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# Memory update of associations in the posterior parietal cortex

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#### Abstract

In our world we are facing constant changes in our environment and somehow our brain is capable to adapt quickly to these changes. When encoding our environment and changes happen, as objects are manipulated or moved, we are still capable of recognizing the same environment as before. The brain seems to be able to associate and encode this novel changes quickly into the previously built neural structure instead of, which would be another possibility, creating a whole new structure apart from the previously built one. In a simplified experiment we could observe such an integration taking place in the posterior parietal cortex (PPC) using scalp EEG on 7 subjects. The experiment was divided into two learning phases, one in which the subject memorized the same associations repeatedly, and a second in which novel items were induced and combined with the previously learned associations. It was observed that during encoding of the stimulus, 50-100 ms after stimulus onset, theta (3-7 Hz) was elevated in power while alpha (8-12 Hz) and beta (15-25 Hz) decreased in power in the PPC. At retrieval, (150-200 ms) after onset, the power of theta constantly increased at each exposure, which we interpret as a constant shift from retrieving first from the hippocampus and then over time from the post parietal cortex. When combining novel items with the previously learned associations it was observed that theta increased its power significantly faster than it did in first place. Our findings do not only suggest that in the low frequencies (<30 Hz) an increase in power of theta and a decrease in alpha and beta promotes the encoding of memory in the PPC, but also that the brain is capable of quickly integrating novel items into preexisting neuronal structures in the posterior parietal cortex.

Keywords: posterior parietal cortex; long-term memory; oscillations; theta; associative learning; episodic memory

# Chapter 1

# Introduction

Without the capability of remembering past events, we would not be able to learn or develop language, relationships, nor develop a personal identity [1]. This capability is referred to as *memory*, which is the faculty by which the brain stores and remembers information.

### 1.1 Memory Background

In the formation and retrieval process of memory, there is distinguished in between two complementary systems which are the *short-term memory* and the *long-term memory*. Short term memory is referred to as the amount of information that we are able to receive, process, and remember in a short time frame of about 30 seconds [2]. The quantity of information that was assumed that we can store in the short term memory is around 5 - 9 items [3]. Whereas the long term memory is a fairly permanent repository for information which is transferred from the short term memory according to the Atkinson-Shiffrin model [2].

### 1.2 Memory Types

Besides the creation and retrieval of information, there is as well distinguished in different kinds of memory. Subcategories of memory are classified as declarative (explicit) and nondeclarative (implicit) memory. Nondeclarative memory refers to skills and habits, priming, simple classical conditioning and nonassociative learning (as habitutes and sensitizations) and is considered as independent of the medial temporal lobe [4]. Whereas declarative memory is subdivided into semantic memory (as facts) and *episodic memory* (as events or personal experiences). Behavioural studies and neuroimaging investigations in humans revealed that the medial temporal lobe (MTL) is from major importance for episodic memory. The MTL encodes associations which then can be build back up together to an episodic memory [5, 6, 7, 8]. It is suggested that in the process of establishing long-term memory for facts and events (declarative memory), the neural system consists of the hippocampus and the anatomically related cortex, including entorhinal, perirhinal and parahippocampal cortices [9].

### **1.3** Interplay of the hippocampus and the neocortex

But how do cortical brain regions interact with the hippocampus? Studies suggest the standard consolidation model, in which the hippocampus integrates information from distributed cortical modules that represents various features of an experience, and connects them together to different parts of the cortex system as a memory trace [6, 10]. The repeatedly recreation of this hippocampal-cortical network strengthens this cortico-cortical connections, which then allows memories to become independent of the hippocampus and to integrate with pre-existing cortical memories [11]. An alternative model to the standard consolidation model would be the multiple trace theory, which has as its main counterpart the prediction that reactivation of memory also leads to new traces in the hippocampus [12].

### 1.4 Associative Learning

The importance of the MTL for episodic memory has been demonstrated repeatedly [5, 6, 7, 8], but the question remained open on how it does look like at the single neuron level. Latest findings point to so called concept cells, or as well known under the name Jennifer Aniston neurons. These cells, located in the MTL (mainly in

the entorhinal cortex and the hippocampus), fire and respond in a very selective way to certain objects or persons, such as i.e. Jennifer Aniston, Luke Skywalker or the Tower of Pisa [13]. Further research on concept cells revealed that single cells respond to previously neutral stimuli after simultaneously presentation with the preferred stimulus. However, whether those hippocampal rapid modulations are reflected in the short to long memory transfer circuitry, is still unclear [14].

