Is it possible to manipulate perceptual processing stages? HsMM-MVPA method for EEG

Bachelor's Project Thesis

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Abstract: Several different scientific branches formed the scientific study of the mind, cognitive science. Since the beginning in the 1950s, cognitive processing stages were a key idea. This study conducted a visual discrimination task in an attempt to manipulate perceptual processing stages. Evidence for this manipulation can be found in the difference in stage durations between two visual discrimination tasks. This was done by comparing the results from a visual discrimination task done in a prior research(Berberyan, van Maanen, van Rijn, and Borst, 2021) to the results of our research. The difference between the studies is the transparency of the stimuli. This study uses more transparent stimuli.
During the task, two forms of data were gathered. Behavioral data in the form of reaction time and error rates were obtained. Furthermore participants' brain activity was measured by using an electroencephalogram(EEG). An HsMM-MVPA method was conducted, in order to discover cognitive stages hidden within the EEG data.
The results of both the behavioral data and the EEG analysis suggest that our research is a replication of the easy stimuli from the study done by Berberyan and colleagues. Thus this study was not able to manipulate perceptual processing stages using transparent stimuli. This does not mean perceptual processing stages can not be manipulated. Future research could experiment with different stimuli or more transparent stimuli.

1 Introduction

The main idea behind this research is that processes in the brain are separated in stages. Donders (1868) designed research in order to 'time the mind' in the early 1860s. Donders attempted to find evidence that processes going on in the mind can be separated in stages. The research Donders conducted is based on reaction times. Several different tasks were performed. Donders hypothesised that the difference between for example a response time task and a discrimination task is the discrimination stage. So by subtracting the time it took to perform the visual response task from the time it took to perform the visual discrimination task, he was able to tell the duration of the discrimination stage. Donders used this subtraction technique to calculate the duration of processing stages.
About 90 years later, in the 1950s the cognitive revolution started, multiple disciplines within science formed the study of the mind, cognitive science. One of the great interests of this branch of science is the discovery of multiple processing stages, which the brain goes through while making a decision. At the start of cognitive science processing stages were still measured using RT-based methods (Sternberg, 1969). Nowadays brain activity is being measured by the use of several methods.
Our research used a method called the electroencephalogram(EEG). A big advantage of an EEG, over other measuring methods, is that the temporal resolution of EEG is excellent. This is the amount of time needed between two data acquisitions. Whereas, for example fMRI (Anderson and Fincham, 2014) has a longer temporal resolution. This makes it hard to consistently time processing stages.
A technique called hidden semi-Markov model multivariate pattern analysis(HsMM-MVPA)(Anderson, Zhang, Borst, and Walsh, 2016) was applied to the recorded EEG data, in order to deduce cognitive stages. Previous research (Borst and Anderson, 2015) showed that cognitive stages could be deduced from EEG-data.

The HsMM-MVPA method is a method for detecting processing stages in a range of cognitive tasks. It relies on the assumption that the start of processing stages is accompanied by a negative or positive peak across different brain regions. The stages in a cognitive task consists of bumps and flats. This is the activity between bumps, and it varies in duration.
Another prior research(Berberyan et al., 2021) demonstrated the validity of the HsMM-MVPA analysis to infer cognitive stages. The results from this research can be used to verify whether the HsMM-MVPA method is reliable by comparing them with this previous work.
During this research two simple visual discrimination tasks were conducted while measuring brain activity using an EEG. The participants had to discriminate between shapes, colors and characters. Both experiments were setup with the same varying visual stimuli, however task difficulty differed between experiments in order to vary decision difficulty. The tasks were designed in such a way that the processing stages during the solving of the task were relatively straight forward. The research concluded that a longer decision stage, in terms of reaction time, was found using the HsMM-MVPA method.(Berberyan et al., 2021). A more challenging task would imply a longer decision stage. Hence the results from the HsMM-MVPA method support the idea of processing stages.
A follow-up research(Kamsteeg, 2020) attempted to manipulate perception by utilizing the same aforementioned simple visual discrimination task. The stimuli were made transparent such that the difficulty of the task did not change, but the way the stimuli were perceived was altered. The idea here is that if reaction times increased compared to the basic stimuli in the original research then this could indicate an increase of duration in the cognitive stage related to perception. The difficulty of the task is not altered here, hence only the simple stimuli of the original research are used. Kamsteeg came up with four alternatives to the basic stimuli; smaller stimuli, stimuli with a dark background, transparent stimuli and stimuli with noise. Out of these stimuli, transparent stimuli seemed to show the biggest increase in reaction time. Therefore, transparent stimuli were used for this research.
The goal of this research is to manipulate perception during a simple visual discrimination task. Similar to those of the experiments in the study by Berberyan and colleagues and the study by Kamsteeg. The latter study is a pilot to this study. Before this research, all stimuli were tested on small sample sizes. Kamsteeg's research aimed to manipulate the duration of reaction time only by manipulating the perception of stimuli, not by the difficulty of the task. This study will try to conduct a visual discrimination task based on the stimulus with the highest effect from Kamsteeg's research.

