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It has been postulated that physiological measures can be a positive indicator of mental workload. One such measure is the electroencephalogram (EEG). It is well known that the EEG signal is easily affected by artifacts. One prominent source of artifacts is eye activity, including blinks and saccades. These contaminates coincide directly with EEG signals, making it difficult to obtain artifact-free data. This paper discusses a methodology that performs artifact separation at the data analysis stage. This technique was used to analyze data from a recent experiment. Workload was manipulated by varying the difficulty of the primary task while responding to mathematical communications on the secondary task. Our findings demonstrate the importance of distinguishing between statistical significances found in the EEG signal as caused by neuronal activity versus those caused by artifacts. The artifact separation approach facilitates this investigation.

Mental workload has been described as an intervening variable that reflects the extent to which the information processing abilities of a participant are engaged during task performance (Gopher & Donchin, 1986). The ability to reliably assess mental workload is important due to the effect increased workload can have on human operator performance. This is vital due to the ever increasing complexities of technology and systems, and the higher demand they place on the human operator (Hankins & Wilson, 1998). The most basic issue in the study of cognitive workload is the problem of how to effectively measure it (Gevins & Smith, 2003). Tsang & Wilson (1997) classified workload measurements into three general categories, which include: performance, subjective evaluation and physiological measures, including electroencephalography (EEG) and electrooculography (EOG).

The Electroencephalogram

EEG is a noninvasive electrical sensing technique that uses electrodes placed on the scalp to measure brain activity. Dependent upon the research, different sites may be used. The locations of these sites are based on the International 10-20 system (Jasper, 1958). Researchers have reported the sensitivity of EEG to changes in mental workload (Gevins & Smith, 2003). It has been shown that the delta band (1-3 Hz) and theta band (4-7 Hz) spectral peaks increase in power during high workload related tasks (Gevins & Smith, 2003). In contrast, multiple studies have shown that power decreases in the alpha band (8-12 Hz) during high workload (Gevins & Smith, 2003).

Although EEG has often been used as a measure of cognitive workload, it has some functional and practical limitations that must be carefully considered before being applied to operational settings. EEG signals are easily corrupted by a number of artifacts. That is, in addition to the brain's electrical activity recorded at the scalp, the EEG signal can include contaminating potentials from rapid eye movements and blinks. (Gevins & Smith, 2003).

The Electrooculogram

The electrooculogram (EOG) is a measure of electrical signals associated with eye activity, including blinks and rapid eye movement (saccades). The vertical EOG (VEOG) is a sensing technique that uses electrodes placed above and below one eye to measure vertical eye activity. The VEOG signal is processed by algorithms to detect blinks and saccades. It has been reported that these eye-based measures can be used to assess changes in cognitive workload (Fogarty & Stern, 1989).

Typical blink measures include: amplitude, duration and frequency. It has been reported that when faced with increased cognitive workload; participants will blink with reduced duration and frequency (Recarte, Perez, Conchillo & Nunes, 2008). Typical saccade measures include: amplitude, velocity, and length. Many studies have reported that the peak saccade velocity will increase as workload increases (Wang & Zhou, 2013).

Among EOG artifacts, blinks cause the largest distortions, mainly because of the movement of the eyelids

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across the surface of the eyes. It is often the case in research that experimental manipulations can result in changes in eye activity. Therefore it is very important that the associated artifacts be dealt with effectively or else the EEG results could be obscured or misleading.

Artifact Mediation Approaches

Considering the effects of artifacts on the EEG signal, a great deal of research has been directed towards artifact mediation (Gevins & Smith, 2003). Common methods of dealing with artifacts in the EEG are artifact avoidance, artifact rejection, and artifact removal. The artifact avoidance method consists of avoiding their occurrence by issuing instructions to the participants to not blink. Designing tasks that do not require gaze changes, thus avoiding saccades, is another way artifact avoidance can be achieved. Artifact avoidance has the advantage of being the least computationally demanding, since it is assumed that no artifact is present in the signal (Fatourechi, Bashashati, Ward & Birch, 2006). It also has several drawbacks including, the inability to control eye and body movements and the understanding that artifacts will always be present in brain signals.

