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Applied Error Related Negativity: Single Electrode Electroencephalography in Complex Visual Stimuli

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APPLIED ERROR RELATED NEGATIVITY:
SINGLE ELECTRODE ELECTROENCEPHALOGRAPHY IN COMPLEX VISUAL STIMULI

by

BEN D. SAWYER
B.S. Colorado State University, 2010

A thesis submitted in partial fulfillment of the requirements
for the degree of Master of Science
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ABSTRACT

Error related negativity (ERN) is a pronounced negative evoked response potential (ERP) that follows a known error. This neural pattern has the potential to communicate user awareness of incorrect actions within milliseconds. While the implications for human-machine interface and augmented cognition are exciting, the ERN has historically been evoked only in the laboratory using complex equipment while presenting simple visual stimuli such as letters and symbols. To effectively harness the applied potential of the ERN, detection must be accomplished in complex environments using simple, preferably single-electrode, EEG systems feasible for integration into field and workplace-ready equipment.

The present project attempted to use static photographs to evoke and successfully detect the ERN in a complex visual search task: motorcycle conspicuity. Drivers regularly fail to see motorcycles, with tragic results. To reproduce the issue in the lab, static pictures of traffic were presented, either including or not including motorcycles. A standard flanker letter task replicated from a classic ERN study (Gehring et al., 1993) was run alongside, with both studies requiring a binary response. Results showed that the ERN could be clearly detected in both tasks, even when limiting data to a single electrode in the absence of artifact correction. These results support the feasibility of applied ERN detection in complex visual search in static images. Implications and opportunities will be discussed, limitations of the study explained, and future directions explored.

Dedicated to my brilliant wife Szuhui Wu.

ACKNOWLEDGMENTS

This work owes its existence to the contributions of many people. My advisor Dr. Waldamar Karwowski was the impetus for the questions explored here, underwrote equipment and provided space. Conversations with Drs. Petros Xanthopoulos, Peter Hancock, Jeffery Bedwell, and Victor Finomore shaped ideas and strategies herein. My crack team of Research Assistants at MIT² helped extensively. Specifically, I want to call out Jenny Walker and Jessica Siler for building stimuli, scheduling and running many of the participants, and simultaneously working on very important ‘Hancocking’ research and development. My wife, Szuhui Wu assisted in every step of post-processing, while also keeping me sane(ish). Finally, I must thank Dr. Stephen J. Luck. The counsel of his book An Introduction to the Event-Related Potential Technique was at my side through this entire learning process, as I have seen it at the side of so many other fledgling EEG researchers. It helped.

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LIST OF ABBREVIATIONS (or) ACRONYMS

ABM	Advanced Brain Monitoring
ACC	Anterior Cingulate Cortex
ANOVA	Analysis of Variance
EDF	European Data Format
EEG	Electroencephalogram
EMG	Electromyography
ERN	Error Related Negativity
ERP	Evoked Response Potential
ESU	External Sync Unit
FRN	Feedback Related Negativity
ICA	Independent Component Analysis
LCD	Liquid Crystal Display
MIT ²	Minds in Technology, Machines in Thought
MoBI	Mobile Brain Imaging
P2PW	Peak-to-Peak Moving Window
RAM	Random Access Memory
SSD	Solid State Drive
USB	Universal Serial Bus

CHAPTER ONE: INTRODUCTION

Error related negativity (ERN) is an evoked response potential (ERP) that occurs when a human actor becomes aware of an error. ERPs are electroencephalographic responses of the brain that occur in direct relation to a motor or sensory event. Relative to the time of an erroneous action, the response-locked ERN appears within 100ms as pronounced negativity in the EEG pattern for error trials as compared to non-error trials. The pattern is centered in the frontal scalp closest to the 10-20 system electrode Cz, (for information on the 10-20 system see Homan, Herman & Purdy, 1987) and so is most commonly measured at Cz, and sometimes at Fz and Pz (Luck & Kappenman, 2011). The ERN is a subjective response, informed by the individual brain's present model of what is 'correct' (Luck & Kappenman, 2011; Hester, Fassbender, & Garavan, 2004). For example, presenting feedback classifying any response an 'error', irrespective of the truth, can elicit feedback related negativity (FRN), which is similar in location and configuration to the ERN, but some 2-300ms greater in latency (Miltner, Braun, & Coles, 1997). Additionally, incidental errors and correction may occur within an overarching task at hand. For example consider that motor corrections during the action of pressing the button which results in a correct response might elicit an ERN on a correct trial (Carter et al., 1998). A participant may detect errors at multiple levels beyond the context of the experiment at hand (Luck & Kappenman, 2011); social errors, 'errors' recalled mid-task, or the error of inattention to the task itself might masquerade as the errors of experimental interest. It is therefore unsurprising that most ERN work is carried out in unambiguous paradigms. Simple visual stimuli such as letters and symbols are the standard, and the most complex visual stimuli

used to date are icon-like images of tools and guns (see Figure 1) (Amodio et al., 2004; Fleming, Brady, & Kimble, 2010).

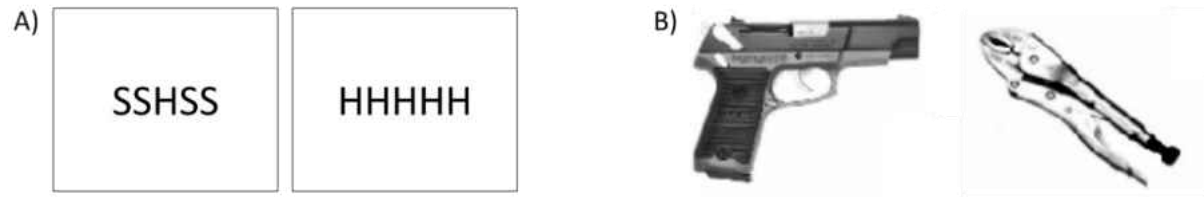


Figure 1: Stimuli used in evoking the ERN

A) The flanker task used in Gehring et al. (1993) elicited errors by asking for a binary decision as to the center letter in an array. When the target was flanked by non-target stimuli, participants show greater reaction time and are more likely to make errors, especially in a speeded task. B) Tools and guns from Amodio and colleagues' 2004 shoot/don't shoot racial bias in decision making study represent the most complex visual stimuli yet used to evoke the ERN.

The ERN was first observed in speed trials of forced choice reaction time tasks (Renault, Regot, & Lesèvre, 1979). Forced choice tasks paired with simple stimuli continues to be a feature of the majority of contemporary studies. Gehring et al. (1993) presented participants with a letter based flanker task (Eriksen & Eriksen, 1974; Eriksen, 1995, see Figure 1). Gehring's experiment manipulated participant goals between accuracy and speed, and he found the ERN to be greater in magnitude for the accuracy-tasked participants. This suggested the ERN was not just the signature of a neural system for detection of errors, but that that magnitude of the ERP response was linked to perceived contextual severity of a given incorrect response. Gehring suggested that the anterior cingulate cortex (ACC) as the neural structure primarily responsible for the ERN, and the resultant neurophysiological localization and mechanism debate comprises much of the subsequent ERN literature. Notably absent from this literature is substantial work exploring applied uses of ERN.

Applied ERN

What is the use of a noninvasive electroencephalographic psychophysiological marker for errors? Clinical psychopathological work seeking to diagnostically use individual differences in the ERN shows promise (for an overview see Olvet & Hajcak, 2008). This approach may have application outside of pathology; one team has found that the ERN magnitude correlates positively with academic performance (Hirsh & Inzlicht, 2010). These applications, while promising, all use the simple forced-choice paradigms of earlier work; the ERN is analyzed as a bellwether for performance in the ‘real world’. The potential of ERN outside these boundaries is considerable.

