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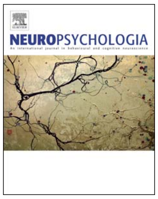

A fast and implicit measure of semantic categorisation using steady state visual evoked potentials

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ABSTRACT

There is a great need for objective measures of perception and cognition that are reliable at the level of the individual subject. Although traditional electroencephalography (EEG) techniques can act as valid bio-markers of cognition, they typically involve long recording times and the computation of group averages. To overcome these well-known limitations of EEG, vision scientists have recently introduced a steady state method known as fast periodic visual stimulation (FPVS). This method allows them to study visual discrimination at the individual level. Inspired by their work, we examined whether FPVS could be used equally effectively to capture abstract conceptual processes. Twenty subjects (20.9 (± 2.1) yrs, 6 male) were asked to complete a FPVS-oddball paradigm that assessed their spontaneous ability to differentiate between rapidly presented images on the basis of semantic, rather than perceptual, properties. At the group level, this approach returned a reliable oddball detection response after only 50 s of stimulus presentation time. Moreover, a stable oddball response was found for each participating individual within 100 s. As such, the FPVS-oddball paradigm returned an objective, non-verbal marker of semantic categorisation in single subjects in under two minutes. This finding establishes the FPVS-oddball paradigm as a powerful new tool in cognitive neuroscience.

1. Introduction

Physicians and psychologists have a long history of measuring people's ability to notice variation. Their interest in doing so frequently arises from the fact that deficits in this ability can signal severe neural impairments. To diagnose colour blindness, for example, physicians typically ask patients to distinguish red from green figures (e.g., using the Ishihara Plate Test, Birch, 1997). Similarly, to detect face blindness, psychologists often require their clients to recognize faces of different individuals (e.g., via the Cambridge Face Memory Test, Bowles et al., 2009). In both cases (as in many other behavioural tests), however, assessing people's ability to distinguish between certain entities requires that they provide active and truthful replies. Yet, some individuals may simply not be able (e.g., children, stroke patients) or willing (e.g., eye witness) to give such replies. Hence, physicians and psychologists are frequently interested in developing tests that can be reliably administered without requiring test-takers' overt replies.

These alternative measures include standard brain imaging techniques, such as electroencephalography (EEG; Chennu et al., 2013) and functional magnetic resonance imaging (fMRI; cf Monti et al., 2010). One popular EEG marker of people's ability to detect variation is known as Mismatch Negativity (MMN). This marker is typically derived by subtracting a person's neural response to a frequently presented standard stimulus from that of a rare oddball stimulus in a so-called oddball paradigm, and can be elicited both with and without the subject's explicit attention (Czigler, 2014; Kimura, 2012; Näätänen et al., 1978; Näätänen and Michie, 1979). In recent years, there has been growing interest in using the MMN as an early marker of attentional deficits in the pre-symptomatic stages of clinical disorders, such as schizophrenia (see Näätänen et al., 2011 for a review). Meta-analyses have repeatedly demonstrated clear MMN deficits in schizophrenia (Bodatsch et al., 2015; Erickson et al., 2016; Umbricht and Krljes, 2005) however despite decades of converging findings, viable clinical tools for assessing these deficits in a reliable manner are still lacking. The great challenge in the translation of experimental EEG findings into viable clinical tools lies in finding measures that are reliable not only at the group level, but at the level of the individual.

This is not just a challenge with MMN, but with EEG measures more broadly (Duncan et al., 2009). To obtain sufficient Signal to Noise Ratio (SNR) using traditional Event Related Potential (ERP) techniques, for

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example, subjects must typically complete hundreds or thousands of experimental trials, resulting in long recording times. This problem is compounded in oddball paradigms in which a minimum number of standard stimuli are required between oddball stimuli in order to ensure their "rareness". An alternative to ERPs is the Steady State Visual Evoked Potential (SSVEP), in which periodic visual stimulation elicits a periodic neural response at an equivalent frequency (see Norcia et al., 2015 for a review). Recently a new technique combining oddball paradigms with SSVEPs has shown considerable potential for solving the issues of SNR that have hampered traditional ERP approaches.

First demonstrated by Heinrich et al. (2009a) and developed extensively by Rossion et al. (e.g. Alp et al., 2016; Liu-Shuang et al., 2016; Rossion et al., 2015) the Fast Periodic Visual Stimulation (FPVS) technique involves frequency tagging standard and oddball stimuli. Standard stimuli are presented at a fast rate typically about 6 Hz with oddball stimuli embedded in the train of standard stimuli at fixed intervals, resulting in a slower equivalent presentation rate for oddball stimuli, typically around 1 Hz (e.g., S S S S S **O** S S S S S **O** S S S S S **O** S S S S S **O)**. The advantage of this approach in signal processing terms is that the noise in EEG signals is distributed across all frequencies. Traditional ERP techniques will inevitably include both the signal and the noise from all frequencies. The FPVS-oddball paradigm examines only the exact frequency of the visual stimulation, that is, 6 and 1 Hz. Noise in neighbouring frequencies does not affect the signal of interest, consequently providing very high SNRs.

