Manipulation of perception: HsMM-MVPA analysis on EEG

Bachelor's Project Thesis

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Abstract: In 1950 the cognitive revolution started, which resulted in a new intellectual movement called cognitive science. One of the great interests of this movement is the discovery of processing stages, which were first discovered by Donders (1869). Nowadays, with advent of neuroimaging, the electrical activity originating from these underlying cognitive processes can be measured by using an electroencephalogram (EEG). We performed a visual discrimination task where we investigated whether the perceptual processing stages are longer for transparent stimuli. Previously, Berberyan, van Maanen, van Rijn, and Borst (2021) showed evidence that the Hidden semi-Markov model multivariate pattern (HsMM-MVPA) analysis can be used to deduce cognitive stages from a visual discrimination task. Our research uses this method directly on EEG data and investigates whether there is a difference in processing stages when compared to the stages resulting from the research done by Berberyan and colleagues (2021). The results showed no significant difference in reaction times as well as in stage durations. From this we concluded that the speed of visual perception is not influenced by transparency of the stimuli. However, we did find further proof that HsMM-MVPA is a valid method for deducing processing stages directly from EEG.

1 Introduction

Processing stages have been at the center of interest, from the beginning of the intellectual movement referred to as cognitive science. Donders started the concept of processing stages (1868). He claimed that people were going through several stages before making a decision. He found these stages by examining the reaction times of his participants. Donders proposed that the time between presenting a stimulus and responding to that stimulus is occupied by a train of successive stages (Sternberg, 1969).
Approximately 100 years later the cognitive revolution started, which sparked a new interest in neuroscience. Nowadays, with advent of technologies, we are able to discover stages directly from electroencephalogram (EEG) data (Anderson, Zhang, Borst, and Whalsh, 2016).
An EEG records electrical activity of the brain. One of the methods which is used to discover stages directly from EEG data is called Hidden semi-Markov model multivariate pattern (HsMM-MVPA) analysis, which was introduced by Anderson and colleagues (Anderson et al., 2016). This method combines Hidden semi-Markov Models and multivariate pattern analysis in order to find the different processing stages. This method identifies where sinusoidal peaks, which they called "bumps", are added to the EEG signal. Anderson and colleagues proposed that these so called bumps mark the start of a new cognitive process.
In a paper published by Berberyan and colleagues (2021) the validity of this method was tested. This was done using a simple visual discrimination task. In this task, the participants were asked to discriminate between either geometric shapes, colors or characters. During the experiment they gathered behavioral data and EEG data, which was then used to perform the HsMM-MVPA analysis. The result of this HsMM-MVPA analysis was compared to the results of a Evidence Accumulation model in order to determine the validity of their HsMM-MVPA analysis. This comparison showed

a high correlation between the results, indicating that HsMM-MVPA analysis is indeed capable of inferring stages.
In this paper, we manipulate perception by performing the same visual discrimination task, using transparent stimuli. The stimuli are made transparent because of the results of Kamsteeg (Kamsteeg, 2020). She conducted a pilot study on 4 participants. From her results she concluded that the transparent stimuli have the biggest potential to lead to longer reaction times and different stage durations. If a HsMM-MVPA analysis on our data results in different stage durations as compared to the results obtained by Berberyan and colleagues (2021), this further proves the validity of the HsMM-MVPA analysis used on EEG in order to deduce processing stages.

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 3.7) 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.

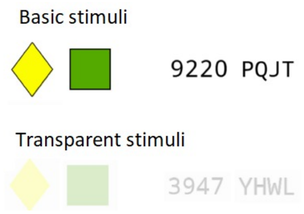

Figure 2.1: Stimuli comparison, figures from Kamsteeg study

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 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 condi-

tion 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

3.1 Behavioral data results

The analysis for this experiment started with the inspection of the reaction times and error rates. Figure 3.1 shows the reaction time of both conditions in milliseconds. Here can be seen that the participants took approximately 100 milliseconds longer for the characters condition compared to the shapes and colors condition. We used a two sided t-test in order to find out whether the difference in reaction time between the two conditions was significant. The results of this test where: t(32) = 2.98 and p = 0.005. The difference in reaction times between the 2 conditions is indeed significant.