Artifact rejection refers to the process of rejecting the data affected by artifacts (Fatourechi, Bashashati, Ward & Birch, 2006). Artifact rejection can be done manually or automatically. During the manual rejection method, data is visually checked by an expert and the contaminated EEG data are removed from the analysis (Fatourechi, Bashashati, Ward & Birch, 2006). Manually rejecting data is not computationally demanding but faces many disadvantages. These disadvantages include the cost of intense labor while the process of selecting the artifact-free data may become subjective and the rejection of artifact-contaminated data may lead to a loss of data (Fatourechi, Bashashati, Ward & Birch, 2006). While manual rejection focuses on human correction, automatic rejection discards segments that are contaminated automatically using the EOG signals or by using EEG signals contaminated with artifacts (Gratton, 1998). Both approaches are less labor intensive but still suffer from sampling bias and loss of valuable data.

Artifact removal is the process of reducing the impact of the artifact on the EEG signal. This may be thought of as an attempt to ‘fix’ the signal in the time domain so that it remains continuous. This artifact mediation approach is relatively simple and involves using mathematical solutions to remove the artifacts. Common methods for artifact removal include: linear filtering, linear combination, regression, blind source separation (e.g., independent component analysis) and principle component analysis. These methods, however, fail when the EOG artifacts lie in the frequency bands of interest. Subtracting the EOG signal may remove part of the EEG signal.

Experimental Background

In our work we explore the use of EEG as an indicator of cognitive workload. In this study we found there was a significant effect of workload on frontal delta. However, we were concerned about this finding because the effect was in the wrong direction. Specifically, spectral power in the delta band decreased in the high workload condition. It has been reported that blink rate decreases under high workload conditions, so it was unclear if the significant frontal delta effects were due to brain activity or EOG artifacts (Wang & Zhou, 2013).

To investigate the concern above, a blink detection algorithm (Epling et al., this volume) was written to process the VEOG data. This algorithm was used to support a technique for addressing artifacts that we refer to as artifact separation. Specifically, the EEG spectral measures that are blink-free are separated from the contaminated measures at the data analysis stage. When this technique was applied to EEG measures, many of the significant effects on frontal delta disappeared. A second algorithm was written to detect saccades using EEG data (see discussion section). When the saccades were separated, the remaining significance in frontal delta disappeared. Each EEG spectral measure is accompanied by two flags to indicate the presence of artifacts (blinks and saccades). We are intending that the contribution of this paper will focus on the artifact separation technique. However, the site-specific saccade detection approach, and a robust blink detection algorithm are also noteworthy.

Methods

Participants

There were a total of 6 participants in this study, with 3 males and 3 females. The age of participants ranged from 19-28 (*M*=22.3). Participants were recruited from a local mid-western university. They read and signed the informed consent document before participating and were compensated for their time. All study procedures were reviewed and approved by the Air Force Research Laboratory Institutional Review Board.

Task

In this experiment, the primary task was to track one or two high value targets (HVTs). The task was implemented using Vigilant Spirit 3.14, which is a remotely piloted aircraft (RPA) simulator. This software was produced by the Air Force Research Laboratory System Control Interfaces Branch (RHCI). Participants were instructed to track the HVT(s) by continuously clicking in each video feed while the HVT traveled by motorcycle. Dependent upon the condition, the HVT on the motorcycle would either take a route through the city or country, during clear or hazy visibility. Half of the trials consisted of tracking one HVT and the other half consisted of tracking two HVTs. The secondary task consisted of answering operationally relevant questions. The composite scoring algorithm was based on components of both the primary and secondary task. For each trial, the maximum possible score was 1,000 points (with 800 primary and 200 secondary). Note: for additional information on the actual task, design and procedure of the experiment, see Hoepf, Middendorf, Epling & Galster, this volume.

