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09.03.01 – «ИНФОРМАТИКА И ВЫЧИСЛИТЕЛЬНАЯ ТЕХНИКА»**

**GRADUATE THESIS FIELD OF STUDY
09.03.01 – «COMPUTER SCIENCE»**

**НАПРАВЛЕННОСТЬ (ПРОФИЛЬ) ОБРАЗОВАТЕЛЬНОЙ ПРОГРАММЫ
«ИНФОРМАТИКА И ВЫЧИСЛИТЕЛЬНАЯ ТЕХНИКА»
AREA OF SPECIALIZATION / ACADEMIC PROGRAM TITLE:
«COMPUTER SCIENCE»**

Тема	**Исследование по измерению и контролю внимания программистов во время работы при помощи электроэнцефалографии**
Topic	**EEG monitoring and controlling programmers' attention during work**

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I dedicate this work to my family. You always support and love me. Thank you for encouraging my pursuit for knowledge

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Abstract

The field of information technology has tightly entered into all spheres of human activity. The core of Computer Science is programming, modern science and industry rely on the work done by them. For improving speed and quality of development of IT projects it is essential to study how to increase the efficiency of developers. One way to improve the quality of developers' work is to help them concentrate better, timely detect a drop in concentration and brain fatigue, which could be done by controlling the level of attention during programming. More and more types of devices for detecting biophysical signals are becoming more accessible. This study focuses on the study of the level of attention of programmers using EEG, as the most promising and realistic for use in this environment. We found that the level of attention can be determined using the control of alpha and beta waves measured using EEG, as well as specific features of the functional state of the brain compared to another type of mental load - driving.

Chapter 1

Introduction

The field of information technology (IT) has tightly entered into all spheres of human activity. The core of Computer Science is programming, modern science and industry rely on the work done by them. For improving speed and quality of development of IT projects it is important to study how to increase the efficiency of developers. One way to improve the quality of developers' work is to help them concentrate better, timely detect a drop in concentration and brain fatigue, which could be done by controlling the level of attention during programming. On the other hand, it is very important to monitor the level of satisfaction and happiness of employees [1] [2] to prevent possible psychological disorders [3]. In order to contribute to the development of this field, for the current work, we formulated and answered the following research questions:

- RQ1: What methods do exist to estimate the attention level during coding?
- RQ2: Can the change of the level of attention during programming be measured using EEG?

- RQ3: Is there the possibility to identify correlations between attention levels and types of mental activity, assuming that the attention level is measured using EEG devices?

This work structured as follows. In the second chapter, we give a literature review about the use of biophysical signals in the studied field. The third chapter is dedicated to describing experimentation and analysis protocols. Implementation details are given in the fourth chapter. The fifth chapter contains the results of the experiments. Conclusion and further work directions in this area are given in the sixth chapter.

Chapter 2

Literature Review

2.1 Chapter overview

The systematic literature review on the measuring of working conditions for people in general and measuring an attention level for programmers is presented in this section. Special attention is paid to the EEG method is one of the most popular and promising. The purpose of this study is to investigate state of the art in the field, find gaps, suggest future work and find answers to the research questions. Current literature review based on Systematic Literature Review (SLR) [4] done by me and my colleagues Repryntseva Anastasiia, Tarasau Herman, Artem Kruglov and Sara Busechian. Original SLR was performed according to Dr Andy Siddaway [5], and Barbara Kitchenham [6] works and consists of an introduction which describes prerequisites for writing current study and general terms, research methods with a description of research methodology, research questions, the definition of the search process and queries used, list of inclusion and exclusion criteria, a results section answers research questions. Subsections 5 and 6 are dedicated to discussion and conclusion, respectively.

2.2 Introduction

The use of biophysical signals in the analysis of human physiological state and well-being got broad popularity in different areas of science. Medical experts use those signals to study the processes in our bodies and how external factors affect those processes. Computer science researches have acknowledged the role of attention and other mental states in the well being of software individuals, teams, and organizations [7]–[16], and use biosignals to build systems that will help people monitor their state and develop new analysis techniques that will help understand the meaning of the collected signals better.

One of the methods for reading brain activity is Electroencephalography (EEG). It studies the functional state of the brain by recording its bioelectric activity. This method provides a wide scope for experiments because it allows us to interpret data online, conduct experiments during various activities since it is portable, non-invasive and does not require the help of doctors.

As was said previously, Computer Science (CS) researchers use EEG in combination with other bio-signals to build Brain-Computer Interfaces (BCI) – systems that can measure the activity of the brain and the central nervous system, analyze it and convert it into artificial output. Using different CS algorithms and techniques, BCIs can clean, enhance or improve the natural output of the brain. Moreover, many data analysis techniques can be applied in BCIs to predict human behaviour or state. Such systems can be used in different fields of research such as e-learning, driving, performance at work and analysis of programmers' behaviour.

The goal of the research is to perform a preliminary review of the current status of the use of bio-signals in the studies of the human physiological state and how EEG was used in the field. Also, it aims to collect a list of EEG analysis techniques that can be referenced in further studies.

2.3 Research method

This section describes the research process and steps performed during the Systematic Literature Review (SLR). First, the formulation of the research questions and their importance is given. Then inclusion and exclusion criteria were given as well as the data collection process is described.

2.3.1 Research Questions

To identify the primary studies that address the topic of our SLR, we formulated three research questions (RQ). Our study aims to answer the following ones:

- RQ1: How biophysical signals were used in determining the conditions of human activity or work?
- RQ2: In the framework of RQ1, how EEG was used?
- RQ3: What kind of EEG analysis techniques were used?
- RQ4: How attention and stress level were studied during programming?

2.3.2 Search Process

Our search process was a manual search in the two largest digital libraries available: ACM Digital Library and IEEE Xplore Digital Library.

For each RQ, the keywords were extracted, and proper search queries were defined using those keywords.

All the results from all 3 search queries were exported to a Rayyan QCRI [17] – a web-application for collaboration on systematic literature reviews.

2.3.3 Inclusion and Exclusion Criteria

During the review process, the studies were checked to satisfy the following inclusion criteria:

- Availability online to ensure paper accessibility
- Focus on biophysical signals and especially brain activity
- Focus on measuring the level of attention or stress to ensure its compliance with the study
- Format of the research paper (thesis, papers, posts, books, videos, etc.)
- Methods description and approaches of brain activity and biophysical signal analysis
- Focus on studies of work environment
- Written in English

The studies of the following topics were excluded from further processing:

- Papers which do not meet any of the inclusion criteria.

