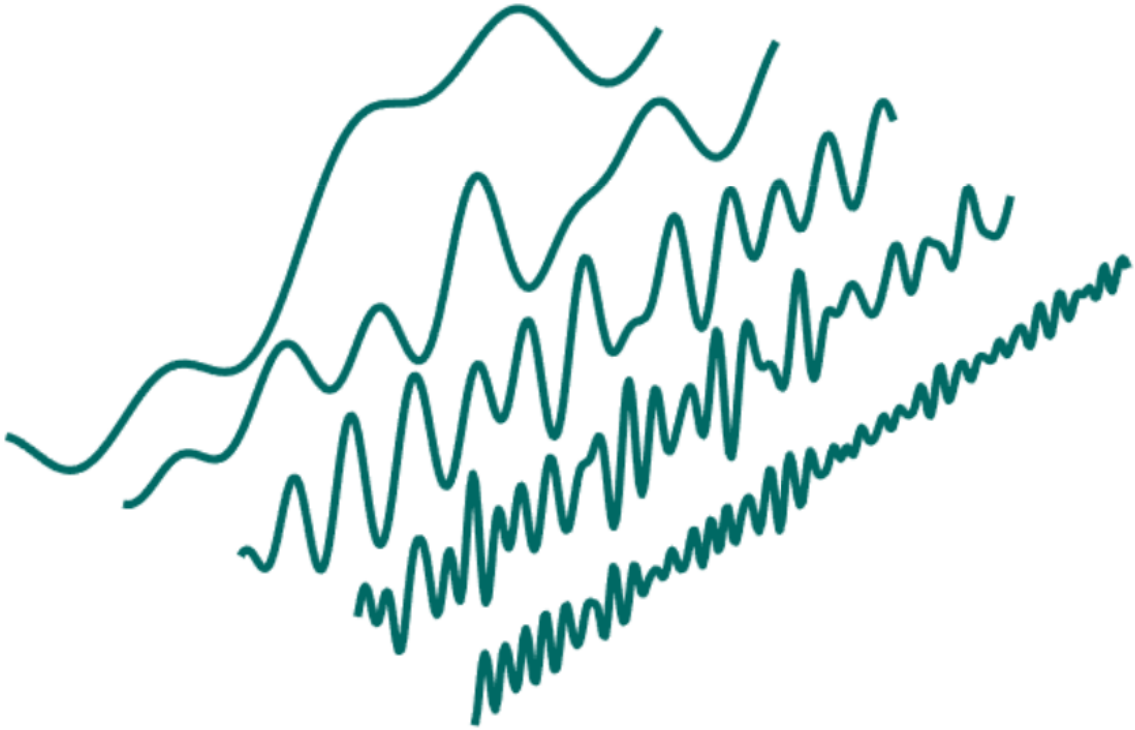

EEG analysis of fatigued drivers exposed to alerting fragrances

Master of Science Thesis in Biomedical Engineering

Isabella Nilsen & Isabella Sanchez

DEPARTMENT OF ELECTRICAL ENGINEERING
CHALMERS UNIVERSITY OF TECHNOLOGY
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Department of Electrical Engineering
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Cover: The five different brain waves from an EEG signal.

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Abstract

Fatigue-related accidents are responsible for a big part of all traffic accidents. Countermeasures that alert the driver have been investigated in earlier research, such as alarming sounds, lights, or a coffee symbol. Those countermeasures usually demand the driver's action as taking a nap or stopping for a coffee, since the alarm itself does not have the desired alerting effect. Research regarding certain types of fragrances has shown promising results in waking people up from sleep, and hence fragrance's effect on fatigued drivers is of interest as an alternative countermeasure.

The purpose of this thesis was to study the effect of fragrances on fatigued drivers by analyzing EEG signals. Focus was to determine the alerting effect of a fragrance that influences the trigeminal sensory system. The EEG signals used in this project were previously measured in a study done by VTI [1]. The main methods to reach the aim included a literature review, processing of EEG signals, and statistical analysis. The literature review mostly focused on former research of driving-related fatigue, preprocessing of EEG signals, EEG as a measure of fatigue and fragrance effect on brain activity.

From the analysis of the EEG signals, it could be seen that in general, the trigeminal substance generated no or a very small alerting effect on the drivers in this particular setting. Hence, further research on trigeminal fragrance related to fatigued driving would be needed if this countermeasure should be used in practice. Focusing on how to optimize the administration of fragrance so possible alertness could be achieved.

Keywords: EEG, automotive, fatigue, alertness, driver, countermeasure, fragrance, olfactory nerve, trigeminal nerve.

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Isabella Nilsen & Isabella Sanchez, Gothenburg, May 2023

List of Acronyms

Below is the list of acronyms that have been used throughout this thesis listed in alphabetical order:

ASR	Artifact Subspace Reconstruction
CRR	Common Recording Reference
DFT	Discrete Fourier Transform
ECG	Electrocardiography
EEG	Electroencephalography
EOG	Electrooculography
ERP	Event-related potential
FFT	Fast Fourier Transform
GND	Ground Electrode
ICA	Independent Component Analysis
PCA	Principal Component Analysis
PSD	Power Spectrum Density
SR	Sleep-related
TR	Task-related
VTI	The Swedish National Road and Transport Research Institute

Nomenclature

Below is the nomenclature of indices and variables that have been used throughout this thesis.

Indices

t_p	Index for time point

Variables

F_{tot}	The average bandpower over the total frequency range
θ	The relative bandpower of Theta waves
α	The relative bandpower of Alpha waves
β	The relative bandpower of Beta waves
ATB	$(\theta + \alpha)/\beta$
$time$	Time variable in the statistical analysis
$frag$	Fragrance variable in the statistical analysis
$fragtime$	Describes the interaction effect between $time$ and $frag$

Contents

List of Figures

List of Tables

1

Introduction

In the world, a total of 1.3 million individuals die each year due to traffic accidents. Distractions, speeding, or the state of the driver are factors that can contribute to crashes, just to name a few [2]. It has been shown that car drivers experiencing fatigue are more likely to cause road accidents compared to alert drivers [3], [4]. One study suggests that the risk is about twice as high [3].

In an attempt to prevent sleep-related accidents, countermeasures that alert the driver are of interest. Today, common methods to warn drowsy drivers are sounds and visual alerts in the form of light, sound, or a coffee symbol on the dashboard [5], [6]. However, this form of alert presumes that the driver has the possibility to stop directly to rest, which is not always the case. Instead, other countermeasures which increase alertness are of interest and are continuously being explored, such as alerting fragrances. The use of fragrances may be a way of increasing the alertness in fatigued drivers, allowing for a further short drive until it is possible to stop. Olfactory stimulation does not provoke an interference with driving actions [7], and is less disrupting compared to other stimulations [8].

In the human body, there are two types of systems that can be triggered by fragrance. The olfactory sensory system provides perceivable smell, and the trigeminal sensory system provides sensational reactions. Previous studies have looked at whether fragrances can increase alertness in drowsy drivers, but usually, there is no focus on the difference between the olfactory and trigeminal sensory system in those studies [9], [7]. There are no former studies on the alerting effect on drowsy drivers exposed to fragrances affecting the trigeminal sensory system. However, such fragrances have been shown to wake people up from sleep [10], [11].

For this reason, a study on trigeminal fragrances on fatigue drivers has been conducted by The Swedish National Road and Transport Research Institute (VTI) in collaboration with Volvo Cars, Moodify, and Karolinska Institutet [1]. In the study, fatigued drivers were exposed to fragrances while several physiological measurements were conducted. The measurements consist of electrooculography (EOG), electrocardiography (ECG), and electroencephalography (EEG). All data except for EEG has been analyzed and presented in the previously mentioned report [1]. EEG has been shown to be effective when measuring sleepiness [12]–[14] but is more complex in comparison to ECG and EOG regarding the analysis, due to the complexity of the brain and the large number of measuring electrodes. Since the EEG data never was analyzed the effect of fragrances on the brain is still unknown, making it an area of exploration for this thesis.

1.1 Aim

The aim of this thesis is to study the effect of fragrances on fatigued drivers by analyzing EEG signals. It is of interest to determine if there is an alerting effect of a fragrance that influences the trigeminal sensory system, and compare this to an olfactory fragrance. Also, the duration of the possible effect will be investigated. The EEG signals used in this project are measured in a study done by VTI [1]. The result of this report concerning EEG will be compared with VTIs study concerning ECG and EOG.

The following set of questions will be investigated during the project.

- What methods are most suitable to use in the pre-processing and data analysis of the EEG signal?
- Do the fragrances have a significant alerting effect on brain activity according to the EEG signal?
- If there is an alerting effect, does it differ between the trigeminal fragrance and the olfactory fragrance used in the trial?
- How long-lasting is the effect?
- Is the effect comparable to the result of ECG and EOG?

1.2 Specification of fatigue

It is well established that sleep and fatigue have a massive impact on the driver's performance [3], [4]. In order to understand the tools and techniques which aim to prevent accidents associated with sleep and fatigue the term driver fatigue first must be understood.

There are various types of driver fatigue which depend on how much the driver has slept, as well as the driving environment which affects the task load of the driver. Hence, driver fatigue can roughly be subdivided into sleep-related (SR) or task-related (TR) fatigue. SR fatigue is associated with sleep loss or being awake for a longer period of time. Also, the time of the day contributes to SR fatigue. This is due to the internal clock of the body which makes humans more prone to sleep during the night. TR fatigue on the other hand is related to tasks being either mentally overloaded or underloaded. Where an overloaded task in a car can be driving in an area with a lot of traffic and action going on. Underloaded tasks can instead be monotonous driving for a long period of time. In cases where the driver is under the influence of both TR and SR fatigue, the driver often is more fatigued than when only being affected by one type of fatigue [15].

In the study on which this thesis is based [1], the test persons were affected by both SR and TR fatigue to maximize their fatigue. They had worked a night shift before the driving sessions and hence were affected by both the internal clock as well as being awake for a long period of time. The two driving sessions were designed to be monotonous where the drivers were instructed to drive for a long period of time (up to 45 minutes). In the result section of this thesis where the level of fatigue will be analyzed from EEG measures the combined SR and TR fatigue will not be analyzed separately. Hence, SR and TR fatigue will simply be referred to as fatigue in that section to avoid confusion.

1.3 The origin of EEG

The brain consists of approximately 100 billion nerve cells, called neurons [16], [17]. Neurons are special in the sense that they are electrochemical, allowing them to transmit electrical signals to other neurons. Each neuron is connected to around 10 000 other neurons, resulting in a massive electrical network. The signals are a form of a chemical called neurotransmitters. They are able to travel through the neural networks due to postsynaptic potential and action potentials occurring in the cell. The process of generating impulses generates voltage. It is this potential change that lays the foundation for EEG. EEG is a non-invasive technique used to measure potential changes in the brain, also referred to as brain activity [16], [17].

EEG technique is only able to measure the voltage generated by a large group of active neurons and not just one or a few active cells. This is due to that the potential generated by a few cells is too low for the device to pick up. The amplitude of an EEG signal measured from the scalp is only around 1-100μV. In comparison, ECG signals have an amplitude of 1-5mV. Due to volume conductance from surrounding tissues and attenuation of the brain signals, EEG signals are mainly detected from regions of the brain closest to the scalp [16]. Hence, the EEG of the inner brain structures can not be recorded due to its position [17].

1.4 EEG measurement

The potential is measured using scalp electrodes, where the number of electrodes varies. For simplification, the electrodes are most often placed in an international standardized way called the 10-20 system [18]. Resulting in a fixed spacing between the electrodes of either 20% or 10% of the total range between them, which is the range from the electrode at the frontmost position to the electrode at the back. Other placements that can be used are the 10-10 and the 10-5 systems.

Every electrode has a name that consists of either one or two letters and a number. It can be derived from the electrode's position on the scalp. The area of the head is divided into five subareas, frontal area (F), central area (C), parietal area (P), temporal area (T), and occipital area (O). Hence, an electrode named CP2 is put on the cental-parietal area. The number indicates how far from the central area it is positioned. A low number is closer to the center while a high number is further away. The center itself is labeled as a "z" instead of a number. If the number is even it is on the right hemisphere and vice versa [16], [17]. The setup of electrodes used to collect the data which will be analyzed in this thesis is shown in Figure 1.1. Here two electrodes called M1 and M2 are used as well, referring to the right and left mastoid process [19].

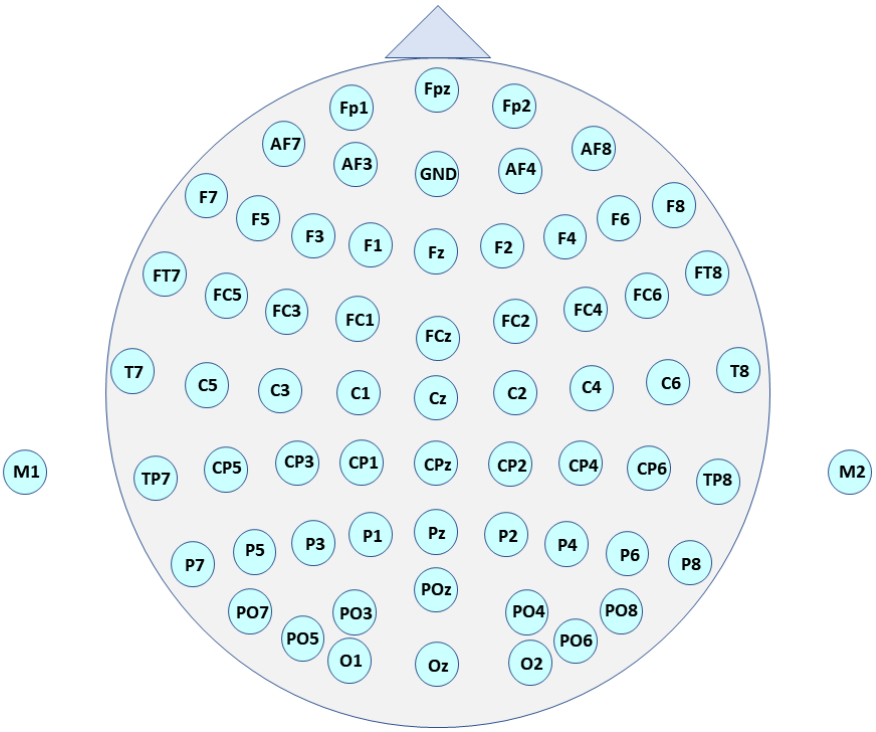

Figure 1.1: Scalp map of electrodes used in this study. Each electrode is named according to its position on the scalp.

The analog EEG signal is measured for all active scalp electrodes as the potential difference between each active scalp electrode and a common recording reference electrode (CRR). The CRR electrode is usually located in the center of the head, normally around Cz and Pz [20]. In addition, there is also a ground electrode (GND) which contributes to a reduction of power line noise. The measurement is accomplished by the use of a differential amplifier. It subtracts the potentials of the two electrodes (active and CRR) to get rid of noise and amplifies the remaining signal [18].

The result is one signal representing the active scalp electrode, referred to as a channel. After the conversion from analog to digital, the measured channels are referenced and displayed in a specific arrangement, called a montage. Depending on the aim of the EEG measurement, the montage can be chosen differently. One type of montage is the referential montage which displays the difference between each active scalp electrode and a set reference electrode. The set reference electrode is usually Cz. Another common montage is the bipolar montage. It takes the difference between the adjacent electrodes in a row. The direction of the row can be chosen differently. The next row's channels are then put beneath in the same way and so on [20], [17]. A referential montage was used during the collection of EEG data in this study using CPz as a CRR electrode.

1.5 Brain waves of EEG

The EEG signal is a visualization of the constant activity going on in the measurable parts of the brain. The main part of the signal consists of various rhythmic oscillations with peak-

to-peak amplitudes up to 75 μV. The main frequency spectrum of these oscillations is in the range of below 1 Hz to around 40 Hz [16]. The EEG can only be measured for frequencies up to 100 Hz. It is common to divide the measurable spectrum into five categories of ranges that are associated with specific mental states: Delta (0.5-4 Hz), Theta (4-8 Hz), Alpha (8-13 Hz), Beta (13-30 Hz) and Gamma (30 Hz and above). The five frequency ranges can be seen in Figure 1.2 over a time period of 1 second.

