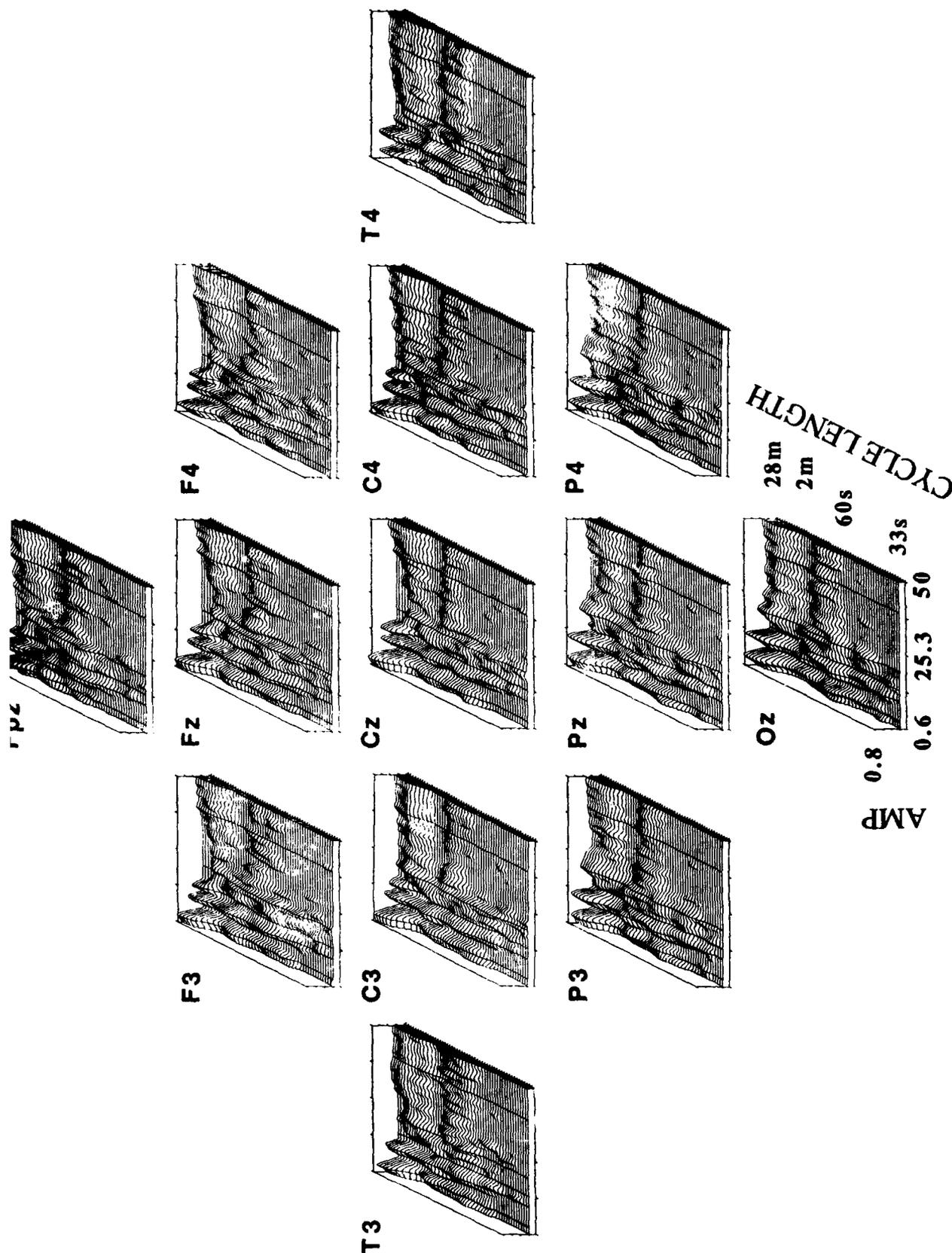


Fig. 4. Coherency (a) amplitude and (b) phase planes for channel Cz (averaged over the same 13 sessions as Fig. 2) for a wide range of EEG frequencies (0.6–50 Hz) and error rate fluctuation cycle lengths (35 sec to 28 min). Only those (frequency  $\times$  cycle length) combinations having significant coherency ( $P < 0.01$  by Monte Carlo simulation) are plotted above baseline; insignificant data points are plotted using baseline values. EEG frequency sampling width is 0.61 Hz. Data at the 5 EEG frequencies with highest coherence (3.4, 9.8, 13.4, 19.5 and 39 Hz) are marked. Note the significant coherence of alpha and beta range EEG (10–20 Hz) with error rate at all cycle lengths, and the sharp 180° reversal in coherence phase near 6 Hz, running along the left side of the coherency phase plane (b).

