Predicting Perceptual Performance From Neural Activity

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ABSTRACT

A key aim of neuroergonomics is to gain an understanding of human neural function in relation to cognitive and behavioral performance in real world tasks. Here we investigated the relationship between neural activity and human performance in a rapid perceptual categorization task. We compared two different modalities to indirectly measure neural activity, functional magnetic resonance imaging (fMRI) and electroencephalography (EEG). We applied a multivariate pattern classifier to predict the individual variability in perceptual performance during a difficult visual categorization task using single trial EEG and fMRI separately. Twenty observers perceptually categorized images of cars and faces embedded in filtered noise while EEG activity from 64 electrodes was concurrently recorded. Another twenty observers performed the same task while their fMRI-

BOLD responses were recorded. Our results showed significant correlations between the neural measures and perceptual performance ($p < 0.05$; $r = 0.69$ for EEG; $r = 0.66$ for fMRI). We were able to reliably identify from their neural activity the best performing individual from two randomly sampled observers (84% for EEG; 75% for fMRI; chance = 50 %). Finally, we demonstrated that EEG activity predicting the performance across individuals was distributed through time starting at 120 ms and sustained for more than 400 ms post-stimulus presentation, indicating that both early and late components contain information correlated with observers' behavioral performance. Together our results highlight the potential to relate individual's neural activity to performance in difficult perceptual tasks and show a convergence in predictive ability across two different methods to measure neural activity.

Keywords: neural correlates, visual perception, pattern classifier, single trial EEG and fMRI

INTRODUCTION

Perceptual tasks remain important in many life-critical professions including airport traffic control, satellite imagery surveillance, airport security screening, and medical imaging. Yet, human errors in these visual tasks are not uncommon. There is also large variability in perceptual performance across individuals (e.g., medical images (Beam et al. 2002)). The traditional approach in human factors and imaging science has been to optimize displays and task performance through direct measurement of human performance or to use metrics of image quality. The rising field of neuroergonomics provides an interesting new approach. Its goal is to utilize emerging knowledge of brain function to design technologies that are well-adapted to neural coding and that lead to optimized human operations. To achieve such a goal, an initial critical step is to develop computational methods that identify neural activity related to an observer's cognitive state, knowledge of the state of the world, or impending decision.

In the last decades, the field of cognitive neuroscience has used different techniques such as electroencephalography (EEG) (Mangun & Hillyard 1990; Vogel & Machizawa 2004), functional magnetic resonance imaging (fMRI) (Grill-Spector et al. 2004; N. Kanwisher et al. 1997; Kamitani & Tong 2005; Harley et al. 2009a), magnetoencephalography (MEG) (Lu et al. 1992), positron emission tomography (PET) (Chugani et al. 1987) to establish a link between brain activity and behavior. For example, a recent study (Harley et al. 2009b) found a significant correlation between behavioral performance of radiologists detecting abnormal growths in chest radiographs and activations in FFA and lateral occipital cortex (LOC). Another study (Ben-Shachar et al. 2007) reported a significant correlation between a widely used measure of reading ability (phonological awareness) and motion responsivity in children's motion selective cortex (MT).

With the advance of computing technologies, analysis techniques have evolved from trial averaging and single electrode/voxel analyses to single trial, multi-variate pattern analysis. Machine learning techniques have been particularly effective for single-trial EEG/fMRI analysis. Use of multivariate pattern classifiers allows to integrate neural activity into a single decision variable to predict either an observer's behavioral response or the stimulus presented (Philiastides &. Sajda 2006; Kamitani & Tong 2005). Arguably, these multivariate techniques provide more powerful tools to relate neural activity to behavioral performance.

In this context, the primary objectives of the present study were to: 1) investigate the neural correlates of perceptual performance in a challenging perceptual task using EEG and fMRI separately by using pattern classifiers to predict the individual differences across observers performing a visual categorization task and 2) to use pattern classifiers and the high temporal resolution of EEG to illustrate the time-epochs that encode neural information predictive of observers' perceptual performance. Improving our ability to relate neural activity to behavioral performance could potentially allow for neural based measures of perceptual performance and image quality that can complement or even replace traditional behavioral measures.

MATERIALS AND METHODS

The observers' task was to identify the correct category (face/car) of the images presented in the screen while their neural signals were acquired concurrently. The details of the experiment for both EEG and fMRI are given in the following section.

