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Attentional preparation in high and low competition contexts

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Abstract

Proactive processes such as attentional selection aid us in responding more efficiently to upcoming demands. However, there is limited knowledge regarding the involvement of selective attention and its dynamic behavior in target-distractor resolution of conflict. In this study we employed electroencephalographic techniques analyzed through multivariate pattern analysis (MVPA) to assess the role of selective attention under two distinct conditions, high and low distractor competition, within a cue-target paradigm. Behavioral results showed expected lower accuracy and higher response time (RT) as well as higher interference effects for High Competition blocks compared to Low. Within same time point classification decoding demonstrated a significant presence of category relevant information whilst cross-condition cluster analysis showed no significant difference. Temporal generalization analysis showed significant clustering within both conditions but none between them. Lastly, correlational analysis between behavioral and decoding results showed no significant relation. These results point towards selective attention as a binary process which can either be engaged or disengaged, a notion which contradicts the expected gradual increase of proactive processes as a function of task difficulty sustained by present models. While these results should be taken with caution due to them arising from an incomplete sample, the analytical methods used prove themselves useful in novel forms of descriptions of cognitive processes.

Introduction

On a daily basis we face tasks that require us to single out a specific stimulus from a myriad of them. Searching for items in the grocery list through supermarket aisles or focusing on a present conversation over background noise are some examples of this phenomena. Since William James' (1980) famous description of attention as the process through which this selection of objects is achievable our conceptualization has significantly evolved (Broadbent, 1958; Treisman, 1969; Kahneman, 1973; Lavie, 2004). While there is yet to be a consensus of the underlying mechanisms of attentional selection, its involvement, in conjunction with cognitive control processes, in both short- and long-term goal establishment seems clear. Cognitive control mechanisms are often conceptualized depending on whether they take place before target-stimulus presentation (i.e., proactive) or afterwards (i.e., reactive; Braver, 2012). Proactive processes bias attentional orientation based on knowledge of some feature of the target (Morishima, Okuda & Sakai, 2010), whereas reactive processes focus attention on the target stimulus and aid in the online monitoring and resolution of conflict (Botvinick, Braver, Barch, Carter & Cohen, 2001). While both proactive and reactive mechanisms play essential and complementary roles in many theoretical models (Desimone & Duncan, 1995; Corbetta & Shulman, 2002) in this study we will focus on the former due to our limited understanding of its functions. Therefore, the main goal of the current experiment is to investigate the role of proactive selective attention in target-distractor conflict resolution through the use of electroencephalographic (EEG) techniques.

Proactive, top-down, processes can be studied using cue-target paradigms (e.g., González-García, Mas-Herrero, Diego-Balaguer & Ruz, 2016). Here, a cue which contains relevant information about the target stimulus, such as its physical characteristics or spatial location, is presented prior to its onset (Posner, 1980). This information is then used to bias processing in favor of the target stimulus and against distractors. (Klotz & Wolff, 1995; Bugg & Crump, 2012). However, this effect can be modulated by distractor competition (Kaiser, Stein, & Peelen, 2014). Due to proactive processes taking place before target onset, behavioral measurements will reflect the effects of both proactive and reactive processes. However, through the use of neuroimaging techniques we are able to solve this problem by gathering data within the cue-target interval.

The traditional approach to the study of cognitive functions through neuroimaging has been to delineate areas suspected of being responsible for their processing. Through this approach regions such as the dorsolateral prefrontal cortex (dlPFC), intraparietal sulcus (IPS) and superior parietal lobe, among others have been associated with current goal representations (McNamee, Liljeholm, Zika, & O'Doherty, 2015; González-García, Arco, Palenciano, Ramírez, & Ruz, 2017; Turnbull et al, 2019; Petersen & Posner, 2012).

Further research has associated goal-oriented behavior to the global activity of a specific set of brain regions, a network constituted of areas such as the IPS, inferior frontal sulcus (IFS) or the anterior insula among others. While this is a more complex approach to cognitive function analysis, it is still rooted on the same regional processing basis. Similarly, EEG based cognitive research has mostly focused on event related potentials (ERP) to provide a fine-grained characterization of the temporal dynamics of selective attention process.

