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Time Frequency Analysis of Neural Oscillations in Multi-Attribute Decision-Making

Iris Lieuw
Scripps College

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Time frequency analysis of neural oscillations in
multi-attribute decision-making

A Thesis Presented

by

Iris Liew

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Abstract

In our daily lives, we often make decisions that require the use of self-control, weighing trade-offs between various attributes: for example, selecting a food based on its health rather than its taste. Previous research suggests that re-weighting attributes may rely on selective attention, associated with decreased neural oscillations over posterior brain regions in the alpha (8-12 Hz) frequency range. Here, we utilized the high temporal resolution and whole-brain coverage of electroencephalography (EEG) to test this hypothesis in data collected from hungry human subjects exercising dietary self-control. Prior analysis of this data has found time-locked neural activity associated with each food's perceived taste and health properties from approximately 400 to 650 ms after stimulus onset (Harris et al., 2013). We conducted time-frequency analyses to examine the role of alpha-band oscillations in this attribute weighting. Specifically, we predicted that there would be decreased alpha power in posterior electrodes beginning approximately 400 ms after stimulus onset for the presentation of healthy food relative to unhealthy food, reflecting shifts in selective attention. Consistent with this hypothesis, we found a significant decrease in alpha power for presentations of healthy relative to unhealthy foods. As predicted, this effect was most pronounced at posterior occipital and parietal electrodes and was significant from approximately 450 to 700 ms post-stimulus onset. Additionally, we found significant alpha-band decreases in right temporal electrodes during these times. These results extend previous attention research to multi-attribute choice, suggesting that the re-weighting of attributes can be measured neuro-computationally.

Introduction

In our daily lives, we often make decisions that require the use of self-control, weighing trade-offs between short-term and long-term consequences. For example, consider choosing between chocolate cake and an apple. Although the apple is less tempting, choosing this healthier option may lead to better long-term outcomes, whereas choosing the tastier option gives an immediate reward but may be associated with poorer health in the long term. By focusing on different attributes such as taste versus health, we can end up overindulging in sweets or foregoing tasty but less healthy options to maintain a healthy state.

Psychologically, this process may be reflected in the level of construal at which we approach a decision. Construals are how individuals perceive, comprehend, and interpret the world around them. Construal level theory (CLT) states that mental construal level is affected by one's "psychological distance" from an object (Liberman & Trope, 2008): that is, the perceived distance of the target in time, space, social status, or the likelihood of occurrence (Bar-Anan et al., 2006). As psychological distance increases, an object will be represented at an increasingly higher (more abstract) level of construal.

In terms of construal, it is not difficult to imagine the concept of "taste," how appetitive a certain food is. What about health? Calories, sodium, sugar, and fats all play a role in a food's healthiness, but health is more abstract and difficult to define than taste. This intuitive difference between taste and health can be characterized in terms of their psychological distance, from concrete or short-term (e.g., taste) to abstract or long-term (e.g., health). Research on construal processes suggests that prediction, evaluation, and planning of psychologically near and distant situations vary in terms of the construal of situation, and not the situation itself. Findings in support of CLT suggest that as psychological distance

increases, people become more certain when predicting distal (farther) outcomes, they evaluate high-level construals more attractively, and they rely less on local concerns and more on global concerns (Liberman & Trope, 2008).

These differences in construal level may play a role in whether and how we exercise self-control. In normal circumstances, the concrete and immediate construal of taste may be more readily activated compared to abstract information about health and considerations of its more distant costs. In contrast, when individuals are explicitly prompted to consider the healthiness of foods, this shift to a higher construal level leads to more healthy food choices (Hare et al., 2011).

How can differences in construal level be measured in the brain? To do this, we must examine areas of the brain that are involved in decision-making. Specifically, we will focus on two regions of the prefrontal cortex: the ventromedial prefrontal cortex (vmPFC) and the dorsolateral prefrontal cortex (dlPFC). As described below, these two areas are implicated, respectively, in value computation and self-control.

Neural Correlates of Value and Self-Control

To further examine how these attributes are represented in the brain, neural circuits related to multi-attribute decision-making must be studied. One area thought to be involved in self-control and decision-making is the prefrontal cortex (PFC) (Mitchell, 2011). The PFC is important in the study of self-control in decision-making due to its large number of anatomical connections with other areas of the brain. These anatomical connections are thought to allow for communication and flow of information (Mitchell, 2011). Because of all the connections that the PFC has with other regions of the brain, integration of information is thought to be an important aspect of the PFC.

Ventromedial Prefrontal Cortex

To make choices, the brain is thought to compute the value associated with each option, and then compare these value signals to select the optimal alternative. Considerable neuroscience research has implicated the vmPFC in the encoding of stimulus values when individuals make choices (Montague & Berns, 2002; Rangel et al., 2008; Rangel & Clithero, 2013). The vmPFC is connected to sensory areas, memory-related structures, and cognitive control regions. These interconnections suggest that vmPFC integrates value attributes (Rangel and Hare, 2010; Harris et al., 2011).

