CZECH TECHNICAL UNIVERSITY IN PRAGUE

FACULTY OF BIOMEDICAL ENGINEERING
Department of biomedical technology

Analysis of PSG in sleep paralysis

Analýza PSG u spánkové obrny

Bachelor's Thesis

Study program: Biomedical and Clinical Technology
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Supervisor: Ing. Marek Piorecký, Ph.D.

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BACHELOR'S THESIS ASSIGNMENT

I. PERSONAL AND STUDY DETAILS

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Branch of study: **Biomedicínský technik**

II. BACHELOR'S THESIS DETAILS

Bachelor's thesis title in English:

Analysis of PSG in sleep paralysis

Bachelor's thesis title in Czech:

Analýza PSG u spánkové obrny

Guidelines:

Analyze whether there is a relationship between distress values in patients with sleep paralysis and fluctuations in power spectra during sleep. Using a quantitative evaluation of the power spectra and variability of cardiac activity, describe the possible contribution to the level of stress for patients suffering from sleep paralysis. Prove the proper analysis during each of the sleep stages.

Bibliography / sources:

[1] Chokroverty, Sudhansu, et al. , "Motor Disorders During Sleep." Atlas of Sleep Medicine: Expert Consult-Online and Print (2013): 193., Atlas of Sleep Medicine: Expert Consult-Online and Print, číslo 193, 2013
[2] Krajča V., Mohylová J. , Číslicové zpracování neurofyziologických signálů, ed. 1st, ČVUT Praha, 2011, ISBN 9788001047217
[3] Udi Nussinovitch M.D., et. all, Reliability of Ultra-Short ECG Indices for Heart Rate Variability, Annals of Noninvasive Electrocardiology, ročník 16, číslo 2, 2011

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Assignment valid until: **18.09.2022**

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DECLARATION

I hereby declare that I have completed this project with the topic Analysis of PSG in sleep paralysis independently, and that I have attached an exhaustive list of citations of the employed sources to the Bachelor's Thesis.

I do not have a compelling reason against the use of the project within the meaning of §60 of the Act No.121 / 2000 Coll., on copyright, rights related to copyright and amending some laws (Copyright Act).

In Kladno "date" ....

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ABSTRACT

Analysis of PSG in sleep paralysis

Sleep paralysis is a common type of sleep disorder that can be characterized by a feeling of paralysis of the whole body and at the same time perception of the environment as awake. This unusual pathology could transmit the negative impact of sleep on a person's natural rhythm when awake. Sleep paralysis could cause disorders of both physical and mental health. To date, there have been insufficient objective studies to record and evaluate this disorder. This project aims to propose a methodology that finds the spectral characteristics of sleep paralysis from a data set of 19 patients with sleep paralysis. The methodology was proposed in the programming language Python and the MATLAB environment. For the methodology implementations the "MNE-Python", "FieldTrip", "NumPy" and "SciPy" signal libraries were utilized. The methodology includes signal preprocessing by analogue and digital filtering, spectral and statistical data analysis. A quantitative comparison of the analyzed results was performed with a control group of individuals without sleep paralysis. The EEG analysis output of the work is the specific nature of sleep paralysis in the NREM2 phase of sleep with predominant theta activity. The ECG analysis resulted in the specific time and frequency domain parameters. Time-domain parameters did not have any significant difference in the statistical comparison between patients with sleep paralysis and the control group. Frequency-domain parameters of heart rate variability displayed no correlation with distress values in patients with sleep paralysis. Thus, the relationship between distress and sleep paralysis displayed no physiological characteristics that would support the theory about the negative impact of sleep paralysis on sleep beyond the occurrence of a sleep paralysis episode during the night.

Key words

Sleep paralysis, EEG, polysomnography, spectral analysis, ECG, HRV, correlation analysis, distress.

ABSTRAKT

Analýza PSG u spánkové obrny

Spánková obrna je často vyskytující druh poruchy spánku který je charakterizován pocitem paralýzy celého těla, a zároveň vnímání okolí jako v bdělém stavu. Tato neobvyklá patologie přenáší negativní dopad spánku na přirozený rytmus člověka za bdělého stavu. Spánková obrna může být příčinou poruch jak fyzického, tak i duševního zdrávi. Doposud nebylo provedeno dostatečné množství objektivních studii, které by zaznamenaly a vyhodnotily tuto poruchu. Cílem této práce je návrh metodiky, která nalezne spektrální charakteristiku spánkové obrny ze souboru dat 19 pacientů se spánkovou paralýzou. Metodika byla navržena v programovacím jazyce Python a prostředí MATLAB. Pro implementaci metodiky byly využity knihovny pro zpracování a analýzu signálů, a to "MNE-Python", "FieldTrip", "NumPy" a "SciPy". Metodika zahrnuje předzpracování signálu, analogovou a digitální filtraci, spektrální a statistické analýzy dat. Kvantitativní porovnání analyzovaných výsledků proběhlo vyhodnocením spolu s kontrolní skupinou jedinců bez spánkové obrny. Výstupem práce z EEG analýzy byla specifická povaha spánkové obrny mimo ataku ve fázi NREM2 spánku s převládající theta aktivitou. Výsledkem analýzy EKG byly specifické parametry v časové a frekvenční doméně. Parametry časové domény neměly žádný významný rozdíl ve statistickém srovnání mezi pacienty se spánkovou paralýzou a kontrolní skupinou. Parametry variability srdeční frekvence ve frekvenční oblasti nevykazovaly žádnou korelaci s hodnotami úzkosti u pacientů se spánkovou paralýzou. Vztah mezi úzkostí a spánkovou paralýzou tedy nevykazoval žádné fyziologické charakteristiky, které by podporovaly teorii o negativním dopadu spánkové paralýzy na spánek mimo epizodu spánkové paralýzy během noci.

Klíčová slova

Spánková obrna, EEG, polysomnografie, spektrální analýza, EKG, HRV, korrelacni analýza, distress.

Contents

List of symbols and abbreviations

List of symbols

Symbol	Unit	Description
Mean RR interval	ms	Mean of RR intervals
NN50	-	Successive RR intervals that differ by more than 50 ms
Mean HR	bpm	Mean heart rate value of an sleep phase
STD HR	bpm	Standard deviation heart rate value of an sleep phase
Min HR	bpm	Minimal heart rate value of an sleep phase
Max HR	bpm	Maximal heart rate value of an sleep phase
SDNN	ms	Standard deviation of NN intervals
SDRR	ms	Standard deviation of RR intervals
SDANN	ms	Standard deviation of the average NN intervals for each 5 min segment of a 24 h HRV recording
SDNNI	ms	Mean of the standard deviations of all the NN intervals for each 5 min segment of a 24 h HRV recording
pNN50	%	Percentage of successive RR intervals that differ by more than 50 ms
RMSSD	ms	Root mean square of successive RR interval differences
HRV TI	-	Integral of the density of the RR interval histogram divided by its height
TINN	ms	Baseline width of the RR interval histogram
VLF	ms^2	Power in VLF range
LF	ms^2	Power in LF range
HF	ms^2	Power in HF range
LF norm	nu	LF power in normalized units
HF norm	nu	HF power in normalized units
LF/HF	-	Ratio LF$[ms^2]$/HF$[ms^2]$

List of Abbreviation

Abbreviation	Description
REM	Rapid eye movement
NREM	Non-rapid eye movement
PSG	Polysomnograph
EEG	Electroencephalograph
EOG	Electrooculograph
EKG	Electrocardiograph
EMG	Electromiograph
ICSD	International Classification of Sleep Disorders
HLA	Human Leucocyte Antigen
NAR	Narcolepsy
SOREMP	Sleep-onset REM period
SP	Sleep paralysis
FIR	Finite impulse response
HLA	Human Leukocyte Antigen
VLF	Very low frequencies
LF	Low frequencies
HF	High frequencies

1   Introduction

Nowadays exists a large amount of scientific publications and researchers which make attempts to understand the principles of human brain functionality. This physiological riddle can be broken into smaller parts. These parts, for example, include mechanisms of thoughts and emotions, learning and sleep. The last one is a physiological process, that has not been fully described and understood. Sleep can be defined as a state of unconsciousness that can be changed. In this state, a person is more responsive to internal stimuli than external. Researchers suggest that sleep is essential for a human being. Sleep has an impact on a person's physiological or psychological health. A lack of appropriate night sleep decreases the ability to concentrate and has a negative impact on the learning process. Furthermore, it could attenuate a person's immune system which causes vulnerability to infections. Consequently, more frequent lack of night sleep, which is called sleep deprivation, could be a start for more severe diseases like diabetes, hypertension, depression and obesity. [1, 2]

Sleep deprivation could be caused by a person's lifestyle or because of a difficult job. On the other hand, a human being might not be the only origin of sleep deprivation. These sources could be more complex problems called sleep pathologies. They also cloud harm physical and mental health. Additionally, sleep pathologies without opportune diagnostic and treatment could be fatal. Diagnostic and research in such a difficult area could be time demanding and problematic for hardware to process. Apart from that, benefits are immeasurable. Polysomnography is the latest technology for sleep measuring. It combines various devices to measure electrical activity on different parts of the body. As a result, polysomnography enables precise recording of the signal. Until today, researchers have been discovered more than 100 sleep pathologies.

Sleep paralysis is one of the pathologies described and discussed in this project. This project aims to conduct a preprocessing and analysis of polysomnographic EEG recordings of sleep paralysis using available libraries for Python and Matlab. Additionally, in the EEG segments for sleep paralysis analysis is also determined the heart rate from the ECG channel and evaluated its variability. The obtained results are quantitatively compared with a control group of healthy patients.

2   Overview of the current state

This section provides general descriptions of the sleep process and recording devices. It also contains a usual sleep pathologies classification. In the final part of this section, sleep paralysis, its relationship with stress and research in this field is described.

2.1   Sleep

An adult human being needs approximately seven to eight hours of proper night's sleep. Children and adolescents require more than eight hours. Despite these average numbers sufficient amount of night sleep is individual for a person and is defined by its "internal biological clocks". So-called circadian rhythms are managed by multiple parts of the brain. Circadian rhythm is 24 hours cycle, during which the person accumulates fatigue throughout the day, which reaches its peak in the evening, forcing the person to fall asleep [3]. This is happening because of a stress hormone which is called adenosine. The hormone is produced by a basal forebrain and is accumulated during the day. Another part of the brain involved in the sleep mechanism is called the hypothalamus. It is a peanut-sized structure deep inside the brain made of nerve cells that control sleep and arousal processes. Additionally, within the hypothalamus is the suprachiasmatic nuclei. Such a cluster of cells receives light information that helps to differentiate between daylight, night light and artificial light. The signals from the described organs help a person's brain to use another hormone called melatonin, which is a cause of sleepiness. After a night sleep, the human body produces cortisol, a hormone that awakes a person. [1, 4, 5]

Sleep is a dynamic process that consists of two main phases. Rapid eye movement or REM and Non-rapid eye movement or NREM. Each of them has its unique electrical activity of the brain, which is possible to monitor by electroencephalography (EEG). During a night's sleep, these REM and NREM phases exchange each other and their duration is also changing. At the beginning of the night's sleep, the NREM phase is prevalent. On the other hand, with upcoming morning REM sleep is dominant. Additionally, NREM sleep is divided into three stages. Laying down in a bed and start falling asleep initiates the NREM1 stage. Its duration is from one to five minutes. In such a short time a person's breathing, heart rate (HR) and eyes movement will slow down, all muscles will be relaxed. Furthermore, this stage is characterised by small random muscles spasm. The brain's electrical activity is also slowing. Right after that, the NREM2 stage proceed. A person falls into a deeper sleep, physiological activity continues slowing, body temperature is dropping, eyes movement stops. In the first sleep cycle, this stage is 10-15 minutes

long and with other cycles, the duration is prolonged. Generally, the NREM2 stage takes up half of a person's sleep during the night. NREM3 stage is more known as deep sleep. During this stage, a person is not concise and does not recognize any external stimuli. Muscles' tonus, breath and heart rate are as slow as possible. Monitoring this sleep stage with the EEG shows a predominance of delta activity and is often seen during the first half of the night. NREM3 is very important for the renovations of a person's organism. The duration of this stage is 20-40 minutes and along the night becomes shorter. REM sleep could firstly appear throughout the first 90 minutes of sleep. On the EEG this stage is described with the dominance of the alpha brain activity. Moreover, such an EEG pattern is also accurate for concise adults with closed eyes. REM sleep is characterised by whole-body paralysis except eyes' and breathing muscles. This is a stage of the colourful dreams. [1, 3, 5]

2.2 EEG and ECG

In depth understanding of such a dynamic process as sleep requires a powerful technology. The technology should accurately depict this process and afterwards qualitatively and quantitatively evaluate results.

