EEG-Based Estimation of Mental Fatigue: Convergent Evidence for a Three-State Model

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Abstract. Two new computational models show that the EEG distinguishes three distinct mental states ranging from alert to fatigue. *State 1* indicates heightened alertness and is frequently present during the first few minutes of time on task. *State 2* indicates normal alertness, often following and lasting longer than State 1. *State 3* indicates fatigue, usually following State 2, but sometimes alternating with State 1 and State 2. Thirty-channel EEGs were recorded from 16 subjects who performed up to 180 min of nonstop computer-based mental arithmetic. Alert or fatigued states were independently confirmed with measures of subjects' performance and pre- or post-task mood. We found convergent evidence for a three-state model of fatigue using Bayesian analysis of two different types of EEG features, both computed for single 13-s EEG epochs: 1) kernel partial least squares scores representing composite multichannel power spectra; 2) amplitude and frequency parameters of multiple single-channel autoregressive models.

Keywords: EEG, mental fatigue, alertness, computational models, situation awareness, performance monitoring, augmented cognition.

1 Introduction

There are countless high-risk occupations today, such as in aviation, transportation, aerospace, military, medicine, and industrial settings, in which fatigued individuals

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routinely operate complex, automated systems. This undesirable state of affairs has contributed to more than a few well publicized—and many not so well publicized—disasters [1]. Recent analyses of crash data confirm that fatigue and inattention pose the greatest known risks to automobile driver and passenger safety, surpassing all other known risks including alcohol and secondary tasks such as cell-phone usage [2]. Accordingly, there continues to be much scientific interest in assessing, monitoring, and predicting fatigue [3],[4],[5],[6].

The risk of errors or accidents in such jobs could be reduced with the aid of automated systems that detect, diagnose and mitigate occupational fatigue. Designs for such automated fatigue-monitoring systems, or AFMS, have been proposed, and their accuracy in research settings has increased dramatically in the last few years. It is highly probable that AFMS will soon be reliable enough for general deployment. Future AFMS may even predict the likelihood of fatigue seconds to minutes before its onset. Most AFMS designs combine physiological or behavioral measures, such as brain activity (EEG), cardiac measures, eye-tracking, pupil size, lid closure, head tilt, or muscle activity (EMG), with intelligent computational systems to estimate present levels of fatigue. Of all these measures, the EEG may be the most informative measure of fatigue, because it is directly related to neuronal activity in the cerebral cortex and is also the key clinical method used for automated classification of sleep stages, which are related to some aspects of fatigue.

Researchers interested in using EEG features to classify mental activity have typically administered a stimulus, recorded EEG, and then applied statistical or machine-learning algorithms to classify EEG features into one or more 'states' (e.g., fatigued/ not fatigued/ high mental workload/ low mental workload). Gevins et al. [7] were among the first to attempt to develop an online, EEG-based drowsiness detector. Based on automated sleep scoring research, they developed a computer program which did a spectral analysis on the EEG data and calculated the ratios of delta to alpha, and theta to alpha activity. Calculated ratios were compared to 'drowsiness threshold' ratios previously calculated and these comparisons were used to estimate operator state. Gevins et al. tested their computerized drowsiness detector on EEG recordings from 31 individuals and found that 84% of testing, epochs were identified as drowsy both by expert scorers and by the drowsiness detector.

We consider the success of drowsiness detection to be akin to sleep staging, which has also been successfully performed by automated systems [8]. However, we are primarily concerned here with *mental fatigue in awake subjects*, which we define as the unwillingness of alert, motivated subjects to continue performing mental work [9]. In this way, mental fatigue differs from the other factors that also impair operator functioning, including sleepiness, lack of motivation, monotony, lack of training, and physical fatigue. The most consistent finding in prior EEG studies is that mental fatigue-related manipulations are associated with increased theta band power at the midline frontal location (i.e., Fz) and decreased alpha band power at one or more parietal locations (e.g., P7 and P8) [10],[11],[12],[13],[14].