Despite the numerous contributions of ERP research and other univariate approaches to the advance of knowledge about cognitive functions, their sensitivity and scope of interpretations that they allow is limited (Luck, 2005). Recently, the field has incorporated other approaches which focus instead on patterns of brain activity. Current theories hold that brain regions code for several different functions, depending on the spatial arrangement of activity (Hanson, Matsuka & Haxby, 2004). To analyze said patterns, newer analysis techniques are employed, commonly known as multivariate pattern analyses (MVPA).

Initially introduced in neuroscience as a tool to analyze discrete unites of activity (i.e., voxels), patterns within functional magnetic resonance imaging (fMRI), MVPA has now become a widespread tool within the field (Freund, Etzel, & Braver, 2021; Li *et al*, 2017). In contrast to the univariate approach in which individual voxels tend to be analyzed separately, MVPA analyzes the contribution of each voxel to the overall pattern by taking into account their covariance. These values become relevant only as factors that aid in the distinction between patterns associated with different experimental conditions of interest. Thus, while univariate approaches deal in an activation centered approach, MVPA focuses on the presence of patterns, or information (Hebart & Baker, 2018; Kriegeskorte & Kievit, 2013).

To distinguish between patterns corresponding to different cognitive functions, machine learning algorithms, commonly referred as classifiers, are used. The classifier is tasked with creating a decision boundary within a multidimensional space (Haxby, Connolly, & Guntupalli, 2014). Just as two points within a two-dimensional plane or a three-dimensional space can be separated with the use of either a line or plane respectively, so can data points within higher dimensional spaces be divided by a hyperplane adjusted by the classifier. This higher dimensionality is caused by the number of features involved in the pattern (e.g., number of voxels in fMRI or number of electrodes and data points in EEG). Classifiers can either be linear or non-linear, depending on the adjustment function on which the machine learning algorithm is built on. Non-linear classifiers are capable of adjusting better to the data used for its training, however greater considerations must be taken in order to avoid overfitting, a phenomenon in which the classifier is unable to generalize its decision boundary to data from the same sample but which it has not been trained with. On the other hand, linear classifiers, such as support vector machine (SVM) or linear discriminant analysis (LDA), are simpler and easier to interpret whilst being more resistant to overfitting. These characteristics have made linear classifiers the preferred method for neuroscience research (Grootswagers, Wardle, & Carlson, 2017), and this is the analytical approach that we applied in the current study.

Here we wanted to compare the influence of proactive processes on selective attention under two levels of distractor competition with both behavioral and neuroimaging methods to fill in the knowledge gap of how these processes dynamically behave and contribute to target stimulus-distractor conflict. Braver's (2012) dual mechanisms of control (DMC) framework holds that proactive processes bias attention in a goal-driven manner. Therefore, under a cue-target paradigm proactive processes triggered by cues should facilitate target-stimulus response. This will be affected by the presence of distractors, specifically if they possess common features with the target which interfere with the response (Kastner, De Weerd, Desimone & Ungerleider, 1998; Duncan, 1980). Thus, we employed a cue-target paradigm with two different levels of distractor competition by either; simultaneous presentation of both target and distractor-stimulus (high competition), or delaying distractor presentation (low competition, see Kastner, De Weerd, Desimone, Ungerleider, 1998). To measure competition, we had congruent conditions, where target and distractor stimuli were associated with the same response, and incongruent ones, with different response. While behavioral results will reflect the common effect of both proactive and reactive cognitive control processes, MVPA analysis based on the EEG data locked at the cue will only reflect the former.

Hypotheses

1. In high competition blocks, behavioral efficiency, will be reduced and an interference effect will appear in incongruent trials. This effect, however, will appear to a lesser extent in low competition blocks.
2. Cues will trigger the pre-activation of specific neural patterns related to the anticipated target stimulus category.
3. During high competition blocks, the EEG activity associated with preparation will contain more information about the anticipated target stimulus than low competition contexts, reflected as higher accuracy rates.
4. Classifier accuracy, that is, the percentage of correct predictions by the trained classifier on novel data, will positively correlate with behavioral measurements such as accuracy and response time in high competition blocks.

