university of groningen / faculty of science and engineering

Manipulation of perception using HsMM-MVPA analysis on EEG data

Bachelor's Project Thesis

Melle Berentschot, s3508072, m.berentschot@student.rug.nl
Supervisors: H. Berberyan & Dr J.P. Borst

Abstract: Back in 1868, Donders claimed that humans go through multiple cognitive stages before making a decision (Donders, 1868). Although he did find indications that cognitive stages exist, he has never been able to measure them directly due to the lack of methods to measure brain activity. However, with the arrival of the cognitive revolution (1950) and the invention of the electroencephalogram (EEG), people have been able to measure the electrical activity of the brain. Evidence was found supporting that cognitive processing stages can be derived from EEG data by using a hidden semi-Markov model multivariate pattern analysis (HsMM-MVPA) by Anderson, Zhang, Borst, and Whalsh (2016). This claim of using HsMM-MVPA as a method to derive cognitive stages out of an EEG signal was supported with evidence found by Berberyan, van Maanen, van Rijn, and Borst (2021). Our research uses the same method in order to investigate whether there is a difference in the perceptual processing stage when using transparent stimuli, compared to Berberyan and colleagues using non-transparent stimuli for the same task. The method was replicated with the difference that we used transparent stimuli in order to accurately investigate whether the use of transparent stimuli made a difference. There was no significant difference found in our reaction times or cognitive stage durations compared to the results of Berberyan and colleagues. This implies that the transparent stimuli used for this experiment did not result in perception manipulation. However, as we did replicate the results of Berberyan and colleagues, it can be said that the validity of using HsMM-MVPA as a method to derive cognitive stages out of EEG data is supported by our findings.

1 Introduction

Over one and a half century ago, the idea of going through different processing stages during a thought process was put forward for the first time (Donders, 1868). Donders claimed that people go through different cognitive stages before each decision they make. He tried to investigate these stages primarily by means of behavioral data such as response times of his participants. He found an indication of the existence of cognitive stages by analyzing the behavioral responses. However, he was never able to support this indication with exact stage durations or temporal onsets of the individual stages, due to the lack of methods to measure brain activity.

The cognitive revolution started about a century after that, this brought back the idea Donders had about cognitive processing stages. This time, better methods to measure brain activity were available to researchers. A well-known method used in order to record brain activity uses an electroencephalogram (EEG), which is used to record electrical activity of the brain. The EEG recordings can be used to directly derive cognitive stages, because EEG enables the ability to measure brain activity as it unfolds in real time, at the level of milliseconds. This is an advantage of using EEG compared to, for example, using MRI or fMRI. As EEG has the ability to measure brain activity at the level of milliseconds and cognitive stages also appear in the range of milliseconds, EEG is the method chosen for this research. A recent method for deriving cognitive stages out of an EEG signal uses a hidden semi-Markov model multivariate pattern analysis (HsMM-MVPA) for doing this (Anderson et al., 2016). Anderson and