2 Method

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 dis-

crimination 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.

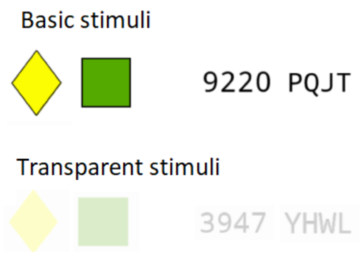

Figure 2.1: Stimuli comparison, figures from Kamsteeg study

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 com-

parison 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.

3 Results

3.1 Behavioral results

For the analysis of the behavioral data we inspected the mean reaction times and error rates of the participants for both the color and shapes conditions as well as the characters condition and compared the reaction times with corresponding data from previous research(Berberyan et al., 2021).

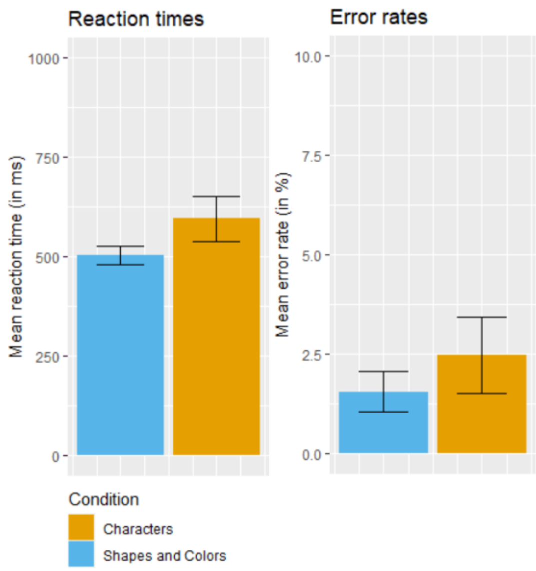

Figure 3.1: Reaction time and error rate comparison between conditions with between-subject standard errors

Table 3.1: results of t-test performed on mean reaction time and mean error rate between conditions

t-test	RT	Error Rate
p-value	0.0055	0.10
t-value	2.98	1.67
df	31.53	36.82
mean shapes/colors	504.68	1.56%
mean character	595.72	2.47%

Figure 3.1 shows the mean reaction times of the participants during the study. This reaction time is the mean time it took for the participants to respond to the stimuli. In the characters condition, longer response times were observed. The vertical axis of Figure 3.1 shows that the mean reaction time among the participants responding to shapes and colors was half a second, whereas to the characters condition people tend to respond slower, approximately 100 milliseconds slower, see Table 3.1. A Welch two sample t-test was applied to this data. The results in Table 3.1 show a t-value bigger than 2 and a p-value below the 0.05 threshold. Therefore the null hypothesis can be rejected. Which means that the mean difference is significant.

