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# Quantifying target spotting performances with complex geoscientific imagery using ERP P300 responses ☆

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ABSTRACT

Geoscientific data interpretation is a challenging task, which requires the detection and synthesis of complex patterns within data. As a first step towards better understanding this interpretation process, our research focuses on quantitative monitoring of interpreters' brain responses associated with geoscientific target spotting. This paper presents a method that profiles brain responses using electroencephalography (EEG) to detect P300-like responses that are associated with target spotting for complex geoscientific data. In our experiment, eight interpreters with varying levels of expertise and experience were asked to detect features, which are likely to be copper–gold rich porphyry systems within magnetic geophysical data. The target features appear in noisy background and often have incomplete shape. Magnetic images with targets and without targets were shown to participants using the "oddball" paradigm. Event related potentials were obtained by averaging the EEG epochs across multiple trials and the results show delayed P3 response to the targets, likely due to the complexity of the task. EEG epochs were classified and the results show reliable single trial classification of EEG responses with an average accuracy of 83%. The result demonstrated the usability of the P300-like responses to quantify the geoscientific target spotting performances.



## 1. Introduction

Interpretation of geoscientific data provides the basis for the modelling and understanding of the earth's sub-surface. These data interpretations directly influence decision making at all levels within resources (minerals, oil, gas and geothermal) industries and other research communities (e.g. ground water research). Indirectly, it will also impact the decisions of government agencies that draw upon these interpretations. Whilst these decisions have significant economic and social implications, geoscientific data interpretations are highly subjective and often inconsistent (Bond et al., 2007; Rankey and Mitchell, 2003; Sivarajah et al., 2013) as they heavily rely on interpreters' ability to recognise and synthesise patterns within data.

Geophysics data specifically represent the earth's physical properties. For example, magnetic data are collected through airborne and ground surveys, and when gridded, they represent spatial variations associated with magnetic susceptibility of rocks in the earth's crust. These variations are usually represented using colour displays as shown in Fig. 1. The interpretation of such geophysics data is based on pattern recognition – identifying geophysical signatures of geological features within data, which are often associated with localised anomalous characteristics and discontinuities, as well as the spatial relationships between features.

Quantitative monitoring of the human data interactions during the interpretation process can provide invaluable information about the impact of different data display methods on the interpretation outcome and helps to identify the effective interpretation practices and strategies used. While it can be argued that user behavioural responses such as button clicks can be captured easily and reliably, the button click reaction times comprise of a number of different cognitive processes and it is difficult to identify the process that attributed to the variation in reaction times (Luck, 2005). In contrast, the neurological responses provide continuous measure during target spotting task (Luck, 2005) and they are known to have lower latency and lower variation in latency than behavioural responses, which has led to the use of neurological responses for practical applications (Huang et al., 2011).

This is the first study of its kind which focuses on monitoring the neurological responses of magnetic data interpreters to

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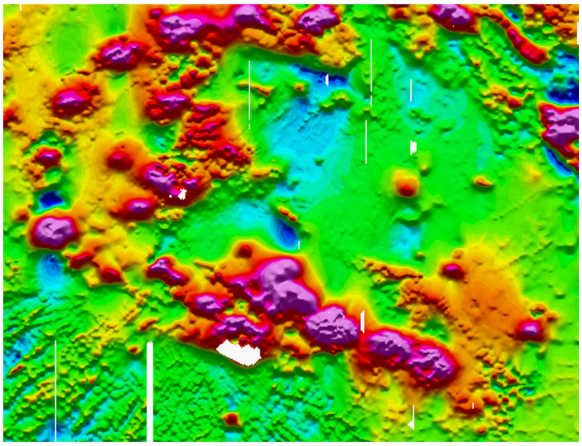

Fig. 1. Magnetic data with multiple porphyry style mineralisation. Courtesy of Barrick Gold of Australia Ltd.

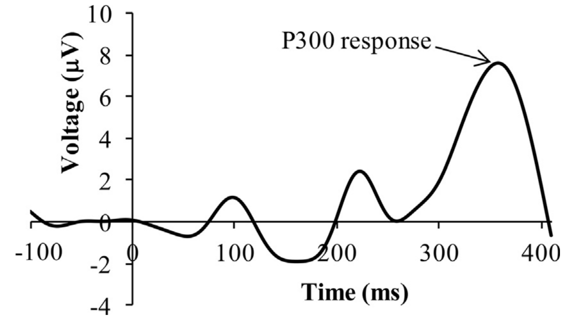


**Fig. 2.** ERP signal obtained for a simple target detection task by averaging across 100 target trials; 0 ms indicates the onset of the stimulus. In this experiment, red and green boxes were shown and the participant was asked to silently count the number of green boxes.

identify their target detection for complex geological features within magnetic geophysical data. This is achieved by identifying event related potential (ERP) P300-like responses that are associated with target detection from electroencephalography (EEG) of interpreters.