### 1.5 Memory Circuits

Traditionally it has been seen that for short term memory it is mainly the hippocampus who is responsible for its creation, while for the slow learning neocortex it would take weeks and months until memory is created [15]. However, Recent findings show evidence that the neocortex is involved in the creation of memory, beyond attentional processes [16], different than initially assumed. Spatial navigation studies, which are a good practice to investigate the process of building up a complex memory system, proposed that the hippocampus was only activated during mental navigation in new environments and in cases of highly familiar surroundings mainly relied on the posterior parietal cortex [17]. However, a study published in 2016 showed that the posterior parietal cortex was active in an virtual-reality navigation task at the time the spatial memory representation was built. The study suggests that the posterior parietal cortex would fulfill all criteria for a hippocampus-independent memory representation [18].

#### 1.6 Hebbian learning rule

But how are these memories created? A very influential theory comes from Donald O. Hebb, called the Hebbian learning rule, which suggests that memories are stored in the synaptic weights in between cells. It says that if a cell A can exit a cell B and it does this repeatedly, a metabolic growth process takes place in one or both cells [19]. This can be imagined like a muscle that is repeatedly trained and through this training, a metabolic process takes place that strengthens the muscle. His rule is also often interpreted as "cells that fire together, wire together". But how is a firing of a

cell assembly expressed? With modern tools as the electroencephalography (EEG) electrodes at the scalp can measure a fluctuation in the local field potential on the human scalp. After some processing, this signal, taken from the scalp, can then be decomposed into a power per frequency graph, a method very common as well in music and other domains of signal processing. After decomposition it becomes visible that there are different neurons of a cell assembly firing at different rates. This can be imagined like the audio file, that shows us only one continuous signal, but when decomposing it, we can find a band of musicians playing with different instruments over different frequency domains. But now there can be determined neurons that fire at different frequencies and those neurons firing together would now increase their strength in between each other which could explain how memories are stored in the synaptic weights of neurons.

#### 1.7 Brain oscillations

It was shown that neurons are capable to excite each other and fire together. When something fires at a certain rate it can be described as an oscillation since it has a form comparable to a sinusoid wave. This oscillating of neurons does not occur randomly, studies could demonstrate that these fluctuations in excitation and inhibition of power is inducing synchronized firing patterns [20] [21], which, if we take the theory of Hebb, would be a measure to strengthen certain connections in between neurons. Therefore oscillations received an increasing interest over the last decade, although there still is little understood about them, they certainly are considered as to be one of the core neural mechanisms for the storage and retrieval of long term memory [22] [23].

#### **1.8** Episodic memory and oscillations

The common opinion in science is that oscillations play a crucial role in encoding and retrieving information, but how does this look like on a neuronal level?

Typically, brain oscillations are divided into different frequency bands which are

named after letters of the Greek alphabet. Some of them but not exclusively are delta (1-4 Hz), theta (4-8 Hz), alpha (8-12 Hz), beta (15-25 Hz), and gamma (40-80 Hz). It is not possible to exactly define these boundaries in between frequencies and they vary considerably in between experiments and species [24].

What happens to these frequency bands during memory encoding and retrieval? In the hippocampus there seem to be two frequency bands that emerge as the key players in forming episodic memories. Studies on human epilepsy patients were able to correlate both, successful encoding [25] and retrieval [26] of memory to an increase in power in the gamma band and a modulation in power in the theta band. It is suggested that gamma oscillations represent individual memory representations while the task of theta is to temporally order these memory representations. These was demonstrated by phase synchronism in between theta and gamma during retrieval and encoding of memory in the neocortex and the hippocampus [27]. However, it has only been very recent that human neuroimaging studies support and additional role in episodic memory of the posterior parietal cortex. Therefore there is only little known yet about oscillations in the posterior parietal cortex and which frequencies would modulate in power during the encoding and retrieval of memory.

### 1.9 Research Question

When encountering new locations repeatedly experiments showed that the posterior parietal cortex becomes active from a very early stage on, proposing that an independent memory representation is build up[18]. This study was done using fMRI, investigating the BOLD value, which is an increase in the blood flow that is associated with oxygen that is transported to a certain region and can then be related to an increase or decrease in activity at that certain region. The question left open are the neural mechanisms behind the encoding of that memory representation.