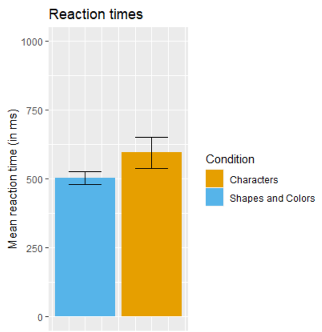

Figure 3.1: Reaction times using 2 conditions

Figure 3.2 illustrates the error rate of the 2 conditions. This figure shows a slightly higher error rate for the characters condition as compared to the the shapes and colors condition. Since we observed a difference we performed a two sided t-test to check if this is difference is significant. The results of this test where: t(37) = 1.67 and p = 0.10. From these values we can conclude the difference in error rate between the two conditions is not significant.

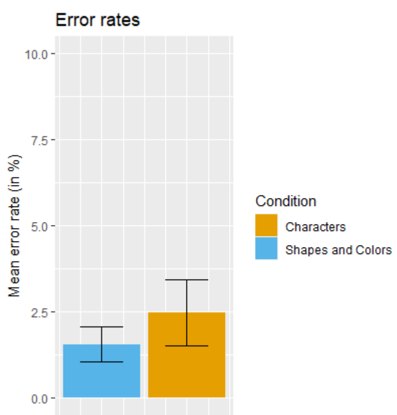

Figure 3.2: Error rate using 2 conditions in percentages

Since the goal of this experiment is to find if transparent stimuli will cause differences in the results as compared to the experiment done by Berberyan and colleagues (2021), the next step is to compare the reaction times of the two experiments. Figure 3.3 shows the reaction times of both experiments next to each other. The reaction time of the shapes and colors condition is approximately 500 milliseconds, while the reaction time for the characters condition is approximately 100 milliseconds higher in both cases. We performed a two-sided t-test to find out of there is a significant difference in reaction time between the 2 datasets. This test resulted in the following values: t(139) = 1.88 and p = 0.06. From these values we can conclude that there is not a significant difference in reaction time between the two datasets.

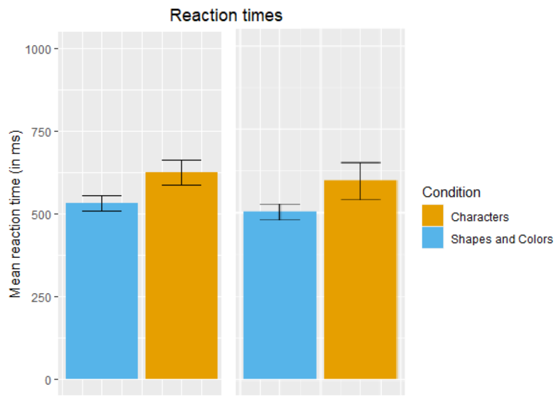

Figure 3.3: Comparison of reaction times

3.2 EEG data results

The EEG data was analyzed using a HsMM-MVPA analysis. The first step in this analysis is fitting a model in order to find the optimal number of bumps. A model is fitted for each number of bumps and these models are then compared using a sign test. The results of this test are illustrated in Figure 3.4. At each number of bumps a dot is added to the graph, if the dot is filled with a red cross it means that number of bumps is significantly better than the previous number of bumps. The last dot which is filled with a red cross is the dot placed at 4 bumps. The graph also displays the amount of participants for which a model with that number of bumps is significantly better than a model with one bump less. For example a model with 4 bumps is significantly than a model with 3 bumps for 19 out of 24 participants, while a model with 5 bumps is only better for 10 out of 24 participants. For those reasons a model with 4 bumps is the best fit for our data.