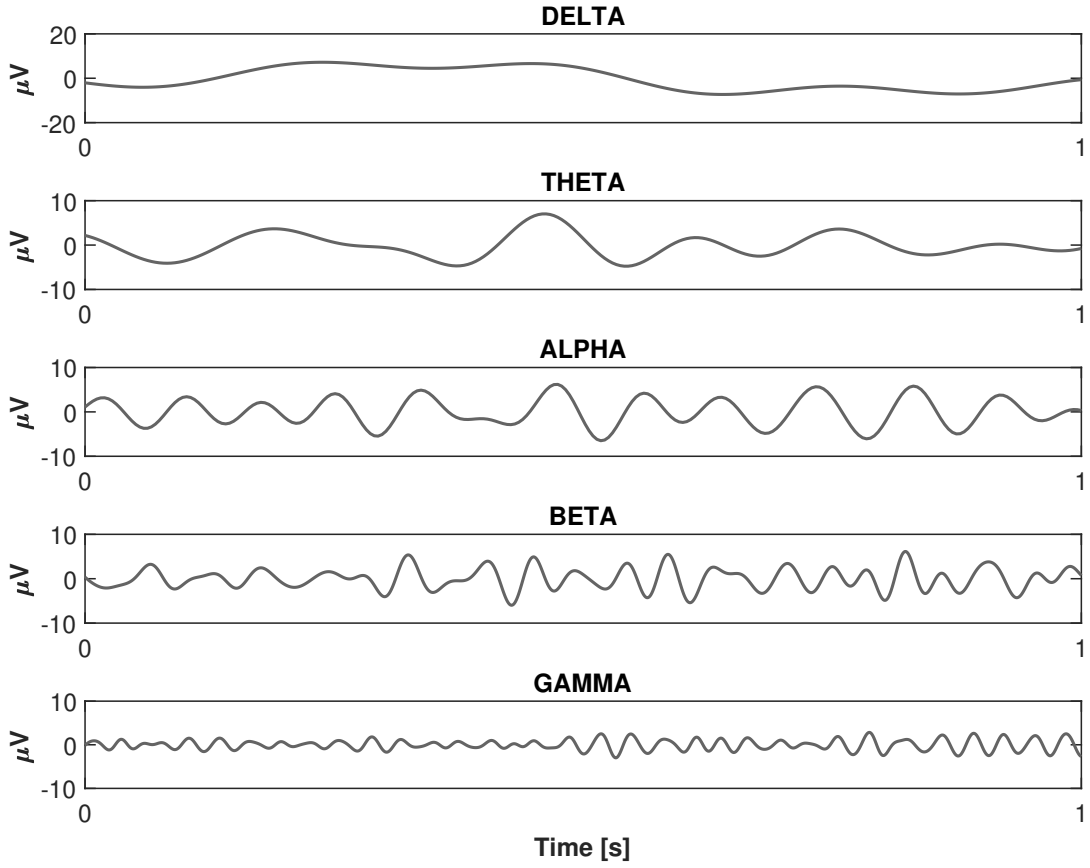

Figure 1.2: The measurable frequencies of EEG over a 1 second time interval. The Figure is done in MATLAB using data from EEG signals in this study.

Characteristics of Delta waves are that they have the lowest frequencies and highest amplitude. The bandwidth of Delta waves is mainly associated with low consciousness, deep sleep, or serious brain disorders [16], [17]. Theta waves are associated with drowsiness, emotional stress such as frustration and disappointment, deep meditation, and some sleep stages [16], [17]. The Alpha frequency band is the most common range to observe in the awake and relaxed state, for instance during rest while eyes are shut [17]. Beta waves are associated with several mental states, for instance, active concentration, problem-solving, and excitement. Gamma waves have the highest observable frequencies [17]. It is associated with cognitive functions such as learning and information processing. The amount of literature regarding the different EEG waves varies and a lot of the cognitive traits can overlap.

1.5.1 Former studies on frequencies associated with fatigue

As previously mentioned in Section 1.5, the lower frequencies (Delta, Theta, and Alpha) are associated with different stages of sleep and fatigue. In several studies where EEG has been used to measure the changes in brain activity it has been shown that an increase in the power of Delta, Theta, and Alpha waves are associated with an increase in drowsiness [12], [13], [14].

In a review on the psychophysiology of driver fatigue, the correlation between the distribution of various EEG frequency bands as indicators of drowsiness was examined by Lal and Craig, [12]. It was concluded that EEG shows promising results in distinguishing fatigued drivers, where the indicator for drowsiness mainly could be seen as an increase in Delta-, Theta- and Alpha-waves.

In a study by Ahlström and Zemblys et al. [13], where the development of sleepiness was studied when driving a manual car compared to a partially automated car, the EEG was measured together with other psychological measurements. The result concluded that partially automated driving results in increased sleepiness where an increase of power in central Alpha-waves, frontal Theta-waves, and central Theta-waves also was shown [13]. Similar EEG results were conducted in a driving simulator study by Ahlström and Anund et al. [14], where the effect of daylight versus darkness on driver sleepiness was examined.

Awais and Badruddin et al. [21] made a study where the aim was to examine the significant changes occurring in the EEG power spectrum when driving monotonously for a period of time. An increase of both Alpha and Theta power could be seen, and it could be concluded that a significant increase occurred when the drivers went from a state of alertness to drowsiness [21].

Also, Beta has been shown to be useful when examining fatigue. A decrease in Beta power can be a sign of increased fatigue since it is more common to see Beta activity in more alert mental states [22], [23]. In a simulated driving study of drowsiness [22], test persons were sleep deprived, and Beta along with other frequency ranges was used as a feature for measuring drowsiness. It was seen that the ratio (Alpha + Theta)/Beta could be connected to the mental alertness level. The ratio was seen to increase after performing several driving periods as a sign of decreased alertness [22].

1.6 Countermeasures for sleepiness

As earlier mentioned in section 1, fatigued drivers have a higher risk of contributing to road accidents. To prevent drivers from falling asleep while driving, technologies that detect sleepiness and alarm the driver has been developed. The system detects traits of sleepiness by monitoring the behavior of the driver in various ways. In case of deviation, an alert goes off. The way of alarming the driver differs but it is common with both a visual and sounding alarm. These alarm systems help the driver recognize sleepiness to take sleep-preventive actions, such as stopping for a break [6]. Also, implementations on the road, such as rumble strips are a way to alert drivers. The stripes warn the driver by emitting both the sound and feeling of vibrations when crossing the stripes [24].

Both the rumble stripes as well as the alarming systems have been shown to have a positive impact on drivers. An implementation of rumble strips along the sides of a highway has been shown to decrease the number of severe crashes involving death by close to 24% [24].

In a study performed by Gaspar and Brown et al. [25], it could be seen that alarm systems improved the driving pattern of drowsy drivers. In the study, commonly used alarming countermeasures were evaluated. Lane departures for drowsy and non-drowsy drivers were measured with and without drowsiness countermeasures. It was concluded that drowsy drivers with countermeasures had fewer lane departures in comparison to drivers without countermeasures [25]. However, in order to induce drowsiness in the drivers in the study they were made to drive at night or in the early morning, meaning that it is uncertain if the systems have the same effect on more sleep-deprived drivers. Such as drivers who are on the edge of falling asleep by the wheel.

Apart from what is implemented inside the car or on the roads to prevent sleep-related accidents the actions of the driver are ultimately the most effective countermeasure for such accidents. Actions such as stopping for a break, taking a nap, or entirely avoid to drive when feeling fatigued. In a survey by Anund and Kecklund et al. [26], the most common self-administered countermeasures when feeling fatigued while driving were requested. The three most commonly reported methods were stopping to take a walk, turning on the radio/stereo, or opening a window. In studies where such countermeasures were evaluated no significant increase in alertness could be seen when having the radio on, nor when blowing cold air in the face of the driver. On the other hand, both consuming caffeine and taking a nap was shown to have a significant effect [27]. A drawback with such countermeasures is that it relies on the fact that the driver has the possibility to stop straight away, which is not always the case. It requires the driver to be enough motivated to take action and that the logistics of the road allows for a nearby stop.

An addition to the current solutions could be to add an alerting element that automatically is administered in case of drowsiness detection, such as alerting fragrances. The use of fragrances may be a way of increasing the alertness in fatigued drivers, allowing for a further drive until it is possible to stop as well as easing the most acute fatigue.

1.7 Olfaction and brain activity

Humans have two cranial nerves in the nasal cavity: the olfactory nerve and the trigeminal nerve. Together these nerves create two different responses if exposed to odorants. The first response is the sense of smell or identification of odorants and is related to the olfactory nerve [28], [29]. Typical odorants triggering the sense of smell are for example vanillin and rose [28]. An image of the olfactory sensory system is shown in Figure 1.3. The second type of response is sensation related to the trigeminal nerve, also connected to protective reflexes [28]. Some examples of trigeminal sensations are burning, stinging and tickling [28], [30]. These sensations can be triggered by mustard oil, capsaicin (a substance in chili) [28] and carbon dioxide (CO_2) [31]. Figure 1.4 shows the trigeminal sensory system.

Figure 1.3: Olfactory sensory system highlighted in orange and yellow [32].

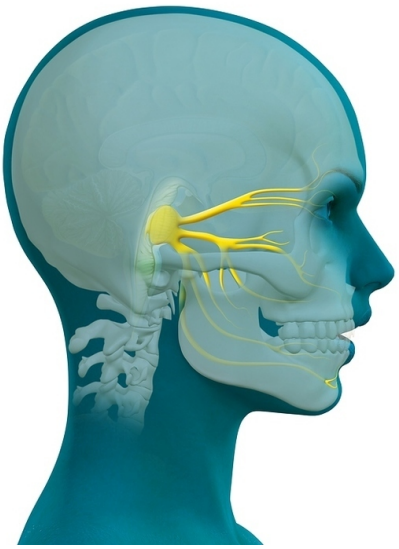

Figure 1.4: Trigeminal sensory system highlighted in yellow [33].

Most fragrances trigger both the olfactory and trigeminal systems simultaneously to some extent [30]. The two responding systems are independent but they have overlapping activation in the brain and can influence each other [30]. A few odorants affect only one at a time, for example, vanillin (the primary taste of vanilla), exclusively affects the olfactory system [28] and CO_2, exclusively affects the trigeminal system [31]. Fragrances are able to cross the blood barrier and reach the central nervous system, thereby directly producing changes in physiological parameters such as blood pressure, muscle tension, brain activity, etc [34]. Fragrances mainly produce reactions in the subcortical brain (inner brain), but may still be shown partly in EEG [35].

1.7.1 Former studies on alertness induced by fragrance

Several studies have looked at alertness induced by olfactory and trigeminal stimulation [31], [29]. Earlier research that led to this work is, for example, a study by Heiser and Baja et al. [10] that investigated wake-up frequency during the night for 10 persons exposed to CO_2. They tried different stimulus durations, 1, 3, 5, and 10 seconds, as well as different concentrations. The interval between stimuli was 60 seconds, and the substance, CO_2, was given from a tube directly into the nostril. Under normal circumstances, people wake up regularly with a certain wake-up frequency, and this frequency increased depending on both concentration of CO_2 and duration of fragrance administration. The definition of arousal was abrupt changes in EEG for either *Alpha*, *Theta*, or frequencies higher than 16 Hz, and this should last for at least 3 seconds, followed after 10 seconds of stable sleep [10].

Another study, also by Heiser and Baja et al. [31], found that olfactory stimulation alone could not induce alertness in a sleeping person, but opposite to this, trigeminal stimulation can. This is because pain sensations result in an alarm mechanism, which is why the person gets alerted. The fragrance used in the mentioned study was CO_2 which only triggers the trigeminal system and results in pain sensation. The level of alertness depends a lot on the concentration and duration of the stimulus. An increase in pain led to increased arousal [31].

Other studies regarding fragrance's effect on sleepiness and or sleepy driving do not mention the trigeminal system in their research, for example [5], [7]–[9], [11]. The results from these studies can still be of interest when looking at trigeminal effects since the fragrances that are included in the studies activate the trigeminal nerve. A fragrance that has been tried out repeatedly is peppermint [5], [7], [9], [11]. Peppermint is known to trigger both olfactory and trigeminal nerve [31], where the trigeminal effect is efficient [11]. It has also been shown to increase alertness [5], [7]–[9], [11] and athletic performance [5].

Different aspects of how to make the alertness effect of peppermint more efficient have also been investigated. One factor is to use an intermittent release of the fragrance which has been shown to increase the alerting effect of fragrances [7]–[9]. In a study by Funato and Yoshikawa et al. [8], it was found that intermittent release of peppermint increased alertness level enough so that the driver could drive steadily. The test persons experienced task-related fatigue but it was not mentioned if they had any sleep-related. In the same study, it was stated that the duration of fragrance presentation is important, and if the periodic cycle was too short it led to adaptation to the fragrance, but if the period was too long, the alertness level decreased. Yoshida and Kato et al. [7], conducted a study where they compared fragrance representation times of 30 and 60 seconds. The test persons had got sufficient sleep the night before so during the test they experienced task-related fatigue. For 60 seconds intervals, the alertness lasted 9 minutes, and for 30 seconds intervals, the driver kept alert for 16 minutes. Raudenbush and Grayhem et al. [9], showed that a significant increase of beta waves was followed after exposure to a periodic presentation of peppermint and cinnamon, separately. Also in this study they looked at task-related fatigue.

Some other factors that have been investigated are tiredness level before fragrance release [36] and adaptation to fragrances, [8]. In [36], it was concluded that fragrance has to be administered above a certain alertness level to have an effect. In this case, the level was when the person is slightly sleepy but not visibly sleepy. A further definition of sleepy is not provided in the study. Regarding adaption to fragrance, a possible method that could prevent this is to switch back

and forth between multiple fragrances [8].

1.7.2 EEG to measure the general effect of fragrances

Several of the studies in section 1.7.1 did not use EEG for deciding if the fragrances had an alertness effect. Instead, they use other methods, for example, image processing to detect eye blinks [7], reaction time [5], steering characteristics, facial expression [8], and more. In this section, some studies are brought up that have looked at the general effect and not only the alerting effect, on EEG signals induced by different fragrances [34], [35], [37]–[39].

Park and Kim et al. [37], measured EEG before and after inhalation of three different fragrances, peppermint, lavender, and coffee. The inhalation was done for three minutes and they looked at changes in Alpha- and Beta-waves. Alpha significantly increased for lavender, indicating a calming effect, while it decreases for peppermint and coffee indicating an alerting effect. Beta changed in the opposite direction. Alpha increased in most brain regions and Beta decreased in prefrontal regions.

A review by Sowndhararajan and Kim et al. [34] stated that EEG is sensitive to brain alteration due to fragrance exposure and has great promise for increasing knowledge about human responses to fragrances. Some findings from different studies mentioned in this review are that inhalation of lavender oil or chamomile decreased Alpha power at parietal and posterior temporal regions, and this decrease is correlated with a comfortable state. Also, unpleasant odors lead to an increase in Alpha power [34]. Beta increased in the left frontal brain for pleasant odors. The effect of fragrance is different between people because of different likings. There are several more studies on various fragrances but there is no common pattern for how EEG signals respond to fragrances in general [35], [39].

In [34], they also found several factors that differed in the methods of studies. Administration of fragrance, number of electrodes, recording time, etc. It was concluded that EEG analysis of the effects of fragrances has limitations because of non-standardized research methods. Fragrance concentration, recording duration, and the number of participants are examples of factors that influence results in different ways. Also, gender has an effect since it is seen that women are more sensitive to fragrances than men [38], [40].

1.8 EEG signal processing

In the following sections, various techniques and knowledge used for the analysis of EEG data will be presented.

1.8.1 Preprocessing

Raw EEG data contains unwanted artifacts from different sources, [41], [42]. As mentioned in Section 1.3, EEG signals are very weak and have to be amplified, which leads to a consequence that also artifacts get amplified. Artifacts can be either physiological or non-physiological, physiological artifacts occur in the body such as muscle activity, eye blinks, and heart rate, while non-physiological artifacts occur from wireless telecommunication, recording equipment, cable wires, etc [41], [42]. In the recorded data, artifacts are usually where the amplitude is higher than the rest of the signal, as well as appearing as peaks and fluctuations [43].

To remove artifacts, data has to go through different steps of preprocessing. The goal of preprocessing is to clean the raw data by removing artifacts while at the same time keeping as much measured brain activity as possible [41], [42], [44]. Preprocessing can be done in various ways depending on the kind of analysis, study goal, and how data is gathered [41], some general steps that often are used will be described in this section.

1.8.2 Filtering

An early stage in preprocessing is to filter the raw data in various ways. Common filters are highpass, lowpass, bandpass, and notch filters [42], [44]. Bandpass is common to use since it includes removal of both low and high-frequency components that are known to contain unwanted information. For example, in EEG analysis it is common to study certain frequency ranges and frequencies that are outside these can be disregarded. However, if too much frequency content is filtered away it can disrupt the waveform of the signal [44]. A common range to use is a low cut frequency of 1 Hz and a high cut frequency of 50 or 60 Hz [44]. Another often-used filter is a notch filter that removes line noise. One type of line noise is power line voltage which occurs at either 50 or 60 Hz depending on which country you are in [45], [44]. Not only cut-off-frequency is important when using filters. Filtering should be applied before dividing a signal into epochs since the filtering can lead to unwanted edge effects [46].

