

# The brain as target image detector: the role of image category and presentation time

Anne-Marie Brouwer<sup>1</sup>, Jan B.F. van Erp<sup>1</sup>, Bart Kappé<sup>1</sup> and Anne E. Urai<sup>1,2</sup>

<sup>1</sup> TNO Human Factors, Kampweg 5, 3769 ZG Soesterberg, The Netherlands

<sup>2</sup> University College Utrecht, P/O. Box 80145, 3508 TC Utrecht, The Netherlands  
{anne-marie.brouwer, jan.vanerp}@tno.nl, bart.kappe@xs4all.nl, anne.urai@gmail.com

**Abstract.** The brain can be very proficient in classifying images that are hard for computer algorithms to deal with. Previous studies show that EEG can contribute to sorting shortly presented images in targets and non-targets. We examine how EEG and classification performance are affected by image presentation time and the kind of target: humans (a familiar category) or kangaroos (unfamiliar). Humans are much easier detected as indicated by behavioral data, EEG and classifier performance. Presentation of humans is reflected in the EEG even if observers were attending to kangaroos. In general, 50ms presentation time decreased markers of detection compared to 100ms.

## 1 Introduction

Recent technological developments have lowered the costs of gathering and storing high volumes of images. Enormous amounts of images are digitally available in fields ranging from internet search engines to security cameras and satellite streams. Finding an image of interest requires a system of image triage through which only a subset of images is selected for further visual inspection. However, in some cases, automatic analysis of image contents is difficult because computer vision systems lack the sensitivity, specificity and generalization skills needed for efficient image triage. The human brain, on the other hand, can be extremely apt at image classification and can recognize target images quickly and precisely. Participants in a study by Thorpe et al. [1] had to indicate whether a previously unseen photograph, flashed for just 20 ms, contained an animal or not by releasing or holding a button. Already 150 ms after stimulus onset EEG (electroencephalography) signals for target and non-targets started to differ reliably– a frontal negativity developed for non-target images. Similar results were found by Goffaux et al. [2] where observers had to categorize types of landscape. An image classification BCI (Brain Computer Interface) may provide us access to these very powerful brain mechanisms to interpret images and enable observers to reliably classify images at very high speeds.

Several groups have already implemented image classification BCIs, usually based on a particular event related potential (ERP) present in the EEG, called the P3. The P3 is a positive peak in EEG that occurs approximately 300 ms after a target stimulus (a stimulus that the observer is attending to) is presented [3]. Sajda, Parra, Gerson and

colleagues [4-7] presented their observers with sequences of 50 to 100 images of natural scenes, where each image was presented for 100 ms. Observers had to press or release a button right after detecting a natural scene containing people, or after the sequence had ended. Each sequence contained 1 or 2 of these targets. They found that both EEG and button presses contributed to correctly ordering images from more to less likely to be a target. Similarly, Huang, Pavel, and colleagues [8-10] presented sequences of 50 satellite images, where each image was presented for 60 to 200 ms. Targets were man-made objects such as ships, oil storage depots or golf courses. Half of the sequences contained 1 target, the other half none. Observers pressed a button directly after detecting the target or after the sequence had ended. They also found that both EEG and button presses contributed to correct classification.