Next to the comparison of the mean reaction time, Figure 3.1 shows the comparison of the mean error rate of the participants regarding both conditions. The mean error rate represents the number of mistakes the participants made during the trial, represented in percentages. One can observe that the mean error rates are lower than 3% for the characters condition and below 2% for the shapes and colors conditions. See Table 3.1 for the exact means. Therefore we can say that the participants were paying attention to the task.
Same as for the previous comparison, a Welch two sample t-test was applied to this data. The results in Table 3.1 show a positive t-value lower than 2. On top of that the p-value exceeds the 0.05 threshold. Therefore the null hypothesis can not be rejected. which means that the mean difference is not significant. This study found significant evidence that participants respond slower to character stimuli than shapes and color stimuli.

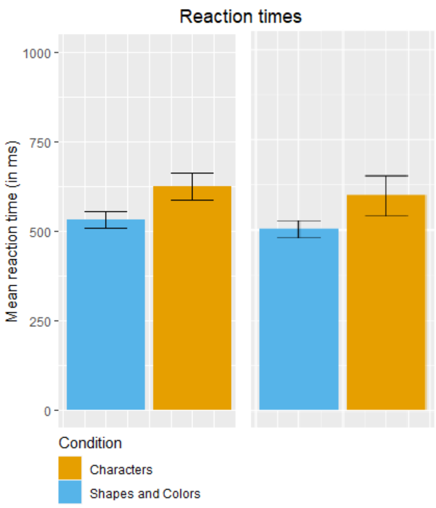

Figure 3.2: Comparison reaction times between Berberyan and colleagues on the left and this study on the right

The comparison between the mean reaction times from the study done by Berberyan and colleagues and the mean reaction times from Figure 3.1 is visible in Figure 3.2. Here one can see that the data looks very similar. The difference between the experiments is the stimuli that is used. The reaction time of the shapes and colors conditions from this experiment are almost the same as the reaction times of the easy shapes from prior research. The same can be implied about the characters condition from this study versus the easy characters condition from prior research.

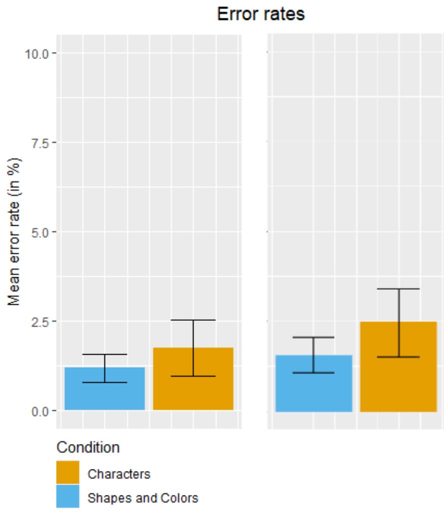

Figure 3.3: Comparison error rates between Berberyan and colleagues on the left and this study on the right

The comparison between the mean error rates from the study done by Berberyan and colleagues and the mean error rates from Figure 3.1 is visible in Figure 3.3. Here one can see that the data looks similar. The error rates from this experiment are higher with larger error bars than the one from prior research.

To see whether there is a significant difference between our data and that of Berberyan and colleagues, a Welch two sample t-test was applied to RT and ER for both conditions combined. The results in Table 3.2 show a t-value smaller than 2 and a p-value above the 0.05 threshold for both RT and ER. Therefore the null hypothesis, that states that the mean difference is equal to zero. can not be rejected for either of the data sets.

Table 3.2: results of t-test performed on mean reaction time and mean error rate between results from this research and the results from Berberyan and colleagues

t-test	RT	Error Rate
p-value	0.062	0.14
t-value	1.88	-1.49
df	138.54	132.03
mean prior study	565.57	1.4%
mean current study	533.16	1.9%

3.2 HsMM-MVPA results

The goal of the HsMM analysis is to discover processing stages from the signal. In this case an EEG signal. From this signal a repeated sequence of cognitive stages can be inferred using the HsMM-MVPA method. This sequence is present throughout the trials and is similar for all participants. The model that is to be determined is used to fit the data in order to compute the closest possible approximation of this repeated signal.