colleagues gathered evidence that the start of each cognitive processing stage is indicated by a negative or positive peak in the EEG signal, referred to as "bumps" in the signal.
The validity of using HsMM-MVPA as a method to derive cognitive stages out of a EEG-signal was tested by Berberyan et al. (2021). This was done by two visual discrimination tasks; one simple and one complex discrimination task. They found that the complexity of the task influenced the response times, and supported this claim by means of an HsMM-MVPA analysis performed on the EEG data. The HsMM-MVPA results showed that the duration of certain cognitive processing stages differed between the simple and complex task, whereas the duration of other stages stayed the same. This supported the idea that some of the cognitive stages are related to decision making, while other cognitive stages are not. The cognitive stages that are not related to decision making are stages one goes through during perceiving the stimuli (at the beginning of a trial) and during motor-related events, pushing the button on the keyboard at the end of a trial in this case.
In this research, the aim is to manipulate perception using similar stimuli as Berberyan and colleagues used in their experiment, with the difference that our stimuli will be presented as transparent stimuli. Manipulating perception will be achieved when the perceptual processing stages (i.e. the cognitive stages during perceiving a stimulus) prolongs, whereas the duration of all cognitive stages that have to do with the decision-making itself stays the same compared to the cognitive stages gathered by the research of Berberyan and colleagues.
The use of transparent stimuli as the method to manipulate perception was chosen because of the results of a pilot study done under supervision of Berberyan (Kamsteeg, 2020). This pilot study was conducted by Kamsteeg using 4 participants and without using EEG data. She suggested that transparent stimuli could possibly cause a prolongation in the perceptual stage duration based on higher response times gathered from transparent stimuli compared to the response times gathered from the basic stimuli and based on the Shifted-Wald models she used as evidence accumulation models (Heathcote, 2004; Matzke and Wagenmakers, 2009). With our research, we aimed to support this finding by Kamsteeg with gathering EEG data in order to perform HsMM-MVPA analysis when using transparent stimuli. We assume that if the perception is manipulated by the use of transparent stimuli, the results of the HsMM-MVPA analysis will show this difference in the duration of the perceptual processing state.

2 Methodology

2.1 Participants

In total 30 participants performed our simple visual discrimination task. Out of these 30 participants, 6 participants had large artifacts in the EEG data. This means that something happened during the recording which caused too much noise to the data. This can be caused by a computer which crashed or because the participant moved too much during the recording, which both happened during multiple experiments.
The participants were all recruited using an advertisement on Facebook. All the participants were right handed and they had normal or corrected-to-normal vision. They all took the EnChroma Color Blindness Test in order to test whether they had normal color vision. The age of the participants ranged from 19 to 29 years old. The mean age of the participants was 22.95 years old.
The participants signed an informed consent form and were paid 8 euros compensation for their participation in this experiment.

2.2 Task Design

The task which the participants had to perform was a simple visual discrimination task. In this task the participants were asked to discriminate between either shapes, colors or characters. The task was divided into 3 blocks. These blocks were presented in a random order.
In the first block the participants had to make a discrimination between different geometrical shapes, which consisted of circles, squares, triangles and rhombuses, while paying no attention to their color. The geometrical shapes were presented in an equal distribution to the participants. This means that the participants for example encountered just as many circles as triangles in a single block.

In the second block the participants had to discriminate between colors of objects. Analogous to the previous block, the participants were asked to ignore their geometric shape. The colors were presented in an equal distribution to the participants. In the final block the participants were shown a string of 4 letters or numbers and were asked to differentiate between the two. The letters and numbers were also presented in an equal distribution to the participants, meaning participants would encounter as many number combinations as letter combinations.

2.3 Stimuli

Whereas in previous research basic stimuli (see Figure 2.1) were used, the stimuli that were used during this study were all transparent versions of these basic stimuli (Kamsteeg, 2020). The transparent stimuli have a transparency of 75% compared to the basic stimuli and the black borders are missing.
The colors of the shape stimuli varied. The options were either red, green, yellow or blue. The characters were set to grey. The geometrical shapes included circles, squares, triangles and rhombuses. The geometrical shapes and colors were used in both block 1 and 2. In each block two shapes and two colors were used. For block 1, two of four shapes and colors were randomly chosen. For the next block, the remaining two shapes and colors were used. The character and number combinations used in block 3 were completely randomized.

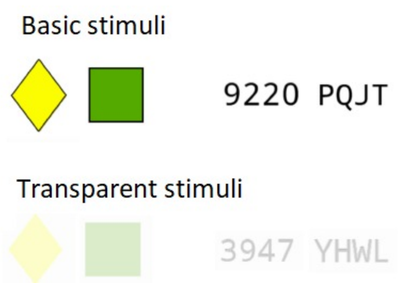

Figure 2.1: Stimuli comparison, figures from Kamsteeg (2020)

