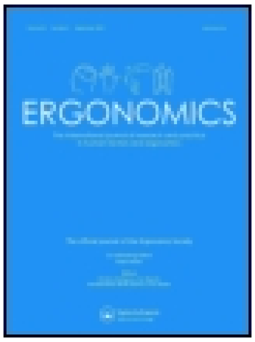

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Detection of error-related negativity in complex visual stimuli: a new neuroergonomic arrow in the practitioner's quiver

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ABSTRACT

Brain processes responsible for the error-related negativity (ERN) evoked response potential (ERP) have historically been studied in highly controlled laboratory experiments through presentation of simple visual stimuli. The present work describes the first time the ERN has been evoked and successfully detected in visual search of complex stimuli. A letter flanker task and a motorcycle conspicuity task were presented to participants during electroencephalographic (EEG) recording. Direct visual inspection and subsequent statistical analysis of the resultant time-locked ERP data clearly indicated that the ERN was detectable in both groups. Further, the ERN pattern did not differ between groups. Such results show that the ERN can be successfully elicited and detected in visual search of complex static images, opening the door to applied neuroergonomic use. Harnessing the brain's error detection system presents significant opportunities and complex challenges, and implication of such are discussed in the context of human-machine systems.

Practitioner Summary: For the first time, error-related negativity (ERN) has been successfully elicited and detected in a visually complex applied search task. Brain-process-based error detection in human-machine systems presents unique challenges, but promises broad neuroergonomic applications.

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Error negativity; applied electroencephalography; visual search; human-machine systems; motorcycle conspicuity

1. Introduction

Error related negativity (ERN) is one of the brain's evoked response potentials (ERP) that occurs when a human actor becomes aware of their own error. Relative to the time of such an erroneous response, for averaged data, the ERN appears within a latency around 100 ms in the form of a pronounced negative deflection for errors as compared to non-errors (see Gehring et al. 2012; for a more detailed overview). ERNs are generally best detected over the frontal scalp, closest to the 'Cz', electrode of the 10–20 system (Homan, Herman, and Purdy 1987), although they can also be measured at the Fz and Pz electrodes (Luck and Kappenman 2011). The anterior cingulate cortex (ACC) has been identified as the most likely primary causal neural structure for the ERN (Gehring et al. 1993; Debener et al. 2005).

The ERN is a well-studied ERP, but very little existing work explores the applied potential of this phenomenon. Clinical psychopathology has sought to diagnostically use individual differences in ERN magnitude, for example, as a marker for potential disturbances (for an overview see Olvet and Hajcak 2008). Similar efforts exist outside of pathology; for example, the ERN's magnitude correlates positively with academic performance (Hirsh and Inzlicht 2010). An ERP marker for error detection would be of great value to the neuroergonomic practitioner (see Parasuraman 2003), but would also need to be robust to the more complex environmental stimuli that occur beyond controlled laboratory environments. This challenge presents distinct difficulties; there has been little exploration of the ERN in complex applied contexts, with associated complex visual stimuli, and no evidence that it could be either elicited or detected in these latter circumstances.

ERN is essentially a subjective response, the elicitation of which is informed by the cognitive model of what is 'correct'. Such models are unique by individual and situation (Hester, Fassbender, and Garavan 2004; Luck and Kappenman 2011). A participant in an ERN experiment may therefore detect errors beyond the context of the experiment at hand (Luck and Kappenman 2011). These include, for example, social errors, past errors recalled in mid-task, the suppression of behaviours (e.g. checking a watch that has been removed for the experiment) or the error of inattention to the task itself; each might

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produce a similar ERN response. The experimenter therefore faces problems disambiguating these from 'correct' errors expected from the experimental protocol itself. Such potential for confounds has understandably led past researchers to adopt conservative choices in their manipulated stimuli. Unambiguous choices such as letters thus prove to be a common choice for ERN experiments (Riesel et al. 2013), and even the most complex visual stimuli used to date have been limited to icon-like images of tools and guns (Amodio et al. 2004; see Figure 1).