Studies of brain-damaged patients, monkey electrophysiology, and human neuroimaging all provide evidence that the vmPFC plays a large role in successful decision-making. Subjects with lesions to the ventromedial prefrontal cortex have severe disruptions in value computation, causing significant inconsistencies in subjects' choices when compared with the choices of healthy control subjects (Fellows & Farah, 2007; Camille et al., 2011; Henri-Bhargava et al., 2012). Frontal lobe lesions without damage to the vmPFC produce behavior similar to that of control subjects, supporting the essential role of the vmPFC in decision-making. In monkey electrophysiology studies, the orbitofrontal cortex (OFC), an area located within the vmPFC (Fellows & Farah, 2007), has been found to encode the values of available options when monkeys are presented with the choice of drinking one of two different volumes of juices (Padoa-Schioppa & Assad, 2006; Kennerley et al., 2011). In studies using functional magnetic resonance imaging (fMRI), OFC activation is also found during value computation in a wide variety of tasks (for a review, see Rangel and Hare, 2010).

Research using event-related potentials (ERP) has suggested how the vmPFC may integrate stimulus information to arrive at value. Using a food choice task, Harris et al. (2011) localized the emergence of value signals over time to regions including the vmPFC. By performing a Granger connectivity analysis, Harris et al. (2011) identified connections from posterior association cortex to vmPFC, suggesting that these brain regions form a network involved in dynamic value computation. Thus, integration of an overall value signal occurs in the vmPFC. Another study that utilized magnetoencephalography (MEG) on subjects making decisions similarly found value signal integration localized to vmPFC (Hunt et al., 2012).

Dorsolateral Prefrontal Cortex

In order for value computation to occur, different attributes associated with food (e.g., taste and health) need to be integrated in vmPFC. How are these value signals adjusted to reflect changing goals like the desire to lose weight? Dorsolateral prefrontal cortex (dlPFC) is one region that has been implicated in this process. Located in the middle frontal gyrus (Brodmann area 9), the dlPFC has rich connections with regions of the temporal and parietal cortex, implicating this region in reward-related decision-making (Mitchell, 2011).

Multiple studies have shown that the dlPFC is involved in working memory (Levy & Goldman-Rakic, 2000; Curtis & D'Esposito, 2004), cognitive control (Miller, 2000), and emotional regulation (Mitchell, 2011). These studies have found that the dlPFC plays an “executive role” in the top-down modulation of other brain areas (e.g., inferior temporal cortex; Miller, 2000) and in the maintenance of information in working memory (Camus et al., 2009).

More recently, studies of self-control in dieting (Hare et al., 2009), craving regulation (Kober et al., 2010), and intertemporal choice (Hare et al., 2014) have suggested that this region plays a role in cognitive regulation. Hare and colleagues (2009) used fMRI to look at neural activity in vmPFC and dlPFC while self-reported dieters made choices about whether to eat various foods. Their results suggest that self-control requires that multiple factors (e.g. different construals such as taste and health) are integrated in vmPFC for the computation of goal values, and that dlPFC activity is required for the abstract construal of health to be incorporated into the vmPFC value signal. In addition, Hare et al. (2009) found that areas of dlPFC that play a role in self-control are also similar to areas involved in cognitive control and emotional regulation.

This modulation of value computation is also seen in studies using transcranial magnetic stimulation (TMS). TMS is a non-invasive neurostimulation and neuromodulation technique that utilizes electromagnetic induction of an electric field in the brain (Rossi et al., 2009). In a study conducted using repetitive TMS (rTMS) over dlPFC, the dlPFC was found to play a causal role in the computation of values at the time of choice during a food-decision making task (Camus et al., 2009). When they applied rTMS to the right dlPFC, they found there was a decrease in the values assigned to food stimuli. A similar study that used TMS stimulation on dlPFC found that dopamine levels changed in ipsilateral anterior cingulate cortex (ACC) and in medial OFC, suggesting that dlPFC plays an important role in the modulation of various brain regions (Cho & Strafella, 2009).

Neurophysiological Mechanisms of Self-Control

As described above, the dlPFC is involved in the modulation of value computation in the vmPFC. However, due to inherent limitations of the techniques involved, these studies cannot address the timing of neural activity associated with self-control. With its high temporal resolution and whole-brain coverage, electroencephalography (EEG) is ideal for measuring the differential timing of activity in dlPFC and vmPFC during self-control.

In a study conducted using EEG on subjects making decisions about food (e.g. tasty and healthy choices), the researchers found that self-control during a food choice task involves both attentional filtering and value signal modulation (Harris et al., 2013). Attentional filtering refers to the modulation of early sensory responses. This process is often attributed to the dlPFC, which is part of a larger attentional network. According to Harris et al. (2013), attentional filtering reduces the amount of neural processing for distracting and irrelevant items. Value signal modulation, as described above, occurs when dlPFC modulates the value signals of vmPFC. Neural activity correlated with subject ratings of taste and health was localized to vmPFC sources overlapping with those for stimulus value, with significant causal connectivity found between dlPFC and vmPFC (from 500 to 600 ms). Their data suggests that the valuation of taste and health attributes occurs late in the trial, approximately 450 to 650 ms after stimulus onset, and further suggests that the dlPFC plays a causal role in decision-making (Harris et al., 2013).