1.8.3 Bad channel detection

Some electrodes can have extreme amplitudes, in both height and fluctuations and can be regarded as bad channels. This can occur due to poor conductance between the electrode and the scalp. A so called z-score is often used to decide which channels that pass a pre-determined threshold and should be classified as bad channels. Another way to classify bad channels is to look at the correlation between channels. If a channel behaves as it should, the correlation across channels is usually seen in low-frequency components [42]. If a correlation still can be seen after removing low-frequency components through highpass filtering, that could be a sign of a bad channel. After bad channels have been removed, it is possible to replace them by interpolating neighboring channels [42], [46].

1.8.4 Removal of bad data segments

Some segments of the data may have large artifacts that are difficult to filter away or remove with the other preprocessing methods. These segments can be rejected by cutting the data. For example, if an artifact lasts for several hundred milliseconds, this time period can be rejected. Data rejection can be done manually by visualization, or automatically by setting a threshold for amplitude [46].

1.8.5 Artifact removal with ASR

Another method that can be used for artifact removal is Artifact Subspace Reconstruction (ASR). It uses principal component analysis (PCA) which is a statistical tool used to reduce dimensionality in the dataset. It distinguishes the amount of variance in the different components of the data [47], [48].

In more pure PCA-based artifact removal methods components in PC-space with the greatest amount of variance gets rejected [47]. This is not the case for ASR. Instead, this algorithm identifies and gathers parts of the raw data that are clean and uses it as a reference to know what components to reject in the PC space [47], [48].

The reference data is identified and sorted out by examining the distribution of signal variance in the raw data. This examination is done repeatedly for short time windows of each channel and they are then analyzed together. The time windows that are identified as clean are then concatenated, resulting in the reference data. This process leads to varying lengths of reference data for different EEG signals depending on the amount of present noise. The rejection criteria or the threshold can then be determined from collected reference data in PC-space [48].

The reference data is projected onto the principal component (PC) space where the thresholds are decided from the mean μ and standard deviation σ calculated from small segments of the data windows. Given the thresholds for the rejection of artifacts ($T_i = \mu_i + k\sigma_i$), the cleaning of data can be done. The parameter k is set by the analyzer. It heavily affects the result of the ASR. In a study where ASR in EEG analysis was evaluated, it was concluded that a k value between 20 and 30 is recommended [48].

For small segments at the time, the principal components of the raw signal are compared with the estimated thresholds. If the component is out of range, it is rejected. When all components that are above the threshold are removed the channel data gets reconstructed from the remaining clean components. As a result, the signal gets cleaned from various artifacts [48].

1.8.6 Artifact removal with ICA

Another method that can be used for artifact removal in EEG signals is Independent Component Analysis (ICA). ICA is a method used to classify the data into brain signals and artifacts related to eyes, muscles, heart, etc [46], [49], [50]. It is a widely used method to remove such physiological artifacts [44], [46], [49]–[52]. ICA is a decomposition method that identifies independent sources of variance and thereby subdivides a signal into additive components [46]. An easy way to look at it is to see it as a cocktail party problem, where you try to isolate a conversation from surrounding conversations or background noise [52], [53]. It is based on the assumption that a signal is composed of statistically independent components and non-Gaussianity [49], [52]. With this assumption, it is possible to isolate artifacts and neural activities in an EEG signal [52].

Mathematically, if you have an N-dimension data vector $X(t) = [x_1(t)...x_N(t)]^T$ at each time point t, ICA will find an unmixing matrix, W, that creates the independent components $Y(t) = [y_1(t)...y_N(t)]^T$, which are a linear combination of W and $X(t)$ [50].

After decomposing an EEG signal with ICA, each component can be classified into either artifactual or neurological [46]. This process is done by the use of a pre-trained classifier [48]. The artifactual components can then be subtracted from the data. After subtraction, the components that are left can be mixed together using the inverse of the unmixing matrix W. Also, ICA can determine where in the brain each EEG source signal is generated [54].

Since most classifiers used to identify artifact components are pre-trained to distinguish common components such as eyeblinks, muscle artifacts, and brain waves they are not adaptive to different datasets. Hence, ICA is in many cases less effective at distinguishing and removing

non-biological artifacts. Such artifacts are usually high in amplitude and caused by sudden motion or other external noise [55], [56].

For ICA to work properly it is important to have enough data points [52] and to also be careful when performing earlier pre-processing steps [55]. In a study by Zakeri and Assecondi et al. [55], it was concluded that chosen preprocessing methods significantly impacted the performance of ICA, while different ICA algorithms produced more or less the same results.

By comparing ICA with ASR, ASR is more adaptive to various datasets since it automatically cleans the data by using the raw signal to create reference data [48]. This makes ASR more effective at removing motion artifacts or other non-biological artifacts [47]. It is therefore often suggested to use ASR as a pre-processing method before ICA, to get an ICA with higher quality [48].

1.8.7 Selection of channels

The number of electrodes used in EEG studies differs a lot and can range between 1 to 256 electrodes [41], [57]. A high number of electrodes increase the spatial resolution but can result in bad-quality data because it is harder to detect and fix potential problems when using many electrodes, but if using too few there is no room for mistakes in case some channels are bad [41].

In a review on EEG-based sleep detection [57], different electrode setups are suggested, and even using only one electrode, some studies reached a high accuracy rate on sleep detection. For example, using F8, the accuracy was 90.60 %, and using Oz, the accuracy was 98.20% [57]. One should have in mind that other things, such as different algorithms, affected these results. The same review lists different electrodes but there is no standard setup [57]. Also in the review [34] which was described in section 1.7, the number of electrodes differs a lot. Examples of the number of electrodes mentioned from several studies are 2, 4, 6, 8, 12, 21, 28, and 31 [17], [34], [35], [37]. Despite not finding any standard selection of electrodes, there are some studies on where certain waves occur in the brain, and the results from these are varied.

Alpha is said to particularly occur over the occipital region in general, and Beta in the frontal area [17]. However, when examining studies concerning EEG during fatigue or fragrance administration, the occurrence of the wavelengths varies between all brain regions [12], [14], [21]. In a study on fatigue, Alpha and Beta occurred in both the occipital and parietal regions when getting from alert to drowsy [21].

Hence, there is no definite rule saying that a certain wavelength occurs in only one area of the brain, and different sources state somewhat different findings. In the review concerning the psychophysiology of driver fatigue, mentioned in section 1.5.1 [12], they point out the importance of selecting electrodes that cover most scalp regions because EEG changes differently at different sites and not always simultaneously.

1.9 Feature extraction

A feature can be described in several ways but in short, it is a distinctive or characteristic measurement, which can be extracted from a pattern [45]. Depending on the aim of the EEG analysis the features of the signal are chosen differently. In the medical field, EEG is usually

used for diagnostic purposes, to examine neurological disorders and other deviations. Such as examining epileptic seizures, and locating the seizure origin in the brain. Other areas such as the effects of drugs, mental disorders, and brain development can also be analyzed [17], [18].

In research where the brain effect of a stimulus is of interest, EEG is often used for analysis. If a stimulus or a movement is time-locked to a very exact time point, the EEG is usually examined by looking for event-related potentials (ERPs). ERP is an average EEG voltage response to a specific event or stimuli [17]. When examining ERP several trials are summed up to an average potential, creating a waveform that can be associated with the specific stimuli [58].

ERP is an example of how to examine the amplitude of the EEG signals in time domain. A drawback with time domain is that it lacks frequency resolution. Feature extraction can also be done using frequency, space, or time-frequency domain [44].

As opposed to ERP analysis, EEG regarding sleepiness is usually not related to a specific stimulus, but rather to frequency changes over a longer period of time, and in that case, the frequency distribution of a signal can be very informative, as mentioned in section 1.5. To include frequency resolution in an analysis, the EEG signal can be examined in the frequency domain where the distributed power of each frequency in the signal can be visualized. It can also be combined with the time domain to include both the temporal aspect as well as the frequency aspect, a so called time-frequency analysis [59].

In former studies on EEG applied to sleepiness detection while driving, feature extraction methods differ, but they usually include frequency domain [57], [60], [61], [62], [50]. It is suggested that when doing research on fragrances one should use time-period analysis rather than spectral analysis because of better sensitivity [35]. However, since this study focuses more on sleepiness level and since the fragrance stimuli are not time-locked to a specific second, a spectral analysis will be used. Some common EEG analysis methods in the frequency domain will be presented in the following sections.

1.9.1 Frequency analysis

By looking at a EEG signal in the frequency domain it is possible to see changes in signal power for specific wavelengths. For example, one can visualize an increase or decrease in Alpha waves and then draw conclusions from this. The fundamental principle behind spectral analysis is the Fast Fourier transform (FFT), which is built upon the fact that every signal can be represented as a summation of waveforms with different phases and amplitudes. FFT can be either continuous or discrete, and since measured signals are discrete, the discrete-time Fourier transform is usually used. The formula for this is followed here, in equation 1.1 [59], [63].

$$X_k = \sum_{n=0}^{N-1} x_n e^{-2j\pi kn/N} \tag{1.1}$$

One problem when applying Fourier analysis on a signal is that it requires the signal to be stationary, which is not the case for real signals and the consequences are that the calculated power spectrum (periodogram) will be biased and contain a lot of variances. There exist many methods to deal with this issue, and one commonly used method, Welch's method will be investigated further in the following section [59], [49].

1.9.2 Welch's method

Welch's method [64], is used to create a modified periodogram with less variability [59], [65]. The method uses Fourier transform on segmented parts of the signal to calculate an averaging periodogram.

Assume the signal of interest is expressed as

$$X(n), \quad n = 0, 1, ..., M-1$$

where M is the number of samples. If the signal is divided into k segments it can be expressed as

$$X_k(n) = X(n + kD), \quad n = 0, ..., M-1 \text{ and } k = 0, ..., L-1$$

where D is the length between each segment's starting point and L is the length of each segment. By doing this an overlap is created between the segments.

Given that there are k segments for the entire signal $X(n)$, then the other parameters are correlated as $kD + L = M$.

Each segment is elementwise multiplied with a windowing function $W(n)$, also referred to as a taper. This is done to avoid edge artifacts that otherwise would occur when transforming the segments into frequency domain. A periodogram of each window-modified segment is then created using the Fourier transform

$$P_k(f) = \frac{1}{LU} \left| \sum_{n=0}^{L-1} X_k(n) W(n) e^{-2j\pi fn} \right|^2 \tag{1.2}$$

where U is the normalized power of the window function

$$U = \frac{1}{L} \sum_{n=0}^{L-1} W^2(n) \tag{1.3}$$

The periodograms are then averaged together creating the final Welch's power spectral density (PSD) of the signal

$$P_{welch} = \frac{1}{L} \sum_{k=0}^{k-1} P_k(f) \tag{1.4}$$

The resulting power spectrum is more smooth than an ordinary periodogram. Making it easier to read and distinguish the distribution of power between frequency bands. Depending on the choice of parameter the resulting spectrum varies [45], [64]. The larger the window size, the more frequency resolution you get, but also more noise.

2

Methods

In order to examine the effect of the fragrances on fatigue drivers, the data from the performed study had to be processed using a variety of signal-processing tools. As mentioned in section 1.8 there is no standardized way to examine EEG data and the methods differ a lot depending on the aim of the analysis. A variety of suitable tools for this specific analysis were conducted by doing a literature review on EEG analysis. In the following sections, the EEG data will be presented in more detail as well as the methods used for preprocessing the data, extracting features, and performing the statistical analysis.

2.1 The gathering of EEG data

The EEG data, as previously mentioned, is collected from an already-performed study [1] and has been anonymized. The data is collected from 21 healthy test persons who each performed two simulated driving sessions. The individuals performing the test were 12 males and 9 females between 30-60 years old with a normal sense of smell. They are all shift workers and performed both driving sessions after finishing their night shift. The test persons drove until they fell asleep, where the definition of falling asleep was when their eyes were closed for more than three seconds. At that point, an administration of one of the fragrances was done. If they did not fall asleep, they were administered with fragrance after 45 minutes. A test observer pressed the administering button when it was seen that the driver fell asleep. The duration of the fragrance release was 3 seconds. After the administration, they continued driving around 20 minutes. At the first driving session for each test person, the administered fragrance was randomly chosen between subjects. The trigeminal fragrance was administered to eleven test persons for the first driving session and ten for the second driving session. Figure 2.1 shows how the fragrance system was attached to the test persons. For more details regarding the collection of data, see [1].

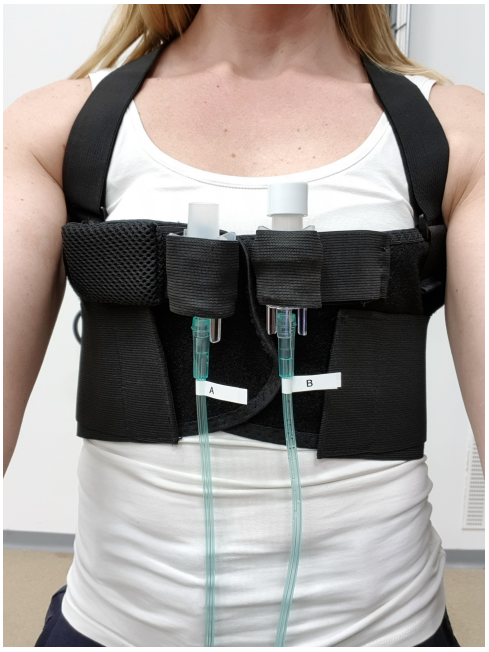

Figure 2.1: The fragrance administration system which was attached to a vest. The two tubes contained the two fragrances (A and B).

From now on the two fragrances used in the study will be referred to as vanilla and trigeminal. Trigeminal is the fragrance that stimulates the trigeminal nerve and vanilla is the fragrance that does not stimulate the trigeminal nerve, with the smell of vanilla. The substance of the trigeminal fragrance is confidential but is created for the purpose of stimulating the trigeminal nerve.

2.2 Preprocessing

The pre-processing steps involving cutting, filtering, and cleaning of data will be described in the following sections.

2.2.1 Cutting of data

The raw data included 42 files, one for each trial. Most of the files were above 45 minutes long, so the data was cut into 22 minutes, where 11 minutes was from before the fragrance administration and 11 minutes after. The time period of interest was selected to be 10 minutes before fragrance and 10 minutes after. However, since the pre-processing steps involve some steps where some data is cut out and therefore shortened an additional minute was added to have room for removal in the cleaning step. The main purpose of cutting the data was because it is most interesting to look at what happens during the minutes closest to the release of the fragrance. From previous studies where fragrance administration was performed, the effect usually does not last longer than around 10-15 minutes, which was also with repeated administration of the fragrance, see Section 1.7.1. Hence, a longer time period than 10 minutes after the administration time seemed unnecessary to analyze.

One thing that had to be taken into account was that during some trials the test persons fell asleep, either after a short time of starting the session or a short time after fragrance exposure. For these trials, it was not possible to extract 11 minutes of data before and after fragrance, and therefore, the cutting length was adjusted depending on how much time was recorded for each individual. In three of the 42 sessions, the drivers fell asleep before 11 minutes, resulting in a shorter signal to analyze for those sessions. The time periods of those sessions were cut to 6, 8, and 10 minutes. Similarly, the driving time period after the fragrance administration differed; six sessions were cut short to 4, 5, 5, 6, 9, and 9 minutes.

After cutting the data, the raw EEG data were preprocessed using the interactive toolbox EEGLAB in MATLAB. EEGLAB is a widely used program for EEG analysis and includes functions within preprocessing, data visualization, ICA, and more [52]. The position of the channels was located inside the EEGLAB's interface to simplify future analysis. Some channels, called BIP, include other types of physiological signals that are not associated with brain signals. All channels named BIP were eliminated. The fragrance event was then added as a marker in each session.

2.2.2 Down-sampling and filtering

In the experiment, the data were sampled at 512 Hz. It was then down-sampled to half the frequency, 256 Hz to optimize computational efficiency. Resulting in a Nyquist frequency of 128 Hz which is appropriate for EEG data which can only measured between 0-100 Hz as mentioned in Section 1.5.

The data was then passed to a bandpass filter, using EEGLABS's inbuilt filter `pop_eegfiltnew` with a low cutoff frequency of 1 Hz and a high cutoff frequency of 60 Hz. The function uses a hamming windowed sinc FIR filter. The frequencies of interest for the spectral analysis are in the range of Alpha, Theta, and Beta waves which are between 4-30 Hz. The reason for not using these limits for the bandpass filtering is that the data can be disrupted if removing too much information, and also to get better ICA results. To remove power line interference a notch filter was applied to remove the 50 Hz frequency. The result from filtering the data can be seen in Figure 2.3 in comparison to the unfiltered data in Figure 2.2. It displays the data for the channels shown in the y-axis over a 10 second interval. The channels are stacked together to easier distinguish changes. The most obvious result from the filter is that the low frequencies are gone. In the unfiltered data, there is a slow, big wave that can be seen, and in the filtered data this wave is almost removed, resulting in the data following a more straight line. It is not as easy to see that the higher frequencies disappear, because the data does not have so much content above 60 Hz.