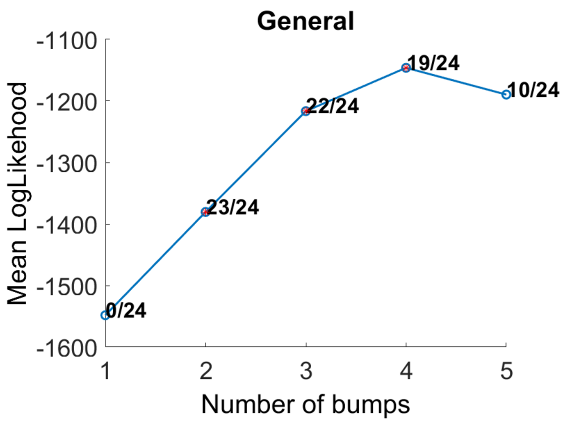

Figure 3.4: Model selection

Figure 3.4 shows how well the number of bumps fit the data. One can see that the number of bumps can be read from the horizontal axis and the mean log-likelihood can be read from the vertical axis. The blue line represent the increase, and later decrease, in how well the number of bumps fit the data. The numbers along the line represent the number of participants that benefited from the extra bump compared to one bump less. A sign test was used to determine whether the increase in mean log-likelihood is significant. This is depicted with a red marker along the blue line. Therefore we can say that a total of 19 out of 24 data sets fit better for a model with four bumps than a model with three bumps. Hence we concluded that the model requires four bumps and five processing stages.

	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: Model selection

Three models were compared in an attempt to fit the data, using four bumps and five stages. The first model, called the Combined model, is a model that assumes there is no difference in scalp topologies and stage durations between the two conditions. The second model, called the 'Bump2Stage3Vary' model, is designed such that the topology of bump two and the duration of stage three differ between the shapes and colors conditions and the characters condition. This was done due to prior knowledge from previous research. (Berberyan et al., 2021) The final models called 'Sum of separate models' assumed that all stage durations and bump topologies could vary.
In order to understand Table 3.3, we have to compare the rows to the columns, and the numbers in the table indicate the number of participants for whom the row-model fits better than the column-model. Table 3.3 shows how well each model fits the data compared with the other two models. The gray cells depict whether the difference between models is significant, based on sign tests. One can see that both 'Bump2Stage3vary' and 'Sum of separate models' show that a significant amount of the data sets fit better in these models compared with the 'Combined' model. The 'Bump2Stage3vary' model outperformed the 'Combined' model and is not significantly outperformed by the 'Sum of separate models' models. On top of that the 'Bump2Stage3vary' model requires less parameters than the 'Sum of separate models' models. Hence, the research chose to proceed with the 'Bump2Stage3vary' model.

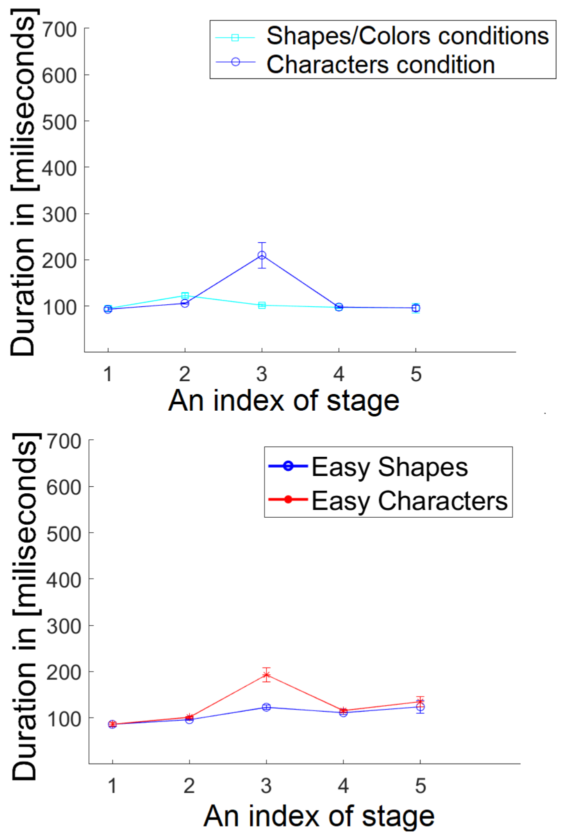

Figure 3.5: Average stage durations with standard errors per condition from the HsMM-MVPA models. On the top the results from this research and on the bottom the results from Berberyan and colleagues