As in other studies, we measured continuous EEG during a task, segmented the EEG, and analyzed the power spectral density of the segments to produce features that could be used to assess the effects of mental fatigue on ongoing brain activity. For overall tests of fatigue effects, we focused our measurements on the frontal midline theta band (4-8 Hz) activity and parietal alpha band (8-13 Hz) because these bands respond systematically to changes in operator state [15]. However, we used the power spectral density estimates at all EEG frequencies and electrodes to create algorithms which accurately classify mental fatigue using single EEG epochs in individual subjects. More specifically, we developed and cross-validated algorithms for classifying 13-s long segments of EEG activity according to fatigue. Indeed, such classifiers were highly successful, usually between 90% and 100% accurate in classifying EEG epochs [16],[17].

Our initial hypothesis was that a classifier could be trained to recognize features of EEG recordings made during periods known to be alert or fatigued by using independent measures of fatigue. These measures included mood estimates, performance and time on task. We examined the hypothesis that the application of such a classifier to EEG epochs from states in which the fatigue level was not known would produce an orderly output, with values of EEG features lying in the range between those of the known fatigued and alert EEG epochs used to train the classifier. Indeed the output of such classifiers indicated an orderly progression of classification scores from alert to fatigued states over time on a task known to induce fatigue [17].

In this paper, we consider the hypothesis that transitions from alert to fatigued states may not be entirely smooth or continuous, much like the quasi-categorical stages of sleep. To do this we examine two different feature extraction methods and statistical models to describe EEG features over a wide range of time, spanning from initial alert conditions to final fatigued conditions. In particular we consider whether the distributions of classification features are more consistent with two-state or three-state models of fatigue and alertness. We find that in a majority of subjects, the data appear to be more consistent with a three-state model than a two-state model.

2 Methods

2.1 Summary of Methods from the Prior Study

A detailed description of experimental and analytical methods for the prior study, from which the current study data were obtained, has been submitted for publication and is available on line [18]. Briefly, data were collected from 16 participants recruited from the San Francisco Bay Area community. The participants included 12 males and 4 females with a mean age of 26.9 y (SD = 7.4 y). Subjective moods were indexed by the Activation Deactivation Adjective Checklist (AD-ACL [19]) and the Visual Analogue Mood Scales (VAMS [20]). Observed behavior included ratings of activity and alertness from videotaped recordings of each participant's performance. The performance measures were response time (RT) and response accuracy. The physiological measures were derived from spontaneous EEGs and EOGs.

Participants sat in front of a computer with the right hand resting on a 4-button keypad and performed arithmetic summation problems, consisting of four randomly generated single digits, three operators, and a target sum (e.g., 4+7–5+2=8), which were displayed on a computer monitor continuously until the subject responded. The participants: a) solved the problems, b) decided whether their 'calculated sums' were less than, equal to, or greater than the target sums provided, c) indicated their decisions by pressing the appropriate key on the keypad. The keypad buttons were labeled “<,” “=,” and “>,” respectively. Subjects were told to answer as quickly as possible without sacrificing accuracy. After a response, there was a 1 s inter-trial interval, during which the monitor was blank. Participants performed the task until either they quit from exhaustion or 3 h had elapsed. All participants performed the task for at least 90 min and eleven participants completed the maximum 3-h period.

During the task, the EEG was recorded continuously using 32 Ag/AgCl electrodes embedded in a Quik-Cap™ (Compumedics USA, El Paso, TX). The reference electrodes were averaged mastoids and the ground electrode was located at AFz. Vertical and horizontal electrooculograms (VEOG and HEOG) were recorded using bipolar pairs of 10 mm Ag/AgCl electrodes (i.e., one pair above and below the left eye; another pair to the right and to the left of the orbital fossi). Impedances were maintained at less than 5 kΩ for EEG electrodes and less than 10 kΩ for EOG electrodes. The EEG was amplified and digitized with a calibrated 64-channel Synamps™ system (Compumedics USA, El Paso, TX), with a gain of 1,000, sampling rate of 500 s^{-1} and a pass band of 0.1 to 100 Hz, then digitized and stored on magnetic and optical media.

Participants: a) were given an orientation to the study, b) read and signed an informed consent document, c) completed a brief demographic questionnaire (age, handedness, hours of sleep, etc.), d) practiced the arithmetic task for 10 minutes, and e) were prepared for EEG and EOG data collection. They then completed the pretest self-report measures (i.e., the AD-ACL and VAMS) and performed the mental arithmetic task until either three hours had elapsed or they were unwilling to continue. After the task, they completed post-test self-report measures and were debriefed.