Apparatus and Measures

Seven channels of EEG data were recorded during this study which included: F7, Fz, F8, T3, T4, Pz and O2. The frequency ranges of the seven bands of EEG were delta (1-3 Hz), theta (4-7 Hz), alpha (8-12 Hz), beta (13-30 Hz), gamma 1 (31-40 Hz), gamma 2 (41-57 Hz) and gamma 3 (63-100 Hz). The VEOG data were acquired using two electrodes placed above and below the left eye, Mastoids were used as reference and ground points. Electrode impedances were below 5kΩ for EEG and 20kΩ for VEOG. The EEG data and the VEOG data were sampled at 480 Hz using the Cleveland Medical Devices BioRadio 150. This device has hardware high pass filters with break frequencies of 0.5 Hz.

Analysis Approach

EEG signal processing. The raw EEG data were split into two-second windows and filtered using a 4th order Butterworth band pass filter with pass bands set as described earlier. A Hanning window was applied and a power spectral analysis was performed. The resulting power in each window was then averaged. The two-second time domain windows had a 50% overlap, thus yielding one average power measure every second for each frequency band and site. This produced a total of 49 measures per second (7 frequency bands at 7 sites).

Blink detection algorithm. The blink detection algorithm uses VEOG to identify blinks in real-time. The main features computed for each blink are its amplitude and duration. After two or more blinks are found, blink rate can be computed. The major components of the blink detection algorithm are threshold generation, feature extraction state machine, scoring & classification and blink save/false detection logic. The blink detection algorithm was validated using truth data (Epling et al., this volume).

Saccade detection algorithm. Due to horizontal EOG not being recorded, an EEG-based saccade detection algorithm was developed. The two-second window of data used for EEG signal processing is evaluated to find the largest saccade in the window, if one exists. A sliding linear fit is performed that is 25 milliseconds long and must have an R^2 value greater than 0.9. The linear fit must also have a high slope (greater than 550 microvolts per second). Once an initial fit is found, its length is allowed to grow until the R^2 value fails. The length, amplitude and velocity of the saccade are then computed from the final linear fit.

Procedure

Participants were brought into the laboratory for one training session and four data collection sessions. For training, participants were asked to read through a PowerPoint presentation briefing them on task instructions. The researchers then provided training on each individual task, followed by eight practice trials. Each participant received performance feedback from the composite score after each trial. At the end of each trial, self-reported workload assessments were obtained using the NASA Task Load Index (TLX) (Hart & Staveland, 1988). On data collection days, participants were equipped with physiological sensors which included EEG and VEOG. Participants then completed eight trials per day, for a total of 32 trials.

Design

There were three independent variables in this study, each containing two levels. The three variables were visibility (clear/hazy), number of high value targets (one/two) and route type (city/country). We utilized a 2 x 2 x 2 full factorial repeated measures design. The performance, workload, and physiological data were statistically evaluated using a three-way (weather, HVT, route) repeated-measures ANOVA.

Results

Performance

Performance in hazy conditions ($M = 785.0$, $SE = 25.6$) was not significantly different than the performance in clear conditions ($M = 776.2$, $SE = 23.4$). Performance score was higher in conditions with country routes ($M = 814.5$, $SE = 19.2$) than in conditions with city routes ($M = 746.7$, $SE = 31.6$), $F(1, 5) = 10.18$, $p < .05$, and higher in one HVT conditions ($M = 873.6$, $SE = 24.1$) than two HVT conditions ($M = 687.6$, $SE = 25.4$), $F(1,5) = 220.30$, $p < .001$.

Subjective Workload

Workload in hazy conditions ($M = 43.5$, $SE = 4.3$) was not significantly different than clear conditions ($M = 43.3$, $SE = 5.0$). Workload was higher in city conditions ($M = 47.6$, $SE = 5.3$) than country conditions ($M = 39.1$, $SE = 4.1$), $F(1, 5) = 18.52$, $p < .01$, and higher in two HVTs conditions ($M = 54.6$, $SE = 6.1$) than one HVT conditions ($M = 32.1$, $SE = 4.2$), $F(1, 5) = 18.97$, $p < .01$.