2.4 Experimental procedure

The participants were tested in a quiet room in front of a computer. They were asked to press a key (either 'n' or 'm' depending on the stimuli) on the keyboard using their right hand. Each block started with an instruction slide, which specified the task for that particular block. After each block the participants had the chance to take a break.
The experiment consisted of, including practice, 420 trials. Per block each participant had 20 practice trials in order to get familiar with the task. This means that each participant performed a total of 360 trials. Each of these trials started with a fixation dot. This dot was visible for a random time, between 1500 and 2250 milliseconds, after which the trial started.
The participants had a timeout of 3000 ms to perform each trial. If this time has passed and the participants did not manage to press 'n' or 'm' then a screen appeared that stated 'Too late!'. If they pressed one of these keys before the time is up, a screen would appear which would either state 'Correct' or 'Incorrect', depending on the answer.
In total, the experiment took approximately one hour, including EEG setup.

2.5 Behavioral data analysis

The relevant data from the behavioral data are error rates and reaction times. When analyzing reaction times, we removed the trials that deviated more than two standard deviations from the mean reaction time. Trials where incorrect answers were given were removed too.
The amount of errors indicate whether the difficulty of the task is manipulated. The reaction time is required to compare with previous studies. A comparison can be the first clue whether the cognitive processes are manipulated in terms of duration. A t-test was performed on both reaction time and the error rates in order to compare them across conditions.

2.6 Recording and preprocessing of EEG data

The participants were seated in front of the screen. Six electrodes were placed on the face. Two vertically aligned above and under the left eye. Two horizontally aligned, one electrode on each temple. And one electrode placed behind each ear. Four out of six electrodes function to measure any muscle movements and eye blinks. The two electrodes behind the ears, mastoid electrodes, function as reference. Afterwards a cap with 32 electrode slots was placed on top of the head. The electrodes used are active Ag-AgCI electrodes (Biosemi Active Two system) digitized with a sampling rate of 512 Hz. The international 10-20 system layout was used to place the electrodes. Next to 32 electrodes a Common Mode Sense (CMS) and Drive Right Leg (DRL) were attached to the cap.
The collected EEG data were passed through a high-pass filter of 1 Hz and a low-pass filter of 40 Hz and finally down-sampled to 256 Hz. Afterwards manual rejection of artifacts was applied to the data. This process required the researchers to manually go through the data and to delete any noise. On average 1.2 % of the original EEG data is deleted during manual artifact rejection.
For three participants, channels were removed.
After manual rejection of data, the data was filtered from eye blinks and muscle contractions detectable in the measured EEG signal. This was done by using a technique called independent component analysis (ICA). On average one to two components were removed per data set.

2.7 HsMM-MVPA

2.7.1 Preprocessing for HsMM-MVPA

To perform HsMM-MVPA analysis further preprocessing was necessary. First, we down-sampled our data to 100 Hz. Then, the data was epoched trial-by-trial from the moment the stimuli was presented until the consecutive response. After that, the data was separated into two conditions, derived from the initial three conditions. In this way, the first condition included all trials of the shape-discrimination task and the color-discrimination task and the second condition included all trials of the character-discrimination task. The merging of the colors and shapes conditions was done because these two tasks are too similar to treat separately. Moreover, both conditions differ with the characters-discrimination condition, we were interested in this difference and this was also a reason to merge the colors and shapes conditions to one condition.
After this, the outliers were excluded based on the response times. Then the data was baselined from 400ms prior to the stimuli until the moment of appearance of the stimuli. Based on the baselined data, only complete trials were kept for analysis and incomplete trials (due to artifact rejection) were removed. This is done to prevent including incomplete trials where the first cognitive stage(s) of the decision process might be missing. Then, by means of a covariance matrix computed for each trial and subject separately, principal component analysis (PCA) was performed on the data. The first 10 PC components were retained. Finally, z-scores were calculated in order to normalize the data.