Methods

Participants

Our sample consisted of sixteen participants (8 females, mean age 21.6, SD = 2.26) with normal or corrected-to-normal visual acuity. All of them were right-handed, Spanish native speakers, and were students at the University of Granada. All participants signed informed consents prior to participation and received economic compensation (10 euros per hour and up to a 5 euros bonus for performance). The sample size was set to accomplish 80% of power, for an expected small effect size, Cohen's d = .02, in a 2*2*2 design, equivalent to a sample size of n = 34 (PANGEA: Power Analysis for General ANOVA designs; Westfall, 2015). However, due to time constraints, we stopped data collection at the current sample size.

Apparatus and stimuli

Twenty-four Spanish person's names and 24 faces (The Chicago Face Database, Correll & Wittenbrink, 2015) were used as targets. Half of these stimuli were female and the other half male. Four different geometrical shapes were used as cues: a square, circle, drop and rhombus. All stimuli were presented on a gray background. The task was implemented on Psychotoolbox (Kleiner, Brainard, & Pelli, 2007). The stimuli were presented on a LCD, 1920x1080 resolution, 60 Hz refresh rate screen. The room was kept lit throughout the experiment.

Procedure and experimental design

The experiment was carried out at the Mind, Brain and Behavior Research Center at the University of Granada. Before the experiment began, we set the electrode cap with all 64 electrodes on the head of the participants. Then, they were instructed about the task they were about to perform, where in each trial a cue was followed by an overlapping face and name. They had to respond as quickly and as precisely as possible to the gender of the target stimulus, either the face or the name, which was indicated by the cue, by pressing either the letter "A" or "L" (counterbalanced across participants). In half of the trial, target and distractor stimuli had the same gender (congruent condition) whereas in the other half their gender was different (incongruent trials).

The task was comprised of a total of 72 blocks divided equally (24) into three different types of blocks (with 24 trials each). Cue target blocks, which varied in the level of competition of the target and distractor stimuli. In High Competition blocks they were both presented simultaneously whereas in Low Competition blocks, distractor onset lagged behind the presentation of the target stimuli (adapted from Kastner, De Weerd, Desimone, Ungerleider, 1998). Each block used four cues, two for each stimulus Category, counterbalanced to avoid perceptual confounds in cue decoding analyses. The association of cues with conditions was fully counterbalanced across participants. The third type were Perceptual Localizer blocks, where face and word stimuli (50% each) were presented individually and participants only responded by pressing the "C" key when they appeared upside-down (10% of trials).

All stimuli were presented at the center of the screen. The sequence of events in the cue-target trials was as follows (see Figure 1): in High Competition blocks a cue appearing for 50 ms was followed by a fixation point (1.51º x 1.51º) lasting 1500ms. Next, both target and distractor appeared for 750 ms before simultaneously disappearing. Lastly, a second fixation point appeared, lasting 1500 ms. Low Competition blocks began with the same structure, however the target was presented by itself initially for 500 ms before the addition of the distractor for a total of 250 ms of target-distractor simultaneous presentation. Next, the target disappeared and the distractor remained on the screen for an additional 500 ms. Lastly, a second fixation point appeared for 1000 ms on average. This time structure ensured that the whole duration of High and Low Competition trials was kept the same (3800 ms). Either face (mean height 9.38º x 6.7º) or name stimuli (2.83º x 10.76º) could be the target or distractor depending on the cue (4.55º x 4.24º). Localizer blocks started with a fixation point lasting 500 ms followed by a stimulus which could be presented upright (90% of trials) or rotated

180º (10%) and which lasted 750 ms. The trial then ended with a 500 ms lasting fixation point. Figure 1 displays a female face as a target with a gender congruent name as distractor across High and Low Competition blocks and the same female face for a go-trial in the Localizer block. Participants could respond as soon as the target appeared and until 1500 ms afterwards.