To date the approach has been used most commonly in studies of face processing and recognition (Dzhelyova and Rossion, 2014; Liu-Shuang et al., 2014, 2016; Rossion, 2014; Rossion et al., 2015). But it has also proven successful in probing low-level visual processing (e.g., orientation encoding; Heinrich et al., 2009a) and basic lexical representations (e.g., word/non-word discrimination; Lochy et al., 2015). To further advance our understanding of the method's potential, our objective was to extend this approach to other domains of mental processing, specifically to an example of higher level cognition, such as abstract semantic categorisation. Semantic categorisation refers to people's ability to group information in a manner that highlights conceptual commonalities or differences between different entities (Rosch, 1975). As it can occur at different levels of specificity, the same entities can be classified in many different ways (Mervis and Rosch, 1981).

Common objects such as furniture, for instance, can be categorised into so-called subordinate categories (e.g., as chairs, tables, beds etc., Mack et al., 2008) which, in turn, can prompt even more fine-grained subordinate classifications (e.g., chairs may be considered dining chairs or office chairs; Tversky and Hemenway, 1984). At the same time, however, furniture can also be categorised according to so-called superordinate categories (e.g., just like vehicles, but unlike tools, as non-graspable objects; Rice et al., 2007) which, in turn, can prompt even coarser superordinate classifications (e.g., furniture, vehicles and tools together can count as man-made rather than natural entities; (Caramazza and Shelton, 1998; Rogers and Patterson, 2007). In short, based on a perceiver's domain-specific knowledge (Tanaka and Taylor, 1991) and/or momentary processing goal (Barsalou, 1991), multi-level conceptual hierarchies can provide numerous levels of specificity according to which objects can be categorised.

To gain an even better hold on the mechanisms of semantic categorisation in the human brain, it seems warranted to develop tasks that can objectively quantify an individual's ability to categorise objects upon perception along various levels of semantic specificity. Such a task would not only be of particular experimental value, but could ultimately also inform the assessment of neural disorders characterized by difficulties with semantic categorisation, such as fronto-temporal dementia. We believe that the newly developed FPVS-oddball paradigm lends itself well for such a purpose. The paradigm has already been used to assess the integrity of face processing in prosopagnosia (Liu-Shuang et al., 2016). Inspired by this prospect, the aim of this study was to extend the FPVS-oddball paradigm to semantic processing. We predicted that increases in power at the oddball stimulation frequencies would be observed when standard and oddball stimuli differed in their semantic categories. We also predicted that when stimuli were scrambled, therefore removing any semantic category level information, oddball responses would not be observed.

2. Method

2.1. Participants

Twenty adults (aged 18–28, mean age 20.9 (± 2.1), 6 males) gave consent to participate in the study. They were recruited from the University of Bristol student population and declared themselves to be in normal health and had normal or corrected-to-normal vision. Ethical approval for our procedures were obtained from the University of Bristol Science Faculty ethics board. Participants provided written informed consent before participating and were free to withdraw from the study at any time.

2.2. Stimuli

Images were selected from a previously validated set of 360 high quality colour images belonging to 23 semantic categories (Moreno-Martínez and Montoro, 2012). Images were selected to form three separate sets expected to prompt semantic categorisation at different levels of specificity. Based on prior work on semantic categorisation (e.g. Chan et al., 2011; Moss and Tyler, 2000), one image set (set A) probed the coarse categorisation of everyday items as natural versus non-natural objects. This set comprised 60 images of natural objects (e.g, birds, mammals, and trees, mean pixel intensity 0.91 (0.06), mean contrast 0.22 (0.08)) and 15 images of non-natural objects (e.g. buildings, clothing, and furniture, mean pixel intensity 0.88 (0.06), mean contrast 0.25 (0.06)). A second set of images (set B) included only natural items and probed the more fine-grained classification of these items as animals versus non-animals (c.f Blundo et al., 2006; Hart and Gordon, 1992). Hence, it comprised 60 images of animals (e.g. mammals, birds, and marine animals, mean pixel intensity 0.91 (0.05), mean contrast 0.22 (0.06)) and 15 images of non-animals (e.g. fruit, vegetables, and nuts, mean pixel intensity 0.92 (0.05), mean contrast 0.19 (0.08)). The third set (set C), finally, contrasted different types of animals (c.f. Naselaris et al., 2012). Specifically, it contained images of 60 birds (e.g., blackbirds, budgies, and owls, mean pixel intensity 0.94 (0.06), mean contrast 0.18 (0.04)) with images of 15 non-birds (i.e., small mammals such as mice, rabbits, and squirrels mean pixel intensity 0.93 (0.02), mean contrast 0.19 (0.04)). As there were not enough bird images in the original Moreno-Martínez and Montoro image set, an additional 30 images were sourced using a Google image search and adapted to match the Moreno-Martínez and Montoro images in relevant physical characteristics. All images were 250 × 250 pixels, 72dpi, subtending 9° visual angle, with the central image cropped to a white background. In order to reduce systematic low-level colour confounds between the standard and oddball categories all images were converted to greyscale. In addition, control images were created by box scrambling the original images using the Matlab Randblock function (https://uk.mathworks.com/matlabcentral/fileexchange/17981-randblock). Box scrambling has been shown to remove semantic category information content, whilst preserving low-level visual content (e.g. Grill-Spector et al., 1998). An example of the images is provided in Fig. 1 and the full image set is available in Supplementary information A.