<sup>5</sup> The large region of insignificant coherency in the lower right portion of the coherency planes is also the region both of lowest EEG power and of lowest error rate fluctuation amplitude. Therefore significant coherency in this region could be obscured by estimation errors introduced by muscle activity, quantization errors, or finite window length.



EEG FREQUENCY (Hz)

Fig. 5. Coherency amplitude planes (computed as in Fig. 4) for all 13 scalp sites. Note the similarity of EEG frequency and cycle length bands across channels, and between-site differences including the prominent coherency near 19 Hz at occipito-parietal sites, near 13 Hz at fronto-central channels, and the relative maximum at fronto-central sites for long cycle lengths at 39 Hz, the steady-state driving frequency.

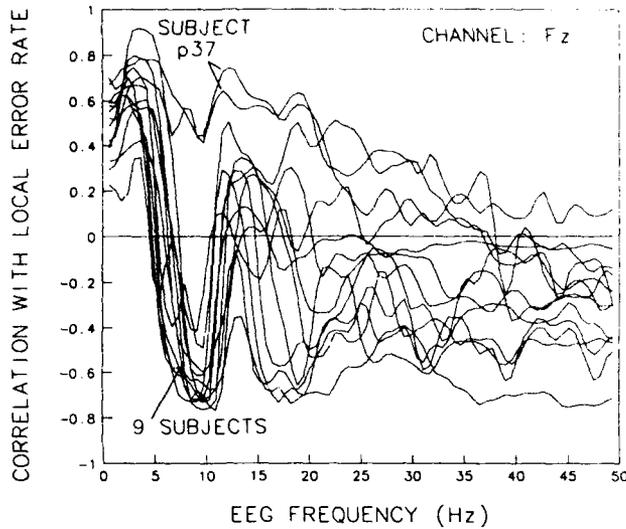


Fig. 6. Correlations between EEG power at Fz and local error rate for each EEG frequency. Same 13 sessions on 10 subjects as in Figs. 4-5. Data smoothed using 2 min moving windows. Note the strong negative correlation near 10 Hz for all sessions except those of subject p37, whose EEG spectrum did not contain an alpha band peak. Note also the net zero correlation in the 5-7 Hz region, in accord with the phase reversal near 6 Hz in the coherence phase plot (Fig. 4b).

for each session, site, EEG frequency, correlations between the EEG power and local error rate time series were computed separately. Results for each frequency at the site (Fz) yielding strongest correlations are shown in Fig. 6.

At frequencies lower than 16 Hz, results for 9 of the 10 subjects are highly similar. Two similar results from 1 subject (p37), however, have no negative correlation peak near 10 Hz. Examination of individual subject EEG spectra confirmed that unlike the other 9 subjects, this subject's EEG spectrum contains no peak in the alpha frequency range.

At EEG frequencies above 20 Hz in Fig. 6, mean correlation between EEG power and performance is nearly flat, although between-subject variability is largest in this range. The phase reversals seen in the Cz coherence phase plane (Fig. 4b) are also seen in these Fz spectral correlations. In particular, the strong reversal in coherence phase at about 6 Hz is paralleled by reversal of the correlation sign for all 9 subjects with alpha peaks in their EEG spectra. As with coherence, mean correlation with performance is largest near 3 and 10 Hz.