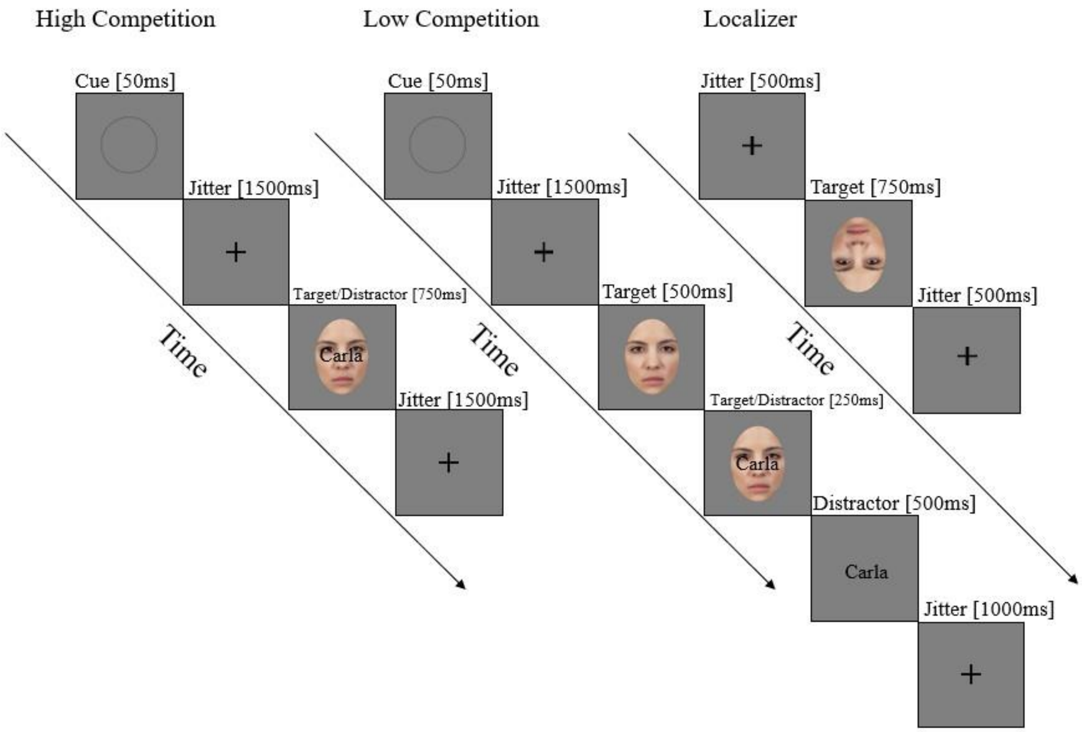

Figure 1. Description of each of the three block types used in this experiment illustrating the succession of stimuli presented in conjunction with their corresponding time intervals within each trial.

Before the experimental session, participants performed 6 practice blocks in which they had to score more than 80% to enter the experimental session. Practice blocks were made up of 2 of each block type. In total the experiment took around 90 minutes to be completed.

The experiment employed a within-subject design, with factors Competition (High vs. Low), Target Congruency (Congruent vs. Incongruent) and Stimulus Category (Faces vs. Names).

EEG recordings and preprocessing

High density electroencephalography was recorded at 1000 Hz using a 64 channel (actiCHap system (Brain Products GmbH, Munich, Germany) with active electrodes positioned according to the 10-20 EEG International System and referenced to Cz. EEG recordings were down sampled offline to 256 Hz, and digitally filtered using a low pass cutoff of 126Hz and high pass cutoff at 0.1 Hz as well as a notch at 50 Hz and 100 Hz. Noisy channels were visually selected and interpolated when needed. On average, 1.38 channels per participant were interpolated. A series of epochs were created based on relevant conditions for later analyses. Eye blink and movement artifacts were identified employing Independent Component Analysis (ICA) computed using EEGLAB, selected by visual inspection and were later removed from raw activity. Afterward, we removed noisy trials based on: abnormal spectra (more than 50dB in the 0-2 Hz frequency window and -100dB or +25dB between 20-40Hz), improbable data (voltage values over 6 SDs from the baseline) and extreme values (range = 150V; see for similar approach (López-García, Sobrado, Peñalver, Górriz, & Ruz, 2020)). This resulted in an average of 258.94 trials removed in the whole sample, keeping an average of 93.42% of the total of correctly answered number of trials).