- Similar papers, which are written by the same authors or describing the same concepts.

2.3.4 Data Collection

The data elicited from the reviewed materials were:

- The main area of the research
- The research question/questions of the study
- The authors of the research
- The summary of the research
- The gaps in the research and the areas of further studies

2.4 Results

2.4.1 RQ1: How biophysical signals were used in determining the conditions of human activity or work

Literature analysis shows that conditions of human activity or work can be slipped into three parts: measuring attention, stress detection, and tracking programmers' activity.

Measuring attention

A study by [18] proposes to use EEG signals for Attention Recognition (AR) and extends previous research that used eye-gaze, face-detection, head pose and distance from the screen to track user's attention. AR is a promising field that can be applied in many areas such as e-learning, driving, and most relevant - in measuring consciousness during video conferences. In [19] EEG was used to determine the attention level, while the subject was performing a learning task. In [20] EEG was used to estimate alertness in real-time. In [21] presented a single channel wireless EEG device which can track driver's fatigue level in real-time on a mobile device such as smartphone or tablet. Measuring attention is very important in many fields, such as detecting drivers' drowsiness and workers' fatigue.

Analyzing all the previously mentioned studies we gathered the techniques for attention measurement into a list, which states that attention could be measured via:

- heart rate variability [22]
- galvanic skin response [22]
- pupil diameter, eye blink frequency [22]
- brain activity measurement (EEG, MEG (Magnetoencephalogram), fNIRS (functional near-infrared spectroscopy), fMRI (functional magnetic resonance imaging), ECoG (electrocorticogram), etc.) [22], TMS (transcranial magnetic stimulation), PET (positron emission tomography), NIRS (near-infrared spectroscopy) [23]
- Conner's Continuous Performance Test (CPT). The method, which is described in the studies [24] and [23] and performed as following: the subject has to react when a rare signal appears.
- The test of variables attention (T. O. V. A.) is an objective neuropsychological examination of attention, which is a simple electronical game

which tracks the response of the subjects to a visual or auditory stimulus. [23] [20], [25] [20]

Stress detection

Several studies presented designs of the systems that monitor the human physical and mental state in the working environment. Using different biophysical signals and environmental measures, they detect stress levels of employees.

A new apparatus [26] was designed to assess the stress levels of call-centre operators. The study uses two types of sensors to monitor the working environment: environmental and physiological. The evaluation of stress relies more on the latter signals. The goal of the authors was to design the system to improve the well-being of the employees with the application of multi-sensor analysis.

The portable system described in [27] measures biophysical signals in real-time and notifies unwanted mental behaviour. The notifications are sent in case the following conditions in the worker are detected: 1) absent-minded/inattentive, 2) stressed, 3) extreme fear, 4) anger, 5) stun/daze, 6) overloaded with work, 7) drowsiness, and 8) dizziness. The author focuses on neuroergonomics as a primary field of study. As well as the previous study, this one aimed to design a system to predict human mental and physical state and increase productivity and well being at work. However, the range of biological signals collected was significantly broader than in [26] and brain, and muscle activity analysis was used.

The device proposed in [28] determines the relaxation level of the user. It consists of the Virtual reality headset and the olfactory necklace. The necklace changes the intensity of aroma, depending on the subjects' EEG datagrams.

In [29], mental stress was measured while solving arithmetic tasks. The [30] detected the difficulty of program comprehension tasks among the students.

The [31] describes a method to determine the drivers' vigilance level.

In the context of the studies mentioned above the following biophysical signals were used:

- heart rate [27] [26];
- galvanic skin resistance [26] – showed that increasing skin conductance indicates the rise of stress level;
- body temperature [27];
- blood pressure [27] - a sensor is placed in the temple part of the head or in the upper part of the shoulder depending on the type of device;
- EEG [27] [28] [30] [30] [32] [33] [34] [35] [36] [37] [38] [31];
- EMG [27];

2.4.2 RQ2: In the framework of RQ1, how EEG was used?

The study conducted by [27] relies on the concept of neuroergonomics design, and especially aspects like stress, attention, drowsiness, and others to design efficient systems to be used by humans. To measure these metrics, several methods are used in neuroergonomics, but one of the most relevant is neuroimaging. The authors of the study designed a system that keeps live feed about human's psychophysiological information and used EEG as their primary method to measure brain activity.

They designed a simple BCI's where one dry EEG electrode sensor is placed on the forehead. The authors use a high-pass filter and a low-pass filter to clean the noise at low/high frequencies and a notch filter to filter specific bands of the signal. After passing all filters and amplification, the resulting signal is then converted to digital format. The study shows how collecting EEG data can help in creating effective and comprehensive BCI systems to monitor behaviour and well-being at work.

Another research from [18] investigates how EEG can extend the techniques for AR. Previously EEG was used mainly for emotion recognition. This study mostly focuses on the methods of EEG data processing, feature extraction, and further attention classification. The EEG data were collected while subjects were reading or watching random content. After finishing each subject filled a self-assessment form. Later, based on the gained results, the data were divided into five classes and preprocessed. The classification algorithms were then applied to the acquired data. By doing so, authors propose to use EEG data for AR and probably supplement the techniques used previously in these kinds of studies.

In [20] study, EEG signals are used to estimate the alertness level by recording the response time for the Test Of Variables Of Attention (TOVA) and the EEG signals in parallel. The correlation between those two measures was then studied. The results of the experiment show that EEG can be used in real-time systems that estimate human alertness.

In [28] researchers conducted the experiments: 5 min control experiment and 5 min with VR headset and olfactory necklace (with lavender aroma), where the 360 degrees beach was shown to test subject. EEG was recorded using commercial *Muse headband*. It provides four flexible electrodes located at 10-20 positions TP9, AF7, AF8 and TP10 with reference for Fpz. After the experiment, a test subject filled in a questionnaire. The authors showed that there is 25% boost of actual relaxation and 26.1% per cent boost with questionnaire study.