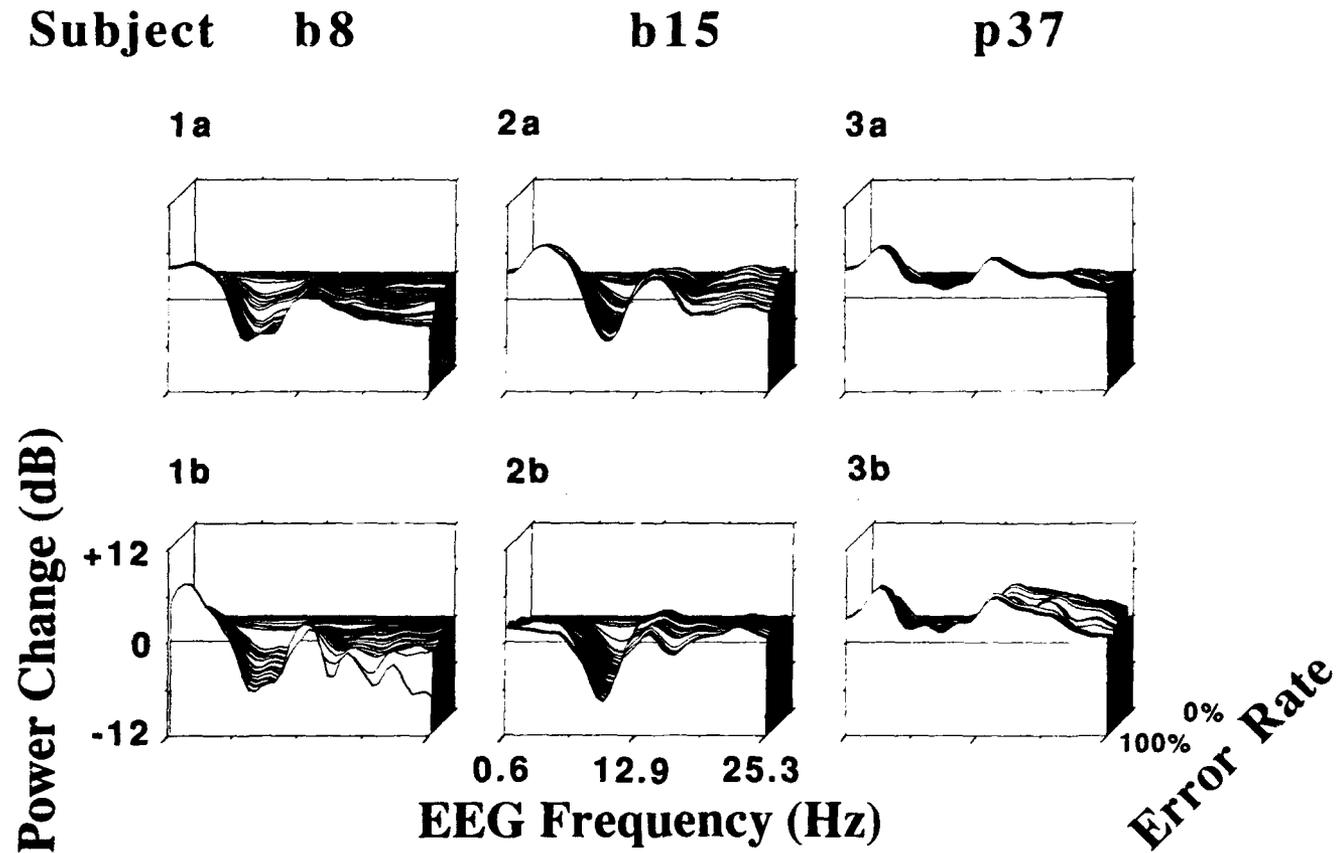


Fig. 7. Error-sorted EEG spectra, normalized by dividing by the mean zero error rate spectrum, sorted by local error rate, and then averaged using a moving window of constant (30%) error rate width and (2%) step-size. Results of 2 sessions each are shown for 3 subjects (p37, b8, and b15). Note the within-subject similarities in the spectral changes accompanying increasing local error rate, as well as the between-subject differences.

### *Error rate sorted spectra*

As a means to confirm our coherence results directly, and to investigate the relationship between performance and EEG within single sessions, we measured the change in the EEG power spectrum as a function of local error rate by sorting the power spectra from each session according to concurrent local error rate, then performing a moving average using a constant width (30%) error rate window which was advanced through the sorted spectra in small (2%) steps. To reveal spectral changes more clearly, we normalized the error rate sorted spectra by dividing each spectrum by the zero error rate spectrum, i.e., by the average power spectrum of all 2.46 sec epochs centered in at least 33 sec of error-free performance.

Fig. 7 shows normalized error rate sorted spectra for 2 sessions from each of 3 subjects, including the sessions shown in the previous figure. In Fig. 7, depth indexes local error rate — greater depths corresponding to lower error rates. In each plot, the deepest (and highest) trace represents the mean EEG spectrum of the 0% error rate epochs, normalized to unity. The frontmost trace represents the ratio between the mean of the 100% error rate epoch spectra and the 0% error rate mean, log scaled in dB. The horizontal axis indexes EEG frequency from 0.6 to 25 Hz.

