

# Image quality assessment through brain signal analysis

H. Cecotti and B. Gardiner

*Intelligent Systems Research Centre, Ulster University, Londonderry, UK.*

## Abstract

The presence of noise in images has a key impact on the difficulty of visual target detection tasks. In this study, we propose to explore the potential of brain signal analysis for discriminating the level of noise in a sequence of images. The data were recorded using a magnetoencephalography from four healthy individuals during a rapid serial visual presentation task in four conditions corresponding to four different levels of noise in the images. The results indicate a clear link between behavioural performance, single-trial detection, and noise level.

**Keywords:** Noise estimation, Brain-Machine Interface, Magnetoencephalography.

## 1 Introduction

Brain-Machine Interface (BMI) systems have been mainly used as a new means of communication for severely disabled people, and for rehabilitation [Millán et al., 2010]. BMIs based on the detection of event-related potentials (ERPs) typically require subjects to pay attention to a specific sequence of stimuli in order to produce a robust and detectable neural response. In a Rapid Serial Visual Presentation (RSVP), a rapid sequence of images are presented sequentially to subjects in the same location on a screen. The stream of images contains different types of visual stimuli, which can be classified as targets or non-targets [Pohlmeyer et al., 2011]. In this paper, we propose to investigate the use of brain signal analysis with magnetoencephalography for estimating the effect of the noise in images during a target detection task, and its relationship with behavioural performance.

## 2 Methods

Four healthy volunteer subjects (s1-s4) participated in the study. Each participant provided written informed consent, reported normal or corrected-to-normal vision, and no history of neurological problems. The experimental protocol was reviewed by the Faculty Ethics Filter Committee of Ulster University, and was in accordance with the Helsinki Declaration of 1975, as revised in 2000. Participants to the experiment had to perform a rapid serial visual presentation task (speed at 2 Hz) where different graylevel images of people (men and women) were presented on the screen. The task was to press a button each time an image of a woman was presented on the screen. Four sessions were recorded. Each session corresponded to a different level of noise in the background of the images (L1: low noise, to L4: high noise). The noise was generated through a uniformly distributed random numbers (see Fig. 1). The data was recorded with an Elekta Neuromag 306-channel MEG system at the Intelligent Systems Research Centre (ISRC), Ulster University, Londonderry, UK. The MEG signal was recorded with a sampling rate of 1 kHz using 204 planar gradiometers and 102 magnetometers, based on thin-film technology. Five head position indicator (HPI) coils were placed on the head to determine how close the head is to the sensors that are collecting the signal. The analysis of the brain response evoked by the presentation of a target (i.e., the image of a woman) was obtained by the area under the ROC curve of the single-trial classification of the different images (i.e., men vs. women). The signal was first bandpassed

Table 1: Behavioural performance and Area under the curve (AUC) for single-trial performance for the four conditions (L1, L2, L3 and L4). Each couple represents the hit rate and the precision of the response.

	Behavioural				Single-trial			
	L1	L2	L3	L4	L1	L2	L3	L4
s1	98.33/96.72	100.0/95.24	100.0/98.36	95.00/95.00	0.964 ± 0.062	0.983 ± 0.029	0.984 ± 0.025	0.910 ± 0.090
s2	98.33/98.33	96.67/95.08	81.36/87.27	45.00/87.10	0.941 ± 0.090	0.981 ± 0.019	0.888 ± 0.077	0.793 ± 0.099
s3	100.0/64.368	90.00/81.818	78.33/92.157	68.33/95.35	0.991 ± 0.017	0.912 ± 0.067	0.943 ± 0.084	0.827 ± 0.074
s4	82.76/34.783	68.52/28.682	50.85/28.302	30.91/20.99	0.856 ± 0.077	0.814 ± 0.138	0.660 ± 0.160	0.592 ± 0.156
Mean	94.86/73.55	88.80/75.21	77.63/76.52	59.81/74.61	0.938	0.922	0.869	0.781
SD	8.10/30.21	14.14/31.65	20.27/32.47	28.08/35.95	0.059	0.080	0.145	0.135

between 0.1 and 10.40 Hz, then downsampled to 31.25 Hz. After spatial filtering, the sets of features from each evoked response, considering a time segment of 800 ms post stimulus, were classified with a stepwise linear discriminant analysis classifier.

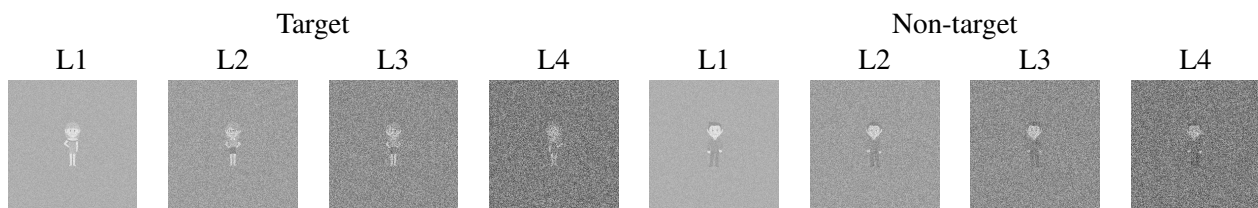


Figure 1: Examples of images for the different levels of noise.

### 3 Results

The results corresponding to the behavioural response and the AUC are given in Table 1. The mean hit rate decreases in relation to the increase of the difficulty of the task, from 94.86% to 59.81%, however the precision seems to not be changed by the level of noise. The mean AUC across subjects decreases in relation to the noise level in the condition, from 0.938 with the condition L1 that has the less noise, to 0.781 for the condition L4 that has the noisiest stimuli.

### 4 Conclusion

The level of noise in an image can have different impacts on the observers. Image quality assessment through brain signal analysis can provide a novel way to analyse the level of noise in images and describe to what extent it can impact the performance of target detection tasks. Future works will include the addition of more subjects to demonstrate the interest of the approach in relation to common image processing techniques.

### References

[Millán et al., 2010] Millán, J. d. R., Rupp, R., Müller-Putz, G. R., Murray-Smith, R., Giugliemma, C., Tangermann, M., Vidaurre, C., Cincotti, F., Kübler, A., Leeb, R., Neuper, C., Müller, K.-R., and Mattia, D. (2010). Combining brain-computer interfaces and assistive technologies: state-of-the-art and challenges. *Frontiers in Neuroscience*, 4(161):1–15.

[Pohlmeyer et al., 2011] Pohlmeyer, E. A., Wang, J., Jangraw, D. C., Lou, B., Chang, S., and Sajda, P. (2011). Closing the loop in cortically-coupled computer vision: a brain-computer interface for searching image databases. *J. Neural Eng.*, 8:036025.