Enhancing Text-Based Analysis Using Neurophysiological Measures

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Abstract. Intelligence analysts are faced with the demanding task of identifying patterns in large volumes of complex, textual sources and predicting possible outcomes based on perceived patterns. To address this need, the Advanced Neurophysiology for Intelligence Text Analysis (ANITA) system is being developed to provide a real-time analysis system using EEG to monitor analysts' processing of textual data during evidence gathering. Both conscious and unconscious 'interest' are identified by the neurophysiological sensors based on the analyst's mental model, as related to specific sentences, indicating relevance to the analysis goal. By monitoring the evidence gathering process through neurophysiological sensors and implementation of real-time strategies, more accurate and efficient extraction of evidence may be achieved. This paper outlines an experiment that focused on identifying distinct changes in EEG signals that can be used to decipher sentences of relevance versus those of irrelevance to a given proposition.

Keywords: EEG, Reading, Relevancy, Alpha, Theta.

1 Introduction

Textual data mining for intelligence analysts involves deriving high quality information based on relevance, novelty, and distinctiveness from large volumes of complex textual sources. The challenge is in transforming information from these unstructured and massive collections into small and precise chunks suitable for reasoning [1]. Scanning immense quantities of data can be tedious and takes time away from the goal of using this information to draw a conclusion. In fact, analysts often spend the majority of their time finding the correct information associated with their research question, leaving little time for analyzing and projecting possible outcomes.

Given that analysts are a key component in the analytic processing of text sources, it is important to devise tools that can aid them in both top-down and bottom-up analysis processes. There are a multitude of software systems available and/or being developed, designed to search through text sources and focus an information analyst on the nugget of information that is important. However, as stated by Cowell (2006), "the majority of analysts use the same techniques they learned in graduate school,

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including printing out hard copies and highlighting, or copying sources into an electronic Word document and arranging material into the required template." [2] This reliance on these basic processes suggests that the tools provided do not target the needs of the analyst. Thus, a distinct point of opportunity is apparent.

An automated intelligent system could support the data foraging stage [3] of the analysis process, within which analysts search vast amounts of information for chunks of evidence that may be buried in various sources. Analyst bias and/or inattention may enter at this early stage and inhibit the extraction of information so that it is unavailable for future hypothesis generation. In order to avoid problems of early evidence rejection, a real-time closed-loop system could be implemented that monitors text processing and associated decision making (i.e., selecting relevant data to include in analysis) and identifies and tracks subconscious 'interest' in unselected text and potential cases for mitigation (e.g., potentially relevant information discarded based on top-down processing or 'explaining away'). Such a tool would ensure that all relevant information (both supporting and opposing the original generated hypotheses) is taken into account when generating hypotheses during later stages of the information analysis process and potentially reduce the effects of analyst bias and inattention.

A real-time analysis system (ANITA) is being developed that uses EEG to monitor analysts' processing of textual data during evidence gathering. The neurophysiological relevance indicator, based on changes in sub-bands of EEG frequencies, is used to auto-extract text snippets from reviewed documents that are relevant to the current analysis goal as reflected in the analyst's mental model, while still allowing the analyst to also manually extract items they perceive as relevant. By monitoring the evidence gathering processes through neurophysiological sensors and implementation of real-time strategies, a more accurate, faster and less biased extraction of evidence may be achieved.

2 Methods

A software-based test-bed presented a series of text analysis scenarios to participants in which single sentences were presented on digital cue cards. The test-bed allowed for real-time data synchronization of EEG and behavioral responses (e.g., key presses). The time boundaries identifying the participants' mental processing of each individual sentence were determined by behavioral responses, and were used to develop distinct, event-specific neurophysiological indicators to indicate the 'relevance' versus 'irrelevance' of assessed information to a provided proposition (analysis question).

2.1 Participants

A total of 27 healthy subjects (15M/ 12F), with an average age of 26.5 (s.d. 8) participated in the experiment. Eighteen participants completed the experiment at the offices of Design Interactive, Inc. in Oviedo, FL, and 9 participants completed the study at the offices of Advanced Brain Monitoring, Inc. in Carlsbad, CA. Participants were free from a history of neurological, psychiatric and attention deficit/hyperactivity disorders, head trauma, use of psychotropic or illicit drugs, or abnormal sleep patterns and sleep quality. No participants were pregnant, nor did they excessively consume alcohol (>5drinks/day) or caffeine, (>800mg/day). The rationale for use of the screening criteria was to exclude conditions that may affect the EEG. All participants had normal or corrected-to-normal vision.