The results of the error rate sorted spectra were consistent with results of the coherence and correlation analyses. As local error rate increased, so did power in frequencies below 7 Hz, while above 7 Hz (and particularly near 10 Hz for most subjects), increases in error rate corresponded in general to decreases in EEG power. Note that the location of peaks in the error rate spectra in Fig. 7 appear to be identical between sessions, although they differ between subjects. The locations of peaks and troughs in the error-sorted spectra are correlated with locations of peaks in same subjects' mean waking EEG spectra (not shown) — subject b8 has a prominent peak at 8 Hz, while subject b15 has a clear peak near 10 Hz, and subject p37 has no alpha band peak at all.

## Discussion

### *Relationship of EEG and alertness*

To evaluate the nature and strength of the linear relationship between alertness and the EEG spectrum, we performed a coherence analysis of fluctuations in moving-average measures of performance and EEG power. Results of the coherence analysis were verified using correlation and error-sorted spectral averaging. These analyses provide strong converging evidence that changes in performance on this auditory detection task are linearly related to specific patterns of changes in the EEG power spectrum at all EEG recording sites

and over a wide range of performance cycle lengths, and that this relationship is relatively variable across but stable within subjects.

### *EEG band structure*

The long-time mean EEG spectrum has a predominant smooth character (Nunez 1981), with little band structure evident other than, for most subjects, a dominant peak in the alpha range. A striking result of our coherence analysis is the sharp behaviorally defined frequency band structure it reveals. For the most part, the stable band structure uncovered by this analysis conforms to traditional EEG bands concepts; strong peaks in coherence appear at delta, alpha, sigma, and beta bands, and these have distinct scalp topographies. However, the critical crossover frequency between cophasic and antiphase coherence occurs near 6 Hz, the center of the traditionally defined (5–7 Hz) theta band. The analysis, therefore, also reveals the limitations of using a priori frequency band averaging to study changes in the EEG spectrum.

For 9 of the 10 subjects analyzed, plots of correlation between EEG power and behavior have at least two features in common — EEG power below 6–7 Hz is highly positively correlated, and EEG power near 10 Hz highly negatively correlated with local error rate — these correlations approaching unity for fluctuations slower than 3 min/cycle. The 13 Hz in-phase peak at long cycle lengths in the coherence planes (Fig. 4) may reflect the emergence of sleep spindles during protracted periods of high error rates. However, Roschke and Aldenhoff (1991) have also noted the emergence of a peak near 13 Hz in the spectrum of auditory and visual evoked responses during sleep. It is also possible, therefore, that the 13 Hz coherency peak in Fig. 4 represents EEG activity prior to emergence of visible sleep spindling or its precursor (Hori 1985).

Our coherence results appear to contradict the claim of Beatty et al. (1974) that occipital theta band EEG is the most reliable spectral indicator of vigilance. Nor do they confirm the recent claim of Ogilvie et al. (1991) that power in all bands increases immediately preceding errors of omission.<sup>6</sup> However, differences in task (our subjects were asked to attempt to continue per-

<sup>6</sup> To examine the claim of Ogilvie et al. (1991), we computed the power spectra for the 5 sec preceding targets presented during the first minute of periods of no response. These were then compared with the power spectra derived from the first 2 min of the corresponding sessions in which performance was nearly perfect (see Fig. 1). Our pattern of results did not change and did not replicate their claims that EEG power increases in all bands during the 1–2 min following first errors of omission. The major difference in most cases was the prominent drop in power in the alpha band, which has also been reported by several other authors during eyes-closed sleep transitions.

forming the task throughout the session) and conditions (our subjects' eyes were closed) could account for some differences from other experiments.

