AN EEG DATA INVESTIGATION USING ONLY ARTIFACTS

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For decades, it has been reported that the electroencephalogram (EEG) is a positive indicator of mental workload. However, EEG signals are easily affected by artifacts. An artifact mediation approach, called artifact separation, was developed to enable the consumer of the EEG data to decide how to handle artifacts. The current investigation uses only data contaminated by artifacts and discards the artifact free data. This was done to solve a problem associated with data collection. Specifically, in an experiment, EEG electrode leads for T3 and Fz were swapped where they were connected to the signal acquisition hardware. To facilitate analysis of the data, it was essential to determine when the swap occurred. This was accomplished using only EEG data that were contaminated by blinks. Power associated with a blink is lower at site T3 than Fz. The artifact separation technique supported this investigation to determine when the swap occurred.

The reliable assessment of mental workload is important due to the effect increased workload can have on human operator performance. One potential solution to offset the risk of operator overload is to monitor workload in real-time and provide assistance before performance decrements occur (Hankins & Wilson, 1998). One challenge in the study of cognitive workload is the problem of how to effectively measure it (Gevins & Smith, 2003). Tsang and Wilson (1997) classified workload measurements into three general categories, which include: performance, subjective evaluation, and physiological measures, including electroencephalography (EEG) and electrooculography (EOG). In the current line of research, EEG data were used for this purpose. However, in this paper, EEG is being used for a different purpose. Specifically, solving a problem when electrode leads were inadvertently swapped.

The Electroencephalogram

Electroencephalography (EEG) is a noninvasive sensing technique that uses electrodes placed on the scalp to measure brain activity (Credlebaugh, Middendorf, Hoepf, & Galster, 2015). 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). These researchers found that the spectral peaks in the delta band (1-3 Hz) and theta band (4-7 Hz) increase in power during high workload tasks. In contrast, multiple studies have shown that power decreases in the alpha band (8-12 Hz) during high workload (Dussault, Jouanin, & Guezennec, 2004; Prinzel, Parasuraman, Freeman & Scerbo, 2003; Wilson, 2002).

Although EEG has often been used as a measure of cognitive workload, it has some limitations that must be considered. 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 (saccades) and blinks (Gevins & Smith, 2003). A handful of existing artifact mediation techniques are widely used, including artifact avoidance, rejection and removal. In many cases, artifacts will eventually be accounted for during data processing and analysis. The existing artifact mediation techniques can facilitate the analysis of artifact-free data. The work presented here is unique because the artifact separation approach allowed only data contaminated by artifacts to be analyzed.

The Electrooculogram

The Electrooculogram (EOG) is a measure of electrical signals associated with eye activity, including blinks and saccades. Typical blink measures include: amplitude, duration, and frequency. It has been reported that

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

Among EOG artifacts, blinks cause the largest distortions in the EEG, mainly because when the eyelid covers the cornea during a blink, it acts as a "sliding electrode" that effectively short-circuits the positively charged cornea to the skin of the eyelid (Picton et al., 2000). This result causes a large potential difference that travels posteriorly across the scalp. The voltage spike creates an EEG artifact that is most prominent in the frontal electrodes and attenuates the further back it travels (Barry & Jones, 1965).

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 include: artifact avoidance, artifact rejection, and artifact removal. The artifact avoidance method attempts to avoid artifacts all together by instructing the participants to not blink. 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, 2007). Having the inability to control eye movements gives this approach a disadvantage.

Artifact rejection refers to the process of rejecting the data affected by artifacts (Fatourechi et al., 2007). 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 et al., 2007). Automatic rejection discards segments that are contaminated automatically using the EOG signals or by using EEG signals contaminated with artifacts (Gratton, 1998). Automatic artifact rejection approaches are less labor intensive than manual approaches but still suffer from the 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. Common methods for artifact removal include: linear filtering, linear combination, regression, blind source separation, and principle component analysis (Gotman, Skuce, Thompson, Gloor, Ives & Ray, 1973; Croft & Barry, 2000). EOG artifacts primarily affect the low frequency bands during EEG analysis. The removal of artifacts in these low frequency bands will also result in the removal of the underlying EEG signals, resulting in the loss of data (de Beer, van de Velde, & Cluitmans, 1995).