Cortical Measures

The EEG measures (power at each site and frequency band) were analyzed for each manipulation, but for conciseness only the significant ($p < .05$) results are reported and the means, standard errors, and F values are not included. There was less power in hazy conditions than clear conditions at the O2 site in the alpha band. For the route manipulation, there was less power in city conditions than in country conditions at 7 sites, including F7, Fz, F8, T3, T4, and Pz in the delta band, and F7 in the theta band. For the HVT manipulation, there was more power for two HVT conditions than one HVT conditions at 15 sites, see Figure 3 (top row).These effects may not be due to neural activity in the brain, but rather artifacts from eye activity (see discussion section).

Eye-Measures

The weather manipulation did not significantly impact blink rate or duration. However, blink rate was lower in city conditions ($M = 18.34$ bpm, $SE = 4.88$) than in country conditions ($M = 19.59$ bpm, $SE = 5.23$), $F(1,5) = 8.23$, $p < .05$. Blink rate was also lower in the two HVT conditions ($M = 16.28$ bpm, $SE = 4.50$) than in the one HVT conditions ($M = 21.65$ bpm, $SE = 5.87$), but this difference was not statistically significant $F(1,5) = 3.98$, $p = .10$. Blink duration was significantly shorter in city conditions ($M = 0.1041$s, $SE = 0.0042$) than in country conditions ($M = 0.1064$s, $SE = 0.0043$), $F(1,5) = 16.77$, $p < .01$, and shorter in two HVT conditions ($M = 0.1005$s, $SE = 0.0047$) than in the one HVT conditions ($M = 0.1099$s, $SE = 0.0041$), $F(1,5) = 13.81$, $p < .05$.

Discussion

The focus of this paper is on an analysis methodology based on artifact separation. One could reasonably argue that artifact separation is the same thing as automatic artifact rejection. One big difference is artifact rejection is typically done in the time domain, and our artifact separation approach is done on the spectral results. Another nuance is that it’s up to the consumer of the data to decide what to do with the artifact flags. The EEG spectral results are available in real time for such applications as machine learning models. In this case a model could decide if it wants artifact free data using the flags.

The number of HVTs manipulation introduced a task-related effect in the EOG data. When one target was being tracked, the participants would focus on one video feed. When two targets were being tracked, the participants had to regularly shift their gaze between the two video feeds, thus introducing substantially more saccades. The original intent in this study was to use EOG to detect blinks, so only the vertical EOG was collected. Due to the task-related effect, most of the saccades were in the horizontal axis. Therefore the VEOG data was insufficient for saccade detection. A new approach was implemented to detect saccades directly in the EEG data.

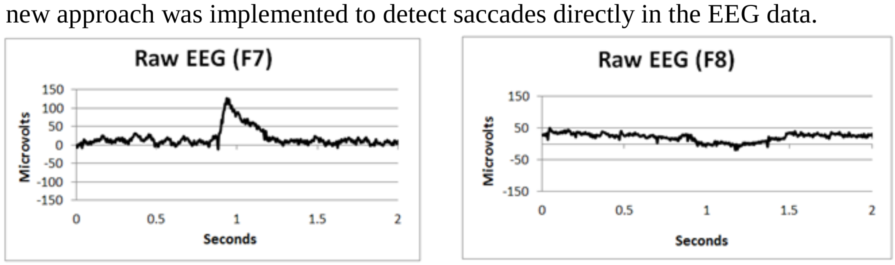

Figure 1. This data illustrates that saccade artifacts can be site-specific

One benefit of EEG-based saccade detection is that it is site-specific. An EOG-based approach would suggest that all sites contain the artifact. Based on examination of raw EEG data it is concluded that a saccade can contaminate one site but not another. Figure 1 shows that F7 is contaminated by a saccade while F8 is not. This is likely due to the angle of the saccade. EEG-based saccade detection results in less data being flagged as contaminated.