2.2 Apparatus

All participants wore the wireless B-Alert® EEG Sensor Headset developed by Advanced Brain Monitoring (ABM), a portable system to record EEG signals as well as heart rate. The initial 18 participants wore the 6-channel differential EEG configuration with electrodes located at Fz, Cz, POz, F3, C3, and C4, according to the international 10-20 system [4]. From these electrode sites, five differential channels were collected (Fz-POz, Cz-POz, C3-C4, Fz-C3, and F3-Cz). The subsequent nine participants wore the 9-channel referential configuration with electrodes located at Fz, Cz, POz, F3, F4, C3, C4, P3, P4; linked reference electrodes were located behind each ear on the mastoid bone. The EEG signal was sampled at a frequency of 256 Hz. To capture eye gaze and pupil size, a stand-alone non-intrusive Near-Infrared (NIR) eye-tracking system was used. Eye tracking results are outside the scope of this paper, and will be reported elsewhere.

A PC was used to drive visual presentation of experimental conditions on a flat panel monitor. Stimuli from the PC were time-synched to the EEG data collection system. Investigators used a Java-implemented experimental software-based text analysis environment that captures the data stream from the B-Alert EEG-Headset to record user neurophysiological data. The test-bed allows for real-time data synchronization and creation of log files of EEG and behavioral response data (e.g., key presses).

2.3 Experimental Tasks

Participants were first shown a short background story that provided the analysis scenario and a related one-sentence proposition (analysis question), and were then asked to view a series of sentences to determine their relevance to the provided proposition. The scenarios were constructed based on two case studies created by Dr. Frank Hughes, professor in the Department of Intelligence Research and Analysis at the Joint Military Intelligence College (JMIC) [5, 6]. Based on solutions provided by Dr. Hughes, 10 relevant (R) sentences were identified. For each proposition, ten additional sentences were created that were completely irrelevant (CI) to the analysis question. Finally, 10 sentences were added to each analysis question that were not relevant for the analysis but contained some of the key words found in the proposition or case study topic (referred to as semi-irrelevant, SI). Thus, 30 sentences (10 of each relevance level) were associated with each analysis question/proposition. The test-bed presented sentences from a narrative text, one at a time, on digital cue cards (Fig. 1), randomized in terms of relevance level, and allowed the participant to either rate the level of interest (directly *relevant* or *not relevant* to previously provided proposition) of each item or advance to the next sentence if they were not yet ready to make a decision. Using this approach, physiological indicators of relevance were collected at

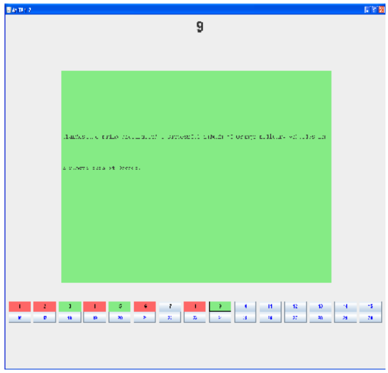

Fig. 1. Sentence-by-Sentence Test-bed Screenshot

the sentence level (i.e., with minimal interference from adjacent textual content), in order to develop template signatures of relevance.

The test-bed presented each sentence as a card on which the participant could click to indicate relevance or irrelevance with regard to the analysis question. Left-clicking a sentence rated it relevant, changing the color of the card and the associated thumbnail at the bottom of the screen to green. Right-clicking a sentence rated it irrelevant, changing the color of the card and the associated thumbnail at the bottom of the screen to red. If a sentence was left unrated, the card and associated thumbnail remained gray, but the number on the thumbnail changed from blue to black to indicate the evidence had been previously viewed. Clicking on previously viewed sentences was possible to change responses if desired, but moving forward was only possible in numerical order (i.e., go to the next unviewed card).

2.4 Analysis Procedure

EEG and test-bed data streams were synchronized in real time. EEG data was analyzed based on participant responses; where clicking on a cue card indicated the beginning of sentence processing, and a relevance decision (participant rating the sentence as either relevant or irrelevant) indicated the end of sentence processing.