2.7.2 HsMM-MVPA analysis

The purpose of applying the HsMM-MVPA analysis is to discover the cognitive stages which can be generalized across all trials of all participants. The HsMM-MVPA analysis aims to find cognitive stages that are hidden in the EEG-signal. These cognitive stages can be identified by bumps and flats. Each bump is followed by a flat, and a combination of a bump and a flat is called a cognitive stage. During the HsMM-MVPA analysis, cognitive stages are tried to be found within each epoch extracted from the EEG data. This is done by looking at the principal components extracted from the EEG signal. This repeated signal consists of n bumps, which results in $n+1$ flats, because the first stage always starts with a flat.
Cognitive stages are obtained from the PC components by searching for the best model to fit the data. The goal of model fitting is to find the model with the optimal number of bumps and thus the optimal number of stages. This will be done by means of the following few steps. First, the best magnitude parameters are obtained for each of the two conditions separately. Then, these parameters are used for performing a leave-one-out cross validation (LOOCV) procedure for both conditions. This procedure is performed to prevent overfitting. The

HsMM-MVPA model on all subjects but one is estimated, and after that the fit of this model is tested on the left-out subject. In this way, training and testing of each model is separated. Multiple models are fitted, ranging from a model with one bump to a model with the maximum number of bumps possible.
Because of the difference in duration across trials, the onset of bumps can occur at different time points at each trial. To account for this, the data is analyzed at the single-trial level while all participants and all trials are taken into account simultaneously. The topology of the bumps is constant for each trial because the method assumes that each trial consists of the same cognitive processes. However, the variability in duration of the cognitive processes is accounted for by making the duration of the flats variable. This makes it so that the width and amplitude of each bump is the same for each trial, yet the stage durations are kept variable by implementing the variability of the duration of the flats between the bumps across the trials. In this way, the maximum number of bumps depends on the duration of the trials. In this case, the maximum was five bumps. Therefore, the fitted models ranged from a model with one bump to a model with five bumps.

For each of these models, the mean log-likelihood was determined among all participants by the LOOCV procedure. For each model with an additional bump, we calculated the number of participants for whom this model fitted significantly better as determined by performing a sign test. Finally, the model with the highest mean log-likelihood was chosen as the model with the optimal number of bumps and stages. This model was used as a final HsMM-MVPA model.

3 Results

In this section, the results gathered from our data will be shown. We gathered two types of data; behavioral data and EEG data. Notice that for the purpose of clarity, from now on, "condition 1" will refer to the condition for which the participants had to distinguish between different shapes or colors. Subsequently, "condition 2" will refer to the condition for which the participants had to distinguish between different characters.

3.1 Behavioral data results

For the results of the behavioral data, the first points of interest are whether there is a difference in reaction time and error rate between the two conditions. Looking at the reaction times in Figure 3.1, it can be seen that the mean reaction time of condition 2 is higher compared to the mean reaction time of condition 1. *Welch Two Sample t-test* was applied to test the difference in mean reaction times between the two conditions. A $p < 0.05$ was obtained (See Table 3.1), thus it can be said that there is a significant difference in reaction times between the two conditions.

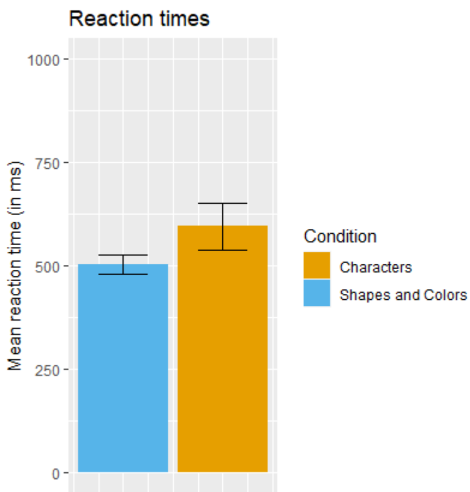

Figure 3.1: Reaction times of 2 conditions

Looking at the mean error rate in Figure 3.2, it can be seen that the mean error rate of condition 2 is higher than the mean error rate of condition 1. Similar to testing the difference in mean reaction times, *Welch Two Sample t-test* was applied to test the difference in mean error rates between the two conditions. A $p > 0.05$ was obtained (See Table 3.1), thus it can be said that there is no significant difference in mean error rates between the two conditions.