Oscillations certainly play a big role in memory formation and retrieval, therefor it must be possible to observe certain changes in power in certain frequency bands. Previous studies showed that theta power modulates during encoding of episodic memory, therefore such a modulation, represented by an increase or decrease of power should be observable in the posterior parietal cortex and could shed light on what the neural mechanisms are behind memory encoding and retrieval in the PPC.

When encoding spatial memory it can be interpreted as an encoding of a complex memory representation of a place. A natural acting environment is not stable so that as a consequence in our everyday lives we are facing constant changes and our brain is somehow capable to adapt to these changes most likely by quickly integrating novel items, which is a change in the environment, into the previously built complex memory representation. It was shown that the posterior parietal cortex gets active from an early stage on when re-encountering the same environment repeatedly, but it was not shown what happens in the posterior parietal cortex if the re-encountered environment changed. Assuming that our brain found a smart way in handling these naturally changing environments, we could assume too that the brain will quickly integrate these novel items into the preexisting memory representation in order to save resources and energy instead of every time creating a whole new memory representation of it. Although this fact yet was largely ignored in science and is not well investigated, we created an experiment that made it possible to see such integrations, using scalp EEG, on the posterior parietal cortex.

# Chapter 2

# Methods

Following is explained the methods and the experimental design that was applied on the experiment.

### 2.1 Hypothesis

It was shown that PPC activity is modulated by the learning state of a memory. Every encounter with the learning material led to a stronger activity in the PPC, whereas the activation of the hippocampus was greatest in the first encounter and then decreased [18].

But how does this look like on a neuronal level? Studies have been shown that the encoding and retrieval of memory is reflected by a modulation in power in the theta band [25] [26]. We therefor hypothesize that theta oscillations promote encoding and retrieval of episodic memory in the posterior parietal cortex.

But what happens if the previously learned material is now embedded in a different context or associated with an additional object or person? Does this enhancement of the learned material lead to a new memory, independent of the initial memory created at the first encounter, or would the brain update the initial memory trace?

We hypothesize that when there is a modification of the initially learned material, the brain will update the episodic memory in the parietal cortex. This will be reflected in an increase in the precuneus activation and a decrease in the hippocampus activation with every encounter.

### 2.2 General Methodology Applied

7 healthy participants (4 female and 3 male, ages 23 - 31 years) were recruited for the experiment. Before starting the experiment, participants were informed about the procedure of the experiment and their consent was obtained. The experiment lasted approximately 30 minutes plus another 30 minutes to set up the scalp EEG.

The experiment was not yet approved by an ethical commission. Nevertheless we intensively discussed a possible harming through our experiment, and decided that there were no obvious risks in health and wellbeing for the participants. After clarifying possible risks with our participants, 7 subjects volunteered to participate.

### 2.3 Experimental design and set-up

The 258 images used for the experiment were taken from a verified source. At trial 100, 200, 300, 400, 500 and 600 the participant had a break. Stimuli were retrieved randomly from the database and presented on a screen size of  $1,280 \ge 1,024$  pixels in the dimensions of either 281  $\ge 197$  pixels or 197  $\ge 281$  pixels. The EEG device used was the Neuroelectrics Enobio-20 EEG device with 20 channels + 3 accelerometers. The participants were seated on a comfortable black chair with arm support with a distance of around 75 cm.

#### 2.4 Experimental procedure

The experiment consisted of two phases, "learning phase 1" and "learning phase 2". In "learning phase 1" participants were encoding pairs of pictures that were beforehand randomly paired. 8 pairs were created with 16 pictures, so to say 2 pictures per pair. This set of pairs was repeatedly presented to the subject in a randomized order, containing catch trials with novel pairs that only appeared once throughout the whole experiment. In "learning phase 2", one novel item per pair



Figure 1: Montage of electrodes. From key interest in this study were the electrodes around the posterior parietal cortex, which are P3, Pz, P4, PO3 and PO4.

was introduced and pairs started changing. Whereas in "learning phase 1" pairs were shown as A - B, B - A, C - D, D - C etc., in "learning phase 2" pairs appeared as A - Z, Z - A, Z - B, B - Z, C - Y, Y - C, Y - D etc., still continuously inducing catch trials with novel pairs of items that only appeared once throughout the experiment.

At every trial, the participant was presented a blank screen, after one second the stimulus was presented for a second, at second two to three the screen turned blank again for a waiting phase following the question "Have you seen this Association before? Yes/ No" in font size 32. The participant then could either press "s" if he has seen the pair of association before or "l" if s/he thought s/he has not.