Figure 3.5 shows that the stage duration for both conditions only differs in stage three for both studies. We can observe that the data from this study looks similar to the average stage durations of the easy shapes and easy character conditions in the Berberyan et al. (2021) study. Both studies use the same model.

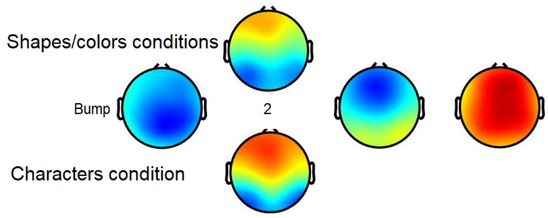

Figure 3.6: The representations of the scalp topologies resulting from the HsMM-MVPA stages plotted per condition.

Figure 3.6 shows the topologies during the trial with four bumps and five stages based on the 'Bump2Stage3vary' model. Only the second bump differs between conditions.

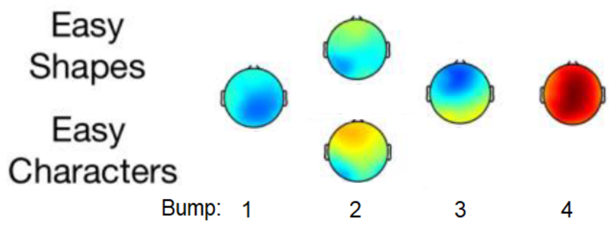

Figure 3.7: The representations of the scalp topologies resulting from the HsMM-MVPA stages plotted per condition from Berberyan and colleagues.

The first, third and fourth bump look similar in both the current study and the previous study, as one can observe in Figure 3.6 and Figure 3.7. For both models, the second bump differs between conditions. This is expected since both studies accepted the 'Bump2Stage3vary' model as the best fit.

4 Discussion

In order to manipulate perceptual processing stages, this study used transparent stimuli. The idea was to perform the same visual discrimination task as in prior research by Berberyan et al. (2021). Then compare the behavioral data and cognitive stage durations with the results from this prior research. If the results from the data significantly differed there would be evidence that altering the transparency of stimuli would manipulate