For example, consider the ERN in the context of human-machine interface. When humans and machines work together, the machine has minimal information regarding the state of the human. As such, automation waits to be invoked by human action, plays a constant passive role, or in technology such as automotive autonomous emergency braking systems, watches the environment for evidence that the human needs assistance. It is worth considering that this one-sided relationship is responsible for some part of the dysfunctional patterns humans and automated systems can fall into (for a focused discussion, see Parasuraman & Riley, 1997). As automation is increasingly able to make decisions on the human’s behalf, the knowledge that a human has made an error in the task at hand will become a powerful piece of information. While humans can communicate their errors through presently available interfaces, as in the ubiquitous ‘undo’ command, the time required to do so can bleed into seconds. This is a detrimental timescale in tasks such as piloting, combat and surgery, where the line between life and death can be measured in milliseconds. The concept of an ‘undo’ command in these high time-

pressure tasks is laughable largely because the human lacks reasonable time, and indeed the physical capacity, to request it. The ERN holds the possibility of detecting human errors in something much closer to real-time, 150ms in one current implementation (Vi & Subramanian, 2012). Such speed would allow human machine systems to be informed quickly of perceived error, allowing automated delay of the offending move, a confirmation check, or the reduction of system thresholds for automated corrective action. However, to effectively harness the applied potential of the ERN, the detection of human error must be moved away artificially simple laboratory conditions in favor of the complexity of real-world environments.

A primary challenge to moving the ERN EEG out of the lab is the difficulty of extracting ERP information in interference filled, but environmentally valid environments. Happily, the bulky and easily disrupted equipment traditionally used in the laboratory is already evolving toward more robust, portable systems. There is evidence that these EEGs are capable of providing data the workplace, battlefield or cockpit (Davis et al., 2009). ‘Noise’ common in such contexts include ambient electrical activity, movement of electrodes relative to the scalp, and skeletal muscular electrical activity such as eyeblinks, saccadic activity, neck movements and stabilization (Luck, 2005). Even with robust hardware, post-processing to mitigate these rouge signals is a likely necessity.

Post-processing tools signal range in complexity and utility. For example, a relatively simple technique ‘moving window peak-to-peak amplitude detection’ (P2PW) uses differences between the highest and lowest voltages within successive windows of time to flag artifacts for removal. A more complex approach, independent component analysis (ICA), relies on the statistical independence of variance accounted for by artifacts to separate them from variance accounted for by brain activity and ‘clean’ them from the signal. ICA benefits from larger

variance-covariance matrices; more data is better. Specifically, the more channels an EEG recording has within a session, the better ICA can isolate components from brain activity. Careful consideration of the trade-offs various data post-processing approaches is necessary, as all have the potential to impact the signal negatively. For example, the above P2PW rejection approach eliminates undesirable sections of data outright. While ICA preserves data, it can be difficult to know if a component identified and ‘cleaned’ by these blind source separation algorithms is in fact independent of the brain activity of interest. It is a practical question with philosophical undertones as to whether certain deletion or potential distortion is the greater evil.

There are further purely practical considerations to applied use of data ‘cleaning’ tools. P2PW rejection requires relatively few computational resources, and might be used in something approaching real-time. ICA approaches require a delayed or fully *post hoc* approach; computational intensity and pre-processing requirements presently limit real-time approaches (for a practical example see Lin et al., 2005). The Swartz Center for Computational Neuroscience’s Mobile Brain Imaging (MoBI) (Gramann et al., 2011) is investigating ICA applications to contextually identify and separate brain data from artifactual noise related to specific activities, like walking. Such targeted approaches may eventually reduce or eliminate the trade-offs associated with the current EEG post-processing toolset. For the present, the divide between the kind of information that can be recorded in a seated laboratory configuration and an active applied setting is significant (for a directed discussion of the present trade-offs and opportunities see Makeig et al., 2009).

In moving the ERN out of the laboratory a concern directly related to post-processing is the practical design question of the number of leads to provide. More leads means greater redundancy and enhances artifact filtering, especially via ICA. Still, a piece of field-ready gear

should be designed to be taken on and off repeatedly, with minimal attention to setup. As each lead must be checked for impedance issues which would prevent or degrade a signal, the optimal number of EEG sensors for detecting ERN is the lowest possible number the human might have to devote precious attention to. Single lead EEG has been investigated in applied contexts including emergency room detection of seizure activity (Brenner et al., 2012; Rubin et al., 2014) and clinical psychopathological diagnosis (Martino, Simon, & Devilbiss, 2014; Ghorbanian et al., 2013). These applications, however, all rely on spectral EEG changes, while ERN requires detection of a time-locked ERP. The single-lead detection of such ERP events has been attempted in only a few instances (ex. Saletu et al., 2002), and remains uncommon.

Even assuming the coming availability of robust mobile single-lead EEG data, ERN detection must be available in complex visual environments. Previous tasks such as identifying letters and icons fall short. ERN in the identification of images of tools (as in Amodio et al., 2004; Fleming, Brady, & Kimble, 2010) presents photographs of objects as stimuli, a level of visual complexity unseen in the ERN literature. Still, for applied exploitation of the ERN to have broad utility, the ERP must be detectable in tasks undertaken in complex environments. Presently, no such task has been attempted.

Is the ERN itself robust enough to be detected in tasks in complex environments? When robust mobile EEG devices evolve, can the ERN be detected in a single electrode's available data? To answer these questions, an applied task equivalent to a known, replicable ERN task needed to be identified. The task needed to take place in a complex visual environment. Because of the previously identified issue of subjectivity in the ERN, it had to be a task that involved as unambiguous a goal as possible. Ideally, it would take place in an applied setting with which participants might already have experience. After evaluating and rejecting a number

of candidate options, a motorcycle conspicuity task was chosen as best fulfilling these requirements.

Motorcycle Conspicuity

Motorcycle conspicuity refers to the ability of motorcycles to attract the attention of other roadway vehicle operators, relative to other vehicles in the traffic stream (Engel, 1971; Engel, 1977). This is a safety issue; in a disproportionate number of motorcycle accidents one party to the collision reports not having seen the motorcycle (Hurt, Oullet, & Thom, 1981; Wulf, Hancock, & Rahimi, 1989). Indeed, the size, shape, color, sound and lighting arrays of motorcycles have all been investigated and successful configurations adapted as remedies to this problem, with limited success (Cole & Hughes, 1984; Cole & Jenkins, 1984; Hendtlass, 1992; Thomson, 1980; Wulf, Hancock, & Rahimi, 1989). In the context of the present study, the unsolved human factors problem of motorcycle conspicuity provides an excellent parallel to the flanker letter task. It too provides a binary decision: motorcycle or no motorcycle, and the traffic stream provides distractors in the form of other roadway vehicles. Indeed, navigating traffic is itself a series of speed trials with forced choice reaction time tasks, adding to the environmental validity of the task in the experimental context. Finally, participants with a driver's license can be assumed to be familiar with the task, which they hopefully perform successfully each time they drive.

Present Study

As a manipulation check, overall error rates and subjective workload via the NASA TLX were collected for each task. It was certain that if the error rate differed greatly, the resultant unbalanced design would influence the outcome. It was further suspected that if the tasks differed greatly in workload, it might affect the EEG context of the ERN.

The present work sought to address three questions, alluded to above. First, could the ERN be detected in the flanker letter task used by Gehring et al. (1993)? Second, could the ERN likewise be detected in the motorcycle conspicuity task, an applied task involving complex visual scenes? Finally, given that the roadway images chosen necessarily involved participant saccadic activity and resultant artifacts, could the ERN ERP be distinguished in single-channel recordings? Data was post-processed first with ICA using all nine channels of data, then P2PW rejection in a single channel, and finally raw EEG collected from a single channel as well. As the site closest to the focus of the ERN signal, Cz was chosen as the single channel.

The result was a 2(task: flanker, motorcycle) x 2(response: correct, incorrect) design, conducted on ICA(9), P2PW(1) and raw data(1). It was predicted that the EEG voltage level at Cz would vary significantly between response types, such that incorrect responses would result in lower voltage. It was further expected this pattern would not be significantly affected by task type. No significant interaction was predicted. Finally, it was expected the main effect of response to be significant only in ICA(9) and P2PW(1) data type, but not in the raw(1) data type. This pattern was expected to be consistent with the ERN being detectable in both the flanker letter task and the motorcycle conspicuity task, but only in filtered data.

