university of groningen / faculty of mathematics and natural sciences / artificial intelligence

Master's Thesis

Shedding light on decision making: Detecting cognitive stages in EEG data using Hidden Multivariate Pattern Models

Kenneth Muller, BSc

January 19, 2024

Internal Supervisor(s):
Jelmer Borst (Artificial Intelligence, University of Groningen)
Gabriel Weindel (Artificial Intelligence, University of Groningen)

Artificial Intelligence
University of Groningen, The Netherlands

Abstract

Cognitive models are among the major tools used to study human behavior. In order to develop these models we require knowledge of the cognitive stages people go through when performing their tasks. For a perceptual decision making task, three cognitive stages are assumed to be present: Encoding (stimuli are perceived), Decision (a choice is made after enough evidence has been gathered), and Response Execution (acting upon the decision). The development of cognitive models used to be done mainly with behavioral results, causing us to only use the reaction time per trial, making it difficult to determine the onset of each cognitive stage. Instead, we want to work with electroencephalography (EEG) data as this provides us with much more information. Significant cognitive events result in EEG peaks, and locating these peaks would allow us to pinpoint when any processing stages would occur. However, even nowadays the identification of processing stages in EEG data remains challenging.

In this project, we test a new method for detecting cognitive stages in EEG data by comparing our results with known results found in previous experiments. To this aim, we collected EEG data from a decision making experiment based on contrast manipulation with 22 participants, and used a pipeline applying a novel approach of Hidden Multivariate Pattern Models (HMP).

Our results confirm and build upon previous findings in a contrast based decision making experiment. Furthermore, we show that HMP is capable of identifying the onset and durations of the expected stages within a perceptual decision making task.

All in all, HMP shows promise when it comes to identifying EEG peaks, which should aid us in the development of more accurate cognitive models in the future.

Acknowledgement

When I am working on a large project such as this thesis I try to be as independent as possible, trying to solve my problems on my own and learning from them as I go. However, occasionally as the task gets rather difficult or repetitive, it might become more difficult to remain motivated to continue on at a steady pace. Of course, for a project as a master's thesis it is expected that you solve most of your problems by yourself, but proper guidance is nevertheless still very much needed.

I would like to thank my two supervisors Jelmer Borst and Gabriel Weindel for their continued support, always offering helpful advice as I fill them in on my progress and seem a bit unsure about what is next. Furthermore, their enthusiasm for any progress that was made always kept me motivated to continue working and to make me feel like the work I was doing was proper, helping me see this project through to the end.

Finally I would like to thank my girlfriend for her support as I worked my way through this project for helping me relax or offering fresh advice whenever I got stuck.

Thank you to all of you.

Contents

1 Introduction

In our daily life there are many moments where we are expected to make decisions. These can vary from mundane decisions such as choosing what to wear or what to eat to decisions where we have to make a fast choice in a short amount of time, for instance, when we are driving and we need to make a split-second decision before colliding into an obstacle. We choose to study the decision making process in humans in order to gain insight into what processes drive decisions in these situations.

To study the decision-making, one would make use of cognitive models. Take for example a cognitive model that is built to solve arithmetic equations, given the task of solving the formula $2+x=5$ (Figure 1). The processes that we assume the model would take are in order:
(1) perceiving the task, to simulate vision;
(2) retrieving related facts from memory, to simulate memory retrieval;
(3) performing arithmetic functions, to simulate thinking;
(4) responding by writing or saying the answer, to simulate a motor response.

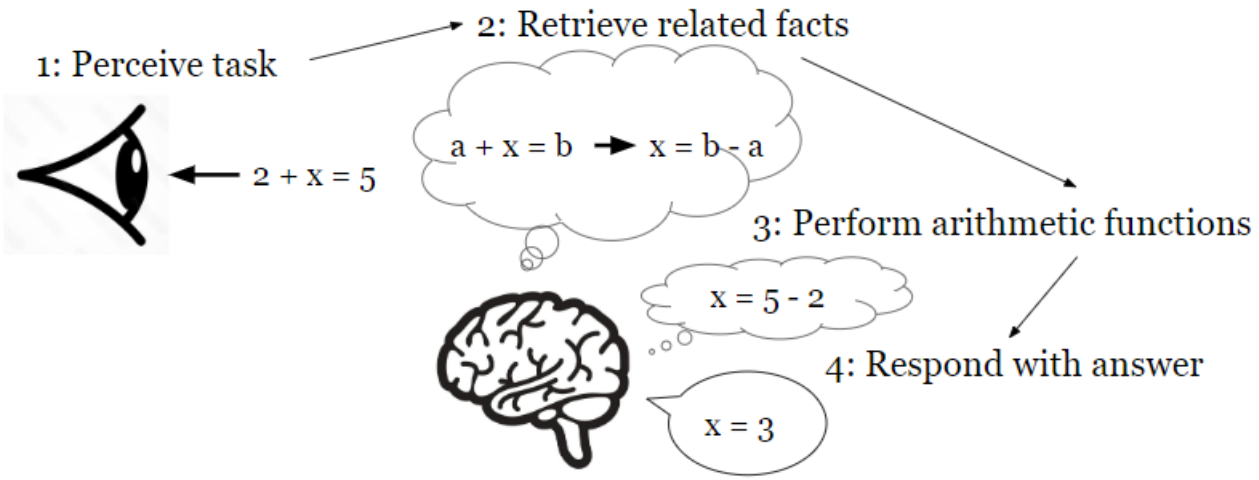


Figure 1: Cognitive processes assumed for a model solving $2+x=5$

In the past, many cognitive models that attempted to capture these cognitive processes were made using behavioral data. The issue is that behavioral data from experiments typically only measure one or two variables, such as response time or whether the given response was correct, making it difficult to distinguish between the various cognitive processes that occur in any task. Recently, researchers started using EEG data to aid in the discovery of these cognitive stages of the human mind due to their high temporal resolution.

In EEG data, significant cognitive events result in EEG peaks that are added to the ongoing EEG oscillations (Makeig et al. (2002); Shah et al. (2004); Yeung, Bogacz, Holroyd, Nieuwenhuis, and

Cohen (2007)). Identifying these peaks will likely lead to figuring out when a significant cognitive event occurs. However, this task is rather difficult since these peaks are not always identical, as they might differ in their temporal location within a trial or per person, or they might have shorter or longer durations depending on the circumstances such as stimulus clarity or complexity of a given task.

To test whether we can infer cognitive processes from EEG peaks, we will be applying the novel method of Hidden Multivariate Pattern Models (HMP models) which can detect these EEG peaks in single trials and allows us to identify these as cognitive events. We intend to do so by recreating an EEG experiment based on perceptual decision making that shows previous results both for monkey data (Reynaud, Masson, & Chavane, 2012) and human data (Weindel, Boris, Alario, et al., 2021). If the behavioral results we obtain from this experiment are similar to the results from human data found in (Weindel et al., 2021), we can assume that the same cognitive processes could be present for both experiments. Afterwards, by applying HMP models to the EEG data we obtained from this experiment, we will attempt to identify which cognitive stages would be seen and in what order while performing said task. In (Weindel, 2022) a comparison has already been drawn between the results found in (Reynaud et al., 2012), where the onset of the first cognitive process can directly be measured, and (Weindel, 2022), where a cognitive model was fitted that could also measure the onset of the first cognitive stage. Some similarities could be found, but there were still limitations when it came to certain conditions. By comparing these findings to the findings of the cognitive stages discovered by our HMP model we aim to determine whether these limitations are due to issues with the way the model interprets these conditions or whether manipulating the conditions of the experiment actually influences what cognitive stages we go through or how long they last.

In the rest of this thesis, our method for applying HMP to detect and identify cognitive stages is outlined. We will begin with an overview of the theoretical framework. Here we will give a more detailed description of the two experiments by Reynaud et al. and Weindel et al.. Furthermore, we will also give an explanation of the cognitive model used to study decision making in (Weindel et al., 2021) and a description of HMP models and how we can use these to develop cognitive models. Finally, we end this chapter by describing our research questions.

After the theoretical framework for this thesis has been established, the rest of the thesis focuses on the experiment we performed and how we interpret our findings. Section 3 *Experiment*, details the experiment that we performed, explaining how we intended to obtain our results, what changes we made compared to the original experiments ((Reynaud et al., 2012); (Weindel et al., 2021)) and our justifications for these changes, by describing both the experimental design and the experimental procedure. This section ends with an explanation of the preprocessing of the data that was obtained by performing this experiment. Afterwards, Section 4 *Results* shows all our results. Starting with the behavioral results and linear mixed models based on these outcomes and following this up with the results from our HMP models, where we describe how we find our models based on found cognitive stages and how we eventually get our final model. Using the results obtained from this model, we show the durations and onset times of these found cognitive stages and compare them to the findings

of Reynaud et al. and Weindel et al.. Finally, Section 5 *Discussion* ties it all together by comparing our findings from the previous section with the research questions we pose in Section 2.5. This section is concluded with some closing remarks on this research and proposed directions for the future of HMP models.

2 Theoretical Framework

2.1 Evidence accumulation models

To study decision making, many decision making models have been introduced. Most of these models assume that a decision is being made through the sequential accumulation of evidence. These models are referred to as Evidence Accumulation Models (EAMs) (e.g. Ratcliff, 1978). The basic idea behind decision making based on accumulation of evidence, as illustrated in Figure 2, is that evidence is collected and stored within a decision variable until enough evidence has been accumulated to be able to commit to a particular choice (Ratcliff, 1978). To put this in perspective with an example regarding perceptual decision making, let us assume that a participant is comparing two visual gratings, A and B as illustrated in Figure 3 on the left and right of the fixation cross, respectively, and the participant is trying to determine which of the two images contains the highest level of contrast. Initially the participant is unsure which of the two gratings has the highest contrast, so the evidence starts around the middle, as the participant does not have enough proof that either image is clearer to see. However, as participants continue to look at these gratings, they will gather evidence showing that image A contains a higher level of evidence, which will make the graph in Figure 2 move upward, towards the threshold of decision A. Once the participant has gathered enough evidence to exceed the threshold, they will be able to commit to their decision and provide their answer, stating that they believe Image A, on the left side of Figure 3, contains the highest level of contrast. When these models are combined with behavioral data, we can usually assume that the reaction time (RT) is the sum of three separate times, which can be linked with the expected present cognitive stages. These times are: *encoding* time (T_E), the time from stimulus onset until evidence accumulation starts, *decision* time (T_D), the time it takes from the start of the accumulation until the threshold has been reached, and finally *response execution* time (T_R), the time it takes to give a response after the accumulation threshold has been reached.

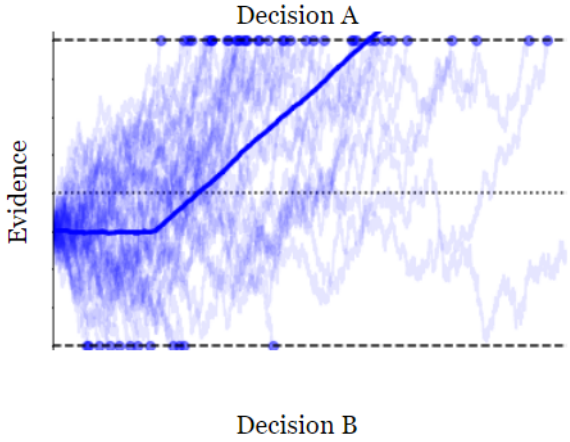


Figure 2: Generic example of the workings of Evidence Accumulation Models (Original image: https://github.com/EoinTravers/Evidently/)

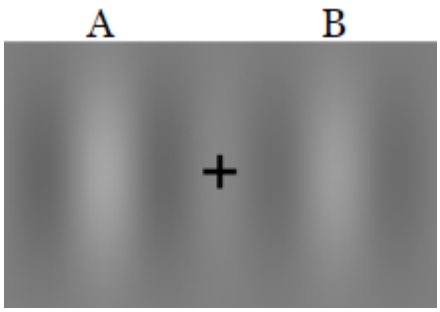


Figure 3: Example of two visual gratings, separated by a fixation cross in the middle

2.2 Perceptual Decision Making Task

In order to verify our method of identifying cognitive stages, we intend to recreate an experiment on a perceptual decision making task presented in Weindel (2022), where an interesting link was discovered between encoding time in a DDM (Weindel et al., 2021), and the onset of visual neurons in monkeys (Reynaud et al., 2012) in two separate studies, but with similar tasks. In this experiment, participants were tasked with identifying which of two images positioned to the left and right of a fixation cross, contained the highest level of contrast (see Figure 4, where the patch to the left of the cross has the highest contrast level). The overall contrast of these images was manipulated while ensuring that the contrast difference between the two shown images remained constant. A total of six different overall contrast levels were shown, ranging from 23% to 93% at intervals of 14%, which can be seen in Figure 5. In these images the patch to the left of the cross always has the lower contrast, but during the experiment the position of the patch with lower contrast is randomized.

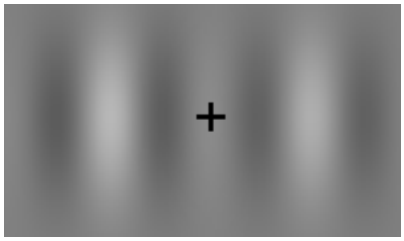


Figure 4: Example of the contrast measurement task (Image from Weindel,2022).