The EEGs were: a) submitted to an algorithm for the detection and elimination of eye-movement artifact, b) visually examined and blocks of data containing artifact were manually rejected, c) epoched around the stimulus (i.e., from –5 s pre-stimulus to +8 s post -stimulus), d) low pass filtered (50 Hz; zero phase shift; 12 dB/octave roll off), and e) submitted to an automated artifact rejection procedure (i.e., absolute voltages > 100 µV). The overall single-epoch rejection rate was 47%. The ‘cleaned and filtered’ epochs were decimated to a sampling rate of 128 Hz. EEG power spectra were estimated with Welch’s periodogram method at 833 frequencies from 0-64 Hz.

2.2 Prior Classification Procedures

We classified single EEG epochs using kernel partial least squares decomposition of multichannel EEG spectra coupled with a discrete-output linear regression classifier (KPLS-DLR [21]). Through extensive side-by-side testing of EEG data, Rosipal et al. found that KPLS-DLR was just as accurate as KPLS-SVC, which uses a support vector classifier for the classification step. KPLS selects the reduced set of orthogonal basis vectors or “components” in the space of the input variables (EEG spectra) that maximizes covariance with the experimental conditions. DLR finds the linear hyperplane in the space of KPLS components that separates the classes. In a pilot study, and in our present data, we found that the first 15 minutes on task did not produce mental fatigue, whereas mental fatigue was substantial in the final 15 minutes. So we randomly split EEG epochs from the first and last 15-min periods into equal-sized training and testing partitions for classifier estimation. Only the training partition was used to build the final models. The number of KPLS components in the final models was set by five-fold cross-validation. The criterion for KPLS-DLR model selection was the minimum classification error rate summed over all cross-validation subsets.

2.3 Statistical Modeling Procedures

The first model we tested was an extension of our earlier work with the KPLS-DLR classifiers trained using multichannel EEG spectra to distinguish alert and fatigue states [16],[17]. The features of this classifier are components that linearly combine the set of multi-channel EEG power spectral densities and represent each EEG epoch with a single score, much like the components of factor analysis or principal components analysis. The KPLS component scores of consecutive 13-s EEG epochs recorded during the mental arithmetic task were analyzed using Bayesian optimal data-based binning methods [22]. To make the problem computationally stable with the limited data available, we used only the scores of the first KPLS component (the component of greatest covariance with the fatigue states identified in the training set of EEG epochs).[1]

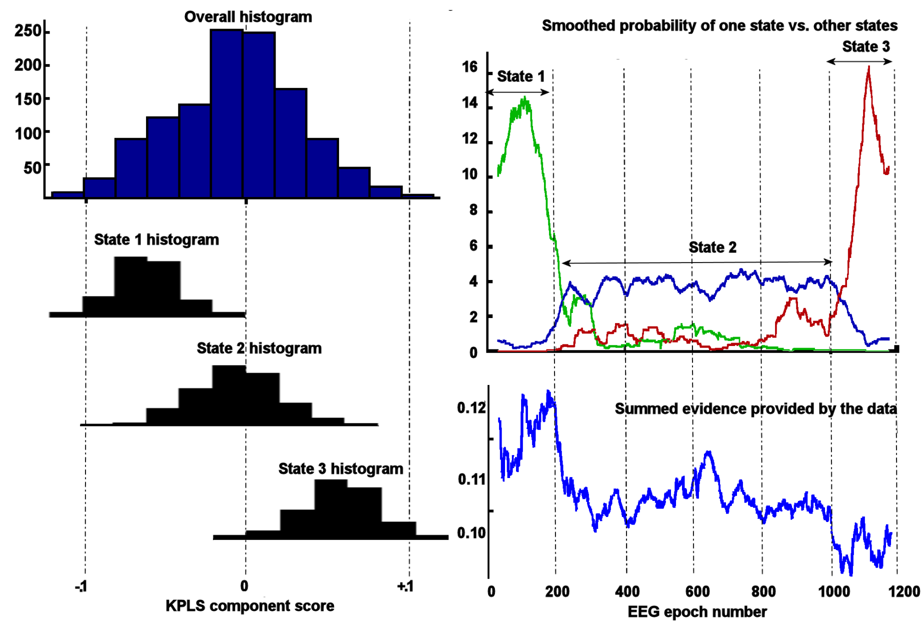

Fig. 1. Development of optimal binning classifier for 3-state model in Subject 13. From upper left to lower left: Overall histogram of KPLS scores across all 15-min blocks. Histogram and evidence (bar graph under histogram) for each of three states. Upper right to lower right: Smoothed quality of evidence for each state vs. the other two states for single EEG epochs spanning the entire session (time also increases from left to right). Summed evidence provided by the data as a function of EEG epochs.