How does attentional modulation affect self-control? Previous behavioral and decision-making studies suggest that attention can change the way construals are integrated (Shimojo et al., 2003; Rieskamp et al., 2006; Rangel et al., 2008; Hare et al., 2011). Using an fMRI food choice task, Hare et al. (2011) explored how attention affects dlPFC and vmPFC

interaction. They found that when attention was directed towards health, there was increased consideration of health in non-dieting subjects, whereas when attention was directed towards taste, there was no difference in choice. Increased healthy choices also correlated with increased vmPFC representation of health ratings, signifying that self-control can be exercised simply by having people weight long-term considerations. Overall, these results provide evidence that attention can indeed affect value computations, specifically, that directing attention to the health of a food increases the weight given to “healthiness” in the vmPFC.

Neural Oscillations and Attention

How does the dlPFC re-direct attention to underweighted construals such as health? In order to examine how this reweighting of attributes occurs, it is important to first understand neural oscillations, a basic bioelectrical mechanism through which neural computations support cognitive processes.

Recordings of neural activity are made up of the synchronized oscillatory activity of large numbers of neurons. Due to its capability of recording neural activity to thousandths of a second, EEG is a particularly useful tool for measuring large-scale neural oscillations. Oscillatory neural activity can be characterized in terms of its power, or overall magnitude, as well as by the degree of phase synchronization between neurons in a localized region or between different areas of the brain (Sun et al., 2012).

The field potentials in EEG recordings can be broken down by frequency bands associated with different neural processes. For example, activity in the alpha band, measured at frequencies of 8 to 12 Hz, is thought to reflect wakeful relaxation. Studies measuring

modulation in alpha activity find that during periods of selective attention, alpha power significantly decreases; and during periods of “ignoring”, alpha power significantly increases (Händel et al., 2011; Klimesch, 2012; Payne & Sekuler, 2014). Thus, alpha band suppression has been thought to reflect variation in attentional reorienting (Foxye & Snyder, 2011; Payne et al., 2013; Payne & Sekuler, 2014; Girges et al., 2014).

In this study, we examined how neural oscillations, specifically alpha band power, correlate with selective attention to various levels of construal (e.g. taste and health). Using the data previously collected by Harris et al. (2013), we analyzed how power in the alpha band oscillation correlates with perceived taste and health when subjects make choices about foods to eat while consciously exercising self-control (i.e., focusing on health).

Predictions

We predicted that goal-relevant changes would be observed in the alpha band during self-control. Greater attentional orienting has been shown to result in decreased power in the alpha band. Therefore, because of the increased attention given to health in this task, we predict that there would be a decrease in alpha band power in trials where the food is rated healthy compared to those when it is rated unhealthy. Furthermore, the decrease in alpha power should occur at posterior sensors of the brain during late value modulation, approximately 450 to 650 ms post-stimulus onset.

Methods

Experimental Procedure

This experiment consists of a re-analysis of data collected by Harris et al. (2013). In

this experiment, data from twenty-eight participants were collected while they performed a dietary choice task in two different sessions: responding naturally (natural condition, or NC) or with an incentive to exercise self-control (self-control condition, or SCC). All subjects fasted for at least two hours before participating in the experiment.

In each session, there were three separate blocks of data collection. In the first block, subjects provided taste and health ratings for 200 different snack foods using a four-point scale (1 = Strong No, 2 = Weak No, 3 = Weak Yes, 4 = Strong Yes). The second block involved performing a decision-making task while EEG recordings were made. On each trial, subjects were shown an image of a food and decided if they wanted to eat it or not at the end of the experiment, again responding using a four-point scale. There were three runs of 200 trials each, for a total of 600 trials per session. In order to make sure that subjects were answering honestly, the subject's decision (eat or not eat) was implemented for a randomly selected trial at the end of the experiment.

Although the procedure in the two sessions was largely identical, these sessions differed in the instructions and incentives provided to the subjects. In the NC session, subjects were told to respond naturally regarding the foods, whereas in the SCC session, subjects were given a financial incentive to lose weight, as measured in a re-weighing session 7-9 days later. Harris et al. (2013) state that these bonuses were provided as a strong incentive for exercising self-control in the SCC session.

EEG Data Acquisition & Preprocessing

EEG data were collected with a 128-channel HydroCel Geodesic Sensor Net (Electrical Geodesics) with AgCl-plated electrodes. The evoked brain potentials were

digitized at 500 Hz and were referenced to the vertex electrode Cz. Online filters were a 200 Hz low-pass Bessel filter and a 0.1 Hz high-pass hardware filter. Impedances were kept below 50 k Ω throughout the experiment. Data preprocessing was performed using the EEGLAB toolbox (Delorme & Makeig, 2004) for MATLAB (MathWorks, Andover, MA). Experimental artifacts were removed using independent components analysis (ICA) that was implemented with second-order blind identification (SOBI). An artifact refers to an electrical signal detected by EEG, but originating from non-cerebral origin. Based on their power spectra, scalp topographies, and activity, these components can be classified as either artifactual or nonartifactual, and artifactual components can be removed.

EEG Time-Frequency Analysis

The goal of this analysis was to examine changes in alpha band power at the time of decision-making in the SCC session. EEG data was saved as EEGLAB files. Frequency analysis was performed using the FieldTrip toolbox (Oostenveld et al. 2011) for MATLAB.