perception. Additionally this research is used to further test the HsMM-MVPA method's ability to infer cognitive stages from EEG data.
First thirty participants had to conduct the visual discrimination task. Their brain activity was measured using an electroencephalogram(EEG). With as goal to deduce a cognitive model inferred from the EEG signal using a method called hidden semi Markov model multivariate pattern analysis(HsMM-MVPA)(Anderson et al., 2016). This cognitive model then provides information about stage durations. These results together with behavioral data in the form of reaction times and error rates is used to compare to prior research that did a similar experiment.
The comparison of reaction times and error rates between conditions proved to be a replication of the study done by Berberyan and colleagues. Participants responded slower to character conditions than the shapes and colors conditions.
In order to analyze the EEG signal the data was first preprocessed such that the HsMM-MVPA method could be applied to the EEG signal.
The analysis concluded that the results from the HsMM-MVPA were a replication of prior research done by Berberyan and colleagues, which means that there is no evidence to suggest that transparency manipulated perceptual processing stages. Because the outcome is similar while the used stimuli differ. Failing to prove that transparent stimuli do not manipulate perception, does not mean that perceptual processing stages can not be manipulated.
Our study, in contrast to previously mentioned prior research, did not apply any evidence accumulated models (e.g. in the form of Shifted Wald models(Anders, Alario, Van Maanen, and et al., 2016)) to our behavioral data. The 'Bump2Stage3Vary' model, mentioned in the results, can be supported by the log-likelihoods shown in Table 3.3. Comparing the stage durations obtained through the HsMM-MVPA method with the data that Berberyan and colleagues gathered (see Figure 3.5), one can observe that the stage durations are similar. No statistical tests were conducted on the two datasets, so nothing conclusive can be said.
When observing the difference between the topologies resulting from the HsMM-MVPA method in Figure 3.6 and Figure 3.7, bumps one, three and four seem very similar. the second bump differs for both studies between conditions, but also do not show as much resemblance between studies as the other three bumps. Replicating a similar topology and stage duration as prior research, with a different population, suggests it is possible to infer meaningful cognitive stages from EEG data, using the HsMM-MVPA method.
Research conducted by Kamsteeg (Kamsteeg, 2020) suggested other variations of stimuli, adding a dark background, adding noise to the stimuli or making the stimuli smaller. Although these versions did not show significant differences. We should note that the data was gathered with a small sample size. Possible reasons that the transparent stimuli did not manipulate perceptual processing stages, could be that the stimuli were not transparent enough. Maybe transparency simply does not change the perceptual difficulty, because the shape of the stimulus is still as much visible as the basic stimulus from Figure 2.1. It is only less colored. The difference between the colors that were used during this experiment is clear. Taking colors such as purple and blue could increase perceptual difficulty, this could also increase task difficulty. However, changing the colors would require another research with non transparent stimuli. Such that a comparison study can be conducted.
Research(Churan and Iig, 2002) concluded that a flickering background impairs both humans and monkeys during stimulant movement discrimination. A flickering background was used to influence the perception of a moving object. A flickering background is not the same as a flickering stimulus. Also the stimulus used in the current study is not moving. The research done by Churan and Iig used neuronal responses to test whether the subjects were impaired by the stimulus. Whereas this study is looking for processing stages. However, the main idea of manipulating how the observer perceives a visual stimulus while discriminating between two options remains intact. Hence I would like to suggest that future research performs trials with flickering stimuli or a flickering background. Future research could look into basic stimuli(see 2.1) that are perceived as flickering. Meaning the stimulus would quickly, in a steady rhythm, flash on and off on the screen. Giving the participant the same amount of time to perceive the stimulus. The

problem is this could alter the difficulty of the task. A flickering background has been proven(Churan and Iig, 2002) to be able to manipulate the perception of a moving object, impairing observers to discriminate in which direction the object went. In the work done by Kamsteeg, one of the tested stimuli was a dark background. Transparent stimuli seemed more promising, based on behavioral data, hence this study did not try to implement a dark background. However, as stated before, a small sample size was used in Kamsteeg's research. There is no conclusive evidence that changing the background does not manipulate the perceptual processing stages. A flickering background could be a good alternative to a flickering stimulus.

5 Conclusion

The study attempted to manipulate perceptual processing stages using transparent stimuli. Behavioral data and EEG data had to be gathered in order to find evidence of manipulation. From the behavioral data the conclusion is drawn that the results do not show any evidence that there is a difference between the mean reaction times of this study and the results from prior research. Nor can the gathered EEG data together with the HsMM-MVPA model support the claim that our transparent stimuli altered the perceptual stage durations. A different research done by Kamsteeg (2020) did find promising results, however the sample size proved to be too small. This current study looks like a replication of the research done by Berberyan and colleagues.

Replicating the prior study would suggest that this study failed to manipulate perception with the used stimuli. A reason for this could be that the transparency of the stimuli is not transparent enough. In order to manipulate perceptual processing stages further research could try to use different forms of manipulation, or an even more transparent stimulus for all conditions.

The research was successful in replicating the study done by Berberyan et al. (2021). The HsMM-MVPA model that was used is similar to that of prior research. Discovering processing stages from EEG data using the HsMM-MVPA method seems a reliable method. Because the results are replicable. The HsMM-MVPA method showed to be capable of using the EEG data and inferring meaningful cognitive stages from it.

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