Unambiguous methods are likewise preferential for ERN experiments. Simple, binary forced-choice tasks were a regular feature of early ERN research (Renault, Ragot, and Lesèvre 1979) and continue to be used to the present. In a classic example, Gehring et al. (1993) elicited ERN with a speeded letter-based flanker task (Eriksen and Eriksen 1974; Eriksen 1995; see Figure 1A). This task proved an effective way to consistently generate errors even with well-trained participants. Flanker tasks and letter stimuli continue to be the most common choice for ERN experiments, alongside similar error-prone, automaticity-resistant options such as Stroop and go/no go tasks (see Riesel et al. 2013 for a discussion).

To date, the most complex stimuli used in eliciting ERN has been icon-like images of tools (Amodio et al. 2004; Fleming, Bandy, and Kimble 2010). Such photographs involve a level of visual complexity previously unseen in the ERN literature. However, they still fall short of revealing whether ERN is robust enough to be detected in applied tasks. Operations in complex environments, where stimuli are complicated by numerous distractive elements, might provoke cortical reactions that effectively mask or suppress the ERN pattern. In order to test whether detection of the ERN was feasible in the face of such challenges, an applied task in a visually complex environment with parity to a known, replicable ERN task needed to be identified. Ideally, the task would be naturalistic, occurring in a context familiar to the participant. Here, we chose a motorcycle conspicuity task in the context of driving as best fulfilling these requirements.

1.2. Motorcycle conspicuity

The relative inability of motorcycles to attract the attention of other drivers, as compared to other vehicles in the traffic stream, has been a subject of study for an extended period of time (Engel 1971, 1977; Thomson 1980; Hancock et al. 1990; Caird and Hancock 1994; Ledbetter et al. 2012). A disproportionate number of motorcycle collisions involve the colliding party's report of not having seen the motorcycle, an effect which can be reproduced in the laboratory (Hurt, Ouellet, & Thom, 1981; Wulf, Hancock, and Rahimi 1989). For the present study, this difficult detection problem was identified as an effective way to consistently generate errors among highly trained participants in an unambiguous applied context. Arguably, the flanker letter task has some parity to this motorcycle detection task. In the former, a series of static images is observed to produce a choice between two letters. This decision is complicated by distractors, while speeded binary responses are collected. In the latter motorcycle task, a series of static images are observed to elicit a binary decision, motorcycle or no motorcycle. This decision is also complicated by distractors in the form of environmental variation and other roadway vehicles, and again, speeded binary responses are collected. In this study, the visually complex motorcycle detection problem becomes a source of applied errors that may be detected through ERP analysis.

Formally, then, the present work sought to determine whether ERN could be elicited in a motorcycle detection task. For comparison purposes, a replication of the flanker letter task used by Gehring et al. (1993) was collected. The result was a within-participant 2(task: flanker, motorcycle) x 2(response: correct, incorrect) design. We predicted that, for both tasks, EEG voltage level at Cz would vary significantly between response types so that incorrect responses would result in a negative deflection. It was further hypothesised that this pattern would not be significantly affected by task type, i.e., no significant interaction of task type on ERN status was predicted. There was a concern that differences in baseline error rate between the motorcycle and

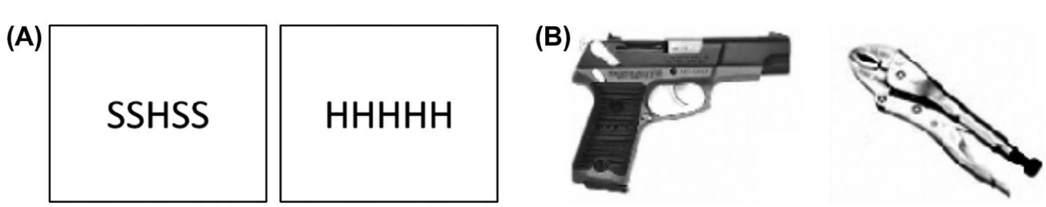

Figure 1. Stimuli previously used in evoking the ERN have been simple and unambiguous. (A) The flanker task used in Gehring et al. (1993) elicited errors by asking for a binary decision regarding the centre letter in an array. (B) Tools and guns from Amodio and colleagues' 2004 shoot/do not shoot racial bias in decision-making study represent the most complex visual stimuli yet used to evoke the ERN.