For each subject, EEG data across trials were sorted into 1100-ms epochs, time-locked to the onset of the stimulus (100 ms pre-, 1000 ms post-stimulus onset). These epochs were then binned by the perceived healthiness of the food presented on that trial, based on each subject's ratings from the beginning of the experiment. Although the original ratings were obtained using 4 possible responses (Strong No to Strong Yes), data from strong and weak responses were combined into "Unhealthy" (Strong No and Weak No responses) and "Healthy" (Strong Yes and Weak Yes responses) for ease of comparison. The preprocessed and time-locked files were then converted to FieldTrip format using the provided `eeglab2fieldtrip` function.

Time-frequency analysis was performed on all trials and all channels using a Morlet wavelet with output saved as power spectrum data. A Morlet wavelet is a Gaussian windowed sine wave and is commonly used because it provides the best trade-off between time and frequency resolution (Bernardino & Santos-Viktor, 2005). The width of the wavelet (i.e. number of cycles) was set to 7 because it allows for the ideal balance between temporal resolution and frequency resolution (Roach & Mathalon, 2008). For visualization purposes, frequencies of interest (FOIs) ranged from 4 to 20 Hz (Payne & Sekuler, 2014). This range, spanning frequencies near the alpha band (8-12 Hz), allows comparisons to be made between the alpha band and surrounding bands. It is important to note however, that all statistics were done on oscillations within the 8 to 12 Hz range. The analysis window was centered on -1 to 1 second, sliding in steps of 0.004 seconds. Time-frequency data was \log_{10} transformed to normalize the frequency distribution. Frequencies below 16 Hz were cut off due to the use of a 2-s epoch length with 1000 ms after stimulus onset.

To identify statistically significant decreases and increases in alpha band activity (FOIs from 8-12 Hz), a dependent samples two-tailed t-test was conducted on the calculated grand averages for all subjects with significance assessed using an overall threshold $p = 0.05$, with significance assessed at each tail equal to $p = 0.025$. To correct for multiple comparisons, we employed a cluster-based test statistic. Samples are selected if their t-value is larger than 0.025. The selected samples are clustered in connected sets based on temporal, spatial, and spectral adjacency (i.e., nearest neighbors in the sensor map). A Monte-Carlo permutation test with 500 permutations was employed to determine significance.

Results

We hypothesized that shifting attention to healthier attributes would create changes in neural oscillations. Specifically, we predicted that during selective attention to health, there would be a decrease in alpha power at posterior sensors around the time of value integration.

In this analysis, we examined data collected during a dietary choice task in which subjects were given a monetary incentive to exercise self-control. Previously, Harris and colleagues (2013) found that contextual changes in subjects' goals (eating what they prefer versus trying to lose weight) are associated with neural re-weighting of taste and health attributes. Stimulus value computations occurred from 450 to 650 ms post-stimulus, and were localized to vmPFC. During this same time period, they found that when naturally making decisions about food, there were greater measures of ERP data for taste attributes than for health attributes. However when attention was shifted towards health, there was little difference in ERP data between taste and health attributes indicating an increase in weighting of the health attribute during self-control.

We hypothesized that the shift toward healthy attributes in SCC trials would be accompanied by a decrease in alpha band power for healthy food versus unhealthy food. This hypothesis is based on previous studies showing that during selective attention, alpha band power at posterior occipital and parietal sensors decreases (Foxye & Snyder, 2011; Händel et al., 2011; Klimesch, 2012; Payne et al., 2013; Payne & Sekuler, 2014; Girges et al., 2014). In addition, we predicted that this decrease in alpha power would be observed around the time of value integration, approximately 400 to 650 ms after stimulus onset.

We tested this hypothesis by using a dependent samples two-tailed *t*-test to compare power in the alpha band in trials showing healthy relative to unhealthy foods from 0 to 800

ms after stimulus onset. We corrected for multiple comparisons using cluster tests. Figure 1A plots the time-frequency representations of power from 4 to 20 Hz in a topographical layout with a fixed window length of -100 to 800 ms. Pictured are all 128 sensors arranged as a scalp map. The figure shows the top of a head, with the nose drawn at the front and the ears drawn at the sides, and all sensors arranged in their correct location. Large-scale decreases in power for Healthy versus Unhealthy, indicated by blue regions in the individual time-frequency plots, are visible across the later half of the time period of interest, starting around 500 ms after stimulus-onset.

Figure 1B is an example of the time-frequency representation at a single electrode. Of particular interest to us is activity in the 8-12 Hz range. As predicted, alpha power in trials involving healthy foods does decrease relative to trials where the pictured food was unhealthy (denoted by the dark blue in the color bar). These effects emerged approximately 500 ms after stimulus onset, however it is important to note that the alpha band has a temporal precision of ± 100 to 140 ms, therefore, the emergence of the effects at 500 ms incorporates data from ~ 360 to 640 ms post-stimulus onset. This occurs because one cycle of the alpha band oscillation covers a large period of time, and therefore measurement is less precise with respect to time. Note that due to the use of a 2-s epoch length with 1000 ms after stimulus onset, only a limited number of cycles could be included for lower frequencies (< 16 Hz). Later time-points that fall outside this bound are represented in this and following figures as uniform areas of green or white.