#### 2.5 Analysis of behavioral data and scalp EEG data

#### 2.5.1 Behavioral analysis

We calculated the probability of correct recall as well as of incorrect recalls for participants in both datasets. The probability was measured by calculating the number of incorrect responses as a proportion of the total number of responses for every participant. The set was split into catch trials, original associations (learning phase 1) and updated associations (learning phase 2).



Figure 2: (A) Example pairs shown in "Learning Phase 1". 8 pairs were randomly created at the beginning of the experiment and then repeatedly shown to the participant. Catch trials with novel items that only occur once throughout the experiments are induced throughout the iteration of 8 pairs. (B) Example pairs shown in "Learning Phase 2". New pairs, containing one novel item per initially encoded pairs is are created. During each iteration in which the pairs were presented to the participant, catch trials were induced. (C) Experimental procedure.

#### 2.5.2 Preprocessing of the EEG data

The main library used for the preprocessing of the data was the mne python library [28] [29]. First, in order to change the format of the file from EASY to SET, that can be red by the mne library, matlabs' EEGlab [30] together with the NE EEGLAB NIC Plugin was used. The raw data was epoched into trial-segments from 1 s pre-stimulus to 2 s after stimulus onset. A 1 Hz - 40 Hz band pass filter was applied in order to remove drift. The sampling frequency was set to 250 Hz through down-sampling. Depending on the datasets thresholds for automatic peak-to-peak amplitude rejection were defined, usually in between 220 and 350  $e^-6$ , to remove coarse artifacts. Bad channels were removed and interpolated, and the data was referenced to average.

An independent component analysis with the fastica algorithm [31] was applied in order to remove artifacts such as eyeblink, heartbeat/ pulse or movement. In a last visual inspection, if necessary, trials that still contained artifacts were removed manually.

#### 2.5.3 Processing of the EEG data

In a first step, all the presented pairs were indexed in the continuous data. The data was split in two sets for the 1st learning phase, in which the pairs stayed constant, and the 2nd learning phase, in which the novel items were induced and mixed with the pairs. Exposures were from interest for the analysis, therefore the pairs were grouped together per exposure, so to say groups were created, containing the indexes of the 1st exposures, 2nd exposures, ..., n th exposure.

Although the main focus of this study became the post parietal cortex with its channels PO3, PO4, Pz P3 and P4, all the results were compared in between the channels as left to right (P3, PO3 vs. P4, PO4), up versus versus down (PO3, PO4 vs O3, O4 vs P3, P4) and the post parietal cortex vs the whole parietal cortex (PO3, PO4, Pz P3, P4 vs. PO3, PO4, Pz P3, P4, P7, P8). In order to extract the event related potential, the time-frequency resolution method *Multitaper* was applied

with one taper, which corresponds to the least frequency smoothing. As Baseline was set 1 second until 300 milliseconds before stimulus onset, which we compared to the times 0.5 - 1 second and 1.5 - 2 seconds after onset. The frequency bands from interest were the theta band (3 - 7 Hz), the alpha band (8 - 12 Hz) and beta (15 - 25 Hz). The power values were extracted by calculating the mean spectral power of all pairs per exposure per frequency band for each subject. Log transformed power values were calculated into change in percent compared to baseline.

In order to calculate the strength and direction between the exposures of each learning phase, a spearman's rang-order correlation was run. A wilcoxon signed-rank test was run in order to compare the two learning phases in between each other at every exposure and overall exposures.

# Chapter 3

# Results

### 3.1 Behavioral Results

Before moving on to the results of the scalp EEG, we want to report the basic behavioral results for the two learning phases (see fig.3). In the analysis we differentiated in between "original", which refers to learning phase 1, "updated", which refers to learning phase 2, and "catch", which refers to the catch trials being showed throughout the whole experiment. In all the 3 categories the participants were capable of segregating with an accuracy of <95 % if they have seen the showed association before or not.



Figure 3: Figure showing the behavioral results from all subjects. Subjects were capable of predicting <95 % correct if they have seen the association before or not.

### 3.2 Time frequency results

In order to identify the neural mechanisms that underly the update of associations in the parietal cortex, we compared the oscillatory power of different frequency bands in the two learning phases, and investigated how this oscillatory power behaves over the amount of exposures. The investigation mainly focused on the frequency bands theta (3-7 Hz), alpha (8 - 12 Hz) and Beta (15-25 Hz) at which we looked at 0.5 -1 s after stimulus onset, during encoding of the stimulus, and 1.5 - 2 seconds after onset, which we claim to be retrieval of the learned material.