The previous studies show the feasibility of image classification BCIs. In our research we want to build a BCI to classify shortly presented images, but in line with virtually all real-life image classification situations and (partly) in contrast to the previous studies, observers are unaware of the number of targets. This may be an important factor. If observers know that one target will be present, they may quit paying attention after target detection, or, if they did not see the target yet, anticipate it towards the end of the sequence. Also note that few compared to many targets may enhance P3 size [3]. We here focus on the role of the image category of the target, or target type, within a fixed collection of context images. It may not be possible to generalize results of the studies mentioned before when other types of targets (within other types of contexts) are searched. When e.g. looking for a human in a natural environment, the observers' expertise of human appearances can support performance. In this study we compare brain responses to attended or unattended images of humans to those of kangaroos. Thus, we compare between groups of images that are always the same, the only difference being which group attention is focused on. Since our European observers are more familiar with recognizing humans than kangaroos, detecting humans amongst other animals may be easier than detecting kangaroos and correspondingly, produce stronger P3s. In addition, specific ERP components that are associated with faces or other highly familiar stimuli such as the N170 may be present [11-13]. If so, and if in a particular image classification case the target of interest corresponds to such a familiar stimulus, these could be used in classifiers. Together with the effect of target type, we examine the effect of presentation time (100 or 50 ms). Interactions between target type and presentation time may occur, such as kangaroo images eliciting P3s when they are presented long, but not when they are presented for a short time. Besides examining the ERPs directly, we also look for effects of target type and presentation time on classifier performance.

## 2 Methods

### 2.1 Participants

Twenty observers (10 men and 10 women) participated in the experiment. Their mean age was 38.9 years (SD= 16.6). As verified by a questionnaire, all participants were

neurologically healthy and had normal or corrected to normal vision. Participants gave their informed consent before the start of the experiment and were given a monetary reward for their time.

## **2.2 Stimuli**

All images were obtained from the Caltech-256 Object Category Dataset [14]. Images that were not clearly recognizable or had written text on them were excluded from the experiment. Only images in portrait format were used. In total 952 images were selected for use in the experiment, including 55 images of humans and 40 images of kangaroos. Images were normalized in size and in luminance using Matlab. Their size was reduced to 280 x 420 pixels. They were then transformed to the CIELAB Lab color space, where the average and standard deviation of luminance (L-component) were set to 30 and 25.2 respectively. Then, the images were transformed back to sRGB. Custom built software presented sequence of 60 images on a Dell 1907 LCD flat panel display (19 inch, 60 Hz, 1280 x 1024 pixels) at a viewing distance of about 70 cm. Each image was presented for 50 or 100 ms. In between image sequences, a white screen was shown for 1s followed by a white screen with a black fixation cross that was presented for a randomly chosen interval between 0.8 and 1.2 s.

## **2.3 Design**

For each presentation time (50 and 100 ms), each participant completed 10 runs with target type human and 10 runs with target type kangaroo. Each run consisted of 5 image sequences of 60 images each. Sequences could contain between 0 and 4 targets as well as 0 to 4 non-targets. Non-targets were images of kangaroos for the human target type and images of humans for the kangaroo target type. The resulting 25 combinations of target and non-target numbers were randomly distributed across runs and occurred twice within each of the four conditions (four combinations of target type and presentation time). Image sequences were generated taking into account the following constraints. There were always at least six fillers (images of animals that were neither humans nor kangaroos) between targets and non-targets. Targets and non-targets were never among the first or last 4 images. Within one run, images were never shown more than once. Half of the participants first performed the task at 100 ms/image and then at 50 ms/image, the other half the other way around. The order of target types was counterbalanced across participants. The 10 runs were order balanced using a latin square.

## **2.4 Task and procedure**

Participants were seated comfortably in front of a monitor in a shielded room. Before the experiment started, the complete procedure was explained to the participants. The participants were asked to blink as little as possible and to limit any other movements during image sequences. The task was to concentrate on target images and count the

number of times they were presented in an image sequence. The participants were informed of the nature of the targets (either humans or kangaroos) before every new target type. Every time that the target type and/or presentation speed changed, participants were given a training run to get used to the target type they had to detect and the speed of presentation. Participants entered the number of targets they had counted on a keypad during a time window of about 2s in between image sequences.