Electroencephalogram (EEG) is a record of a brain's electrical activity. It represents a summary of a brain's electrical activity. EEG is a rapidly changing, non-linear, stochastic, multi-channel signal. This technology is used by doctors and scientists for a better understanding of brain functionality and identifying the nature of brain disorders like epilepsy, insomnia, physiological or neurological disorders and brain injuries. Extensive sleep studies require more than just one EEG device. It requires a combination of different devices that monitor electrical activity of different organs. Such a device is called polysomnograph (PSG). Usually, PSG includes a combination of EEG, electrooculography (EOG), electromyography (EMG) and electrocardiography (ECG), which record the electrical activity of eyes, muscles and heart respectively. The aim of PSG usage is an analysis of sleep phases and diagnosis of sleep pathologies. PSG is a golden standard for whole-night sleep studies, which brings a priceless advantage to a person's health. [6, 7]

EOG measures electrical potential generated by some changes in the eye's retina, which allow us to monitor the eyes' movements. Those movements might interfere with EEG frontal channels signal, which is close to the eyes, and cause artefacts. Preprocessing with EOG signals enables removing such artefacts from EEG signals. EMG measures the electrical activity of muscles generated by movements of a body. During sleep, a person might move the body causing artefacts in the EEG record. [7]

A recording of heart electrical activity or electrocardiogram (ECG), on which we see the time course of changes in the electrical potential of the heart that origins at the sinoatrial node. The ECG serves as a basic diagnostic element to detect heart disorders. It stores signal in both the time and frequency domain, thanks to which we are able to perform ECG analysis, even for purposes other than cardiology. Unfortunately, its raw form can be distorted and contaminated with unwanted elements and other artefacts. So that we can perform an analysis or extract useful features from the ECG, we must process the signal. After preprocessing is performed the ECG signal could be used for feature extraction. These features are P-wave, T-wave, R peaks and, the most popular, QRS complex detection, see 2.2. There are various techniques of feature detection such as wavelet transformation, differentiation, thresholding and neural networks. Apart from cardiology, this noninvasive diagnostic method is also used in sleep analysis to evaluate epileptic spikes. [6, 8, 9]
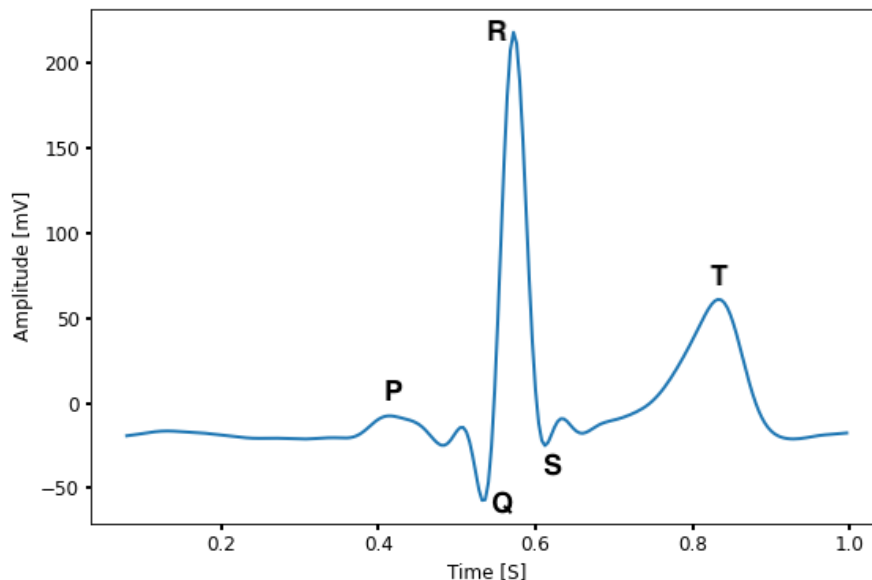

Figure 2.1: Example of a QRS complex in an ECG recording.

2.3   Pathology

Unfortunately, each of the physiological processes has some irregularity and sleep is not an exception.

Generally, sleep pathology is a state which affects the quality, duration and timing of the sleep process. Consequently, this state leads to a negative effect on natural processes during the daytime. Sometimes sleep pathologies could result in a disease, which at first glance does not correlate with sleep at all. In 1990, the International

Classification of Sleep Disorders (ICSD) [10] was created for a better understanding of already discovered sleep disorders and as a motivation to find new pathologies. The publication aimed to simplify communication between international sleep researchers. The ICSD consists of 8 categories: insomnia, breath related disorders during sleep, hypersomnia, parasomnia, movement-related disorders during sleep and others. Each category describes a pathology from a diagnostic, epidemiologic and pathophysiologic perspective. [10]

Insomnias are chronic disorders that are related to the processes of falling asleep or staying asleep and overall sleep quality. Such pathologies could cause sleepiness or even worth things, for example mental problems. Breath related disorders during sleep are different variations of sleep apnea. During the night a person with sleep apnea suddenly stops breathing which causes an awakening. This event could appear repeatedly which causes worsening of sleep scores. Hypersomnia is linked to a daytime sleep of a person. A person with hypersomnia could suddenly fall asleep during the day despite good night's sleep. There are known serious types of hypersomnia where a person could fall asleep during some activity, for example driving a car. A parasomnia is a group of sleep disorders that could cause unwanted and unusual behaviour during sleep. An event could occur during different sleep stages and sometimes is dangerous for the physical and mental health of a person. Examples of parasomnia are sleepwalking, sleep terrors and sleep talking. [11]

2.4 Sleep Paralysis

Sleep paralysis (SP) is a common kind of parasomnia. During sleep paralysis, a person usually experiences a negative event. Sleep paralysis occurs in a moment of falling asleep or arousal from sleep. Throughout the course of the event, a person is conscious and simultaneously feels whole-body paralysis. Additionally, SP could be accompanied by hallucinations, for example, levitation, a feeling of somebody's presence or someone is pressing a person's chest. [12]

The ICSD defines sleep paralysis as REM-sleep parasomnia or a transitional state between sleep and consciousness with elements of REM sleep [13]. There were signs of sleep paralysis even in the ancient world but what causes SP or its mechanism is unknown. A little number of objective studies were held, because of the complexity of sleep paralysis. It is difficult to find a large enough dataset for an objective study. Even more difficult to record such a short and unpredictable event in a sleep laboratory. [12, 14]

My research of the literature in the field of sleep paralysis showed that most of the studies utilized interview or questionnaire methods to acquire and compare data. These studies were mostly interested in the occurrence of SP episodes and their

difference in a person's demographic, gender and age. In the work "A systematic review of variables associated with sleep paralysis" written by Denis D. et al were compared 42 different scientific publications related to sleep paralysis [12]. Most of them were using interview or questionnaire methods mentioned above. Denis D. et al did not find a significant difference in the demographic, gender or age of a person with SP [12]. The study also compared such variables as alcohol or coffee intake and smoking, where the occurrence of SP episodes is higher in people who drink alcohol and smoke than others. An interesting observation was found about coffee intake and its little impact on SP occurrence despite its known bad infancy on sleep in general. Other variables are stress, mental traumas, inheritance and physical health. All of the variables are important in sleep paralysis research. Unfortunately, there were a small number of objective studies which successfully record sleep paralysis in a sleep laboratory. All of them used PSG as a golden standard in their work.

Walther and Schulz [15] compared 10 patients with SP and 10 patients with narcolepsy (NAR) and 10 healthy persons (CON). They found that sleep latency duration was bigger in a group with SP compared to others (SP 40.6 ± 25.3 min; NAR: 19.5 ± 8.8 min; CON: 19.2 ± 15.6 min). A conclusion of the study was a discovery of variables that differentiate SP as a symptom of narcolepsy from SP as an isolated pathology. The variables are inherited alleles of Human Leukocyte Antigen (HLA), sleep latency and REM latency. Additionally, they mentioned the disability to record SP episodes during night sleep. Hence, there is still a question about the connection between the REM sleep phase and SP. [15]

Another study manages to measure SP episodes in 16 participants for seven nights in the laboratory. Takeuchi T et al. [16] induce SP episodes by means of systematic sleep interruption. In the first of 40 minutes of sleep, when a person's sleep phase transitions from NREM to REM. Right after a person's sleep phase changed to REM the person was awakened and completed a brain performance test then went to sleep again. During the study, the authors conducted sleep interruption 64 times and recorded only six SP episodes. Each episode occurred after the brain performance test and in the moment of falling asleep. One of six SP episodes showed non-physiological behaviour when a person immediately fell into the REM sleep phase, which was called the sleep-onset REM period (SOREMP). The same author confirmed a connection between SOREMP a sleep paralysis in his later study. A method of systematic sleep interruption was used again. Eight SP episodes were induced from 184 sleep interruptions in the later study. The main assumption from both studies was a close connection between the REM sleep phase and SP episodes. Stress influence on SP episodes occurrence remained unknown. [16, 14]

The last study, held by Mainieri et al [17] investigated spectral characteristics of sleep paralysis. Their results were five SP episodes from five patients. The recorded

data were separated into three seconds long mini-epochs. The data from an EEG spectral analysis were compared with the health group. EEG spectrum of alpha, delta and theta activity in SP episodes were without deviation from spectral power of physiological REM sleep. The fundamental discovery was a predominance of theta activity in mini-epochs' spectral analysis. The authors concluded that a person's brain is more in a sleep state than in a conscious state. The limitation of this study was the small number of EEG channels and participants. Hence, they could not create a topological map of an electrical potential location.

2.5 Distress and Sleep Paralysis

According to a newspaper the Lancet [18] the prevalence of sleep paralysis is 5-62 %. The numbers include isolated episodes and also recurrent episodes of sleep paralysis. Referring to subsection 2.1, sleep is an essential process its deficiency or even absence could result in dangerous health and mental issues. The appearance of sleep paralysis episodes was linked with sleep deprivation and sleep cycle disturbance. Patients diagnosed with this sleep pathology usually report aggressive and terrifying dreams. Hence, such a negative experience from a vital process such as sleep gives rise to harmful stress or so-called distress. [12, 18]

Psychological distress is a general term used to describe unpleasant feelings or emotions that impact a person's level of functioning. In other words, it is psychological discomfort that interferes with his or her activities of daily living. Psychological distress can result in negative views of the environment, others, and the self. Sadness, anxiety, distraction, and symptoms of mental illness are manifestations of psychological distress. So, no two people experience one event the same way. Psychological distress is a subjective experience. That is, the severity of psychological distress is dependent upon the situation and how a person perceives it. Traumatic experiences are causes of psychological distress. Psychological distress occurs because of the inability to cope with external events or stressors. In general, scientists believe that physiological, cognitive and social influence take a part in causing distress since those factors form person-environmental interaction. [19]

As stated by Denis D. [20] 10 % of the human population who experienced sleep paralysis episodes had a significant level of distress. Solomonova E. et al. [21] agree with this statement. Furthermore, she adds that the prevalence of distress within sleep paralysis patients is bigger in hallucination type of episodes, more precisely filling of an intruder's presence. As mentioned above, two persons' reactions to the same stressor are different. Additionally, Solomonova claims that distress predisposition increase distress appearance during and SP episode.

2.6 Heart Rate Variability

Stress is a body response to some changes in the environment that can be stimulating or devastating [19]. Psychological distress might affect biological processes contributing to existing health problems or developing new ones [22]. Such a response is fully autonomous neural activity. Sympathetic activity, which is a part of the autonomous nervous system, predominantly is the cause of such responses [23]. The human heart might be a good indicator of stress since it is regulated through an autonomous neural system (ANS). Additionally, an indication of the involuntarily regulation of the heart is heart rate variability (HRV) [24]. HRV is a measurement of the variability of the intervals between consecutive heartbeats and not heartbeats themselves. Much literature was written evaluating the fitness of HRV metrics to be a good stress indicator [25, 26]. Few literature concluded that psychological distress affects HRV. Others studied sleep pathologies like sleep apnea and insomnia and concluded their influence on physiological HRV values [27].

HRV can be characterized by the time and frequency domain parameters. Time-domain parameters are used for the analysis of heartbeat or an interval between them. For the calculation of time-domain parameters, the QRS complex detection on a continuous ECG signal is utilised. The detection result is then used mainly for HR or RR intervals calculation. RR interval is an interval between R-R peaks. Mean RR interval value, mean HR value, the difference between longest RR and shortest RR, and the difference between HR value in day and night time are usual parameters. Additional parameters can be calculated from the simple time-domain parameters with the help of statistical methods. The table 2.1 represents regular statistical HRV time-domain measures. [28, 22, 29]

Table 2.1: HRV time-domain metrics [29]

Parameter	Unit	Description
SDNN	ms	Standard deviation of NN intervals
SDRR	ms	Standard deviation of RR intervals
SDANN	ms	Standard deviation of the average NN intervals for each 5 min segment of a 24 h HRV recording
SDNN index (SDNNI)	ms	Mean of the standard deviations of all the NN intervals for each 5 min segment of a 24 h HRV recording
pNN50	%	Percentage of successive RR intervals that differ by more than 50 ms
HR Max - HR Min	bpm	Average difference between the highest and lowest heart rates during each respiratory cycle
RMSSD	ms	Root mean square of successive RR interval differences
HRV triangular index	-	Integral of the density of the RR interval histogram divided by its height
TINN	ms	Baseline width of the RR interval histogram

Spectral parameters of HRV are frequency ranges of the spectrum that describes an influence of either parasympathetic or sympathetic activity. HRV spectral characteristics can be used not only for the assessment of parasympathetic and sympathetic influence on heart rate but also as parameters of the tone (tonus) of the autonomous nervous system. Spectral characteristics have more information about physiological processes than time-domain characteristics in short-term recording, less than 24 hours. Typically the power spectral density (PSD) is calculated by means of non-parametric and parametric methods. The table 2.2 represents regular frequency-domain parameters. [30, 31, 28]

Table 2.2: HRV frequency-domain metrics [29]

Parameter	Unit	Description
VLF	ms^2	Power in VLF range ($\leq$0.04 Hz)
LF	ms^2	Power in LF range (0.04 - 0.15 Hz)
HF	ms^2	Power in HF range (0.15 - 0.40 Hz)
LF norm	-	LF power in normalized units
HF norm	-	HF power in normalized units
LF/HF	-	Ratio $LF[ms^2]/HF[ms^2]$

Concluding the above studies, the mechanism of sleep paralysis is unknown. A danger to the physical and mental health of a person that holds this pathology is also yet to be fully described. Such finding is a motivation for quantitative research of sleep by means of biological signals and a more robust dataset.