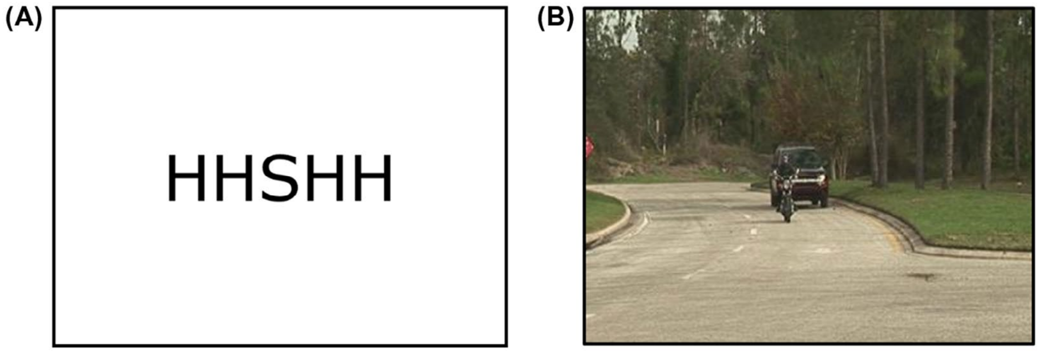

Figure 2. The present study elicited errors through discrimination tasks in simple and complex stimuli. (A) Simple stimuli used in the letter flanker task. The target in this trial, an 'S', is present in the central position and should be reported. Participants made errors in 7.7% of such letter flanker trials. (B) Complex stimuli used in the motorcycle conspicuity task. The target in this trial, a motorcycle, is present, and should be reported. Participants made errors in 6.2% of such motorcycle conspicuity trials.

letter flanker tasks could unbalance the design, as could a substantial difference in cognitive workload between tasks. Therefore, as a manipulation check, overall error rates and subjective workload via the NASA TLX (Hart and Staveland 1988) were collected for each task.

2. Method

2.1. Participants

Twenty-five participants, who were undergraduates at a major southeastern university, provided three hours of participation in return for class credit. Two participants were removed from the study due to hairstyles that would not allow the attachment of EEG leads. An additional participant was removed due to the occurrence of seasonal allergies so severe as to prohibit effective EEG recording. As a result, our final sample included 22 participants, 12 males and 10 females, who ranged in age from 18 to 59 years (mean = 20.00, SD = 10.36).

All participants were required to have 20/20 or corrected to 20/20 vision, a valid driver's license and no self-reported history of neurological disorders. All were additionally right-handed. No participant had a motorcycle endorsement on their license or reported any history of motorcycle or scooter use. The sample contained a mix of novice and experienced drivers; omitting one very experienced driver (with 19 years' experience) the average experience reported was 4.5 years.

2.2. Apparatus

An Advanced Brain Monitoring (ABM) X-10 nine channel, wireless EEG collected data at 256hz from sensors over prefrontal, ventral, parietal and occipital regions (sites F3/F4, C3/C4, Cz/PO, F3-Cz, Fz-C3 and Fz-PO). This unit applied a hardware 0.1 Hz high bandpass filter and a 5th order low bandpass 100 Hz filter to all data. An ABM External Sync Unit (ESU) connected wirelessly to the EEG providing time-stamping of data packets and response signals.

Informed consent was administered and collection of demographic data was performed using Qualtrics (2013) survey software. Experimental data collection and stimuli were handled by a single i7 Windows 8 laptop with 8 GB of RAM and a 512 GB SSD. To minimise interference, this machine was positioned over two meters from the EEG collection area. Visual stimuli were presented on a Dell LCD monitor at 1024 × 768 resolution (Hancock, Sawyer and Stafford 2015). Responses were recorded on a Dell QWERTY keyboard with all keys removed except 'a' and 'apostrophe', both of which were blacked out, resulting in an input device with symmetrically placed left and right keys. Tasks were built in ePrime (Schneider, Eschman, and Zuccolotto 2002), which presented stimuli, recorded user responses, and transmitted response signals via USB-to-serial adapter to the ESU for time-stamping.