#### Time structure

Most previous studies of EEG and vigilance have used relatively low performance sampling rates which could not be used to reveal the time structure of fluctuations in performance and EEG or their interrelationship. In this study, analysis of coherence between EEG and performance appear to reveal a band structure in performance cycle lengths orthogonal to the frequency band structure of the EEG itself. We do not have an explanation for the distinct band of coherence at cycle lengths near 90 sec which appears at higher EEG frequencies in the coherence plane. This feature reflects an apparent tendency for behavior and high frequency EEG power to covary on this time scale.

although it is not accompanied by peaks in the raw error rate spectrum (Fig. 2). However, although there has been relatively little study of basic neurophysiological processes that may underlie minute scale performance fluctuations (Churchland and Sejnowski 1988), fluctuations on the 100 sec scale have been reported for memory and magnitude estimation tasks (Wertheimer 1953; Augenstein 1955; Stebel and Sinz 1971; Treisman 1984) and, in subcortical multi-unit activity, as increasing in strength during drowsiness (Moiseeva and Aleksanian 1986). It is possible, therefore, that the 90 sec EEG coherence phenomenon might have more general behavioral correlates.

When we feel drowsy, we often say we feel "half awake." The smoothed measure of performance we construct here and then predict from fluctuations in EEG spectral power, local error rate, gives a behavioral index of alertness or wakefulness also ranging between 0 and 1. Technically, however, our local error

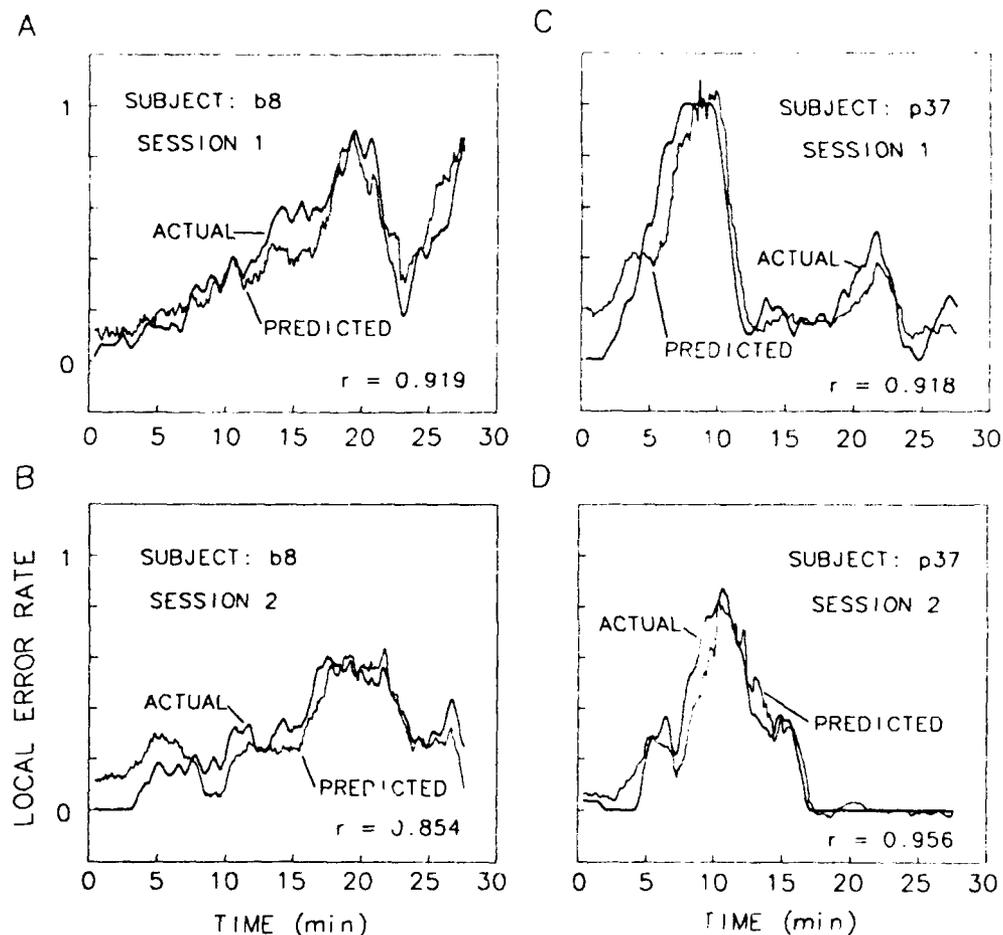


Fig. 8. Linear regressions of EEG power at Cz on error rate using the 5 coherence peak frequencies marked on the coherence planes (Fig. 4), overlotted against actual error rate records. Two minute moving windows were used to average both performance and EEG data. For 2 subjects (b8 and p37), EEGs from sessions shown in the upper panels were used to determine regression weights. Success in predicting local error rates using these same weights on separate sessions from these same 2 subjects is shown in the 2 lower panels.