	Welch Two Sample t-test				
	Estimate condition 1	*Estimate condition 2*	*t value*	*df*	*p-value*
Mean reaction time	504.6783	595.7232	2.9823	31.525	0.005479
Mean error rate	0.01562500	0.02470238	1.6685	36.828	0.1037

Table 3.1: Results of Welch Two Sample t-test

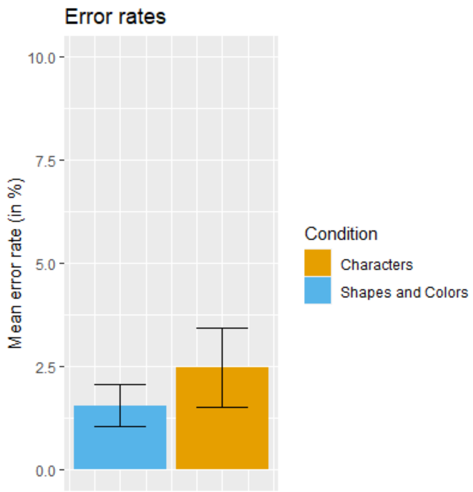

Figure 3.2: Mean error rate of 2 conditions

Now that the difference in reaction times and error rates between the two conditions are determined, the next step is to compare our behavioral results with the behavioral results of Berberyan et al. (2021). Looking at Figure 3.3, the mean reaction time of the results of Berberyan and colleagues can be seen on the left plot and our reaction times can be seen on the right plot. It can be seen that there are a number of similarities between the two plots. For both datasets, the mean reaction times for condition 2 is higher compared to condition 1. It can also be seen that the mean reaction time of condition 1 is around 500 milliseconds for both datasets. Also, the mean reaction time for condition 2 is around 600 milliseconds. It can be seen in the figure that the reaction times of Berberyan and colleagues is even a bit higher compared to our reaction times. This suggests that there is no significant difference between the two datasets. This claim is supported by the results of the Welch Two-Sample t-test performed on the difference in mean reaction times, for $p > 0,05$ (see Table 3.2).

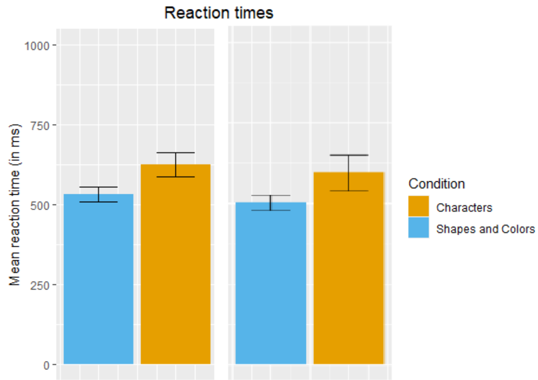

Figure 3.3: Comparison of reaction times, data by Berberyan et al. (2021) on the left versus our data on the right.

When comparing our error rates with the error rates gathered by Berberyan and colleagues (Figure 3.4), it can be seen that the error rate of condition 1 are similar. It can also be seen that the error rate of condition 2 is higher for our data compared to the data of Berberyan and colleagues. However, there is no significant difference in error rates, as indicated by $p > 0.05$ in Table 3.2.

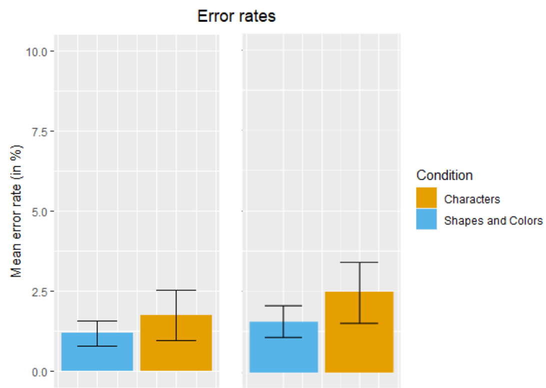

Figure 3.4: Comparison of error rates, data by Berberyan et al. (2021) on the left versus our data on the right.