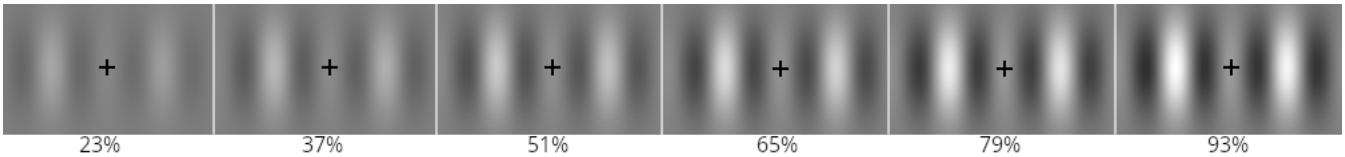
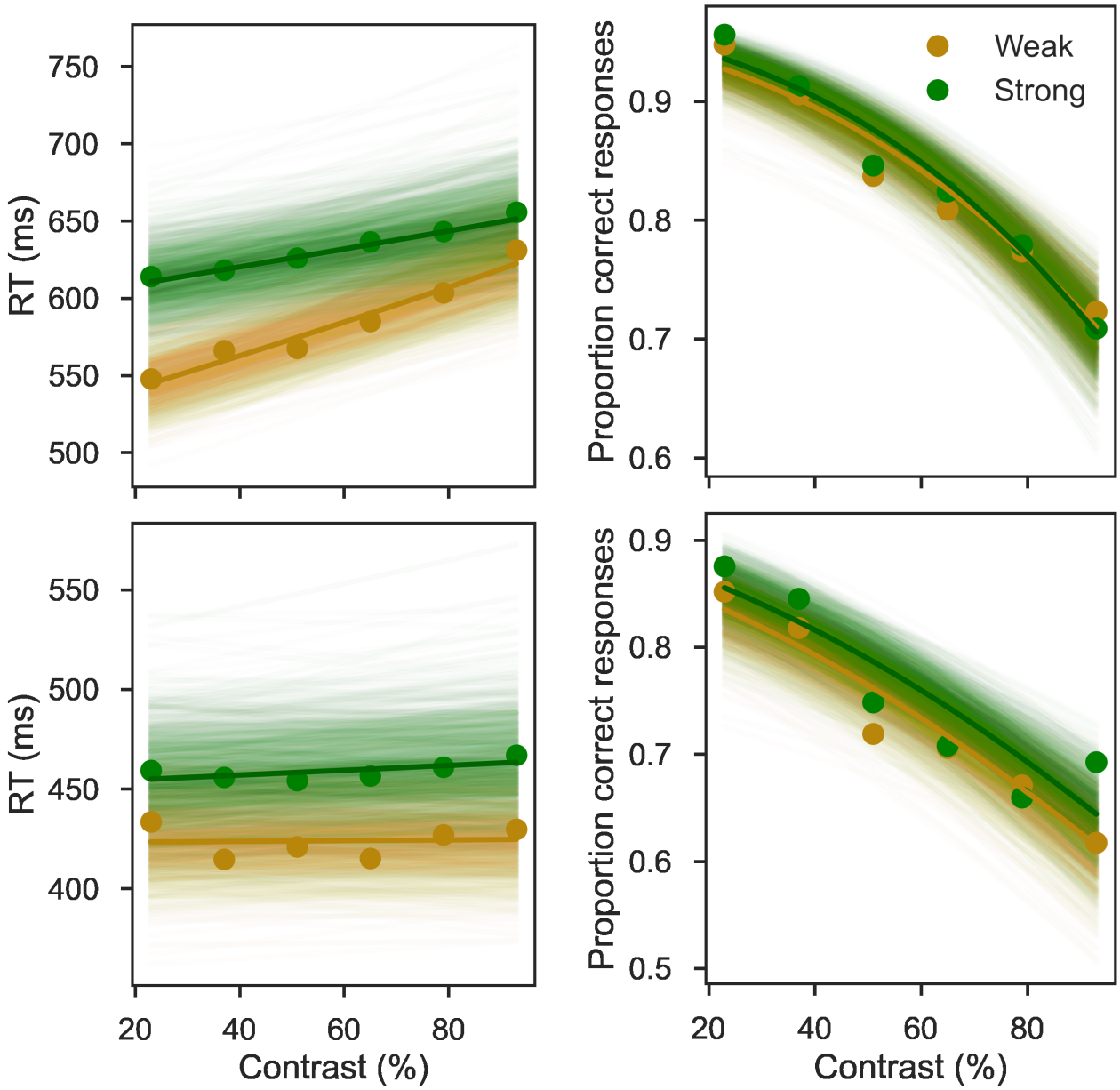


Figure 5: The measurement task with increasing overall contrast values, in this example the left side of the image always has the highest contrast (Image from Weindel,2022).

In addition to measuring the effects of contrast manipulation on cognitive stage durations, the effects the speed-accuracy trade-off (SAT) had on these durations were also studied in (Weindel et al., 2021). This manipulation was performed by verbally instructing participants before an experimental block started to either focus on speed by decreasing the reaction time of their responses, or to instead focus on accuracy by trying to increase the proportion of correct responses. This manipulation is expected to affect the threshold parameters of the DDM, meaning that when participants are trying to focus on speed, this is usually accompanied by a lower threshold requirement for making a decision to speed up this process, while a focus on accuracy might increase this threshold instead to ensure that more evidence is gathered before reaching a conclusion. Previous studies on SAT have also suggested that this manipulation affects the speed of both encoding processes and response execution processes (Steinemann, O'Connell, & Kelly, 2018).

Behavioral results of Weindel et al. (2021) can be seen in Figure 6, where the effects of the overall contrast levels have been plotted against the reaction time (Figure 6a) and the proportion of correct responses (Figure 6b). In the original experiment the effects of force required to respond were also studied, as can be seen with the different colored lines, with the green lines indicating that more force had to be applied to register a response. However, since we are concerned with reporting on the differences between the monkey and DDM results discussed in Weindel (2022), and the effects of force were not tested by Reynaud et al. (2012), this manipulation is not of interest to our study; instead we will only focus on the effects of contrast level and the speed-accuracy trade-off. Therefore we are only interested in the yellow lines of these Figures. What these Figures show is that as the overall contrast increases, the proportion of correct responses (left hand plots of Figure 6) decreases and the reaction time (right hand plots of Figure 6) increases. Based on these results we can surmise that comparing the patches becomes more difficult as the overall contrast level increases even though the contrast difference within images remains the same.



(a) (b)

Figure 6: Effects of contrast manipulation on the reaction time (left) and proportion of correct responses (right) for both the accuracy (top two figures) and speed (bottom two figures) conditions (Images from (Weindel et al., 2021))

The Drift Diffusion Model (DDM) (Ratcliff & Tuerlinckx, 2002) used for this experiment decomposed the reaction times into two separate times, the 'pre-motor time' (PMT) which is the time from stimulus onset until Electromyography (EMG) onset (when a muscle response is recorded, indicating the start of the response execution stage), and a 'motor time' (MT) which is the time from

EMG onset until the behavioral response has been given. This dissection of the reaction time can be seen in Figure 7, once again taking only into account the green lines, we see the results for the accuracy condition in the top two graphs and the speed condition at the bottom, with the left plots showing MT and the right plots describing PMT. Most of these results show barely any effect of contrast level on these durations, although we do notice an increase in PMT for the accuracy condition (top right corner of Figure 7) as contrast level increases.

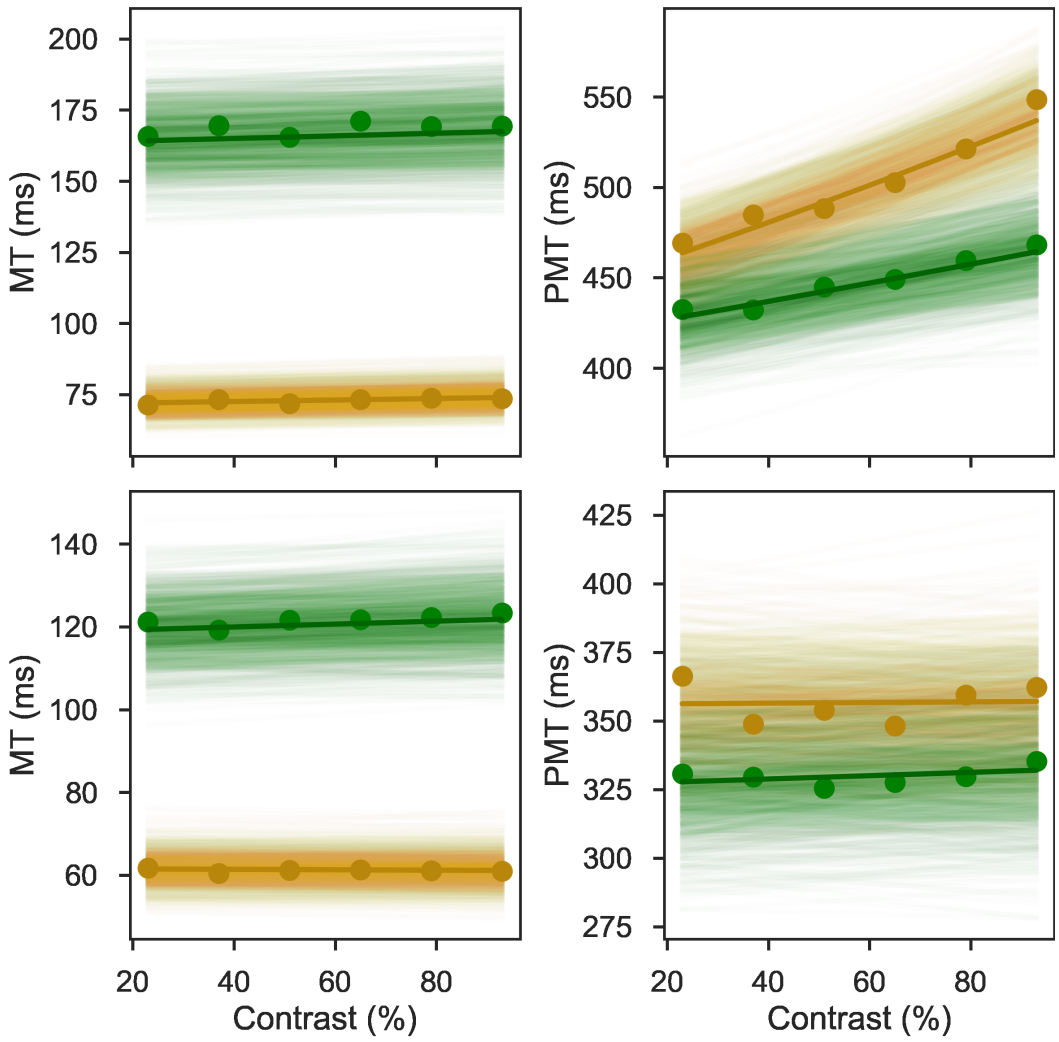


Figure 7: Effects of contrast manipulation on Motor Time (left) and Pre-motor Time (right) for both the accuracy (top two figures) and speed (bottom two figures) conditions (Image from (Weindel et al., 2021))

2.3 Comparing encoding times

Building on the results from Weindel et al. (2021), in Weindel (2022) some additional findings on the effects of contrast on encoding time were reported. This article focuses on the findings that visual encoding time decreases, even though the difficulty of the task increased. To support this theory, a comparison was reported between the representation the DDM gives of visual encoding time and the temporal dynamics of visual neurons in the primary visual cortex, V1, of monkeys in response to visual stimuli similar to those shown in Figure 4 (Reynaud et al., 2012). Both of these findings can be seen together in Figure 8, the green line indicating the onset times of visual neurons (V1 predictions) in monkeys Reynaud et al. (2012) and the red dots (T_e estimates) showing the predictions of the encoding time generated by the DDM within the speed condition from Weindel et al. (2021). No fitting occurred between the V1 predictions and T_e estimates, the variables have only been centered by subtracting each data point by the mean of each variable, keeping only the relative difference of each data point to the mean of their respective variable. These results show us that a behavioral model fitted on human decision making data actually resembles measurements of primary visual neurons found in monkey data. However, this similarity is only found for the speed condition. When the same comparison is made with DDM predictions based on the accuracy condition, as shown in Figure 9, these similarities can no longer be found. This effect is quite surprising, as we would not expect a different encoding stage depending on condition. Therefore, it will still be interesting to determine whether there is in fact a different encoding stage for the accuracy condition, or whether the DDM does not succeed at estimating this stage for the accuracy condition.

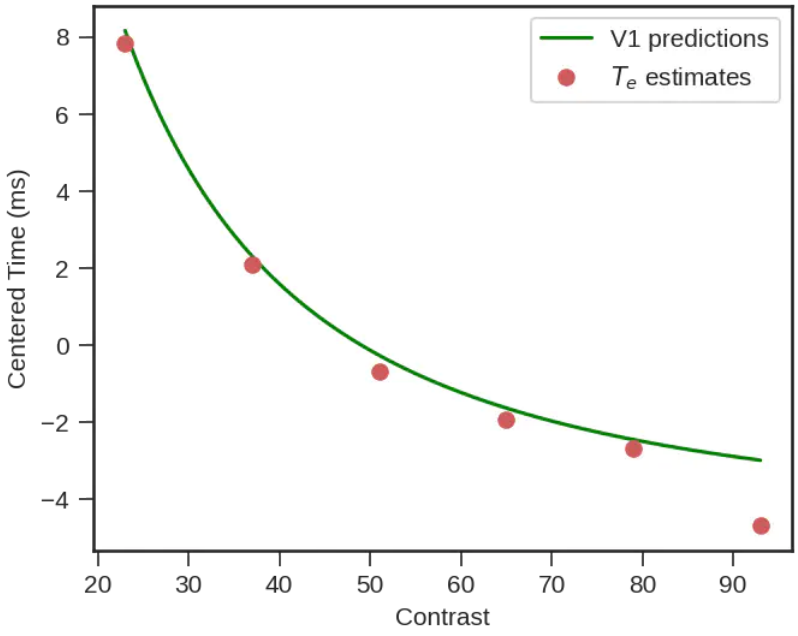


Figure 8: Comparing T_E in a speed condition with V1 neuron response times (Image from (Weindel, 2022)).