2.3. Stimuli

Two categories of stimuli were built. Letter flanker stimuli (Figure 2A) displayed an array of five letters, each an 'S' or an 'H'. The centre letter either matched or did not match the four outer letters, which were the same. As such, the possible letter arrays were HHHHH, HHSHH, SSSSS and SSHSS. For motorcycle stimuli (Figure 2B), various images of the same intersection were presented. In these images, one or more of the following elements could appear: pedestrian, traffic cone, car, SUV, mail truck and motorcycle. The same motorcycle and rider were present in half of all images. These images were drawn from a stimuli set previously used in the motorcycle conspicuity work of Ledbetter and colleagues (2012) and Al-Awar Smither and Torrez (2010).

2.4. Task

Motorcycle and letter flanker stimuli shared a similar presentation format. Before every trial an asterisk appeared in the centre of the screen for 1 s. Participants were instructed to orient on this symbol and wait for the stimuli. Flanker letter stimuli consisted of an array of five letters and participants were trained to press the left key if the centre letter was an 'S', and the right key if the letter was an 'H'. In the motorcycle conspicuity, task participants were presented with a photo of a traffic scene. Participants were trained to press the left key if a motorcycle was present, and the right key if no motorcycle was present.

2.5. Procedure

After informed consent, participants were asked to surrender all electronics, which were held outside the experimental area. Each participant sat in a chair facing the LCD screen while a research assistant fitted the EEG cap and checked impedance at all electrode sites. During both training and actual trials, no experimenter was in the room, although participants could summon one upon request. Participants were instructed to follow on-screen instructions and not to speak unless necessary. The training portion of the experiment guided participants through 16 practice trials of each set of stimuli. This was followed by an opportunity to ask questions and repeat the training if desired. The experimental portion consisted of four blocks of 64 trials of each task, for a total of 512 trials; 256 on each task type. Between blocks, the experimenter entered the room and asked the participant to get up and move around, a request facilitated by the wireless nature of the X-10 EEG device. Upon participant's return to the seat, the researcher again checked impedance levels and made any necessary corrections. Participants were then verbally advised that they should try to beat their previous speed. On-screen instructions before each block further instructed participants to go as fast as they were able. Upon completing all trials, participants completed a demographic survey while the EEG headset was removed by the researcher. After disclosure, participants were thanked for their time and released.

2.6. Post-processing and Analysis

All EEG data was analysed in MATLAB. (2012) using EEGLAB 12.0.1.0b (Delorme and Makeig 2004) and ERPLAB (Lopez-Calderon and Luck 2014). Recordings were hand-trimmed to include only the experimental tasks. The result was submitted to the EEGLAB runica function, an implementation of Bell and Sejnowski's (1995) infomax ICA (for a more detailed discussion see Delorme and Makeig 2004). Identified components primarily containing eyeblinks, saccades and/or EMG were removed, although in the case of any doubt components were retained. Data were then imported into ERPLAB, and individual time-stamped event markers were assigned to four bins based upon task (flanker letter or motorcycle conspicuity) and response (correct or incorrect). All data were then segmented into 400 ms epochs, from −100 ms before the time-stamped event to 300 ms after. In each epoch, the mean amplitude between 0 and 100 ms was calculated at the Cz electrode, relative to a baseline of −50–0 ms. These mean values were averaged by bin within each participant and then transferred to R 3.1.0 (R Development Core Team, 2008) for statistical analysis in a 2(response type: correct, incorrect) x 2(task type: flanker, motorcycle) within-participant repeated measures ANOVA. Visualisations were also produced using the ERPLAB pop_gaverager function run against all participant data sets and results were submitted to the ERPLAB pop_ploterps function. This output was saved as an .eps file, and final adjustments to fonts and the legend were made with Adobe Illustrator.

3. Results

3.1. Manipulation check results

As a manipulation check, error rates and subjective workload were collected for each task. Across participants, the error rate for the flanker letter task (Figure 2A) was 7.7%, as compared to 6.2% for the motorcycle detection task (Figure 2B). Likewise, across participants the NASA TLX composite workload score for the flanker letter task was 49, and 48 for the motorcycle detection task. The two tasks elicited comparable rates of error and subjective workload.

3.2. Graphical results

Visula inspection of aggregate waveform data (Figure 3) reveals that error state, but not task type, is clearly discriminable. The negative deflection seen in error trials conforms to previously described error related negativity (ERN) evoked response potential (ERP) patterns (for example, Gehring et al. 2012).