rate measure is the result of low-pass filtering an alternating series of hits and lapses. For example, a local error rate of 0.5 means that of the approximately 6 targets presented in a 33 sec moving window, 3 were detected and 3 not detected. It is possible that rather than remaining in a 50% alert state throughout the 33 sec window, more rapid fluctuations in both alertness and electrophysiology are actually taking place which our local error rate does not measure, perhaps connected to the reported 10–20 sec cycles in alpha abundance (Evans 1991) and multi-unit firing rates (Moiseeva and Aleksanian 1986), or the near 40 sec cycles reported in sleeping EEG (Scheuler et al. 1987, Terzano and Parrino 1988; Pastelak-Price et al. 1990).

Although coherence analysis can detect phase shifts other than 0° or 180° and time leads or lags of up to a half a performance cycle, our coherence results give no evidence for either. That is, the linear relation between EEG and vigilance in these experiments did not involve a measurable constant time lag between one and the other. This is not to say, however, that higher-order, non-linear measures may not reveal time ordering of changes in EEG and behavior. For example, Hori (1985) has claimed that increased variance, a second-order measure, of sigma (13 Hz) EEG power precedes the onset of decrement in alpha power at transition to sleep.

#### *Possible applications*

Elsewhere we have reported the relationship between local error rate and averaged brain responses evoked by the task-irrelevant probe tones presented during these experiments (Makeig et al. 1990), and discussed the prospects of using evoked responses to estimate performance. However, for such purposes evoked responses have two drawbacks: they can only be recorded intermittently, and they must then be averaged or otherwise aggregated to separate them from the EEG background, which is itself continuously changing with subject state. EEG monitoring, on the other hand, can be continuous, and power of the ongoing EEG is nearly always greater than power in evoked responses.

Since strong linear relationships between EEG spectral power and local error rate are indicated by the coherence and correlation analyses, a lower bound on the performance of an optimum algorithm for estimating vigilance level from EEG data can be obtained from multiple linear regression. To demonstrate a potential application of our results, the clear band structure visible in results of the coherence analysis was used to select 5 characteristic frequencies to enter into a multiple regression predicting local error rate from EEG power. These EEG frequencies are those traced in Figs. 4 and 5. For each recording site, power at these 5 frequencies and the local error rate time series

were each normalized to zero mean and unit variance and entered into a standard multiple regression algorithm.<sup>7</sup>

The upper panels of Fig. 8 plot the local error rate time series superimposed on the best fitting linear regression estimates of local error rate, from EEG power at site Cz, for first sessions of two subjects. Since coherence analyses indicated maximum coherence computed from EEG power at each site occurs for cycle lengths of 4 min and longer, we computed the multiple regressions using error rate and power spectrum data using a 2 min moving window. In the lower two panels, the regression equations derived to fit the first sessions were used to predict error rates in second sessions for the same subjects. The subject in the right panels was the low-alpha subject, p37. The subject shown on the left, b8, had an alpha peak in his EEG spectrum, and this difference was reflected in the different relative weights of the two subjects' 3 and 10 Hz regression weights. However, as can be seen in the figure, for both subjects the regression procedure accurately predicted the changes in local error rate that occurred throughout the sessions.

Note that these results do not imply that all types of errors of omission are predictable from mean changes in the EEG spectrum. In particular, isolated errors during periods of low error rate may not be detectable, even though the linear regression prediction error may remain low (see for example Fig. 8d, end of session). Some performance lapses might arise from momentary distraction, failure of signal detection, willful neglect, etc., factors not necessarily accompanied by changes in arousal or mean EEG spectrum. As Townsend and Johnson (1979) state, "changes in the frequency content of the EEG appear to be predictive of performance only when they are secondary to changes in arousal which in turn affects performance." However, the high coherence values obtained in these experiments suggest that under laboratory conditions, most detection errors can be accounted for by the existence of multi-minute scale fluctuations in alertness associated with slow changes in the EEG power spectrum.