[1] In prior tests, we had already found that most of the discriminatory power for mental fatigue lies in the first KPLS component and that often, only a single component is necessary.

The specific procedure involved four main steps (also illustrated in Fig. 1):

1. First, the optimal histogram of the entire task session was computed, and this served to delineate the number of histogram bins, and their positions for further analysis.
2. The data were then broken into blocks of 15-min duration, and optimal bins were computed for each block. For two-state models, a characteristic set of blocks was chosen as exemplars for each state: State 1 (alert) and State 3 (fatigued). For three-state models an additional characteristic set of blocks was chosen as exemplars for State 2 (normal). The set for State 2 was chosen by eye, and the first and last blocks were always included in the sets of blocks for States 1 and 3 respectively. There are ways we could automate the choice of blocks for each state in the future.
3. Then for each set of exemplar data, another histogram-style density model was generated to be used as a model of the likelihood function. Note that this is not exactly a histogram, since empty bins are given some probability mass, i.e., no bin may have a probability of zero. We used the optimal bins derived from the KPLS scores and some heuristics to generate likelihood functions for either two or three fatigue states. We now have estimated likelihood functions for each state and we assume equal a priori probabilities for all states.
4. We then computed the evidence for the two-state or three-state models from the sum of the likelihood functions. This describes the evidence that the data provides about a given state and allows for a comparison of the two- or three-state model fits to the data. Low evidence implies that the algorithm cannot be sure about its conclusions, whereas high evidence implies confidence.

The second model we tested was an application of autoregressive or AR models developed independently for each EEG electrode and each single EEG epoch [23]. The data were grouped into the same 15-min blocks used for the optimal binning method. The 13-s epochs of the EEG time series served as the input to the model construction procedure. This procedure consists of three main steps:

1. We first fit AR models to all the 13-s EEG epochs from the first and last 15-min blocks with the goal of extracting the frequencies that characterize alert/fatigue states or alert/normal/fatigue states. Fitting the AR models means that an optimal model order needs to be found (i.e., how many lags will be considered in the AR model). For each subject we chose the "optimal model order" as the one that does the best job in terms of correctly classifying epochs in the first and last intervals as epochs from alert and fatigue states, respectively. The best AR model order for a given individual is chosen using an optimality criterion based on which order does the best in terms of discriminating fatigue and alert states, i.e., discriminating between epochs from the first and final blocks in the EEG frequency range averaging over all the EEG channels recorded.
2. We then proceeded to select which channels do best in terms of correctly classifying alert and fatigue epochs in the first and last blocks. This was done by applying the *k-means* clustering method with two (or three) classes to all the frequencies and

moduli[2] of the AR models fit to the EEG epochs from the 15-min blocks. Specifically, we used data from the first and last 15-min blocks and grouped them into 3 clusters using k-means. We labeled the alert cluster as the one that had the best performance in terms of classifying epochs from the first 15-min and the "fatigue cluster" as that that had the best performance (measured as classification accuracy). The remaining cluster was labeled as the normal cluster. We hypothesize that some epochs recorded after the first 15-min and prior to the last 15-min would belong to this new cluster. Then, the accuracy of this classification method is computed for each channel. Finally we retained only the channels that had a minimally acceptable accuracy of $X\%$, where X varied with the subject. Different values of X were considered; based on our analyses across subjects, $X \in (60; 85)$ was suggested.

3. Once the channels were selected, we ran the classifier for the remaining epochs and for each epoch computed the probability of fatigue and alert (or fatigue, alert, and normal) states using the combined information provided for the channels chosen in Step 2. This was done by giving the same weight to all the channels.