3.3. Statistical results

A significant main effect of response type was shown between error and no error trials Wilk's Lamda = .426, $F(3, 11) = 4.94$, $p = .02$, $\eta^2_p = 0.57$. No significant main effect of task type was present, Wilk's Lamda = .76, $F(3, 11) = 1.14$, $p = .38$, $\eta^2_p = 0.24$. Likewise, no significant interaction between task type and response type was evident, Wilk's Lamda = .86, $F(3, 11) = .62$, $p = .62$, $\eta^2_p = 0.14$. These results

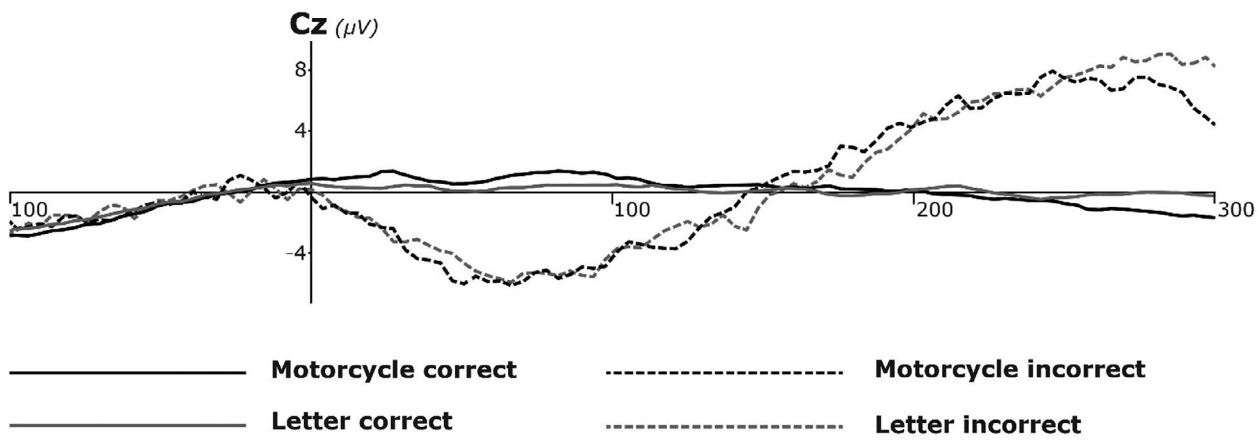

Figure 3. Inspection reveals a pronounced negative deflection for error trials, as is typical for the error related negativity (ERN) evoked response potential (ERP) (as in Gehring et al. 2012).
Notes: This pattern is similar for both letter and motorcycle stimuli, suggesting that the visual complexity of the latter is not a barrier to detection of the ERN ERP. Waveform data are plotted negative-down relative to a 50 ms baseline, while a full 100 ms of preresponse activity is shown for evaluative purposes (see Luck 2005).

indicate that the presence or absence of errors was discriminable in ERN data of both tasks, and furthermore that the task type did not significantly impact ability to discriminate ERN.

4. Discussion

As hypothesised, the ERN was detectable in the flanker letter task (for a visual representation, see Figure 3), which represents a successful evocation of this ERP using the methods of Gehring et al. (1993). These results represent a replication of extant findings using the traditional method to elicit ERN. Aggregated trials in which an error was committed revealed a pronounced negative deflection in activity measured at the Cz electrode, as compared to trials in which no error was committed. The similarity between data from this successful replication and that collected in the motorcycle detection task is striking. Despite the muscular and cognitive 'noise' associated with searching a more complex image, a clear ERN pattern emerged in the latter motorcycle detection (Figure 2). ERN thus joins the company of other ERPs shown to be robust in applied settings, such as the N2pc, a marker for selective attention, and the P300, a marker for evaluation of stimuli as novel (Woodman and Luck 1999). This important new evidence reveals the ERP as a practical neuroergonimic (Parasuraman 2003) tool that can be immediately applied to a wider spectrum of experimental procedures and applied concepts.