CHAPTER TWO: METHODOLOGY

Participants

Twenty participants were sourced from UCF's SONA system and provided three hours of participation in return for class credit. An additional five participants were recruited by advertisement on a volunteer basis. Two participants were removed from the study due to hair that would not allow the attachment of our EEG leads, one with elaborate braiding and another with a stitched skullcap that could not be removed. An additional participant was removed due to seasonal allergies so severe as to prohibit effective EEG recording, and indeed basic laboratory hygiene. As a result, our final sample included 22 participants, 13 male and 9 female, ranging 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 history of neurological disorders (see Appendix B for a copy of the survey used). All participants were right handed, and 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 two very experienced drivers (19 and 27 years experience) the average experience reported was 4.5 years.

Apparatus

An Advanced Brain Monitoring (ABM) X-10 nine wireless channel 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). An External Sync Unit (ESU) connected wirelessly to the

ABM EEG providing time-stamping of EEG data packets and response signals. It is important to note that this unit applied a hardware 0.1 Hz high bandpass filter and the 5th order low bandpass 100Hz filter to all data.

Presentation of informed consent and collection of demographic data were performed on an internet connected Celeron laptop using Qualtrics (2013). A researcher script and schedules coordinating researchers were kept in Google Docs.

Experimental data collection and stimuli were handled by a single i7 Windows 8 laptop with 8GB of RAM and a 512GB SSD. To minimize interference, this machine was separated from the EEG collection area. Visual stimuli was presented on an external Dell LCD monitor at 1024x768 resolution. Participant responses were recorded on a Dell QWERTY keyboard with all keys removed except 'a' and 'apostrophe', both of which were blacked out. The result was an input device with left and right hand keys. Both tasks were built in ePrime (Schneider, Eschman, & Zuccolotto, 2002), which presented stimuli, recorded user responses and transmitted response signals to the ESU for time-stamping. EEG data was recorded through B-Alert, which also received externally time-stamped event markers from ePrime by way of a USB serial adapter. The intent of this ESU time-stamping was to minimize operating system induced delay, which can introduce significant latency (Guger et al., 2001). The necessary inclusion of a serial to USB adapter on our modern laptop may have limited these benefits by introducing its own delay.

Task

Both tasks and training were built in ePrime. Before every trial an asterix appeared in the center of the screen for 1 second. Participants were instructed to orient on the cross and wait for the stimuli. In the flanker letter task participants were presented an array of five letters and

instructed to respond only to the center letter (see Figure 1, and also Appendix A). If the letter was an 'H' they were to press the right key, and if the letter was an 'S' they were to press the left key. In the motorcycle conspicuity task participants were presented with a photo of a traffic scene. These pictures were stills from filmed stimuli sourced, with permission, from a previous motorcycle conspicuity experiment (Smither & Torrez, 2010). If a motorcycle was present participants were asked to press the left key, and if no motorcycle was present they were to press the right key. In both tasks an incorrect responses resulted in a red X being displayed at screen center for 1 second, while a correct response displayed a blank screen for the same period. Trials of each tasks were presented in alternating blocks of 64 such trials.

Procedure

After informed consent participants were asked to power off and remove all electronics, which were held outside the experimental area. Each participant sat in a chair facing the stimuli LCD while a research assistant wiped down the nine sensor sites and area behind the ears with alcohol, then fitted the EEG cap. Care was taken not to tighten the attachment straps too tightly. A dual lead ground was attached over the mastoid bones and impedance was checked at all electrode sites. During trials, no experimenter was in the room. Participants were instructed to read on-screen instruction, not to speak unless necessary. An initial training block consisting of simple on-screen instructions followed by 16 practice trials of each task. This was followed by 4 experimental blocks of 64 trials of each task, for a total of 512 experimental trials, 256 of each task type. Between blocks the experimenter entered the room and asked the participant to get up and move. Upon the participant's return the researcher again checked impedance levels on the EEG and made any necessary corrections. Participants were then verbally advised 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 were provided a demographic survey (see Appendix B) while the EEG headset was removed. After disclosure participants were thanked for their time and released.

Post-processing & Analysis

All EEG data was converted to standard EDF format using B-alert Lab and imported into MATLAB (2012b) using EEGLAB 12.0.1.0b (Delorme & Makeig, 2004). Three data types were constructed in post-processing. An unedited copy of the EEG data was saved as the raw(1) output. P2PW(1) analysis was processed by the ERPLAB 4.0.2.3 (Lopez-Calderon & Luck, 2014) pop_artmwpth function. Artifacts flagged by this process were rejected, and a copy of the data was saved as the P2PW(1) output. To produce the ICA(9) output, individual participant's EEG recordings were first hand-trimmed of spans of time irrelevant to the experiment, such as sneezes (the data was recorded during allergy season) and times when the headset was left running. The result was submitted to the EEGLAB runica function. This implementation of Bell & Sejnowski's infomax ICA (1995) is beyond the scope of this writing (for a full explanation, see Delorme & Makeig, 2004). The returned components were hand sorted with the goal of identifying for removal only those components representing eyeblinks, saccades or EMG. When in doubt, components were retained. The result was saved as the ICA(9) output.

Each of the three data types was imported into ERPLAB and individual time-stamped event markers were assigned to bins based upon task (flanker letter or motorcycle conspicuity) and response (correct or incorrect). All data was then segmented into epochs of one second, from

-400ms before the time-stamped event to 600ms after. The final number of epochs at this point varied by data type, as some types of post processing had removed data and at times the EEG data was not recorded (see Table 1). In each epoch, mean amplitude between 0 and 100ms was calculated at the Cz electrode. The values were averaged by bin within each participant. These mean amplitude data were transferred to R 3.1.0 for statistical analysis, where the three ERP data types (raw data(1), P2PW(1), and ICA(9)) were submitted to a 2(response type: correct, incorrect) x 2(task type: flanker , motorcycle) within-subjects repeated measures ANOVA.

Visualization was accomplished by running the ERPLAB pop_gaverager function against all participant data sets and submitting the result to the ERPLAB pop_ploterps function. Many of these processes were automated (for scripts see in Appendix C). The output was saved as an .eps file and final adjustments were made with Adobe Illustrator.

Table 1

Task data loss by post-processing type

Data type	Flanker Letter				Motorcycle Conspicuity			
	correct	incorrect	total	error%	correct	incorrect	total	error%
All*	5848	488	6336	7.7%	5942	394	6336	6.2%
Raw output	5394	463	5857	7.9%	5427	380	5807	6.5%
ICA output	5350	460	5810	7.9%	5349	373	5722	6.5%
P2PW output	2888	161	3049	5.3%	2946	144	3090	4.7%
Raw data loss	7.8%	5.1%	7.6%		8.7%	3.6%	8.3%	
ICA data loss	8.5%	5.7%	8.3%		10.0%	5.3%	9.7%	
P2PW data loss	51%	67%	52%		50%	64%	51%	

Note. The final number of epochs by data type, by post-processing type.

* “All” shows original trials recorded in ePrime. At times, due to technical failure, EEG data was not recorded. This loss is reflected in differences between “All” and “Raw”. Data loss percentages are relative to “All”.

CHAPTER THREE: RESULTS

Manipulation Check Results

As a manipulation check, error rates and subjective workload were collected for each task. Across participants, the error rates for the flanker letter task was 7.7%, as compared to 6.2% for the motorcycle conspicuity task. The two tasks had comparable rates of error. Likewise, across participants the TLX composite workload score for the flanker letter task was 49, and 48 for the motorcycle conspicuity task. The two tasks had very comparable subjective workload.

Experimental Results

No significant interaction between task type and response type was shown, Wilk's Lamda = .86, $F(3, 11) = .62$, $p = .62$, $\eta^2_p = 0.14$.

A large and significant main effect of response type was shown Wilk's Lamda = .426, $F(3, 11) = 4.94$, $p = .02$, $\eta^2_p = 0.57$. This effect was significant in all three data types: raw data, $F(1, 13) = 13.57$, $p = 0.003$, $\eta^2_p = 0.51$, P2PW, $F(1, 13) = 15.75$, $p = 0.002$, $\eta^2_p = 0.55$, and ICA, $F(1, 13) = 13.35$, $p = 0.003$, $\eta^2_p = 0.50$.