2.3. Procedure

Participants were seated 55 cm from the monitor and instructed to maintain their gaze within a blue fixation square in which images were presented. They were instructed to press a hand held button every time the blue fixation square turned green. Images were presented onscreen

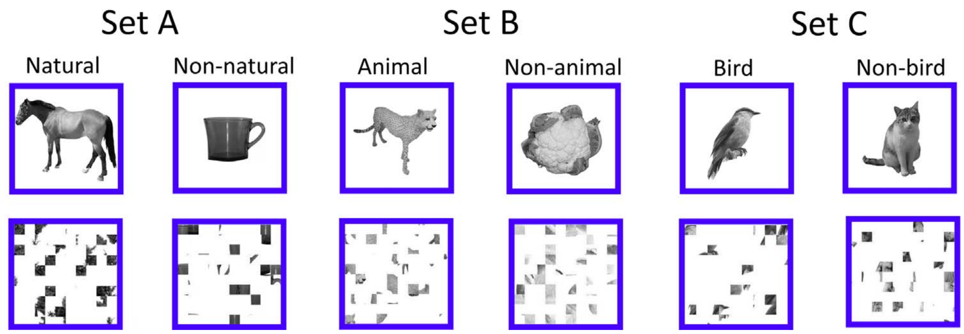

Fig. 1. Examples of image sets and the equivalent scrambled control images.

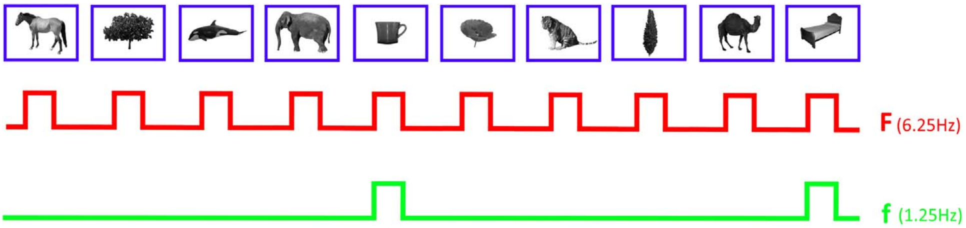

Fig. 2. Oddball steady state design and hypothesised neural steady state responses. A base frequency ***F*** is elicited in response to the presentation of every image at 6.25 Hz, the oddball response ***f*** is elicited only to stimuli that violate the previously established semantic category of the standard stimuli. In the example above the standard stimuli are living objects and the oddball stimuli are non-living objects.

for 80 ms with an inter-stimulus interval of 80 ms. The study used an oddball paradigm presented in a steady state method as developed by Rossion and colleagues (e.g. Liu-Shuang et al., 2016; Rossion et al., 2015).

Images were presented in sequences of five images, with the first four images being selected from the standard category and every fifth image being drawn from the oddball category. An example of this sequence is presented in Fig. 2. This design elicits two distinct steady state responses. The standard presentation frequency of 6.25 Hz, and the oddball presentation frequency of 1.25 Hz.

Stimuli were presented in runs of 75 stimuli (60 standards and 15 oddballs) in a pseudo-randomised order ensuring 4 standard stimuli and a fifth oddball stimulus were always presented sequentially. Targets (fixation square turning green) only occurred on the second stimulus of the run of five, with a 10% probability of occurring for each run. This was repeated 15 times with a different randomised order each time resulting in 1125 stimuli presentations over 180 s.

Six conditions were presented: Image Sets A, B and C and their equivalent scrambled control image sets. The order of these blocks were counterbalanced across subjects using a balanced latin square design.

To allow researchers to easily try this new method we have developed a free open-source toolbox to present stimuli and analyse the subsequent data. The Fastball toolbox is a free, open-source Psychopy (Peirce, 2007) and Matlab (Mathworks Inc.) toolbox we have made available at https://gstothart.github.io/Fastball/. It allows the user to easily present stimuli in an FPVS-oddball paradigm with many modifiable parameters, and analyse the subsequent EEG data.

2.4. EEG recording

EEG signals were sampled at 1000 Hz from 64 Ag/AgCl electrodes fitted on a standard electrode layout elasticised cap using a BrainAmp DC amplifier (Brain Products GmbH) with a common FCz reference and online low-pass filtered at 250 Hz. Impedances were below 5 kΩ. Recordings were analysed offline using Brain Electrical Source Analysis software v5.3 (BESA GmbH), Matlab (Mathworks Inc.) and the Fieldtrip toolbox (Oostenveld et al., 2011). Artifacts including blinks and eye movements were corrected using BESA automatic artifact correction (Berg and Scherg, 1994).