To specifically test the role of alpha suppression for Healthy versus Unhealthy items, we further analyzed power changes specifically within the alpha band. Although effects were significant across the later time window, we focus here on results from approximately 500

ms after stimulus onset, based on our predictions. Figure 2 is a topographical plot illustrating the difference between power in Healthy and Unhealthy trials at 500 ms post-stimulus onset. Consistent with our hypothesis, we found multiple sensors at which the alpha power was significantly lower during viewing of healthy foods compared to unhealthy foods (denoted by white circles). As predicted, these sensors are located throughout posterior regions, in line with previous results on alpha suppression. Unexpectedly, there was also significance recorded at right anterior temporal regions, which we may wish to explore in future research.

Finally, we examined the average power over all significant sensors. Consistent with our hypothesis, a differential response to healthy versus unhealthy items occurred from approximately 452 to 716 ms after stimulus onset (Fig. 3). The black box denotes the area of interest in the 8-12 Hz range. As seen here, the earliest significant alpha suppression effect emerges from 452 ms, consistent with the onset of value integration signals from 450 to 650 ms after stimulus onset.

Discussion

In our everyday lives, we must often utilize self-control to make optimal decisions. In this study, we re-analyzed EEG data collected from subjects as they participated in a dietary choice task with an incentive to exercise self-control (Harris et al., 2013). Although the original experiment demonstrated changes in the neural weighting of taste and health information during the time window of value integration, the cognitive and neural mechanisms underlying this process were left unexplored.

Construal Level Theory provides a psychological framework for thinking about the changing values applied to taste and health information in this self-control task. This change

in construal level, from focusing on taste to considering more abstract health information, has been proposed to rely on attentional processes (Hare et al., 2011). Therefore, in this study, we used a time-frequency analysis to examine changes in selective attention to healthy foods relative to unhealthy foods when subjects were thinking about losing weight.

In line with previous work that has shown alpha power suppression during selective attention (Foxye & Snyder, 2011; Händel et al., 2011; Klimesch, 2012; Payne et al., 2013; Payne & Sekuler, 2014; Girges et al., 2014), we observed a significant decrease in alpha power in trials depicting a healthy food relative to trials where the food being presented was unhealthy. The changes in alpha power, observed in occipital and parietal electrodes on the scalp, are in line with the results of recent work (Michels et al., 2008; Payne et al., 2013) indicating the involvement of posterior regions of the brain in alpha-band activity. However, we also unexpectedly observed changes in alpha power in right anterior temporal sensors. We speculate that the reason for this decrease in power may perhaps have been due to activity in regions of the anterior temporal lobe because of their involvement in selective attention and stimulus processing of visual input (Nobre & McCarthy, 1995).

These effects emerged relatively late in the trial time course, from 452 to 716 ms after stimulus onset. This observation follows research indicating that the cognitive shift in health weighting occurs at approximately 450-650 ms after stimulus onset (Harris et al., 2013), and is consistent with the idea that there is increased selective attention for healthier items.

There is one notable difference between our results and those of previous attentional research: during data collection, previous studies utilized cues that instructed subjects whether to ignore or attend the subsequent trial (Payne et al., 2013; Payne & Sekuler, 2014). This is different from the current experiment, where subjects were not instructed in advance

how to deploy attention, and multiple attributes of the same item could be differentially attended. The fact that we still observed similar alpha suppression for the attended property of healthiness indicates that this attentional effect can occur without the presence of explicit external cues. In this way, our results extend previous attentional research to the domain of multi-attribute choice.

These results provide a new understanding of the neural mechanism by which selective attention can contribute to multi-attribute choice. However, several improvements could further strengthen the analysis and interpretation of this data. As mentioned previously, sections of our time-frequency representations are cut off. In order to provide a fuller picture of changes in the power of low frequencies (<16 Hz), future research should expand the time-window of the recordings to include a larger segment of post-stimulus neural activity.

Future studies also need to be done to link these results to the behavioral context, or “current goal” of the subjects. Most critically, a comparison of alpha power between the self-control condition (SCC) and the natural condition (NC) would show if there were any differences in how health attributes are weighted when subjects respond naturally versus using self-control. We predict that there would be no difference in alpha power in the NC, because subjects would not be selectively attending to health. Behavioral and neural data from Harris et al. (2013) indicates subjects in the NC session do not appear to use health information in their choices, instead picking foods on the basis of taste information alone.

In addition, future research should examine how alpha power correlates with individual differences of self-control. Such differences could be related to factors like frequency of dieting, as frequent dieters would be expected to attend to health more readily, and may not exhibit decreases in alpha power as extensive as subjects who do not diet

regularly. Another potential area of expansion to our research would include analyses of other frequency bands. Gamma band oscillations are also implicated in selective attention, with increased phase synchronization during increased attention (Womelsdorf & Fries, 2007; Fries, 2009; Sun et al., 2012; Polania et al., 2014). Analysis of gamma phase synchronization, local and long-distance, could provide further insight into regions of the brain that are involved in selective attention during multi-attribute choice.

Together, our results provide a better understanding of one type of neuro-computational process that occurs during a dietary choice task involving selective attention. Further understanding of the mechanisms of self-control in the brain could perhaps play an important role in treating real-world issues such as obesity and addiction, as these issues may partly arise from a lack of self-control.