P300 signals are widely researched in the areas of brain computer interfaces (BCI) (Birbaumer and Cohen, 2007) and in clinical studies (Duncan et al., 2009; Polich and Herbst, 2000). P300 responses are normally elicited using the "oddball paradigm", where infrequent target stimuli ("oddball") and frequent standard stimuli are presented in a random sequence. In these exercises the task is to identify the infrequent target stimuli either by mentally acknowledging or by pressing a button. The process of stimulus evaluation, especially to a successful response to the target stimulus will elicit the requisite P300 response.

The P300 signal is mainly characterised by its amplitude, latency and the scalp distribution. The P300 signal amplitude and latency are mainly affected by biological factors and experiment modality. Some of these factors include gender, seasonal cycles (Deldin et al., 1994), exercise (Yagi et al., 1999), age (Fjell and Walhovd, 2001), arousal level (Polich and Kok, 1995), complexity of the task (Caryl and Harper, 1996; Luo and Sajda, 2009; Ting et al., 2011), inter-stimulus interval (ISI) (Polich, 1990), target to target interval (Gonsalvez and Polich, 2002), target probability (Polich, 1990) and image presentation sequence. The amplitude of the P300 response is defined as the maximum voltage within the time window, with respect to the pre-stimulus mean baseline voltage. The P300 amplitude is maximal in the midline region and decreases from the parietal region to the frontal region (Johnson Jr., 1993). This scalp distribution changes significantly with age (significant reduction in P300 response in the parietal region for older subjects) (Smith et al., 1980). It is very difficult to identify the P300 response (which is on the order of few microvolts) from raw EEG signals due to the strong background EEG activity (which is on the order of tens of microvolts). Conventionally, the P300 response is obtained by averaging the EEG traces across multiple trials (Fig. 2). This process, termed grand averaging, eliminates the background EEG activity and channel noise and enhances the P300 response. Grand averaging is not preferred in many cases since it is not possible to identify the trial by trial variations in ERP (amplitude and latency variations) and it requires a large number of samples.

Analysis of variations in brain responses during target spotting requires the identification of the P300 responses from a single trial or few trials. However, the variations in the P300 response (amplitude, latency and scalp distribution) and the difficulty in removing the background EEG activity from the raw EEG makes the detection of P300-like signal from a single trial sample more complicated and challenging. There have been different approaches proposed by the researchers for the classification of the signals with or without P300 responses. Support vector machine (SVM) (Thulasidas et al., 2006) and linear discriminant analysis (LDA) (Hoffmann et al., 2008) are widely used techniques in the field of BCI.

Conventionally, detection of P300 responses is applied to simple classification tasks (e.g. identification of shapes, colours, letters etc.). However, there have been few studies that used more complex tasks. For example, P300-like responses were used for the detection of people (Gerson et al., 2006) within images, where task complexities are associated with variations in position, scale and pose of the people. A study by Luo and Sajda (2009) used P300 and behavioural responses to prioritise the images (by moving the target images in front of an image stack). In other studies (Huang et al., 2011; Mathan et al., 2008) ERP responses were used to search for visual targets within satellite images.

In our study, P300 responses were used to identify the detection of magnetic anomaly patterns of likely copper–gold rich porphyry systems. A typical footprint for these mineral systems appears within magnetic data as an elevated sub-circular feature with surrounding annular lows (Holden et al., 2011) (see Fig. 3).

Magnetic porphyry target spotting is considered as a highly complex task since the patterns are contrasted with noisy background and vary significantly in shape and size within data. These are due to complex geological background and data sampling noise. Fig. 4 shows some of the target (top row) and non-target (bottom row) images used for the experiment.

In this paper, Section 2 explains our methodology including the experiment setup, data acquisition and pre-processing, classification and the electrode selection. Section 3 presents the results and discussion which includes the ERP analysis and the classification performance. Finally in Section 4 the summary and on-going research are presented.

## 2. Methodology

### 2.1. Experiment setup

Eight healthy participants (five females and three males with ages ranging between 22 and 34) with varying levels of experience and expertise participated in this study. The small number of participants was due to the fact that participants require some experience or knowledge about porphyry footprints within magnetic data. This is a specialized field and we only had an access to a limited number of potential candidates. All of our participants are