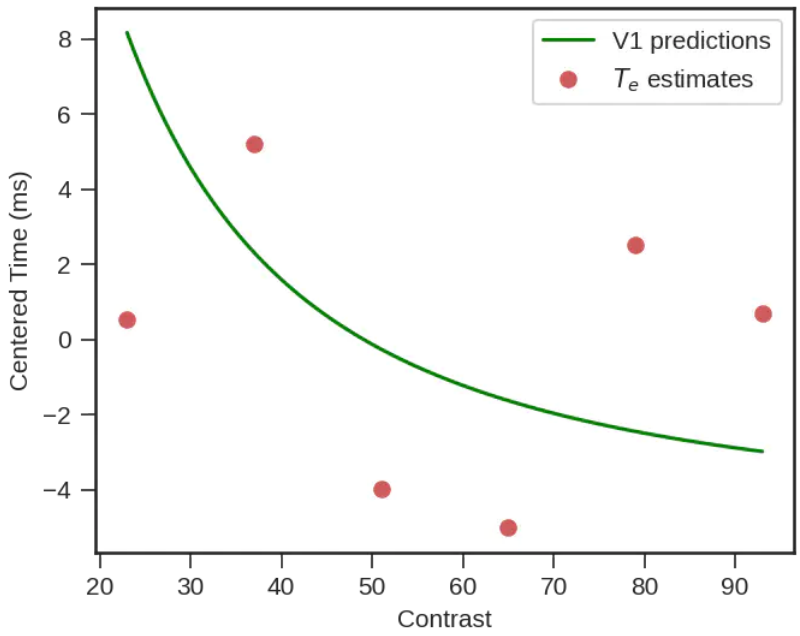


Figure 9: Comparing T_E in an accuracy condition with V1 neuron response times (Image from (Weindel, 2022)).

2.4 Hidden Multivariate Pattern Models

If we manage to measure EEG peaks in single trials, we would be able to identify these various cognitive processing stages, which we can then use to develop cognitive models. We will attempt to solve this problem by applying the novel method of Hidden Multivariate Pattern models (HMP models) (Weindel, Borst, & van Maanen, in preparation). This method is based on an earlier method which combined Hidden semi-Markov models with multivariate pattern analysis (Anderson, Zhang, Borst, & Walsh, 2016) to integrate all information present across all trials of all participants for the purpose of identifying peaks in single trials (Borst & Anderson, 2022).

HMP models describe a multivariate time-series, in our case of EEG channels as illustrated in Figure 10, where we can see simulated EEG data plotted over the time course of a trial, observed from the starting time of a trial until the end (for example measured in RT in ms), as a linear succession of cognitive stages. It does so by analysing patterns in the data, looking for peaks that would signify the onset of a cognitive event and generates a model based on the events found this way as shown in Figure 11, where each event is indicated as a dashed vertical line and a visualisation of the brain topology indicating the polarities of the EEG signals on the scalp at the time of measurement (indicated in color temperatures, with red indicating positive polarity, yellow being neutral and blue indicating negative polarity). The cognitive stages are then described as the time between two subsequent events, the time between trial onset and the first event, or the time between the last event and the end of the trial. If we take a closer look at Figure 11, we can infer that this HMP model consists

of four events, which are indicated by the first four vertical lines followed by a brain topology image. Furthermore we can conclude that the HMP model shown in Figure 11 contains five stages. The first stage would be the time between the start of the trial and the onset of the first event, the second stage the time between the onset of the first event and the onset of the second event, up until we reach the fifth stage which is the time between the fourth event and the end of the trial.

In order to illustrate the usefulness of HMP models on real data, Weindel et al. also replicated a study by Van Maanen, Portoles, and Borst (2021). In this study, participants were tasked with performing a Perceptual Decision Making task, and they were given instructions to either favor the speed or accuracy of their response. The results of this study showed that a two event HMP model fit the data of the speed instructions better, while a three event HMP model actually fit the accuracy instructions better, which led to the conclusion that an additional cognitive stage might actually be present within the accuracy condition. The replication of this experiment by Weindel et al. (in preparation) also showed that HMP detects an additional event for the accuracy condition, however, this replication detected four events for the speed condition and five for the accuracy condition instead of the aforementioned two and three events respectively. Finally, the effects of SAT could also be tested by computing the stage durations and testing how they differ between conditions, which is represented as the time that was required to go from the current event to the next one (so for stage 2 this would be the time it takes to go from event 1 to event 2), under the assumption that events are sequential. Here Weindel et al. show that SAT does indeed affect the stage duration, showing a decrease in all stage durations when participants follow the speed instructions.

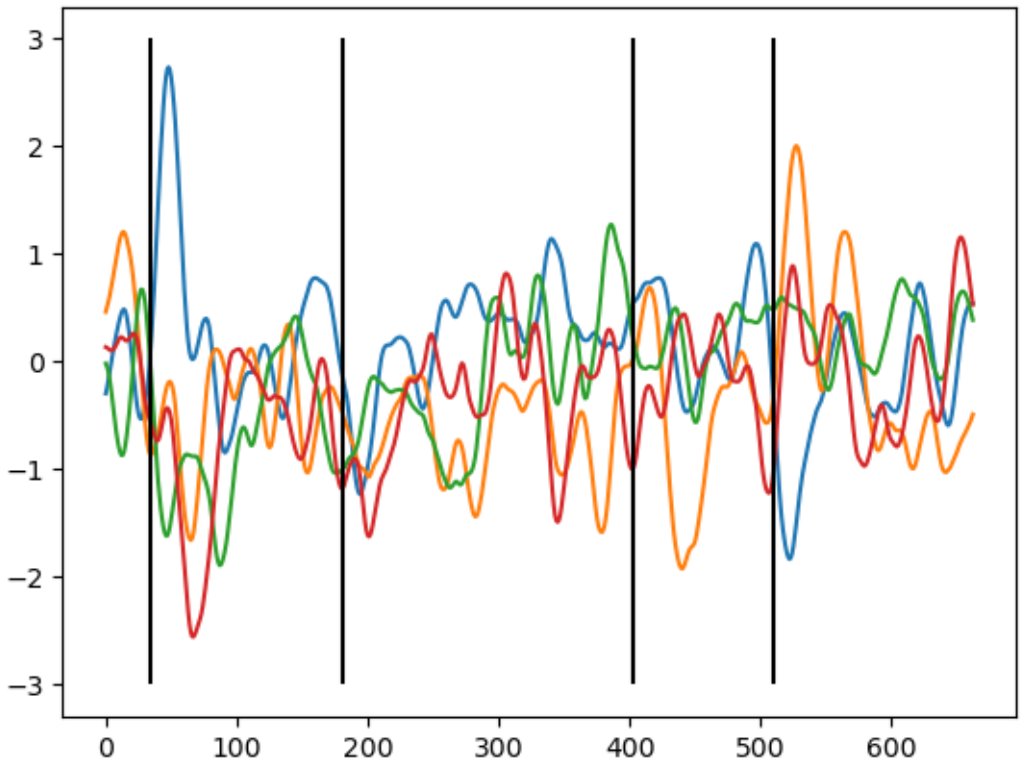


Figure 10: Example simulated EEG data where the detected onsets of cognitive stages by HMP have been marked with vertical lines

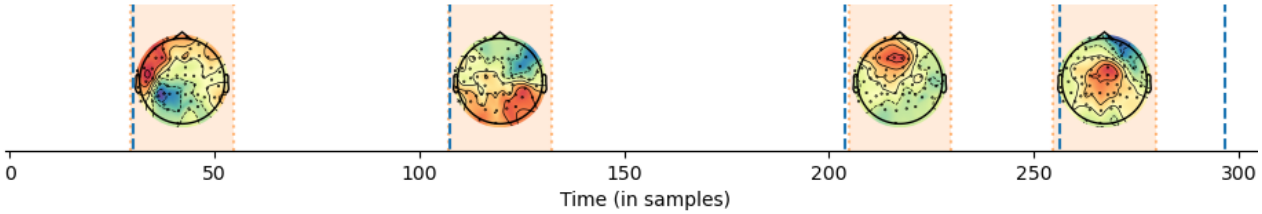


Figure 11: Onsets of cognitive stages as discovered by HMP plotted over the time-course of a single trial

2.5 Research question

We will be recreating the experiment described in Section 2.2 in order to answer our main research question: Can we pinpoint and identify cognitive processing stages from EEG data? In order to provide more evidence for our findings, we will also attempt to answer some additional questions.

First of all, we are recreating the perceptual decision making task discussed in section 2.2. The evidence for the findings of our discovered stages would be stronger if the behavioral results of our

experiments are also matching. Therefore we will find out whether our behavioral results can match the previous findings. Secondly, we have discussed the dissection of reaction time into T_E, T_D and T_R. We expect these times to coincide with the *encoding* stage, *decision* stage and *response execution* stage we expect to find when performing a Perceptual Decision Making task. We would need to confirm whether these coincide and if they do, study the durations and onsets of these cognitive stages and what affects them. Additionally, since we are testing the effects of the speed-accuracy trade-off we will attempt to identify the differences between these two conditions. Not only in terms of behavioral results, as we are also interested in studying whether we can detect additional cognitive stages when people are asked to focus on accuracy instead of speed. We are interested in the effects of SAT on the decomposition into stages, both in terms of number and stage durations

3 Experiment

Our experiment will be based on the findings described in Section 2.2. We intend to work with the same type of stimuli and to measure the effects of the speed-accuracy trade-off where participants are either urged to focus on decreasing their reaction time (speed) or to focus on giving correct responses (accuracy). One change we have implemented is that we expand upon the range of shown stimuli in order to confirm whether the graphs in Figure 6 follow the shown slope when given a wider range of data. The range we intend to expand upon can be found in Figure 12. The area within the blue vertical lines is the current range of stimuli (23% to 93%) tested on by Weindel et al.. We expand this to a continuous range shown by the green vertical lines (3.5% to 95.5%). Afterwards, we intend to use HMP to detect the cognitive stages present in this EEG-based Perceptual Decision Making task.

Furthermore, due to the reported differences in onset of *encoding* time in Section 2.3, we will also be monitoring for the differences in cognitive stages when testing on the speed-accuracy trade-off with our methods. Previous studies have also suggested that the reported cognitive stages might be different when participants are tasked to alternate between being fast or accurate within a task (Van Maanen et al., 2021). One possibility is that participants might even enter an additional cognitive stage when asked to focus on accuracy instead of speed, we will keep this possibility in mind when working on our HMP models.

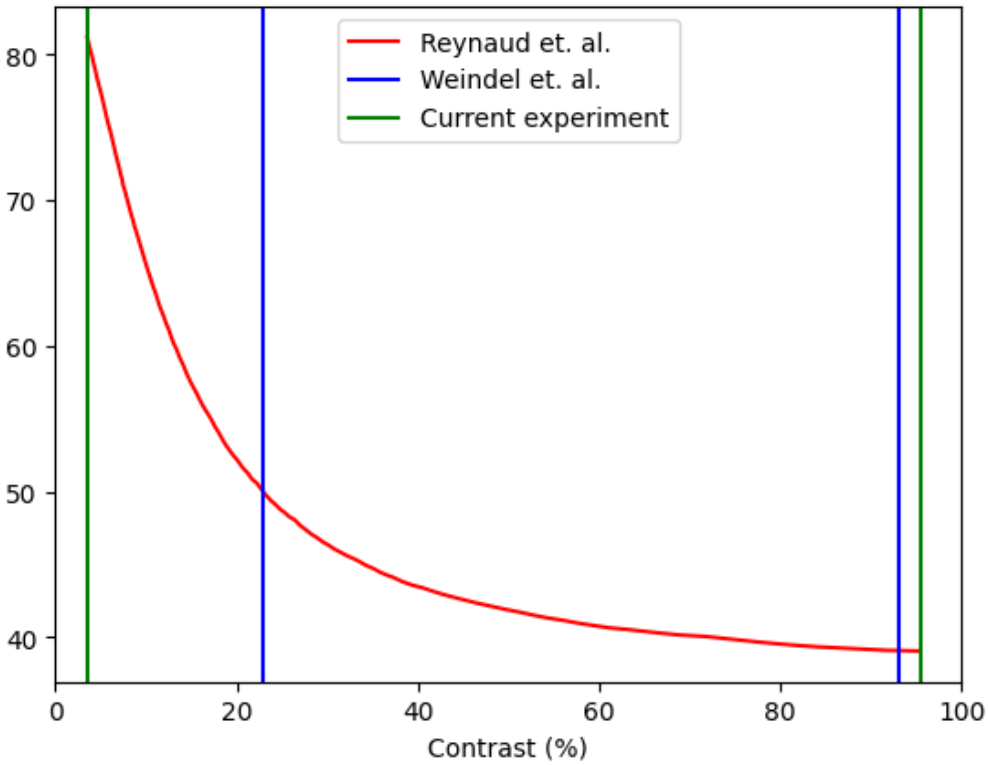


Figure 12: The full range of stimuli found in Reynaud et al. (2012), compared to Weindel et al. (2021) and our current experiment

3.1 Experimental Design

3.1.1 Participants

A total of 26 participants (12 male and 14 female, mean age = 23.96 years, 2 left-handed) took part in our experiment. The majority of the participants were students living in or near the city of Groningen. All participants had normal or corrected-to-normal vision. Additionally, all participants signed an informed consent form before participating in the experiment. Finally, all participants were compensated €12 for 90 minutes of their time. The Research Ethics Committee (CETO) has established that our research protocol follows internationally recognized standards to protect the research participants (ID 94056673).

