Prestimulus Alpha as a Precursor to Errors in a UAV Target Orientation Detection Task

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Abstract

Unmanned Aerial Vehicles (UAVs) have become an important component of military aviation operations and skilled UAV operators are a valuable part of this component. Currently there is a need for improved methods of facilitating the development of mission level skills among operators, including target identification and maintenance of navigational awareness. Toward this aim, we examined the extent to which transient neurophysiological states could be used as an index of engagement within a visual detection training paradigm. Participants learned to distinguish stationary indicators of directional change in movement for target tanks located within a complex vehicle formation background. Fast alpha activity (10-13 Hz) one second before targets were presented differed as a function of type of error that would be made and task difficult. Prestimulus alpha shows promise as a candidate metric for on-line monitoring of learner engagement and workload.

Introduction

Electroencephalographic (EEG) recordings have been used extensively as an index of task engagement and working memory load

(Berka et al., 2007; Gevins, Smith, McEvoy, & Yu, 1997; Kerick, Hatfield, & Allender, 2007). For example, increases in frontal midline theta activity (5-7 Hz) and decreases in both slow (7.5-10 Hz) and fast (10-13 Hz) alpha activity are associated with current working memory demands in both spatial and verbal tasks (Gevins et al., 1997; Smith, McEvoy, & Gevins, 1999). Alpha activity is also affected by training and practice, with increased activity associated with increasing skill level on a given task (Smith et al., 1999).

To date, consensus has yet to be reached regarding the best approach for examining spectral changes in EEG recordings (see discussions in Klimesch, Freunberger, Sauseng, & Gruber, 2008; Makeig, Debener, Onton, & Delorme, 2004). While overall changes in alpha and theta range activity have been shown to change with task difficulty, others have argued for examination of spectral changes associated with particular working memory processes or task locked to particular events.

Though macro level changes in EEG activity show promise for a wide variety of applications, considerably less attention has been given to micro level changes (Huang, Jung, Delorme, & Makeig, 2008; Mazaheri, Nieuwenhuis, van Dijk, & Jensen, 2009). Micro level changes have traditionally been examined with event-related potentials (ERPs). While important in many applications, ERPs may provide an index of a relatively small portion of on-going neural activity (Huang et al., 2008; Klimesch et al., 2008). Additionally, ERP extraction techniques require the averaging of neuronal responses time locked to a number of discrete stimuli that may not be present in many real world operational environments (Huang et al., 2008). For these reasons, methods of examining both tonic and phasic fluctuations in neural activity suitable for operational use remain a goal of many neuroergonomics investigations.

Simultaneous monitoring of spectral changes stemming from both relatively long-term or tonic changes in levels of engagement as well as more rapid phasic changes, such as from event related spectral perturbations (ERSPs), show promise for operational neuroergonomics. For example, Sauseng et al. (2005) observed that event related synchronization (ERS) of alpha range activity distinguishes between retention and active manipulation of visuospatial information in working memory. Huang et al. (2008) have observed tonic changes in alpha bandwidth activity coupled with phasic changes in multiple bandwidths during periods of high visuomotor tracking error.

An approach with particular practical significance would be to utilize micro-level or phasic bandwidth changes to predict transient states when an operator might be less engaged in a particular task (i.e., overloaded or distracted) and thus be more likely to be error prone. A recent approach for examining micro level spectral changes shows promise in this regard.

Examination of prestimulus alpha, which is spectral activity in the alpha bandwidth occurring immediately prior to the onset of a stimulus, is one such approach. Examination of prestimulus alpha shows promise as a means of predicting when alertness may have temporarily decreased to a point where errors are more probable (Ergenoglu et al., 2004; Mazaheri et al., 2009).

For example, using magnetoencephalographic (MEG) recordings, Mazaheri and colleagues (2009) demonstrated that elevated occipital alpha activity prior to the onset of a visual stimulus predicted whether or not participants would make an error in an upcoming trial. Using EEG, Ergenoglu and colleagues (2004) observed significantly elevated alpha activity in a 1 second prestimulus period when participants missed near threshold visual stimuli relative to when they were detected. The aim of the current investigation was to examine the extent to which prestimulus alpha activity might be used to predict an operators' current level of engagement and thus predict errors before they occur in a challenging visual detection task.

Methods

Participants

Twenty-two participants (18-28 years, M = 23.27, SD = 2.62) with self reported normal or corrected to normal vision and hearing voluntarily participated in the study after providing informed consent. Participants were further screened for far and near static visual acuity using the Snellen and Rosenbaum eye tests, respectively. The majority of participants had completed at least some college classes. Participants currently enrolled in University courses received partial credit toward a class. Participants recruited from the community were provided with a small amount of financial compensation.