STIMULATION AND DISPLAY

The stimuli consisted of 290 x 290 pixel 256-level grayscale images, 12 faces (six frontal views, six 45° profile) and 12 cars (six frontal views, six 45° profile). All images were filtered to achieve a common frequency power spectrum (the average of all images). Twelve images of each class, face and car, (six frontal view, six 45◦rotated) were used as stimuli. Gaussian white noise was then added to these 24 base images to build a stimuli set of 720 images (360 face, 360 car). Noise was generated by filtering independent white Gaussian noise fields (standard deviation of 3.53 cd/m^2) by the average power spectrum of the car/face stimuli. The noise fields were added to the original car/face images.

EXPERIMENTAL SET UP

For EEG recording, observers sat 125 cm from a monitor with each image subtending 4.57° of visual angle and for fMRI, observers were situated 65 cm from the image surface with each image spanning 5.13° of visual angle. Contrast energy (CE) of all face and car stimuli were matched to be 0.3367$^{\circ 2}$,where CE is defined as the sum of the squared contrast values of the stimuli multiplied by the spatial extent of a pixel.

OBSERVERS AND PROCEDURES:

EEG: Twenty naive observers (ages: 18–26) participated in the study. Observers were initially presented with 1000 stimulus-familiarization trials on the first day and 100 more practice trials immediately preceding the current experiment on the second day. The actual study consisted of 1000 trials split into 5 successive blocks, each having 200 trials. The observers fixated on a central cross and pressed a mouse button to indicate the beginning of the trial (Fig 1). The stimulus appeared for 40 ms. after a variable delay of 0.5-1.5 seconds. The stimulus was followed by a blank screen presented for 0.5-1.5 seconds followed by the response window. Observers were asked to rate how confident they were that they saw either a face or a car, with a rating of 1 indicating complete confidence that a face was presented and a rating of 10 indicating complete confidence that a car was presented. Confidence responses were recorded by mouse clicks on the rating buttons of the response window.

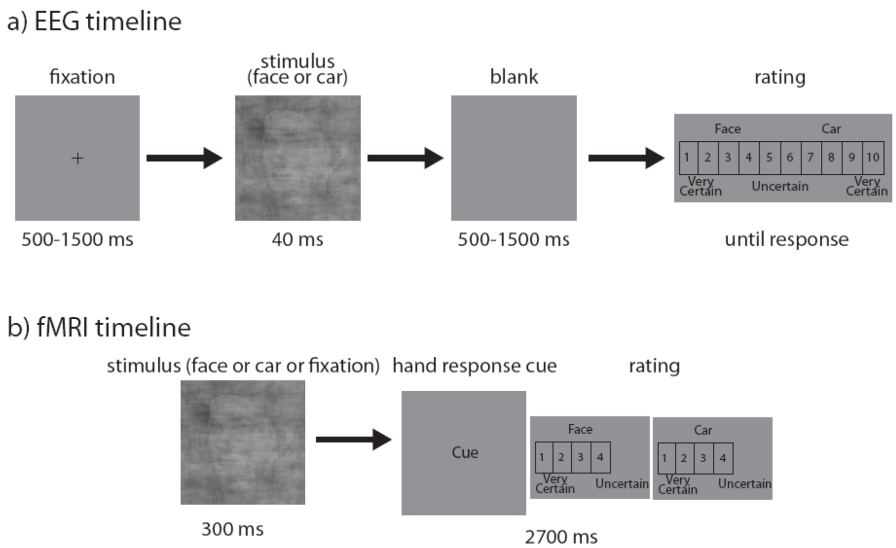

FIGURE 1 Illustration of psychophysical procedure for EEG and fMRI study

fMRI: Twenty different naïve observers with normal vision from the University of Birmingham participated in the experiment. 720 images (360 cars, 360 faces) divided into 8 blocks were used as stimuli with each trial matched for history (2-back). Each blocks consisted of 127 test trials (45 instances cars, faces, and fixations, along with 2 trials at the beginning of the block to equate the history for trials 3 and 4). Each block had a 9 second fixation period at the beginning and end.