3 Results

3.1 Relevant Results in the Prior Study

Detailed results and statistics in the prior study appear in a preceding report [18]; only summaries of the most relevant results will appear here. The AD-ACL data indicated that time on task led to decreased general activation (i.e., self-reported energy) and preparatory arousal (i.e., self-reported calmness) and increased general deactivation (i.e., self-reported tiredness). The VAMS subscale scores (i.e., afraid, confused, sad, angry, energetic, tired, happy, and tense) did not significantly change with time on task (i.e., pretest vs. posttest), suggesting that time on task, despite its effects on activation and arousal, did not influence moods. Significant effects of time on task for behavioral observations indicated that there was a linear decrease in alertness and a linear increase in activity. Within-subjects contrasts also showed a significant linear increase in RT with time on task. There were no significant effects of time on task for response accuracy. Our prior analysis showed that time on task was linked with progressive increases in frontal midline theta and parietal midline alpha power.

3.2 KPLS Classification Results from the Prior Study

We applied the KPLS-DLR classification procedure to EEG recordings from 14 of the 16 subjects (two subjects had too few EEG epochs for model estimation). The EEG epochs were synchronized with the onset of each math problem, extending from –5 s to +8 s relative to each stimulus onset. We also reduced the likelihood of electromyogram artifacts by low-pass filtering the EEG with either an 11-Hz or 18-Hz cutoff. For each subject we constructed a KPLS-DLR model using either linear or nonlinear kernel functions and selected the best model as described above. Classification accu-

[2] The characteristic roots of the AR model are described in terms of their frequencies and moduli. The amplitude of each frequency in the power spectrum is a function of the moduli. We fitted an AR model to each epoch and computed the roots of the characteristic AR polynomial at the posterior mean of the AR coefficients.

racies across both classes for 18-Hz filtered EEG ranged from 91.12 to 100% (mean = 98.30%). The corresponding range for 11-Hz filtered EEG was 89.53 to 98.89% (mean = 98.30%). The number of KPLS components ranged from 1 to 4 (mean 2.77) for 18-Hz EEG and from 1 to 5 (mean 3.76) for 11-Hz EEG.

3.3 Optimal Binning Classification Results

We applied the optimal binning procedure to the KPLS scores for each subject and compared the histograms and quality of evidence for 2-state and 3-state models (Fig. 1). In every case (n=14) the evidence for the three-state model was greater than the evidence for the two state model (Fig. 2).

3.4 AR Model Classification Results

We applied the AR classifier construction method to the EEG epochs across all 15-min blocks for each subject, comparing the model fits and classification accuracy for 2-state and 3-state models. Subjects 2 and 14 were not included due to insufficient EEG epochs for the analyses. In 9 of the 12 remaining cases, a 3-state model was superior to a 2-state model (Fig. 3).

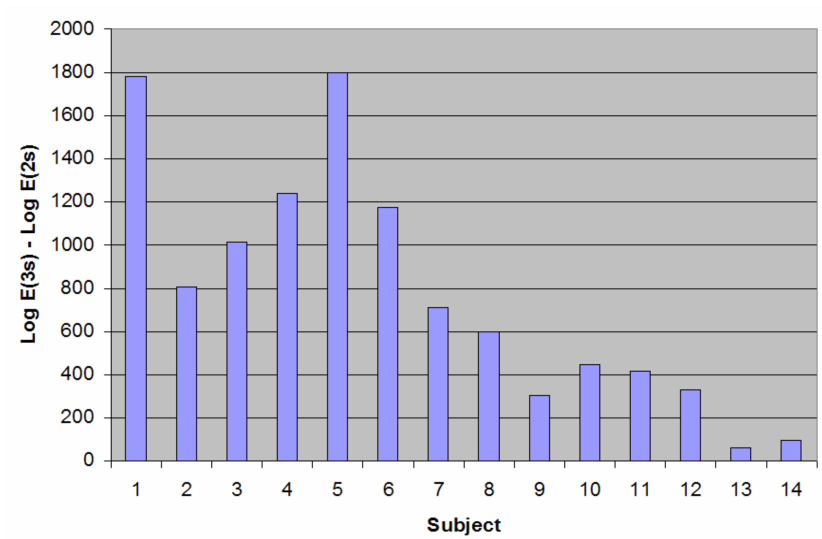

Fig. 2. The quality of 3-state models vs. 2-state models was gauged by the difference in the log of the evidence for the models. In all subjects tested, this difference was large, ranging from 60.8 log units for Subject 13 to 1795.3 log units for Subject 5. Subjects are ordered 1 to 14 by the log evidence for their 2-state model. Subjects 7-14 had relatively high baseline evidence for a 2-state model. For these subjects, the range for improvement that could be obtained with a 3-state model was more limited than for the Subjects 1-6, who had relatively less 2-state model evidence.