	Welch Two Sample t-test				
	Estimate condition 1	*Estimate condition 2*	*t value*	*df*	*p-value*
Mean reaction time	533.4673	533.1585	1.8752	138.54	0.06287
Mean error rate	0.01851107	0.01400377	-1.4936	132.03	0.1377

Table 3.2: Results of Welch Two Sample t-test when comparing our behavioral data to the behavioral data of Berberyan et al. (2021).

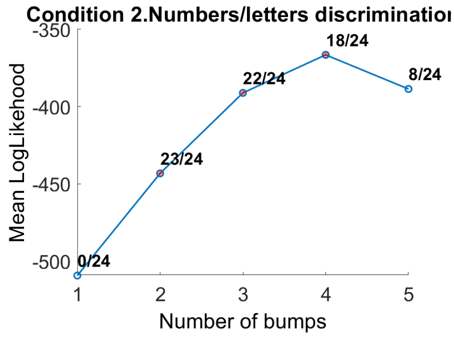

Figure 3.6: Log likelihoods for all number of bumps for condition 2, significance of number of participants is indicated with the red star inside of the points

3.2 HsMM-MVPA results

To gain more insight in the different processing stages during each trial, the HsMM-MVPA analysis was performed separately for the two conditions to find the optimal number of stages in order to fit the model. Looking at Figure 3.5 and Figure 3.6, it can be seen that for both conditions, the mean log likelihood (acquired as explained in section **2.7.2**) is the highest for a model with four bumps. Also, looking at the number of participants for whom adding the fourth bump is significantly better when performing a sign test, it can be seen that this is the case for 21 out of 24 participants for condition 1 and for 18 out of 24 participants for condition 2. Therefore, a model with four bumps fits best to the data for both conditions. This implies that there will be five stages in the optimal model.

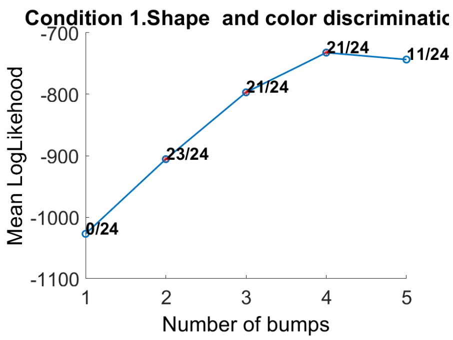

Figure 3.5: Log likelihoods for all number of bumps for condition 1, significance of number of participants is indicated with the red star inside of the points

Now that the optimal amount of bumps and stages is found, we want to find out whether there is a difference in the bump topologies and stage durations between the two conditions. To test this, three different HsMM-MVPA models were constructed which investigated whether there are shared bumps and stage durations between the two conditions. The first model fit is a combined model in which it is hypothesized that the bumps and stage durations are the same for the two conditions (*Combined model* in Table 3.3). For the second model it was hypothesized that only the second bump and the duration of the third stage would vary between the two conditions (*Bump2Stage3Vary* in Table 3.3). The third model hypothesized that all bumps and stage durations would vary between the two conditions, all bumps and stage durations were separated for this model fit (*Sum of separate models* in Table 3.3). The model fitting was done with a forward stepsize fiting routine. This was done to prevent random effects potentially leading to statistical errors. The model fits were compared for each participant, in Table 3.3 the number of participants for whom the row-model fits better than the column model is indicated in the cells. A model was preferred if the fit improved compared to a simpler model for a significant number of participants, the cells for which this is the case are indicated with a grey background in Table 3.3. The best estimated model is indicated with an asteriks (*).