3   Aims of the project

The aim of this project is to propose a methodology for the analysis of PSG in patients with sleep paralysis in the Python programming language and MATLAB environment. The methodology will include processing and analysis of the ECG and EEG data using the "MNE-Python", "FieldTrip", "NumPy" and "SciPy" signal libraries. The results of the methodology should help to explain part of the mechanism of sleep paralysis together with a comparison of parameters found in previous studies.

The EEG processing will result in the spectral characteristics of sleep paralysis. ECG processing will result in heart rate variability metrics in the time and frequency domain. The signal processing will utilize a data set with 19 patients with sleep paralysis. A quantitative comparison will be performed together with a control group of individuals without SP. The findings should help explain part of the mechanism of sleep paralysis together with a comparison of parameters found in previous studies.

4 Methods

Within the Methods chapter, the used data set of sleep EEG records and distress questionnaire is described. Subsequently, this chapter describes the methods of preprocessing, spectral and statistical analysis of the EEG and ECG data in the programming environment Matlab [32], programming language Python [33] and the usage of the publicly available libraries for signal processing like MNE-Python [34], SciPy [35] and NumPy [36].

4.1 Experiment and Data

Data files containing sleep records in subjects suffering from sleep paralysis were measured in the National Sleep Laboratory Institute of Mental Health during the years 2018-2020. The measurement involved 19 probands with sleep paralysis and 19 healthy individuals as a control group. Individual measurements were performed using a standard routine - polysomnographic recording during the night.

The EEG assembly was unipolar - the electrodes were connected to the reference electrode [6]. The placement of the electrodes was arranged according to the international system 10-20. The provided data were checked and the individual sleep phases were described (scored) by the physician. One of the outputs of the classification process is a graph that displays an overview of the interchangeable sleep phases called a hypnogram, see figure 4.1. No SP episode occurred during measurements and was confirmed by the doctor. For this project 19 recordings was used for preprocessing and analysis.
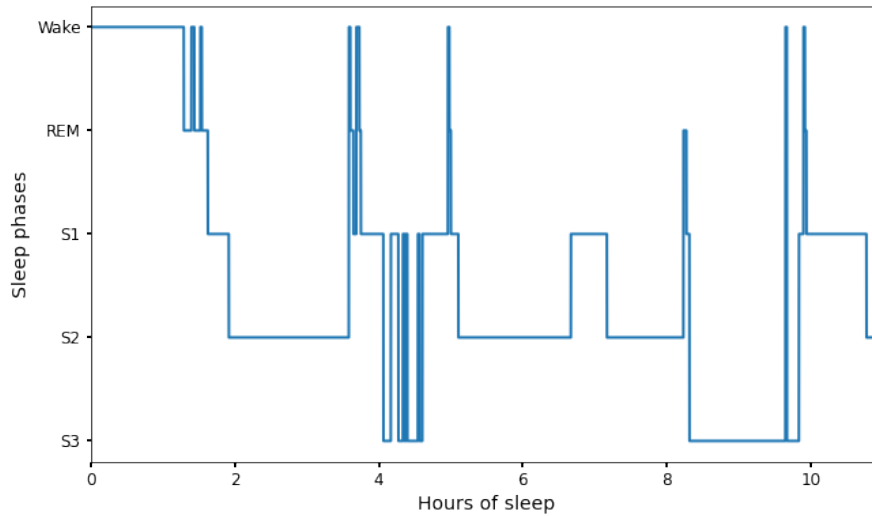
Figure 4.1: Hypnogram for one of the PSG recordings

The mean sample length of the data is 6546726 samples or approximately seven and a half hours. Figure 4.2 shows a 30 second segment [37] from the original signal of one patient with SP. Original data files were transformed to a specific format supported by the MNE-Python library. FIF-file were exported from MATLAB's mat-file with all its information. MATLAB's mat-file was utilized as well.
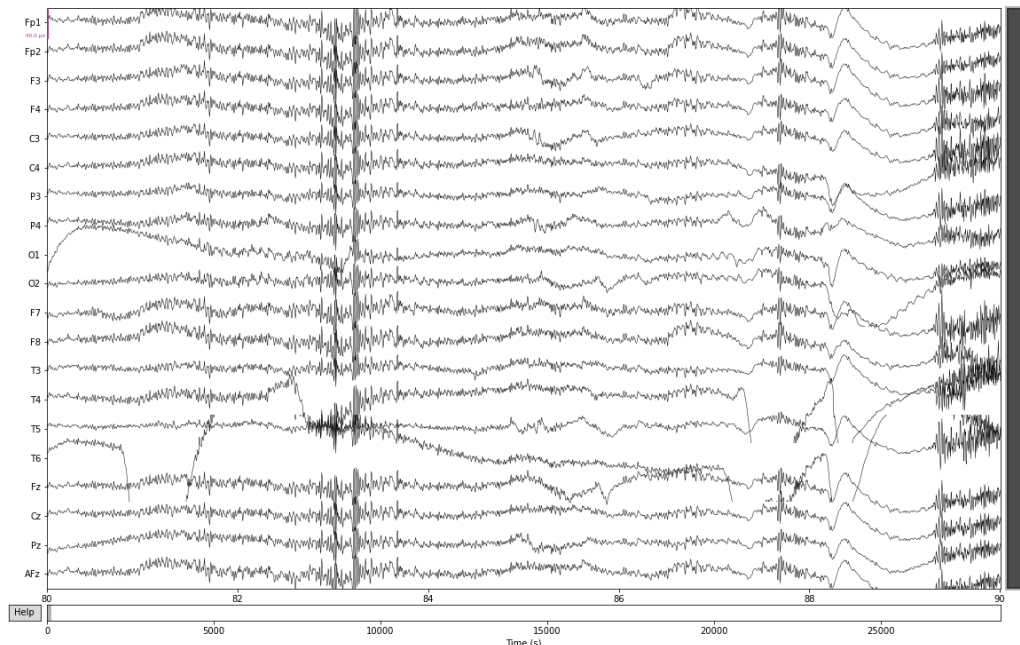
Figure 4.2: Polysomnogram recording of the 10 seconds length of one of the patients before filtration.

Additionally to PSG measurements, participants undergo an adjusted Fearful Isolated Sleep Paralysis Interview. The interview aims to evaluate the frequency and stress level of the SP episodes for each person in general [38]. Every person in this dataset was interviewed to evaluate their stress level from experience with SP episodes. The results were numbers from one and without a limit, where one represents no stress and anything other represents the severity of the distress caused by SP episodes.

4.2 Data processing

The subsection dives into details of the EEG and ECG signals preprocessing. Additionally, the subsection explains the selection, extraction and calculation of the parameters of interest from the EEG and ECG signals.

4.2.1 Filtration

Biological signals have a quasi-stationary to a non-stationary character. In addition, each biological signal could be contaminated with unwanted artefacts. In the case of EEG, these are line noise, electrical circuit noise, blinking, limb or head movement. In order to analyze the measured data and obtain relevant results, it is necessary to get rid of these undesirable properties of biological signals using analogue and digital filtering.

For the EEG signal, a FIR (Finite impulse response) filter of the order of 1000 was used as a bandpass in the defined frequency band, from 0.5 Hz to 40 Hz. For the ECG signal, an IIR (Infinite impulse response) filter of the order of 16 was also used as a bandpass in the defined frequency band, from 0.5 Hz to 20 Hz. This eliminated the slow changes (drift) of the EEG and ECG signals, line noise, and frequencies outside the scope of this sleep research. Baseline correction and linear trend suppression from the data were also performed.

4.2.2 Epochs creation and artifacts rejection

In fulfilment of successful analysis, long and continuous EEG and ECG signals need to be divided into smaller epochs. For this purpose, additional information such as epochs' labels and their duration were extracted in a special format from original mat-files. A file with epochs information was also loaded to MNE-Python [34]. After filtration, the continuous recording was divided into 30-second epochs and arranged into individual groups according to the sleep phase. The original data structure was separated into four data structures corresponding to these sleep phases: NREM1,

NREM2, NREM3 and REM [37]. The awake phase was not taken into account due to the irrelevancy with SP. As the filtration did not remove all the artefacts in EEG, muscle artefacts were a significant problem.

Therefore, an amplitude-assisted signal thresholding function implemented in the MNE-Python library was used. Using an iterative mechanism, the function scans each sample in each EEG channel and removes entire epochs in which any value exceeds amplitudes greater than 150 or less than -150, see 4.3. This procedure extracted signals for further analysis that did not contain significant artefacts.
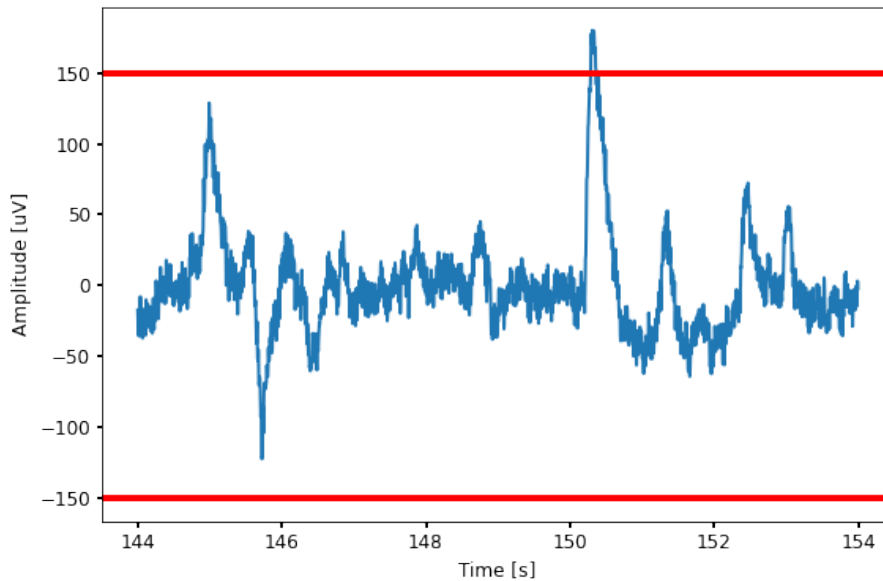
Figure 4.3: Example of an amplitude-assisted signal threshold

4.2.3 R-peaks detection

Component detection is an essential part on which the evaluation of an ECG recording is based. The goal of detection is to reliably identify and locate specific components, which are the subject of ECG analysis. Thanks to the detected components, the signal can be segmented and evaluated.

The filtered and segmented ECG signal was used for the detection procedure. Identification of the heart rate variability metrics needs R-peaks detection. The detection procedure was performed by means of a function called `find_peaks()` from a signal processing library SciPy [35]. The function searches for the local maxima of an ECG signal depending on the specified threshold amplitude and the minimum distance between successive R waves. The amplitude threshold was chosen to be

22

0,9 mV and a minimum distance between two peaks was 150 samples. The figure 4.4 illustrates an example of the output from this function.
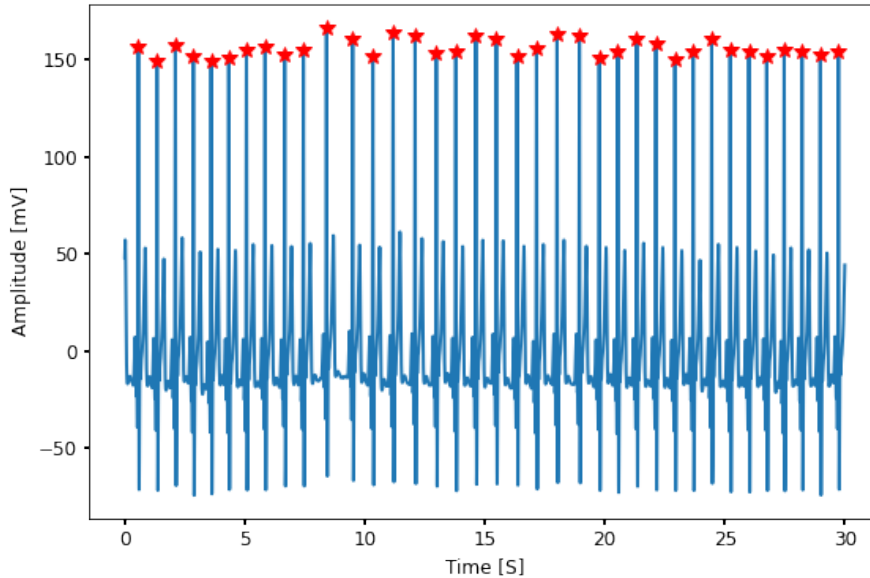
Figure 4.4: Example of the R-peaks detection

The R-peaks information is used as raw data for the calculation of heart rate (HR) and RR intervals. Those two are intermediate steps for the final calculation of different parameters in the time and frequency domain for ECG and cardiac condition analysis. A RR interval is a difference between consecutive R-peaks. This difference was calculated utilizing a function called `ediff1d()` from the NumPy library. For this project, RR intervals were calculated for each sleep phase and subject separately. Since the whole continuous PSG recording was divided into 30 seconds epochs (see 4.2.2), the obtained RR intervals values were very short. Separately from EEG epochs, RR intervals were combined into 5 minutes epochs. From the extracted RR intervals a tachogram was created. Tachogram represents RR interval duration as a function of progressive beats. Due to the physiology of the cardiac oscillation, the RR intervals are not equally spaced in time [28]. Thus, for proper exploitation of the tachogram for the spectral analysis RR intervals were normalized as:

$$I_k = \frac{I_k - I_{mean}}{I_{mean}} \tag{4.1}$$

, where I_k is a consecutive duration of a RR interval and I_{mean} is a mean duration of RR intervals per a 5-minute recording. The normalized tachogram was finally resampled on 1024 samples per 5-minute epoch. The result is an equally spaced tachogram of 5 minutes. [28, 39, 40]

23

4.2.4 Spectral analysis

The filtered EEG signal and tachogram were converted from the time domain to the frequency domain using different methods in Python and MATLAB.