## 2.5 EEG recording

EEG activity was recorded at the Fpz, Fz, Fp1, Fp2, Cz, Pz, P3, P4, Oz, POz, PO7 and PO8 electrode sites of the 10-20 system [15] using Au electrodes mounted in an EEG cap (g.tec medical engineering GmbH). A ground electrode was attached to the scalp at the AFz electrode site. The EEG electrodes were referenced to linked mastoid electrodes. The impedance of each electrode was below 5 k $\Omega$ . Data were sampled with a frequency of 256 Hz and filtered before storage by a 0.1 Hz high pass-, a 60 Hz low pass- and a 50 Hz notch filter (USB Biosignal Amplifier, g.tec medical engineering GmbH). Additional electrodes (Kendall Neonatal ECG electrodes from Tyco Healthcare Deutschland GmbH) were positioned above and below the left eye, and close to the outer canthi of the eyes to monitor EOG (electro-oculography - blinks and eye movements). EOG electrodes were referenced to each other. Data recording was controlled by a combination of custom-built software and Matlab/Simulink tools.

## 2.6 Analysis

**EEG Signal Analysis.** The EEG/EOG data were processed using Brain Vision Analyzer 2.0 (BrainProducts). We started out with data from the interval between the first fixation cross to 2s after the last image of the run. All EEG channels were automatically inspected for bad episodes, using standard settings of Brain Vision Analyzer. This identified most of the eye blinks, which mainly occurred in between image sequences in accordance with experimental instructions. Bad episodes were excluded from the analysis. The remaining data were manually inspected for further irregularities to remove all eye blinks and other artifacts from the data. EOG data were not further used. Segments were then selected starting at 200 ms before image onset and 600 ms after image onset. Since there were many more filler segments than target and non-target segments, only every fourth of the filler segments was used. Segments were baseline corrected using an interval of 200 ms to 0 ms before stimulus onset. Averages were calculated for targets, non-targets and fillers per participant and condition. Visual inspection of these averages revealed that the N170 component appeared between 100 and 350 ms after stimulus onset. The P3 component appeared between 300 and 550 ms after stimulus onset. The area in  $\mu\text{V}\cdot\text{ms}$  within these timeframes was taken as a measure for the magnitude of the respective components.

For further P3 analysis, we selected data recorded at Pz because Pz is known to be a good location for measuring P3 [16] and these indeed distinguished well between targets and non-targets. More specifically, all electrodes distinguish well between targets and non-targets except for Fpz, Fp1 and Fp2. At these locations, paired t-tests

on P3s per participant, electrode, targets and non-targets do not indicate significant differences between targets and non-targets ( $p$ -values  $> 0.11$ ). For all other electrodes,  $p$ -values are  $< 0.01$ .

For further N170 analysis, we selected data from P4 since in our study, these appeared to distinguish best between images of humans and kangaroos. When target type is human, the N170 is larger for targets (human) than non-targets (kangaroo) at all electrodes (paired  $t$ -tests on N170 per participant, electrode, target and non-target resulted in  $p$ -values  $< 0.03$ ). When target type is kangaroo, the N170 tends to be larger for non-targets (human) than targets (kangaroo) at all electrodes; significantly so for Pz ( $t_{19}=2.60$ ,  $p=0.02$ ), P3 ( $t_{19}=2.75$ ,  $p=0.01$ ), P4 ( $t_{19}=2.88$ ,  $p<0.01$ ) and PO7 ( $t_{19}=2.21$ ,  $p=0.04$ ).

We computed dP3 as the difference between the P3 elicited by targets and the P3 elicited by non-targets, separately for participants and conditions. A positive dP3 reflects a larger P3 for targets than for non-targets. This is the part of the P3 that we are interested in and that we want to check for sensitivity to target type and presentation time. Similarly, we computed dN170 as the difference between the N170 elicited by human images and the N170 elicited by kangaroo images, separately for participants and conditions. A positive dN170 reflects a larger N170 for human images than for kangaroo images.