During encoding of the stimulus in the first time window we could observe an increase in theta and a strong decrease in alpha and beta (Fig. 3). The observations for the 1 st learning phase and 2 nd learning phase were convergent per frequency band and time window and are convergent with observations of other studies in the literature about encoding of episodic memory in the parietal cortex. A wilcoxon signed rank test did not reveal any significant differences in between the two learning phases. During retrieval of episodic memory in the second time window we could observe an increase in theta, alpha and beta. A wilcoxon signed rank test revealed significance in between the two learning phases at the theta band (p< 0.05). For additional graphs showing the evolution of power over exposures see appendix A.

#### 3.2.1 Spectral power over exposures at time of encoding

For our analysis it is not only from interest how the frequency bands behave on a global scale, but as well on how the power in the different frequency bands changes over time. In order to visualize the change over exposures, we created a plot containing the first and second learning phase power over exposures. To make the plots visually more aesthetic we grouped together the exposures in groups of three. So to say, we took the mean of all the power values of each participant at three exposures. At the first time window, 0.5 - 1 seconds when an encoding of the material takes place, the graphs stay relatively flat for all the frequency bands.

A wilcoxon signed rank test was used in order to determine any significant differences



Figure 4: (A) Total mean over all exposures in theta (3-7 Hz) at the time window 0.5 - 1 second and 1.5 - 2 seconds. Time windows exhibiting significant differences in between the two learning phases in theta are presented with an asterisk. (B) Total mean over all exposures in alpha (8 - 12 Hz) at the time window 0.5 - 1 second and 1.5 - 2 seconds. (C) Total mean over all exposures in beta (15-25 Hz) at the time window 0.5 - 1 second and 1.5 - 2 second and 1.5 - 2 seconds.

Time window 0.5 - 1 sec after stimulus onset								
Frequency	1st phase		2nd phase					
band	mean	std error	mean	std error				
Theta	13.65~%	4.51 %	6.95~%	8.63 %				
Alpha	-22.76 %	2.89~%	-25.21 %	3.09~%				
Beta	-10.56 %	1.86~%	-12.05 %	2.23~%				
Time window $1.5 - 2$ sec after stimulus onset								
Theta	15.23 %	6.09 %	8.19 %	4.68 %				
Alpha	11.36~%	5.16~%	8.83 %	5.20~%				
Beta	14.61 %	$2.3 \ \%$	12.2 %	2.06 %				

Table 1: Total mean and standard error values for learning phase 1 (0.5 - 1 seconds) and learning phase 2 (1.5 - 2 seconds) compared to baseline in percent

in between early exposures and late exposures for each learning phase individually, but no significant difference could be found. A comparison in between the individual exposure groups of the two learning phases gave significance for the 3th exposure group in alpha (p = 0.049). However, a Spearman's rank correlation gave significance to the frequency band theta in the first learning phase (p = 0.0013) and second learning phase (p = 0.0095) over all 30 exposures in the first and 19 in the second learning phase.

#### 3.2.2 Spectral power over exposures at time of retrieval

In the second time window from 1.5 - 2 seconds, to which we refer as retrieval of the encoded episodic memory, we could observe an increase over the exposures. In theta we could observe that the power of the first exposure group in the first and in the second learning phase begins very similar, whereas then it increases over time differently, in the first learning phase slowly and in the second learning phase the theta power mounts on relatively a similar power level as in the first learning phase in only half the amount of exposures. For alpha a similar pattern could be observed, whereas beta stayed stable over all the exposures. In order to determine any significant differences in between early exposures and late exposures a wilcoxon signed rank test was used , which revealed significance (p = 0.0047) for theta in the first learning phase, as well as for alpha in the second learning phase (p = 0.00068). Theta in the second learning phase was nearly significant (p = 0.066). In order to calculate early and late exposure, for the first learning phase the first 11 exposures and exposure 19 to 30 were taken together and compared. For the second learning phase, same was done for the first until 7th exposure for early exposure and 12th until 19th exposure for late late exposure. Reason for the difference in the amount of exposures that were compared with each other in the different phases was, that participants were more exposed to learning phase 1 than learning phase 2.