2.5. EEG analysis and steady state response

Data were re-referenced offline to a common average reference. Epochs from 0 to 180 s around block onset were defined for each condition. The steady-state response was calculated according to the procedures described in Rossion et al. (2015). Epochs were defined as the entire 180 s trial period associated with each semantic or control condition. This epoch length represents an integer number of cycles (225) of the oddball stimulus (1.25 Hz) ensuring that a frequency bin corresponding to the exact oddball frequency and its harmonics, including the standard frequency (6.25 Hz), were created. The frequency resolution was 0.0056 Hz. Epochs were first linearly de-trended and the DC component was removed. The epochs were tapered with a Tukey window (matlab's tukeywin function) with the first and last 4 s of the epochs being cosine tapered in order to remove discontinuities at the edge of the epochs. For each participant and each electrode, amplitude was computed on these windows using the fast Fourier transform (FFT). Amplitude was then corrected by dividing the amplitude in each frequency bin by the mean amplitude of surrounding bins within a ± 0.45 Hz range (e.g. Alp et al., 2016; Srinivasan et al., 1999) excluding the immediately adjacent bins (first neighbouring bin on each side). The ± 0.45 Hz range was chosen to give an amplitude correction that was comparable with previous research (e.g. Alp et al., 2016; Srinivasan et al., 1999), and represented 81 bins either side given the frequency resolution of this study. Excluding the immediately adjacent bins from this correction meant that the amplitude correction was less likely to include any spread of the signal to proximal frequency bins (e.g. for 1.25 Hz adjacent bins were 1.2444 & 1.2556 Hz).

Previous research has shown a robust SSVEP response to the oddball frequency and many of its harmonics (e.g., Rossion et al., 2015; Norcia et al., 2015), so following the procedure outlined in Rossion et al. (2015) we determined the range of harmonics across which to analyse the data. Grand-average amplitudes (uncorrected) were created for each electrode and then pooled across all electrodes. The z-score for each frequency bin was then calculated using the mean and standard deviation of ± 0.45 Hz bins, excluding the immediately adjacent bins (as described above). Harmonics of the oddball frequency in excess of $z = 3.29$ ($p < 0.001$) were defined as significant (see Table 1). The harmonics used in later analysis were based on the largest range of consecutive and significant harmonics across all 6 presentation conditions. From 1.25 Hz upwards (e.g. 2.5, 3.75, 5 Hz…), once a harmonic failed to reach significance, we capped the range for that condition as the last harmonic that was significant. Harmonics that related to the standard frequency (e.g. 6.25 Hz, 12.5 Hz…) were excluded. Following the procedures of Rossion et al. (2015) and Heinrich et al. (2009b) the corrected amplitude was calculated for 3 values: the standard frequency

Table 1
Across participant z-scores at oddball frequency and its harmonic (scalp-average). Bold indicates significance at $p < 0.001$.

Harmonic (Hz)	Condition					
	Set A	Set A control	Set B	Set B control	Set C	Set C control
1.25	**5.07**	2.65	**6.02**	**3.36**	**3.45**	1.53
2.5	**18.61**	**4.88**	**10.20**	**7.42**	**5.60**	3.20
3.75	**23.05**	**7.75**	**12.61**	**6.99**	**19.99**	**5.63**
5	**21.22**	**7.31**	**11.58**	**5.49**	**13.48**	**4.34**
7.5	**3.54**	1.87	**10.78**	**6.06**	**5.98**	**3.77**
8.75	2.86	2.55	0.98	1.44	2.74	1.66
10	2.62	**3.65**	1.05	0.71	0.21	2.05
11.25	1.49	1.01	2.29	0.70	0.49	1.45
13.75	2.09	0.94	0.90	0.39	0.16	−0.13
15	0.21	1.04	−0.24	0.17	1.50	−0.68
16.25	−0.46	2.46	−0.63	0.48	0.17	−0.22

F (6.25 Hz), the oddball frequency ***f***, and the sum of the oddball frequency and significant harmonics ***f***+ (i.e. sum of 1.25, 2.5, 3.75,5 & 7.5 Hz). These three values were calculated for each participant and electrode across the six experimental conditions. We have made all the analysis code freely available and modifiable through the Fastball toolbox, https://gstothart.github.io/Fastball/.

Using Fieldtrip software (Oostenveld et al., 2011), the difference in ***f*** + between original and scrambled images for the three levels of semantic categorisation was statistically assessed across all electrodes using cluster-based permutation analysis (see Maris and Oostenveld, 2007) with 10,000 permutations. For image Sets A and C the initial alpha value for cluster formation was lowered from alpha < 0.05 to alpha < 0.001, and for Set B it was lowered to alpha < 0.01, as the difference was so large between experimental and control conditions that one large cluster spanning the entire scalp emerged. This is one weakness of the cluster permutation approach highlighted recently by Mensen and Khatami (2013). As a “sanity check” for the appropriateness of the cluster-based electrode selection a split-halves analysis was undertaken in which the subjects were split into two groups of 10. The 10 electrodes showing the strongest effect in subgroup 1 were then used to examine the experimental effects in the subgroup 2, and vice versa. All experimental effects were maintained and validate the cluster-based approach.