No significant main effect of task type was shown, Wilk's Lamda = .76, $F(3, 11) = 1.14$, $p = .38$, $\eta^2_p = 0.24$.

Taken together these data suggest that ERN can be successfully discriminated in all three data types, including the raw signal, and that the task type did not significantly impact ability to discriminate ERN.

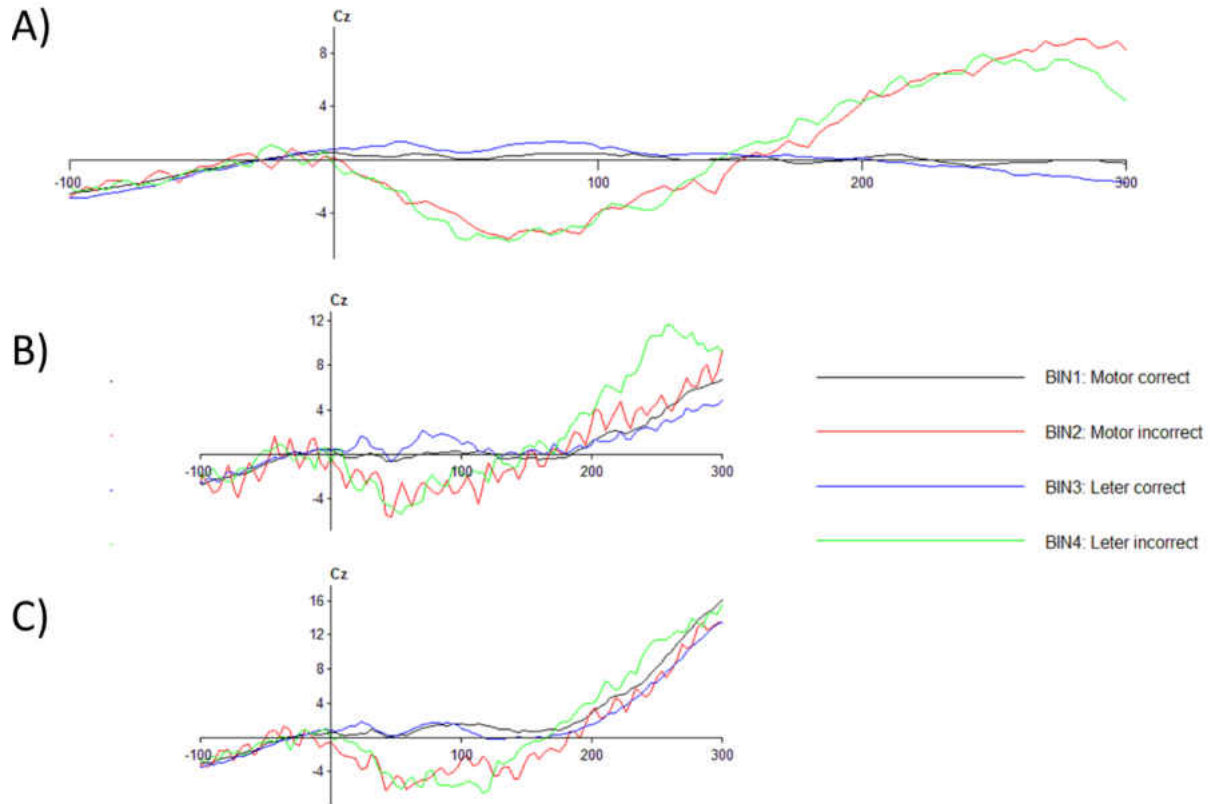


Figure 2: Grand average time-locked ERP waveforms for three data types. Negative is plotted down, and all waveforms are plotted relative to a 50ms baseline time-locked against participant response by keypress. A full 100ms of pre response activity is shown here for evaluative purposes. Bin numbers are included in the key for reference (see the MATLAB code in Appendix C). The waveforms for ICA(9) in part (A) show the clearest ERN pattern, but the negative trend of erroneous results and separation between correct and error trials can be clearly seen in the P2PW(1) and raw data (1) waveforms in (B) and (C), respectively.

CHAPTER FOUR: DISCUSSION

As hypothesized, the ERN was detectable in the flanker letter task (for a visual representation, see Figure 2), a successful evocation of this ERP using the methodology of Gehrig et al., (1993). Despite the muscular and cognitive ‘noise’ of searching a complex image, a clear ERN pattern emerged in the motorcycle conspicuity task as well (Figure 2). The ERN as an ERP seems robust enough to be detected in complex visual search, and so joins ERPs such as the N2pc and P300 (Woodman & Luck, 1999). This important new evidence can be immediately applied to new experimental and applied concepts, with the caution that the motorcycle conspicuity task provided an exceptionally controlled context for errors and a binary response. Also, while our stimuli is more complex than that in previous studies, it was nonetheless an image presented on a monitor. A participant asked to perform search in a larger scene might incur a greater number of artifacts.

It was hypothesized that single lead detection of the ERN would be possible only in the P2PW data, much of which was removed due to artifacts, and that ICA, with its requirement of multiple EEG sensors, would be a likely alternative. Surprisingly, the ERN pattern was easily detected in raw EEG data from a single lead, Cz. Although the ICA filtered data provided slightly tighter confidence intervals, the performance of the raw data was impressive, given that it had been processed only by hardware applied and computationally cheap high and low bandpass filters. These filters may in fact have hampered the present effort by introducing artifactual noise in the baseline (Gehring et al., 2012). Such filters can nonetheless be quite beneficial, and the results at hand leave little current room for complaint. In fact, taken together

these results suggest that single-lead applied uses of the ERN may lie within the reach of present EEG technologies.

Next Steps

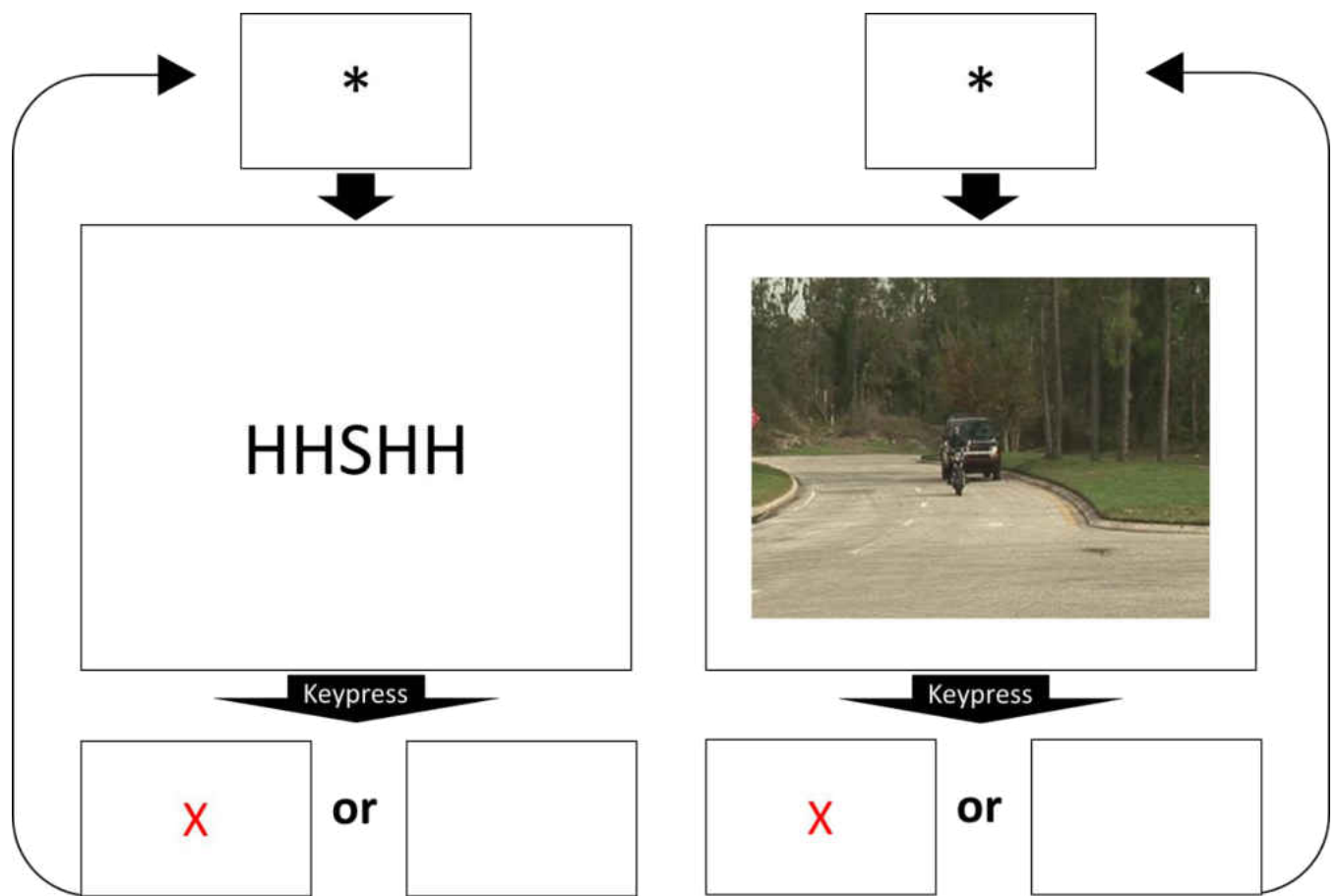
Given the above findings, a number of new questions present themselves. The present experiment detected ERN in averaged data, but that applied systems will likely need to detect it in real time. Real time ERP classification has been investigated for some time (Vidal, 1977), and efforts to classify the ERN in simple stimuli have approached sensitivity and specificity of over 85% in under 150ms (Ventouras et al., 2011; Vi & Subramanian, 2012). Trials of real-time ability to detect the ERN in complex visual stimuli seem a logical progression from this effort, and are necessary to understand the viability of many potential applications.