The artifact separation technique was applied to see if significant frontal delta effects for the route (country vs. city) manipulation were due to eye activity, or if they were due to an actual neurological phenomenon. When all of the data were used (no artifact separation), there was a significant effect of increased workload at six EEG sites. When blinks were separated, only two sites remained significant. These two sites lost significance with both blinks and saccades were separated (Figure 2).

The task-related effect led to widespread significant effects in the EEG data due to the number of targets manipulation (Figure 3). Applying the artifact separation technique had little impact on the widespread effects. We believe this is a side effect of the band pass filter that is used in the EEG signal processing. When a saccade passes through the filter it will ring at, or near, the center frequency of the pass band. The power due to the ringing of the filter overwhelms the power found in EEG signal alone (Figure 4). The so called “artifact free” data is not truly artifact free because only the big saccades are detected and flagged. Therefore, many smaller saccades go undetected and the task-related effect is still prominent.

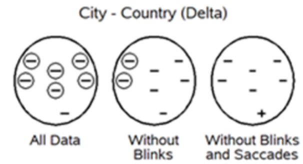

Figure 2. The sign shows the direction of the difference in log power. The size of the sign is the relative absolute value of

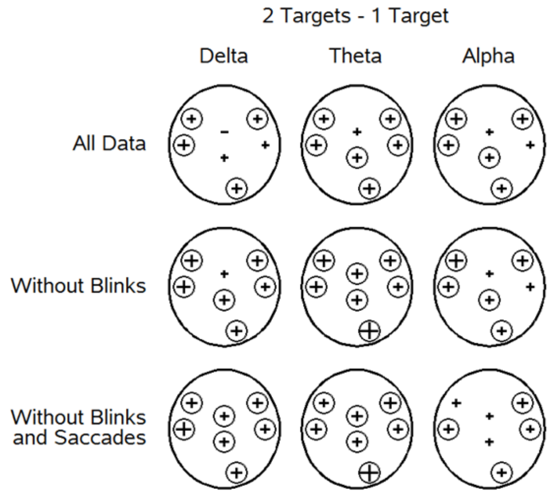

Figure 3: The sign shows the direction of the difference in log power. The size of the sign is the relative absolute value of the t statistic. If the sign is circled then p≤0.05.

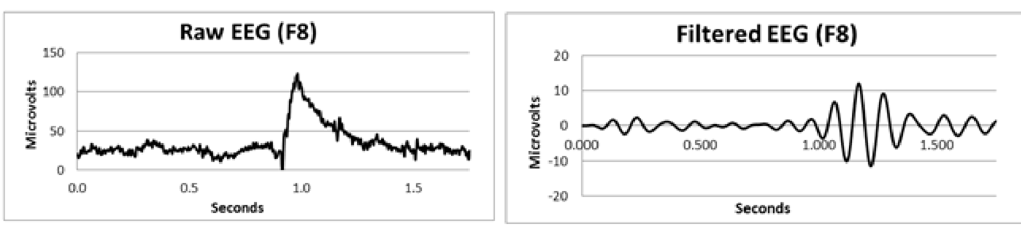

Figure 4. Increase in alpha power due to the ringing of the band pass filter.

Conclusions

The artifact separation technique seems to have real promise. In particular, it does not attempt to ‘fix’ the signal in the time domain. One drawback is that it can result in less data being used in the analysis stage. Secondly, the EEG signal processing algorithm needs to be enhanced to more effectively account for power from artifacts crossing window boundaries. The choice of filter types and order should be systematically evaluated.

The EEG-based saccade detection algorithm has the benefit of retaining more artifact free data because it is site-specific. One downside to this approach is it is good at finding big saccades and not as reliable for the smaller ones. The performance of this algorithm could be substantially improved if it is coupled with a polar-based saccade detection algorithm using EOG data (Middendorf, Epling, Hoepf & Galster, this volume). This enhancement and others are planned for future research. Lastly, when attempting to use EEG to assess cognitive workload, carefully evaluate the experimental manipulations to see if they introduce a task-related effect that systematically changes eye activity.

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