2.6. *Presentation durations required to measure the steady state response*

To examine the time required to detect a reliable steady state oddball response, the steady state response was calculated over 15 increasing epoch lengths from 12 to 180 s (12 s increments). All lengths included an integer number of cycles at the oddball frequency. The steady state response was calculated in a similar way to the procedure described in the previous section except that amplitude values were converted to z-scores using the mean and standard deviation of the frequency bins ± 0.45 Hz (excluding the immediately adjacent bins). This allowed the significance of the steady state response at the oddball ***f***, oddball plus harmonics ***f***+, and standard frequency ***F*** to be assessed relative to alpha levels of 0.05 ($z = 1.96$) and 0.001 ($z = 3.29$), for a similar approach see (Rossion et al., 2015). The electrodes selected were those showing the largest ***f***+ response (PO10 for image sets A and C, PO9 for image set B). For the group-level analysis, the across-participant mean z-score for each epoch length was then calculated for each image set separately so that the detectability of the steady-state

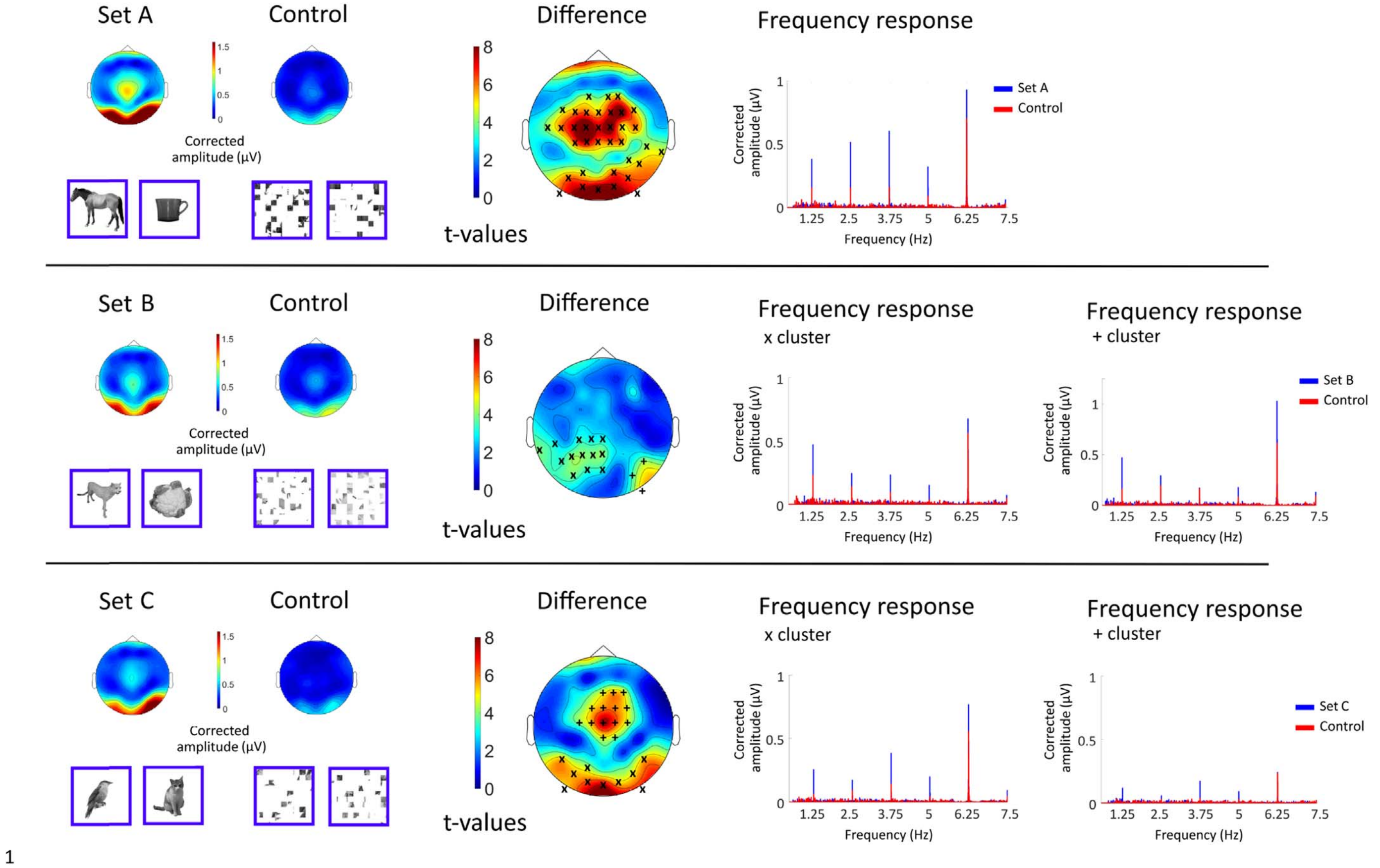

Fig. 3. Topography plots indicating significant differences between image sets compared to their scrambled controls in the spectral power of ***f***+ (sum of 1.25 Hz and its harmonics at 2.5 Hz, 3.75 Hz,5 Hz and 7.5 Hz) at regions of interest identified by cluster permutation analysis. Spectral plots represent the mean corrected amplitude of the electrodes included in the clusters identified with **x** and + markers.

response to $\boldsymbol{F}$, $\boldsymbol{f}$ and $\boldsymbol{f}+$ could be investigated over increasing lengths of stimulus presentation.