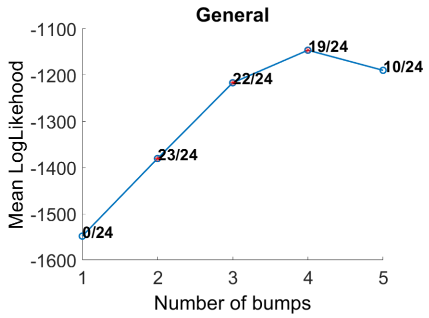

Figure 3.4: Mean log-likelihood of the number of bumps

The previous figure has shown the optimal number of bumps for our model. The topologies and stage durations can differ between conditions and the next step to fit a model is to find out which topology or stage duration we should keep constant. We fitted three different models and compared them. The first model stated in the Table 3.1 is the combined model. For this model we hypothesized that the topologies and stage durations were the same for both conditions.
The second model is the Bump2Stage3Vary model, for this model we hypothesized that the second bump and the third stage would differ between conditions. This model is chosen for this comparison because Berberyan and colleagues (2021) also used this model in their HsMM-MVPA analysis, because they found it was the best model when comparing to a range of models.
The last model is a sum of separate models, for this model each topology and stage differs between the 2 conditions. Table 3.1 shows for how many participants the model stated on the row fits better than the model stated on the column. For example the Bump2Stage3Vary fits better than the Combined model for 20 participants, this is a significantly better fit. The Bump2Stage3Vary model fits better than the sum of separate models for 10 participants, which is not significant, since we had a total of 24 participants. The sum of separate models is also a good fit for the data, since it is also significantly better than the combined model.
From these results we can conclude that both Bump2Stage3Vary and sum of separate models fit the data well. The Bump2Stage3Vary model is less complex, because for this model only one bump and one stage differ, while in the Sum of separate models every stage and bumps differs. Since the Sum of separate models did not perform significantly better than the Bump2Stage3Vary model, we will use the latter in our analysis.

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

Table 3.1: Comparison of different models

Figure 3.5 illustrates the duration of each stage per condition, in milliseconds. This figure shows no difference of duration for stages 1,2 and 5 between the 2 conditions. It shows a slight difference in duration of stage 2 and a difference of approximately 100 ms for stage 3. Figure 3.6 shows that duration of each stage in the experiment conducted by Berberyan and colleagues (2020). This figure also shows a difference of approximately 100 ms for stage 3 between conditions and some slight differences for the other stages. Taking all this into account we can conclude that both figures are similar, although not a perfect replica.

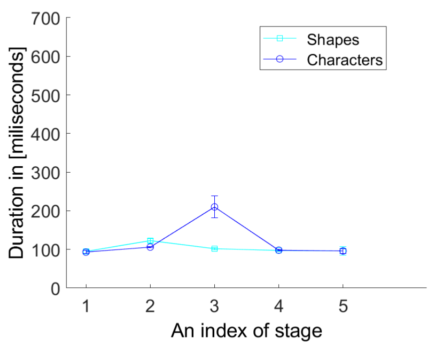

Figure 3.5: The duration of each stage per condition using transparent stimuli

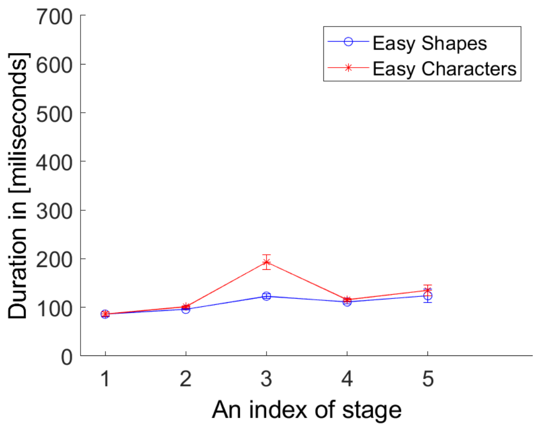

Figure 3.6: The duration of each stage per condition using normal stimuli

Figure 3.7 shows the topologies which where deduced from the HsMM-MVPA analysis. This figure shows that the topology from bump 2 differs between conditions, while the topologies for the other bumps are all exactly the same.