It is possible that fluctuations in performance on more cognitively demanding tasks might be better predicted by somewhat different combinations of EEG spectral information (Belyavin and Wright 1987). In our experiments, the strength and character of the relationship between performance and alpha band EEG may have been partly determined by our instruc-

<sup>7</sup> Maps of multiple correlations computed independently for each site showed maximum predictive capability at Fz and F4. A slight right-sided bias in correlation was found at all 4 homologous right/left channel pairs, but was not significant by *t* test across the 10 subjects.

tion to subjects to keep their eyes closed during these sessions. Under eyes open conditions, alpha EEG power has been observed to first increase and then decrease with increasing drowsiness (Torsvall and Åkerstedt 1988), a relationship which may complicate alertness estimation. Future work should explore the relation of fluctuations in EEG and performance of complex cognitive tasks with eyes open, both features of most work environments in which alertness monitoring might find practical use.

### Conclusions

Our results show that changes in EEG power constantly accompany slow and irregular, multi-minute and near-minute scale fluctuations in arousal and cognitive state of which we may not be fully aware. The changes in the EEG spectrum accompanying performance changes in these experiments appear to be those associated with drowsiness, though, like the EEG spectrum itself, the exact pattern of correspondence between EEG and behavior differs for different individuals. This relationship, however, appears to remain stable within individuals across sessions, a fact which could lead to practical applications involving alertness monitoring.

The authors wish to thank Steven Hillyard, Terrence Sejnowski, Laverne Johnson and Robert Galambos for helpful advice and criticism of early versions of this paper, and to acknowledge the valuable contributions of F. Scot Elliott in collecting and archiving the data, and of Lcdr. David Kobus for his enthusiastic support of the project. Portions of these data were presented at meetings of the Human Factors Society, Orlando, 1990, the Society for Psychophysiological Research, Chicago, 1991, and the Society for Neuroscience, New Orleans, 1991.

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# REPORT DOCUMENTATION PAGE

Form Approved  
OMB No. 0704-0188

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1. AGENCY USE ONLY (Leave blank)		2. REPORT DATE May 1992		3. REPORT TYPE AND DATE COVERED Interim	
4. TITLE AND SUBTITLE Lapses in Alertness: Coherence of Fluctuations in Performance and EEG Spectrum				5. FUNDING NUMBERS Program Element: 63726N Work Unit Number: M0070.03-RS34H21 ONR Reimb	
6. AUTHOR(S) Scott Makeig & Mark Inlow					
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) Naval Health Research Center P. O. Box 85122 San Diego, CA 92186-5122				8. PERFORMING ORGANIZATION Report No. 91-39	
9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES) Naval Medical Research and Development Command 8901 Wisconsin Ave Bethesda, MD 20889-5606				10. SPONSORING/MONITORING AGENCY REPORT NUMBER	
11. SUPPLEMENTARY NOTES Published in: <u>Electroencephalography and Clinical Neurophysiology</u> , 1993, <u>86</u> , 23-35					
12a. DISTRIBUTION/AVAILABILITY STATEMENT  Approved for public release; distribution is unlimited.				12b. DISTRIBUTION CODE	
13. ABSTRACT (Maximum 200 words)  Thirteen subjects detected noise burst targets presented in a white noise background at a mean rate of 10/min. Within each session, local error rate, defined as the fraction of targets detected in a 33 sec moving window, fluctuated widely. Mean coherence between slow mean variations in EEG power and in local error rate was computed for each EEG frequency and performance cycle length, and was shown by a Monte Carlo procedures to be significant for many EEG frequencies and performance cycle lengths, particularly in 4 well-defined EEG frequency bands, near 3, 10, 13, and 19 Hz, and at higher frequencies in two cycle length ranges, one longer than 4 min and the other near 90 sec/cycle. The coherence phase plane contained a prominent phase reversal near 6 Hz. Sorting individual spectra by local error rate confirmed the close relation between performance and EEG power and its relative within-subject stability. These results show that attempts to maintain alertness in an auditory detection task result in concurrent minute and multi-minute scale fluctuations in performance and the EEG power spectrum.					
14. SUBJECT TERMS  EEG spectrum      Sleep      Vigilance Coherence      Alertness      Sonar				15. NUMBER OF PAGES 13	
				16. PRICE CODE	
17. SECURITY CLASSIFICATION OF REPORT Unclassified		18. SECURITY CLASSIFICATION OF THIS PAGE Unclassified		19. SECURITY CLASSIFICATION OF ABSTRACT Unclassified	
				20. LIMITATION OF ABSTRACT Unlimited	