**Classification.** We performed a cross-validation using a type of discriminant analysis as described in [17] which, in short, works as follows. EEG data was segmented in 1 sec epochs, starting at stimulus onset. EEG segments were normalized such that their average value was zero. For each participant and each run, segments following target stimuli were averaged across all electrodes. Segments following filler and non-target stimuli were averaged likewise. This was done using all sequences minus one. The difference between the two average responses (target minus filler/non-target) or ‘template’ was multiplied by single segments from the sequence left out when constructing the template. If for a certain segment, the mean result exceeded a certain threshold, it was interpreted as a response to a target, and otherwise as a response to a filler/non-target. The threshold was chosen such that we had equal percentages of target responses that were wrongly classified as filler/non-target responses and filler/non-target responses wrongly classified as target responses. This prevented the problem of judging a classifier that labels all segments as filler/non-targets as a good classifier since it only makes an error about twice in a sequence. The percentage of wrongly identified responses that we get when applying the threshold as described above is termed Equal Error Rate (EER). It is a measure of classification performance, where an EER of 50 means that a target or a non-target/filler has a 50% chance of not being identified as such, thus reflecting chance performance, and an EER of 0 means perfect performance.

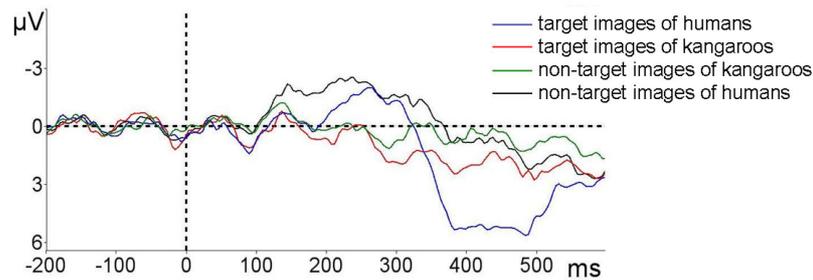
**Statistical analysis.** Repeated measures ANOVAs were used to test for effects of target type (human or kangaroo) and presentation time (50 or 100 ms) on dP3, dN170, EER and counting error. Counting error was the absolute difference between the number of targets present in an image sequence and the number as reported by the participant. When appropriate, Tukey HSD post-hoc tests were performed to establish

the nature of an effect. One sample t-tests were used to examine whether dP3 and dN170 were different from zero in all four conditions.

### 3 Results

#### 3.1 ERPs

**General.** Figure 1 gives a general impression of the ERPs. It shows Pz grand averages of EEG separately for targets and non-targets, and for human and kangaroo images. Human targets appear to elicit both a negative component between 100 and 350 ms after stimulus onset (N170) and a positive component between 300 and 550ms (P3). Non-target images of humans seem to elicit an N170 as well, but no P3. Images of kangaroos do not seem to generate a N170 or a P3, although the EEG seems slightly more positive for kangaroo targets than for kangaroo non-targets towards the end.

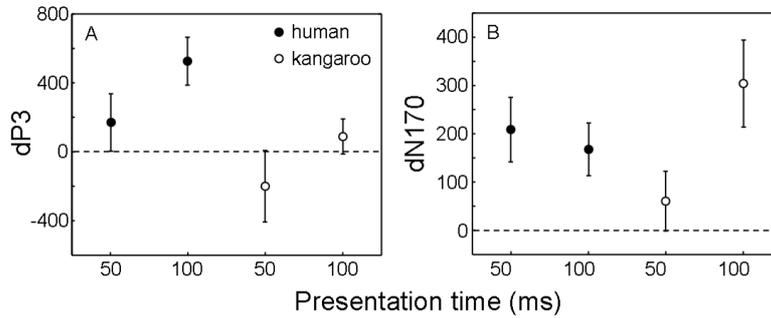


**Fig. 1.** EEG grand averages recorded at Pz, separately for targets and non-targets, and for human and kangaroo images. Time 0 corresponds to stimulus onset.