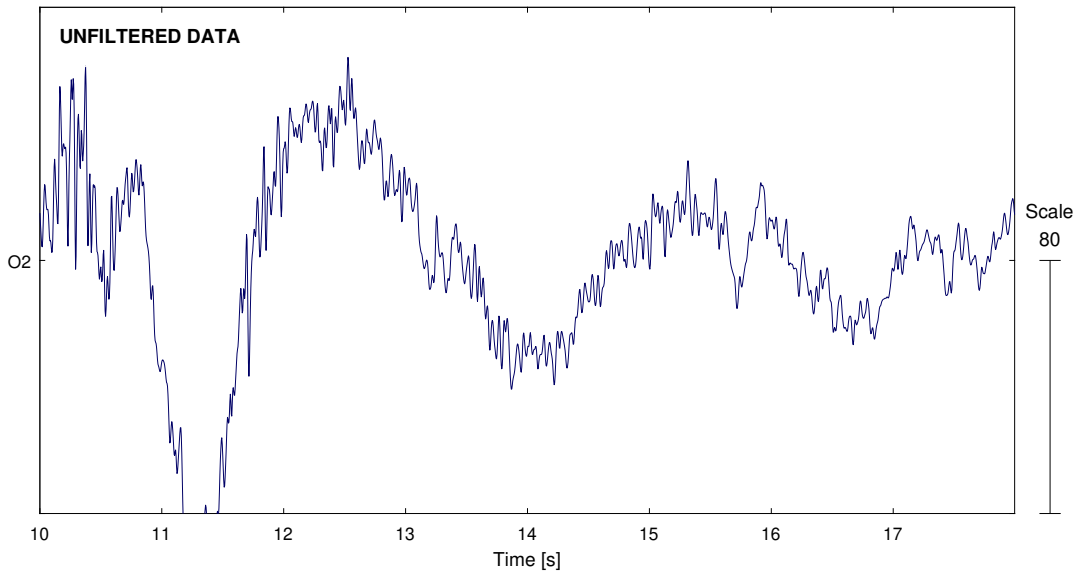

Figure 2.2: The unfiltered EEG-signal after downsampling but before filtering. It is shown for channel O2 over an 8 second interval.

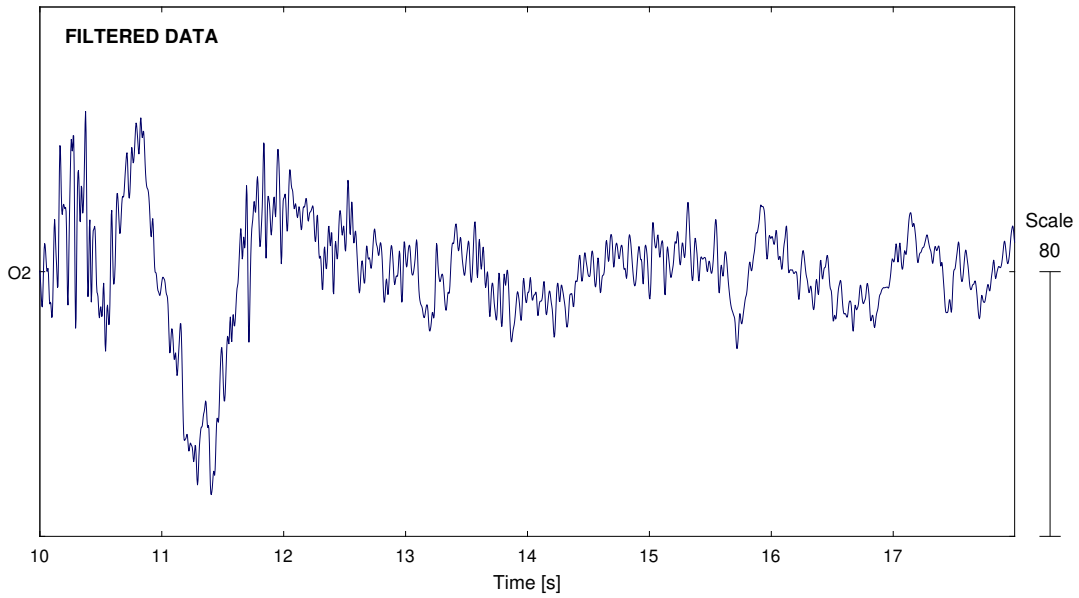

Figure 2.3: The EEG-signal after highpass and lowpass filtering for channel O2 over an 8 second interval.

2.2.3 Cleaning of data

The next step, after filtering, was to clean the data using EEGLAB's function `clean_rawdata`. This function makes the cleaning more controlled and standardized compared to cleaning every data file manually. Properties of the function include the removal of bad channels, subspace reconstruction of noisy data segments, and sometimes the removal of bad data periods. For most parameters in the function, EEGLAB's default values were used, if no information was found elsewhere regarding a certain parameter. To check if these settings were a good choice, a few trials were done changing some parameters. Similar results were seen for the different cases, which led to keeping most of the default settings.

Removing bad channels includes three inputs that control the classification of bad channels. First, a channel was considered bad if the signal was flat for more than 5 seconds, second, if the maximum high-frequency standard deviation was above 4, and lastly, if the correlation with nearby channels was below 80%.

The subspace reconstruction in the function is done using the ASR method where the threshold, which was referred to as the k parameter in section 1.8.5, was set to 20. The ASR method is described further in 1.8.5. An additional way of removing bad data periods was used in case ASR fails for some data periods. This criterion is based on how many channels that pass a certain threshold in a given time window. Here the parameters were set to 25 and -Inf 7, where 25 is the percent of channels allowed to cross a given threshold, and -Inf 7 is the acceptable power range including standard deviation.

After the first try of using the `clean_rawdata` function, it was found that three trials lost their fragrance event as a consequence of the automatic removal of bad data segments. To fix this, manual data removal was performed for those trials around the fragrance event, before using the `clean_rawdata` function. Noisy data were removed as close to the event as possible to inhibit the function to further clean around the event. This method worked to keep all the events and the three trials could then be analyzed together with all other trials. The process of removing bad segments also resulted in a shortened length of the total data. This was not considered an issue since the total amount of removed data where a few seconds which is a neglectable amount compared to 20 minutes. Also, the statistical analysis is done on averaged time intervals of 10 seconds, and thereby the removed segments are averaged out.

The result of `clean_rawdata` can be seen in figure 2.5 in comparison to the data that was only filtered, in figure 2.4. The figures show the data for five channels shown in the y-axis over a time period of 5 seconds. The reason behind looking at those specific channels is motivated in section 2.3. In figure 2.4 there is a peak around 32 seconds that is probably from an eyeblink, and it is seen most clearly at channel AF4. This peak is removed for all channels in figure 2.5.

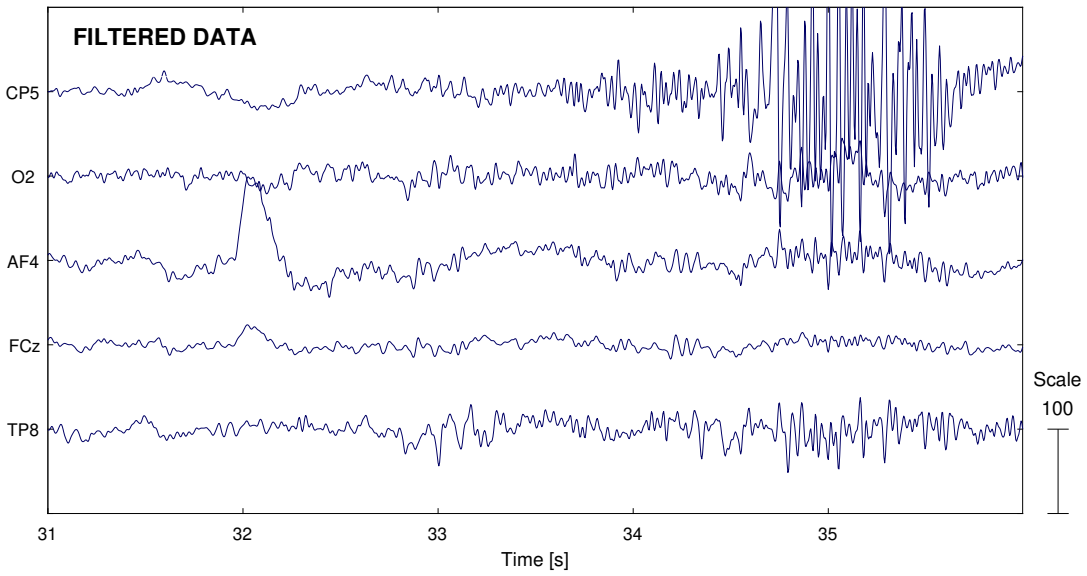

Figure 2.4: The filtered EEG signal for channels CP5, O2, AF4, FCz and TP8 over a 5 second interval. A peak can be seen around 32 s for AF4, which is probably an eye blink. Also, an artifact can be seen around 35 s for CP5.

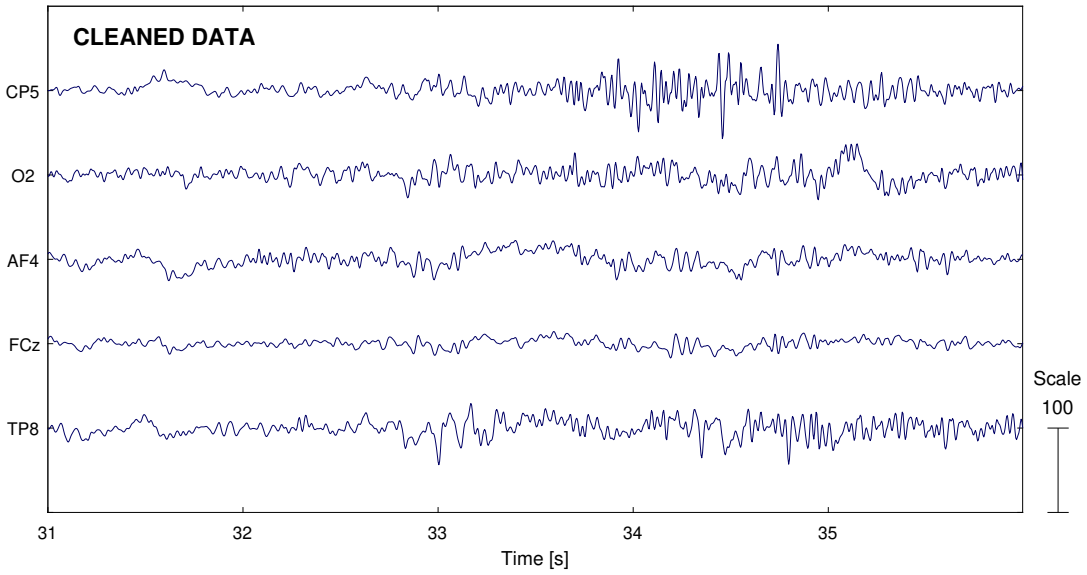

Figure 2.5: The filtered and cleaned EEGsignal for the channels CP5, O2, AF4, FCz and TP8 over a 5 second interval. The artifacts that could be seen for AF4 and CP5 in Figure 2.4 are removed.

2.2.4 ICA decomposition

The last preprocessing step was to perform ICA decomposition, which was the most computer-heavy step of the process. The inbuilt function called `pop_runica` from EEGLAB was used to perform the ICA algorithm. The decomposed components were extracted using the `ICAlabel` function which classifies the components as either brain, eye, muscle, or other activities with a certain percentage. The components that were classified as eye and muscle with at least 90% certainty were then removed from the data, restoring the data without these components. When lowering the percentage to 80% or 70% certainty, a few more components, mainly those classified as muscle artifacts, were discarded. This difference was barely visible and it was decided to keep the 90% limit in case of unnecessarily losing important data. Figures 2.6 and 2.5 show the effect of applying ICA compared to when only cleaning the data. It can be seen that some high frequencies have been removed.

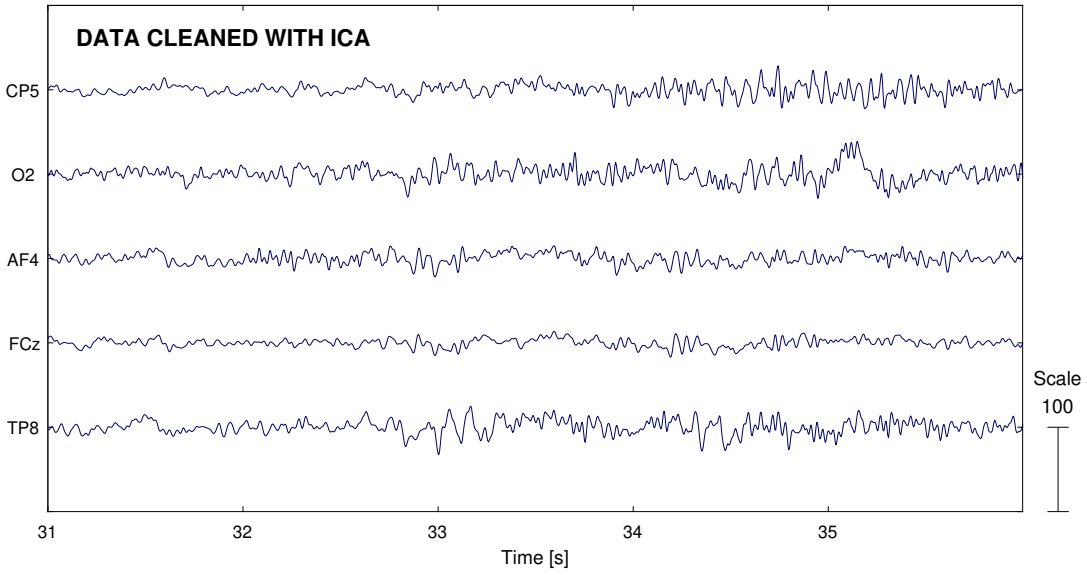

Figure 2.6: The EEG signal cleaned with ICA for the channels CP5, O2, AF4, FCz and TP8 over a 5 second interval. If looking carefully it can be seen that some high-frequency components have been removed, for example in channel CP5.

2.3 Selection of channels to analyze

When the pre-processing was finished, some channels had been removed for all trials. Since there were 64 channels to begin with, the reduction could be useful to determine which channels that should be further analyzed. In other studies, it is common to interpolate bad channels, but this was decided unnecessary since there were many channels to choose from and only a few were needed in the statistical analysis. As mentioned in Section 1.8.7, it is common to analyze a small number of channels in EEG studies on sleep or fragrance. At the same time,

it is important to have a spread of regions that you analyze. It was decided to choose five channels to analyze further in this study.

The electrodes were chosen gradually, and the first step was to keep all channels that had passed the cleaning process for at least 39 out of the 42 trials. Then the channels from different brain regions were plotted in small groups of five to six channels at a time, where one channel from each group was kept. The channel that was kept was the one that looked like a good representation of the group. In other words, if five channels from one area had a diversion in amplitude or shape, it was chosen to keep one channel that did not differ too much from any of the other channels. In this way, it was eventually decided to keep the following five channels: AF4, CP5, FCz, O2, and TP8 for further analysis. A visualization of all channels is shown in Figure 2.7. The chosen channels are marked with yellow to easier see the dispersion between them.

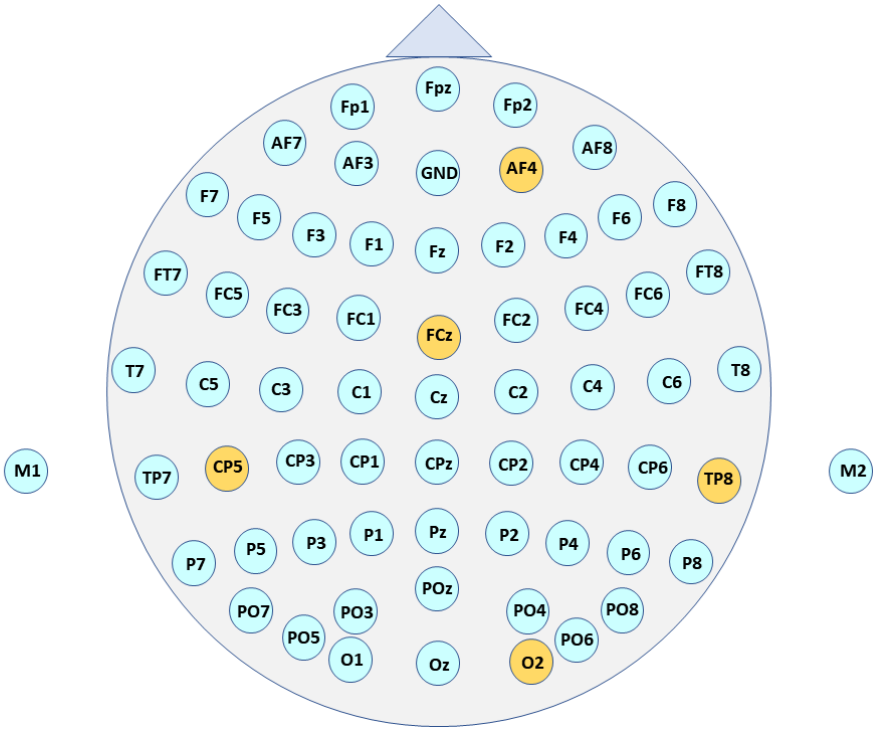

Figure 2.7: Scalp map of electrodes used in this study, the five chosen channels for analysis are marked in yellow. They are spread out over most brain regions.