A new technique for artifact mediation, known as artifact separation, was recently developed (Credlebaugh et al., 2015). This technique relies on blink and saccade detection algorithms using EOG data. EEG data is typically analyzed using time domain windows. If a blink or saccade occurs during a window, the spectral results are flagged as contaminated. Having the spectral results flagged as containing an artifact, means that the consumer of the data has the freedom to decide how to use the artifact flags during data analysis. This paper will focus on the artifact separation technique and how it was used to resolve an unusual issue associated with data collection.

One could reasonably argue that artifact separation is the same thing as automatic artifact rejection. One difference is artifact rejection is typically done in the time domain, and the artifact separation approach is applied during data analysis.

Problem Description

In this paper three studies are discussed. They are referred to as Study 1, Study 2, and Study 3; with the main focus of the paper on Study 3. In Study 3, physiological measures (EEG & EOG) were collected and explored as indicators of cognitive workload.

In the course of conducting this experiment, it was discovered that the EEG channels Fz and T3 were swapped on the signal acquisition hardware. The exact date when the electrodes were inadvertently swapped was unknown. Realizing the serious implications due to the mislabeled data, the date when the swap occurred was needed so that the EEG data could be properly processed. The artifact separation technique was used to solve this problem.

Methods

Participants

There were a total of 13 participants in Study 3, with 6 males and 7 females. The age of participants ranged from 19-25 (M=21.8). 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

Each trial consisted of two separate primary tasks and one secondary task. Trials were presented to the participants as a simulated remotely piloted aircraft (RPA) mission. Each trial started with a surveillance task and then transitioned into a tracking task. The same secondary task was present during both primary tasks. The secondary task was a communications task in which the participants were asked cognitively demanding questions. These tasks were implemented using a RPA simulator called Vigilant Spirit. This software was produced by the Air Force Research Laboratory Supervisory Control Interfaces Branch (RHCI).

For the surveillance task, participants were required to search a market for high value targets (HVTs). The number of distracters (non-HVTs walking around in the market) and the visibility of the camera served as experimental manipulations to affect workload. During some conditions, an automation feature was implemented to help the participants find the HVT. When the HVT was within the sensor footprint, a tone would play in the headset. The participant would then simply need to examine the entities within the footprint rather than search other areas of the market.

In the tracking task, participants were instructed to track one or two HVT(s) using RPAs. This was accomplished by continuously clicking in each video feed while the HVT(s) traveled by motorcycle. Dependent upon the condition, the HVT would either take a route through the city or country. Half of the trials consisted of tracking one HVT and the other half consisted of tracking two HVTs. Similar to the surveillance task, an automation feature was incorporated that would help the participant track one HVT. In this situation, an experimenter would take over tracking of one HVT.

Procedure

Participants were brought into the laboratory for two training sessions and eight 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 (surveillance and tracking), followed by eight practice trials. On data collection days, participants were equipped with physiological sensors which included EEG and EOG. Participants then completed four trials per day, for a total of 32 trials.

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 EOG data were acquired using four electrodes. Two were placed above and below the left eye and the other two laterally to the outer canthus of the eyes. Mastoids were used as reference and ground points. Electrode impedances were below 5kΩ for EEG and 20kΩ for EOG. The EEG and EOG 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 vertical EOG 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. See Epling et al., 2015 for a detailed explanation of the blink detection algorithm.