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Figures

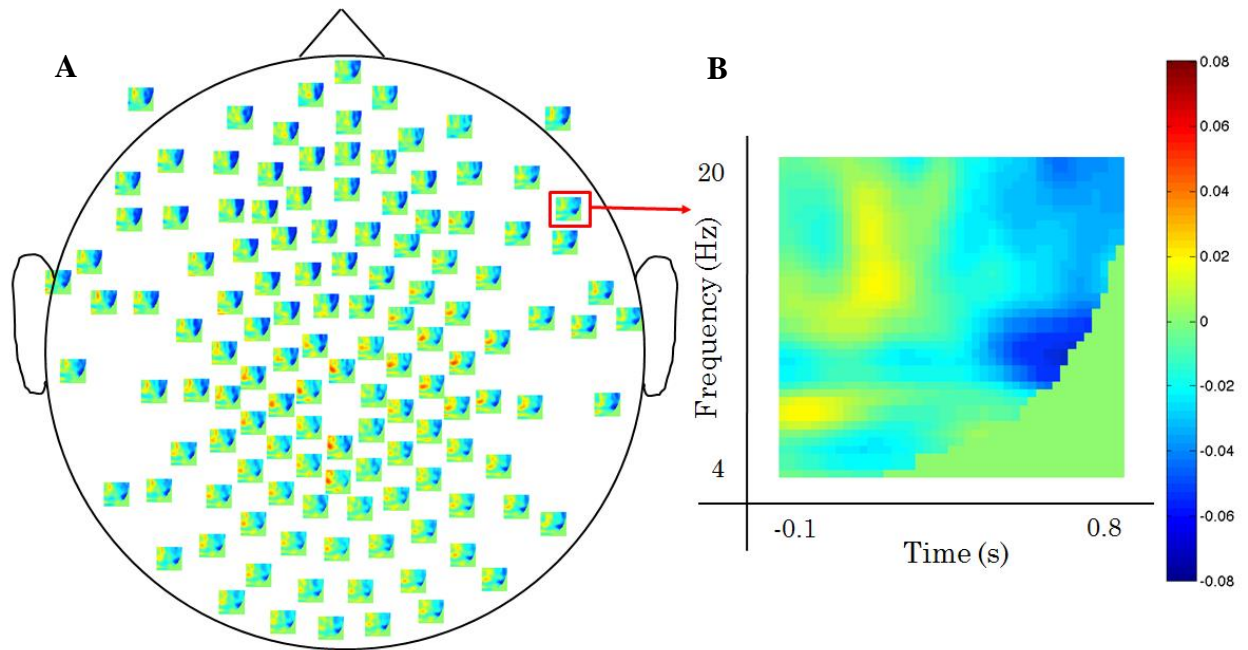


Figure 1. Topographical plot of time-frequency representations (TFRs) illustrating the change in power at individual sensors in healthy relative to unhealthy trials. **A**, Scalp electrode map of all 128 sensors and their corresponding TFRs. **B**, Each plot was measured from -100 to 800 ms, with frequency from 4 to 20 Hz. Blue denotes a decrease in alpha power, red denotes an increase.

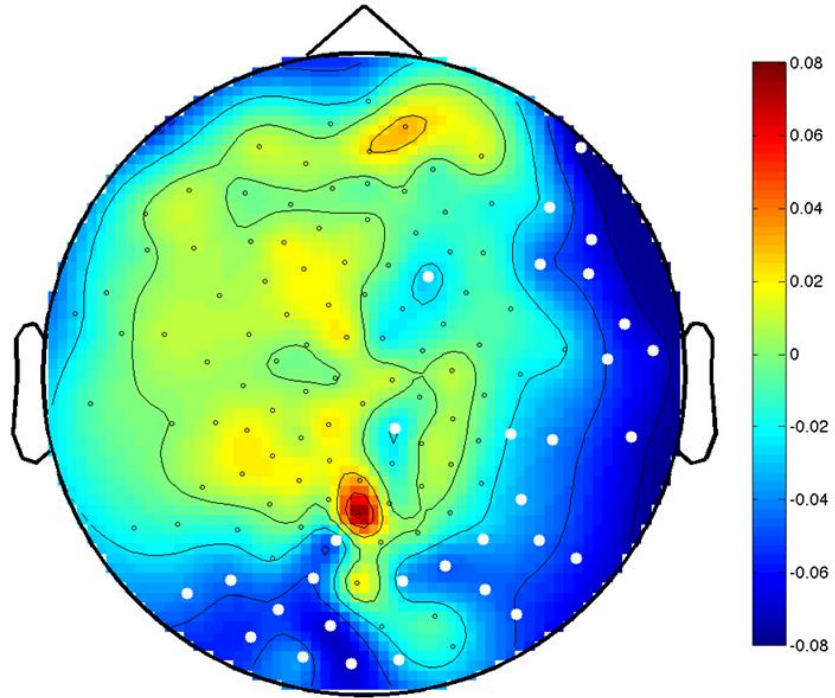


Figure 2. Topographical map illustrating change in alpha power from healthy to unhealthy trials at significant sensors (white circles) 500 ms after stimulus onset. Sensors denoted with white circles are significant at a threshold of $p < 0.05$ (cluster-corrected).