Some appropriate caution is well advised. This is because our motorcycle detection task was ultimately a controlled stimuli set and binary response a controlled method. Applied contexts are likely to require more latitude of stimuli and response. However, there remain many cognitive phenomena that require binary response to complex images that have found utility in the applied domain. For example, the implicit association test (IAT, Greenwald, McGhee, and Schwartz 1998) is used as a part of bias training in police departments (Rudman, Ashmore, and Gary 2001). We anticipate that other realms will now become available for exploration via the ERN assessment (e.g. nuclear power control design; Reinerman et al. 2015).

4.1. Next steps

From detecting ERN in a static scene, it appears to be a feasible step to attempt detection in more dynamic environments. There are, however, some theoretical complications. ERN is a subjective, time-locked ERP, and out-of-context ERNs that fall outside of experimenters' expectations seem more likely to arise from tasks where the stimuli are constantly changing. In the face of the flow of time, modality matters as well, as auditory or tactile stimuli onset can be far more easily temporally defined (Hancock et al. 2013). Further, in immersive visual stimuli, mere presentation does not mean a target is perceptually available; participants must look before they can see. This visiomanual requirement of a foveal fixation means that, at the least, eye tracking will be a bridging requirement for accurate time-locked response data in dynamic environments. It is however well documented that visual-manual requirements, even when met, may not result in perception of a target, especially if the observer is engaged in multitasking (Strayer, Drews, and Johnston 2003). This 'looking without seeing' (O'Regan et al. 2000;) represents both a challenge and a potential opportunity, as applied use of the ERN might provide valuable evidence in applied differentiation of errors of structural versus cognitive origin (a question posed in Sawyer et al. 2014).

The present experiment detected ERN in averaged data, but applied systems will likely need to detect in real time. Real-time ERP classification has been available for some time (Vidal 1977), and efforts to classify ERN in simple stimuli have since approached sensitivity and specificity of over 85% in under 150 ms (Ventouras et al. 2011; Vi and Subramanian 2012). There is a question as to whether these present findings will generalise to such real-time applications. Future efforts to develop a real-time ability to detect ERN in complex visual stimuli seem a logical progression from the present effort. Such steps are vitally necessary to understand the viability of many potential applications.

It is in application of the ERN where the most interesting future questions lie. Consider, for example, the ERN in the context of training. As novices move toward proficiency, they pass through various skill acquisition stages in which they may be well aware what is correct and yet still provide an incorrect answer (for a detailed discussion of such skill acquisition, see Anderson 1983). Expert teachers often use their own intuition and experience to determine whether a pupil has made a misstep of which they are conscious or, in contrast, an unwitting error. While the former might warrant a mild rebuke (itself optional, a witting error often needs no feedback), the latter necessitates time to educate the student as to what connotes the correct action. In machine-tutoring systems, such subtleties are lost, and students are punitively drilled on material they know, but have not yet completely mastered. ERN distinction could provide an automated system using a context to approach training in a much more intelligent fashion, or provide a human teacher augmented insight. Both would save time and resource while facilitating the learning process.

The crux of the aforementioned issue is that when humans and machines work together, at present, the machine has relatively minimal information regarding the state of the human (Parasuraman and Riley 1997). Humans can communicate their errors through manual interfaces, such as keyboards or mouse-driven 'undo' commands. While in word processing this may still be considered an acceptable interface, it is woefully inadequate for tasks where the time in which an error must be reported falls within the threshold of human response time. The idea of an undo button in tasks such as piloting, combat, and surgery is, at present, somewhat grimly humorous, and precisely so because of the severe consequences that stopping the task to push such a button would entail. ERNs hold the possibility of making such interface a reality, recruiting the operator's own error detection capacity to inform automation in much closer to real-time (150 ms in Vi and Subramanian 2012). Latencies of this order would allow human-machine systems to be informed quickly of perceived errors, and to weight possible ameliorative actions accordingly.

Such advanced neuroergonomic applications are only hinted at by the present step forward. It is tempting to relegate notions of brain-activity-mediated human–machine interaction to the realm of science fiction, but this future is approaching. To effectively harness the applied potential of ERN, the detection of human error must be moved away from artificially simple laboratory conditions in favour of the complexity of real-world environments. It is through present exploration and iterative implementation of such applied ERN detection that this tool may be understood and intelligently applied to future critical systems.

Disclosure statement

No potential conflict of interest was reported by the authors.

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