Stimulus was presented for 300 ms followed by an interval of 2700 ms for response. Observers responded using button box and both hands and were informed beforehand by means of response cues which category corresponds to which hand. The response cues were alternated with half the time the right hand used for a car response while the left hand was used for a face response, and vice versa (Figure1). Each button box had four buttons corresponding to observers' fingers (thumb excluded) and represented confidence ratings with index always being the highest rating and little finger the lowest. Observers completed 7-8 blocks.

DATA ACQUISITION AND PREPROCESSING

EEG: Each subject's electroencephalogram was recorded from 64 Ag/AgCl sintered electrodes mounted in an elastic cap and placed according to the International 10/20 System. The horizontal and vertical electrooculograms (EOG) were recorded from electrodes placed 1 cm lateral to the external canthi (left and right) and above and below each eye, respectively. The data were sampled at 512 Hz, re-referenced offline to the signal recorded from the central midline electrode (Cz), and then band-pass filtered (0.01-100Hz). Trials containing ocular artifacts (blinks and eye movements) detected by EOG amplitudes exceeding ±100 mV or by visual inspection were excluded from the analysis. The average ERP waveforms in all conditions were computed time-locked to stimulus onset and included a 200 ms pre-stimulus baseline and 500 ms post-stimulus interval.

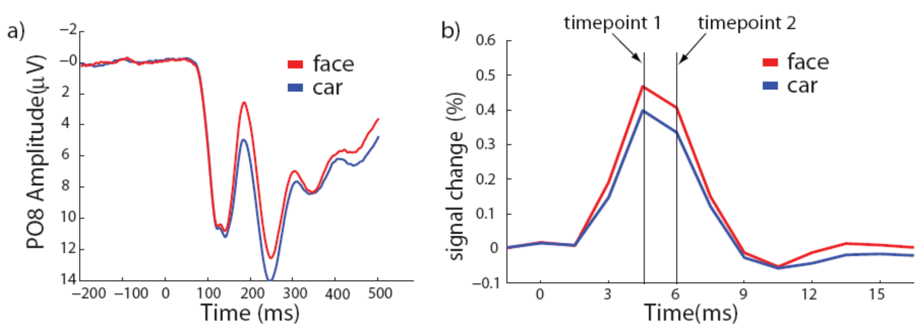

FIGURE 2a) Event-related potential (ERP) for face and car trials for PO8 electrode averaged across all observers. b) Time course for face and car stimuli from the FFA region from one of the observers in the fMRI sessions showing increased response to faces compared to cars.

fMRI: A 3T Achieva scanner (Philips, Eindhoven, and The Netherlands) was used for the experiments conducted at the Birmingham University Imaging Centre. EPI and T1-weighted anatomical (1 x 1 x 1 mm) data was collected with an eight channel SENSE head coil. 24 slices (whole brain coverage, TR: 1500 ms, TE: 35

ms, flip-angle: 73 degrees, 2.5 x 2.5 x 4 mm resolution) were acquired for EPI data (Gradient echo-pulse sequences) for the face/car categorization task. Localizer scans used 32 slices (whole brain coverage, TR: 2000 ms, TE: 35 ms, flip-angle: 80 degrees, 2.5 x 2.5 x 3 mm resolution). Data preprocessing was done using Brain Voyager QX (Brain Innovations, Maastricht, The Netherlands) and included slice-scan time correction, motion correction, temporal high-pass filtering (3 cycles) and linear trend removal. No spatial smoothing was applied on the functional data. The fMRI images for each observer were aligned to a T1-weighted high resolution (1 x 1 x 1 mm) anatomical data and finally all observers' data were transformed into Talairach space at the standard resolution of 3 x 3 x 3 mm.

DATA ANALYSIS USING PATTERN CLASSIFIERS

Recently, multivariate pattern classifiers has been successfully used in research related to functional magnetic resonance (Haynes and Rees, 2005; Norman et al., 2006; Kamitani and Tong, 2005) and/or EEG (Philiastides and Sajda, 2006b,a). In this study, we used a regularized linear discriminant analysis (LDA) (Fisher 1936) for classification analysis on both modalities' data sets. LDA is perhaps the most widely used feature extraction technique. The objective of LDA is to perform dimensionality reduction while enhancing class separability, normally by maximizing an objective function. Details for both modalities are given below.