In [29] the test subject filled the demographic form PSS. Then 10 seconds of a calm picture was shown in the beginning and at the end of the experiment. After that subject was asked to solve 10 arithmetic questions. After the experiment test subject was asked to determine highly stress stages, namely before, during or after the mental induced task. EEG was used to record data from the test subject. *The Mindset 24 Topographic Neuro Mapping Instrument by Nolan Computer Systems LLC* was used. The 10-20 recording system was used, namely: Fp1, Fp2, F7, F3, Fz, F4, F8, T3, C3, Cz, C4, T4, T5, P3, Pz, P4, T6, O1 and O2. Sampling frequency: 256 Hz, impedance $<$5 kOm, cutoff range: -80 to 80

In [30] a relax screen was shown to test subjects, then they solved 3 practice questions and 9 ordinary questions using TPS. Between each question, the relaxing screen was showed to take a break. EEG was used to record the programming activity. *Emotiv Epoc device* with 16 channels: 14+2 reference, following the 10-20 international system. Sampling frequency: 128 Hz.

In [31] the subject completed the 90 minutes simulated driving. The subjects obliged to lie on a bed if they feel sleepy. The EEG was recorded with *Neuroscan* with 64 electrodes, 2 of them were EOG.

In [39] the impact of in-vehicle secondary tasks on driver mental state while driving was measured. This was done by capturing the changes in EEG waves. Authors used a portative data acquisition platform to collect wireless EEG data from six subjects during a driving session and found six potentially distracting scenarious.

In [40] shown the growth of mental fatigue in a Stroop task with a help of EEG using independent component analysis (ICA) approach. Particularly, they studied mental effort and mental engagement by the continuous frequencies changes from frontal independent component (IC) related to cognitive control and posterior ICs related to attention.

2.4.3 RQ3: What kind of analysis of EEG results was used?

This section describes the main techniques to analyze EEG data. It starts with Machine Learning Techniques and proceeds with others. A lot of the papers used Machine Learning techniques for analysis of EEG data. They can be divided into three groups: Neural Networks, Classification Algorithms, and Other techniques.

Machine Learning Techniques

Nowadays, *Neural Networks* is a widely used machine learning approach. In [41] study, authors train an MLP NN to learn characteristics of EEG that define attention state. The main goal of this study was to investigate the hidden nature of attention mechanisms while recording the subject's EEG data. The novelty of the proposed method is in using four levels of attention instead of 2, as was used in previous studies. Also, the authors emphasize the fact that identifying an attentive state is easier than inattentive because of more noise and irrelevant information recorded during the inattentive state. The [42] research focuses on the continuous detection of changes in human alertness and EEG power spectrum on a minute time scale. Authors emphasize the variability of EEG dynamics and say that group statistics used in previous studies cannot be used effectively. So information collected from each operator is then fed to a neural network to adapt to individual differences in EEG dynamics. The results are then compared to linear models. A novel approach was described in [35]. The authors used Convolutional Neural Network as a feature extractor. The data was preprocessed, first, by statistical indicators, to remove points with the subject's score standard deviation of more than 2 times the mean. Then two feature vectors were built: linear by Pearson's coefficients and nonlinear by SL matrix. Then, linear and nonlinear features are fused by the CNN framework.

The more classical approach is *K-nearest neighbours.* In [18] the authors of the study introduce EEG measures to track emotions and attention. The project applies classification algorithms to the EEG signals, and k-NN was one of them. After extracting 13 important features, a k-NN classifier was used to divide the data into both 3 and 5 attention classes. The [43] shows how to detect driving fatigue based on k-NN and the correlation coefficient of the subject's Attention and Meditation. Naive Bayes classification is also a widely used machine learning algorithm. In [30] authors measured task difficulty. EEG data were first normalized by computing the mean on all channels and subtracting it from each channel for each subject. Then filtering was done on 1-second segments by Elliptic Infinite Impulse Response filtered described by Manoilov. Then four types of features were extracted: Energy, Event-Related Desynchronization, Frequency ratio, and Asymmetry ratio. After that, the Naive Bayes classifier was used to classify the data from each feature vector.

Other methods

There are several techniques worth mentioning, for example, P300. P300 (also called P3) wave [44] is an endogenous potential that surfaces itself as a positive deflection in the voltage with an average latency of roughly 250 to 550 ms depending upon the task [45]. It is captured during the process of decision making and appears after 300 ms of the presence of the stimulus. Authors concluded that the P300 amplitude significantly decreases while fatigue takes place.

Another commonly used approach is the Independent Component Analysis (ICA) [46]. ICA is a widely used method for decomposing multichannel data into components that are statistically independent (ICs). In the context of EEG data analysis, some components should represent brain activity, while others should represent noise resulting from eye and muscle movements.

2.4.4 RQ4: How attention and stress level were studied during programming?

Several methods for measuring attention and stress level of programmers have been presented in the literature. A study [47] presents a method for identifying programmers' stress based on keystroke dynamics. Authors collected data using special background program while students solved tasks. Two examples of keystroke data were captured for each subject, the first while programming in normal conditions without pressure, the second under time pressure and consequent stress. After data collection, statistical data analysis was applied to assess the significance of keystroke dynamics differences. Authors concluded that some of the features might be indicators of stress.

Pupillography method was used in [48] to capture meta-information of the programmers' emotional and mental state (whether they experience stress, cognitive workload, level of mental workload, attention, etc.). Authors performed experiment on 30 professional developers and concluded that the developers' mental workload and cognitive load indicated by the pupillography is consistent with developers' own estimation of this parameters and load reported by the programmers using NASA-TLX task load index.

The relation between pair programming and developers' attention level was studied in [49]. Authors collected data using PROM [50] tool, which is installed at the developer's computer and records information about the programs used. It does not distract the user from work and thus provides more precise information about real working scenarios. Authors concluded that pair programming helps people to focus better on the work. Developers spend more time for project, less switch the windows while work in pairs.

A study [51] shows how EEG can be applied to understand the mental activities of programmers during pair programming. Here, a portable multi-channel EEG device was used to understand if there is any difference in the mental processes of the minds of developers when they use different development approaches. The data were collected during several pair programming sessions where two developers played the role of a "driver" and "navigator" consecutively. The goal then was to determine whether those activities induce a higher level of concentration.

Another study [52] in this field compares the cognitive activities of novice and expert developers and assesses their programming language comprehension. By conducting an EEG experiment, they showed that indeed there is a clear difference in how these two groups understand programming languages. There was a higher brain activation in certain electrodes. Expert programmers showed better short-term memory and comprehension abilities in general.

Analyzing the results, it can be said that the approach of using EEG to analyze the brain activity of developers is rather effective and practical, as it can be used in the normal programmers surrounding and show good results in distinguishing between different brain activity patterns.

It was observed that EEG is one of the most popular and easy ways to measure people's attention and stress because of its ease of use and relatively accurate results.