To analyze EEG data, identification and decontamination of spikes, amplifier saturation, and environmental artifacts was accomplished using methods described in Berka, 2004 [7]. The EEG signal was then band pass filtered to select for the following frequencies: slow theta (3-5Hz), fast theta (5-7Hz), total theta (3-7Hz), slow alpha (8-10Hz), fast alpha (10-12Hz) and total alpha (8-12Hz). To measure the change in each EEG frequency band related to sentence processing, the rate of change in power of each band was measured for each EEG channel during (a) entire sentence processing, (b) the first second of sentence processing, and (c) the last second of sentence processing (the second preceding a response). The rate of change in power of a given frequency band was calculated by fitting a line through a sequence of data points representing the time evolution of the power of the band over the selected period (whole sentence, the first or last second). The slope of the derived regression line was taken as a measure of the rate of change in power of the analyzed frequency band. A positive linear regression value indicates an increase (synchronization) in a frequency band, while a negative linear regression value reflects a decrease (desynchronization). Only items in which the participant responded correctly the first time a sentence was viewed were included in the current analyses.

3 Results

EEG analysis focused on single trial evaluation of linear trends in theta and alpha activity in order to identify template signatures of processing a relevant item as compared to an irrelevant item. The 6-channel differential configuration (used to collect data from n=18) provides a relatively global view of EEG activity, while the 9-channel referential configuration (n=9) allows for more localized and lateralized analyses.

3.1 Data Collected with 6-Channel Eeg Configuration

The slope of regression lines for each frequency sub-band was calculated for each differential channel during the entire sentence, first second, and last second of processing. An ANOVA revealed a significant effect in slow theta (3-5Hz) for channel CzPOz that distinguishes the slope of the regression line for CI sentences from R and SI , F (2,1455) = 4.535, $p < 0.05$. As seen in Fig. 2, CI sentences had significantly greater synchrony in CzPOz than both the R and SI sentences; however R and SI sentences were not different from each other

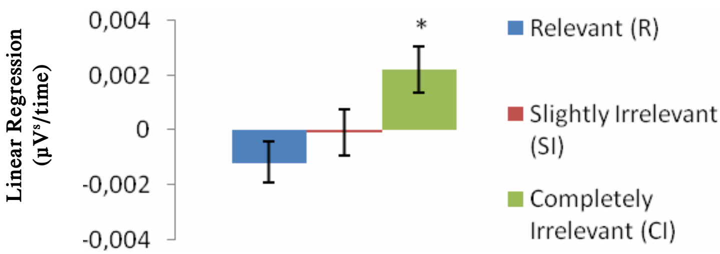

Fig. 2. Slope of regression lines of the Slow Theta band (3-5 Hz) during processing of R, SI, and CI sentences, averaged across 9 participants. Measurement began at time of sentence presentation, and ended at time of keyed response.

CI sentences showed an increase in slow theta power from start of sentence presentation until response. SI sentences showed little change in power, and R sentences showed a negative change in power. Because the differential channels emphasize differences between brain regions, but make changes occurring synchronously in the two regions less visible, the team collected further recordings with the 9-channel monopolar system.

3.2 Data Collected with 9-Channel Eeg Configuration

The 9-channel referential EEG configuration reveals more localized and lateralized patterns. As can be seen in Fig. 3, the fast theta band (5-7 Hz) *increased* in power during the processing of CI sentences more than during the processing of R or SI sentences. The effect was most prominent at the right-hemisphere sites (F4, C4, P4), and at the posterior sites (P3, POz, P4). An ANOVA revealed significant mean differences between fast theta linear regression values of sentences of differing relevancy at electrode sites F4, C4, P4, and POz [F's (2,370) ≥ 3.382, p's ≤ 0.05]. The effect was strongest at POz, F (2,370) = 5.684, $p < 0.01$. Although CI was significantly more synchronized compared to both R and SI categories, R and SI were not significantly different from each other.