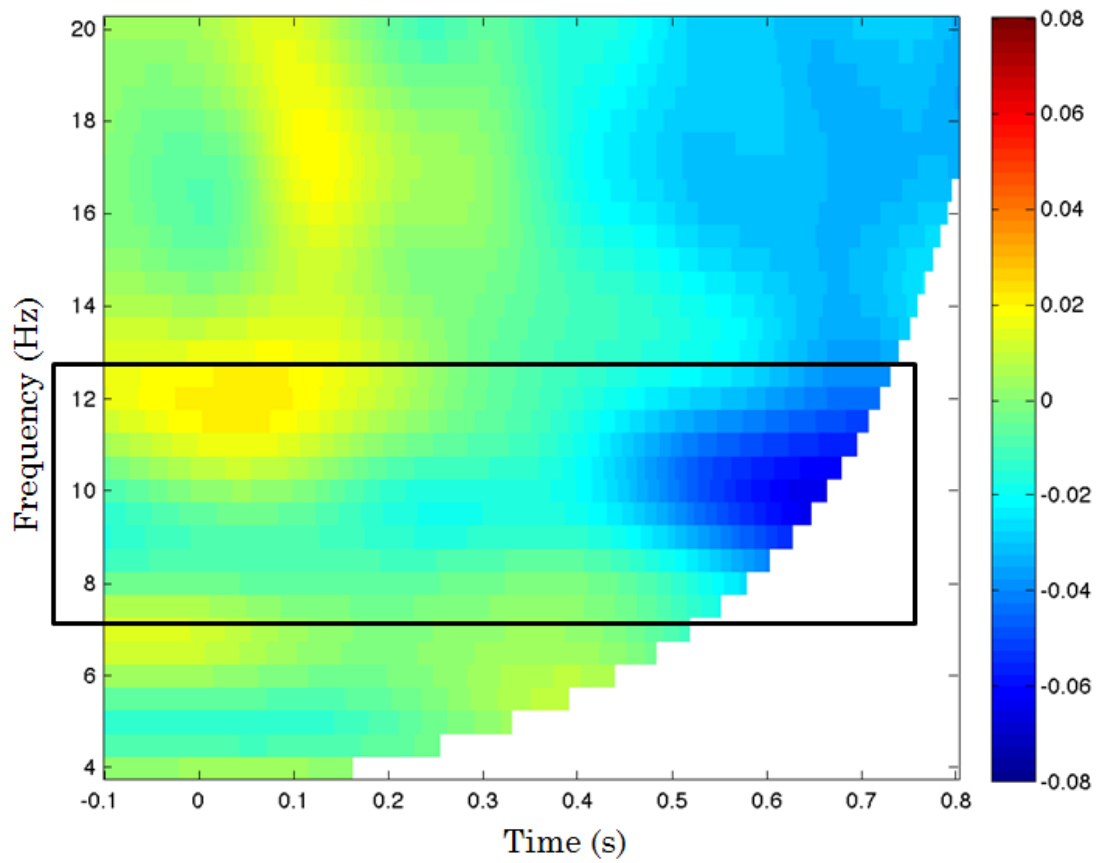


Figure 3. Average change in alpha power over the sensors of interest depicted in Figure 2.

The black box roughly denotes the alpha frequency band (8-12 Hz).

Appendix I: Analysis Code

```

%
% FreqAnalysis_FT.m
%

%% Set up analysis directory
GroupSubjectInfoSC;
RootDir = ['/Users/harrislab/Documents/SelfControlData_Jun2013/' ...
           'SelfControl_ERP/'];
cd(RootDir);

load SensorDefs_Anat128
%% Run frequency analysis on all subjects
for s=1:NumSubjects
    %% Go to subject directory
    SubjectID = SubjectList{s};
    SubjectDir = [RootDir SubjectID '/Healthy_Session2_NoCSD/'];
    cd(SubjectDir);

    %% Load EEGLAB files
    ALLEEG = []; EEG = []; CURRENTSET = 0;
    Conds = {'StrongNo', 'WeakNo', 'WeakYes', 'StrongYes'};
    for c=1:length(Conds)
        filename = [SubjectID '_' Conds{c} '.set'];
        EEG = pop_loadset('filename',filename,'filepath',SubjectDir);
        [ALLEEG,EEG,CURRENTSET] = eeg_store(ALLEEG,EEG);
    end
    %% Merge Strong and Weak for No and Yes responses
    UnhealthyEEG = pop_mergeset(ALLEEG,1:2);
    HealthyEEG = pop_mergeset(ALLEEG,3:4);

    %% Convert EEGLAB files to FieldTrip format
    UnhealthyData = eeglab2fieldtrip(UnhealthyEEG,'preprocessing','none');
    HealthyData = eeglab2fieldtrip(HealthyEEG,'preprocessing','none');

    %% Perform time-locked analysis
    tlcfg = [];
    tlcfg.channel = 'all';
    tlcfg.trials = 'all';
    tlcfg.covariance = 'no';
    tlcfg.keeptrials = 'yes';
    tlcfg.vartrllength = 0;
    tlcfg.feedback = 'none';
    [tlunhealthy] = ft_timelockanalysis(tlcfg,UnhealthyData);
    [tlhealthy] = ft_timelockanalysis(tlcfg,HealthyData);

    %% Perform time-frequency analysis
    freqcfg = [];
    freqcfg.keeptrials = 'no';
    freqcfg.keeptapers = 'no';
    freqcfg.output = 'pow'; % output is power spectrum
    freqcfg.channel = 'all';
    freqcfg.method = 'wavelet'; % use Morlet wavelet