2.5 Discussion

This section represents different findings of this Systematic Literature review. The Systematic Literature review aimed to identify current progress in biophysical signal usage in IT and cross fields. From 317 publications, 40 publications have answered the Research questions. The result of the review showed that in recent years, from 2015 till 2019, there is a high interest in developing systems with the help of biophysical signals. This study mostly focused on describing methods for attention, emotion recognition and experimental procedures.

With the recent increased interest in Machine Learning and availability of such data sets as DEAP [53] and AMIGOS [54], a high number of studies described Machine Learning methods for attention.

Some studies focused on the feature extraction of data for future usage in classification algorithms. The development of such methods is a good indicator of interest in biophysical signal-based systems.

A little number of studies used the programmers as the main experiment subjects. Thus, giving research opportunity to investigate new methods based on biophysical signals. Such research should help to develop a system of attention recognition for IT developers, giving industrial companies sufficient information about the performance of their employees.

Also, the primary data collection method was EEG. Several studies used other biophysical signals such as EMG, heart rate, blood pressure. The potential combined usage of different biophysical signals is an open question.

2.6 Conclusion

The Systematic literature review clearly shows the high interest in using EEG based systems for attention and emotion recognition. Mostly, all studies are developing new techniques in Machine Learning signal processing.

Analysis and processing techniques were separated into different groups according to the ML method used. Based on the review of the techniques **Section 3.3** gives sufficient information regarding data preprocessing and classification methods used. As there is a lack of study on programmers' performance, future research should be more focused on this topic, also focusing on metrics and open systems [55]–[57] and understanding the dynamics of the collaboration between people [58]. The question: "How can we help programmers perform better using the biophysical system?" remains open. Researchers may try to answer this question with the help of methods described in this Systematic Literature Review.

Chapter 3

Design and Methodology

The chapter firstly presents the background of the experimentation. Secondly, it reports about the experimental methodology used in this work to understand software developers attention level during programming, discussing first the existing research, to substantiate the subject and methods of the study, secondly the sequence of experiments performed, then the data collection process, and finally the data analysis protocol.

3.1 Background

In this section, we will describe the main concepts of the research, paying attention to different types of brain waves and what is essential to know before reading about the experimentation. However, we do not describe state of the art and approaches could be used for the capturing and analysis of the brain since this subject has been already covered in Chapter 2. This section describes the different types of brain waves firstly. Then it proceeds with specific patterns, which are in our interest in the experimentation.

3.1.1 Brain Waves

Delta band (1 - 4 Hz)

Delta band is in the range from 1 to 4 Hz and is the highest and slowest by its amplitude. Delta waves could be seen during deep non-REM sleep and correlate with the deepness of sleep. Usually, delta waves could be seen more in the right hemisphere and generated in the thalamus brain part. Delta waves help us to consolidate gathered information, so they are essential for long-term memory and learning new skills [59].

Theta band (4 - 8 Hz)

Theta band waves are in the range from 4 to 8 Hz. Research show [60] [59] us that the frontal theta waves are correlated to the high level of mental workload, attention or memorising. The higher level of theta frequencies, the higher level of the task is [61]. Theta waves usually could be captured from all over the cortex. Theta is typically used for studying spatial navigation and monitoring brain activity in operational environments.

Alpha band (8 - 12 Hz)

Alpha band waves are in the range from 8 to 12 Hz were discovered in 1929 by Hans Berger [59]. Alpha frequencies are related to memory, sensor and motor tasks. It positively correlates with physical relaxation with closed eyes, so it is studied in research about meditation [62]. On the other hand, alpha waves are decreased during mental or body activity, so they used as an indicator of mental workload [63]. The alpha band could be captured from posterior cortical lobes, such as occipital, parietal and posterior temporal.

Beta Band (12- 25 Hz)

Beta band waves are in the range from 12 to 25 Hz. The beta band usually correlates with mental concentration and active thinking [59]. Beta power increases when the subject wants to execute movements and could be seen in central cortex. Noticeable, it also increases when we observe movements of other subjects, because of activations in "mirror neuron system" [64]. Beta frequencies are generated in posterior and frontal regions.

Gamma Band (above 25 Hz)

Gamma band waves are in the range from 25 to 140 Hz. For now, the exact role of Gamma waves is unclear. Some of the researches report that the gamma waves do not reflect cognitive processes and are a by-product of processes related to eye-movement [65] [66] and micro-saccades. On the other hand, other authors report that gamma waves are correlated with work of memory and attention, similar to theta [67] [68]. Future research will have to address the role of gamma in more detail.

3.1.2 Signs of Attention and Mental Workload

Alpha and Theta Waves

[69] In [70] authors analyzed attention using N-back task and observed that the theta power was increased during difficult task relative to a simple task, whereas power of alpha band tended to be increased in the simple task compared to difficult tasks. Similar results reported for also working memory (WM) task [71], and for more complex cognitive tasks [72]. In [73] authors found the following correlation: as task difficulty increased, frontal midline

theta EEG activity increased while parietal midline alpha reduced. Authors of [74] suggested that theta activity is associated with multiple processes, such as working memory, problem-solving, self-monitoring. They found that many parts of the brain involved in the activation of theta waves and conclude that theta band reflects comprehensive functional brain states.

Event-Related Desyncronization

Event-Related Desynchronization (ERD) measures how much neuron populations no longer synchronously react after being triggered to perform the given task [75]. More difficult tasks cause bigger ERD difference between resting and working samples. The ERD is equal to the percentage of change of power band between the resting period before a working sample and the working sample itself. Authors of [76] report the following conclusions:

- Lower alpha band desynchronization indicates an attention
- Upper alpha band desynchronization indicates reflects semantic memory performance
- Theta band synchronization indicates episodic memory and the processing of new information

Theta/Beta Ratio

The Theta/Beta ratio (TBR) is a power of the slow theta band divided by the value of the fast beta frequency band. Authors of [77] and [78] report that TBR negatively correlates with attentional control among healthy subjects. In [79] authors performed an experiment on twenty-six participants.

Firstly, baseline EEG was recorded, then subjects had to do a 40-minute breath-counting task while EEG was recorded. Participants pressed the button when they experienced Mind Wondering (MW) episodes during the session. Authors concluded in [79] that the frontal TBR correlates with MW, which means a state of reduced control over thoughts and low level of attention.

3.2 Experimental Design

3.2.1 Purpose

Based on questions stated in section 1.1, the following hypotheses were derived for RQ2 and RQ3. RQ1 was answered in Chapter 2. The goal of the current section is to prove or disprove those hypotheses, providing sufficient justification.