The function called `ft_freqanalysis()` was used in the MATLAB environment from Fieldtrip library for the conversion of the EEG signal to the frequency domain. This function performs frequency analysis of any time epoch using a conventional single window or, in this case, were used multiple windows based on discrete prolate spheroidal sequences or Slepian sequences (DPSS) [41, 42]. As mentioned in subsection 4.2.2, the signal was divided into 30-second epochs, which is the standard length when describing sleep EEG data [6, 14]. Sleep, in the EEG, is divided into several bands according to the individual frequencies that prevail in a given band. For the evaluation of data in this work, I selected three frequency bands that correspond to separate EEG activities. These are the delta, theta, and alpha bands, which correspond to ranges 1-4 Hz, 5-8 Hz, and 9-12 Hz, respectively. The output of the spectral analysis is a data structure containing these three EEG bands of interest for each sleep phase. Power spectral density has absolute units that were converted to relative units and relative spectral density, respectively. Hence, relative spectrum represents a percentage of power in a frequency band and enables precise statistical comparison [6]. Conversion to relative spectrum was utilizing a newly created function in MATLAB called `relpowerband()`. The mathematical description of this function states as:

$$RP = \frac{P_{f_b}}{P_f} \tag{4.2}$$

,where P_{f_b} is a power of a specific frequency band, P_f is a sum of power across the whole spectrum. The output is a relative spectrum for specific sleep phase.

The tachogram obtained from the subsection 4.2.3 was converted to the frequency domain as well. A function from the SciPy library in Python programming language was exploited. This function computes a power spectral density by means of the periodogram method. The function's parameters were set to use a single Hann window, a sampling frequency of four hertz and a constant detrending method.

4.2.5 HRV characteristics

RR intervals were used for subsequent extraction of HRV metrics in both the time and frequency domain. Parameters in the time domain are chosen because of their frequent clinical use and simple computation [29]. Parameters in the frequency domain are chosen because of the comprehensive representation of autonomous physiological processes [28].

Full list of the time domain parameters that were chosen for HRV analysis in this project are listed below.

- $\overline{RR}$ [ms] – Mean of RR intervals

- $SDRR$ [ms] – Standard deviation of RR intervals

- $RMSSD$ [ms] – Root mean square of successive RR interval differences

- NN_{50} [-] – successive RR intervals that differ by more than 50 ms

- pNN_{50} [%] – percentage of successive RR intervals that differ by more than 50 ms

- $\overline{HR}$ [bpm] – mean heart rate value of a sleep phase

- $STDHR$ [bpm] – standard deviation heart rate value of a sleep phase

- $MinHR$ [bpm] – minimal heart rate value of a sleep phase

- $MaxHR$ [bpm] – maximal heart rate value of a sleep phase

Full list of the frequency domain parameters that were chosen for HRV analysis in this project are listed below.

- LF [ms^2] – Power in LF range (0.04-0.15 Hz)

- HF [ms^2] – Power in LF range (0.15-0.40 Hz)

- $LFnu$ [-] – LF power in normalized units

- $HFnu$ [-] – HF power in normalized units

- LF/HF [-] – Ratio $LF[ms^2]/HF[ms^2]$

Mean RR interval was computed according to [29] as:

$$\overline{RR} = \frac{1}{N} \sum_{i=1}^{N} RR_i \tag{4.3}$$

,where $\overline{RR}$ is the calculated average of RR intervals and N is the number of RR intervals.

Standard deviation of RR intervals (SDRR) was computed according to [29] as:

$$SDRR = \sqrt{\frac{1}{N-1} \sum_{i=1}^{N} (RR_i - \overline{RR})^2} \tag{4.4}$$

,where $\overline{RR}$ is the calculated average of RR intervals, RR_i is a successive RR interval and N is the number of RR intervals.

Root mean square of successive RR interval differences (RMSSD) was computed according to [29] as:

$$RMSSD = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(RR_{i+1} - RR_i)^2} \tag{4.5}$$

,where RR_{i+1} and RR_i are successive RR intervals and N is the number of RR intervals.

Percentage of successive RR intervals that differ by more than 50 ms (pNN_{50}) was computed according to [29] as:

$$pNN_{50} = \frac{NN_{50}}{N-1} \cdot 100\% \tag{4.6}$$

,where NN_{50} is a count of successive RR intervals that differ by more than 50 ms and NN is the number of RR intervals.

Mean heart rate value of an sleep phase was computed according to [29] as:

$$\overline{HR} = \frac{1}{N}\sum_{i=1}^{N}HR_i \tag{4.7}$$

,where HR_i an HR value and N is the number of HR values.

Standard deviation of a heart rate value of an sleep phase was computed according to [29] as:

$$STDHR = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(HR_i - \overline{HR})^2} \tag{4.8}$$

,where $\overline{HR}$ is the mean heart rate value, HR_i is a successive HR value and N is the number of HR values.

Power in LF and HF range was calculated utilizing implementation of a numerical integration method in NumPy library [36] in programming language Python. Parameters of the function called `numpy.trapz()` were power spectral density values and a range of frequencies that defines the boundaries of an integral [43]. Computation of LF power in normalized units was conducted as:

$$LFnu = \frac{LF}{LF + HF} \cdot 100 \tag{4.9}$$

Same logic was used for the computation of HF power in normalized units:

$$LFnu = \frac{LF}{LF + HF} \cdot 100 \qquad (4.10)$$

4.3   Statistical analysis

Statistical analysis was performed on the extracted data set, see section 4.2. The comparison was made at the level between groups, where the unit of analysis is a single person. This comparison makes it possible to extract sleep paralysis information across subjects. For the EEG analysis were used spectral characteristics. On the other hand, HRV metrics were used to perform ECG statistical analysis. The utilized dataset contains 19 subjects with sleep paralysis. The same number of subjects was in the control group.

It was decided to use non-parametric testing for the given set of sleep data, more precisely permutation testing. In the Fieldtrip library in MATLAB, this statistical analysis is implemented within the function `cfg.method = 'montecarlo'` and the number of randomisation was selected as `cfg.numrandomization=1000`. The classical independention of T-test was used to calculate the test statistics, which is marked in the library as follows `cfg.statistic = 'indepsamplesT'`. [44, 45]

HRV metrics in the time domain were tested in the SciPy library. This statistical analysis is implemented within the function `ttest_ind(parameters)`. It takes many parameters such as numbers of randomization for permutation testing, the equivalence of variance and whether it creates a two-side or one-side alternative hypothesis. [35]

Another setting for statistical analysis is the selection of the multiple comparison correction method. The False discovery rate (FDR) method was used for the EEG data analysis, which obtains the division constant from the probability distribution. For the time domain HRV metrics, Bonferroni correction was used, which does the same but with different relation to p-values. [46]. Both corrections checks the probability of a type I error and thus determines the critical p-value. [45]

Finally, a correlation analysis was performed between distress values in patient with SP and frequency domain HRV characteristics (see 4.1 and 4.2.5). A function in NumPy library called `corrcoef()` was used. The function return Pearson product-moment correlation coefficients.

5 Results

In this chapter, the outputs from the signal processing, spectral and statistical analysis subsections were described (see 4.2, 4.2.4 and 4.3).

5.1 Signal processing

The raw data after the experiment in the sleep laboratory of the National Institute of Mental Health was subjected to the filtration method described above, see 4.2.1. Figure 4.2 shows a 10 seconds sample of a polysomnogram recording of one of the patients before filtration, where all channels are visible. Amplitude of each EEG channel on the figure is in microvolts. In Figure 5.1. is a similar example of a record but a filtered signal from a polysomnogram of the same patient of the same length.
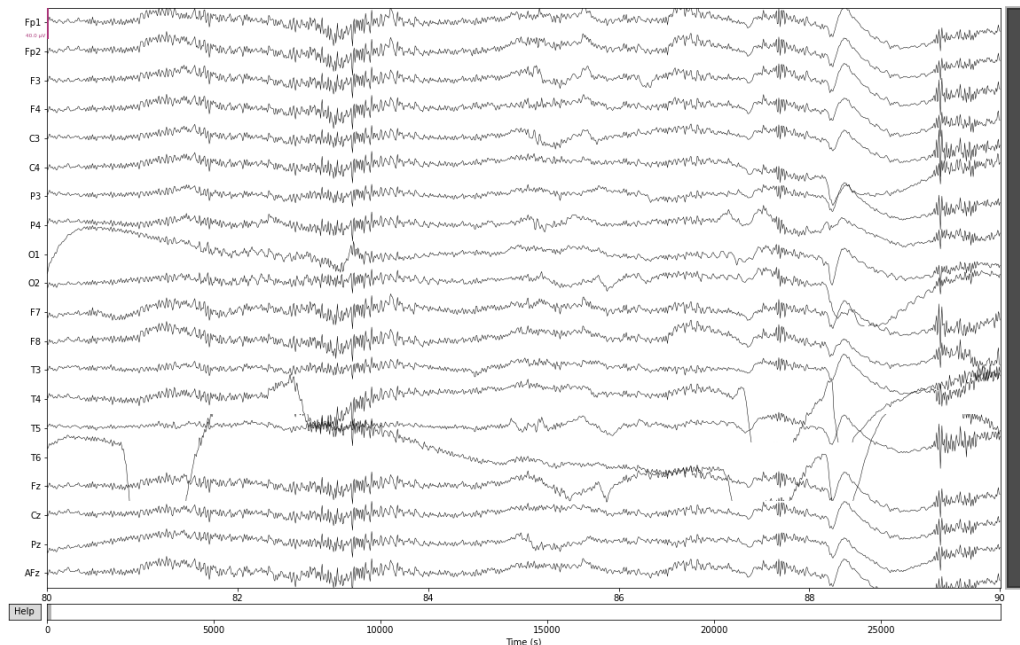
Figure 5.1: Polysomnogram recording of the 10 seconds length of one of the patients after filtration.

The next two figures listed below (figures 5.2 and 5.3) represent a complete overview of the filtration results by visualization of a one channel. Figures 5.2 and 5.3 present the records from the Fp1 electrode of one of the patients without filtration and after filtration. The record length is 10 seconds. An amplitude reduction is visible in some areas on the figure 5.3 in comparison to the figure 5.2. Unfortunately, muscle artefacts continued to exist.
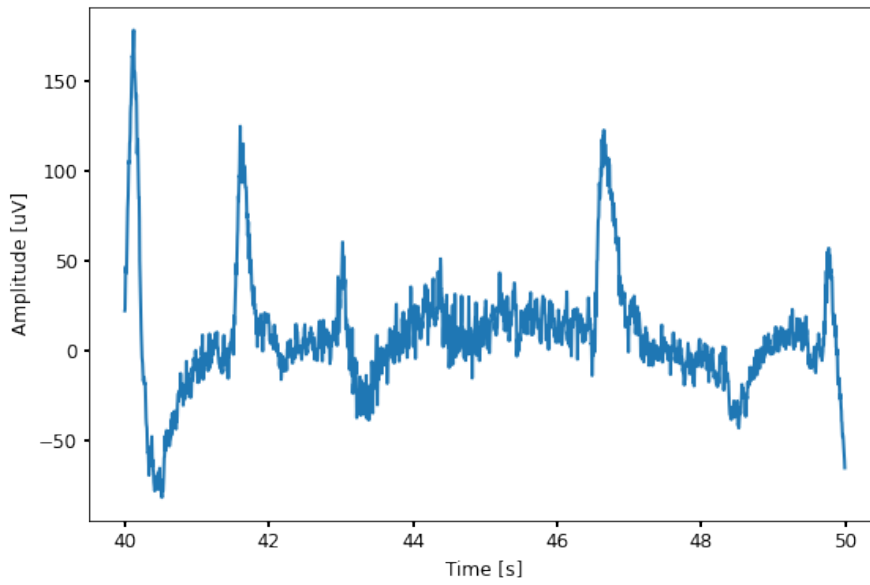
Figure 5.2: Fp1 channel recording of the length of 10 seconds of one of the patients before filtration.
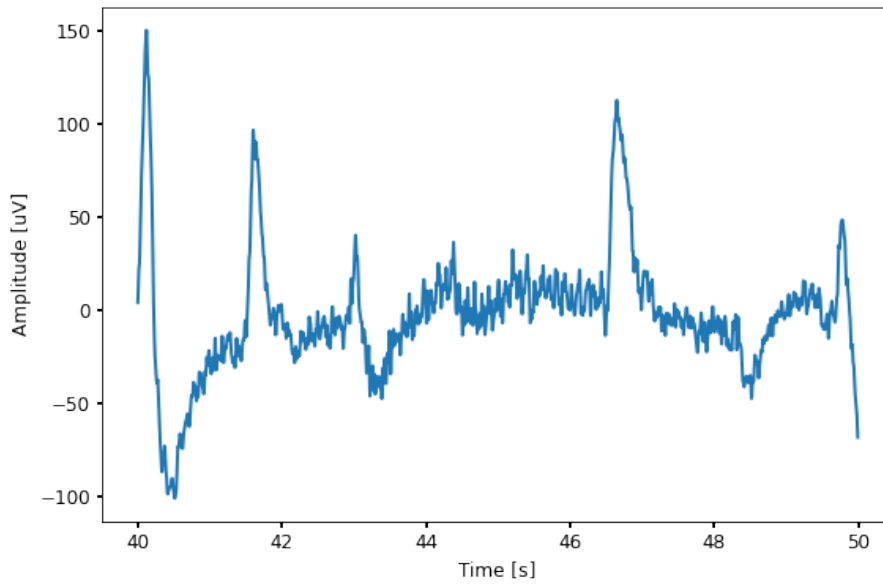
Figure 5.3: Fp1 channel recording of the length of 10 seconds of one of the patients after filtration.