EEG Recording and Analysis Procedures

A Neuroscan NuAmps 40 Channel Amplifier (with Neuroscan 4.4 software) and a 40 channel Neuroscan QuickCap were use to collect EEG data. The EEG signals were band-passed filtered at 1 to 70 Hz and sampled at 500 Hz. The EEGLAB toolbox (Delorme & Makeig, 2004) in conjunction with MATLAB v.2007b (The MathWorks, Natick, MA) were used for analysis of the EEG recordings. After collection, EEG was re-referenced to the average of the left and right mastoid processes, and low-pass filtered at 30 Hz. The 1 second of EEG preceding each behavioral response was subset from the overall recorded EEG, divided according to whether the response was a hit, miss, false alarm, or correct rejection. Any 1 second pre-response epoch that contained activity exceeding +- 75 μV on the ocular channels was rejected due to ocular artifact contamination. The mean log spectrum for the set of remaining epochs of each type was calculated, and the peak dB power in each of three frequency bands (theta: 4-7.5 Hz, slow alpha1: 7.5-10 Hz, fast fast alpha2: 10-13 Hz) was identified separately for EEG preceding each type of behavioral response, in each of the two difficulty levels, at three electrode sites of interest, Fz, Cz, and Pz.

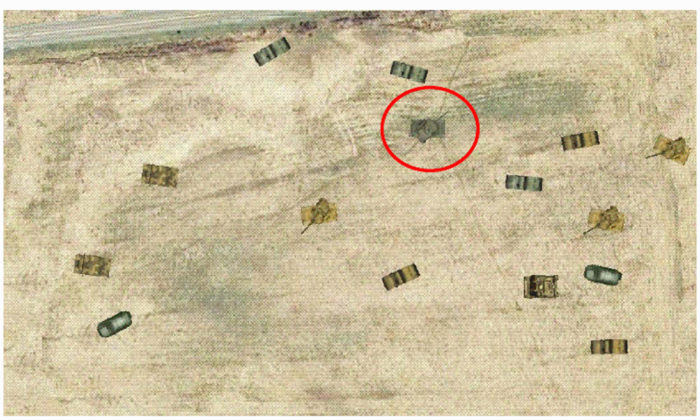

Figure 1: ***Example image from the normal difficulty condition (notice that none of the beige tanks are moving in the opposite direction as the non-tank military vehicles. The target is circled in red (notice that it is a green tank, moving in the opposite direction as the non-tank military vehicles.***

Experimental task

Participants performed two difficulty levels (Easy and Hard) of a visual search task that simulated the role of a UAV operator. In both difficulty conditions the target was defined as a green tank heading in the opposite directions of all other non-tank military vehicles (distracters). In the Easy condition, only the target (if present) could be heading in the opposite direction of all other non-tank military vehicles (see Figure 1). However, in the Hard condition there were also other (distractor) beige tanks that could be heading in the opposite direction of all other non-tank military vehicles (see Figure 2). The added variability of these distractor tanks made the task considerably more difficult, as confirmed with pilot testing. This increased difficulty was intended to increase mental workload while participants performed the difficult visual search task.

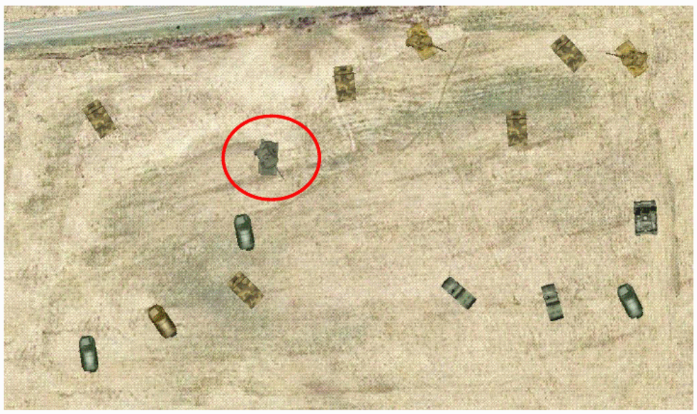

Figure 2: ***Example image from the Hard condition (notice that one of the beige tanks is moving in the opposite direction as the non-tank military vehicles. The target is circled in red (notice that it is a green tank, moving in the opposite as the non-tank military vehicles.***

The experimental task was written and displayed using Microsoft Visual Basic 6 software. Each condition of the task consisted of 200 static images displayed on a 19 inch CRT monitor (Dell M992) for 750 ms each. The interstimulus interval was 1.8 s. Images were generated from a static image consisting of a background desert-like scene obtained from Google maps. Each scene contained 15 military vehicles (i.e., tanks, jeeps, and other vehicles) obtained from a UAV simulator. The position of the vehicles was randomly changed in each scene. Of the 15 military vehicles, a green tank (vehicle of interest-VI) was always present.