EEG Analysis

For the purpose of this TFM, we focused on Multivariate Pattern Analysis (MVPA) of the cue-locked EEG data to study proactive processes of High and Low Competition conditions separately. While MVPA encompasses a wide range of approaches, here we exclusively focused on decoding analysis. With this method we are able to take into account the relationships between variables to predict a model from our data, in this case, to determine if the participant was presented with either a Face or Name cue within either Competition conditions. To accomplish this task, recorded EEG data is assumed to contain condition induced activity patterns within a high dimensional space. To then distinguish between these condition-patterns we trained a classifier, LDA, using a subset of our epoched data. This data consisted of epochs between -100ms before cue onset, so as to set a baseline, to 1500ms post cue.

During training an iterative process takes place in which the classifier continuously keeps adjusting its decision boundary to better fit the training data that it has been supplied with. When training is completed, this decision boundary constructed by the classifier is then tested on new data (which has been previously withheld from). To take full advantage of the gathered data we used cross-validation, a process in which every trial is used for both training and testing. This was accomplished through the *k-fold* (5) method: all trials were subdivided into five separate groups, four of which were used to train the classifier and the fifth to test its accuracy. This process was repeated five times, altering between which of the groups were used to test and train, therefore using all the data for both goals, and outputting the final accuracy rates as the average value of all five folds. If testing accuracies are significantly above random chance it is indicative of the classifiers ability to generalize and of the presence of distinct information patterns within our collected the data.

The high temporal resolution characteristic of EEG enables us to test the classifier's accuracy rates both within and across time points. While the former informs us of the general relevant information present at a given time, the later, known as temporal generalization, is indicative of the underlying dynamics of our condition specific information processing. Thus, exclusively diagonal patterns indicate the involvement of a highly dynamic process with a continuously changing representation of the targets underlying information. On the other hand, a wide spread pattern would indicate that a given configuration of the classifier produced by trained data at a given time point is also suitable for other temporal points. This would then indicate a static processing of information.

We therefore tested category classification rates of our LDA classifier both within and across time points for both High and Low Competition conditions. Additionally, we compared within same time points classification rates between conditions (High and Low) through the use of cluster analysis to assess if higher demand trials implied high classification rates possibly due to an increase of proactive process reliance in order to aid target response.

Due to the high noise to signal ratio present in neuroimaging we used supertrials (3), the averaging of three equal condition trials into one to reduce data dimensionality.

Behavioral and Decoding Correlations

To study the relevance of the information contained in proactive processes we correlated behavioral and decoding results through a Person's correlational analysis. High and Low Competition condition accuracy and RT were correlated with their corresponding decoding accuracy results. Decoding values were extracted per participant from the average highest classification rate interval spanning 20 data points.

Results

Behavioral Results

Accuracy and RT were analyzed with two separate 3-way repeated-measures ANOVAs, with Competition, Target Congruency and Stimulus Category as factors. In order to break down interactions we used a two tailed paired sample Students t-test.

Overall accuracy in the task was 94% (see Figure 2). The ANOVA showed that accuracy was lower in High compared to Low Competition blocks, $F = 10.84$, $p = .005$, $\eta^2 = .05$, Incongruent compared to Congruent trials, $F = 44.33$, $p <.001$, $\eta^2 = .3$, and showed no significant differences between Stimulus Category conditions (Faces vs Names) $F < 1$. All the 2-way interactions between the variables were significant. The Competition*Congruency's interaction, $F = 38.4$, $p <.001$, $\eta^2 = .21$, was driven by an effect of congruency in High Competition blocks ($t = 7.63$, $p <.001$), but not in Low Competition ones ($t = .93$, $p = .37$). The interaction Competition*Category, $F = 10.86$, $p = .02$, $\eta^2 = .01$, was due to the effect of competition being larger for Faces ($t = -5.33$, $p < .001$) than for Names ($t = -.87$, p = .4). Also, the interaction of Congruency*Category, $F = 7.39$, $p = .02$, $\eta^2 = .01$, stemmed from the effect of congruency being larger for Faces ($t = 7.68$, $p <.001$) than for Names ($t = 3.98$, $p = .001$). In addition, the three-way interaction between Competition*Congruency*Category was also significant, $F = 6.62$, $p = .02$, $\eta^2 = .01$, given that the interaction between Congruency and Category was significant in the High Competition block ($F = 11.15$, $p = .01$, $\eta^2 = .03$) but not in the Low Competition one ($F < 1$).

