High Throughput Screening for Mammography using a Human-Computer Interface with Rapid Serial Visual Presentation (RSVP)

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Abstract

The steady rise of the breast cancer screening population, coupled with data expansion produced by new digital screening technologies (tomosynthesis/CT) motivates the development of new, more efficient image screening processes. Rapid Serial Visual Presentation (RSVP) is a new fast-content recognition approach which uses electroencephalography to record brain activity elicited by fast bursts of image data. These brain responses are then subjected to machine classification methods to reveal the expert's 'reflex' response to classify images according to their presence or absence of particular targets. The benefit of this method is that images can be presented at high temporal rates (~10 per second), faster than that required for fully conscious detection, facilitating a high throughput of image (screening) material. In the present paper we present the first application of RSVP to medical image data, and demonstrate how cortically coupled computer vision can be successfully applied to breast cancer screening. Whilst prior RSVP work has utilised multi-channel approaches, we also present the first RSVP results demonstrating discriminatory response on a single electrode with a ROC area under the curve of 0.62- 0.86 using a simple Fisher discriminator for classification. This increases to 0.75 – 0.94 when multiple electrodes are used in combination.

Keywords: Electroencephalography (EEG), Brain-Computer Interface (BCI), Single-Trial Analysis, Rapid Serial Visual Presentation (RSVP), Breast Cancer, Mammography.

1. Introduction

National breast screening programmes face growing demands from the increasing size of screening populations, the larger data sets produced by the next generation of digital imaging technologies (tomosynthesis and breast CT), and within many Western countries, financial pressures to provide greater throughput at reduced costs. In the absence of substantial increases in funding, there is a need to produce faster methods for screening image data and to reduce the timescales needed to train expert radiological observers. In order to respond to these challenges, this work presents the first attempt to harness brain-computer interface (BCI) techniques involving Rapid Serial Visual Presentation (RSVP) in the medical domain. This approach has proved highly successful in analysing large quantities of image data at high rates of throughput in the military arena¹⁻⁶ with area under the receiver operating characteristics (ROC) curve (AUC) statistics of up to ~0.9. These techniques take advantage of the advanced visual processing capabilities of the human brain by measuring the expert's semi-conscious response, known as the P300, whilst viewing image stimuli in rapid succession (~10 Hz), wherein the rate of image presentation is faster than that needed for conscious discrimination. Typically the neural response to 'target' images differs compared to 'non-target' images, allowing the detection of target image presence from EEG data through machine learning methods. BCI techniques using RSVP may therefore offer great potential for high throughput medical screening applications, and might also be developed for rapid feedback during training of expert observers. This work presents the first proof-of-concept study to examine the use of RSVP in a medical domain, and has not been published or presented elsewhere before.

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2. Methodology

In the current study we tested a BCI system with two distinct image datasets: (a) mammogram targets containing a single biopsy-proven lesion or simulated lesion with realistic appearance¹⁰ against non-targets consisting of lesion-free background mammography segments (Fig.1a), and for comparison (b) a set of green and red stimuli set against a set of random blobs as non-targets (Fig.1b). All mammography screening image data were derived from the Optimam image database⁹.

These two experiments allowed us to contrast BCI performance with different stimulus types. In both experiments a series of images was rapidly presented to the observer in 3-second bursts, consisting of 30 images, each presented for 100ms. Image data were pre-designated as non-target or target although this information was not presented to participants.

Each experiment was split into two phases. Firstly, a classifier training phase, consisting of 608 image bursts, and a classifier testing phase of a further 608 bursts in which different exemplars of the same target and non-target images were presented to the observer (see Figure 1c). In each phase half the bursts were randomly comprised of entirely non-targets (i.e. non-target bursts), and the other half contained a single target image at a random position within the burst, located between the 4th to the 27th image (i.e. target bursts). Sixteen unique target images were used in each phase (training/testing) of each experiment. In the mammogram experiment, the target images were all mammogram segments containing a mass in the centre of the image, whereas in the comparative colour experiment red squares were used for training stimuli and green squares for testing. A set of 150 unique non-target images were used in each phase. All images were 5 cm² in size and presented against a grey global background. EEG data were recorded in DC mode with a sampling rate of 1kHz from 64 standard electrode sites placed according to the 10-20 system⁷ as shown in Fig 3. Impedances were below 5 k Ω , and a 50Hz notch filter applied during recording. Eye movements were monitored with bipolar horizontal and vertical electrooculogram electrodes, and an average reference used for analysis.

First a high cut-off filter of 40Hz was applied to the raw EEG to remove muscle artefacts. The filtered data were then segmented into 1100ms epochs (-100ms to +1000ms) relative to the onset of target/non-target presentation. Non-target segments were taken relative to one image from each non-target burst selected at random, excluding the first and last three images of each burst. All segments were then baseline corrected and any that contained eye or muscle artefacts were removed. ROC curves may then be produced via perturbation of the bias value of the decision hyper-plane in this initial trial within the context of a Fisher classification space.