3. Results

Fourier analysis of responses to the three image sets showed large steady state responses at 6.25 Hz ($\boldsymbol{F}$), 1.25 Hz ($\boldsymbol{f}$) and its harmonics at 2.5 Hz, 3.75 Hz, 5 Hz and 7.5 Hz ($\boldsymbol{f}+$) (see Table 1). Cluster permutation analyses demonstrated significantly increased $\boldsymbol{f}+$ for the all three image sets compared to scrambled controls, clearly demonstrating that $\boldsymbol{f}+$ responses were not due solely to low-level visual differences but reflected deviance detection due to semantic categorisation differences.

3.1. Set A

Initial cluster analysis at cluster formation alpha < 0.05 revealed one large cluster which included all electrodes. To identify the strongest areas of activity on the scalp, electrode clusters were formed with an entry alpha < 0.001, which revealed a cluster with activity strongest in occipital and central areas including electrodes FCz, F4, FC5, FC1, FC2, FC6, T7, C3, Cz, C4, CP1, CP2, TP10, P8, PO9, O1, Oz, O2, PO10, F1, F2, FC3, FC4, C5, C1, C2, C6, CP3, CPz, CP4, TP8, P6, PO7, PO3, PO4, PO8, cluster $p < 0.0001$, see Fig. 3.

3.2. Set B

Cluster analysis at cluster formation alpha < 0.01 revealed a left hemisphere dominant centro-parietal cluster comprising electrodes CP1, CP3, CPz, PO7, PO3, TP9, P7, P3, Pz, TP7, P5, P1, POz, cluster $p < 0.001$, and a right hemisphere dominant parieto-occipital cluster comprising electrodes P8, PO10 and PO8, cluster $p = 0.008$, see Fig. 3.

3.3. Set C

Initial cluster analysis at cluster formation alpha < 0.05 revealed one large cluster which included all electrodes. To identify the strongest areas of activity on the scalp cluster formation alpha < 0.001 revealed an parieto-occipital cluster including electrodes P8, PO10, PO8, PO7, PO3, P7, PO9, O1, Oz and O2, cluster $p < 0.0001$, and a central cluster comprising electrodes CPz, F4, FC1, FC2, C3, Cz, C4, CP2, F2, FC4, C1, C2, FCz and Fz, cluster $p < 0.0001$, see Fig. 3.

It was observed that $\boldsymbol{F}$ reduced when images were scrambled. To verify that any reductions in $\boldsymbol{f}+$ observed were due to the removal of semantic content (as opposed to simply being a consequence of image scrambling) the percentage change in $\boldsymbol{F}$ from original to scrambled was calculated. The difference in $\boldsymbol{f}+$ at electrode PO7 was then examined in a 1-way (original vs scrambled) repeated measures ANCOVA with percentage change in $\boldsymbol{F}$ as a covariate. The $\boldsymbol{f}+$ to scrambled images was significantly reduced image sets A ($F(1,18)=35.64$, $p < 0.001$), B ($F(1,18)=6.75$, $p < 0.05$) and C ($F(1,18)=17.26$, $p < 0.001$) after controlling for the percentage reduction in $\boldsymbol{F}$ from original to scrambled images.

3.4. Presentation durations required to measure the steady state response

3.4.1. Group effects

The main analysis demonstrated a SSVEP to the oddball stimuli demonstrating the detection of a change in semantic categorisation that occurred during the 3 min trial period. As a follow-up analysis, we investigated the presentation duration of the stimuli needed for the across-participant amplitude at the oddball frequency of experimental trials to be detectable as statistically significant. By analysing the Z score over increasing presentation durations, we were able to investigate the time necessary for a stable and measurable steady state response to occur, see Fig. 4. The Z score of $\boldsymbol{F}$ was greater than $p = 0.001$ after 30 s in all three conditions. The Z score of $\boldsymbol{f}+$ in response to image set A was greater than $p = 0.05$ after 36 s and greater than $p=0.001$ after 72 s. The Z score of $\boldsymbol{f}+$ in response to image set B was greater than $p = 0.05$ after 72 s and greater than $p=0.001$ after 168 s. The Z score of $\boldsymbol{f}+$ in response to image set C was greater than $p = 0.05$ after 48 s and greater than $p=0.001$ after 96 s. A 3-way repeated measures ANOVA (Set A, Set B, Set C) indicated no significant effect of image set on onset time of $\boldsymbol{F}$ $F(2,38) = 1.80$, $p = 0.178$, or $\boldsymbol{f}+$ $F(2,38) = 2.29$, $p = 0.115$. For image sets A and C the sum of 1.25 Hz and the subsequent four harmonics ($\boldsymbol{f}+$) was a stronger than 1.25 Hz alone ($\boldsymbol{f}$). In image set B they were equivalent.