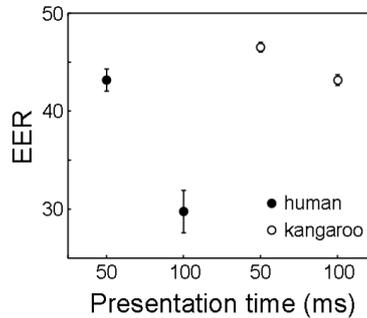
**P3.** Figure 2A shows dP3 (P3 at Pz for the target minus that for the non-target) for each target type and presentation time. The mean values are larger than zero, except for the kangaroo target presented at 50 ms, suggesting that generally an attention driven P3 is present. However, only for the human target presented at 100 ms the dP3 is significantly larger than 0 (one sample t-test  $t_{19}=3.78$ ,  $p<0.01$ , other p-values  $>0.32$ ). A repeated measures ANOVA indicates that the dP3 is affected by target type ( $F_{(1,19)}=5.61$ ,  $p=0.03$ ) with the human target producing larger dP3s than the kangaroo, and presentation time ( $F_{(1,19)}=7.04$ ,  $p=0.02$ ) with 100 ms producing larger dP3s than 50 ms. There is no interaction between target type and presentation time ( $F_{(1,19)}=0.04$ ,  $p=0.84$ ).

**N170.** Figure 2B shows dN170 (N170 at P4 for the human image minus that for the kangaroo) for each target type and presentation time. An N170 is present as indicated by mean dN170 values being significantly larger than zero for the human target types ( $t_{19}=3.08$  for 100 ms presentation time and  $t_{19}=3.12$  for 50 ms, both p-values  $<0.01$ ) and the kangaroo target type at 100 ms presentation time ( $t_{19}=3.37$ ,  $p<0.01$ ). For the kangaroo type - 50 ms condition dN170 is not significantly larger than zero ( $t_{19}=0.34$ ,

$p=0.98$ ). A repeated measures ANOVA indicates that there is no main effect of target type ( $F_{(1,19)}=0.01$ ,  $p=0.93$ ) on dN170. There is an effect of presentation time ( $F_{(1,19)}=5.59$ ,  $p=0.03$ ) and an interaction between target type and presentation time ( $F_{(1,19)}=6.36$ ,  $p=0.02$ ). Tukey HSD post-hoc tests shows that for human target type conditions, presentation time does not affect the dN170 while for kangaroo target type conditions, dN170 is larger when presentation time is 100 ms compared to 50 ms (difference between the different presentation times for kangaroo target type conditions:  $p=0.02$ ; all other comparisons  $p$ -values  $>0.28$ ).



**Fig. 2.** dP3: P3 at Pz for the target minus that for the non-target (A) and dN170: N170 at P4 for the human image minus that for the kangaroo (B) for each target type and presentation time. Error bars represent standard errors of the mean.



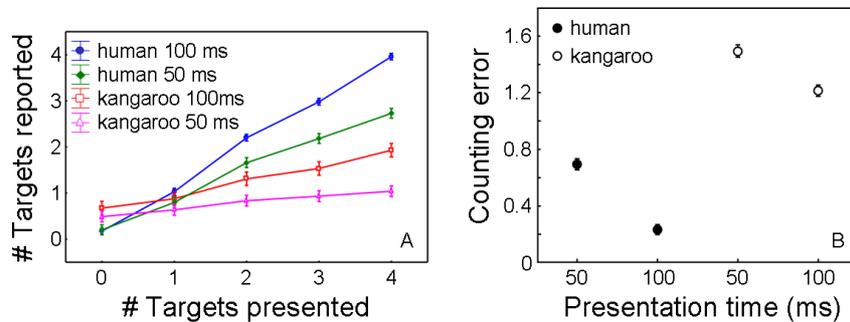
**Fig. 3.** Equal error rate for each target type and presentation time. Perfect classification performance would be at 0 and chance performance at 50. Error bars represent standard errors of the mean.