In both conditions, a random variable was used to generate a global direction on a 360 degree axis for all vehicles to face within each generated image. In the Easy condition it was only possible for the green tank to violate this directional display (via random variable) and become a target. However, in the Hard condition it was also possible for the beige tanks to violate this directional display (via random variable). To increase the difficulty of the task in both conditions, an additional random variable allowed for each individual vehicle to deviate from the global direction by 30 degrees. However, as apparent in figures 1 and 2, it is still possible to perceive the global direction in which all non-tank military vehicles are heading. Random variables were also used to generate the color of the non-tank military vehicles (green or beige) as well as their location on the screen.

Procedure

All Individuals were first tested to ensure that they had normal vision as assessed via the Rosenbaum and Snellen metrics. They were then fitted with the Neuroscan QuickCap and it was aligned on the head in accordance with the standard 10-20 system. Standard EEG saline gel was used to ensure a good connection between the electrodes and the scalp and all impedances were measured to be below 5 k ohms. Electrocortical activity was recorded from 15 electrode sites, including midline sites Fz, Cz and Pz, as previous research evidenced their effectiveness as indicators of visual working memory and mental workload (Gevins, 1997, 1999; Ergenoglu et al., 2004; Mazaheri et al., 2009). An in-cap ground located just anterior to Cz was used and all electrodes were referenced to an electrode placed on the left mastoid. However, EEG data from an electrode attached to the right mastoid (also referenced to the left mastoid during recording) was also recorded to allow for an averaged reference of the two mastoids to be computed offline for sites Fz, Cz and Pz. Electrooculogram activity was also recorded with two electrodes, one placed above and below the left eye, in order to detect ocular artifacts.

Participants were then briefed with task instructions and were shown examples of the experimental task and were provided with a short practice session. Following this, individuals completed the two difficulty levels of the task in a counterbalanced order as behavioral and EEG data were recorded. The behavioral data consisted of participants' response accuracy and response time (RT). Responses were categorized within a signal detection framework of Hits (detecting the presence of a orientation change in the VI where there was one), a Miss (failing to detect the orientation change of the VI when there was one), a False alarm (reporting an orientation change of the VI when there was not one) and a Correct Rejection (not reporting an orientation change when in fact there was not one). Participants indicated their response by clicking the mouse when they believed a target was present

Results and Discussion

Behavioral Data

The number of hits, misses, false alarms, and correct rejections were calculated for each participant in each condition. Next, d' and β scores were calculated. This calculation revealed that 4 participants had d' scores of less than .6 in the Easy condition. These participants were eliminated from all subsequent data analysis. Analysis of the behavioral data for the remaining 18 participants confirmed our difficulty manipulations. Examination of the proportion of hits revealed that participants made significantly fewer hits in the hard detection condition (M = .51, SD = .16) relative to the easy detection condition (M = .74 SD = .13), t(17) = 7.63, p <.001 . Likewise, false alarms (indicating a directional orientation difference for the target tank when one was not present) occurred significantly more often in the hard detection condition (M = .27, SD = .15), relative to the easy detection condition (M = .16, SD = .08), t(17) = -4.3, p <.001. Average d' scores also differed significantly between the easy and difficult conditions, t(17) = 7.16, p <.001, with means of 1.76 and .66, respectively. Average β scores were .82 and .85, respectively.

Prestimulus EEG Analyses

A 2 (task difficulty- easy and hard) x 2 (target presence-yes or no) by 2 (accuracy -correct or incorrect) repeated measures MANOVA was implemented to examine relative power in the theta, slow alpha, and fast alpha bandwidths for the one second period proceeding each stimulus presentation. Separate MANOVAs were analyzed for each electrode. Due to space limitations only analysis of Pz is presented here, though it should be noted that similar patterns were observed at electrode sites Fz and Cz. At Pz, a significant multivariate three-way interaction was observed between task difficulty, target presence, and accuracy, F(3,15) = 5.12, p = .01, partial $\mu^2 = .5$. Univariate analyses revealed that both slow Alpha1, F(1,17) = 4.6, p = .04, partial $\mu^2 = .21$, and fast Alpha2 F(1,17) = 5.13, p = .03, partial $\mu^2 = .23$, contributed to the significant multivariate effect. The three-way interaction is depicted graphically in Figure 3 for slow alpha and Figure 4 for fast alpha.