A comparison of significant differences in between learning phase one and learning phase two with the wilcoxon test revealed significance for theta from the first until 20th exposure (p = 0.029) and for alpha from the 7th until the 20th exposure (p = 0.036). A Spearman's rank correlation gave significance to the frequency band theta in the first learning phase (p = 0.0000000102) as well as for alpha (p = 0.000000416) and beta (p = 0.0057). For the second learning phase theta (p = 0.0023) and beta (p = 0.008) showed significance whereas alpha was nearly significant (p = 0.055).



Figure 5: One group of exposures equals the mean of the spectral power of all subjects at 3 exposures on following after the other (A) In the time of encoding of the stimulus (0.5 - 1 seconds), the relative change in spectral power over the amount of exposures does not show tendencies to increase or decrease, which is supported by the wilcoxon test that did not reveal any significant differences in between early and late exposure per phase. Generally theta increased in power and alpha and beta decreased in power compared to baseline. The spectral power of the 1st learning phase compared to the 2nd learning phase seems relatively convergent, which is supported by a wilcoxon test that was run comparing the two phases and that did not reveal any significant differences. (B) In the time of retrieval of the encoded associations (1.5 - 2 seconds), there can be observed a clear response of the spectral power over the amount of exposures in theta and alpha. A wilcoxon test proved significant difference in between learning phase 1 and 2 in theta from first until 20th exposure (p < 0.05) and in alpha from 6th until 20th exposure (p < 0.05). A Spearman's rank-order correlation showed a significant monotonic relationship of the two phases in theta (first phase(p = 0.0013); second phase(p = 0.0095))



(a) Beta (15-25 Herz) during encoding in the first learning phase (p = 0.028)



Figure 6: Left and right electrodes showed significant differences for beta during first and second learning phase during encoding and retrieval. Only graphs are shown where significance occurred according to wilcoxon.

### 3.2.3 Inter-comparison in between left and right hemisphere of the posterior parietal cortex

In order to compare the left posterior parietal cortex with its right posterior parietal cortex with each other, a wilcoxon test was run in between the different pairs of electrodes. The test showed significance for the left (PO3 and P3 electrode) versus the right posterior parietal cortex (PO4 and P4 electrode) in the alpha frequency band during encoding (p = 0.000000047) and retrieval (p = 0.0011) in the first learning phase, and in the second learning phase only during encoding (p = 0.028), see figure 6.

For beta, right versus left differed during encoding in the first learning phase (p = 0.0091) and during retrieval in the second learning phase (p = 0.000079), see figure 7. For additional graphs of comparing the other frequency bands and times see appendix B.





(a) Alpha (8-12 Herz) during encoding in the first learning phase (p = 0.000000047)

(b) Alpha (8-12 Herz) during retrieval in the first learning phase (p = 0.0011)



(c) Alpha (8-12 Herz) during encoding in the second learning phase (p = 0.0091)

Figure 7: Left and right electrodes showed significant differences for alpha during the first and second learning phase during encoding and retrieval. Only graphs are shown where significance occurred according to wilcoxon

## Chapter 4

# Discussion

In our world we are facing constant changes in our environment and somehow our brain is capable to adapt quickly to these changes. When encoding our environment and changes happen, as objects are manipulated or moved, we are still capable of recognizing the same environment as before. The brain seems to be able to associate and encode this novel changes quickly in the previously built neural structure instead of, which would be another possibility, creating a whole new structure apart from the previously built one.

It was shown that when encoding episodic memory in a spatial environment regions of the parietal cortex gets active from a very early exposure on [18]. Although work was already done on investigating the encoding of episodic memory in the posterior parietal cortex, not only the underlying neural mechanisms were largely ignored in previous research, but especially the integration of novel items into previously learned associations is a topic barely touched by previous studies. Therefore this study was not only aiming to shade light into which of the lower frequencies are modulating when encoding and retrieving episodic memory, but to investigate how this is reflected when novel items are associated with previously learned items.

In order to investigate associative memory formation in the brain we investigated EEG spectral power during encoding and retrieval as 7 participants performed an associative memory task. In the task participants did not only encode the same associations over time, but in a second learning phase of the experiment the previously encoded pairs were enhanced with novel items and repeatedly shown. We examined low frequency activity of theta (3 - 7 Herz), alpha (8 - 12 Herz) and beta (15 - 25 Herz) and found that encoding of associative memory was accompanied by an increase in theta and a decrease in the alpha and beta frequency bands, which is in line with other studies that observed a similar pattern in the encoding of episodic memory [32]. Moreover could we observe that with an increasing number of exposures the spectral power of each frequency band stayed relatively at the same power level. However at the retrieval of that previously encoded associative memory we could observe that theta increased over the number of exposures and that there was a significant difference in power in between early exposures and late exposures. Similar could be observed for alpha, which was not significant according to a wilcoxon test.