3.1.2 Apparatus

The participants performed the experiment in a window-less EEG Lab, where they were seated at a distance of approximately 90 cm from a 24-inch LCD screen with a refresh rate of 60 Hz. To provide responses during the experiment, participants were provided a standard QWERTY-keyboard which

they could position in front of them in a way that felt comfortable. Responses had to be provided with their right hand.

Our EEG data was acquired from 32 electrodes using a BioSemi Active Two system (see *https://www.biosemi* at a sampling rate of 1024Hz. Three additional electrodes (two horizontal, one vertical) were used to measure eye movements and two additional electrodes were attached to the mastoids to be used as reference. For most of the participants, scalp impedance of the electrodes was kept at < 20 kΩ, except for two participants where it was kept at < 30 kΩ. The data was recorded using the BioSemi acquisition program ActiView 811.

3.1.3 Stimuli

During the experiment, visual stimuli were presented to the participants using the software PsychoPy (Peirce et al., 2019). These stimuli consisted of two vertically oriented Gabor patches displayed on the screen with varying contrast levels for each trial, separated by a fixation cross shown in the middle of the screen, as shown in Figure 13. Contrast levels varied between 3.5% to 95.5%, with 1% intervals, resulting in a list with a total of 93 predetermined contrast values.

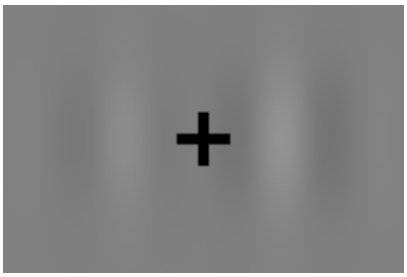


Figure 13: The stimuli shown during the experiment

In each trial, a mean contrast value was used to generate the stimuli, for example 12.5% in Figure 13. Subsequently, one of the patches would randomly be assigned a contrast value that was 2.5% lower (For Figure 13 this would be the left side, with a contrast of 10%), while the other received a contrast value 2.5% higher (the right side of Figure 13, with a contrast of 15%), ensuring that the two patches always maintain a constant 5% contrast difference. The participants' task was to identify which of the two patches exhibits the highest contrast value in each trial. All stimuli were preceded by a fixation cross (which can also be seen in the middle of Figure 13), which remained present after the stimuli were shown, until a response was given. Example code to generate this contrast range can be found in the Appendix (Listing 1)

3.2 Experimental Procedure

3.2.1 Differences with original study

Even though we based our experiment on the one described in Section 2.2, there are still some changes that were made, which we tested through both exploring some options ourselves and eventually experimenting in five pilot sessions to ensure we get similar results.

In the original experiment, the contrast difference between the two displayed patches was 14%, however in our initial testing we found that when working with this difference our behavioral findings for the accuracy condition were not matching as our participants' proportion of correct responses was much higher in comparison. Furthermore, working with a lower contrast difference also allows us to test for a wider range of stimuli. After thorough testing of several different contrast differences we decided to settle for a 5% difference, since this value made it more difficult for participants to reach high mean correct % across trials in the accuracy condition but staying above 80% on average, while keeping this value above guess-level (50%) for the speed condition. The difference in contrast strength can be observed in Figure 14, with the stimuli from the original experiment labelled *old* and those from our experiment labelled *new*. Note that even though the overall contrast for both the old and new stimuli is around 23%, the *new* stimuli are more difficult to differentiate compared to the *old* ones because the difference in contrast between the two patches is much smaller.

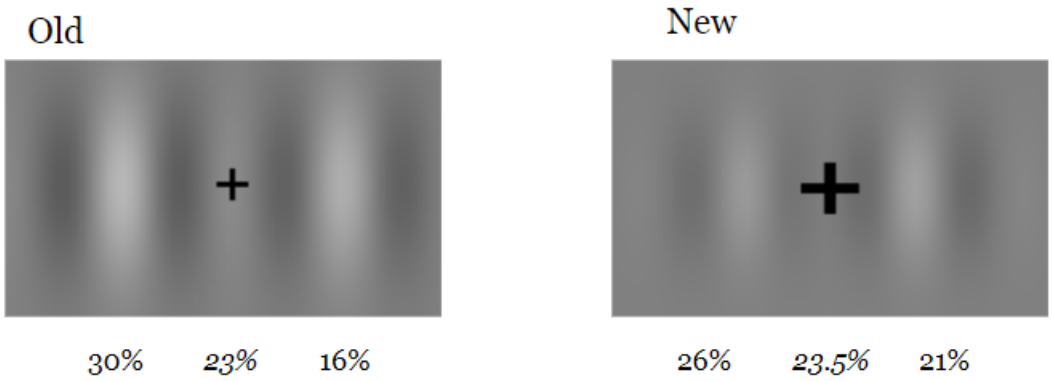


Figure 14: Stimuli for the original experiment (left) and our experiment (right)

Another decision we had to make was what range of values we wanted to work on and how often we wanted to show all of our stimuli. In the experiment described in Section 2.2, participants were shown stimuli with six mean contrast levels, and a decrease in the proportion of correct responses and an increase in response time were measured as stimulus strength increased. In order to get a clearer grasp on the effect of contrast level on these variables, and to confirm whether this was also true for contrast levels outside of this range, we decided to work with a broader range of mean contrast levels. This resulted in us working with a mean contrast range of 3.5% to 95.5% with 1% intervals for a total of 93 unique stimuli, instead of the range of 23% to 83% with 14% intervals for a total of six unique stimuli shown previously, as can also be seen in Figure 15. Final testing taught us that we could show this exact range a total of three times each block for a total of 12 times without exceeding 60 minutes, leaving us with ample time for preparation and training.

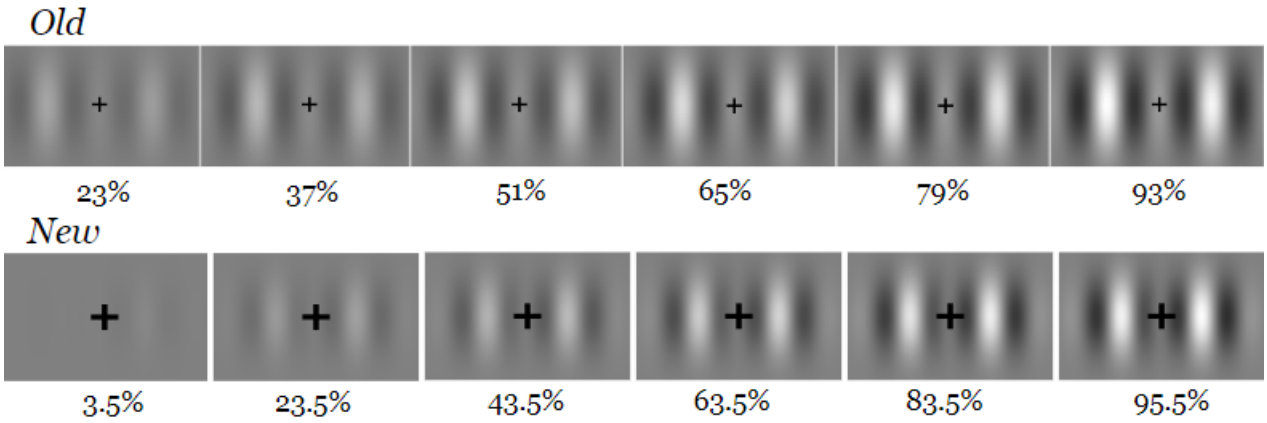


Figure 15: Comparison of the range for the original experiment (top) and our experiment (bottom)

3.2.2 Experiment

All participants were asked to partake in a single experimental session. A full experimental session lasted for approximately 90 minutes and could be divided into preparation, a training session and the experiment itself including some self-paced breaks. During preparation participants were asked to read and sign an informed consent sheet. Afterwards they were given the instructions on the experiment while electrodes would be attached to their skin and fitted on an EEG cap. During the training and experimental sessions, participants were shown visual stimuli such as the one shown in Figure 13 as they were urged to keep their gaze on the fixation cross in the middle of the screen and to perform the task according to either a speed or accuracy condition which was always prompted at the start of a block.

Training consisted of four blocks of 20 trials each, with participants being prompted to focus on accuracy for blocks 1 and 3 and to focus on speed for blocks 2 and 4. Prior to the training participants would be instructed that during the speed condition, they are expected to have an average reaction time between 500ms and 600ms while for the accuracy condition we specified that the mean percentage of their correct responses should be around 85%. Participants received feedback at the end of each block, detailing both their average reaction time and speed of the block. If either of these required some correction, participants could be urged to respond faster during the speed trials or to be more precise during the accuracy trials.

The experiment itself consisted of four blocks of 279 trials for a total of 1116 trials. In this session participants also alternated between the speed and accuracy conditions for each block. Whether participants started with speed or accuracy was counterbalanced across participants (participant 1 started with speed, participant 2 with accuracy, participant 3 started with speed again and so on). Per block, participants were shown each value within the range explained in section 3.1.3 exactly three times in a fully randomized order. Participants were instructed to take a break for as long as they deemed useful approximately halfway through a block (after 139 out of 279 trials) and another one after a full block was finished. During each planned break session participants once again received feedback similar to the training session, detailing their average reaction time and the percentage of

their correct responses during the prior half-block. If deemed necessary, participants could also be asked to follow the instructions more closely during these breaks.

3.3 Preprocessing

The EEG data contains the recordings of all electrodes for the entire duration of the experiment, including markers to indicate the start of a trial, shortly followed by the contrast level and the expected (correct) response, and finally the given response after a participant presses one of the response keys. Before we can analyse this, however, some preprocessing is required to clean our $\sim$45 minutes of data.

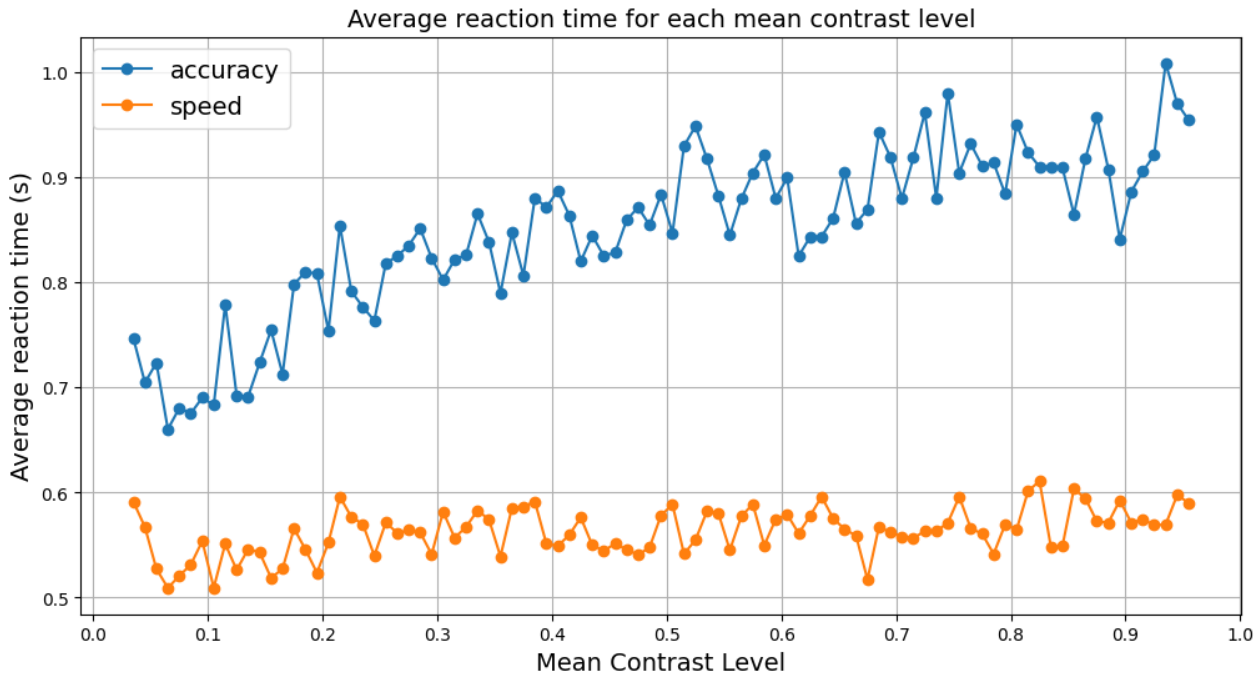
Preprocessing was conducted with python scripts in a jupyter notebook, making use of the mne library (Gramfort et al., 2013). The data was first referenced using a REST reference. Afterwards, a high-pass filter of 1 and low-pass filter 100 Hz were applied. We then manually detected whether any electrodes were faulty and searched for artifacts in the data. For our dataset this meant that for our 26 participants, 14 channels were removed. We excluded trials that lasted longer than 2.5 seconds as breaks and trials that lasted for less than 250ms were also removed. Beyond that we manually annotated trials to not be used for analysis where participants were either blinking during stimulus presentation or were making unrelated muscle movements such as scratching. Furthermore, we removed trials that were noisy across all electrodes. For the next step, Independent Component Analysis (ICA) was applied and components containing eye blinks or muscle movements were manually removed. For most participants we ended up removing one component, but for some participants we decided to remove two or three components, resulting in a total of 36 removed components for 26 participants. Afterwards, the removed channels were interpolated based on the signals of good (non-removed) surrounding electrodes. Finally, the autoreject library (Jas, Engemann, Raimondo, Bekhti, & Gramfort, 2016) was applied, which automatically detects bad trials and attempts to repair the bad signals, if it cannot do this then it will reject them and they will not be taken into account during analysis. We ended up removing four participants from the dataset due to unrecoverable noise in the shape of high alpha wave activity or high EMG noise on a large amount of trials. After all these processes have been applied we ended up rejecting 4463 of our 25668 trials.