2.4 Extraction of analysis parameters

In order to analyze the frequency distribution of the preprocessed data, while still keeping some time resolution, the data was cut into 10 seconds segments. These data segments were then converted into the frequency domain and used as data points in the analysis. In this way, each datapoint represents the average power during 10 seconds of data. By doing this it is still possible to see the change of frequency over time. It was concluded that a 10 second segmentation was a good choice for this study, which will be further explained later in section 2.5.

The process of converting the data from the time domain to the frequency domain was done by the use of Welch's method. Welch's PSD was calculated for each segment, see Section 1.9.2 where Welch's method is explained. A 10 second Welch's PSD is visualized in figure 2.8 when using different time windows of 1, 4, and 7 seconds, all with an overlap of 75%. The grey signal is the periodogram of the same 10 second data segment calculated using discrete Fourier transform (DFT). It was calculated with the same number of discrete data points as the number of datapoints in the un-transformed signal. As can be seen, when decreasing the time window, the variance of the signal also decreases. This is due to an increase in the amount of averaging segments, hence the signal gets more averaged and a lot of frequency resolution gets lost. On the contrary, it can be seen that the frequency resolution, as well as the noise, gets very high when increasing the time window. It was concluded that a time window length of 4 seconds with an overlap of 75% was appropriate for our analysis. Hence, the time window resulted in a frequency resolution of 0.25 Hz which is below the lowest frequency of interest (4 Hz).

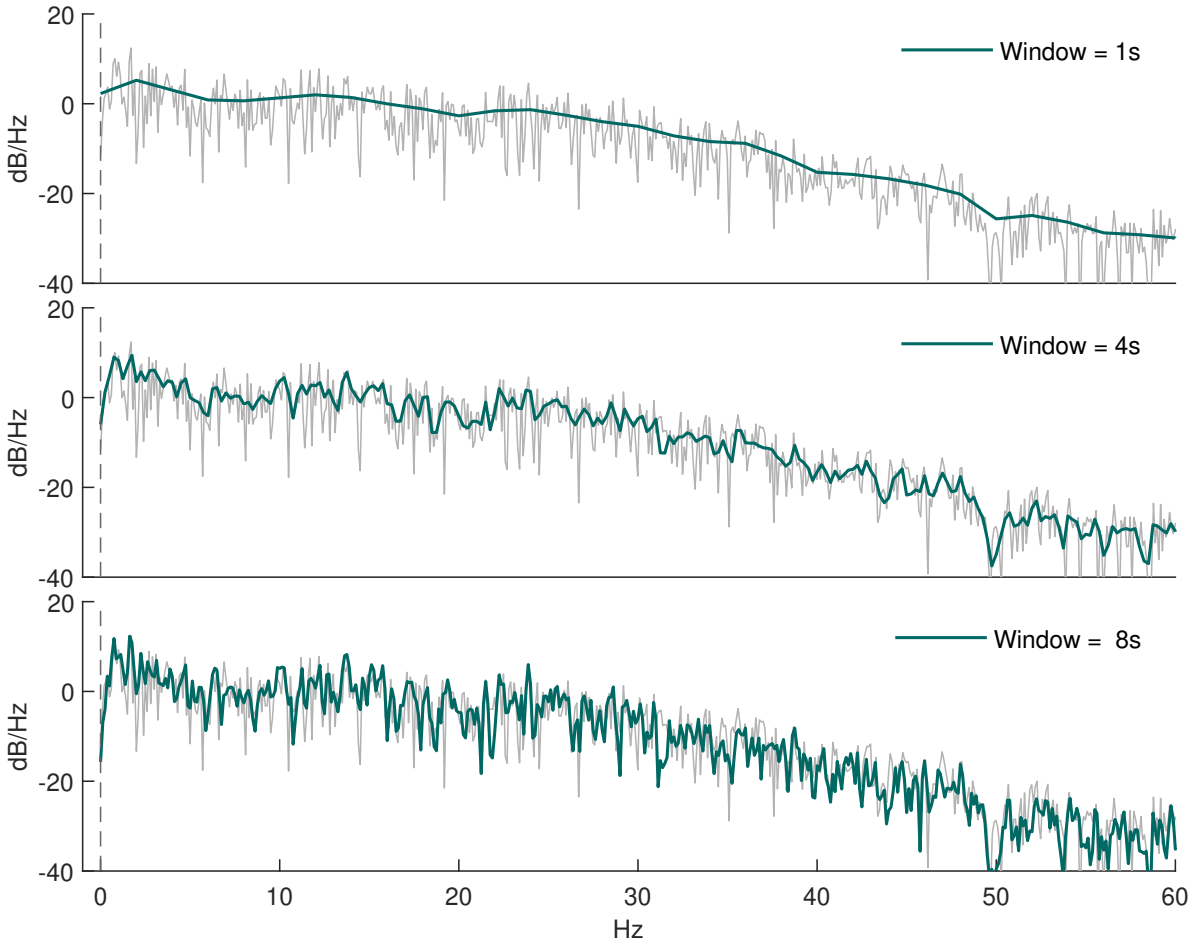

Figure 2.8: The signal shown in green is a visualization of Welch's PSD for a 10 second data segment with various window lengths of 1, 4, and 8 seconds, with an overlap of 75%. The grey signal is the periodogram of the same 10 seconds data segment. A 4 second window length was used in this analysis.

After creating Welch's PSD of the 10 second segment the bandpower of various frequency

intervals was extracted in order to gather features of interest to analyze. Theta, Alpha, and Beta were chosen as analyzing features since they have shown to be good indicators of fatigue, as mentioned in the introduction section. The average bandpower of the total frequency range (F_{tot}), as well as the average bandpower of Theta (θ), Alpha (α), and Beta (β), was calculated.

In order to make the band powers easier to analyze in a group the band powers were converted to relative bandpowers by dividing each of the frequency bands of interest (θ, α, and β) by F_{tot}. Creating a percentage of each feature of interest for every 10 second segment. Hence, "an increase in θ/F_{tot}" will simply be referred to as "an increase in θ". Another ratio that also was created was $(\alpha + \theta)/\beta$ which is a way to summarize the three features in one expression. To simplify further on, the ratio $(\alpha+\theta)/\beta$ will be referred to as ATB. The features were used as a measure of fatigue, where an increase of θ and α, or a decrease in β indicates that the driver is getting more fatigued. Followed from this is that ATB will increase when the driver is getting more fatigued.

The result of this extraction is that the change of the features of the EEG signal can be visualized in the time domain, as 120 time points (t_p) where every t_p represents the feature during 10 seconds, and with the fragrance administration occurring between t_p 60 and 61. To clarify, t_p 60 includes the 10 last seconds before fragrance administration, and t_p 61 includes the 10 first seconds after fragrance administration. Figure 2.9 shows ATB over a 20 minute period. The data is averaged over all sessions and the chosen channels. The x-axis is a discrete timeline of the 120 time points. Also, it shows the gradient from start to finish, where the overall trend is that ATB increases over time.

2.9.

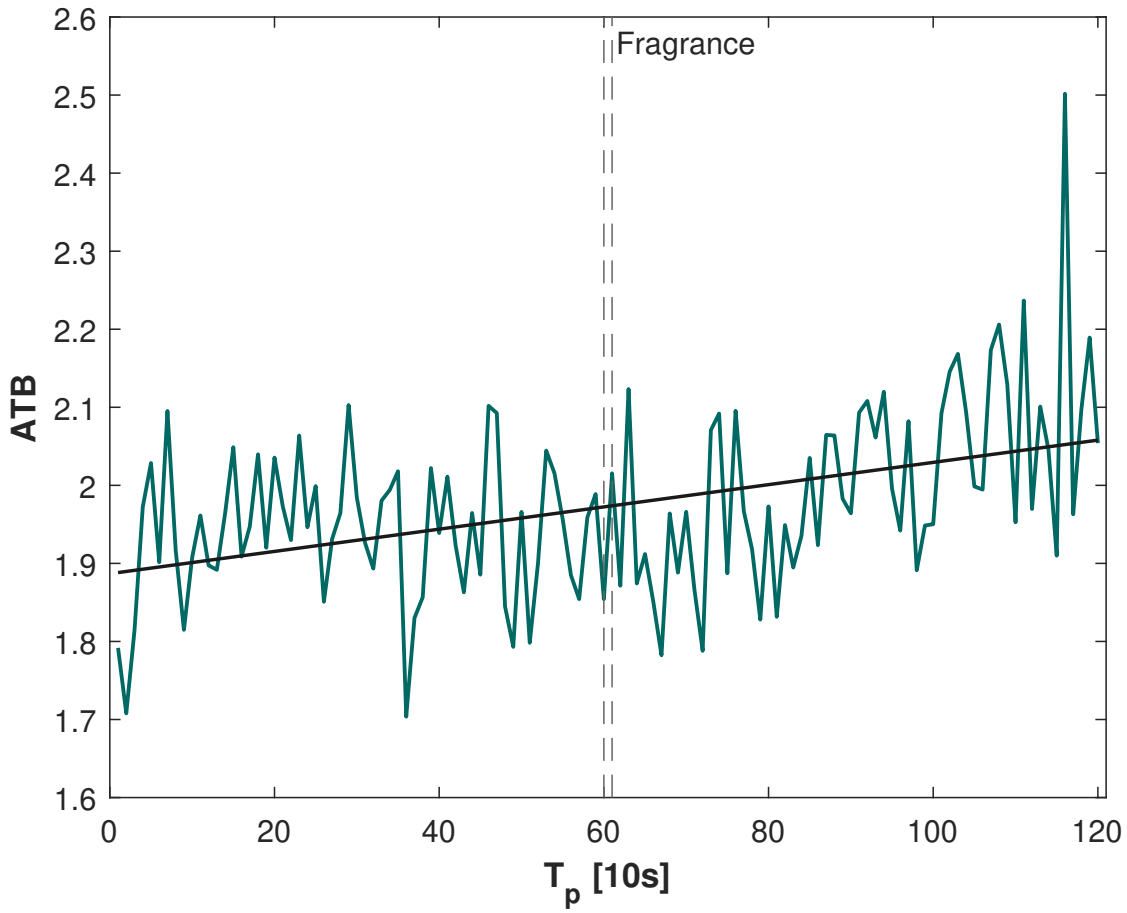

Figure 2.9: ATB data shown for 20 minutes with time points of 10 seconds intervals, an average of all trials, and the channels AF4, CP5, FCz, O2, and TP8. Fragrance release is shown with two dashed lines. The first line represents the 10 last seconds before the fragrance release, and the second line is the 10 first seconds after the fragrance release. The general trend of the data is shown with a gradient in black.

To examine if there were any deviations from the trend in the area of fragrance release a closer look at the time points closest to the fragrance administration was performed. This was done by plotting the data in various ways and by doing statistical analysis using ANOVA.

2.5 Statistical analysis

By using One-sample Kolmogorov-Smirnov test it could be checked whether the data followed a normal distribution, and it was concluded that it did. Statistical analysis of the extracted features over time was then analyzed using a two-way ANOVA for repeated measures design.

The statistical analysis was performed with ATB as the dependent variable. The two within-subject variables were t_p (before versus after) and fragrance (vanilla versus trigeminal). The analyzed time points were 10 seconds before and after fragrance administration (t_p 60 and t_p 61) and an average of 20 seconds before and after fragrance (average of t_p 59 and t_p 60, and

average of t_p 61 and t_p 62). The reason to include the 20 second average and not only the 10 second period was because the data is fluctuating and the neighboring time points often differ a lot in amplitude, see Figure 2.9.

One could motivate to look at the effect on a scale of around one second, but there are several reasons to not do this. First, this study focuses on alertness more than the fragrance effect in general so it is not really interesting to know if a person gets alert during just one second. The other reason is that the fragrance was administered for three seconds, and it is likely that the fragrance did not reach the nose of the driver exactly at the fragrance release time due to that it was given from a distance of the nose, see Figure 2.1.

By looking the other way around and discussing longer periods, the reason for analyzing intervals equal to or shorter than 20 seconds is that after a longer period of time, it is uncertain if the fragrance has any effect on brain activity. If there is any effect it should be visible before then since the time it takes for a stimulus in the form of an odor to reach the brain is around 150 ms [66]. Also, when plotting the feature time points for the entire 20 minute period around fragrance release, see Figure 2.9, no major deviation can be seen. It was decided to primarily look at only 10 and 20 second intervals, and if a significant alertness effect was found, it would be further investigated how long this effect would last.

The used ANOVA design outputs statistical parameters (degree of freedom, F, and p-value) for the variables $time$, $frag$ (fragrance), and their interaction $timefrag$. The time variable outputs the difference between the time points. This is a good measure for examining if fragrances (without separating them) have an alerting effect on the drivers. The interaction variable outputs if there is an interaction effect between the two fragrances as well as the two time points. It is this variable that is of most interest when examining the different effects of the two fragrances over time. The $frag$ variable on the other hand only shows the total difference between the two fragrances without the time aspects. Meaning it only shows if the feature value is significantly different between the two fragrances without the time aspect. Since this analysis only focuses on the change of frequencies for the two fragrances together or separately over time the $frag$ variable gives poor information and hence will not be analyzed in the result section.

The two-way ANOVA for repeated measurements design requires the compared data to be equal in size. Meaning that the number of sessions with vanilla needs to be equal to the number of sessions with trigeminal. In cases where one of the channels is missing for one session the data set becomes unbalanced. To solve this, both driving sessions for the participant with a missing channel get discarded to re-balance the data set.

For the significant values for $timefrag$ in ANOVA, a post hoc test was done using Tukey correction to compensate for multiple comparisons. This was done to see in what direction and how much the variable(s) changed. This was done with the MATLAB function `mult_compare`.

3

Results

Included in the result section are a presentation of the preprocessed data, statistical results from the ANOVA and post hoc analysis as well as a further analysis of group divisions.

3.1 Presentation of processed data

Figure 3.1 shows all the features separately over 20 min. If looking at how the features move from beginning to end, α is the one that most clearly increases during the total period. θ is increasing slightly while β is almost constant but has a hardly noticeable decrease. It can also be seen that the average amplitude level differs between the features, β is higher than α and θ, which are quite similar.

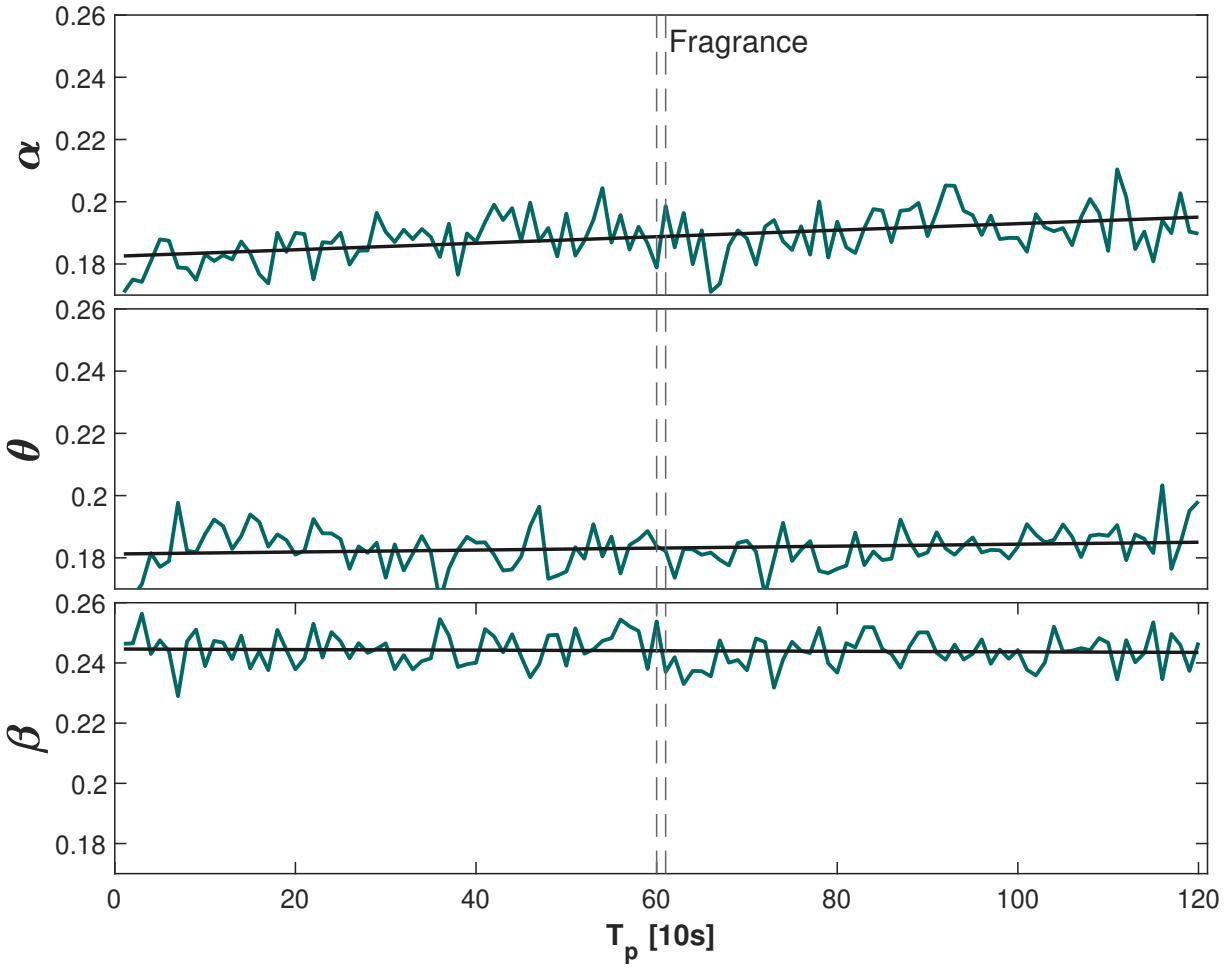

Figure 3.1: Presentation of the features α, β, and θ over a time period of 20 minutes with time points of 10 seconds intervals, an average of all trials, and the channels AF4, CP5, FCz, O2, and TP8. The fragrance administration time is marked as a vertical dashed line. Trend lines are shown for all features.