Figures 5.4 and 5.5 show a 10 seconds example of an ECG channel recording of one of the patients before and after the filtration.
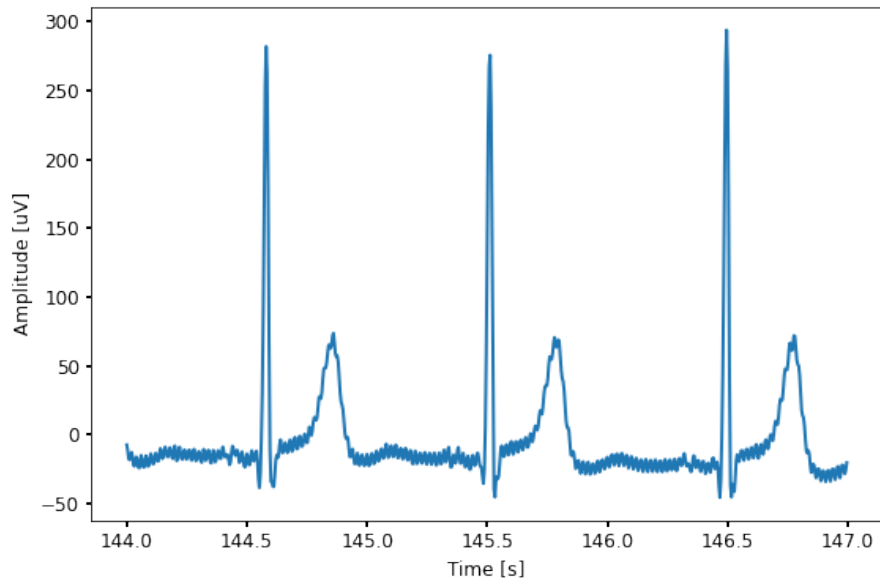
Figure 5.4: ECG channel recording of the length of 10 seconds of one of the patients before filtration.
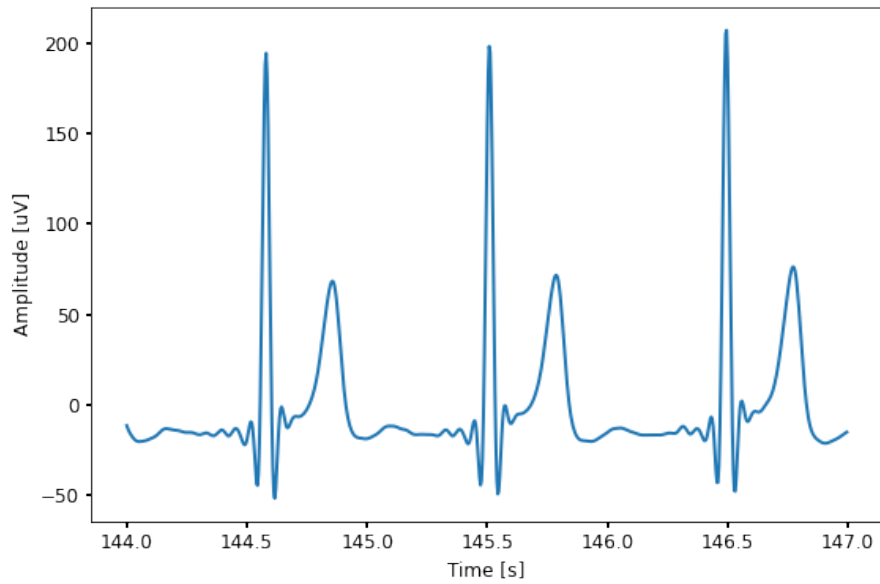
Figure 5.5: ECG channel recording of the length of 10 seconds of one of the patients after filtration.

After filtration, the continuous signal was divided into 30-second epochs and assigned to the appropriate phase of sleep. Figure 5.7 shows how the created epochs are located on the filtered signal.
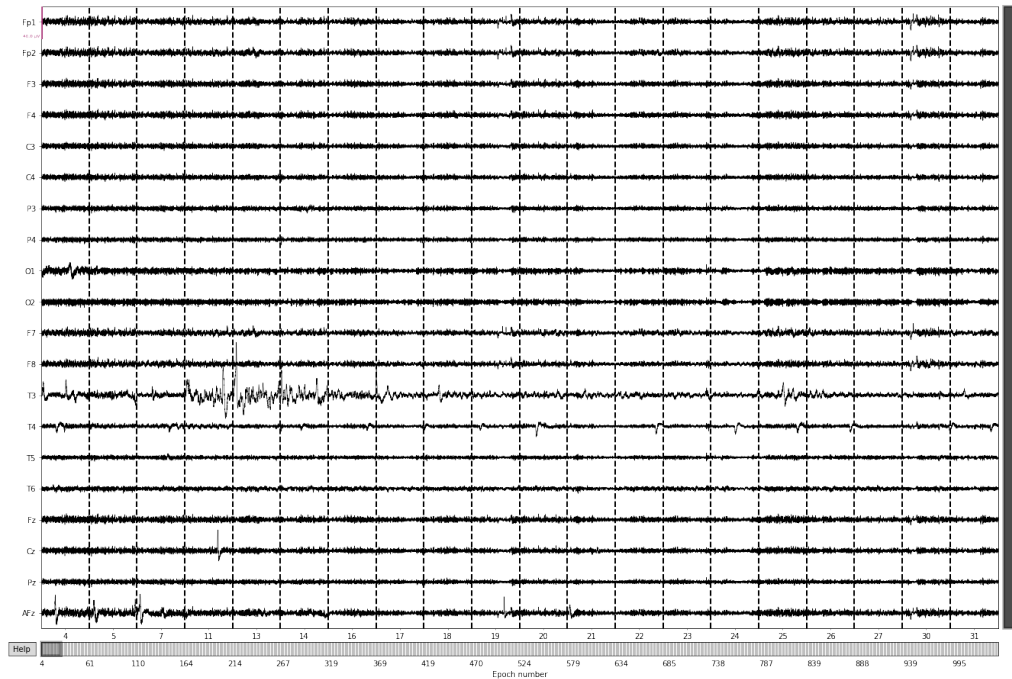
Figure 5.6: Epochs assignment example

5.2 Spectral analysis of the tachogram

Results from the spectral analysis of the tachogram were visualized as PSD. Since the output from the spectral analysis of the tachogram yield 18 PSDs for each sleep phase of interest. One for every subject. The PSDs were averaged for better representation. The next figures (5.7, 5.8, 5.9, 5.10) represent a PSD for one sleep phase of interest. Each PSD has coloured areas that represent the frequency range of the VLF, LF and HF parameters. See section 4.2.5 for more details on the calculation of the spectral HRV parameters of interest.

In these four figures, we can distinguish the difference in the power between REM (fig. 5.7), NREM1 (fig. 5.8), NREM2 (fig. 5.9), and NREM3 (fig. 5.10) stages of sleep. Stating with the NREM1 (fig. 5.8) stage the total power was decreasing with each following stage and become very low in the NREM3 (fig. 5.10) stage which corresponds to the deep sleep.

31
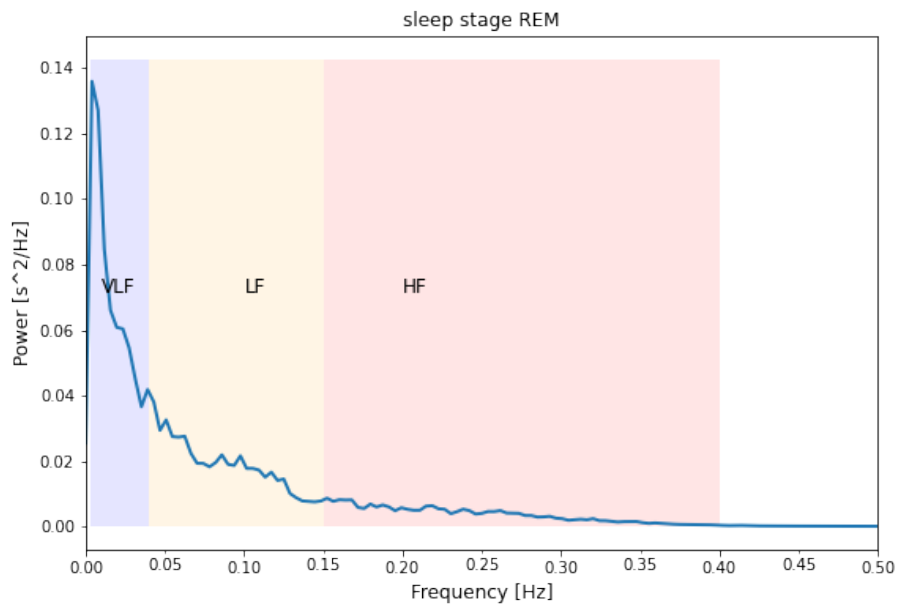
Figure 5.7: PSD of the tachogram for REM sleep phase

The difference in total power between NREM1 (figure 5.8) and REM (figure 5.7) stages is small in comparison to others. That is because NREM1 and REM is closer to the awake state then others.
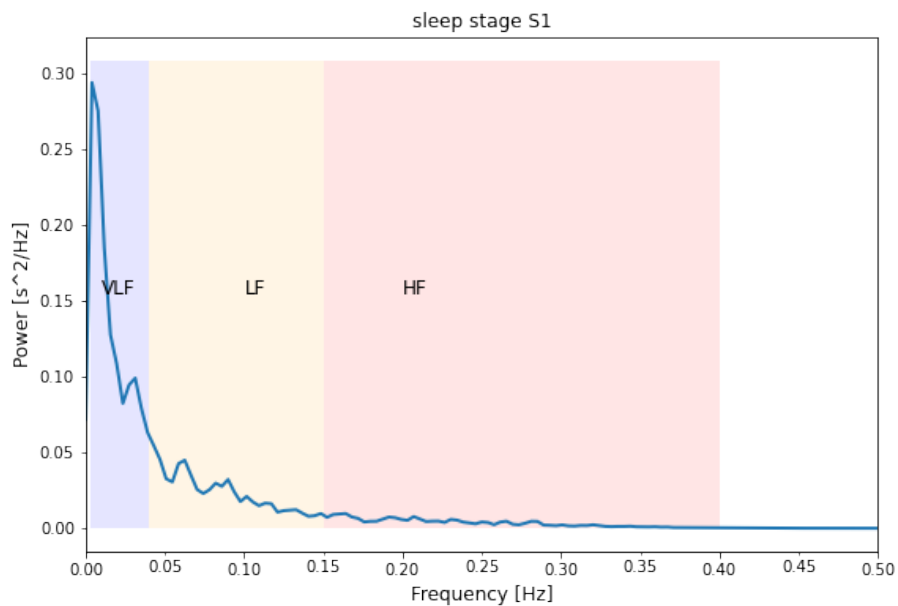
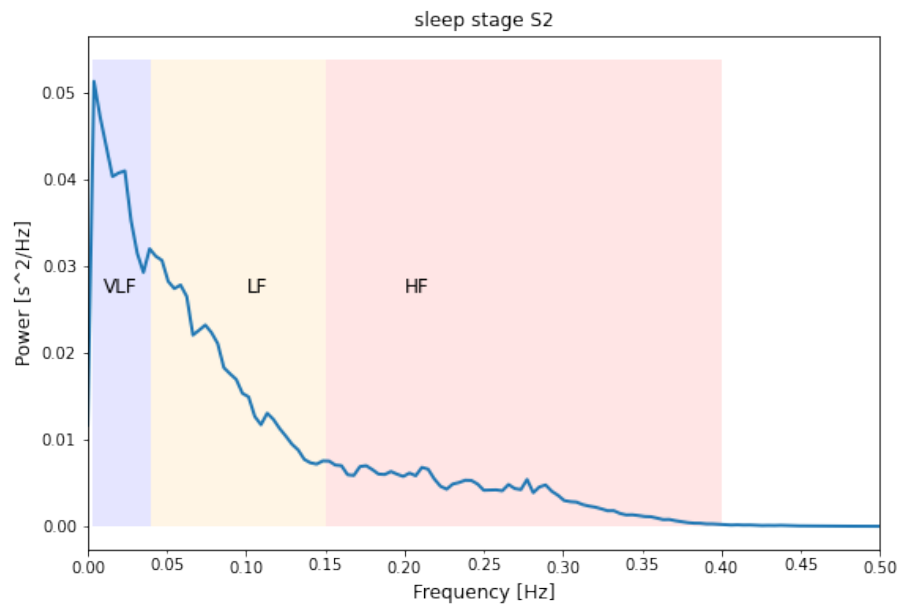
Figure 5.8: PSD of the tachogram for NREM1 sleep phase