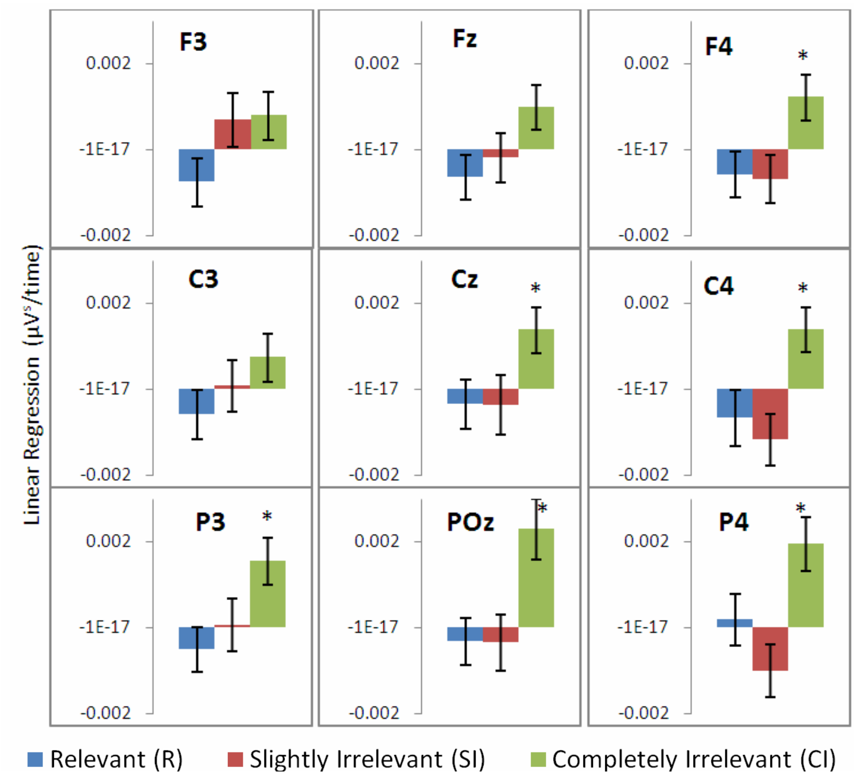

Fig. 3. Slope of regression lines of the Fast Theta band during processing of R, SI, and CI sentences, n=9. Measurement began at time of sentence presentation; ended at keyed response.

Significant effects were also found in the slopes of regression lines of slow alpha (8-10 Hz) during the first second of sentence processing (Fig. 4). ANOVA tests revealed significant differences at channels F4 [F (2,370) = 6.194, $p < 0.01$] and C4 [F (2,370) = 5.218, $p < 0.01$]. Post hoc comparisons found that in channels F4 and C4, the mean linear regression of CI sentences is significantly different from both R and

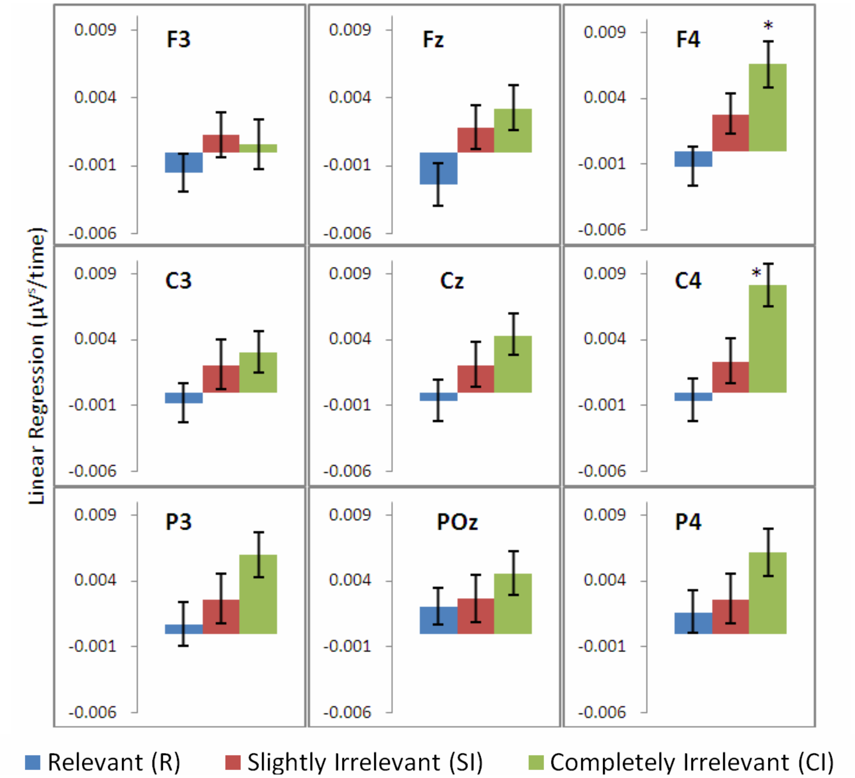

Fig. 4. Slope of regression lines of the Slow Alpha band during processing of R, SI, and CI sentences, n=9. Measurement began at sentence presentation; ended one second later, regardless of when response occurred.

SI sentence types, although R and SI are not different from each other. These findings match the right-lateralized pattern found in fast theta during the entire duration of sentence processing. However, contrary to the fast theta findings, the increase in slow alpha for CI sentences is stronger in the frontal and central regions than in the posterior region.