No major changes in the trends can be seen after the fragrance release. α and β potentially decrease to some degree after fragrance. The ATB plot, figure 2.9 from section 2 can be seen as a summary of the three plots and here the increase over time is stronger since it combines the changes from the three features. To get an overview of the entire data set and individual differences, the average ATB datapoints for all channels were plotted in a scatterplot for each test person. Figure 3.2 presents scatter plots for the trials with vanilla and trigeminal separately (3 min of data) where half the time is after fragrance release. The x-axis shows each test person and the y-axis displays the dispersion for each individual. It can be seen that the individual difference is bigger than the difference between vanilla and trigeminal. Some people are generally low and others are generally high regarding ATB. Also for some people, the dispersion is slightly wider for vanilla, and for others, it is slightly wider for trigeminal.

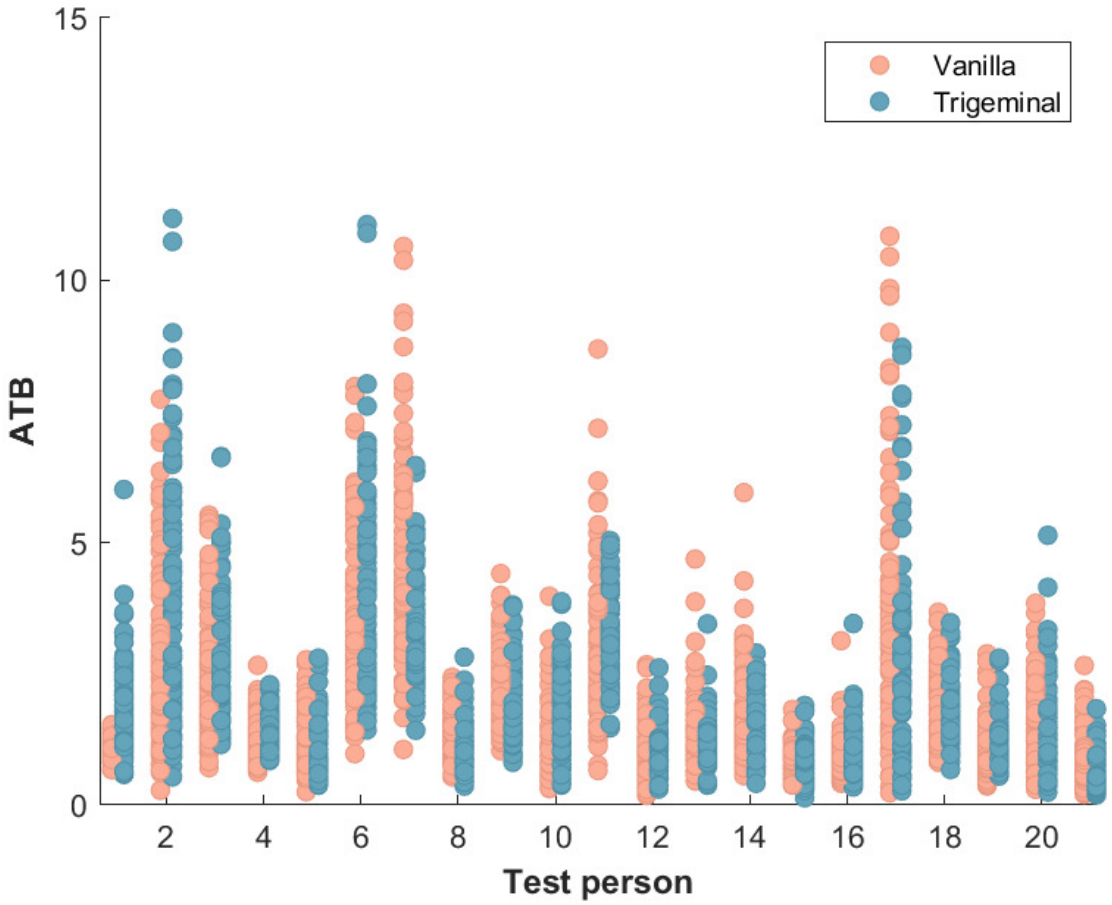

Figure 3.2: Scatter plot of average ATB datapoints over the channels AF4, CP5, FCz, O2, and TP8 for each individual. The dataset is divided between two sets depending on the fragrance.

It is known that the drivers are fatigued and most certainly are getting more fatigued throughout the trial. By dividing the ATB data into the two driving sessions and plotting it as the mean of all test persons and channels a difference can be seen in Figure 3.3. During the second drive, the amplitude is constantly higher compared to the first drive. This difference together with the increasing trend seen in figure 2.9 indicates that the ATB feature is an appropriate measure for fatigue.

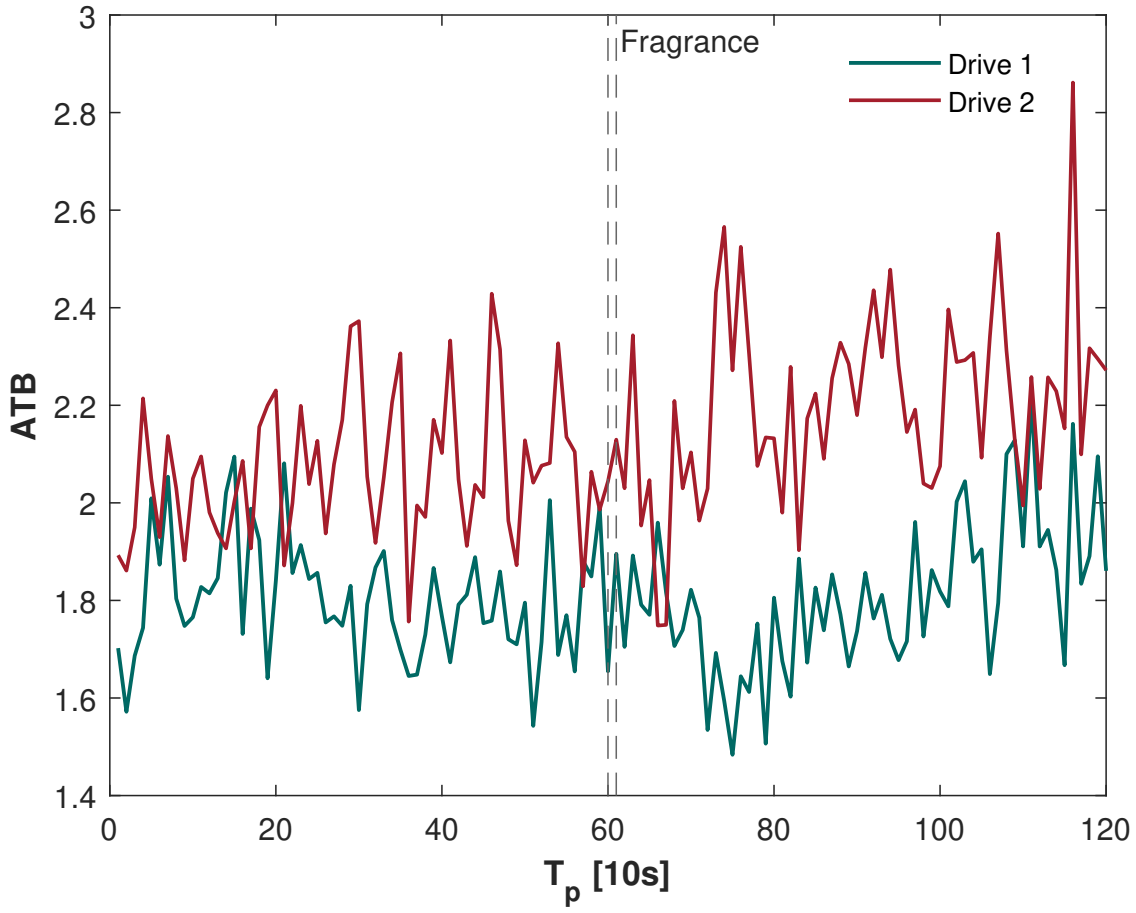

Figure 3.3: Drive 1 and drive 2 for ATB over a time period of 20 minutes with time points of 10 seconds intervals, an average of all trials, and the channels AF4, CP5, FCz, O2, and TP8. The fragrance administration time is marked as a vertical dashed line.

The five channels used for this analysis have different amplitudes for all the features. Figure 3.4 shows the distribution around fragrance time of all features separately for the chosen channels. α has a bigger variation between channels compared to the others, and in the figure with α the channel names are shown for each color. There is a quite big variation in how the channels behave between features. For α, it can be seen that CP5 has a constantly higher amplitude than the rest of the channels, while FCz and AF4 are similar in amplitude. For θ and β, it is the other way around, where FCz is high in amplitude while CP5 is either low or in the middle of the channels. Since the features have varied strength over brain regions, it can be assumed that by using the ratio ATB in combination with a spread in regions, fatigue-related information could be captured in a good way.

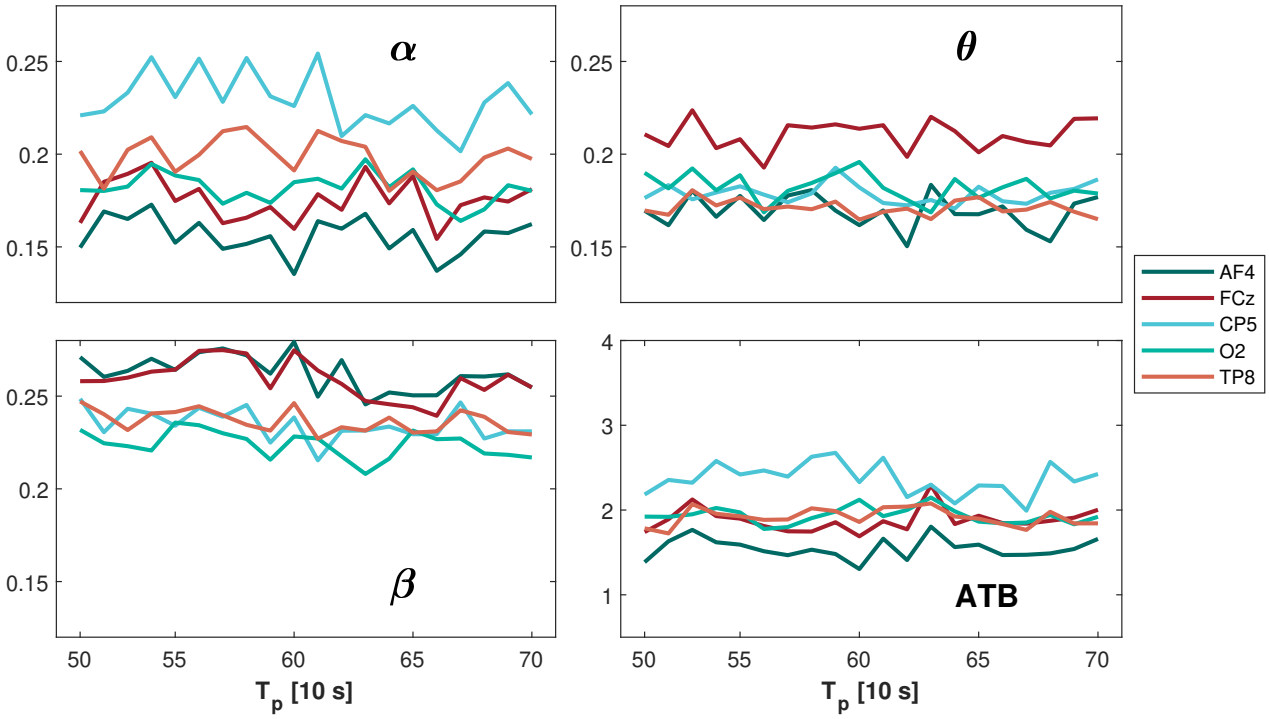

Figure 3.4: Channel comparison for α, β, θ and ATB over a time period of 20 minutes with time points of 10 seconds intervals, with an average of all trials. Each channel is related to one color, according to the legends to the right.

3.2 Analysis of data over time

To begin with, an analysis of only time was conducted to see if the exposure of any fragrance seemed to affect the drivers. This was done by plotting the mean value of ATB at the t_p before fragrance and the t_p after fragrance (10 s before and after) for all channels, see Figure 3.5. The error bars seen at each t_p are the standard deviation of ATB for all test persons.

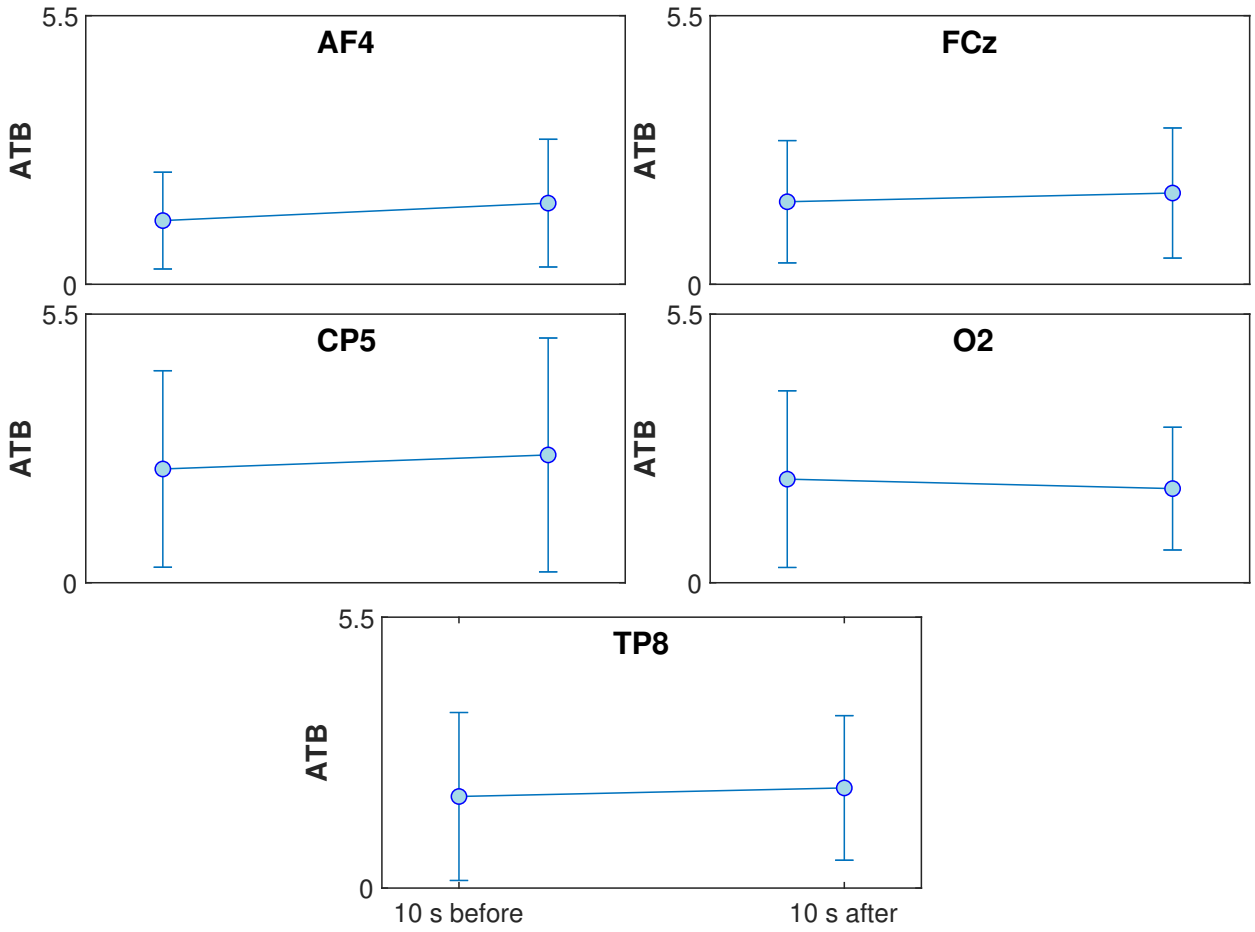

Figure 3.5: *ATB* mean plot over all trails for each channel 10 seconds before and after fragrance. The vertical lines are the error bars representing the standard deviation of *ATB* over all trails.