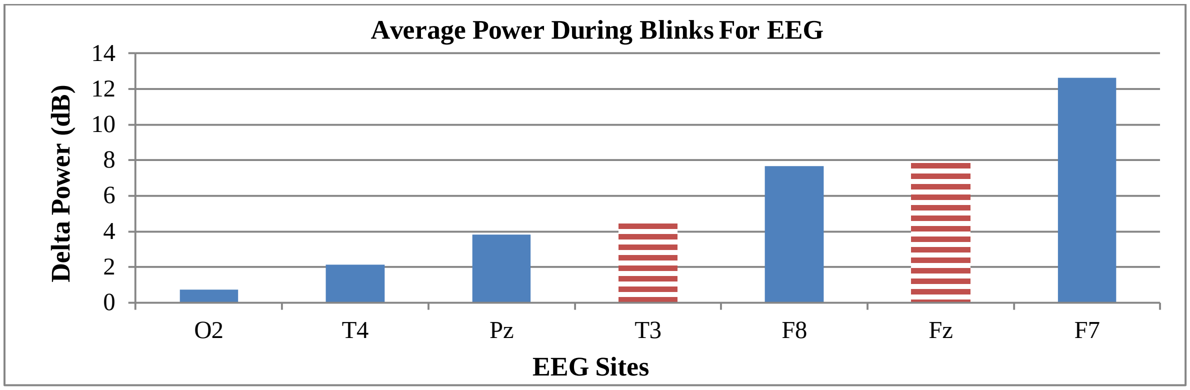
Saccade detection algorithm. A saccade detection algorithm was used to process EOG data and detect saccades. The algorithm uses both vertical EOG and horizontal EOG, and reports saccades in magnitude and angle (polar coordinates). See Middendorf et al., 2015 for a detailed description of the polar saccade detection algorithm.

Propagation of a blink

When determining whether to use blinks or saccades at sites Fz or T3 to solve the swapping problem, literature was consulted. Picton et al. (2000) states, ocular potentials can be recorded at some distance from the eyes and can thus distort recordings of the EEG. Blink potentials are mainly produced by the downward movement of the upper eyelid over the cornea (Matsuo, Peters, & Reilly, 1975; Antervo, Hari, Katilla, Ryhanen, & Seppanen, 1985). The EOG contamination is at its highest in the electrodes near the eyes and decreases with increasing distance away from the eyes (Picton et al., 2000). Picton et al. (2000) reported blink potentials are significantly larger than the saccade potentials at Fz. The data from Picton et al. (2000) also suggests that Fz will record more low frequency power during a blink than T3. This investigation uses power in the delta frequency band.

Results

The artifact separation technique discussed earlier was used to determine the delta power due to blinks at each EEG site, using data from the surveillance task for one participant. The artifact flags were used to look only at EEG spectral data that coincided with blink artifacts. This data was used to generate a graph that represents the average power due to blinks at each EEG site in the delta band (Figure 1).



The delta band is used in the graph because it shows the greatest power due to blinks compared to other frequency bands (Gevins & Smith, 2003). The difference between sites is clear; Fz shows a greater power when a blink occurs than T3. This knowledge allows the signals to be differentiated from each other based solely on a characteristic of the data.

Graphs were created showing just these two sites for every trial of participant seven. This is the participant that was running when the problem was discovered and the electrodes were swapped back to the proper configuration. This occurred just prior to trial 25. Figure 2 shows the average power in the delta band at sites Fz and T3. The average power is computed using only blink contaminated data. This data is for participant seven for all trials from the surveillance task. A trend is easily seen in the data; the two sites clearly show a different response to a blink. For the first 24 trials T3 shows higher power than Fz, however the last eight show the opposite. The data from the last eight trials show the expected behavior, and were collected after the electrodes were corrected. This means the data from Fz and T3 were mislabeled for the first 24 trials for this participant.