	Combined model	Bump2Stage3Vary	Sum of separate models
Combined model	0	5	4
Bump2Stage3Vary*	20	0	10
Sum of separate models	19	14	0

Table 3.3: Results of model comparison for the estimated HsMM-MVPA models

It can be seen in the table that *Bump2Stage3Vary* and *Sum of separate models* are improved fits compared to the combined model for a significant number of participants. Therefore, all three appointed models fit better than the combined model. As stated before, a model was preferred if the fit improved compared to a simpler model. However, looking at the complexity of the two models, it can be said that the *Bump2Stage3Vary* model is a simpler model compared to *Sum of separate models*, for *Sum of separate models* requires more parameters because it assumes all bumps and stage durations vary between the two conditions instead of the one bump and one stage duration which *Bump2Stage3Vary* assumes. Looking at Table 3.3, *Sum of separate models* does not improve the fit compared to the *Bump2Stage3Vary* model for a significant number of participants. Therefore, it can be said that *Bump2Stage3Vary* is the preferred model to fit the data.
Looking at the scalp topologies of the four bumps for the two conditions (Figure 3.7), it can be seen that the topologies of bump one, two and four are shared between the two conditions. However, looking at the scalp topology of the second bump, it can be seen that there is a difference here between the two conditions. The activation of the second bump seems higher for the characters condition compared to the shapes and colors condition.

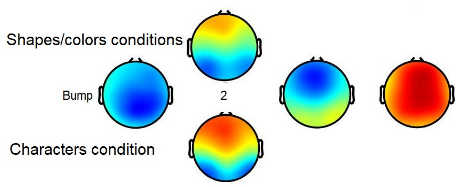

Figure 3.7: Scalp topologies for the two conditions from the Bump2Stage3Vary model, where the first, third and fourth bump are shared and the second bump differs.

Looking at our stage durations (top of Figure 3.8), it can be seen that the stage durations of stage one, four and five are the same for the two conditions. It can also be seen that the duration of stage two slightly differs between the two conditions and that the duration of stage three differs over 100 ms in duration between the two conditions.

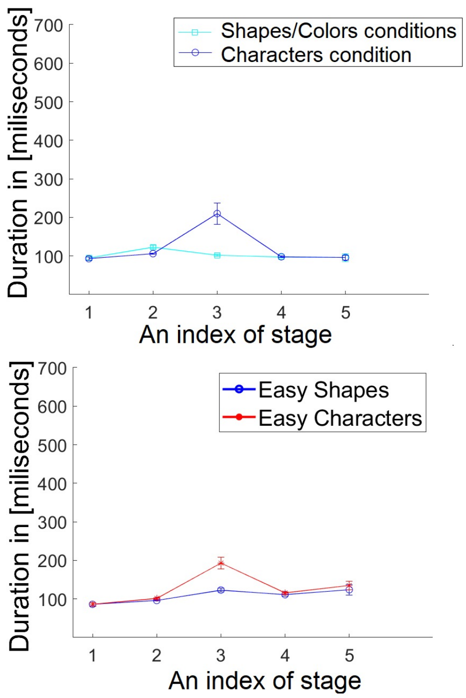

Figure 3.8: Stage durations of the five stages. Top figure shows the results of our data. Bottom figure shows the results of data gathered by Berberyan et al. (2021).

Finally, these stage durations have to be compared with the stage durations of Berberyan and colleagues, because we are interested in whether there is a difference in stage durations which might have been caused by using transparent stimuli. Comparing the stage durations of Berberyan and colleagues with the stage durations of our data (Figure 3.8), it can be seen that the difference in the third stage duration is also present for the results of Berberyan et al. (2021). The duration of the third stage for the characters condition is the only stage with a duration above 200 ms for both data sets. The durations of stage 1, 2, 4 and 5 seem to be similar between the two conditions for both data sets.