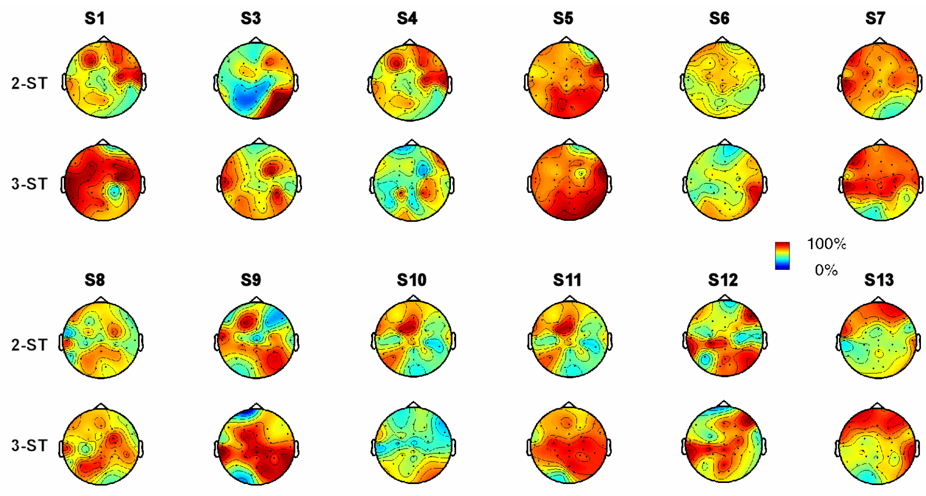

Fig. 3. Accuracies of 2-state and 3-state AR-model based classifiers for 12 subjects (S2 and S14 were omitted). Each topographical plot depicts the accuracy of classification as a function of electrodes. The overall accuracy may be controlled by exclusion of channels that do not meet minimal accuracy criteria. In 9 of the 12 subjects, the accuracy of the 3-state model exceeded that of the 2-state model.

4 Discussion

We considered the main hypothesis that EEG features drawn from a long and tiring mental arithmetic task are better explained by three-state models of mental fatigue than by two-state models. Previously, we had found that the accuracy of a two-state KPLS-DLR classification of single-trial EEG epochs ranged from 90% to 100% with a mean of 97% to 98% [18]. While the performance of these classifiers was highly accurate for single EEG epochs and may serve as the basis for monitoring mental fatigue in operational settings, they do not fully illuminate the underlying structure of fatigue states over time. In this study we found that both optimal binning methods and AR-model based classifiers of EEG features distinguish three distinct states: State 1 appears to be one of brief, but heightened alertness, being present when subjects were fresh, but giving way to State 2 after 15 to 45 minutes on task. State 2 typically lasted longer than State 1, and corresponded to the main body of time on the task. We provisionally consider State 2 to be a state of "normal" alertness, which is distinct from heightened alertness. State 2 is also distinct from State 3, which appeared later in the task, and overlapped with the end-state of fatigue.

Some important implications for future studies are underscored by our results. First, as others have found [24],[25], EEG classification algorithms benefit greatly by being both individualized and multivariate. The development of more general models, which apply to a broad set of subjects or tasks, will require considerable additional research. For example, a well-known problem in the applied EEG community is that the performance of classification algorithms from day to day, or at different times of day is unstable [26]. Additional research is needed to develop methods for stabilizing the link between EEG features and mental states such as fatigue or alertness over long periods of time. Quite possibly, the delineation of discrete states of mental alertness and fatigue could lead to more general and reliable classification algorithms. For example, if states are marked by distinct clusters of features, as compared to a continuous variable, then we can devise normalizations of those features which preserve the groupings from day to day, task to task, and even subject to subject.

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