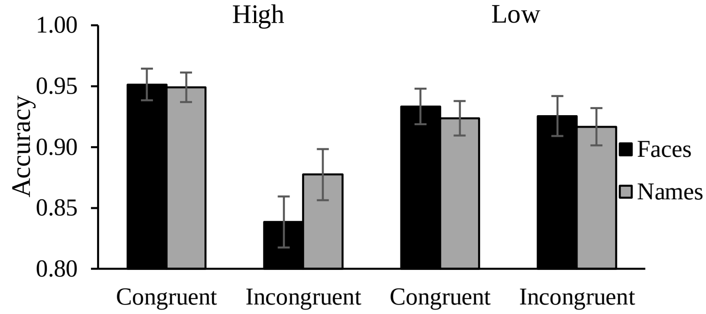

Figure 2. Graphical representation of the average accuracy per condition (bar pairs corresponding with Congruency and color with Category conditions within High or Low Competition blocks).

For RT analyses we filtered trials with erroneous responses (6%) as well as outliers (values over and under 2 SD from the average computed across conditions and participants; (3.17%). The ANOVA showed that RT (see Table 1 for the average RT per condition) was higher for High compared to Low Competition blocks ($F = 7.2$, $p = .02$, $\eta^2 = .13$), Incongruent compared to Congruent trials ($F = 138.98$, $p < .001$, $\eta^2 = .16$), and trials whose target were Names compared to Faces ($F = 15.86$, $p = .001$, $\eta^2 = .05$). Only Competition*Congruency (see Figure 3) showed a significant two-way interaction ($F = 92.04$, $p > .001$, $\eta^2 = .22$), as the amount of competition was larger in High Competition blocks (54 ms) than in Low Competition ones (-8 ms).

Table 1. Mean RT values (with Standard Deviation, SD) per experimental condition combination.

	High				Low			
	Congruent		Incongruent		Congruent		Incongruent	
	Face	Name	Face	Name	Face	Name	Face	Name
Mean	.509	.521	.567	.591	.513	.531	.509	.525
SD	.072	.064	.089	.077	.083	.085	.080	.085
Maximum	.400	.420	.430	.460	.390	.410	.400	.410
Minimum	.610	.600	.710	.680	.690	.650	.660	.670

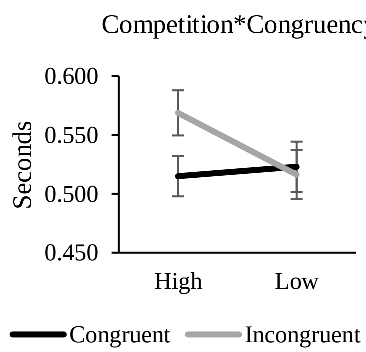

Figure 3. Graphical representation of the two-way interaction, Competition*Congruency. Bars represent RT in seconds for both Congruency conditions (depicted in different colors) within High and Low blocks.

Multivariate Pattern Analysis

Within Time Point Classification

Once computed, the classifier's accuracy in Category distinction was plotted for both Competition conditions within a [-100, 1500] ms cue-locked interval as shown in Figure 4. Significant differences for each condition against random chance (50%) seem to be divided into three intervals; an initial synchronous peak for both Competition conditions, [100, 330] ms, a secondary peak appearing directly after the initial one but ending earlier for High (~400 ms) than Low Competition (~530 ms), and tertiary peaks spread asynchronously between conditions.

The cluster analysis employed to asses the presence of significant differences (p<.05) between the accuracy of the classifier in high and low competition conditions across time showed no significant results.