4 Discussion

The goal of the current paper was to investigate the possibility of using transparent stimuli as a method to manipulate perception. That is, we wanted to investigate whether presenting transparent stimuli instead of basic stimuli would prolong the perceptual processing state. This is done by gathering both behavioral data and EEG data, and by comparing the results with the results gathered from the simple stimuli used by Berberyan et al. (2021). First, we compared the behavioral data, it can be said that the difference in response times and error rates was not significant, this does not support the idea that perception is manipulated when using transparent stimuli. Second, we used HsMM-MVPA to process and analyze the EEG data. The HsMM-MVPA results were compared with those of Berberyan and colleagues. There was no significant difference found in bump topologies or stage durations between the HsMM-MVPA results. A suggestion for explaining the lack of a difference in results might be that the stimuli were not transparent enough, which would explain why the stimuli were perceived in a similar way as non-transparent stimuli were perceived. Future research could investigate whether using more transparent stimuli would result in a difference in the duration of the perceptual processing stage.

The idea of using transparent stimuli was derived from a pilot study done by Kamsteeg (2020), she found a difference in her behavioral data results when using transparent stimuli compared to using basic stimuli. The fact that she did find a difference in behavioral data and we did not could be explained by the fact that she only gathered 4 participants, which could have caused the results to be unreliable.

Both Kamsteeg and Berberyan and colleagues used drift diffusion models in order to accumulate evidence for their findings about stage durations. The kind of drift diffusion model they used was called a Shifted-Wald model (Heathcote, 2004; Matzke and Wagenmakers, 2009). The goal of such a model is to measure both the non-decision and the decision time. Kamsteeg used a Shifted-Wald model to support her finding about the prolongation of the perceptual processing stage. She found that the non-decision time prolonged and the decision time stayed similar when comparing them with the Shifted-Wald models found by Berberyan and colleagues. We did not use any drift diffusion model to support our findings. Since we did not find any prolongation in the perceptual processing stage, it would be interesting to see whether there would also be no difference in non-decision time when fitting a Shifted-Wald model. Future research could use a drift diffusion model in order to accumulate any evidence found by performing HsMM-MVPA on EEG data.

5 Conclusion

The goal of this experiment was investigate whether it is possible to manipulate perception using transparent stimuli. This could have been supported by the fact that our data resulted in higher reaction times compared to the data of Berberyan et al. (2021). After that, we had to check which stage duration prolonged when using transparent stimuli compared to basic stimuli by means of HsMM-MVPA. If the perceptual processing stage would have prolonged when using transparent stimuli, then we would conclude that it is possible to manipulate the perceptual processing stage using transparent stimuli. This would then also confirm the possible evidence of manipulating perception using transparent stimuli by Kamsteeg (2020). However, this was not the case, as our results and the results of Berberyan et al. (2021) were too similar. This similarity can be found for both the behavioral results and the HsMM-MVPA results. Therefore, it can be said that there is no evidence found for manipulating the duration of the perceptual processing stage when using transparent stimuli. However, it can be said that because of the similarities of our results and the results gathered by Berberyan and colleagues, the validity of using HsMM-MVPA as a method of deriving cognitive stages out of EEG data is supported by our findings.

References

J. R. Anderson, Q. Zhang, J.P. Borst, and M. M. Whalsh. The discovery of processing stages: Extension of sternberg's method. *Psychological review*, 2016. [1]

H. Berberyan, L. van Maanen, H. van Rijn, and

J. P. Borst. Eeg-based identification of evidence accumulation stages in decision making. *Journal of Cognitive Neuroscience*, 2021. [1, 2, 6, 8, 9]

F. C. Donders. Over de snelheid van psychische processen. 1868. [1]

A. Heathcote. Fitting wald and ex-wald distributions to response time data: An example using functions for the s-plus package. *Behaviour Research Methods, Instruments and Computers*, 2004. [2, 9]

I. Kamsteeg. Manipulating perceptual stage durations in a simple visual discrimination task. 2020. [2, 3, 9]

Dora Matzke and Eric-Jan Wagenmakers. Psychological interpretation of the ex-gaussian and shifted wald parameters: A diffusion model analysis. *Psychonomic bulletin review*, 16:798–817, 10 2009. doi: 10.3758/PBR.16.5.798. [2, 9]