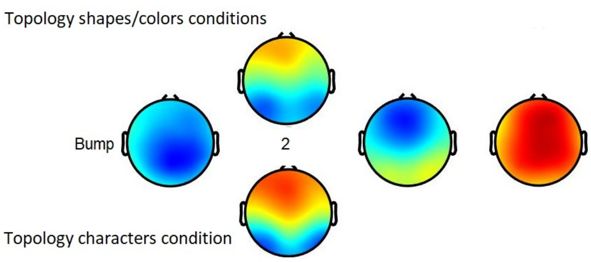

Figure 3.7: The topologies deduced from HsMM-MVPA analysis

4 Discussion

The goal of our experiment was to manipulate perception using transparent stimuli and thereby prove that HsMM-MVPA analysis is a reliable method for deducing stages from EEG data. This was done using a visual discrimination experiment with transparent stimuli. During this experiment 2 sets of data were gathered, behavioral and EEG data. For the behavioral data we examined the reaction time and the error rate and also compared this to the experiment performed by Berberyan and colleagues (2021).

There was almost no difference in reaction time between normal stimuli and transparent stimuli. This indicates that the participants perceived normal stimuli just as fast as transparent stimuli.
We decided to use transparent stimuli since Kamsteeg (2020) did a pilot experiment with 4 participants in which she compared different versions of the stimuli to examine which one had a significant effect on the reaction time of the participants. From this experiment she concluded that the transparent stimuli had the most potential to be able to manipulate perception. She based this conclusion on reaction times as well as on the Shifted-Wald models (Heathcote, 2004) she created.
A Shifted-Wald model gives a more detailed description of how the reaction time is composed. It splits the reaction time up in 2 stages, decision and non-decision time. Non-decision time is the time in which underlying processes such as perceptual encoding occur. In the research done by Kamsteeg (2020) a Shifted-Wald model is fitted which indicated an increase in non-decision time when using transparent stimuli. This increase in non-decision time suggests that transparent stimuli would also lead to a longer perceptual processing stage. Since we did not find a longer perceptual processing stage, it would be interesting to see if the non-decision time in our experiment was also increased.
Even though Kamsteeg (2020) found that transparent stimuli had the most effect on the reaction times of the participant, we did not find evidence to back up this claim. We used the exact same stimuli as Kamsteeg in her experiment, but the results did not significantly differ from the results using normal stimuli. This is why we propose that future researchers use more transparent stimuli, because we expect based on the pilot performed by Kamsteeg that there still is a connection between reaction times and transparency of the stimuli. The EEG data was analyzed using a method called HsMM-MVPA analysis. This method, proposed by Anderson and colleagues (2016), aims to identify processing stages directly from EEG. The duration of the processing stages identified in this experiment does not differ as compared to the duration of the stages found by Berberyan and colleagues (2021). This could indicate that people perceive transparent stimuli just as fast as normal stimuli, which was also indicated by the lack of difference in reaction

times.

5 Conclusion

The results have not shown any significant difference as compared to the results obtained by Berberyan and colleagues (2021). The reaction times for both conditions were identical to the reaction times recorded by Berberyan and colleagues (2021). The stage durations were similar to those recorded by Berberyan and colleagues. From these results we can conclude that the manipulation of the stimuli does not influence the reaction time of the participants. We were not able to find a significant difference in the duration of cognitive processing stage or even a significant difference in reaction times. In conclusion, we were not able to manipulate perception using transparent stimuli. We can however conclude that our results support the claim that HsMM-MVPA analysis is capable of deducing cognitive stage durations directly from EEG data. The reaction times showed no difference when compared to the results gathered by Berberyan and colleagues (2020), which would infer that the stage durations deduced in this experiment should also be similar to the stage durations in their experiment, which they were.

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