When introducing novel items to the previously learned associations we could observe a similar pattern as in the first learning phase in which the associations reoccurred always with the same pair, just that when combining a novel item with a previously encoded association, theta took significantly less time to increase its power than compared to the first phase. Similar could be observed for alpha, whereas beta stayed elevated for the whole period of the memory replay.

Our findings suggest that when manipulations of previously encoded association happen the posterior parietal cortex integrates this novel items into the previously created neuronal assembly. This could be observed in the relative quick rise of power in theta after only a couple of exposures to the novel association in the second learning phase, compared to the first learning phase. However, if an integration would not take place, we would have expected to observe a similar slope in power increase over exposures as observed in the first learning phase.

Not only could we observe an integration taking place of that novel item in a previously build neural structure, but as well the encoding of the initial associations and of the new associations are accompanied in the low frequencies (< 25 Herz) by an increase of the theta frequency band, and a decrease in the bands of alpha and beta. This observations are in line with previous findings in other experiments [33], where a modulation in the theta band and a decrease in beta and alpha was observed to promote the encoding of memory.

When it comes to retrieving the previously encoded associations, we observed a positive slope of theta and alpha which leaves open the question of why, if the association is encoded in the posterior parietal cortex from an early exposure on, the retrieval does increase over time and is not elevated from the very beginning on? We suggest that, by combining our findings with observations of others studies [18], that the hippocampus acts as the fast learner and the neocortex as the slow learner. Our interpretation of the observations is that although there is an encoding taking place from a very early stage on, the retrieval is shared in between the posterior parietal cortex and the hippocampus. They act as a complementary learning system, which moves over time its computational power from the hippocampus to the neocortex, and is convergent with findings of a recent paper that investigated the interplay of hippocampus and posterior parietal cortex during the encoding of spatial memory with fMRI [18].

Further investigations of differences in between the right and left side of the posterior parietal cortex showed that there were, depending on the time and frequency band, significant differences in between the two hemispheres. Especially alpha showed in 3 of the 4 time windows tested, significance in the difference in between the left versus the right electrodes. During encoding the alpha band on the right hemisphere had a significant stronger decrease in power than the left hemisphere. For beta there could be observed in two time windows a significant difference in between the two hemispheres. Once during encoding in the first learning phase, in which the right hand side had a significant bigger drop in power than the left hand side over all exposures, and in the second learning phase during retrieval of memory, where the right hemisphere showed a significant bigger increase.

Previous studies already demonstrated differences in between the two hemispheres. It could be observed that during encoding of verbal material alpha/beta power decreases were most evident in the left inferior prefrontal cortex [24]. However, in our study no clear pattern for differences in between the right and left hemisphere emerged. It stays open for speculations why these frequency bands behaved as such at the different tasks of encoding and retrieval of episodic memory.

### Chapter 5

# Conclusion and open questions

One of the questions that remains open is how the high frequency bands (>30 Hz) behave during encoding and recall of the associations and for integration of novel items? Having a look into previous work dedicated to that topic would suggest that the power in the high frequencies (40 - 100Hz) will increase together with theta [34] [27].

Also it would not only be interesting to look into the event-related potential of gamma, but in science there is an increasing interest in phase coupling of these two frequency bands. Researches demonstrated already increases of theta-gamma coupling during leaning of context associations in rats in the hippocampus [35], as well as for visuospatial attention tasks in the posterior parietal cortex of rats [36]. Can we assume that when encoding episodic memory, and furthermore integrating novel items into the previously learned neuronal assemblies a phase coupling of theta and gamma will occur in the posterior parietal cortex, as already demonstrated in the hippocampus?

Another important aspect that could not be validated in our experiment was, how this encoded associations are going to behave over time in the posterior parietal cortex. It is known that there is an interaction taking place in between the prefrontal cortex and the PPC in the retrieval of episodic memory [37], so a joint examination of the two regions during retrieval of associations with novel items over time would be from interest, specifically of how they behave after hours or even days of learning the material.

After having demonstrated that associations of episodic memory are created in the posterior parietal cortex, our experiment does not explain how these works on a neuronal level. After the discovery of the "Jennifer Aniston Cells" in the hippocampus [13] this topics received a lot of attention over the past years in the research of episodic memory. Could we now assume that there might be similar cells in the posterior parietal cortex getting active when associations are created? This remains subject of future research.