Hypothesis for RQ2:

- Level of attention during programming EEG can be measured using EEG.

Hypothesis for RQ3:

- A relationship between types of mental activity and an attention level could be investigated using data captured by EEG.
- There is a specific pattern of brain activation during programming which could be seen in EEG data.

3.2.2 Data Sources

We collected programming dataset by ourselves, as described in section 3.4. To compare programming with another type of mental activity, we decided

Characteristic	**Value**
EEG channels	24
Reference	A1, A2, (A1+A2)/2, Cz, REF
Frequency band	0(DC) 70 Hz
Sampling rate	2000 Hz
Storage rate	250 Hz
Noise	1.2 μV peak-to-peak
Input range	$\pm$300 μV

Table 3.1: Technical characteristics of EEG Smart BCI cap

to select driving, because both programming and driving require a high level of attention and concentration, and both of them produce high mental workload. As a driving dataset, we used data from [80]. This dataset includes original EEG recordings of twelve healthy persons in two states: driving and resting. Data collected by a 40-channel Neuroscan amplifier in .cnt format.

3.2.3 Equipment and Tools

EEG Smart BCI cap was used in the experimentation. It is a 24-channel wireless cap by Mitsar company, which transmits the data using Bluetooth. Data were cleaned, processed and partially analyzed in the Mitsar EEG studio. Electrodes were placed according to standard 10-20 scheme [81]. Eighteen scalp electrodes were used: F7, F3, Fz, F4, F8, Fp1, Fp2, T3, C3, C4, T4, T5, P3, Pz, P4, T6, O1 and O2 with the reference electrode Cz.

For the analysis, we used MNE 0.19.2 on MacOS, Python 3.7.4 and Jupyter notebook 6.0.1.

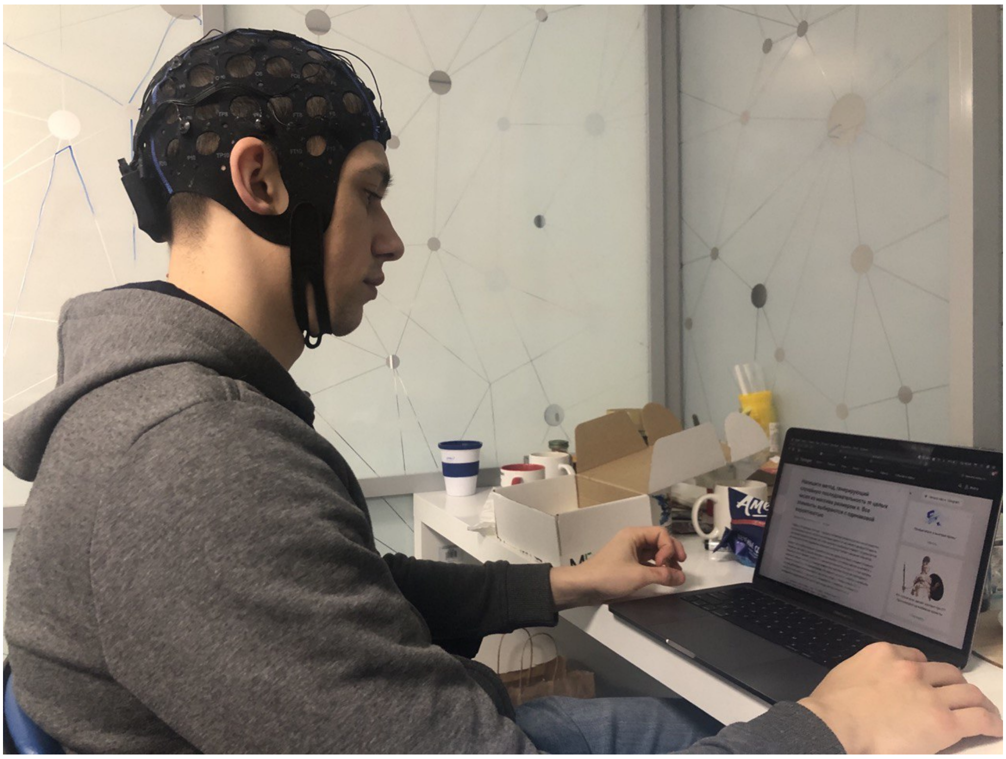

Figure 3.1: Student during experimentation session

3.3 Participants

To make the data more homogeneous and closer to real life, the following restrictions on experimental subjects were chosen:

- We invited to take part not novice programmers but software developers with at least two years experience in different types of projects. This would help them feel more confidently and not worry during the experiment to avoid noises and unwanted signals.

- Programmers with different levels of experience may develop software differently, so we needed to have software developers with almost the same level of expertise.

We decided to invite to participate 10 bachelor students of Innopolis University because they were the best suited to the object of the study and had enough time to take part in the experimentation. Each participant filled the questionnaire with the following questions:

- Gender
- Age
- Working experience to verify that all participants have almost the same experience. Three options were given:
  - Beginner (less than 1 year of experience)
  - Intermediate (1-3 years of experience)
  - Advanced (more than 3 years of experience)

After the experiment, we sent to the participants posterior questionnaire to evaluate their feelings and perceptions about the experiment with the following questions.

- How comfortable it was to wear an EEG device during programming (from 1 to 10). Question intended to assess the applicability of the EEG device in real life during programming.
- The most uncomfortable thing in the experiment. Question intended to improve future experiments.
- How difficult the task was for you: easy, moderate or hard. For most of the participants, the task was average; for the others, it was easy.
- The feeling about concentration level during solving the task (from 1 to 10).

3.4 Data collection protocol

3.4.1 Experimentation Settings

The experiment was conducted at the Innopolis University Library. Before the experiment, each subject answered questions about their music preferences and the programming experience. Programmers were divided into three groups of experience: Elementary, Intermediate and Advanced that defined the difficulty of the task given. Subjects solved a given task using their preferred programming language. The environment was the same for all experiments:

- Time of the day: 12.00 - 18.00
- Time of experiment: 20-30 minutes
- Environment: open space hall in Innopolis University

As this was the first observational study, it was necessary for us to follow the experiment with strict procedure and rules, so that it would be beneficiary for our future large scale experiments. EEG was recorded according to the following procedure:

- Eyes closed: 2 minutes
- Eyes opened: 2 minutes
- Main experiment: test subject solving given task

The time for solving task was different for each person, but they did not exceed 20 minutes. If the test subject did not solve the task in the given time, the researcher stopped the experiment.