The mean for most channels is higher in the second interval after the fragrance release and by looking at the plots it does not seem like the drivers are getting less fatigued after the fragrance. The one channel which shows the opposite is O2, where the mean is lower after fragrance. Although, as can be seen, the length of the error bars in each figure are very similar to each other which also indicates that no major deviations occur for any of the channels.

3.3 Effect of vanilla and trigeminal separately

This section shows some descriptive analysis of the effect of vanilla and trigeminal separately. The following figures, 3.6 and 3.7 show how *ATB* changes over a total of 20 minutes for respective channels. As seen in 3.4 the pattern between the channels differs which can also be seen here.

Before the fragrance, the data is expected to be similar for both fragrances since there has been no fragrance administration yet. At all channels, *ATB* for vanilla is above *ATB* for trigeminal at the start, especially at O2. In general, they overlap and cross over several times. Just after

fragrance, there is no evident pattern, but for CP5, ATB for trigeminal lie mostly below ATB for vanilla after the release, for some time, 1-3 min.

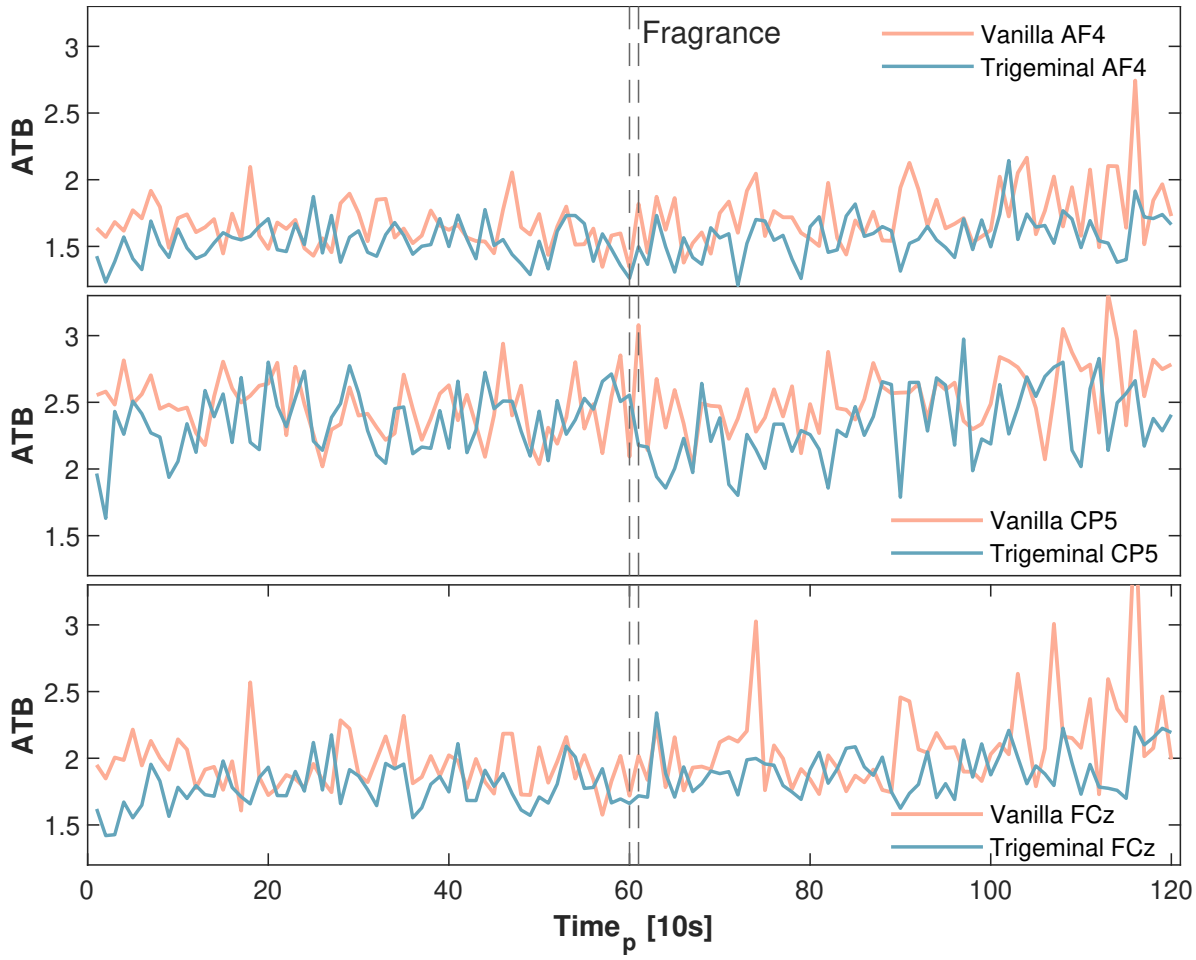

Figure 3.6: ATB vanilla and ATB trigeminal over a time period of 20 minutes with time points of 10 seconds intervals, an average of all trials. The fragrance administration time is marked as a vertical dashed line. It is shown for AF4, CP5, and FCz.

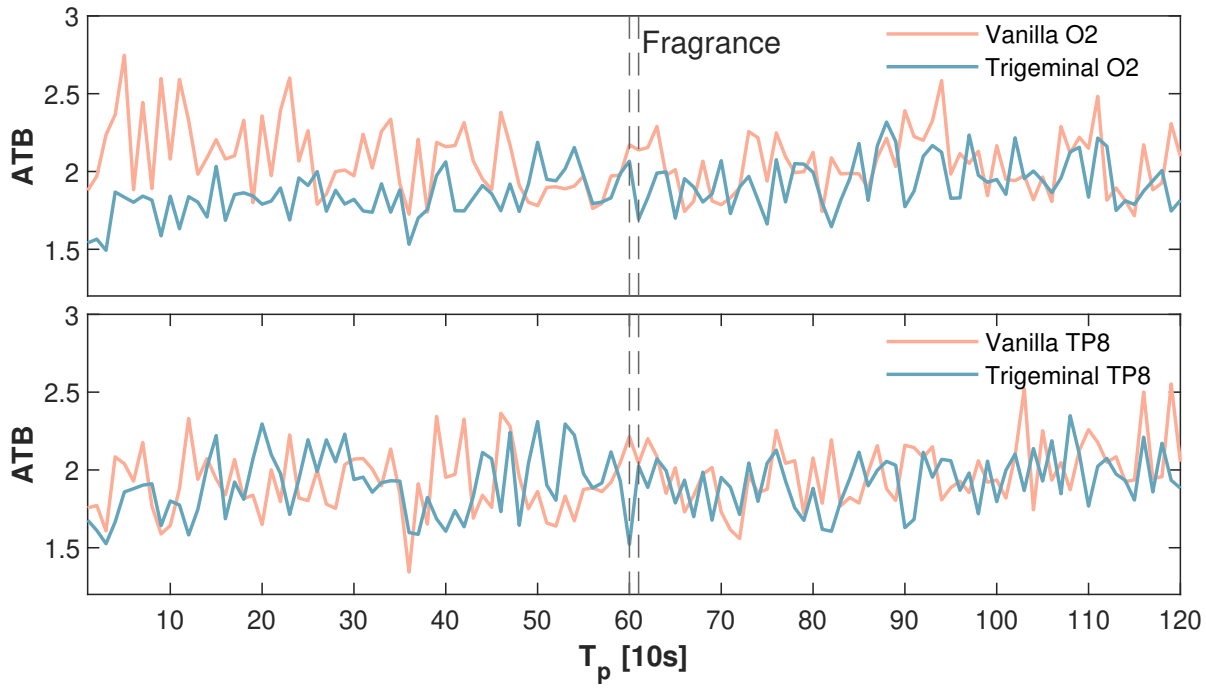

Figure 3.7: ATB vanilla and ATB trigeminal over a time period of 20 minutes with time points of 10 seconds intervals, an average of all trials. The fragrance administration time is marked as a vertical dashed line. It is shown for O2 and TP8.

To get a further visualization of how the separated data behaved around fragrance administration, the gradient of ATB for vanilla and ATB for trigeminal from the t_p 10 s before fragrance to the time point t_p 10 s after the fragrance is shown in figure 3.8. In the first four channels, the slope of ATB of trigeminal has a lower value than for ATB of vanilla. Where ATB for both fragrances show an increase, trigeminal increase less than vanilla, and if both decrease, trigeminal decrease more than vanilla. In CP5, ATB increase for vanilla, and decrease for trigeminal. TP8 behaves differently than the other channels, where ATB decrease for vanilla while it increases for trigeminal.

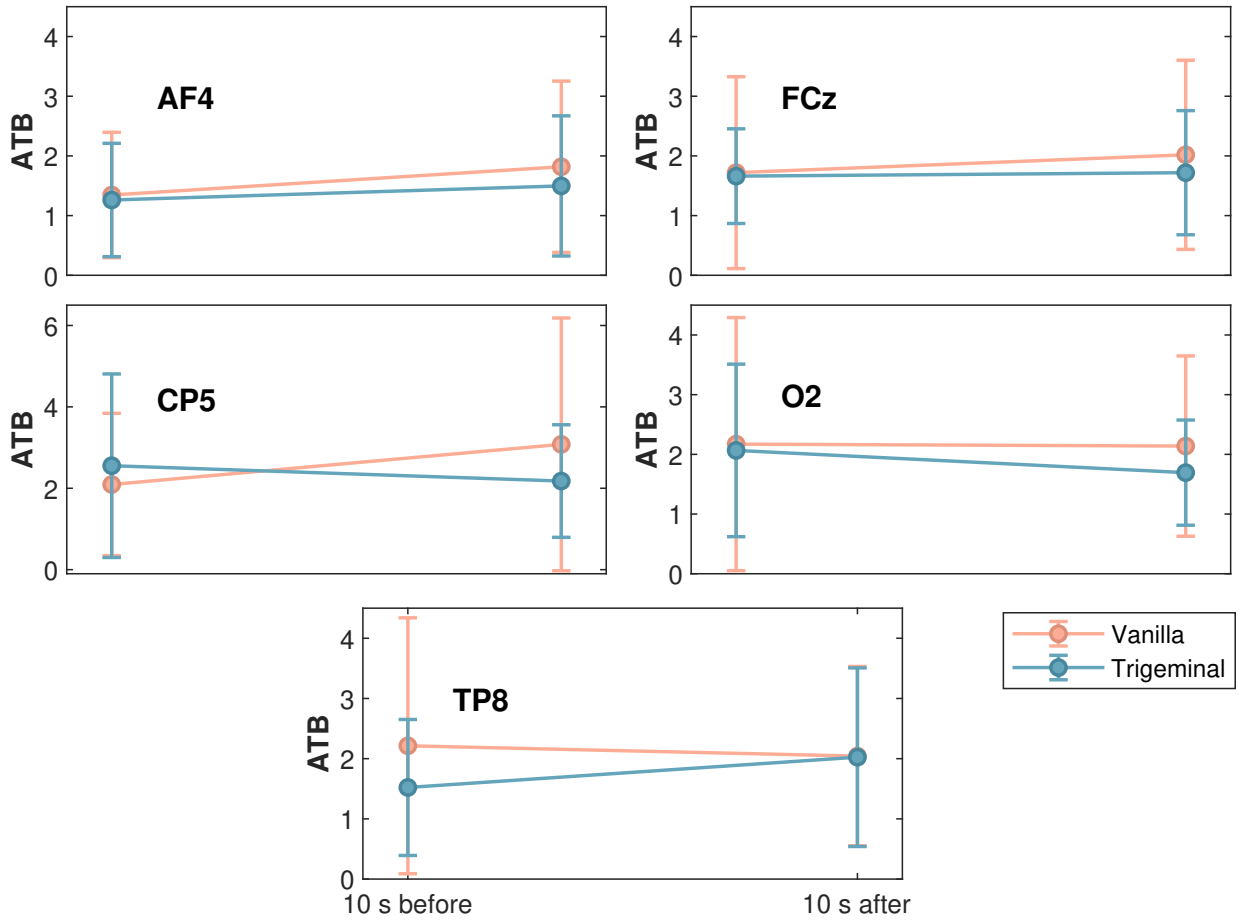

Figure 3.8: ATB mean plot for vanilla and trigeminal separately. Each data set is plotted over all trails for each channel 10 seconds before and after fragrance. The vertical lines are the error bars representing the standard deviation of ATB over all trails. Vanilla is pink and trigeminal is blue.

3.4 Statistical results

The ANOVA results from comparing the 10 s time interval before and after the fragrance release can be seen in table 3.1. It shows the F and $p-value$ for $frag$, $time$, and their interaction effect $fragtime$. The significant effects vary among channels and are highlighted in blue (p-value $<$ 0.05). An ANOVA table is also shown for the 20 s mean before and after fragrance release, see 3.2.

Table 3.1: 10 s before and after fragrance

ANOVA for 10 s

Channel/Variable		ATB	
		F-value	p-value
AF4	Frag	2.849	0.108
	Time	5.818	0.026
	FragTime	0.776	0.389
CP5	Frag	0.200	0.660
	Time	0.905	0.354
	FragTime	8.314	0.010
FCz	Frag	0.795	0.383
	Time	1.074	0.312
	FragTime	1.235	0.280
O2	Frag	1.343	0.262
	Time	0.723	0.406
	FragTime	2.447	0.135
TP8	Frag	1.639	0.216
	Time	0.449	0.511
	FragTime	3.989	0.060

Table 3.2: 20 s before and after fragrance

ANOVA for 20 s mean

Channel/Variable		ATB	
		F-value	p-value
AF4	Frag	2.849	0.108
	Time	1.801	0.195
	FragTime	0.057	0.814
CP5	Frag	0.523	0.479
	Time	0.455	0.509
	FragTime	9.027	0.008
FCz	Frag	1.126	0.301
	Time	0.081	0.779
	FragTime	0.019	0.892
O2	Frag	1.819	0.194
	Time	0.391	0.539
	FragTime	4.947	0.039
TP8	Frag	2.256	0.150
	Time	0.383	0.544
	FragTime	1.071	0.314

To answer the question of whether the fragrances together have an alerting effect on the fatigued drivers the *time* variable from table 3.1 and 3.2 were examined. As can be seen, only one location is significant for *time* in table 3.1, at channel AF4. By looking at the descriptive data of AF4 before and after the fragrance administration it can be seen that ATB is higher 10 s after. This result corresponds to the trends shown in the lineplot in figure 3.5, that no major deviations occur and the drivers only seem to be getting somewhat more fatigue.

To analyze the interaction effect of time and fragrances the $fragtime$ variable in ANOVA was used. The three significant effects seen for $fragtime$ in table 3.1 and 3.2 were put in a post hoc test.

The post hoc tests showed significant p-values for two of three significant effects seen in the ANOVA tables. For CP5 at 10 s and O2 at 20 s mean.

For CP5 at 10 s ATB for vanilla increased (p = 0.013), while ATB for trigeminal in this case decreased but not significantly (p = 0.402). When comparing the fragrances at certain time points, the result showed no significance. Before fragrance (tp_1), ATB for trigeminal is higher than ATB for vanilla (p = 0.294) and after fragrance (tp_2) ATB for trigeminal is lower than ATB for vanilla (p = 0.097).

For O2 at 20 s mean, it was a significant difference between the fragrances at tp_2 (p = 0.042), where ATB for trigeminal was lower than ATB for vanilla. At tp_1 they did not differ significantly (p = 0.747). Regarding ATB for vanilla, it increased non-significantly (p = 0.462), and ATB for trigeminal decreased non-significantly (p = 0.069).

CP5 at 20 s mean, did not show any significance at post hoc tests. ATB for vanilla increased (p = 0.424) and ATB for trigeminal decreased (p = 0.08). At tp_1, ATB for trigeminal is higher than ATB for vanilla (p = 0.764), and at tp_2, lower than ATB for vanilla (p = 0.078).

A summation of these results is that there is not much significance and that there are few indications of an effect of either of the fragrances. Although, it can be seen that ATB for vanilla increases while ATB for trigeminal decreases for the significant elements in the post hoc tests.