4 Results

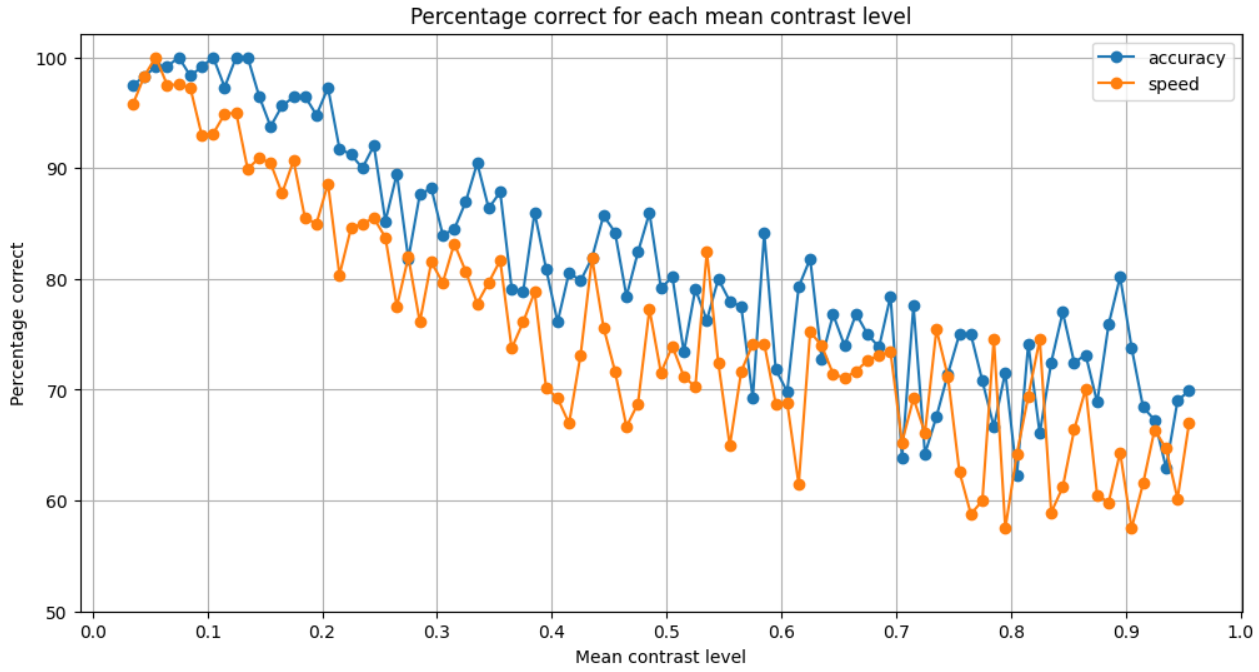
4.1 Behavioral analysis

For the behavioral results, we were interested in the effects of average contrast level on both the reaction time in milliseconds (RT) and the proportion of correct answers (%). These can be seen in Figures 16(a) and 16(b) respectively. If we take a closer look at these graphs, we see in 16(a) that reaction time increases as the mean contrast level increases for both conditions, with a larger increase for accuracy than for speed. Furthermore, in Figure 16(b) we notice that the proportion of correct answers decreases, nearing chance level as contrast level decreases. However, in both figures for the first few observations, the reaction times are actually higher than we would expect, and similarly the proportion of correct answers are actually lower than expected.

To get a better grasp of the data, we fit two separate Linear Mixed Models (LMMs) (Seabold & Perktold, 2010) on reaction time and on the proportion of correct responses. For these models we are fitting either rt or proportion correct on the condition (accuracy or speed), the stimulus (contrast level varying from 0.035 to 0.955) and the interaction between condition and stimulus, with participants seen as random effects. For the model fitted on reaction time, we see a significant influence of the speed condition, the stimulus and the interaction between stimulus and the speed condition on the reaction time (P close to 0.00 for all terms). For the model fitted on proportion of correct responses we see similar results with significant influences of the speed condition and stimulus on the proportion of correct responses. However, we don't get enough evidence for influence of the interaction between stimulus and condition on this value ($P = 0.713$). After fitting these models, the plotted predictions for the reaction times and proportion of correct responses can be seen in Figure 17, with the predicted reaction time over the mean contrast level on the left, and the prediction proportion of correct responses on the right. What these results show us is that the we can expect the reaction time to increase and the proportion of correct responses to decrease as the mean contrast value goes up, which seems to be in line with the findings from the original experiment in Figure 6.



(a) Average reaction time over each contrast value



(b) Proportion of correct responses for each contrast value

Figure 16: Average values for (a) Reaction time and (b) proportion correct over each contrast value over all preprocessed data. The orange lines represent the values during the speed condition, with blue showing those for the accuracy condition.

Mixed Linear Model Regression Results

Model:	MixedLM		Dependent Variable:			rt
No. Observations:	21205		Method:			REML
No. Groups:	22		Scale:			0.0833
Min. group size:	821		Log-Likelihood:			-3809.1522
Max. group size:	1058		Converged:			Yes
Mean group size:	963.9					
	Coefficient	Standard Error	z	$P > \|z\|$	[0.025	0.975]
Intercept	0.733	0.033	22.390	0.000	0.669	0.797
condition[speed]	-0.190	0.008	-22.984	0.000	-0.207	-0.174
stimulus	0.252	0.011	23.844	0.000	0.232	0.273
stimulus:condition[speed]	-0.215	0.015	-14.598	0.000	-0.244	-0.187
Group Var	0.023	0.025				

Table 1: Model summary for the LMM fitted on RT

Mixed Linear Model Regression Results

Model:	MixedLM		Dependent Variable:			correct
No. Observations:	21205		Method:			REML
No. Groups:	22		Scale:			0.1550
Min. group size:	821		Log-Likelihood:			-10370.2077
Max. group size:	1058		Converged:			Yes
Mean group size:	963.9					
	Coefficient	Standard Error	z	$P > \|z\|$	[0.025	0.975]
Intercept	0.991	0.015	66.937	0.000	0.962	1.020
condition[speed]	-0.055	0.011	-4.896	0.000	-0.078	-0.033
stimulus	-0.354	0.014	-24.481	0.000	-0.382	-0.325
stimulus:condition[speed]	-0.007	0.020	-0.367	0.713	-0.047	0.032
Group Var	0.003	0.003				

Table 2: Model summary for the LMM fitted on proportion of correct answers

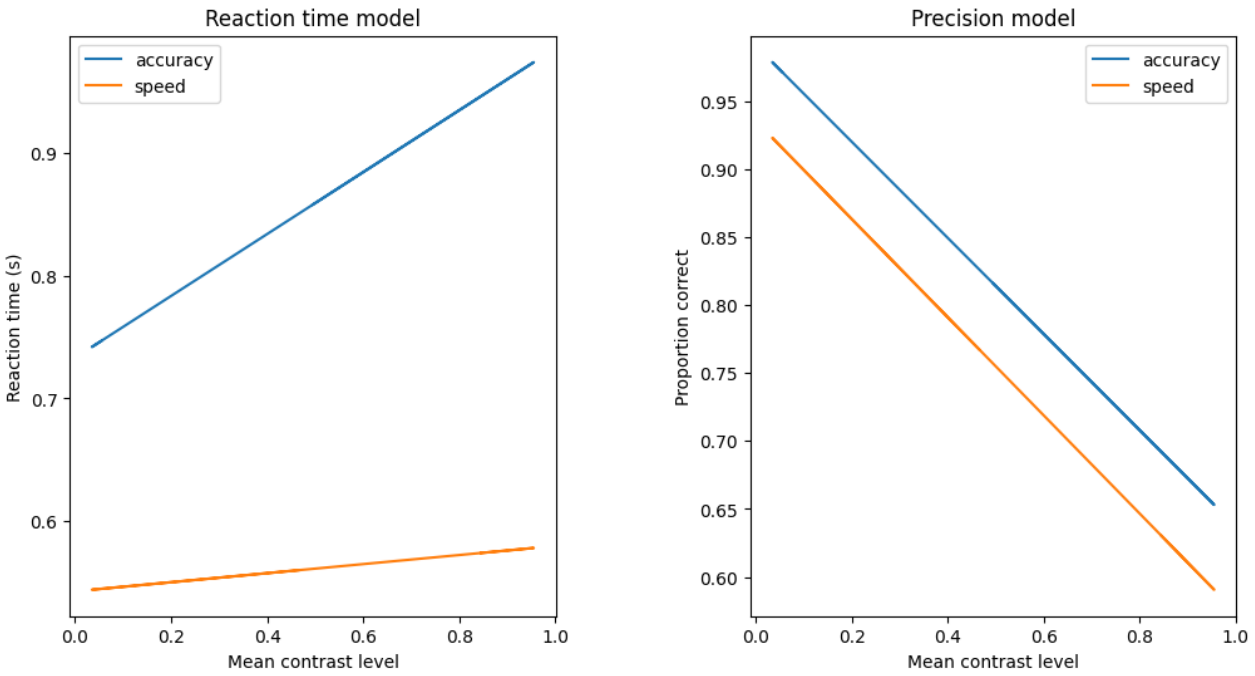


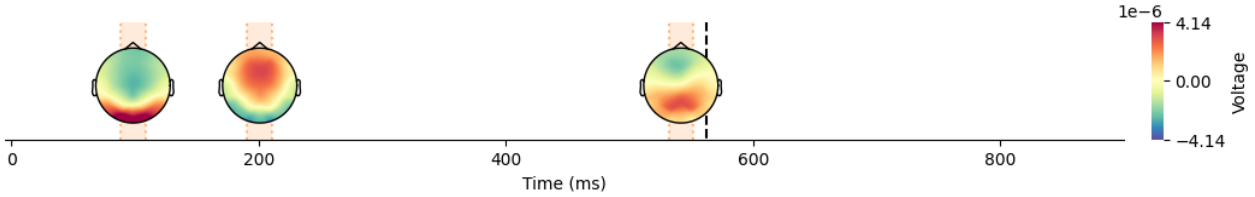
Figure 17: LMM predictions for reaction time (left) and proportion of correct answers (right) plotted against mean contrast level

4.2 HMP results

In order to determine how many cognitive stages we can expect to find based on the preprocessed data, we fit a model which can determine how many events can be found within the trials. We initially fit a single HMP model on all conditions and participants to determine the maximum amount of events. The results can be seen in Figure 18, where we see onsets of identified events illustrated as top-down brain topologies with the frontal side at the top of the image. These visualisations not only grant us insight into when a certain cognitive event takes place, based on how far along the x-axis (RT in ms) the event is shown, they also offer us an estimate of polarities of each event at the different recorded sites where our EEG was placed, indicated by the colors of the regions shown in the legend on the right of the image (with red being more positive than average and more negative than average, yellow indicating average levels of activity). Based on our initial findings in Figure 18 we can determine that at most we can expect four events, and therefore five cognitive stages.

Since we expect some differences within conditions to occur, we split up this model into two separate models, one using only the data of the trials in the *speed* condition, and the other using only the results of the trials performed in the *accuracy* condition. These estimates can be found in Figure 19. Here we notice that when we only look at the speed results, the model estimates one fewer cognitive event to be present.

Figure 18: Estimates of cognitive stages present during Perceptual decision making task



(a) Speed

(b) Accuracy

Figure 19: Estimates of cognitive stages present for (a) the speed condition and (b) the accuracy condition

However, these models provide us with a 'maximum solution', providing us with all events with some evidence supporting their presence in the data. Next, we will apply a combination of backward estimation and Leave-One-Out Cross Validation (LOOCV) to determine which model has the highest likelihood. Backward estimation takes our 'maximum solution' model and iteratively finds a model with 1 event removed with the highest likelihood of describing the data until a 1 event model remains. On its own this method will usually tell us that the model with most events is most likely to describe the data, as with more parameters we are usually more likely to describe the data more accurately. Therefore, we will also want to ensure that these solutions generalize to all of our participants, which we can do with LOOCV. This method will fit our found models to all participants except one and then evaluate the likelihood of this left out participant given the estimated parameters of the other participants and it will repeat this process for all participants. By combining these two methods, we can fit all backward-estimated models on all participants to determine which model is most likely to describe our data.

The LOOCV results can be seen in Figures 20 and 21. These graphs tell us how likely a transition from an n to an $n+1$ model are for all subjects. If we focus on the speed model, we can tell that for 18 out of 22 subjects, a 2-event model explains the data better than a 1 event model and that for 21 out of 22 subjects ($p = 0.004$), the 3-event model explains the data better than the 2-event model (p close to 0), but a 4-event model only explains the data better for 9 out of 22 participants ($p = 0.523$). Therefore we will assume that the 3-event model explains our data the best. For the accuracy model, these results are slightly more complex, as we do not find enough evidence supporting the fact that a 2-event model works better than a 1-event model ($p = 0.523$, and is only better for 13/22 participants). However, since we deem it very unlikely that only one cognitive process occurs for a trial, we assume it is unlikely that a 1-event model can explain all the data. Therefore we decide to assume a 3-event model instead, since this does explain the data better than a 2-event model (p close to 0, explains the data better for 20/22 participants). The 3-event models can be found in Figures 22 and 23.