From detecting ERN in a static scene it is a short step to attempting detection in a dynamic environment. There are, however, some theoretical complications. The ERN is a time-locked ERP, and so there may be out-of-context ERNs that arise from tasks where the stimuli is constantly changing. For example, in some dynamic tasks, responses about the stimuli could be errors due either to a quality judgment or temporally missing a window or cue. For a subjective ERP like the ERN, time opens a Pandora's Box of perceived errors that may fall outside of experimenters' expectations.

Indeed, should the ERN be used in human-machine pairings, context and subjectivity will undoubtedly be the greatest and last challenge faced. This should be an area of immediate investigation, for preponderance as to the nature of acceptable jobs for the ERN can usefully come before the technology to facilitate them. The ERN would seem certainly to have a place in training and intelligent tutoring systems, where the ground truth is known but the human's

metacognitive evaluation of their performance is not. From this example it seems likely that ERN enabled automation would be appropriate in contexts where the human makes a time-specific, unambiguous action, and knowledge of their evaluation of success could influence a system-level decision. Making an error in a voice command, deleting a message, pulling a trigger ... all could fit this description. A future in which brain activity affects how technology interacts is coming. The present work sheds light on what may be expected from it. It is imperative that Engineers and Psychologists begin understanding tools like ERN detection now, that they may be intelligently applied later.

APPENDIX A: STIMULI



APPENDIX B: DEMOGRAPHIC SURVEY

You

Participant # (to be filled out by the research assistant):

What is your age?

What is your major?

What is your gender?

☐ Male

☐ Female

☐ Other

Right or left handed?

'Forced Handedness' means you use one hand because you are unable to use the other.

☐ Right

☐ Left

☐ Ambidextrous

☐ Forced Handedness

Have you ever been diagnosed with any neurological disorder?

☐ Yes

☐ No

Please explain briefly.

Is English your first language?

☐ Yes

☐ No

Are you fluent in any other languages?

- ☐ Yes
☐ No

Please list which languages you speak.

Do you wear corrective lenses?

- ☐ Yes, glasses
☐ Yes, contacts
☐ No

Driving History

Do you have a driver's license?

- ☐ Yes
☐ No

What kind of motor vehicle do you drive most often?

- ☐ Car
☐ Van
☐ Truck
☐ Motorcycle
☐ Scooter
☐ Motor Trike

Do you drive regularly?

- ☐ Yes
☐ No

Describe the vehicle you drive most often.
This question concerns the vehicle you normally drive.

	Not Very													Very
	0	1	2	3	4	5	6	7	8	9				
Fast														
New														

[illegible]

For how many years have you been driving?

- ☐ Other (please input number only) :

10/10/2014

How often do you drive?

- ☐ Never
- ☐ Less than once a week
- ☐ Less than twice a week
- ☐ every other day
- ☐ Daily

Letter TLX

Please answer the questions below in relation to the LETTER TASK. Advance each slider to AT LEAST ZERO.



LETTER TASK?	
How Physically demanding was the LETTER TASK?	
How hurried or rushed was the pace of the LETTER TASK?	
How successful were you in accomplishing what you are asked to do in the LETTER TASK?	
How hard did you have to work to accomplish your level of performance in the LETTER TASK?	
How insecure, discouraged, irritated, stressed or annoyed were you in the LETTER TASK?	

Motorcycle TLX

Please answer the questions below in relation to the **MOTORCYCLE TASK**. Advance each slider to **AT LEAST ZERO**.

[illegible]

6/17/2014

Qualtrics Survey Software

[illegible]

APPENDIX C: MATLAB CODE

```

% eeg_Path_n_Name_v1.m
%Matlab script for setting file paths
%Version 1.0 : 1st run EEG ICA before ERP processing(Bin, Epoch,
Computing)

%% Paths
pStart='C:\\Users\\Karwowski X-10
PC\\Dropbox\\Szuhui2Ben\\~DATA\\NeEEg\\';
pData=strcat(pStart,'All_Data_edf',filesep); %location of all data.edf
files
pEvent=strcat(pStart,'~Event_list',filesep); %location of all event_list
files
pDset_ind=strcat(pStart,'~1.Dataset_EEG_individual',filesep); %Individual
datasets
pDset_mer=strcat(pStart,'~2.Dataset_EEG_merged',filesep); %Merged datasets
pDset_cln=strcat(pStart,'~3.Dataset_Clean',filesep); %Cleaned datasets **
pDset_ICA=strcat(pStart,'~4.Dataset_ICA',filesep); %ICA-processed datasets
(**NOT YET PRUNED**)
pDset_ICA_pruned=strcat(pStart,'~5.Dataset_ICA_pruned',filesep); %ICA-
pruned datasets
pDset_ICA_bin=strcat(pStart,'~6.Dataset_ICA_Bin',filesep); %ICA-pruned
datasets with BINLISTER
pDset_ICA_epoch=strcat(pStart,'~7.Dataset_ICA_Epoch',filesep); %ICA-pruned
datasets with Epoching
pERPset_ICA=strcat(pStart,'~8.ERPset_ICA',filesep); %ICA-pruned ERP sets
pERPset_no_ICA=strcat(pStart,'~9.ERPset_no_ICA',filesep); % ERP sets with
NO filters
pDset_P2P_epoch_ar=strcat(pStart,'1st_run_P2P_artifact_noICA_06122014\\~5.D
ataset_Artifact',filesep);
pERPset_P2P=strcat(pStart,'1st_run_P2P_artifact_noICA_06122014\\~6.ERPset',
filesep);

%% Files
fChannel=strcat(pStart,'9_channels.ced'); %channel location file
fBin=strcat(pStart,'binlister.txt'); %Binlister file
fLog=strcat(pStart,'eeg_result_log.csv');

chan=1:9; %channels
epoch_pre=-400; %window for epoching in msec
epoch_post=600; %window for epoching in msec

cd(pStart);