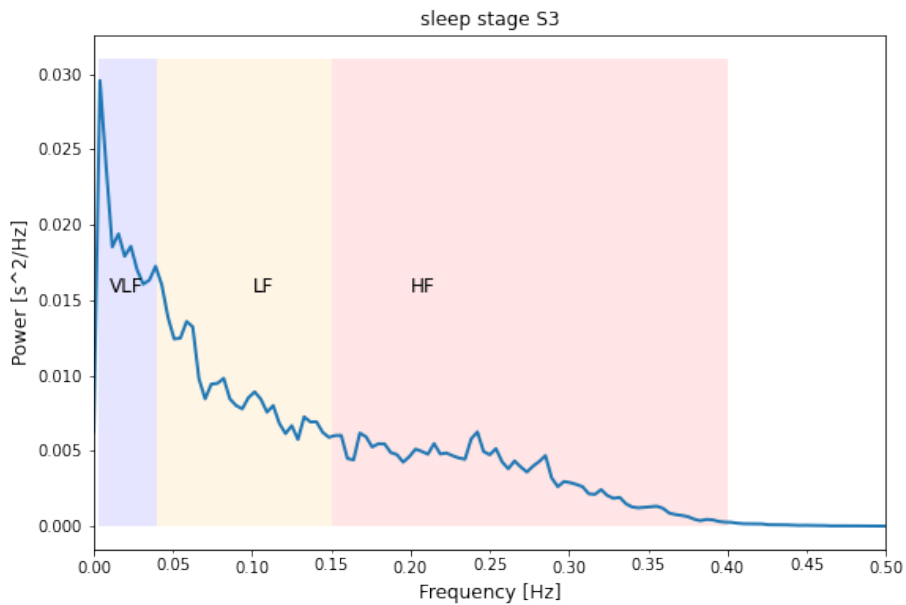Figure 5.9: PSD of the tachogram for NREM2 sleep phase

Figure 5.10: PSD of the tachogram for NREM3 sleep phase

5.3 Statistical analysis of HRV characteristics

Results from the chosen time domain HRV measures were visualized using the box-plot method. Each figure illustrates one of the time domain HRV metrics to each sleep phase. For each sleep phase was created two boxes for SP patient and health

person respectively. Each square box represents the median; the top of the bar indicates 75 percentile; the bottom of the bar indicates 25 percentile. [47]
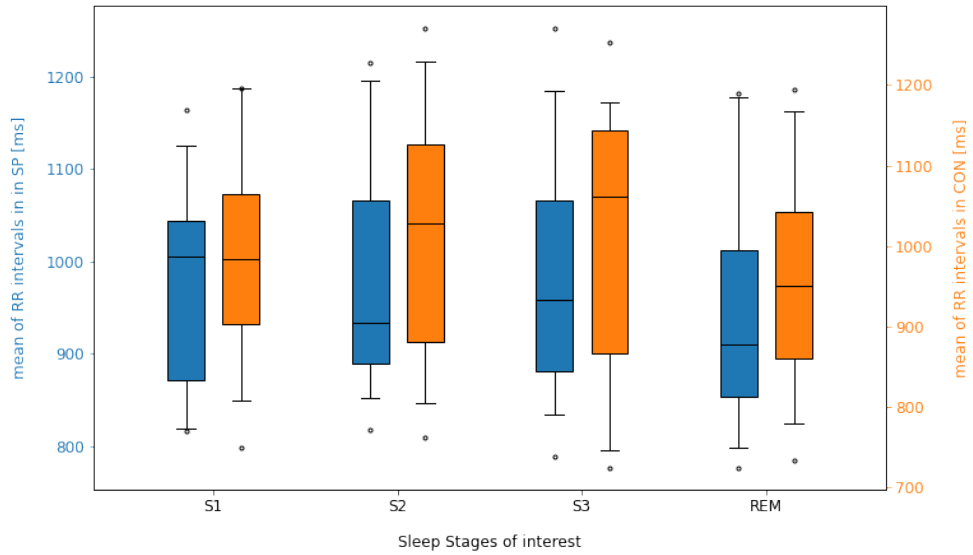
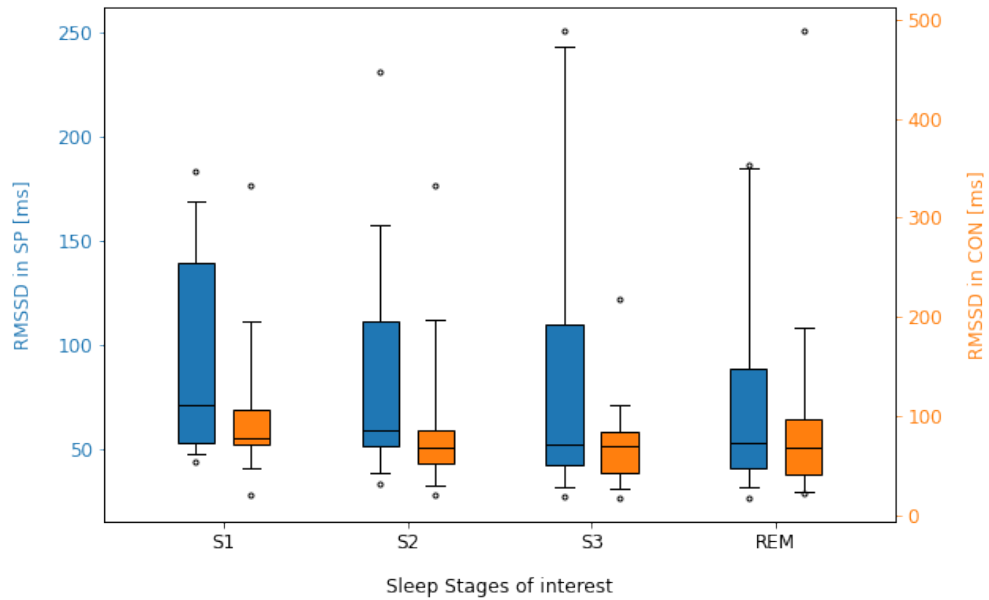Figure 5.11: Mean of RR intervals of SP and CON for sleep phases of interest

Figure 5.11 indicates the mean RR intervals of patients with SP and control group for each sleep phase of interest. At the first sight, there is a small difference between groups, but on a confidence level of 5 % there is no statistical significant difference between groups.
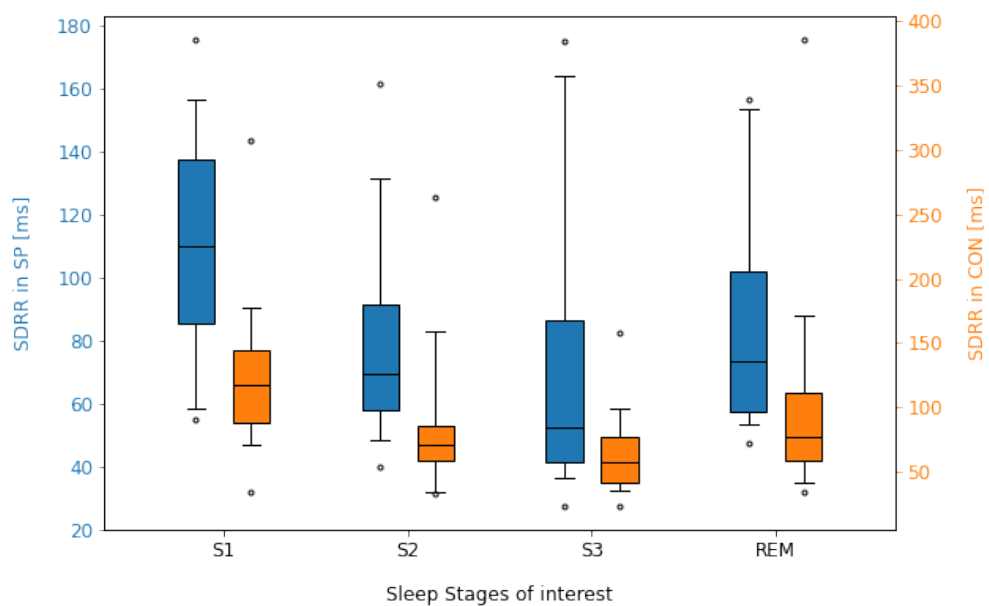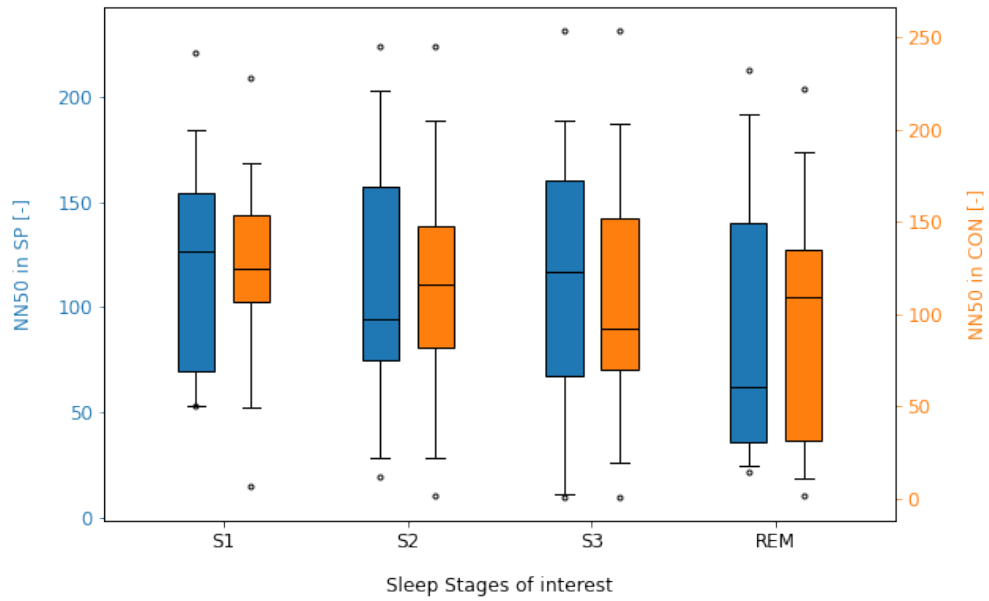

Figure 5.12: SDRR of SP and CON for sleep phases of interest

Figure 5.12 indicates standard deviation of RR intervals of patients with SP and control group for each sleep phase of interest. From the first sight there is a small difference between groups, but there on a confidence level of 5 % there is no statistical significant difference between groups.

Figure 5.13: RMSSD of SP and CON for sleep phases of interest

Figure 5.13 indicates RMSSD of RR intervals of patients with SP and control group for each sleep phase of interest. From the first sight there is a small difference between groups, but on a confidence level of 5 % there is no statistical significant difference between groups.
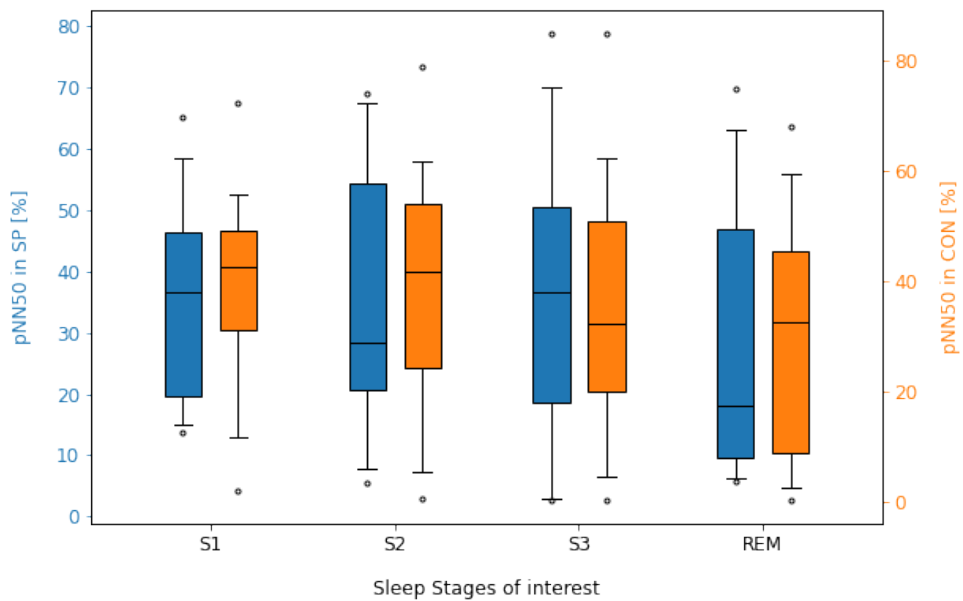
Figure 5.14: NN50 of SP and CON for sleep phases of interest

Figure 5.14 indicates NN50 of RR intervals of patients with SP and control group for each sleep phase of interest. From the first sight there is a small difference between groups, but on a confidence level of 5 % there is no statistical significant difference between groups.