3.5 Group comparison

So far, all test persons have been presented in the analysis. During the analysis, some plots showed a big variation between subjects. By dividing the test persons into males and females, it was seen that a majority of the variations could be explained by gender, where males have a constantly higher amplitude and more fluctuations compared to females when looking at ATB.

Another group division was investigated as well, using the fact that some people had fallen asleep during the trials. About half of the test persons had fallen asleep in at least one of the drives, and all these were put in the "sleep group". The rest were put in the "wake group". Both group divisions are shown in figure 3.9. ANOVA tests were done on the different groups using the group as a between factor. The result showed only one significance, for male and female at AF4. However, there was no significance regarding the group's reaction to fragrance. Hence, the difference that is seen in the images does not impact how the groups react to the fragrances. The ANOVA table for the group division can be seen in appendix A.1 and A.2.

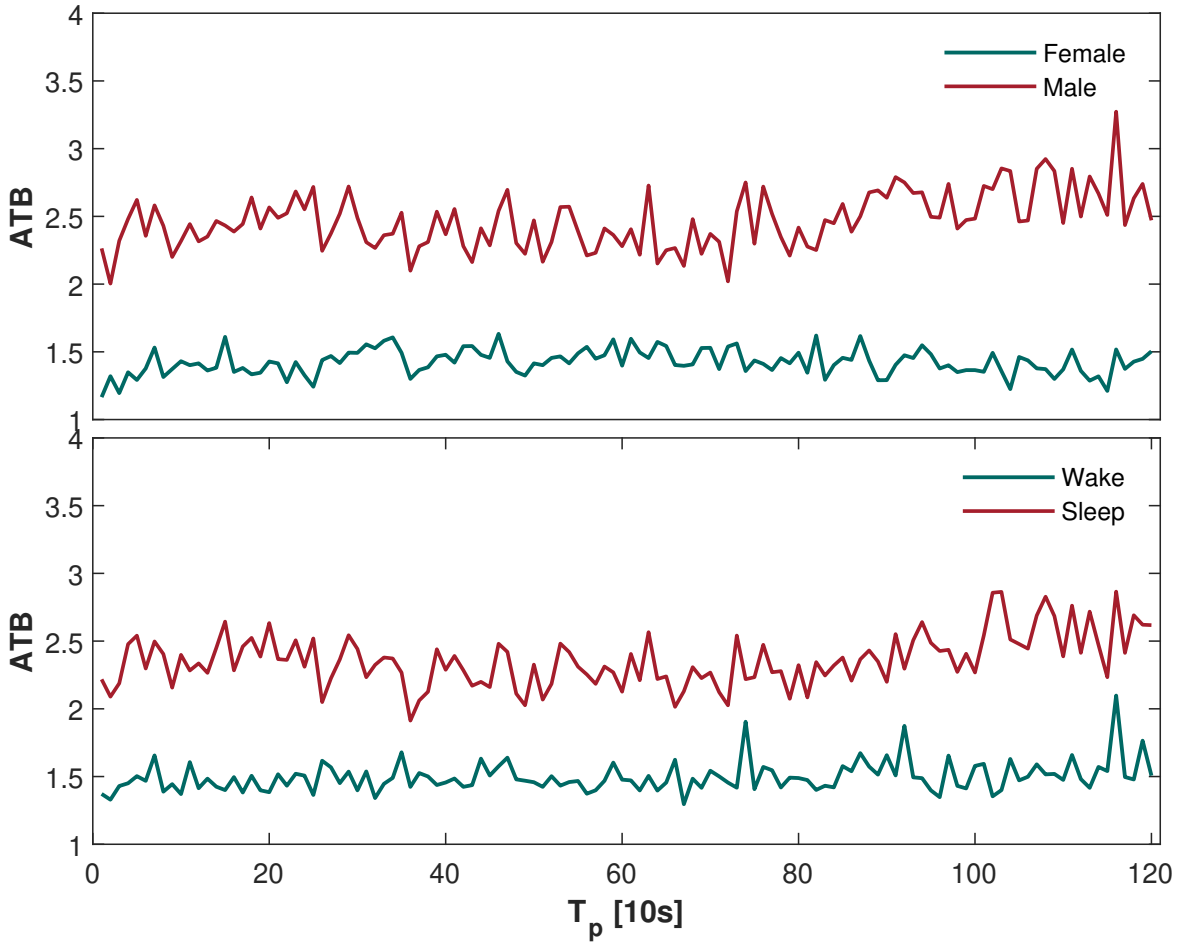

Figure 3.9: A visualization of the variation of ATB between the two group divisions (male versus female and sleep versus wake), over a time period of 20 minutes with time points of 10 seconds intervals, an average of all trials, and the channels AF4, CP5, FCz, O2, and TP8.

4

Discussion

In this section, discussions regarding the results as well as the methods used in the data collection and analysis will be presented. Also, connections to former studies and possible improvements for the future will be included.

4.1 Effect of fragrance

From the *time* variables analysis, no significant alertness effect was found in association with the time of fragrance release. The only channel which was significant instead showed an increase in fatigue. Hence, the event of administering a fragrance did not show any obvious effect on brain activity.

However, this does not say anything about the vanilla or trigeminal since they could potentially have opposite effects that together get canceled out. When analyzing the $fragtime$ variable, it is rare to see any significance associated with an alerting effect. When looking at the two fragrances to compare their effect it can be seen that there was a significant increase in the level of fatigue after vanilla exposure, which is not the case for trigeminal.

By looking at the Figure 3.8 it is seen that for ATB, vanilla generally increases more than trigeminal. The ANOVA results together with the general behavior suggest that vanilla makes the test persons more tired, but it can not be concluded whether this is due to vanilla or that they would get tired anyhow. EEG after trigeminal exposure behaves a bit differently from vanilla and decreases for some channels but it is only significant for two channels. Since the effect was so small, no further analysis was done over a longer period.

Regarding the behavior of the channels, apart from CP5 and O2, their p-values show no significance for the $fragtime$ variable. CP5 and O2 are also the only ones that show a decrease for ATB of trigeminal in Figure 3.8. CP5 deviates the most from the other channels and alone also shows a significance at 10 s for $fragtime$. This could just be a coincidence, however, what also makes CP5 stand out from the rest of the channels is that it is positioned in the left hemisphere where the rest are either in the center or on the right side. It was investigated whether other left channels behaved similarly to CP5. For example, T7 which is even more to the left than CP5, also had a higher amplitude than CP5, suggesting that there was a difference between the left and right hemispheres. This was not analyzed further but could in that case explain the difference. No information was found regarding a difference between the left and right hemispheres during fatigue.

4.1.1 Difference between groups and individuals

It was seen in the results Figure 3.2 that the individual differences are bigger than between fragrances. In Figure 3.9 it also looks like a big difference between females and males as well as the sleep and wake group. These differences did not show any significant impact on how the groups reacted to the fragrances, even though females are known to react more to fragrances in general as mentioned in Section 1.7.1.

4.1.2 Data trends

The long time trend of the features is in line with the theory of signs of fatigue, see Section 1.5 and 1.5.1. Where an increase of θ and α and a decrease of β are an indication of increased fatigue. Hence, this result indicated that the test persons got more tired throughout the driving sessions. This is reasonable since they were already tired as they started and performed a task that required focus and energy, leading to an increased combination of both SR and TR fatigue. The same pattern could be seen for ATB in Figure 3.3. Where the amplitude of ATB of the second drive is higher in comparison to the first drive.

However, since the data were fluctuating it was difficult to visualize any obvious trends for shorter periods of time. It would be possible to average the data further to allow for a more smooth data but since it would risk discarding a lot of important information it was not done. A reason for the fluctuations could be that some test persons experienced microsleep several times before they slept long enough to allow for fragrance administration. Those moments with microsleep could create reactions in the brain signals that may have influenced the general data trends such as fluctuations, and also have an impact on the statistical results.

4.1.3 Connection to results of ECG and EOG

The result for the EEG parameters is similar to the results from the ECG and EOG parameters in the sense that there are few significant effects seen when measuring the alertness effect. Mean beats per minute (bpm) and heart rate variability were used as measures of fatigue for the ECG parameter. Neither of the measures showed any significant effect when examining time, fragrance, and the interaction effect.

The measures used when examining fatigue using EOG as a parameter was mean blink duration and the number of long blinks (>150 ms). It could be seen that the mean blink duration decreased significantly one and two minutes after fragrance release. However, this behavior could not be linked to the effect of fragrance. Neither was there any effect of fragrance on the number of long blinks.

Since the study on ECG and EOG was done for one minute or longer, it is difficult to compare with the study on EEG. Also, since the measuring parameters are very different from each other it is hard to compare the result in more detail.

4.2 Methods and limitations

4.2.1 Feature of fatigue

A limitation with the used features for this type of analysis is that they are associated with several different mental states. The driving session did not just involve fragrance as a stimulus but also the stimulus from driving the simulator. This makes it hard to know why a certain feature increase or decrease at a certain time when it was a lot that happen at the same time. Also, unpleasant odors have been seen to increase Alpha, and if the trigeminal substance is unpleasant but also alerting, how will this be seen in the brain waves, will they go up or down, or up at one brain region and down in another? There are several examples of similar mental states that could either increase or decrease the different wavelengths. This is just another evidence of how complex the brain is and also proves how important it is to standardize EEG analysis (in equivalent research) as much as possible when it comes to choosing electrodes, preprocessing, selection of features, etc.

4.2.2 Channels

One issue with the chosen channels is that even though they covered several brain regions, they were not chosen symmetrically. Only one channel, CP5, is located in the left brain. It was not possible to select more channels on the left since the others only remained for less than 39 trials after preprocessing. Since CP5 showed more significant changes in the statistical analysis compared to the other chosen channels, it is important to not neglect this significance even though it was just for one channel, since CP5 represents a bigger part of the brain.

If it had been known earlier that the left channels behaved differently than the right channels regarding the sleep parameters, the analysis would have been done on a more symmetric set of channels with equally many channels from the left and right brain regions. To be able to do this, it would have been necessary to interpolate missing channels after the cleaning steps in the preprocessing.

4.2.3 Connection to earlier research

According to former studies, trigeminal stimuli have woken people from sleep and it should show more reaction than it does in this study. There are several reasons that could explain why the results are not as expected. Some aspects are the concentration of a trigeminal substance, the kind of fragrance, the time of exposure, how the fragrance was administered, and the environment of the study.

In several studies of fragrances that include trigeminal substances, it has been seen that the duration of exposure is key to getting an alerting effect, as well as how many times the person is exposed. In this study, since it was only a first-level study, the fragrance was only given once and for a duration of 3 seconds. Future studies could consider investigating different durations of fragrance release as well as giving the fragrance repeatedly.

During the literature study, it was found that most research in this area that has seen an alerting effect, either has continuous fragrance administration for some time, or administration many times with certain intervals between. A suggestion is to try the study but with a longer

fragrance release and also a better way of releasing the fragrance to make sure that it reaches the nose more directly. An example is to use a tube directly into the nose, which makes the fragrance effect more effective. However, such a setup would not be convenient to use when driving a car.

The level of fatigue is another factor that could have influenced the results. The test persons had worked a night shift where they stayed awake all night, thereby experiencing very high sleep-related as well as task-related fatigue, making it very difficult to alert them. In former studies where fragrances have shown an alerting effect while driving, the test persons have mostly experienced only task-related fatigue, see Section 1.7.1. The exception is the studies where CO_2 which is purely a trigeminal stimulus, has woken people from sleep. In this case, CO_2 where directly placed into the nose and the concentration level was very important. Fragrances may have a certain effect depending on the kind of fatigue and situation. If a person is asleep, the brain may react differently from when doing a task. There are many factors that could influence the brain's reaction to fragrances. If an alerting fragrance only works on task-related fatigue, a relevant question would be if these fatigue-related accidents are more often related to task-related or sleep-related fatigue. If the answer is sleep-related fatigue, then there is no point in going further with research on alerting fragrances, but if the answer is task-related fatigue, then these fragrances could be a great way to decrease the number of accidents.

So, if another study setting succeeds to get a significant alerting effect, this effect should last for several minutes, optimally 10-15 minutes. If the effect is just around 1 minute, it is comparable to other countermeasures such as opening a window, listening to music, or hearing an alarm.

4.2.4 Preprocessing off EEG data

It is difficult to point out whether a specific step in the preprocessing stage, such as filtering the data, was done in the most optimal way since there was no reference data to control it with. Also, as mentioned earlier, due to the fact that there is no standardized way of analyzing EEG data. However, since the result showed trends that were expected to see according to the literature, such as the trend of the features for 20 minutes seen in Figure 3.1, it can be concluded that it was most likely done appropriately for this analysis. However, there are other similar methods and tools that could have been used which probably would have landed in a very similar result. Such as using other filtering parameters and cleaning tools.

In addition to the literature review on appropriate parameter values for the filtering or cleaning process, the trade-off between the removal of noise and the removal of possibly important information had to be considered. Hence, depending on the goal of the EEG analysis, certain types of noise and artifacts matter more or less. The literature concerning preprocessing of EEG signals in association with a certain stimulus was often written with the goal of doing an ERP analysis in the end. This sometimes made it difficult to know whether the specific method was also useful for this specific spectral analysis or not.

5

Conclusion

The event of administering vanilla and trigeminal fragrance did not show any significant alerting effects when analyzing them together over time. Neither did the trigeminal fragrance in general have a significant alerting effect on the brain activity according to the chosen EEG features. A difference between vanilla and trigeminal was seen in the descriptive data but it was mostly non-significant. From analyzing the descriptive data it can be seen that the trigeminal fragrance potentially slows down the pace of increased fatigue but it does not seem to stop nor reverse it. Since no significant alerting effect could be seen for short time analysis no further analysis on long-lasting effect was done. The presented result is similar to the result seen when analyzing fatigue using ECG and EOG. The preprocessing method and the extracted features used in this analysis were concluded to be suitable, confirmed by a combination of images of the descriptive data, and that ATB behaved as expected.

From the result of this thesis, it can be concluded that the use of trigeminal fragrances is not effective in alerting fatigued drivers in this particular setting. Further, research on trigeminal fragrances related to fatigued driving and the administration and concentration of the substance would be needed.

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A

Appendix 1

Table A.1: ANOVA, 10 s before and after fragrance, for sleep and wake.

ANOVA for 10 s, sleep and wake group.

Channel/Variable		ATB	
		F-value	p-value
AF4	Frag	2.798	0.112
	Time	5.846	0.026
	FragTime	0.751	0.397
	Group	0.752	0.397
	G:Frag	0.692	0.416
	G:Time	1.090	0.310
	G:FragTime	0.408	0.531
CP5	Frag	0.282	0.602
	Time	0.927	0.349
	FragTime	7.256	0.015
	Group	0.094	0.763
	G:Frag	0.377	0.547
	G:Time	0.090	0.767
	G:FragTime	0.570	0.461
FCz	Frag	0.750	0.397
	Time	0.984	0.334
	FragTime	1.129	0.301
	Group	0.034	0.855
	G:Frag	0.002	0.966
	G:Time	1.871	0.187
	G:FragTime	0.976	0.336
O2	Frag	1.220	0.285
	Time	0.636	0.436
	FragTime	2.537	0.130
	Group	1.264	0.277
	G:Frag	1.013	0.328
	G:Time	0.828	0.376
	G:FragTime	0.693	0.417
TP8	Frag	1.566	0.227
	Time	0.554	0.466
	FragTime	3.566	0.075
	Group	1.931	0.182
	G:Frag	0.012	0.913
	G:Time	0.694	0.416
	G:FragTime	0.649	0.431

G: Group

Table A.2: ANOVA, 10 s before and after fragrance for male and female.

ANOVA for 10 s, male and female group

Channel/Variable		ATB	
		F-value	p-value
AF4	Frag	2.057	0.169
	Time	4.576	0.046
	FragTime	0.619	0.442
	Group	5.401	0.032
	G:Frag	1.372	0.257
	G:Time	2.363	0.142
	G:FragTime	0.075	0.787
CP5	Frag	0.171	0.685
	Time	0.848	0.370
	FragTime	7.297	0.015
	Group	2.794	0.113
	G:Frag	0.010	0.920
	G:Time	0.003	0.960
	G:FragTime	1.971	0.178
FCz	Frag	0.561	0.463
	Time	0.851	0.368
	FragTime	1.384	0.254
	Group	3.519	0.076
	G:Frag	0.820	0.377
	G:Time	0.369	0.551
	G:FragTime	0.420	0.525
O2	Frag	1.566	0.228
	Time	0.534	0.475
	FragTime	3.164	0.093
	Group	0.355	0.559
	G:Frag	0.585	0.455
	G:Time	0.353	0.560
	G:FragTime	1.686	0.211
TP8	Frag	1.422	0.249
	Time	0.372	0.550
	FragTime	2.954	0.103
	Group	1.510	0.235
	G:Frag	0.021	0.885
	G:Time	0.022	0.884
	G:FragTime	2.360	0.142

G: Group

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