4 Discussion

Previous research suggests that phasic (event-related) changes in theta and alpha EEG frequencies reflect different types of cognitive processing [8-11]. Theta band synchronization (increase in power) is positively correlated with the encoding of new information, i.e. working memory or episodic memory in particular [12], while alpha band desynchronization (decrease in power) has been suggested as indicative of greater attentional demands [10].

The current findings suggest that the processing of relevant compared to completely irrelevant items causes differential changes in the EEG theta and alpha bands, particularly fast theta (5-7 Hz) and slow alpha (8-10 Hz). The significantly greater increase in power of the fast theta frequency band during the processing of CI sentences over that of R or SI sentences most likely reflects the encoding of novel information [8-11]. CI sentences contain items of random, non-relevant facts that could not be fit into the pre-existing mental model that represents the context of the analysis question. For example, in a scenario regarding suspicious Al-Qaeda activity, a CI sentence read, “Most children prefer cookies to vegetables, unfortunately for their health-conscious parents.” Therefore we propose that the processing of these new, ‘out-of-context’ snippets of information cause the fast theta band to increase in power. The opposite pattern is seen in the processing of relevant items. At all sites other than P4, R sentences produce a decrease in fast theta power. This is most likely due to the matching of this information with the participants’ mental model of the analysis context. SI sentences show a pattern most similar to that of relevant items. The ‘key words’ contained in SI sentences likely cause the participant to immediately try to fit the new piece of information within the context of the analysis question. Therefore the same novel response as seen in the CI sentences is not observed. It should be noted that the similarity of the SI and R EEG patterns indicate a risk of False Alarms with the current assessments, and this issue will be addressed as we continue to develop the system.

The localized patterns of fast theta response are also of interest. The slope of regression lines for CI is most positive in the right-hemisphere sites, and at the posterior sites. The greatest increase in fast theta power for CI is found at POz. The right-hemisphere lateralization may reflect the content of the CI sentences that were often novel, surprising and even humorous in the context of the serious nature of the material deemed relevant to the hypotheses. The decrease in fast theta during the processing of R sentences is most negative in the left hemisphere, and at frontal sites. The F3 electrode site shows the greatest decrease in fast theta for items of relevance. It is possible that the left lateralized theta decrease is related to the perceived match to the mental model, thus reducing the requirement for further analysis of the context or the semantics of the sentence.

Responses in the slow alpha band (8-10 Hz) are similar to those observed for fast theta: slow alpha power increased significantly more for CI sentences than for R or SI sentences. In fact, slow alpha power for R sentences decreased at most electrode sites. Our findings (alpha desynchronization for relevant sentences) are consistent with previous research indicating that demanding and/or relevant tasks are associated with a greater level of alpha desynchronization than less demanding and/or irrelevant tasks [13]. Additionally, significant differences between CI and SI sentences and R sentences are strongest on the right hemisphere at electrode sites F4 and C4. Increased alpha power on the right hemisphere for CI and SI sentences may represent increased attention to a surprising or novel event. Boiten (1991) [11] reported an increase in alpha power in the right hemisphere that occurred when an input was surprising, complex or novel, which in our experiment could represent the presentation of CI (and to an extent SI) sentences.

It is important to note that while our study documents significant differences between CI, SI and R sentences for both fast theta and slow alpha levels, there is still a large amount of inter-individual variance. Fast theta and slow alpha bands were selected to represent 5-7 Hz and 8-10 Hz respectively. However, these bandwidths are arbitrary and optimal theta and alpha ranges may differ between individuals. Age, brain volume, neurological disorders, education, memory performance etc., all influence peak alpha and theta frequencies [12-14]. Our fixed frequency bands may in fact be an intermingling of "true" alpha and theta for each individual, and thus may not accurately isolate the physiological effects of processing R, SI and CI sentences. In other words, our "Fast Theta" may actually represent some slow alpha activity and vice versa. For future studies it may be necessary to define the alpha and theta bands individually for each subject, in a similar manner as that described by Klimesch [13], in order to accurately isolate the neurophysiological components of processing R, SI and CI sentences in single trials.

Though preliminary, these findings highlight the role of task demands and task relevancy in triggering changes in the EEG theta and alpha bands. The data supports the concept of an automated relevancy indicator based on neurophysiological responses. By monitoring the evidence gathering process through neurophysiological sensors and implementation of real-time strategies, more accurate and efficient extraction of evidence may be achieved.

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