### 3.2 Classification

Figure 3 shows mean equal error rate (EER) for each target type and presentation time where 0 indicates perfect classification performance and 50 chance performance. A repeated measures ANOVA showed an effect of presentation time ( $F_{(1,19)}=94.43$ ,  $p<0.01$ ), target type ( $F_{(1,19)}=36.69$ ,  $p<0.01$ ) and an interaction ( $F_{(1,19)}=42.34$ ,  $p<0.01$ ). Tukey HSD post-hoc tests indicated that the EER for human target at 100 ms was lower than the EER in all other conditions ( $p$ -values  $<0.01$  for all comparisons) while there were no other significant differences between the EERs ( $p$ -values  $>0.11$ ).

### 3.3 Counting error

Figure 4A plots the number of targets reported against the number of targets presented, separately for each target type and presentation time. The figure shows a clear pattern of better performance for human compared to kangaroo targets, and for long compared to short presentation times. Better performance is reflected by stronger positive relations between counted and presented number of targets. Figure 4B shows the mean counting error for each target type and presentation time. Target type ( $F_{(1,19)}=405.00$ ,  $p<.01$ ) and presentation time ( $F_{(1,19)}=75.39$ ,  $p<.01$ ) both have an effect on counting error. There is an interaction between presentation time and target type ( $F_{(1,19)}=8.80$ ,  $p<.01$ ) that indicates that counting human targets benefits more from a longer presentation time than kangaroo targets does.



**Fig. 4.** Counting performance for each target type and presentation time as indicated by the number of targets reported against the number of targets presented (A) and counting error (B). Error bars represent 95% confidence intervals.

## 4 Conclusions

Our results clearly indicate that target type (in combination with the type of fillers) can affect performance of image classification BCIs. Images of humans as targets elicit stronger P3s than images of a less familiar species, kangaroos. In line with this, classification performance was better for human targets (when images were presented for 100 ms) as well as counting performance. Detecting kangaroos in between animals appeared close to impossible with the short presentation times used and this was reflected in all dependent measures.

Human images also elicited an N170 whereas kangaroo images did not. For the presentation time of 100 ms, this even held when observers focused on detecting images of kangaroos (in line with [18]). This means that besides the P3, the N170 can be used in classification algorithms when the goal of the image classification BCI is to find images of humans. Our finding that an electrode at the right hemisphere tended to display the N170 best is in line with previous findings (e.g. [19]). However, better N170 results are expected when EEG electrodes are placed more temporally than in the current study [20, 21].

Besides target type, presentation time also affected the results. As demonstrated before, shorter presentation times (below 500 ms – [22]) result in smaller or harder to detect P3s and lower classification rates [4, 8, 23]. This is probably caused both by the fact that short presentation times limit processing time and because they increase overlap of ERPs resulting in noisier signals. Presentation time also interacted with target type. Presentation time did not affect the N170 with a human target, but when the target was a kangaroo, 100 ms presentation time produced a clearer N170 than 50 ms (in which case dN170 was not significant). For classification, longer presentation time increases performance, though not significantly so for the kangaroo, perhaps because this target type was just too difficult. Similarly, an interactive effect of presentation time and target type occurred for counting performance with longer presentation time increasing performance, but especially so for the human target.

In the present study, we focused on targets and non-targets, leaving ERPs elicited by the fillers largely aside. In general we can say that for the P3, filler and non-target data are virtually indistinguishable. The fact that non-targets do not elicit larger P3s than fillers, indicates that observers succeeded in switching attention between target types. Fillers elicit N170s that are in between those elicited by human images and kangaroo images. This is probably caused by filler images that resemble humans, like images of other primates. Note that the N170 would probably have been stronger when only images of human faces had been used instead of the broader category of images of humans that also included whole body pictures.

In conclusion, performance of image classification BCIs cannot simply be generalized to situations in which other types of targets are being searched. Image classification BCIs will probably be most successful when typical human expertise can be used, such as detecting human faces. In that case even unintentional detection could be tapped. In addition, future studies should take care not to design image classification BCIs for cases that can be effectively dealt with by computer algorithms.

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