EEG: Input data to the classifier was taken for the time epoch beginning at stimulus presentation through 512 ms post-stimulus, yielding 256 time points. Each trial thus provided 16,128 independent inputs (256 time points for 63 electrodes) rendering traditional LDA unfeasible. We have used Principal Component Analysis (PCA) to reduce dimension of the EEG signals thereby avoiding the small sample size problem before applying LDA. We used a 10-fold stratified cross validation where the dataset was randomly divided into 10 non overlapping folds of equal size, each having 100 trials. One of the folds was designated as test data while the remaining 9 folds constituted the training set.

fMRI: Various regions of interest (ROI) were identified for each observer including : 1) Retinotopic areas , 2) lateral occipital complex (LOC), and 3) fusiform face area (FFA) using standard ROI mapping procedures (Engel et al. 1994; DeYoe et al. 1996; Sereno et al. 1995; Kourtzi & N Kanwisher 2000; N. Kanwisher et al. 1997). For each region of interest, voxels were sorted based on a *t*-statistic computed by comparing responses to all stimulus conditions versus a control fixation on a blank screen condition. The time course for each voxel was normalized separately for each session to account for baseline differences across runs. Input data to the classifier consisted of the raw blood-oxygen-level dependent (BOLD) signal sampled at 2 time points (3 and 4.5 seconds post-stimulus in order to account for the hemodynamic response lag; see Figure 2b). We implemented a leave-one-session-out validation wherein the pattern classifier was tested on one session (90 test trials: 45 faces, 45 cars) and trained on the remaining sessions. The pattern classifier performance was evaluated by using a non-parametric measure of area under the Receiver Operating Curve (ROC), AUC, which quantifies the relationship between hit rate and false alarm rate for all possible decision criteria. To reduce the variance of estimated area under the curve (AUC), the overall cross validation procedure was repeated 8 times, each time selecting a new testing session and the overall performance is given by the mean AUC.

FIGURES OF MERIT TO EVALUATE NEURAL METRICS

The ability of various metrics to predict behavioral perceptual performance was evaluated by using a Pearson linear correlation and rank ordering of individuals' performance based on neural metrics. Rank ordering was performed by selecting the best performing individual out of two randomly sampled observers from their neural activity and validating based on the behavioral performance of the chosen observers. The rank ordering measure is more similar to a Spearman Rank Correlation which does not penalize departures from linearity and is complementary to the Pearson correlation.

RESULTS

We used LDA to predict the perceptual performance of observers performing the visual task. The pattern classifier was evaluated using AUC. Figure 3a shows the statistically significant positive correlation ($r=0.69$; $p = 0.0005$) between pattern classifier performance (AUC) using EEG activity and behavioral performance (AUC). Similar analyses using fMRI response yielded consistent results. Figure 4 shows the correlation between behavioral performance (AUC) and classifier performance (AUC) using fMRI (see also Table 1). Consistent with the EEG results, there was a statistically significant ($r=0.66$; $p = 0.0005$) correlation between classifier performance identifying car/face stimulus and subjects' behavioral performance.

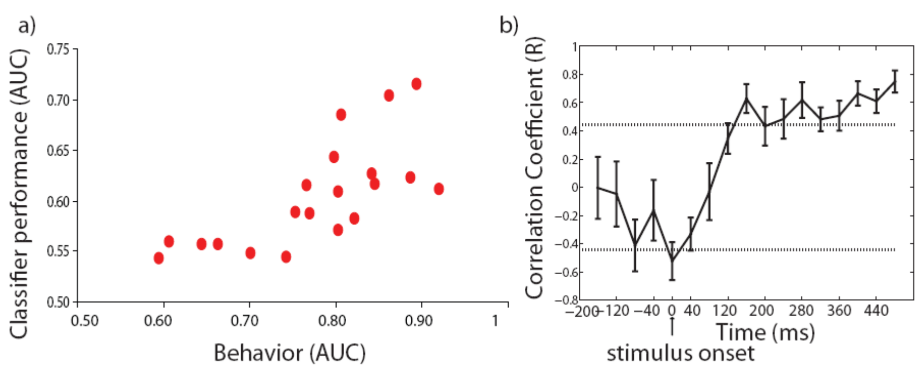

Fig3:a) EEG measures: AUC of pattern classifiers trained on only EEG trials vs. the

behavioral performance (AUC) of all 20 observers. b) Correlation between AUC of pattern classifiers of 20 observers taken over time intervals and their behavioral performance(AUC).(|r| >= 0.444 for statistically significant R using 95% confidence interval is marked with dotted line).