Figure 5.15: pNN50 of SP and CON for sleep phases of interest

Figure 5.15 indicates pNN50 of RR intervals of patients with SP and control group for each sleep phase of interest. From the first sight there is a small difference between groups, but on a confidence level of 5 % there is no statistical significant difference between groups.
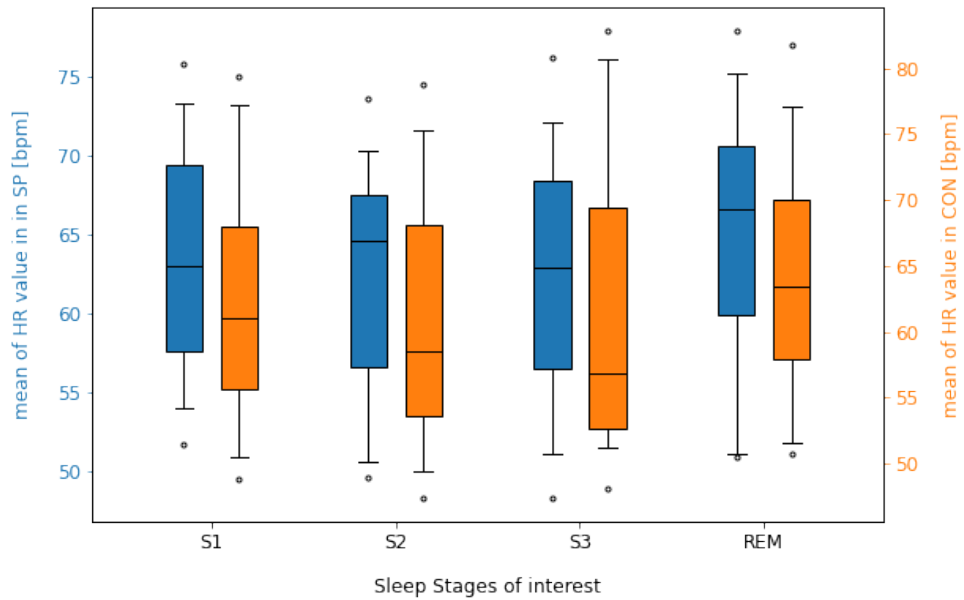

Figure 5.16: Mean of HR value of SP and CON for sleep phases of interest

Figure 5.16 Mean of HR values of patients with SP and control group for each sleep phase of interest. From the first sight there is a small difference between groups, but on a confidence level of 5 % there is no statistical significant difference between groups.
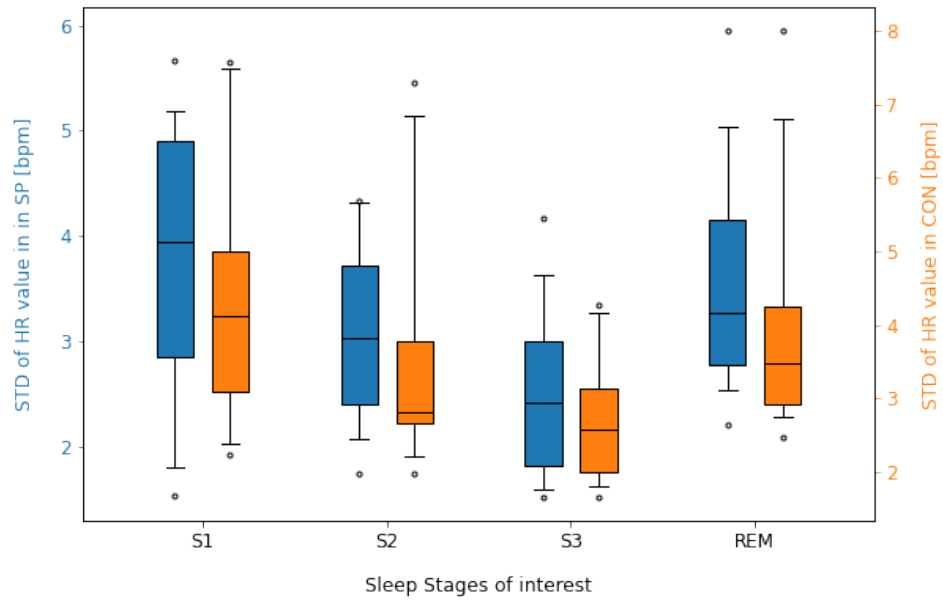
Figure 5.17: Standard deviation of HR value of SP and CON for sleep phases of interest

Figure 5.17 Standard deviation of HR values of patients with SP and control group for each sleep phase of interest. From the first sight there is a small difference between groups, but on a confidence level of 5 % there is no statistical significant difference between groups.
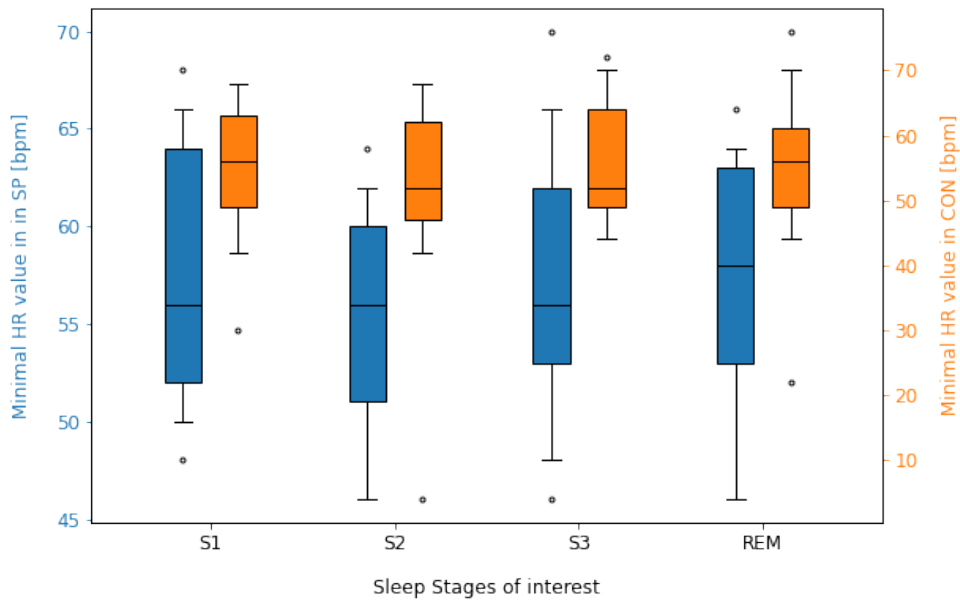

Figure 5.18: Minimal HR value of SP and CON for sleep phases of interest

Figure 5.18 Minimal HR value of patients with SP and control group for each sleep phase of interest. From the first sight there is a small difference between groups, but on a confidence level of 5 % there is no statistical significant difference between groups.

Figure 5.19 Maximal HR value of patients with SP and control group for each sleep phase of interest. From the first sight there is a small difference between groups, but on a confidence level of 5 % there is no statistical significant difference between groups.
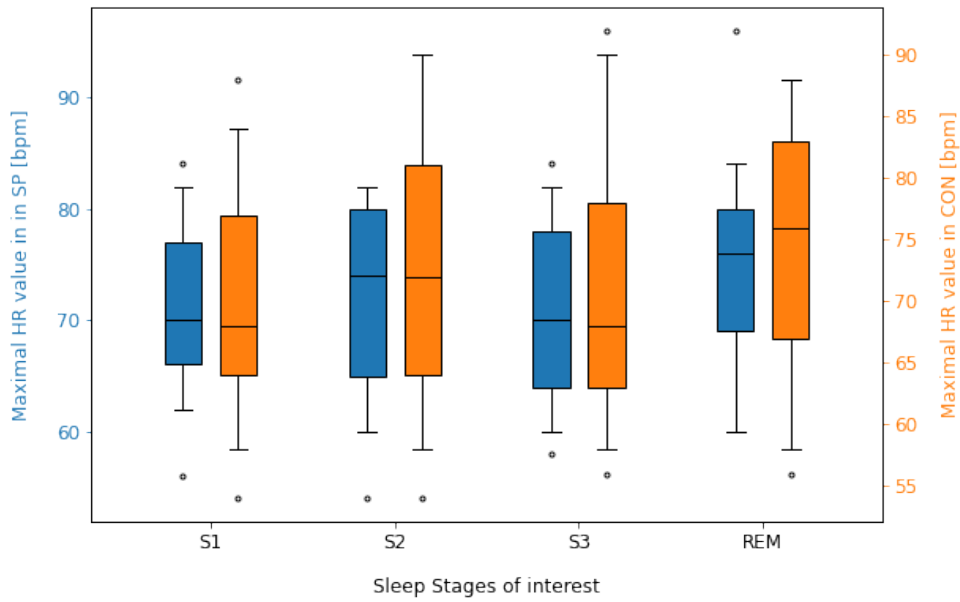

Figure 5.19: Maximal HR value of SP and CON for sleep phases of interest

The frequency-domain HRV characteristics underwent a correlation analysis with distress values in patients with SP acquired from FISPI interviews, see sections 4.3 and 4.1. Table 5.1 represents Pearson's correlation coefficients of the spectral parameters of interest for each sleep phase.

Table 5.1: Results form the correlation analysis

Sleep stages	HRV spectral parameters				
	LF $[ms^2]$	HF $[ms^2]$	LF nu [-]	HF nu [-]	LF/HF
REM	0.14836501	0.26751616	-0.28124906	0.28124906	-0.22015227
NREM1	0.31613668	0.3100433	-0.19916464	0.19916464	0.07766186
NREM2	0.38807724	0.36010269	-0.19765156	0.19765156	0.05467698
NREM3	0.32999391	0.31153337	-0.0668048	0.0668048	0.14786891

Correlation analysis yielded no correlation between distress values in patients with SP and spectral HRV characteristics. Correlation coefficient values from the table 5.1 were in $-0.39 \leq x \leq 0.39$ range and was considered as no correlation.

5.4 Statistical analysis of EEG spectral characteristics

The results of the statistical analysis of EEG data were represented by topographic mapping, see 4.3 for a detailed overview of the statistical analysis methods used. The comparison was made between patients and a control group of healthy individuals. The colour scale follows the same principle. Red to brown colour represents higher relative spectral performance in patients with sleep paralysis. The blue colour represents the predominance of the relative spectrum in the control group of healthy individuals. Statistically significant results at the site of individual electrodes are highlighted with a white asterisk "*".
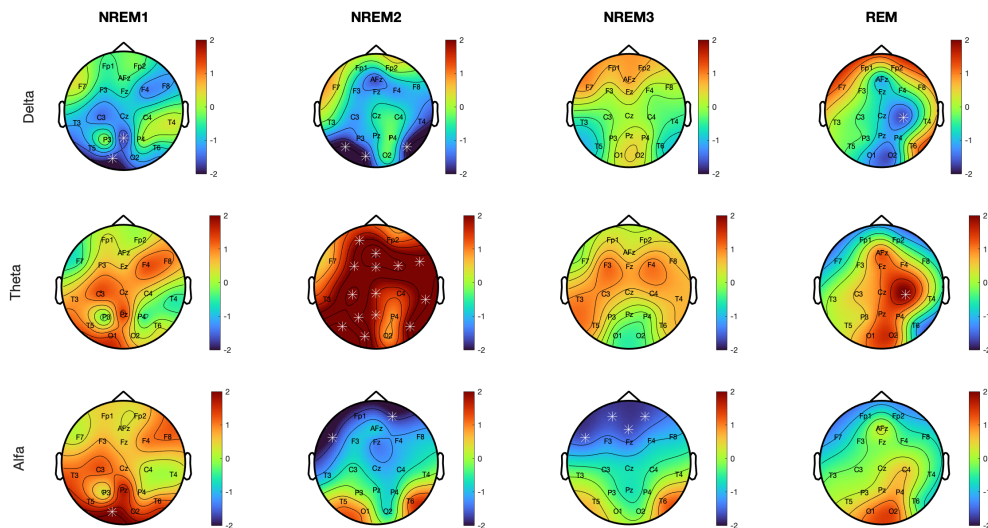

Figure 5.20: Topographic map of statistical results

The image 5.20 shows a larger amount of statistics of significant results, especially in the sleep phase NREM2. For a more detailed overview, the individual brain activities in the NREM2 phase are shown below.
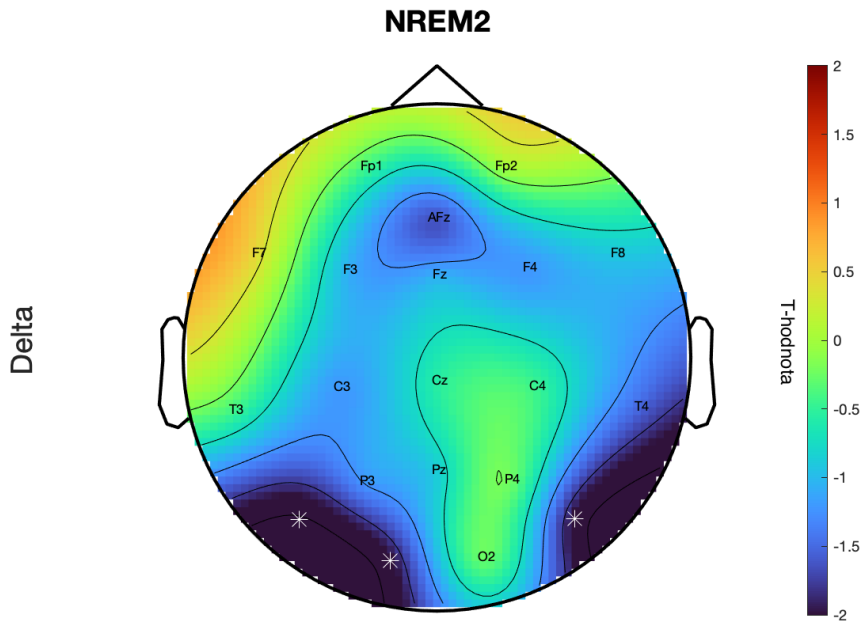
Figure 5.21: Topographic map of delta activity in NREM2 sleep