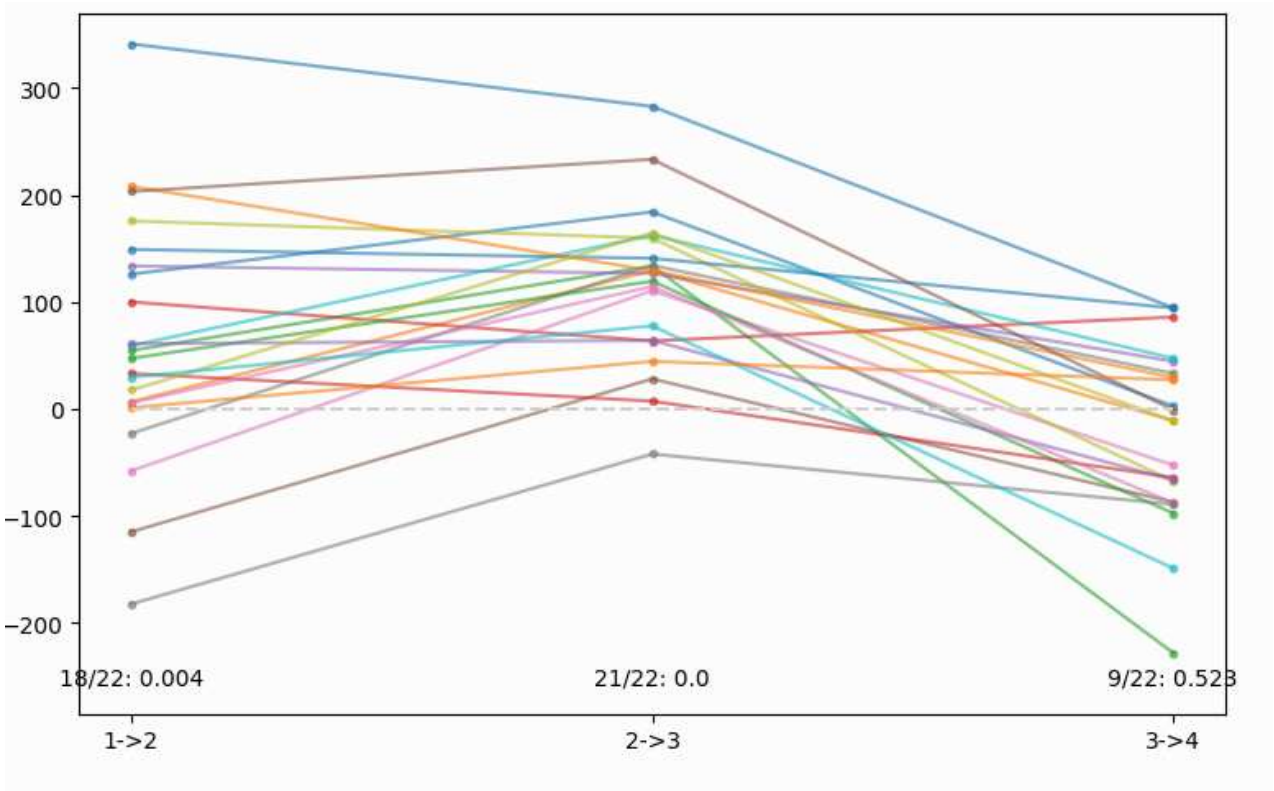


Figure 20: LOOCV results for the speed model

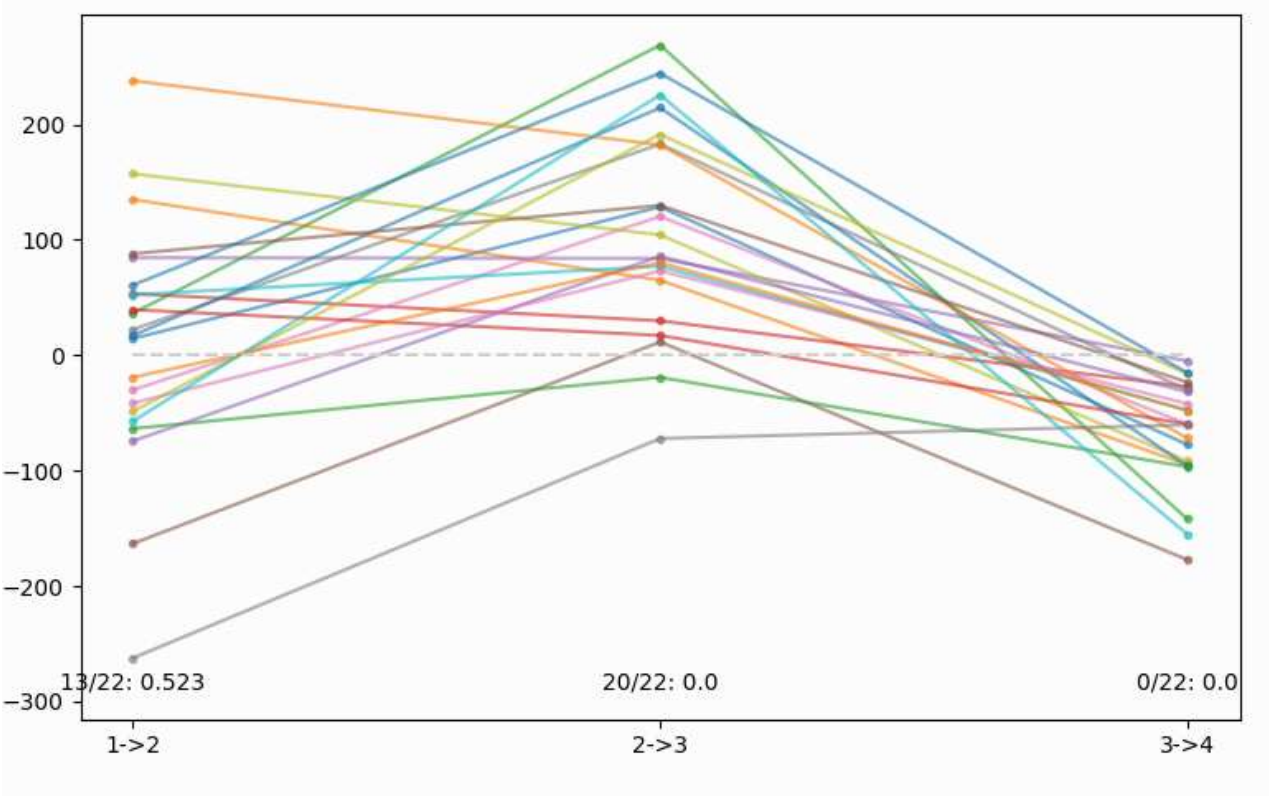


Figure 21: LOOCV results for the accuracy model

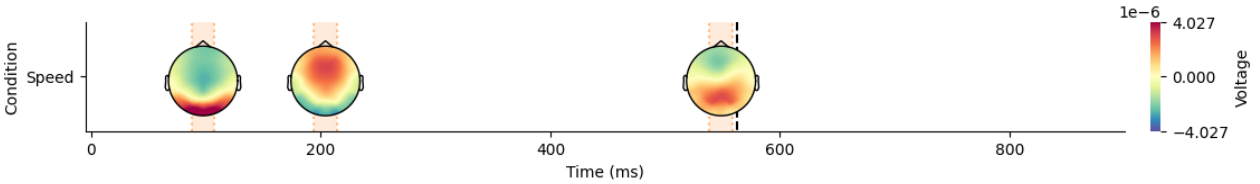


Figure 22: Estimates of cognitive stages present in the speed model based on LOOCV

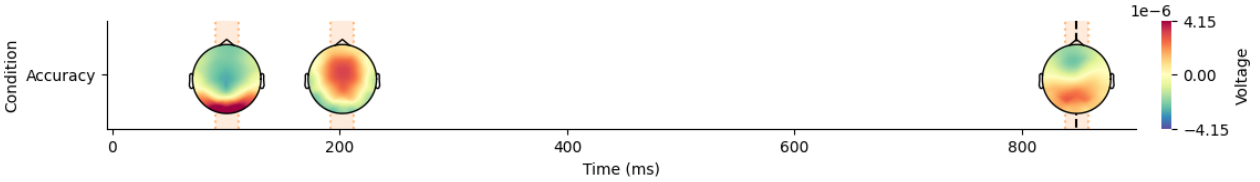


Figure 23: Estimates of cognitive stages present in the accuracy model based on LOOCV

What we notice when comparing both models is that they seem to contain similar cognitive stages, the main difference lies in the duration of the decision stage (the stage between the second and third cognitive event). Seeing as all cognitive events seem to overlap, we would like to combine these two models to determine whether we can make a more general model which can explain the data similarly but with fewer parameters, namely working with only three events in a single model instead of six events spread out over two models. To do so we combine and average the parameters and magnitudes used to fit our two separate models and use those to fit a single model where we can analyse the effects of the stimuli on both conditions separately while allowing a different gamma distribution between speed and accuracy to accommodate for different stage durations between the two conditions. The resulting model can be found in Figure 24. In order to determine whether this model describes the data at a similar or better level than the two separate models, we also apply LOOCV on this combined model and compare the log-likelihood per participant of the combined model with the summed log-likelihoods of both the speed and accuracy models. Our findings show that for 18 out of 22 participants the combined model has a greater log-likelihood ($p < 0.0004$), which is why we choose to prefer this model over the two separate models. Using our combined model, we can attempt to tackle our non-behavioral research questions.

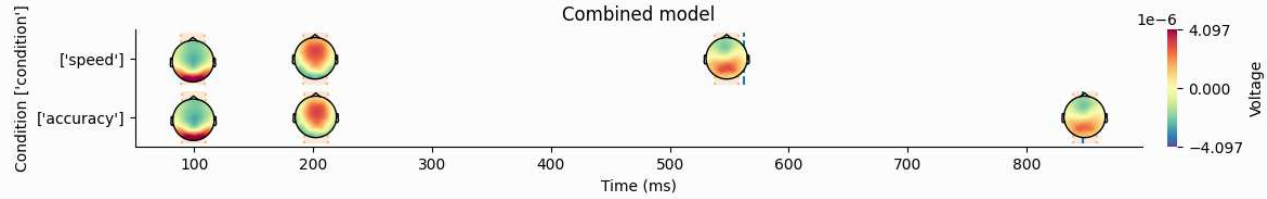


Figure 24: HMP model with combined parameters

Finally, to take a closer look at the cognitive stages found in our combined model, we want to look at onset times and durations of these stages. As described in Section 2.4, we refer to a cognitive stage as the time between two sequential events, the time between trial onset and the first event, or the time between the final event and the end of the trial. To put this in perspective, our HMP model in Figure 24 contains three events and four cognitive stages for each condition. We have numbered them in order of sequential appearance. Stage 1 is the stage between trial onset and the first event, in this stage the participant will not have gained any information yet, so we will call it the *pre-attentive stage*. Stage 2 is the stage between the first and second event, here we expect participants to encode the stimuli in the *encoding* stage. Stage 3 is the stage between the second and third event, this is the stage with the longest duration for both conditions, which we expect to be dedicated to decision making and would therefore be the *decision* stage. Stage 4 is the stage between the third event and the end of the trial, this fairly short stage is likely allocated to motor functions in the *response execution* stage.

Figure 25 shows us three plots which indicate the onset time (in ms) of each of the three processing events, plotted against the mean contrast level. Here we notice that for higher mean contrast levels, the time it takes for the encoding stage to start does seem to decrease. Figure 26 on the other hand shows us the average durations for each cognitive stage, which is the measured by looking

at the difference between the onset of the cognitive event signaling the start of this stage, and the next (or the end of the trial, for the last event), also plotted over mean contrast level. Do note the difference in scales between these three plots, when we look at the plots for decision stage the difference between the minimum and maximum value is around 500 ms, while for the response execution stage this difference is smaller than 0.5 ms. In terms of the effect of mean contrast on the stage durations, we mostly note the increase in duration in the decision stage as contrast level increases for the accuracy condition, whereas there is not as much change within the speed condition.