```

```

% eeg_DataImport_merge_run.m
% Matlab script for EEG:
% (1)running the main script for importing individual data(.edf)
% (2)merging(append) datasets by selecting Ss# (single or multiple)

clear all % clear all objects in Workspace
close all % delete all unhidden figures
clc % clear Command Window
[ALLEEG EEG CURRENTSET ALLCOM] = eeglab;

cd('C:\\Users\\Karwowski X-10 PC\\Dropbox\\Szuhui2Ben\\~DATA\\NeEEg\\');

Path_n_Name='eeg_Path_n_Name_v1'; %Path and Name definition script *in the
same folder*
open(strcat('C:\\Users\\Karwowski X-10
PC\\Dropbox\\Szuhui2Ben\\~DATA\\NeEEg\\',Path_n_Name,'.m'));
run(Path_n_Name);

choice = questdlg('Which task would you like to run?', 'Task', 'Import
individual data.edf file(s)', 'Merge(append) datasets', 'Import individual
data.edf file(s)');
switch choice
    %% import individual data.edf file(s)
    case 'Import individual data.edf file(s)'

        cd(pData);
        main_import='eeg_DataImport_main'; %data import main script *in
the same folder*
        open(strcat('C:\\Users\\Karwowski X-10
PC\\Dropbox\\Szuhui2Ben\\~DATA\\NeEEg\\',main_import,'.m'));

        choice = questdlg('Which data file(s) would you like to import?',
'Data Processing Methods', 'Choose one file', 'Run all files', 'Run all
newly-added file(s)', 'Choose one file');
        switch choice
            case 'Choose one file'
                fName=uigetfile('*.edf');
                EEG = pop_biosig(fullfile(pData,fName),
'channels',[1:9] , 'importhevent','off', 'importannot','off', 'blockepoch','of
f');

                cd(pStart);
                run(main_import);

                fprintf('Subject = %s\\n', Ss);
                fprintf('Session = %s\\n', Sn);
                fprintf('Sampling Rate = %d\\n', EEG.srate);
                fprintf('# of Channel = %d\\n', EEG.nbchan);
                fprintf('# of events = %d\\n', event_no);

                msgbox(strcat(EEG.filename, ' is saved. # of events =
',num2str(event_no)));

```



```

case 'Run all files'
    fNames = dir( fullfile(pData, '*.edf') );
    fNames={fNames.name};

    for f=1:length(fNames)
        fName=fNames{f};
        EEG = pop_biosig(fullfile(pData,fName),
'channels',[1:9] , 'importevent','off','importannot','off','blockepoch','of
f');

        cd(pStart);
        run(main_import);

    end

    fprintf('Number of files processed: %d\n', f);

    save('fNames.mat','fNames');
    msgbox(strcat('Number of files processed: ', num2str(f)));

case 'Run all newly-added file(s)'
    load('fNames.mat');
    fNames_re = dir( fullfile(pData, '*.edf') );
    %fNames_re = strcat(pData, filesep, {fNames_re.name});
    fNames_re={fNames_re.name};
    fNames_chk=~ismember(fNames_re,fNames);
    fNames_new=fNames_re(fNames_chk);
    f_diff=numel(fNames_re)-numel(fNames);

    for f=1:length(fNames_new)
        fName=fNames_new{f};
        EEG = pop_biosig(fullfile(pData,fName),
'channels',[1:9] , 'importevent','off','importannot','off','blockepoch','of
f');

        cd(pStart);
        run(main_import);

    end

    fprintf('Number of files processed: %d\n', f);
    fprintf('Number of files difference: %d\n', f_diff);

    fNames=fNames_re;
    save('fNames.mat','fNames');
    msgbox(strcat('Number of files processed: ', num2str(f), '.
Number of files difference: ', num2str(f_diff)));

end

eeglab redraw;
erplab redraw;

```

```

cd(pStart);

%% Merge(append) datasets
case 'Merge(append) datasets'
    fTemp=csvread(fLog);
    Ss_list=fTemp(1:length(fTemp));
    Ss_list=unique(Ss_list);
    Ss_list=arrayfun(@num2str,Ss_list,'unif',0);

    clear fTemp

    cd(pDset_ind);
    Ss_select=listdlg('PromptString','Select Subject
# :','SelectionMode','multiple','ListString',Ss_list);
    Ss_select=Ss_list(Ss_select);

    for m=1:length(Ss_select);
        Ss=Ss_select{m};
        if length(Ss)==1; Ss=strcat('S0',Ss); else
Ss=strcat('S',Ss); end
        Dset_list=dir(fullfile(pDset_ind, strcat(Ss, 'n*.set')));
        Dset_list={Dset_list.name};

        for n=1:length(Dset_list);
            Dset=Dset_list{n};
            EEG =
pop_loadset('filename',Dset,'filepath',pDset_ind);
            [ALLEEG, EEG, CURRENTSET] = eeg_store( ALLEEG, EEG,
0 );

            end
            %     n=length(Dset_list);
            %     EEG =
pop_loadset('filename',{Dset_list},'filepath',pDataset_ind);

            EEG = eeg_checkset( EEG );
            EEG = pop_mergeset( ALLEEG, [1:n], 0);
            [ALLEEG EEG CURRENTSET] = pop_newset(ALLEEG, EEG,
n+1,'setname',Ss,'savenew',strcat(pDset_mer,Ss),'gui','off');
            ALLEEG = pop_delset( ALLEEG, [1:n+1] );

            eeglab redraw;
            erplab redraw;

        end

        msgbox('Done. ');

        cd(pStart);
end

```

```

% eeg_DataImport_main.m
% Matlab main script for EEG- importing individual data(.edf)

Ss=strcat('S',fName(3:4));
Sn=strcat('n',fName(length(fName)-4));
fName=strcat(Ss,Sn);
[ALLEEG EEG CURRENTSET] = pop_newset(ALLEEG, EEG,
0,'setname',fName,'gui','off');

%import channel
EEG=pop_chanedit(EEG, 'load',{fChannel 'filetype' 'autodetect'});
[ALLEEG EEG] = eeg_store(ALLEEG, EEG, CURRENTSET);

%import event list
EEG = eeg_checkset( EEG );
fEvent=strcat(pEvent,'elist_',fName,'.txt');
EEG = pop_importevent( EEG, 'event',fEvent,'fields',{'latency'
'type'},'skipline',1,...
'timeunit',1,'append', 'no');
event_no=length(EEG.urevent);
[ALLEEG EEG] = eeg_store(ALLEEG, EEG, CURRENTSET);

%save dataset
EEG = eeg_checkset( EEG );
EEG = pop_saveset( EEG,
'filename',strcat(fName,'.set'),'filepath',pDset_ind);
[ALLEEG EEG] = eeg_store(ALLEEG, EEG, CURRENTSET);

Log=[str2double(fName(2:3)),str2double(fName(length(fName))),event_no,EEG.
pnts,EEG.srate,EEG.nbchan];
dlmwrite(fLog,Log,'-append');