3.4.2 Prepatation Procecedures

Before the experimentation sessions, EEG device was charged, and the following procedures were carried out:

- Cleaning the device and electrodes with alcohol wipes and cleaning the electrodes with a special brush
- Putting the cap on the test subject and making it comfortable for the subject: place ears in special positions, fasten chin closure.
- Filling the electrodes with conductive gel.
- Launching the EEG studio and connect the device via Bluetooth channel to the computer, synchronize it with the EEG studio
- Choosing the reference electrode (Cz) and montage in EEG studio
- Verification electrodes one by one: checking that the signal is in the acceptable range and there are no sharp drops or rises of the signal. If the electrode does not work properly, checking its position and putting additional gel for a snug fit to the skull if needed.

3.4.3 Experimentation Steps

The steps for the experiment are listed below.

- EEG machine calibration. The calibration is made up of two parts. The first is when subjects sit in a relaxed state with their eyes closed in front of the screen and the second is the same but with their eyes opened.
- Subject reads the task (1-3 mins).

- Subjects solved the task (6-15 mins).
- Subject takes off the cap
- Disconnecting and switching off the cap
- Cleaning the device and electrodes with alcohol wipes and cleaning the electrodes with a special brush to remove gel

3.5 Data analysis protocol

3.5.1 Channel selection

Right channel selection is a trade-off between various parameters, such as quantity and redundancy of data, cleanness, information from different parts of scalp etc. For example, frontal electrodes are affected by eye and face muscle movements. During the processing, we found out that frontal electrodes can not be cleaned using filters or Individual Component Analysis (ICA) and manual filtering. To capture valid and clean data, we decided to analyze only central electrodes (F3, Fz, F4, C3, C4, P3, Pz, P4 with Cz as a reference) since they provide data which can be used in further analysis.

3.5.2 Data preprocessing

The process of data preprocessing included the following steps:

- Notch filter is used to remove noise from AC lines, which has a frequency of 50 Hz in Russia.

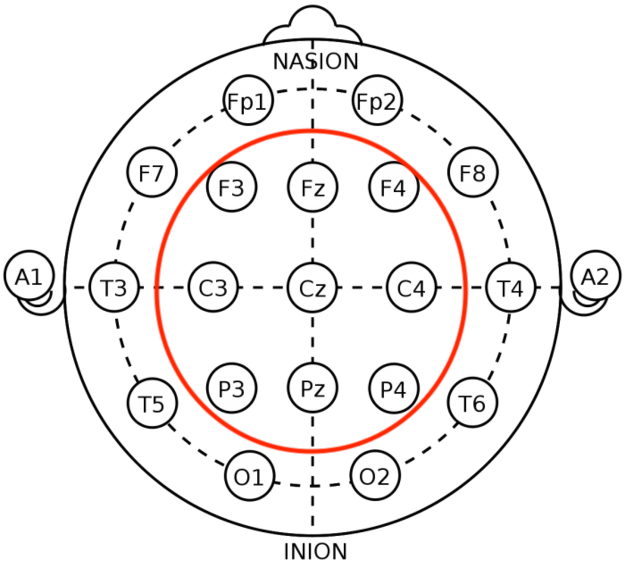

Figure 3.2: Selected channels

- Calculating the mean signal from the channels showed in Figure 3.2 Applying filters for particular bands (L1A, L2A, UA, Th): high and low pass filters for frequencies for intervals listed in section 3.5.3.

- manual and automatic artifacts detection

3.5.3 Feature selection

The set of the possibles features was:

- Theta/Beta Ratio

- Changes in Alpha and Theta frequencies

- Comparison of mean values of lower-1 alpha (L1A), lower-2 alpha (L2A), upper alpha (UA) and Theta (Th) frequencies of samples

TBR is mostly related to the control of visual attention and, mostly studied in regard to concentration disease, so it is not well-suited goals of current research. Second feature well suits our needs, because it considers functional state of the brain during long continuous process [70] [71] [72] [73]. Theta power increasing during difficult task relative to a simple task, whereas alpha power increase in the simple task compared to difficult tasks. Theta activity is associated with multiple processes, such as working memory, problem-solving, self-monitoring [74], which also is characteristics of the development process.

The third feature also considers the age of the participants. To compute Alpha band sub-bands, we need to know Peak Alpha Frequency, which depends on the participant's age and computes as the following [82]:

$$IAF = 11.95 - 0.053 * .Age$$

The sub-bands computed as the following:

- L1A: from IAF - 4Hz to IAF - 2Hz
- L2A: from IAF - 2Hz to IAF
- UA: from IAF to IAF + 2Hz
- Th: from IAF - 6Hz to IAF - 4Hz

This division to sub-bands improves the precision of the results and reflects different processes in the brain in the following way. The L1A and L2A bands show an increase in attention, whereas the UA band reflects semantic memory processes [82]. Increase in power of theta band and decrease in alpha indicates cognitive and memory performance, according to [83].

Chapter 4

Implementation and Results

4.1 Participants Statistics

During the experimentation, we asked some questions from participants about their age, education level, programming experience, the results of solving the task (solved or not), was the task difficult or not. The results are the following:

- Age: all subjects were 21 years old, except for one who is 22
- Education level: all subject were Bachelor level students of 4th form
- Programming level: distribution shown in figure 4.1.
- Result: 62,5% of participants solved the task
- Assessment of the difficulty of the task: distribution shown in figure 4.2

After the experimentation, we conducted one more survey about the personal feelings of the participants about the EEG, which will help to improve