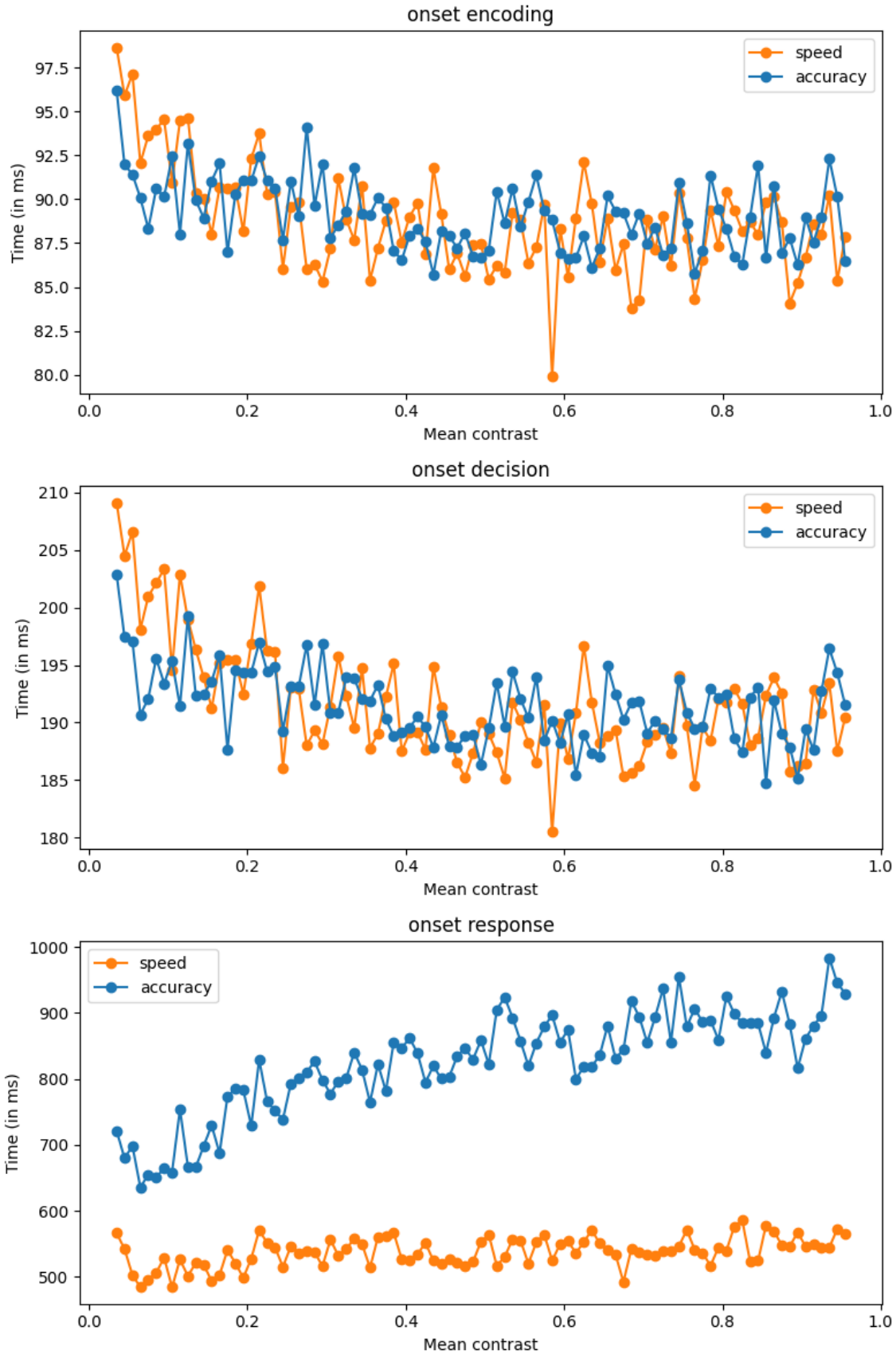


Figure 25: Average onset times for all cognitive stages compared

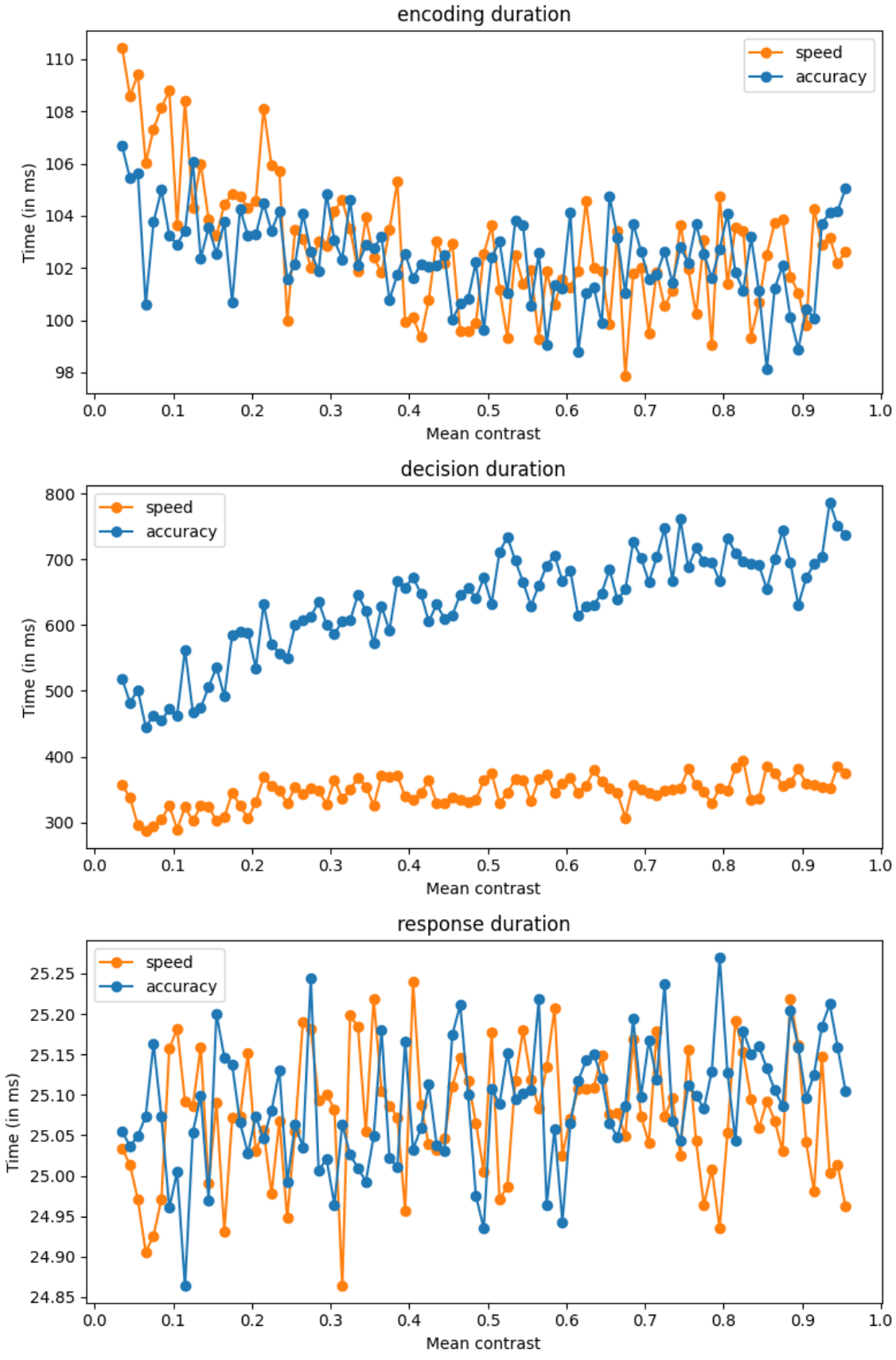


Figure 26: Average durations for all cognitive stages compared

For a deeper dive into the effects of both mean contrast level and SAT on stage durations, we fit some additional LMMs for each of our stage durations (*encoding* in Table 3, *decision* in Table 4 and *response execution* in Table 5) on condition, stimulus and the interaction between condition and stimulus. For both *encoding* and *decision* stages we notice a significant influence of condition, stimulus and the interaction between condition and stimulus on the stage durations ($P <= 0.002$ for all terms). However, for the duration of the *response execution* we do not notice a significant influence of condition or stimulus ($P = 0.256$ for condition, $P = 0.354$ for stimulus), but the interaction between these two seems to have a stronger influence ($P = 0.023$). The predictions of all three LMMs can be seen plotted in Figure 27, with the stage durations in ms plotted over mean contrast level in %. These results show us that time spent in the *encoding stage* decreases as contrast level increases, while time spent in both *decision* and *response execution* increases as mean contrast level increases.

Mixed Linear Model Regression Results

Model:	MixedLM		Dependent Variable:			rt
No. Observations:	21205		Method:			REML
No. Groups:	22		Scale:			277.3479
Min. group size:	821		Log-Likelihood:			-89795.3526
Max. group size:	1058		Converged:			Yes
Mean group size:	963.9					
	Coefficient	Standard Error	z	$P > \|z\|$	[0.025	0.975]
Intercept	105.371	1.726	61.063	0.000	101.988	108.753
condition	-1.496	0.474	-3.153	0.002	-2.426	-0.566
stimulus	-0.053	0.006	-9.000	0.000	-0.065	-0.042
stimulus:condition	0.033	0.009	3.848	0.000	0.016	0.049
Group Var	63.089	1.179				

Table 3: Model summary for the LMM fitted on encoding time

Finally, we wanted to compare our findings with the findings from Reynaud et al. (2012), similarly to what was done in Figures 8 and 9, where the DDM interpretation of the encoding time of Weindel et al. (2021) was compared to visual neuron onset in monkeys but by using our onsets of the *encoding stage* instead. These can be seen plotted in Figure 28, where we compare the data of Reynaud et al. with the onset of our *encoding* stage for the speed condition (indicated in orange) and the accuracy condition (indicated in blue). We notice some similarities in the data, as in all cases the onset of the encoding stage does seem to decrease as the mean contrast level increases in all of these plots.

Mixed Linear Model Regression Results

Model:	MixedLM		Dependent Variable:			rt
No. Observations:	21205		Method:			REML
No. Groups:	22		Scale:			77786.4699
Min. group size:	821		Log-Likelihood:			-149546.2783
Max. group size:	1058		Converged:			Yes
Mean group size:	963.9					
	Coefficient	Standard Error	z	$P > \|z\|$	[0.025	0.975]
Intercept	320.811	31.311	10.246	0.000	259.443	382.179
condition	193.873	7.946	24.399	0.000	178.299	209.447
stimulus	0.483	0.099	4.856	0.000	0.288	0.677
stimulus:condition	2.093	0.143	14.673	0.000	1.814	2.373
Group Var	20889.132	23.243				

Table 4: Model summary for the LMM fitted on decision time

Mixed Linear Model Regression Results

Model:	MixedLM		Dependent Variable:			correct
No. Observations:	21205		Method:			REML
No. Groups:	22		Scale:			0.6324
Min. group size:	821		Log-Likelihood:			-25276.9648
Max. group size:	1058		Converged:			Yes
Mean group size:	963.9					
	Coefficient	Standard Error	z	$P > \|z\|$	[0.025	0.975]
Intercept	25.061	0.024	1045.087	0.000	25.014	25.108
condition	-0.026	0.023	-1.136	0.256	-0.070	0.019
stimulus	0.000	0.000	0.926	0.354	-0.000	0.001
stimulus:condition	0.001	0.000	2.267	0.023	0.000	0.002
Group Var	0.007	0.003				

Table 5: Model summary for the LMM fitted on response execution time

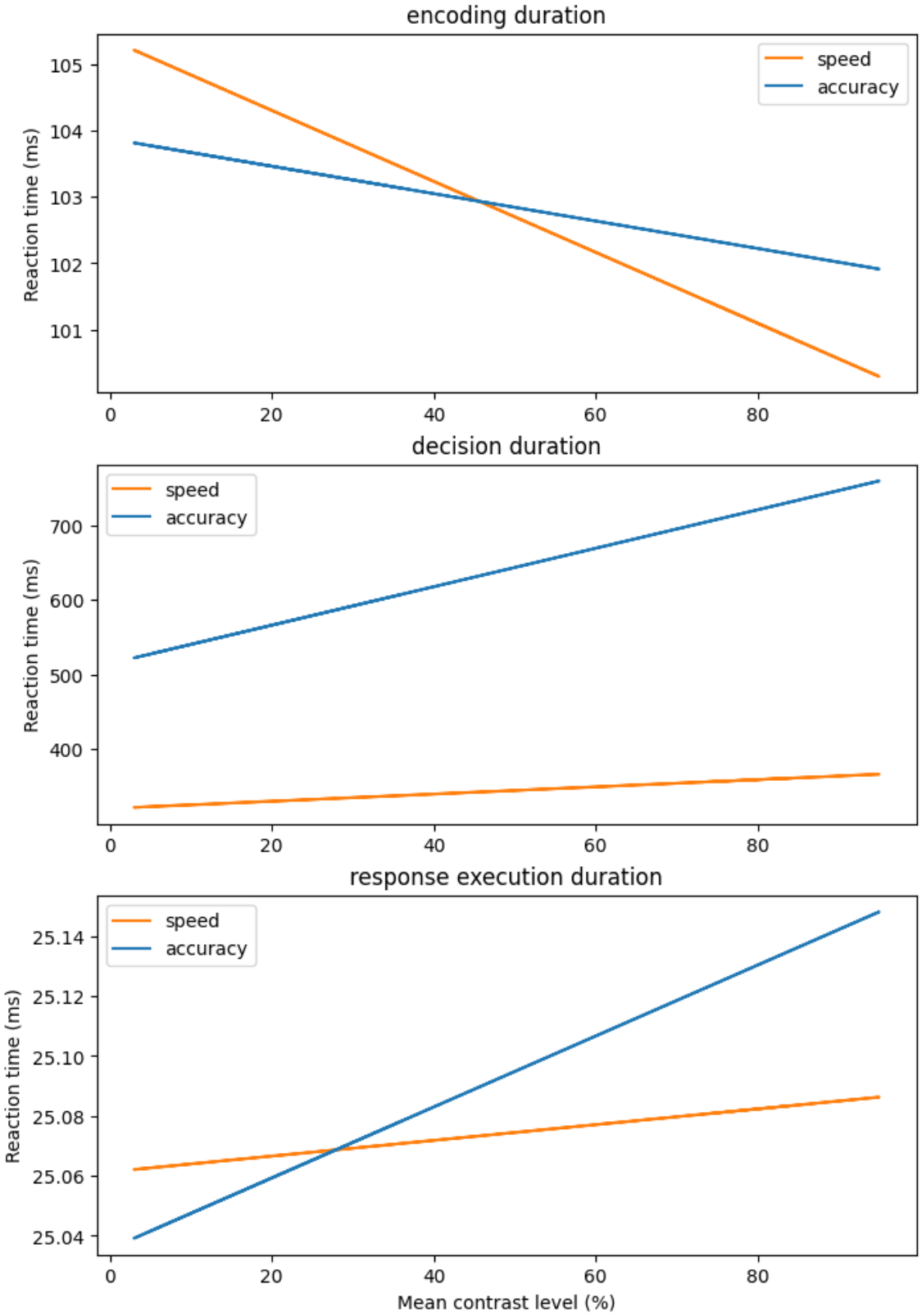


Figure 27: LMM predictions for stage durations for encoding, decision and response execution stages