However, our experiment demonstrated that an increase in theta and a decrease in the spectral bands of alpha and beta are promoting an encoding of episodic memory. Furthermore could we show that when inducing novel items into previously learned associations, the posterior parietal cortex integrates these novel items into the previously created memory traces.

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# Appendix A

# First Appendix

### A.1 Modulation of power over exposures in theta

Following we show the graphs of the theta band (3-7 Herz) as power in percentage compared to baseline over number of exposures. When plotting the graphs we tried to keep the y axis constant over the graphs, however sometimes this could not be achieved because of big standard errors. Be careful when reading the plots and keep attention to the axis.



Figure 8: Graph showing the change in power compared to baseline (-1 - 0.3 seconds) over number of exposures in the theta band (3 - 7 Hz).



Figure 9: Graph showing the change in power compared to baseline (-1 - 0.3 seconds) over number of exposures.



Figure 10: Graph showing the change in power compared to baseline (-1 - 0.3 seconds) over number of exposures in the theta band (3 - 7 Hz).



Figure 11: Graph showing the change in power compared to baseline (-1 - 0.3 seconds) over number of exposures in the theta band (3 - 7 Hz).

### A.2 Modulation of power over exposures in alpha

Following we show the graphs of the alpha band (8-12 Herz) as power in percentage compared to baseline over number of exposures. When plotting the graphs we tried to keep the y axis constant over the graphs, however sometimes this could not be achieved because of big standard errors. Be careful when reading the plots and keep attention to the axis.



Figure 12: Graph showing the change in power compared to baseline (-1 - 0.3 seconds) over number of exposures in the alpha band (8 - 12 Hz).



Figure 13: Graph showing the change in power compared to baseline (-1 - 0.3 seconds) over number of exposures in the alpha band (8 - 12 Hz).



Figure 14: Graph showing the change in power compared to baseline (-1 - 0.3 seconds) over number of exposures in the alpha band (8 - 12 Hz).



Figure 15: Graph showing the change in power compared to baseline (-1 - 0.3 seconds) over number of exposures in the alpha band (8 - 12 Hz).

### A.3 Modulation of power over exposures in beta

Following we show the graphs of the beta band (15-25 Herz) as power in percentage compared to baseline over number of exposures. When plotting the graphs we tried to keep the y axis constant over the graphs, however sometimes this could not be achieved because of big standard errors. Be careful when reading the plots and keep attention to the axis.



Figure 16: Graph showing the change in power compared to baseline (-1 - 0.3 seconds) over number of exposures in the beta band (15 - 25 Hz).



Figure 17: Graph showing the change in power compared to baseline (-1 - 0.3 seconds) over number of exposures in the beta band (15 - 25 Hz).



Figure 18: Graph showing the change in power compared to baseline (-1 - 0.3 seconds) over number of exposures in the beta band (15 - 25 Hz).



Figure 19: Graph showing the change in power compared to baseline (-1 - 0.3 seconds) over number of exposures in the beta band (15 - 25 Hz).

# Appendix B

# Second Appendix

Following we present the graphs of the comparison in between the left and the right hemisphere of the posterior parietal cortex. Graphs that are presented here were insignificant and only serve in order to provide all the other graphs that were not presented in the results section.

# B.1 Comparison of modulations in power over exposures of the two hemispheres in the first learning phase



Figure 20: Graph showing the change in power compared to baseline (-1 - 0.3 seconds) over number of exposures in the theta band (3 - 7 Hz).



Figure 21: Graph showing the change in power compared to baseline (-1 - 0.3 seconds) over number of exposures in the theta band (3 - 7 Hz).



Figure 22: Graph showing the change in power compared to baseline (-1 - 0.3 seconds) over number of exposures in the beta band (15 - 25 Hz).

B.2 Comparison of modulations in power over exposures of the two hemispheres in the second learning phase



Figure 23: Graph showing the change in power compared to baseline (-1 - 0.3 seconds) over number of exposures in the theta band (3 - 7 Hz).



Figure 24: Graph showing the change in power compared to baseline (-1 - 0.3 seconds) over number of exposures in the theta band (3 - 7 Hz).



Figure 25: Graph showing the change in power compared to baseline (-1 - 0.3 seconds) over number of exposures in the alpha band (8 - 12 Hz).



Figure 26: Graph showing the change in power compared to baseline (-1 - 0.3 seconds) over number of exposures in the beta band (15 - 25 Hz).