To further evaluate the ability of the EEG/fMRI metric to predict the variation in perceptual performance across individuals we performed a simple simulation calculating the accuracy of the different metrics in rank ordering the behavioral performance of two randomly sampled observers based on their neural activity (190 simulation trials). Table 1 shows the mean percent correct rank ordering of two random observers using either EEG or fMRI. Rank ordering of behavioral performance produced statistically significant results (chance=0.5) consistent with the correlation for both EEG (proportion correct=0.84) and fMRI (proportion correct=0.75).

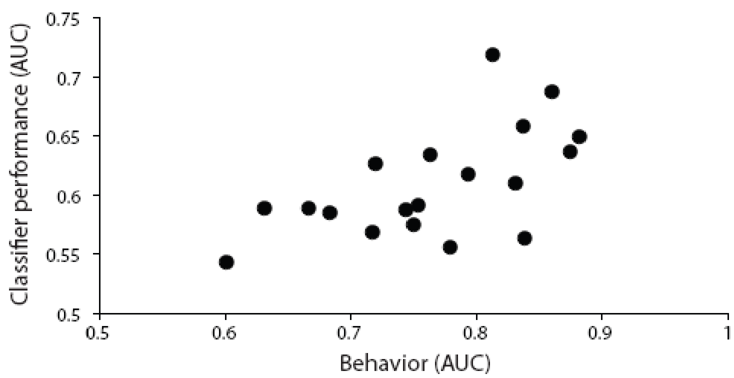

Fig4: fMRI measures using pattern classifiers. Scatter plot showing AUC of pattern classifiers vs. the behavioral performance (AUC) of all 20 observers

Finally, we analyzed the EEG signals in the temporal domain by dividing the signals into 40 ms intervals starting from 200 ms before the stimulus was presented to 480 ms post-stimulus. Each of the 40 ms time epochs was separately fed to the pattern classifier. The correlation coefficient between the pattern classifier performance and the observers' behavioral performance for each 40 ms temporal window starting at 200 ms pre-stimulus onset is shown in Figure 3b. The correlation was negligible pre-stimulus onset and it increased monotonically, showing a rapid increase until about 120 ms, followed by a more gradual increase continuing beyond 400 ms. There was a statistically significant correlation between observers' behavioral performance and the EEG measure obtained from pattern classifier from 170 ms onwards demonstrating that significant information discriminating face and car was coded during that time epoch.

Table 1 The correlation coefficient between behavioral data and EEG measures and rank ordering using pattern classifiers under for 20 observers

Modality	Correlation Coefficient	Rank Order (proportion correct)
EEG	0.69 (±0.15)	0.84(±0.01)
fMRI	0.66 (±0.17)	0.75(±0.09)

DISCUSSION AND CONCLUSION

Recent EEG and fMRI studies have shown that pattern classifiers can be used to infer from neural activity the identity of visual stimuli presented to humans for objects, faces (Philiastides & Sajda 2006) and orientation of simple patterns (Kamitani & Tong 2005). The current study extends previous work by applying pattern classifiers to EEG and fMRI data to predict variations in perceptual performance across a large number of individuals in a categorization task (faces vs. cars). We show comparable ability to predict observers' performance using fMRI and EEG signals in conjunction with pattern classifiers, demonstrating the convergence in predictive power across neuroimaging and electrophysiology modalities. We also demonstrated that the efficacy of EEG activity in predicting the performance across individuals increased 120 ms post stimulus presentation and continued for more than 400 ms. Our finding is consistent with the existing studies (Philiastides & Sajda 2006) using similar stimuli and demonstrates the presence of both early and late components which contain significant information that correlates with observers' behavioral performance.

Together, our results show the potential of neural measures to infer an observer's knowledge about a briefly presented perceptual stimulus. These neural metrics could potentially be used to rapidly evaluate the quality of a visual display. For example, a recent study (Luo & Sajda 2006) has shown that during a very rapid sequence of image presentation, EEG in conjunction with the mean response time, obtained from behavioral response of observers, can be used to estimate the target onset time more accurately compared to using only behavioral response. In addition, neural activity could allow for a measure of an individual's knowledge of the presence of an object for tasks in which an observer is occupied with a different primary task (e.g. piloting a vehicle) and is not explicitly providing a report about the presence/absence of the object of interest.

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