Statistical results in the figure 5.21 show the predominance of delta activity in the control group of individuals compared to giant sleep patients.
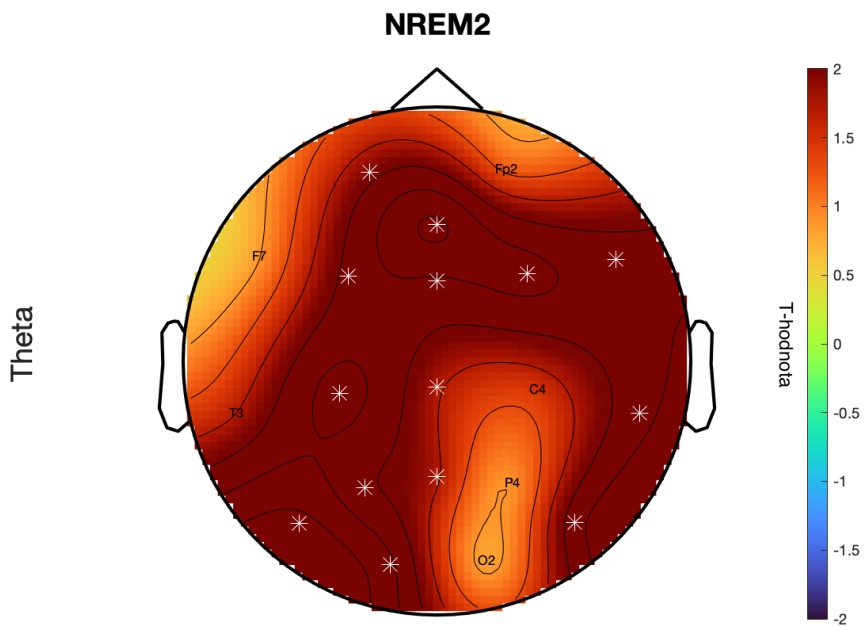

Figure 5.22: Topographic map of theta activity in NREM2 sleep

The figure 5.22 represents the predominance of theta activity in patients with sleep paralysis in contrast to the control group.
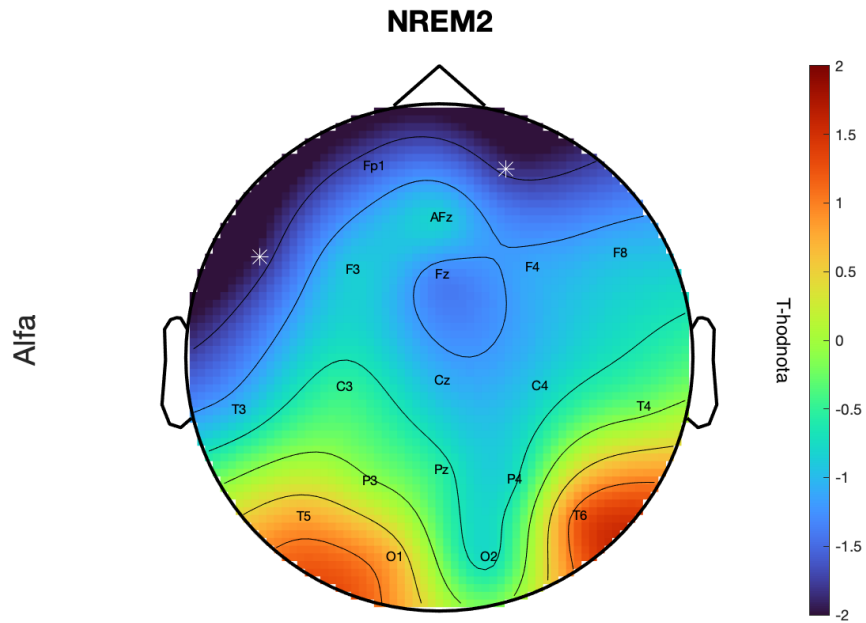
Figure 5.23: Topographic map of alpha activity in NREM2 sleep

The figure 5.23 shows a similar result as figure 5.21 but the predominance of alpha activity in the frontal brain of the control group compared to patients with sleep paralysis.

6 Discussion

The project proposed a methodology in Python programming language and the MATLAB environment for preprocessing, spectral and statistical analysis of the unique data set of 19 patients with sleep paralysis. It is so far the only data set that surpasses its predecessors [16], [14], [17], [15] in the main limitation, in terms of the number of subjects. On the other hand, 19 subjects in the data set are not enough and it is more appropriate from a statistical point of view to have a larger sample of subjects in the future studies.

For the implementation of the methodology was chosen Python programming language which is currently very popular in the scientific field. Additionally, SciPy and Numpy libraries written in Python have diverse functionality not only for signal processing but also for spectral and statistical analysis. In the proposed methodology MNE-Python liberally was also used. MNE-Python is used mainly for neuroscience purposes. I used it for EEG and ECG filtration and tried to use it for spectral analysis. MNE-Python has a lot of functionality for time-frequency analysis and less for spectral analysis alone. Hence, MATLAB environment with Fieldtrip library was used. It gives greater flexibility regarding spectral analysis. Additionally, statistical capabilities were stronger in Fieldtrip than in MNE-Python for this project. [41, 33, 34, 35, 36]

The decision was made to go with standard procedures of the signal filtration because of the tolerably clean measurements results [45, 6, 41, 48, 49]. Filtration was followed by splitting the continuous record into 30-seconds segments, which is the standard for sleep scoring [50, 9]. Some authors are using even smaller segments which depends on the project's aims [17]. For this project, epochs with a smaller length than 30-seconds were unnecessary. Subsequently, the EEG epochs were subjected to amplitude-assisted signal thresholding because of the remained muscle artefacts after filtration. An undesirable effect of the utilization of this function was the loss of data, namely the erasure of the entire epoch when a threshold value in the signal amplitude was found. The function enables the usage of various parameters making the output severe or gentle. In this project, I exploited standard exploitation recommendations [34]. However, It will be better to set up gentle parameters for this function in the future. In addition, manually examine the signal, for example, by visual inspection due to false-positive artefacts.

The detection of the R peaks was performed using the threshold method. This method was chosen after visual inspection of the filtered ECG signal which was not contaminated with a lot of artefacts. Furthermore, the method was chosen because of its stability and speed. The function in SciPy library (see 4.2.3) also gives the resources to enhance the complexity of the function like an adaptive threshold, which

was unnecessary for this signal but might be useful with contaminated signal [35]. The outcomes of the detection process were sufficient for this project.[9]

Results from the detection procedure were subsequently used for HRV metrics calculation in the time and frequency domain. Usually, HRV analysis utilizes 24-hour ECG recording and many time-domain parameters are much more accurate for a longer duration of an ECG recording. Depending on the ECG measurement duration, some HRV metrics in the time and frequency domain might be interchangeable. HRV characteristics derived from long ECG recordings correlate in both domains, but spectral characteristics from long recordings are hard to interpret. That is because of non-stationary cardiac cycle modulation and day-night difference. On the other hand, time-domain parameters like $RMSSD$, $pNN50$ or $NN50$ are better estimates for short term recording. Additionally, they highly correlate with the HF power. Hence, HRV metrics listed in section 4.2.5 were mainly chosen to be a short term due to the duration of the ECG recording, which was less then 24 hours (approximately seven hours). [28, 29]

Spectral analysis of the EEG signal was performed using functions in FieltTrip library and their implementation of the Fast Fourier Transform algorithm, see 4.2.4. In this setting, the DPSS window was chosen due to satisfactory results for use in other spectral-related projects EEG signal analysis. [41, 51, 52, 53, 54]

EEG data often do not meet the condition of normality of data distribution, therefore non-parametric tests are widely used. Unlike parametric testing, non-parametric permutation tests do not consider assumptions about data distribution and do not take into account the characteristics describing the distribution of the evaluated data. This guarantees the possibility of comparison between conditions. The given type of testing determines the distribution from the analyzed data by calculating test statistics and finding values where the null hypothesis is fulfilled, i.e. there is no difference between the conditions [45]. Permutation testing ideally requires an infinite amount of random data sorting and calculation of test statistics for each distribution. The result of these random steps is a permuted data distribution and a corresponding permutation p-value. In practice, however, it is not possible to perform a permutation test with an infinite number of permutation operations. Maris and Oostenveld offered to approximate the extracted p-value using a Monte Carlo estimate. It performs the final but a large number of the above operations and also compares the obtained random test statistics with the original test statistics before randomization. The Monte Carlo estimate used in this project is a proportion of randomizations where the observed test statistic is greater than the value selected from the permutation distribution of the data. Thus, the complex nature of sleep paralysis and obtained EEG signal requires sophisticated statistical

analysis. The proposed statistical model is found to be satisfactory for the purpose of this project. [44, 45]

In addition to its advantages, this setting also brings disadvantages associated with multiple comparisons. Such an effect on the p-value can cause skewed results of the statistical analysis. There are many methods to correct this problem such as Bonferroni correction, Holm-Bonferroni correction and my FDR correction. FDR correction was used, which is less critical in p-value correction [45]

Spectral analysis of EEG signal resulted in a symptom of sleep paralysis in the NREM2 phase of sleep with predominant theta activity, see 5.4. Theta activity alone represents sleep transition between sleep and waking. Brain awakening can be seen in 5.22 as faster frequencies increase. At the same time, however, the brain remains inhibited due to slow theta waves. This result is partially identical to previous work on the topic, see 2.4. Recent studies also describe the predominance of theta activity [17]. In contrast to this project, mini-epochs were not studied, but the standard 30-second and also sleep phases were designated REM and not NREM2. The comparison raises the question of the connection between sleep paralysis and both phases of sleep in terms of its transition during one sleep cycle.

On the other hand, statistical analysis of cardiac conditions in time-domain parameters between groups did not find any significant difference. From the figures represented in subsection 5.3, a small difference between groups can be observed. Additionally, each of the figures contains small dots that represent outliners. For future improvement of statistical test performance, they must be removed but only with the increase in the number of subjects. Frequency-domain HRV characteristics were in physiological range but outliers were also present. They also need to be removed in future studies with bigger subject dataset. Spectral HRV metrics subserviently underwent a correlation analysis to evaluate the relationship between the distress values in patients with SP and fluctuation in HRV power spectra. Pearson's correlation coefficient display no correlation, see 5.1. Distress values obtained from the FISPI interviews represent only a general evaluation of a person's stress related to the SP episodes occurrences over lifetime and not after episode itself. [55, 56]

It is also worth mentioning that during every PSG measurement no SP episode was captured. On the other hand, inability to capture such short and complex process is understandable Some authors tried to artificially produce an SP episode during whole-night PSG measurement which might produce biased results [16], [14], [17]. Thus, interpretation of the result of this project is more generally related. The results suggests appearance of the negative symptoms of sleep paralysis only with the occurrence of an episode during the night and having no symptoms during normal night's sleep. The ideal future studies would be with a sufficient number of subjects and at least one captured SP episode during whole-night PSG measurement.

7 Conclusions

This project proposed a methodology for the analysis of sleep paralysis in the Python programming language and MATLAB environment. The methodology includes processing and analysis of the ECG and EEG signals.

Signal processing was made in Python for ECG and EEG as well as in MATLAB only for EEG. Popular signal processing libraries were used in Python, namely "MNE-Python", "NumPy" and "SciPy". In the MATLAB environment, only the "FieldTrip" library was used. Spectral analysis of the EEG was made in both programming languages but only the results from the MATLAB FieldTrip were used. Spectral analysis of the ECG signal was made only in Python with the help of "MNE-Python", "NumPy" and "SciPy" libraries. Statistical analysis of the EEG spectral characteristics was made in MATLAB FieldTrip. A quantitative comparison was performed together with a control group of individuals without SP. Statistical analysis of the time and frequency domain ECG parameters was made in Python.

The EEG analysis resulted in the spectral characteristics of sleep paralysis. Specifically in the unusual brain activity or a sign of sleep paralysis in the NREM2 phase of sleep with predominant theta activity. ECG analysis resulted in heart rate variability metrics in the time and frequency domain. The signals for processing were used on a data set with 19 patients with sleep paralysis. Time-domain parameters were in the physiological range and were compared with the same parameters of the control group. The comparison resulted in a slight difference between the parameters which was not statistically significant. Frequency-domain HRV parameters also were in the physiological range. Correlation analysis was performed between distress values in a patient with SP and obtained frequency-domain HRV parameters. Finally, the Pearson's correlation coefficients for different frequency-domain HRV parameters display no correlation in any of them.

The findings can be interpreted as an explanation of the part of the mechanism of sleep paralysis. Absence of the correlation between distress values in a patient with SP and obtained frequency-domain HRV parameters means that a sleep paralysis episode might be harmful to a person only while experiencing the episode during the night. In other words, if a person was not experiencing a sleep paralysis episode, he or she could have a regular night's sleep without any harm to a person's health.

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Appendix A: Contents of the attached ZIP

```
/
├── src
│   ├── ScriptsPy..................................Python notebooks
│   │   ├── EEG_mne.ipynb
│   │   ├── HRV_time.ipynb
│   │   ├── HRV_spectr.ipynb
│   │   ├── BT_Py_requirements.txt
│   ├── ScriptsM....................................... Matlab scripts
│   │   ├── Preproc_Freq_analysis.m
│   │   ├── relpowerband.m
│   │   ├── stat_analysis.m
│   ├── thesis............... Source code of the bachelor's thesis in LaTeX
├── doc
│   ├── abstract_cs.txt.............................. Abstract in Czech
│   ├── abstract_en.txt.............................Abstract in English
│   ├── BTassignment.pdf ............. Bachelor's thesis assinment in PDF
│   ├── 17PBBBP_469971_Vladyslav_Isaienko.pdf  Bachelor's thesis in PDF
```