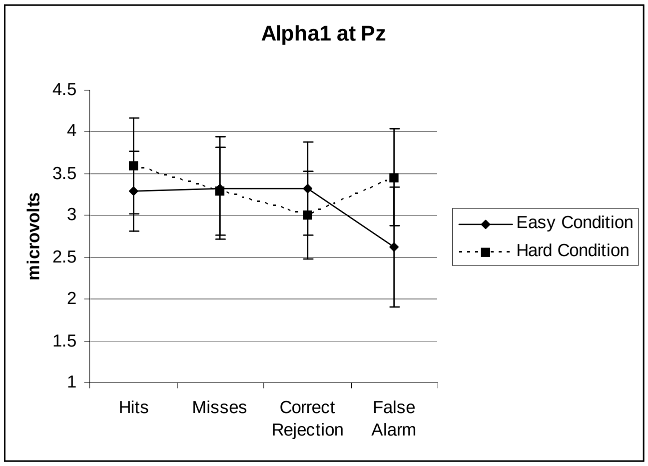

Figure 3: Slow Alpha1 at Pz as a function of Target Presence, Accuracy, and Difficulty Level. Error bars reflect the standard error of the mean.

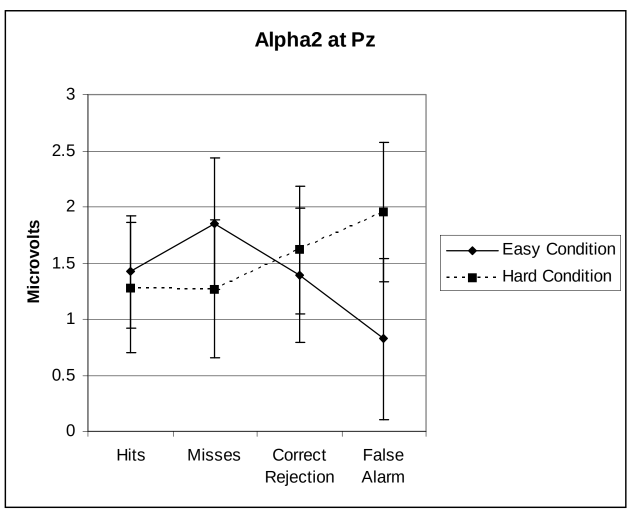

Figure 4: Fast Alpha2 at Pz as a function of Target Presence, Accuracy, and Difficulty Level. Error bars reflect the standard error of the mean.

Prestimulus alpha activity, and particularly fast alpha (10-13 Hz), differed significantly between the types of errors made in the Easy and Hard condition. In the Hard condition, fast alpha activity increased in the one second period immediately prior to a miss, relative to correct detections and also relative to false alarms. A reverse pattern was observed in the Easy condition. In the Easy condition, fast alpha did not differ between correct and incorrect trials when the target was present, but decreased significantly for false alarms. The largest differences in prestimulus alpha activity observed for both slow and fast alpha occurred between False Alarms in the Easy and Hard conditions. Both fast and slow alpha increased for False Alarms in the Hard condition, but decreased for these same target absent error types in the Easy condition.

POTENTIAL APPLICATION

The current results demonstrate potential for using on-line monitoring of phasic changes in alpha bandwidth activity as an index of when an operator may be more error prone or when a learner may be reaching a state where he or she is less likely to benefit from an instructional strategy. The prestimulus alpha activity examined in the present experiment reflected both task difficulty and the type of error likely to be made. For example, if alpha levels increased significantly and participants were making a significant number of False alarms, the present results suggest that there would be a greater than average chance the participant found that task particularly difficult. However, this same pattern of False alarm errors coupled with decreased alpha activity could indicate that the participant had become less engaged in the task or that perhaps the task was not challenging enough. Observation of a reverse pattern coupled with miss-type errors could be used to confirm this interpretation of the data.

This information could potentially be used in conjunction with other algorithms to improve the diagnostic capabilities of an adaptive training paradigm. On-line monitoring of phasic changes in alpha bandwidth activity coupled with performance metrics could be used to provide an indication of when a pedagogical change was needed. If alpha activity was out of range (either above or below tonic limits) no further learning would be expected to occur. Using this information in conjunction with the pattern of behavioral performance observed could be used to distinguish whether to make the learning environment more or less challenging. Further research into the applicability of these results for determining individual differences in learning styles and for use in a neurophysiologically based adaptive training program are currently underway.

ACKNOWLEDGEMENTS

This work was conducted as part of a series of investigations sponsored by the Office of Naval Research, Human Performance, Training & Education Program, Roy Stripling, Program Manager.

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