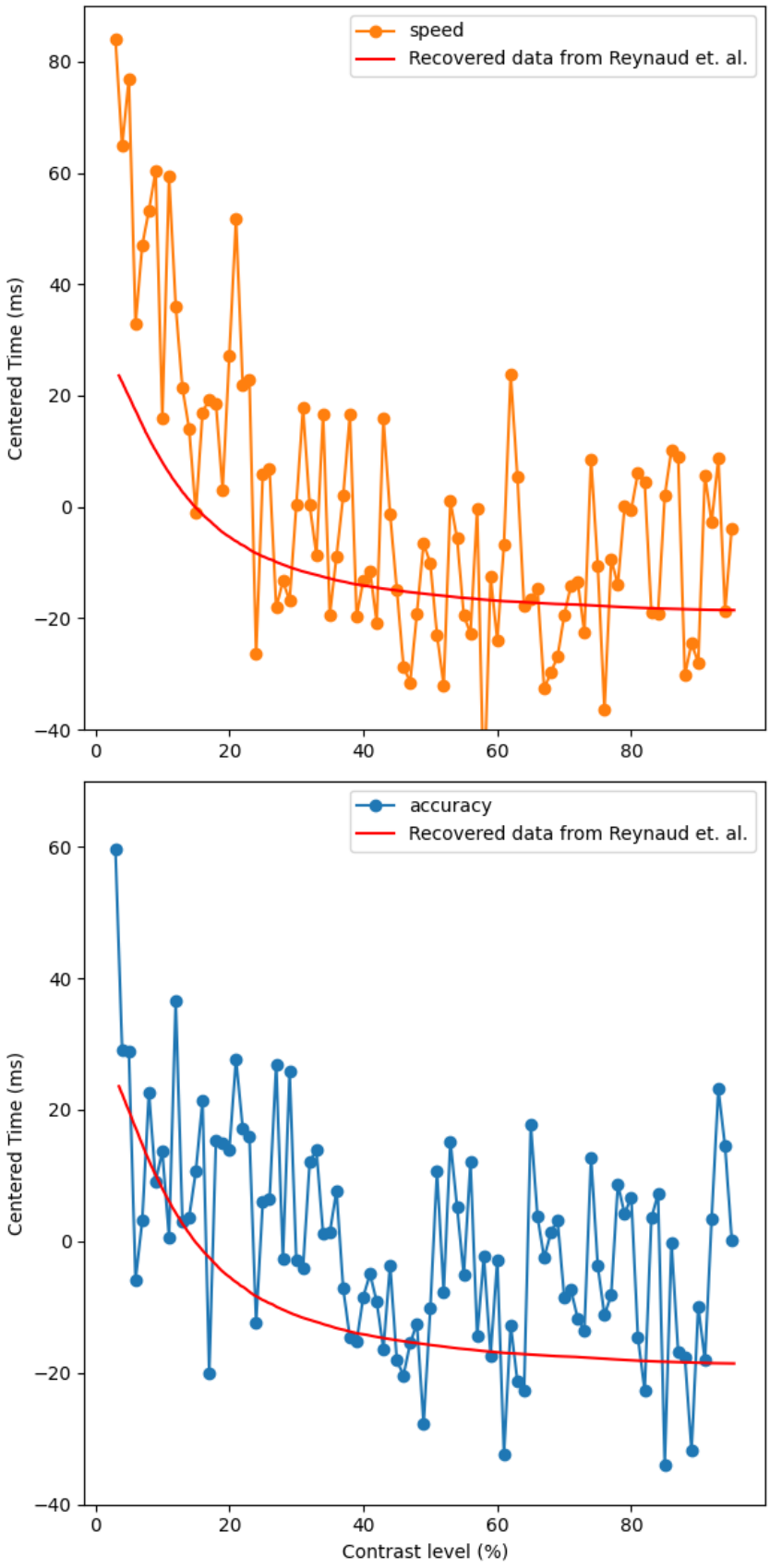


Figure 28: Comparing onset time of *encoding* stage to monkey data

5 Discussion

5.1 Behavioral Results

For this Perceptual Decision Making task, we expected the reaction times to increase and proportion of correct answers to decrease in an almost linear fashion as contrast level increased. For the majority of our data this does seem to be the case as shown in both the graphs in Figure 16 as well as the fitted models in Figure 17, similar to what was reported in previous studies. However, for very low contrast levels we do not notice this effect. What seems to happen instead is that participants seem to find this part of the task more difficult again, described by the increase in both the reaction time and the amount of errors. This might be due to the fact that it becomes very difficult the distinguish the presence of images when very low contrast levels are used, as we can for example notice in Figure 29. Here we barely see anything on the left-hand side of the fixation cross, which should have a contrast level of 1%, while its counterpart on the right side is also difficult to discern but is much more noticeable at 6%.

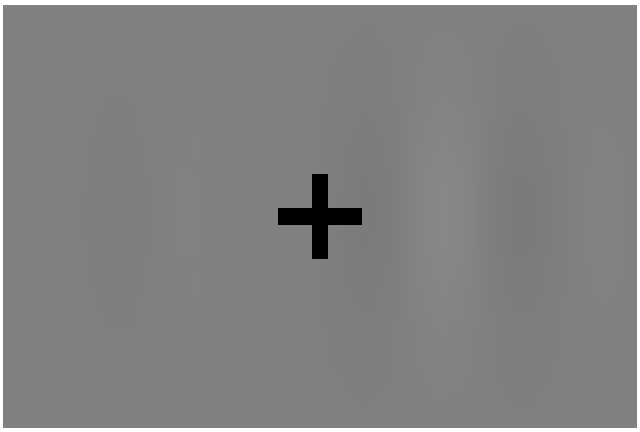


Figure 29: For low contrast levels, it becomes difficult to recognize images

5.2 HMP Results

Using obtaining our final HMP model (Figure 24), we can attempt to answer our research questions from Section 2.5.

We initially asked whether we could detect the expected processing stages using our HMP models. As a reminder, we are expecting three stages: *encoding*, *decision* and *response* in this order. For both conditions in our generalized model (Figure 24) we do notice three significant cognitive events, indicating the presence of four stages. In order to reason about the stages that we actually detected, we can look at the topologies of the events, the durations of the stages and perhaps most importantly the order in which the stages occur, as we would expect that *encoding* has to occur before a *decision* can be made, and it would be odd to execute a *response* if we are still busy deciding. We would assume that for the first cognitive stage, which lasts from the start of the trial until the first event, no

cognitive processes have started yet, since we do not yet record any significant activity in the brain. We name this the *pre-attentive* stage and assume that as we near the first event, participants actually start encoding the stimuli. We could argue then that the second cognitive stage is the *encoding* stage, based on the fact that this would be the first cognitive stage related to performing our task. Furthermore we notice that the topology of the brain activity looks similar to early visual event related potentials as additional evidence. For our third cognitive stage we can argue that we have entered a *decision* stage, as we expect this stage to be the one where participants spend the most time in, which we can notice here by looking at the distance on the x-axis between the second and third event in Figure 24 (and also described more in-depth in Figure 26, which will be discussed later on). Finally, the stage we would most likely expect towards the end of the experiment is the *response execution* stage, and we notice that this stage duration is fairly constant, which we expect since the contrast level should have no effect on the time it takes to respond. This is in line with findings by Weindel et al. (2021), where they did not observe an effect of stimulus on response execution time. Taking into account the fact that we find these stages for both of our conditions, we have obtained a good amount of evidence showing us that by using HMP models, we can detect and identify processing stages within a Perceptual Decision Making task.

Next, we wanted to identify the effects of the speed-accuracy trade-off on our models, and determine whether they had any noticeable differences within the results or the models. Within our behavioral results described in Section 5.1 we already concluded that the reaction time and proportion of correct answers was generally lower for the speed condition. However, perhaps we can identify differences within the cognitive processes present in our model (Figure 24). Within our combined model the found cognitive stages are the same, with the only difference being that the trials on average take longer for the accuracy condition (average RT for speed condition is 562.68 ms, for accuracy 847.77 ms). We can expand upon this by looking at the durations of cognitive stages as contrast level increases, displayed in Figures 26 and 27. We notice that in both the *encoding stage* for both the speed and accuracy conditions the duration decreases as mean contrast level increases, while for the *decision* stage and the *response execution* stage the duration increases as mean contrast level increases. However, the scale of this change is much higher for the *decision* stage where the difference between highest and lowest value in graph is $437.12ms$, while for the *encoding* stage and *response execution* stage this difference is $4.91ms$ and $0.11ms$ respectively. We notice that for most stages, the changes in stage duration are similar for both conditions. The exception to this is the *decision* stage, where the duration in the speed condition remains fairly similar, while in the accuracy condition we see that the overall duration increases as contrast level increases. The main difference we can therefore identify between both of our conditions lies in the fact that the effect of contrast level on the duration of the decision stage is much stronger in the accuracy condition, compared to the speed condition.

Afterwards, we were curious about time spent in the *encoding* stage. In the theory section we described the finding that as contrast level increased, the images would be easier to perceive, and therefore the time it takes to enter the *encoding* stage would decrease. This can be seen in the first plot of Figures 25, where we notice for both conditions that encoding time decreases as contrast level

increases. To further look into this comparison, we have plotted our findings against the findings of Reynaud et al. (2012) in Figure 28. Here we do not see the matching level that was noticed in the encoding stage, but we still see a promising resemblance. Another interesting observation is that, unlike for our findings in **??** where we noticed that the reaction time increased for the extreme low values for mean contrast level, the decrease of encoding time actually moves more linearly, without any outliers for early values.

Finally, we mentioned the potential existence of an additional cognitive stage within the accuracy condition, such as reported by Van Maanen et al. (2021). Although we are capable of finding a four-event accuracy model as depicted in our 'maximum estimate' (Figure 19b), our LOOCV results in Figure 21 show that there is not enough evidence for us to prefer this over a 3-event model. Additionally, in the original text this additional stage occured after the decision stage, while in our estimate it would occur even before the encoding stage. Since we see no evidence for a 4-event model and we do not see it as likely that an additional cognitive stage would occur before the encoding stage, we cannot make an argument regarding the existence of an additional stage in the accuracy condition within Perceptual Decision Making tasks.

Of course, this paper has only given an indication of the capabilities of HMP models. Within this paper we have determined whether we can identify cognitive stages within one particular Perceptual Decision Making task. Perhaps by performing a different task, with a stimulus other than sinusoidal gratings, we might encounter different results, perhaps even capable of identifying an additional cognitive process which is only present within accuracy conditions, or simply disproving the theory by providing even more models with similar amounts of cognitive processes when testing on SAT. Additionally, we have now only tested whether we can develop a model which finds comparable onset times for the *encoding* stage when compared to onset of V1 neurons in monkeys (Reynaud et al., 2012). Perhaps we can move on to also compare the other cognitive stages with other physiological measurements, by for example comparing *response execution* stage onsets and/or times with motor functions recorded by EMG measurements.

5.3 Conclusion

To conclude, the study described in this thesis indicates that HMP models can be successfully used to detect and identify cognitive processes using data obtained from EEG experiments. Since our proposed method is novel, further investigation in its capabilities and uses are of course still required. Nevertheless, our initial findings show promising prospects for the future of the detection of cognitive stages to assist in the development of cognitive models.

Appendices

Listing 1: Psychopy code for generating and saving our range of stimuli

```
from psychopy import visual, core, monitors, event
import numpy as np

#Definition screen
mon = monitors.Monitor('myMonitor')
resolution = [1024,768]
mon.setDistance(90) #cm
mon.setWidth(33) #cm
mon.setSizePix(resolution)
mon.saveMon()

# Get the screen resolution
screen_width, screen_height = resolution

# Calculate the center of the screen
center_x = screen_width / 2
center_y = screen_height / 2

# Set 'position' to the center of the screen
position = [center_x, center_y]

# Create a smaller window to display the stimuli in the center
win_size = [150, 100]  # Adjust the size as needed
win = visual.Window(size=win_size,
                    monitor=mon,
                    color='gray',
                    units='deg')

def create_and_save_gabor_patch(contrast_value, filename,
                                position):
    # Create the fixation cross
    fixation = visual.GratingStim(win=win, mask='cross',
                                  size=0.4, pos=[0, 0], sf=0,
                                  color='black')

    # Create the left Gabor patch
    gabor_left = visual.GratingStim(win, tex="sin", mask="gauss",
                                  texRes=256, pos=[-0.6, 0],
                                  size=2.5, sf=[1.2, 0], ori=0,
```

```
                                        name='gabor_left')
    gabor_left.contrast = contrast_value - 0.025
    gabor_left.draw()

    # Create the right Gabor patch
    gabor_right = visual.GratingStim(win, tex="sin", mask="gauss",
                                     texRes=256, pos=[0.6, 0],
                                     size=2.5, sf=[1.2, 0], ori=0,
                                     name='gabor_right')
    gabor_right.contrast = contrast_value + 0.025
    gabor_right.draw()

    # Draw the fixation cross
    fixation.draw()

    win.flip()

    win.getMovieFrame()
    win.saveMovieFrames(filename)


# Set the contrast levels and create/save the Gabor patches
cList = np.arange(0.025 + 0.01,0.99 - 0.025,0.01)
contrast_levels = cList  # List of contrast levels for the patches
for idx, contrast_value in enumerate(contrast_levels):
    filename = f"gabor_contrast_{contrast_value*100:.1f}.png"
    create_and_save_gabor_patch(contrast_value, filename,
                                position=position)

# Close the PsychoPy window
win.close()
```

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