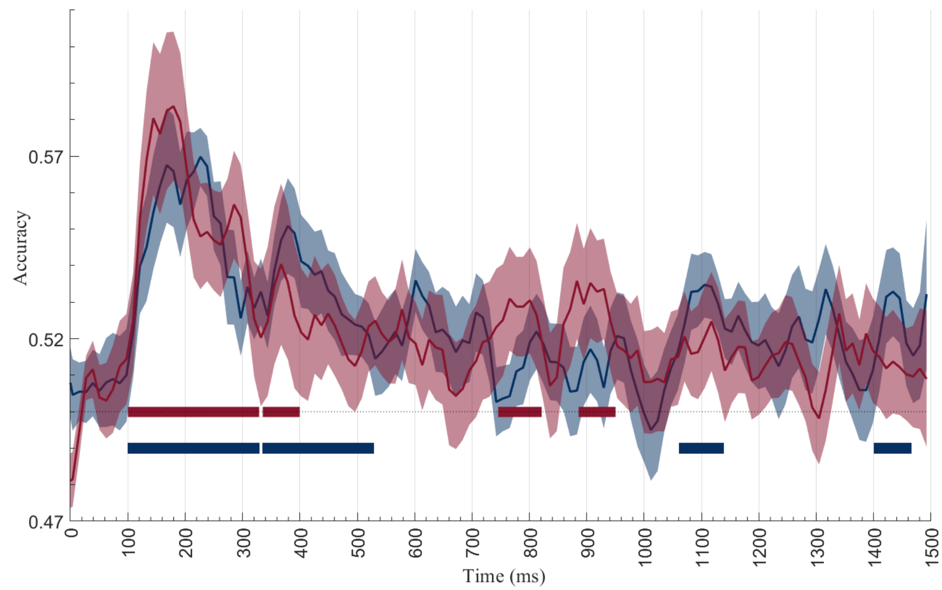

Figure 4. Area under the curve (accuracy) for both High (Red) and Low (Blue) competition conditions across time, spanning -100ms before cue onset to 1500 after cue onset. Significant intervals are depicted as the red (High) and blue (Low) lines.

Temporal Generalization

Figure 5. shows the results from our temporal generalization analysis. Color grading indicates accuracy rates of the classifier which has been trained with data gathered at a certain time point (indicated by the X axis) and then tested against withheld data across different time points (indicated by the Y axis). We then proceeded to compare temporal generalization information contained within both Competition conditions. Through cluster analysis we obtained no significant clusters between conditions. Therefore, while visual analysis may indicate different dynamic patterns between High and Low conditions, cluster analysis shows there are none.