3. Results & Discussion

Fig. 2 displays the average EEG activity for targets and non-targets at electrodes C1, Cz, C2, P1, Pz, P2, O1, Oz and O2 for the two observers in the colour experiment and another four volunteers in the mammogram experiment. The potential generated by target stimuli appears similar to the P300 wave⁸, a large positive deflection largest at central-posterior sites. This potential is absent in non-target trials. The larger difference in amplitude between targets and non-targets for mammogram images compared to colour images could be due to the difference in semantic associations between the content of the two datasets, as the P300 potential has been shown to be sensitive to semantic inference associated with various stimuli⁸. Using Fisher discriminant analysis we obtained ROC AUCs of 0.75 and 0.78 for the two participants tested in the colour experiment. In the mammogram experiment we found ROC AUCs of 0.85, 0.80, 0.94 and 0.88 for the four participants tested in the mammogram experiment.

4. Conclusions & Further Work

The current study demonstrates that BCI technology can successfully detect the presence of well-delineated mass targets against normal mammography architecture with a very high degree of accuracy. These results suggest that BCI technology might eventually be developed to efficiently search through large quantities of mammogram screening data. This also suggests that only a small number of electrodes may be needed, facilitating the use of low cost EEG technology and rapid set-up. Such an approach might also find application in ‘tuning’ the responses of expert observers during clinical training.

The current pilot study was deliberately confined to well-delineated masses, in order to test for an RSVP response and compare this to a strong colour-based visual response. Although differences in signal potentials between the two datasets are evident, the ROC AUC suggests little difference in performance, suggesting that the classification process has performed robustly with respect to differences in EEG input data. This motivates further work in developing more challenging datasets with a larger cohort of expert volunteers. This trial is currently underway and will be reported on in the final paper. We will also report on analyses in optimising the number of electrodes, and in extending the analysis to include a comparison with using support vector machines for decoding a larger range of input image data.

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Figure 1. [A] Exemplar target/non-target (lesion/non-lesion) mammographic image segment. [B] Exemplar target/non-target (colour / random blob) colour image segment. [C] The recording set-up used to acquire EEG data whilst an observer undergoes an RSVP trial. The image is presented at the centre of the screen. Images are presented at a small size (5 cm²) in order to minimize eye movements.

Figure 2. The averaged (mean) EEG activity at electrode sites C1, Cz, C2, P1, Pz, P2, O1, Oz and O2 in response to target (solid lines) and non-target stimuli (dashed lines) for and colour stimuli (top) and mammogram stimuli (bottom). Different colours refer to different participants who took part in the study. The standard deviation for each plot was approximately 30 % of the mean amplitude values.

Figure 3. A, B: Difference topographies for the averaged EEG data, calculated by subtracting the activity evoked by target stimuli from the activity in response to non-target stimuli in a time range of 300 – 800 ms post stimulus onset. C: Scalp map of standard electrode array placement, the electrodes used to record EEG are highlighted in green. The electrodes where the maximal difference between targets and non-targets was found are highlighted in blue. D: Voltage scale used to plot difference topographies.

Figure 4. ROC curves from two different volunteers in the colour experiment and four in the mammogram experiment using Fisher Discriminant analysis, AUC values are included in the figure legend.

A

image type	participant	best single electrode	best single electrode AUC	multi-electrode AUC
colour	p01	Oz	0.62	0.75
colour	p03	P04	0.78	0.78
mammogram	p04	CPz	0.84	0.85
mammogram	p05	P3	0.71	0.80
mammogram	p06	TP9	0.82	0.94
mammogram	p07	PO7	0.86	0.88

B

Figure 5. A: The electrode positions across participants of the single best electrode for image classification and their ROC AUC values as well as multi-electrode ROC AUCs for the group of electrodes that produced the best classification performance on the validation data. B: Positions of electrodes on the scalp according to the 10-20 system.

participant	Fp1	Fpz	Fp2	AF7	AF3	AFz	AF4	AF8	F7	F5	F3	F1	Fz	F2	F4	F6	F8	FT7	FC5	FC1	FCz	FC2	FC4	FC6	FT8	FT10	T7	C5	C3	C1	Cz	C2	C4	C6	T8	
p01 colour																																				
p03 colour	7	5	10	17	8	14	18	29			24	22	21																							
p04 mammogram				11																																
p05 mammogram			10	15		17	12	11								3	7							9	13											
p06 mammogram																		12	14					22												
p07 mammogram	19	14			11	13				22	18	15	12	16							23	20														
participant	TP9	TP7	CP5	CP3	CP1	CPz	CP2	CP4	CP6	TP8	TP10	P7	P5	P3	P1	Pz	P2	P4	P6	P8	PO7	PO3	POz	PO4	PO8	O1	Oz	O2								
p01 colour								7	3						6		9						4		5		1	2								
p03 colour								16	20	27	26				23	25	9	11	2	4	15		13	3	1	6	28	19	12							
p04 mammogram					10	1	2	8							12	5	9																			
p05 mammogram					14									16	1	2	4	8				5	6													
p06 mammogram	1	7			18	15	5	2	13	17	4				16	11	9	10	20	23			19													
p07 mammogram										9	2	8							17	5	1	7		21	3	4	10	6								

Figure 6. the electrode positions, highlighted in red, which produced the best classification using the multi-electrode classification method. The data are plotted in successive rows of electrodes from the front of the head to the back, where green bars mark the beginning of a new row. Highlighted electrodes are numbered based on their classification performance when considered in isolation, with 1 referring to the best classification performance.