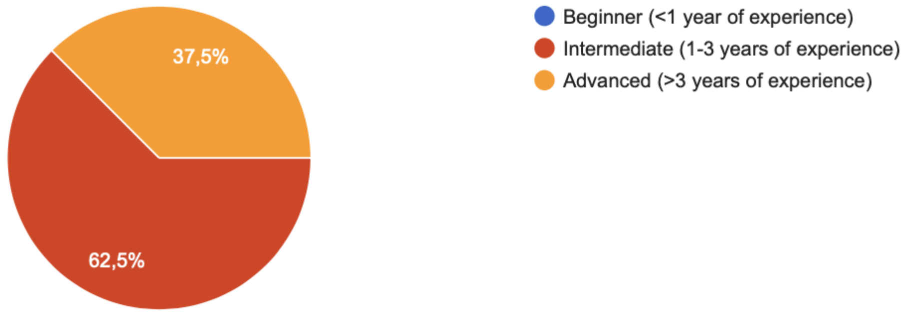

Figure 4.1: Programming experience of the participants

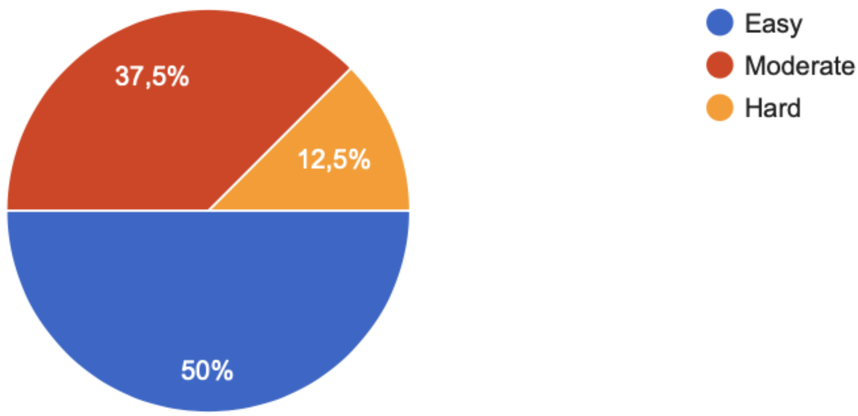

Figure 4.2: Difficulty of the task for the participants

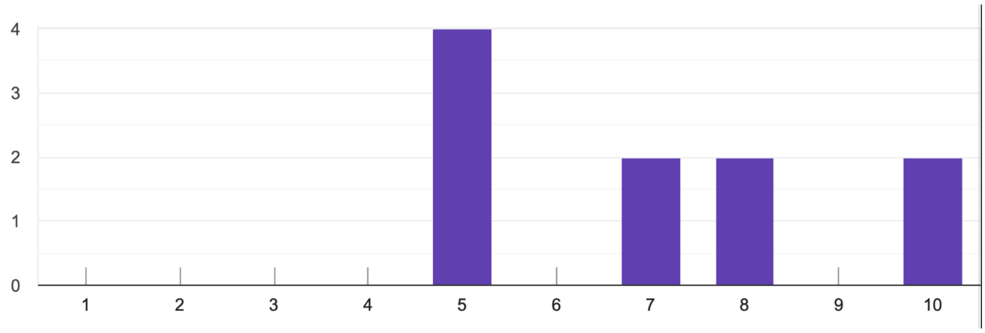

Figure 4.3: Level of the comfort of participants

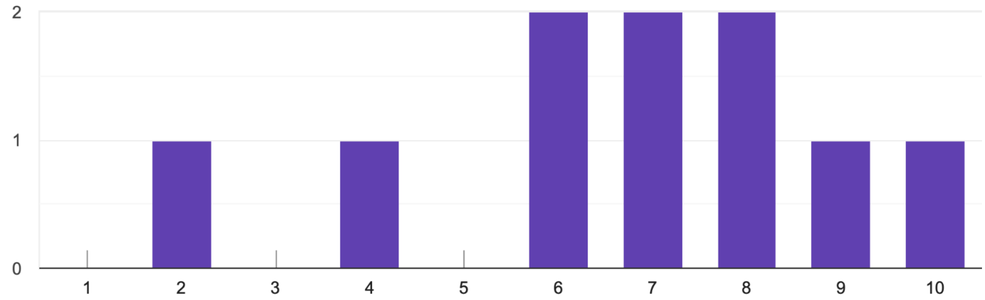

Figure 4.4: Level of the focus of participants

experimentation process in future and to investigate the applicability of the EEG in industrial programming. The questions and were the following:

- Level of the comfort of wearing EEG device The answer is presented in figure 4.3

- The most uncomfortable thing while wearing the EEG device. Participants noted factors such as liquid gel on the head and the need to wash hair after the experiment, restricted movements (they introduce noise), the difficulty of putting a cap on the head, the difficulty of putting on glasses while capturing EEG.

- Level of focus while solving a problem. Results are presented in figure 4.4

4.2 Data Capturing

For the data collection, we used EEG studio by Mitsar. This is a collection of tools, which includes database handler, Acquisition and Analysis modules. The user interface of EEG Studio is presented in Figure 4.5. Main advantages of EEG Studio are:

- It developed by the same designed by the same manufacturer as the EEG cap, so it perfectly interoperates with Mitsar EEG cap from the box
- It allows selecting reference electrode
- It supports export to many formats, which was very handy because some part of processing was done in MNE tool
- It has a user-friendly interface and allows to apply filters, visualise data and automatically detect artifacts

4.3 Data Processing

4.3.1 Channels Selection

EEG device is very sensitive to movements; that is why frontal electrodes are subject to distortion due to eye and face movements. People have different structures of scalps, so EEG cap does not perfectly suit everyone, and occipital electrodes in some subjects it does not fit snugly, especially in those with thick hair. These factors became reasons to exclude some electrodes from consideration. Selected channels were listed in section 3.5.1. Table 4.1 shows the list of electrodes with information about inclusion or the reason for exclusion.

Channel	Included / The reason of exclusion
Fp1	Excluded due to eye and muscle movement
Fp2	Excluded due to eye and muscle movement
F7	Excluded due to eye and muscle movement
F3	Included
Fz	Included
F4	Included
F8	Excluded due to eye and muscle movement
T3	Poor contact between occipital electrodes and skin for some participants due to skull structure
C3	Included
C4	Included
T4	Poor contact between occipital electrodes and skin for some participants due to skull structure
T5	Poor contact between occipital electrodes and skin for some participants due to skull structure
P3	Included
Pz	Included
P4	Included
T6	Poor contact between occipital electrodes and skin for some participants due to skull structure
O1	Poor contact between occipital electrodes and skin for some participants due to skull structure
O2	Poor contact between occipital electrodes and skin for some participants due to skull structure
Cz	Included as a reference