```

```

% eeg_EEG2ERP_no_ICA.m
% Matlab script for ERP(all "merged" datasets) :
% (1)ERP- BINSLLISTER
% (2)ERP- Epoching
% (3)ERP- Computing and saving ERP

cd('C:\\Users\\Karwowski X-10 PC\\Dropbox\\Szuhui2Ben\\~DATA\\NeEEg\\');

clear all % clear all objects in Workspace %*turn on/off when necessary
close all % delete all unhidden figures %*turn on/off when necessary
clc % clear Command Window %*turn on/off when necessary
[ALLEEG EEG CURRENTSET ALLCOM] = eeglab; %*turn on/off when necessary

Path_n_Name='eeg_Path_n_Name_v1'; %Path and Name definition script *in the
same folder*
open(strcat('C:\\Users\\Karwowski X-10
PC\\Dropbox\\Szuhui2Ben\\~DATA\\NeEEg\\',Path_n_Name,'.m'));
run(Path_n_Name);

%% Bins+Epoch+ERP

cd(pDset_mer);

fNames = dir( fullfile(pwd,'*.set') );
fNames_list={fNames.name};

fNames=listdlg('PromptString','Select
File :','SelectionMode','mutiple','ListString',fNames_list);
fNames=fNames_list(fNames);

for f=1:length(fNames)

    fName=fNames{f};
    Ss=fName(1:3);
    EEG = pop_loadset('filename',fName,'filepath',pwd);
    [ALLEEG, EEG, CURRENTSET] = eeg_store( ALLEEG, EEG, 0 );
    EEG = eeg_checkset( EEG );
    n=1;

    EEG = pop_creabasiceventlist( EEG , 'AlphanumericCleaning', 'on',
'BoundaryNumeric', { -99 }, 'BoundaryString', { 'boundary' } );
    [ALLEEG EEG CURRENTSET] = pop_newset(ALLEEG, EEG,
n+1,'setname',strcat(Ss,'_elist'),'gui','off');

    EEG = pop_binlister( EEG , 'BDF', fBin, 'ExportEL',
strcat(pERPset_no_ICA,'elist_erp_',Ss,'_bin_no_ICA.txt'), 'IndexEL', 1,
'SendEL2', 'EEG&Text', 'Voutput', 'EEG' );
    [ALLEEG EEG CURRENTSET] = pop_newset(ALLEEG, EEG,
n+2,'setname',strcat(Ss,'_elist_bins'),'savenew',strcat(pERPset_no_ICA,Ss,
'_elist_bins'),'gui','off');
    EEG = pop_epochbin( EEG , [epoch_pre epoch_post], 'pre');

```

```

[ALLEEG EEG CURRENTSET] = pop_newset(ALLEEG, EEG,
n+3, 'setname', strcat(Ss, '_elist_bins_be'), 'savenew', strcat(pERPset_no_ICA,
Ss, '_elist_bins_be'), 'gui', 'off');
    EEG = eeg_checkset( EEG );
    ERP = pop_averager( EEG , 'Criterion', 'good', 'DSindex',1,
'ExcludeBoundary', 'on', 'SEM', 'on' );
    ERP = pop_savemyerp(ERP, 'erpname', strcat(Ss, '_ERP_no_ICA'),
'filename', strcat(Ss, '_ERP_no_ICA.erp'), 'filepath', pERPset_no_ICA,
'Warning', 'on');

    ALLEEG = pop_delset( ALLEEG, [1:n+3] );
    eeglab redraw;
    erplab redraw;

    clear n

end

msgbox('Done. ');

cd(pStart);

```

```

% eeg_ICA.m
% Matlab script for EEG running ICA (all "Clean" datasets) :

cd('C:\\Users\\Karwowski X-10 PC\\Dropbox\\Szuhui2Ben\\~DATA\\NeEEg\\');

clear all % clear all objects in Workspace
close all % delete all unhidden figures
clc % clear Command Window
[ALLEEG EEG CURRENTSET ALLCOM] = eeglab;

Path_n_Name='eeg_Path_n_Name_v1'; %Path and Name definition script *in the
same folder*
open(strcat('C:\\Users\\Karwowski X-10
PC\\Dropbox\\Szuhui2Ben\\~DATA\\NeEEg\\',Path_n_Name,'.m'));
run(Path_n_Name);

%% Run ICA
cd(pDset_cln);

fNames = dir( fullfile(pwd,'*.set') );
fNames={fNames.name};

for f=1:length(fNames)

    fName=fNames{f};
    Ss=fName(1:3);
    EEG = pop_loadset('filename',fName,'filepath',pwd);
    [ALLEEG, EEG, CURRENTSET] = eeg_store( ALLEEG, EEG, 0 );
    EEG = eeg_checkset( EEG );
    EEG = pop_runica(EEG, 'extended',3,'interrupt','on');
    [ALLEEG EEG] = eeg_store(ALLEEG, EEG, CURRENTSET);

    [ALLEEG EEG CURRENTSET] = pop_newset(ALLEEG, EEG,
1,'setname',strcat(Ss,'Clean_ICA'),'gui','off');
    EEG = pop_saveset( EEG,
'filename',strcat(Ss,'Clean_ICA.set'),'filepath',pDset_ICA);
    [ALLEEG EEG] = eeg_store(ALLEEG, EEG, CURRENTSET);

    eeglab redraw;
    erplab redraw;

end

msgbox('Done. ');

cd(pStart);

```

```

% eeg_ICA2ERP.m
% Matlab script for ERP(all "ICA-pruned" datasets) :
% (1)ERP- BINSLLISTER
% (2)ERP- Epoching
% (3)ERP- Computing and saving ERP

cd('C:\\Users\\Karwowski X-10 PC\\Dropbox\\Szuhui2Ben\\~DATA\\NeEEg\\');

clear all % clear all objects in Workspace %*turn on/off when necessary
close all % delete all unhidden figures %*turn on/off when necessary
clc % clear Command Window %*turn on/off when necessary
[ALLEEG EEG CURRENTSET ALLCOM] = eeglab; %*turn on/off when necessary

Path_n_Name='eeg_Path_n_Name_v1'; %Path and Name definition script *in the
same folder*
open(strcat('C:\\Users\\Karwowski X-10
PC\\Dropbox\\Szuhui2Ben\\~DATA\\NeEEg\\',Path_n_Name,'.m'));
run(Path_n_Name);

%% Bins+Epoch+ERP

cd(pDset_ICA_pruned);

fNames = dir( fullfile(pwd,'*pruned.set') );
fNames_list={fNames.name};

fNames=listdlg('PromptString','Select
File :','SelectionMode','multiple','ListString',fNames_list);
fNames=fNames_list(fNames);

for f=1:length(fNames)

    fName=fNames{f};
    Ss=fName(1:3);
    EEG = pop_loadset('filename',fName,'filepath',pwd);
    [ALLEEG, EEG, CURRENTSET] = eeg_store( ALLEEG, EEG, 0 );
    EEG = eeg_checkset( EEG );
    n=1;

    EEG = pop_creabasiceventlist( EEG , 'AlphanumericCleaning', 'on',
'BoundaryNumeric', { -99 }, 'BoundaryString', { 'boundary' } );
    [ALLEEG EEG CURRENTSET] = pop_newset(ALLEEG, EEG,
n+1,'setname',strcat(Ss,'Clean_ICA_elist'),'gui','off');

    EEG = pop_binlister( EEG , 'BDF', fBin, 'ExportEL',
strcat(pEvent,'elist_erp_',Ss,'_bin_ICA.txt'), 'IndexEL', 1, 'SendEL2',
'EEG&Text', 'Voutput', 'EEG' );
    [ALLEEG EEG CURRENTSET] = pop_newset(ALLEEG, EEG,
n+2,'setname',strcat(Ss,'Clean_ICA_elist_bins'),'savenew',strcat(pDset_ICA
_bin,Ss,'Clean_ICA_elist_bins'),'gui','off');
    EEG = pop_epochbin( EEG , [epoch_pre epoch_post], 'pre');

```

```

[ALLEEG EEG CURRENTSET] = pop_newset(ALLEEG, EEG,
n+3, 'setname', strcat(Ss, 'Clean_ICA_elist_bins_be'), 'savenew', strcat(pDset_
ICA_epoch, Ss, 'Clean_ICA_elist_bins_be'), 'gui', 'off');
    EEG = eeg_checkset( EEG );
    ERP = pop_averager( EEG , 'Criterion', 'good', 'DSindex', 1,
'ExcludeBoundary', 'on', 'SEM', 'on' );
    ERP = pop_savemyerp(ERP, 'erpname', strcat(Ss, '_ERP_ICA'), 'filename',
strcat(Ss, '_ERP_ICA.erp'), 'filepath', pERPset_ICA, 'Warning', 'on');

    ALLEEG = pop_delset( ALLEEG, [1:n+3] );
    eeglab redraw;
    erplab redraw;

clear n

end

msgbox('Done. ');

cd(pStart);