3.4.2. Individual subject effects

Analysis of individuals' amplitudes after increasing presentation durations demonstrated that the oddball $\boldsymbol{f}+$ response was detectable at a statistically significant ($p < 0.05$) threshold in 1–2 min for the majority of subjects. Fig. 5 illustrates the distribution of individual subjects' times, individual values are available in Supplementary Info B.

4. Discussion

Across three levels of semantic categorisation subjects showed clear and distinct steady state responses to standard and oddball stimuli. Oddball responses were significantly increased compared to scrambled controls demonstrating that they were a result of a change in the semantic category of the visual object, and not due to systematic differences between standard and oddball stimuli in their basic visual properties or the overall reduction in steady-state responses to scrambled images. Examination of the amplitude of the oddball steady state responses after increasing presentation durations showed they were significant at group level at $p < 0.05$ in under 72 s in all three conditions. Individual subjects typically showed significant responses within ~60 s. We have demonstrated that the FPVS-oddball paradigm is a powerful, sensitive and most importantly easily modifiable tool that can used to examine abstract conceptual processing in single subjects and groups.

The extension of this approach to abstract conceptual processing, e.g. semantic categorisation, is an important addition to the work of Rossion and colleagues in the field of face perception (e.g. Rossion, 2014). While the paradigm has also been demonstrated to be viable with lexical discrimination tasks (Lochy et al., 2015) ours is the first study demonstrating its validity in assessing abstract conceptual processing, e.g. semantic knowledge. There is considerable evidence for the ability of the visual system to classify objects after short presentation times during explicit target detection, e.g. during Rapid Serial Visual Presentation (Potter, 1975, 1976), and that classification can be made on the basis of higher level visual properties (e.g. VanRullen and Thorpe, 2001). Importantly however, we demonstrate that the FPVS-oddball paradigm is sensitive to implicit processing as participants were instructed simply to pay attention to all images presented and were not cued in any way to attend to the semantic category. Consequently, we are able to objectively measure the extent of pre-attentive discrimination without having to include the additional noise associated with the impact of masking and memory recall performance on explicit responses. The paradigm is therefore easily adaptable, and what constitutes an oddball and elicits an oddball response can be defined in low level visual or abstract conceptual properties.

We propose that the $\boldsymbol{f}+$ response in the current study reflects a combination of the visual MMN (vMMN) and a semantic category specific neural response. E.g. for image set A, the oddball response will reflect both change detection and the neural populations that respond specifically to non-living objects. These populations are stimulated at a rate of 1.25 Hz, which we propose results in less neural habituation than in those being stimulated at 6.25 Hz. Roving standard paradigms in traditional MMN studies have addressed the issue of neural habituation, and the extension of the FPVS-oddball paradigm to other oddball designs would be a worthy avenue for future investigation and

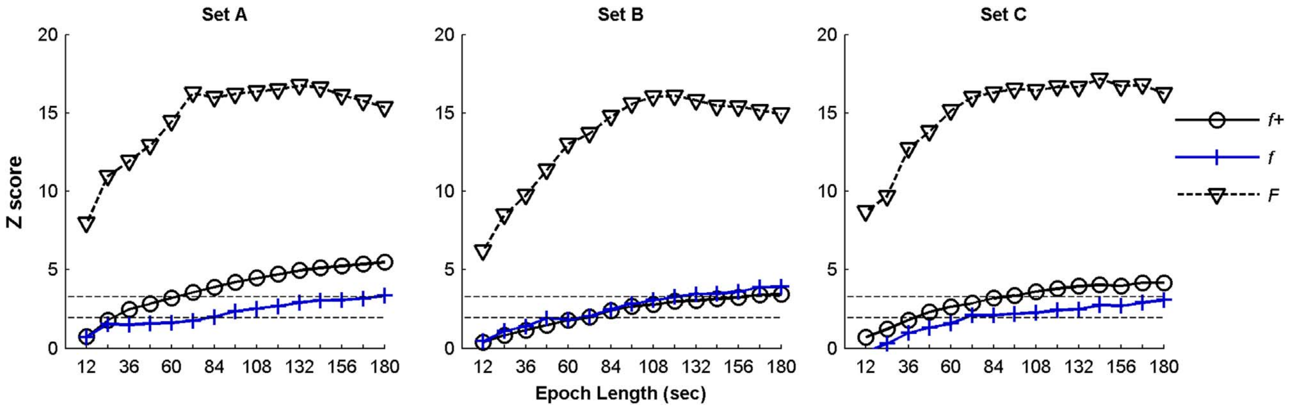

Fig. 4. The ***F, f*** and ***f*+** steady state responses over increasing presentation durations for image sets A and C at electrode PO10 and image set B at PO9. Z-scores reflect the deviation of amplitude at the specific frequencies of stimulation (***F, f* & *f*+**) from surrounding frequencies (± 0.45 Hz). The horizontal dashed lines indicate the z-score thresholds associated with conventional levels of statistical significance ($z = 1.96$, $p = 0.05$; $z = 3.29$, $p = 0.001$).