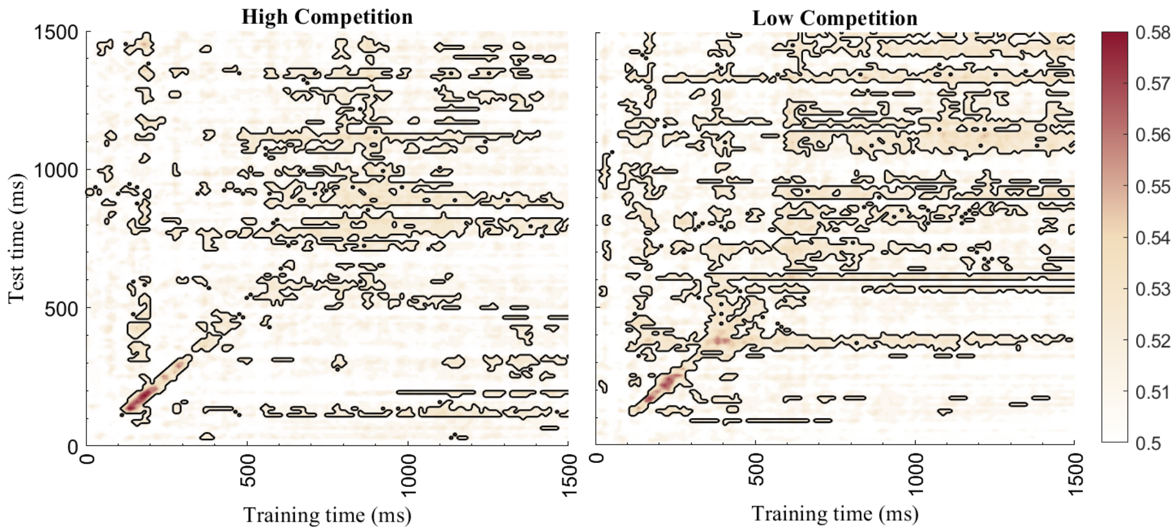

Figure 5. Temporal generalization matrix for both High (left) and Low (right) Competition conditions. Black lines display classification accuracy significantly above chance, as evaluated with a cluster statistical analysis (p < .05).

Behavioral and Decoding Correlations

We average the classification rates per participants within the [100, 300] ms interval for both the High and Low Competition condition, and then correlated with its behavioral counter parts (accuracy and RT). All correlations were found non-significant when calculated (all *ps* >.1)

Discussion

In this experiment, we investigated the role of proactive selective attention in target-distractor conflict resolution using a cue-target paradigm and MVPA decoding of EEG dynamics. Our results revealed the presence of cue-induced stimulus category information the quantity of which did not vary between competition conditions nor did it relate to behavioral efficiency measurements. Caution should be exercised when viewing these results due to the lack of power caused by the incomplete sampling.

In line with our hypothesis, behavioral results showed a reduction in accuracy and slower RTs for High compared to Low Competition conditions. An expected greater interference effect appeared within High Competition blocks. This constitutes evidence that the experimental design employed is effective in creating two measurably distinct difficulty levels which affect differently the behavioral output of attentional selection (Kastner, De Weerd, Desimone & Ungerleider, 1998; Duncan, 1980).

Within and across time points MVPA-EEG classification accuracy results show the presence of category relevant information with temporal generalization at several time points for both conditions. This implies reactivation of target information through several distinct signals which lasts since their appearance up to target presentation. However, accuracy rates did not vary between Competition conditions for neither within or between time point analysis, thus quantity of target information and specific signal dynamics are equal between conditions.

Lastly, correlational analysis between the averaged value of the primary peak from the within time point MVPA-EEG classification and, behavioral accuracy and RT, showed no significant relation for neither Competition conditions. Therefore, the degree of target information present within the cue-target interval does not appear to be related to the behavioral outcome. However, these results could be due to a lack of power caused by the incomplete sample.

Due to the equal behavior that attentional selection has both within and across time points under both difficulty conditions and the inconclusive relation between the amount of category information and the observed increase in accuracy and decrease in RT we hypothesized that this process may act through a dual state in which it can either be engaged or disengaged. This goes against current proactive theories (Braver, 2012; Desimone & Duncan, 1995) which hold that while lower cognitive demanding task can be resolved efficiently through bottom-up processes, higher demanding task require of top-down biasing. Therefore, one would expect a gradual increase in category information elicited by the cue as a function of the task difficulty it precedes. While our results do not support this hypothesis, we cannot rule out the possibility that the reduced sample size, potential ceiling effects for distractor induced difficulty or an unfavorable noise to signal ratio might be hiding the expected increase in category information within higher cognitively demanding tasks.

The approach presented demonstrates the possibilities which MVPA-EEG analysis can offer regarding temporal descriptions of cognitive functions. Once the previous issues are addressed, this study can serve as both a basis for future comparisons with other proactive processes as much as with spatial attentional selection descriptions based on MVPA-fMRI analysis in order to obtained a more profound description of said process.

Conclusion

In this study, we found evidence that suggests that selective attention, as a proactive process, might act equally for different task difficulties which contradicts main theories that hold that greater difficulty tasks require a larger implication of proactive processes to be resolved efficiently. While these contradictory findings may be due to the limitations of the present study, they here set a precedent for the viability of information pattern-based analysis due to the novel insight that it grants us, specifically in this experiment, a description of the temporal dynamic behavior of the proactive process of attentional selection.

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