```



```

% eeg_DataMerge_P2P_ERP.m
% Matlab script for EEG+ERP: (**file pathes are NOT UPDATED!!!)
% (1)EEG- mergeing(appendig) datasets by selecting Ss#
% (2)ERP- BINSLLISTER
% (3)ERP- Epoching
% ** (4)ERP- Detect artifacts with "Peak to Peak"
% (5)ERP- Computing and saving ERP

clear all % clear all objects in Workspace
close all % delete all unhidden figures
clc % clear Command Window
[ALLEEG EEG CURRENTSET ALLCOM] = eeglab;

cd('C:\\Users\\Karwowski X-10 PC\\Dropbox\\Szuhui2Ben\\~DATA\\NeEEg\\');

Path_n_Name='eeg_Path_n_Name_v1'; %Path and Name definition script *in the
same folder*
open(strcat('C:\\Users\\Karwowski X-10
PC\\Dropbox\\Szuhui2Ben\\~DATA\\NeEEg\\',Path_n_Name, '.m'));
run(Path_n_Name);

fTemp=csvread(fLog);
Ss_list=fTemp(1:length(fTemp));
Ss_list=unique(Ss_list);
Ss_list=arrayfun(@num2str,Ss_list,'unif',0);

clear fTemp

cd(pDset_ind);
Ss_select=listdlg('PromptString','Select Subject
# :','SelectionMode','mutiple','ListString',Ss_list);
Ss_select=Ss_list(Ss_select);

for m=1:length(Ss_select);
    Ss=Ss_select{m};
    if length(Ss)==1; Ss=strcat('S0',Ss); else Ss=strcat('S',Ss); end
    Dset_list=dir(fullfile(pDset_ind,strcat(Ss,'n*.set')));
    Dset_list={Dset_list.name};

    for n=1:length(Dset_list);
        Dset=Dset_list{n};
        EEG = pop_loadset('filename',Dset,'filepath',pDset_ind);
        [ALLEEG, EEG, CURRENTSET] = eeg_store( ALLEEG, EEG, 0 );
    end

    EEG = eeg_checkset( EEG );
    EEG = pop_mergeset( ALLEEG, [1:n], 0);
    [ALLEEG EEG CURRENTSET] = pop_newset(ALLEEG, EEG,
n+1, 'setname',Ss, 'savenew',strcat(pDset_mer,Ss), 'gui','off');

```

```

    EEG = pop_creabasiceventlist( EEG , 'AlphanumericCleaning', 'on',
    'BoundaryNumeric', { -99 }, 'BoundaryString', { 'boundary' } );
    [ALLEEG EEG CURRENTSET] = pop_newset(ALLEEG, EEG,
n+2,'setname',strcat(Ss,'_elist'),'gui','off');

    EEG = pop_binlister( EEG , 'BDF', fBin, 'ExportEL',
    strcat(pEvent,'elist_erp_',Ss,'_bin.txt'), 'IndexEL', 1, 'SendEL2',
    'EEG&Text', 'Voutput', 'EEG' );
    [ALLEEG EEG CURRENTSET] = pop_newset(ALLEEG, EEG,
n+3,'setname',strcat(Ss,'_elist_bins'),'savenew',strcat(Ss,'_elist_bins'),
    'gui','off');
    EEG = pop_epochbin( EEG , [epoch_pre epoch_post], 'pre');
    [ALLEEG EEG CURRENTSET] = pop_newset(ALLEEG, EEG,
n+4,'setname',strcat(Ss,'_elist_bins_be'),'savenew',strcat(Ss,'_elist_bins
    _be'),'gui','off');
    EEG = pop_artmwppth( EEG , 'Channel', chan, 'Flag', 1, 'Threshold',
    100, 'Twindow', [ -398.4 597.7], 'Windowsize', 200, 'Windowstep', 100 );
    [ALLEEG EEG CURRENTSET] = pop_newset(ALLEEG, EEG,
n+5,'setname',strcat(Ss,'_elist_bins_be_ar'),'savenew',strcat(Ss,'_elist_b
    ins_be_ar'),'gui','off');

    EEG = eeg_checkset( EEG );
    ERP = pop_averager( EEG , 'Criterion', 'good', 'DSindex',1,
    'ExcludeBoundary', 'on', 'SEM', 'on' );
    ERP = pop_savemyerp(ERP, 'erpname', strcat(Ss,'_ERP'), 'filename',
    strcat(Ss,'_ERP.erp'), 'filepath', pERPset_ICA, 'Warning', 'on');

    ALLEEG = pop_delset( ALLEEG, [1:n+5] );
    eeglab redraw;
    erplab redraw;

end

msgbox('Done.');
```

cd(pStart);

APPENDIX D: IRB APPROVAL LETTER



University of Central Florida Institutional Review Board
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Orlando, Florida 32826-3246
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Approval of Human Research

From: **UCF Institutional Review Board #1**
FWA00000351, IRB00001138

To: **Benjamin Sawyer**

Date: **March 14, 2014**

Dear Researcher:

On 3/14/2014, the IRB approved the following human participant research until 3/13/2015 inclusive:

Type of Review:	UCF Initial Review Submission Form
Project Title:	Electrophysiological Measures of Human Error
Investigator:	Benjamin Sawyer
IRB Number:	SBE-14-10161
Funding Agency:	
Grant Title:	
Research ID:	N/A

The scientific merit of the research was considered during the IRB review. The Continuing Review Application must be submitted 30 days prior to the expiration date for studies that were previously expedited, and 60 days prior to the expiration date for research that was previously reviewed at a convened meeting. Do not make changes to the study (i.e., protocol, methodology, consent form, personnel, site, etc.) before obtaining IRB approval. A Modification Form **cannot** be used to extend the approval period of a study. All forms may be completed and submitted online at <https://iris.research.ucf.edu>.

If continuing review approval is not granted before the expiration date of 3/13/2015, approval of this research expires on that date. When you have completed your research, please submit a Study Closure request in iRIS so that IRB records will be accurate.

Use of the approved, stamped consent document(s) is required. The new form supersedes all previous versions, which are now invalid for further use. Only approved investigators (or other approved key study personnel) may solicit consent for research participation. Participants or their representatives must receive a copy of the consent form(s).

In the conduct of this research, you are responsible to follow the requirements of the Investigator Manual.

On behalf of Sophia Dziegielewska, Ph.D., L.C.S.W., UCF IRB Chair, this letter is signed by:

IRB Coordinator

APPENDIX E: DEFENSE ANNOUNCEMENT

Announcing the Final Examination of Mr. Ben D. Sawyer for the degree of Master of Science

Date: July 3, 2014

Time: 9:30 am

Room:

Dissertation Title: APPLIED ERROR RELATED NEGATIVITY:
SINGLE ELECTRODE ELECTROENCEPHALOGRAPHY IN COMPLEX VISUAL STIMULI

Error related negativity (ERN) is a pronounced negative evoked response potential (ERP) that follows a known error. This neural pattern has the potential to communicate user awareness of incorrect actions within milliseconds. While the implications for human-machine interface and augmented cognition are exciting, the ERN has historically been evoked only in the laboratory using complex equipment while presenting simple visual stimuli such as letters and symbols. To effectively harness the applied potential of the ERN, detection must be accomplished in complex environments using simple, preferably single-electrode, EEG systems feasible for integration into field and workplace-ready equipment.

The present project attempted to use static photographs to evoke and successfully detect the ERN in a complex visual search task: motorcycle conspicuity. Drivers regularly fail to see motorcycles, with tragic results. To reproduce the issue in the lab, we presented static pictures of traffic including or not including motorcycles. A standard letter flanker task replicated from a classic ERN study (Gehring, 1993) was run alongside, with both studies requiring a binary response. Results showed that the ERN could be clearly detected in both tasks, even when limiting data to a single electrode in the absence of artifact correction. These results support the feasibility of applied ERN detection in complex visual search in static images. Implications and opportunities will be explored, limitations of the study explained, and future directions explored.

Outline of Studies:

Major: Industrial Engineering: Human Systems & Ergonomics

Educational Career:

B.S., 2010, Colorado State University

Committee in Charge:

Dr. Waldemar Karwowski

Dr. Peter A. Hancock

Dr. Xanthopolis

Approved for Distribution by Dr. Waldemar Karwowski, Committee Chair, on June 18, 2014.

The public is welcome to attend.

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