```

```

freqcfg.width      = 7;
freqcfg.foylim    = [4 20]; % analyze from 4 to 20 Hz
freqcfg.t_ftimwin = 4./mean(freqcfg.foylim); % time window = 0.5 sec
freqcfg.toi       = -1:0.004:1; % time window -1 to 1 s in steps of 0.004 s
freqcfg.correctt_ftimwin = 'yes';
freqcfg.feedback  = 'text';
[frequnhealthy]   = ft_freqanalysis(freqcfg,tlunhealthy);
[freqhealthy]     = ft_freqanalysis(freqcfg,tlhealthy);

%% Log transform time-frequency data
frequnhealthyCorr = frequnhealthy; freqhealthyCorr = freqhealthy;
frequnhealthyCorr.powspectrm = log10(frequnhealthyCorr.powspectrm);
freqhealthyCorr.powspectrm = log10(freqhealthyCorr.powspectrm);

%% Save output and create filelist for grand average function
save([SubjectDir SubjectID '_Unhealthy_FreqCorr'],...
     frequnhealthyCorr);
save([SubjectDir SubjectID '_Healthy_FreqCorr'],'freqhealthyCorr');
UnhealthyFiles{s} = [SubjectDir SubjectID '_Unhealthy_FreqCorr.mat'];
HealthyFiles{s} = [SubjectDir SubjectID '_Healthy_FreqCorr.mat'];
end

%% Grand average for statistical analysis (keep all subjects)

% Unhealthy grand average - all subjects
ugavgcfg = [];
ugavgcfg.keepindividual = 'yes';
ugavgcfg.inputfile = UnhealthyFiles;
[unhealthygrandavg_allS] = ft_freqgrandaverage(ugavgcfg);

% Healthy grand average - all subjects
hgavgcfg = [];
hgavgcfg.keepindividual = 'yes';
hgavgcfg.inputfile = HealthyFiles;
[healthygrandavg_allS] = ft_freqgrandaverage(hgavgcfg);

%% Perform statistics on grand average data
% Define layout for stat clusters
layoutcfg = [];
layoutcfg.layout = [RootDir 'AvgChanLocs_Session2.sfp'];
layout = ft_prepare_layout(layoutcfg,unhealthygrandavg_allS);

% Run statistics
statcfg = [];
statcfg.channel      = 'all';
statcfg.latency     = [0 0.8];
statcfg.method       = 'montecarlo';
statcfg.statistic    = 'ft_statfun_depsamplesT';
statcfg.correcttail  = 'alpha';
statcfg.frequency    = [8 12];
statcfg.avgoverfreq  = 'yes';
statcfg.correctm     = 'cluster';
statcfg.clusteralpha = 0.05;
statcfg.clusterstatistic = 'maxsum';
statcfg.clustertail  = 0;
statcfg.minnbchan    = 2;
statcfg.tail         = 0;

```

```

statcfg.alpha = 0.025;
statcfg.numrandomization = 500;
cfg_neighb.method = 'distance';
cfg_neighb.layout = layout;
statcfg.neighbours = ft_prepare_neighbours(cfg_neighb,...
    unhealthygrandavg_allS);

% Define experimental design
design = zeros(2,NumSubjects*2);
design(1,:) = [1:NumSubjects 1:NumSubjects];
design(2,:) = [ones(1,NumSubjects) ones(1,NumSubjects)*2];
statcfg.design = design;
statcfg.uvar = 1;
statcfg.ivar = 2;

[statalpha_healthyVunhealthy] = ft_freqstatistics(statcfg,...
    healthygrandavg_allS,unhealthygrandavg_allS);

%% Grand average for visualization (combine subjects)

ugavgcfg = [];
ugavgcfg.keepindividual = 'no';
ugavgcfg.inputfile = UnhealthyFiles;
[unhealthygrandavg_avgS] = ft_freqgrandaverage(ugavgcfg);

hgavgcfg = [];
hgavgcfg.keepindividual = 'no';
hgavgcfg.inputfile = HealthyFiles;
[healthygrandavg_avgS] = ft_freqgrandaverage(hgavgcfg);

%% Plot results
% Topographical plot of statistical clustering at 500 ms
plotcfg = [];
plotcfg.alpha = 0.025;
plotcfg.parameter = 'stat';
plotcfg.colorbar = 'yes';
plotcfg.xlim = [0.5 0.5];
plotcfg.layout = layout;
plotcfg.highlight = 'on';
plotcfg.highlightchannel = soi;
plotcfg.highlightsymbol = '.';
plotcfg.highlightsize = 20;
plotcfg.highlightcolor = 'w';
figure; ft_topoplotTFR(plotcfg, statalpha);

% Plot healthy vs unhealthy at sensors of interest
healthygrandavg_avgS.raweffect = healthygrandavg_avgS.powspctrm - ...
    unhealthygrandavg_avgS.powspctrm;

plotcfg = [];
plotcfg.parameter = 'raweffect';
plotcfg.xlim = [0 0.8];
plotcfg.channel = 'all';
plotcfg.interactive = 'yes';
plotcfg.layout = layout;
figure;ft_multiplotTFR(plotcfg,healthygrandavg_avgS);

```