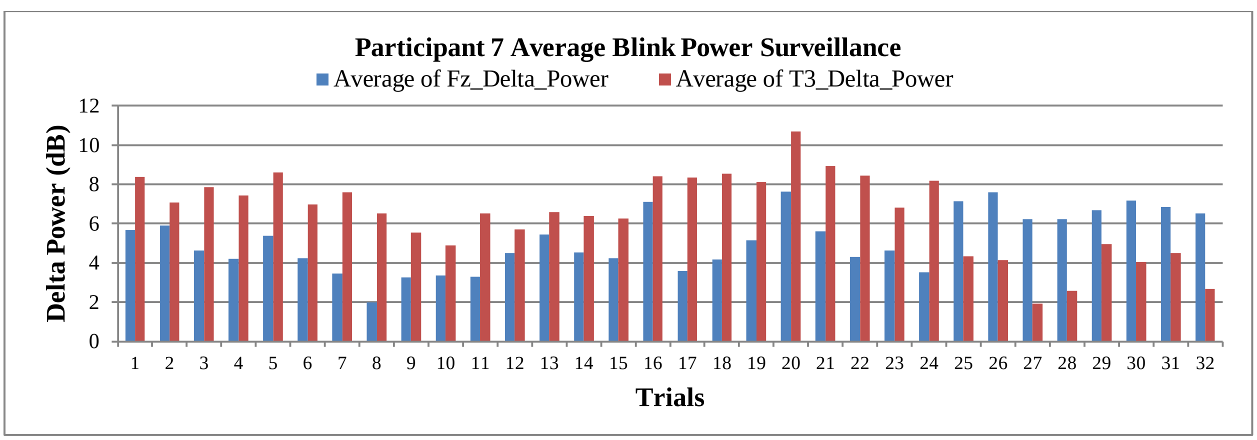


Figure 2. Average power in the delta band at Fz and T3, during a blink. Note that the average power at T3 and Fz changed on trials 25-32. This is when the electrodes were swapped back to the correct locations.

This technique was then applied to the data for every participant. Graphs were used to isolate when the electrode leads were plugged in to the wrong locations. This was accomplished by observing the power at Fz and T3 over the course of all trials for each participant. A timeline of the study, during which the problem was corrected, was developed using these graphs (Figure 3). This was possible because these graphs allowed us to see when T3 and Fz did not fit the expected behavior. This timeline shows the data being mislabeled from the beginning of the study. Therefore, previous studies had to be examined to determine the date when the swap occurred.

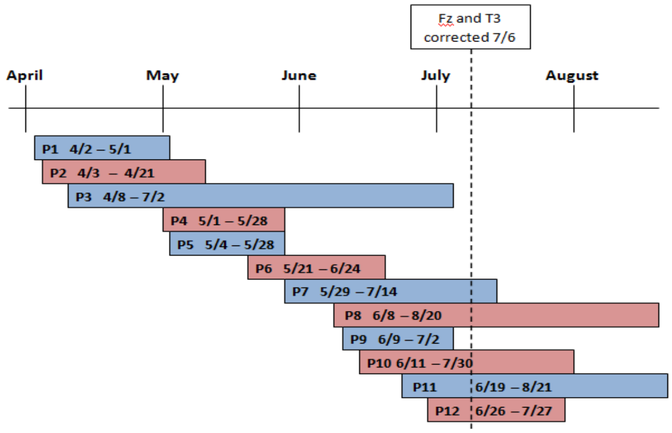
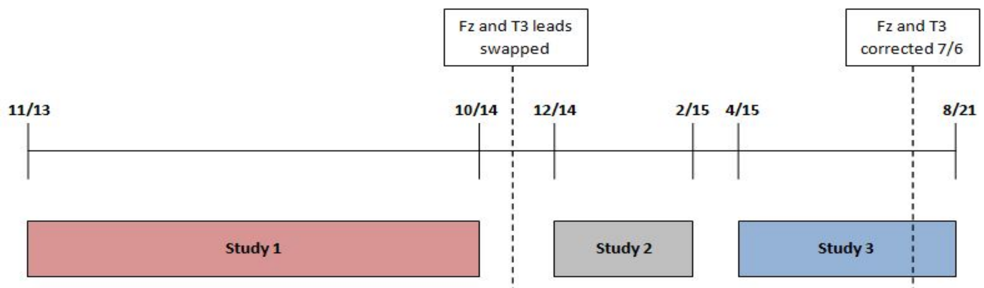


Figure 3. Timeline of when the participants started and completed the current study. Note that the abbreviation P1 indicates participant one, P2 indicates participant two, etc.

Data from two previous studies (Study 1 & Study 2) were processed with this technique and a larger timeline was determined (Figure 4). This figure shows the three studies conducted in the laboratory. The time when the electrodes were initially swapped was determined to fall between Study 1 and Study 2, as shown by the dotted line labeled "Fz and T3 leads swapped." Now that the date of the swap has been found, the EEG spectral data can be easily corrected using software.



Conclusion

The artifact separation technique is a powerful tool for data analysis. An important feature of the technique is that, it does not attempt to 'fix' the signal in the time domain and the technique allows the user of the data to decide what to do with the artifacts. In this case, contaminated data was flagged and later analyzed to determine when the electrode leads were initially swapped. The date when the electrodes were swapped was obtained and data was later reprocessed. The fact that the electrodes were swapped for part of the study had no negative repercussions.

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