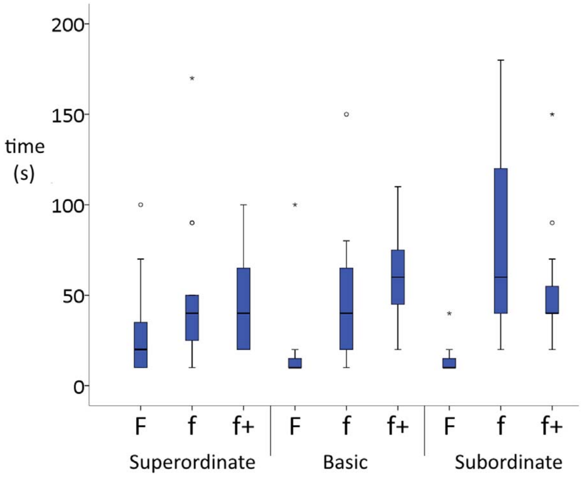

Fig. 5. Time for individual subjects' ***F,f*** and ***f*+** to reach $z = 1.96$, $p = 0.05$. Circles indicate subjects with times greater than 1.5 x Interquartile Range, asterisks indicate subjects with times greater than 3 x Interquartile Range.

may help to delineate the MMN response from that of differences in neural habituation.

The topographic distribution of responses to original images was broadly similar across the image sets, with the greatest power in lateral occipital sites, and a weaker but consistent central site. Scrambled images showed a considerably weaker but comparable pattern of lateral occipital and central activity. Cluster permutation analyses identified these areas as significantly different in both image sets A and C. The difference in central areas is intriguing and points to neural generators beyond the visual cortex. The vMMN, which we propose forms part of the ***f*+** response, has been demonstrated to involve neural generators in the Inferior Frontal Gyrus (Hedge et al., 2013). The temporal lobe, as part of the visual ventral stream, has repeatedly be shown to be involved in semantic categorisation (e.g. Anzellotti et al., 2010; Huth et al., 2016; Kreiman et al., 2000; Moss and Tyler, 2000). It is beyond the remit of the current study to make any claims about the neural generators of the oddball response but is certainly an avenue of interest for future studies, as the very high signal to noise ratio of the current approach would lend itself well to spatial modelling. While the topographies in response to original and scrambled images in image set B were similar to sets A and C, the cluster permutation analysis revealed a parietal and right hemisphere occipital cluster, which were less statistically significant than the clusters in sets A and C. It is possible that the distinction between standards and oddballs in set B was less clear than sets A and C, resulting in a weaker change detection response. This was neither anticipated or desired, but may be helpful in demonstrating the sensitivity of the approach to varying degrees of differentiation between standards and oddballs. MMN magnitude increases as the difference between standards and oddballs increases (Näätänen et al., 2004; Pakarinen et al., 2007), therefore we maintain that although vMMN is not the sole driver of the ***f*+** response, the weaker vMMN to a standard-oddball pairing that is not as distinct as others may explain the difference in results. An alternative explanation is that the difference in topographies is due to different neural generators for the different semantic categories. Dzhelyova et al. (2017) demonstrated distinct topographic patterns to different facial expressions using a similar FPVS-oddball paradigm. However we should be cautious in drawing immediate parallels between face and object processing, and further studies using a wide range of semantic categories is required to explore this possibility.

We have also demonstrated that the approach is remarkably stable and sensitive at the level of the individual subject, with most participants showing statistically significant oddball responses after only 60 s. This has not been possible with traditional event-related paradigms, and resulted in an inability to translate promising experimental findings at group level to viable clinical tools at the individual level. In combination, the adaptability, speed, stability at the individual participant level, and sensitivity to implicit processing mean that with rigorous validation this approach has the potential to provide a reliable, objective, non-verbal measure of many aspects of cognition.

Finally, small **f+** responses were observed to the scrambled images. This was unexpected and is likely due to systematic differences in visual properties between the standard and oddball images that were not totally disrupted by box scrambling. E.g. in image set C birds vs non-birds feathers and fur would have been distinguishable even in the scrambled images. Additionally box scrambling created a small difference in the visual angle of the control stimuli as they were less concentrated in the centre of the fixation square. This highlights the need for the careful control of low-level visual characteristics when assessing higher level processing. Future studies should make every effort to ensure systematic differences are minimised, and investigate the efficacy of alternative techniques for generating control stimuli, e.g. phase, texture or diffeomorphic scrambling (Stojanoski and Cusack, 2014). Additionally future studies could include the reversal condition of standard and oddball stimuli, e.g. non-living objects as standards and living as oddballs, in order to investigate any hierarchical preference in the visual system for particular semantic categories. While participants were not formally assessed for their explicit awareness of standard/oddball categories, anecdotally they indicated that they did not notice any change. Future studies should formally measure whether participants noticed any categorical change during the task, this would also allow direct comparisons with the Rapid Serial Visual Presentation literature.

In summary, we have demonstrated that the FPVS-oddball paradigm is a powerful new tool in cognitive neuroscience capable of being adapted to assess a wide range of cognitive functions. Stable and reliable at the level of the individual subject the technique has considerable clinical potential and provides an objective, non-verbal measure of abstract conceptual processing.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at http://dx.doi.org/10.1016/j.neuropsychologia.2017.05.025.

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