Table 4.1: Included and excludes electrodes

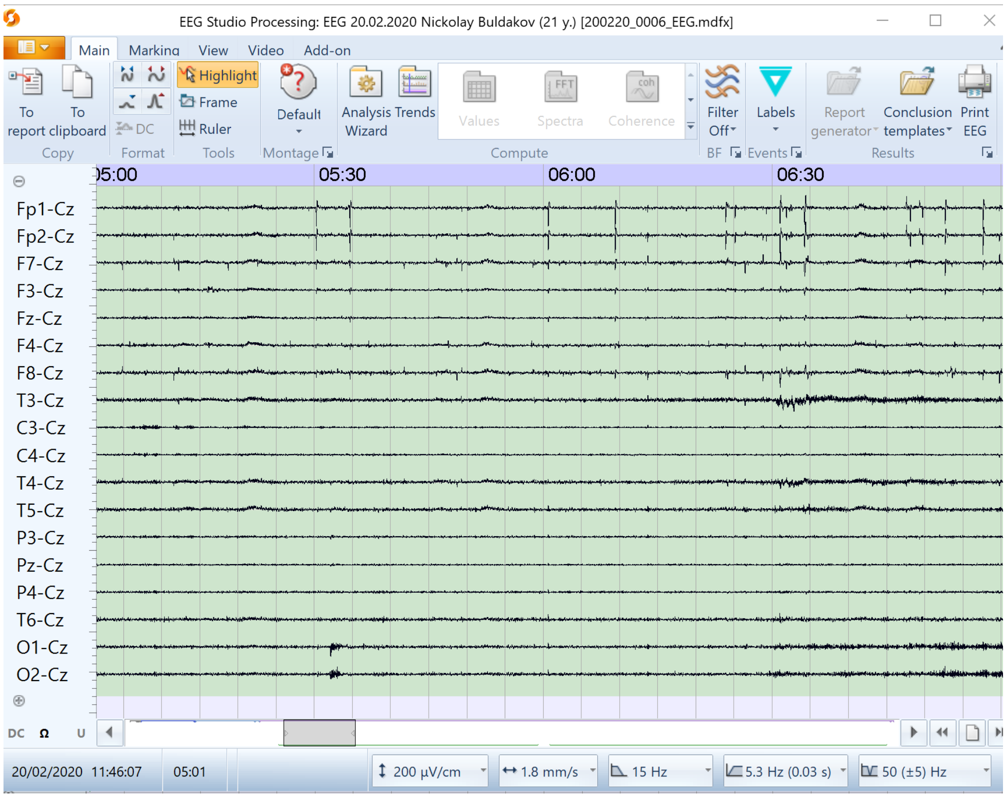

Figure 4.5: Mitsar EEG Studio

4.3.2 Data Preprocessing

Artifact detection

For artifacts detection, we used a manual method and automatic one, provided by MNE studio. Example of the manual method was shown in Figure 4.7. Automatic artefact detection in MNE was configured as follows: all data which amplitude changed for more than 200μV in 200ms were considered as a doubtful region and excluded it with a $\pm$200ms around it. The example of noisy data cleaned by MNE is shown in Figure 4.6.

Filtering the data

EEG device is intended to capture tiny electrical activity oscillations of the brain. That is why it is susceptible to noises from the environment, such

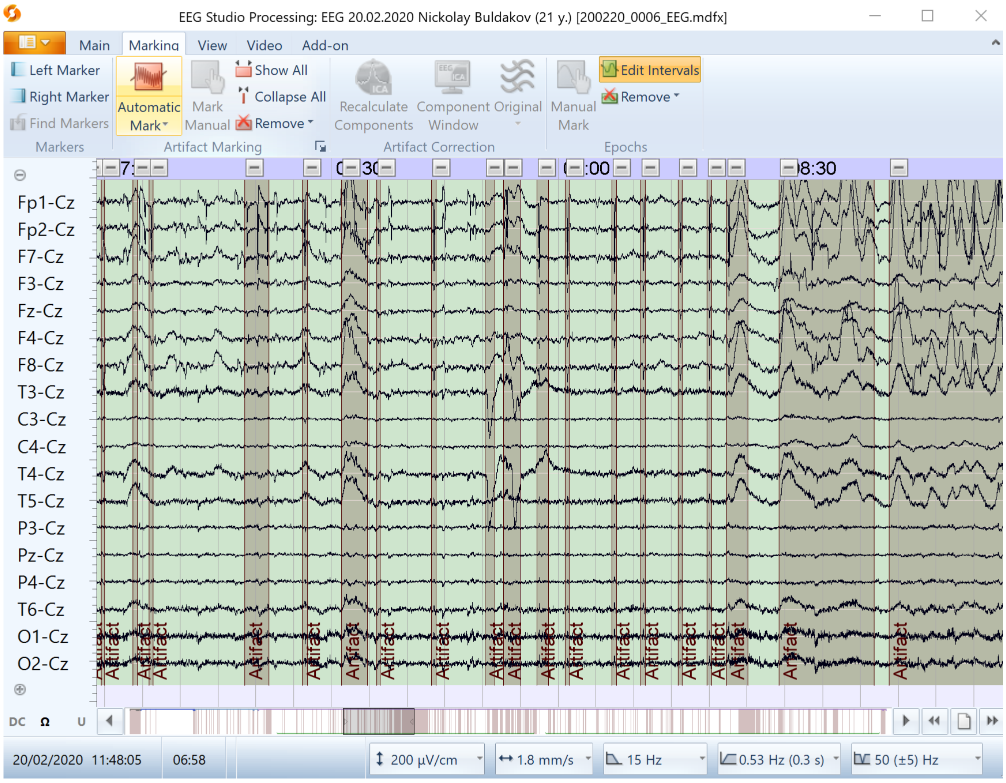

Figure 4.6: Automatic artifacts detection

Figure 4.7: Example of artifact in data

as AC lines, muscle movements, Wi-Fi and Bluetooth waves, electronic devices. In current work, we want to study the functional state of the brain in the real environment in the process of software development, that is why our data is subject to interference from the outside. To get consistent results, we need to clear data properly. First of all, we needed to remove noises from AC lines, which frequency in Russia is 50Hz, which intersects with EEG bands of our interest. To perform this kind of filtering, we used Notch filter of 50Hz.

```
raw = mne.io.read_raw_cnt(filename, preload=True)
data = mne.filter.notch_filter(x=raw.get_data(),
                               Fs=sfreq,
                               freqs=[50])
```

To gather the data from bands listed in Section 3.5.3 we used low-pass and high-pass filters to keep only the range of waves that we are interested in (L1A, L2A, UA, Th).

```
experiment_sub_bands['L1A'] =
  mne.filter.filter_data(data=np.mean(data.get_data(), axis=0),
                         l_freq=IAF_p - 4,
                         h_freq=IAF_p - 2,
                         sfreq=sfreq)
```

4.3.3 Feature Extraction

Levels of Attention

To study levels of Attention, we selected the cleanest samples and then divided samples to halves and compared mean values of Alpha and Theta bands.

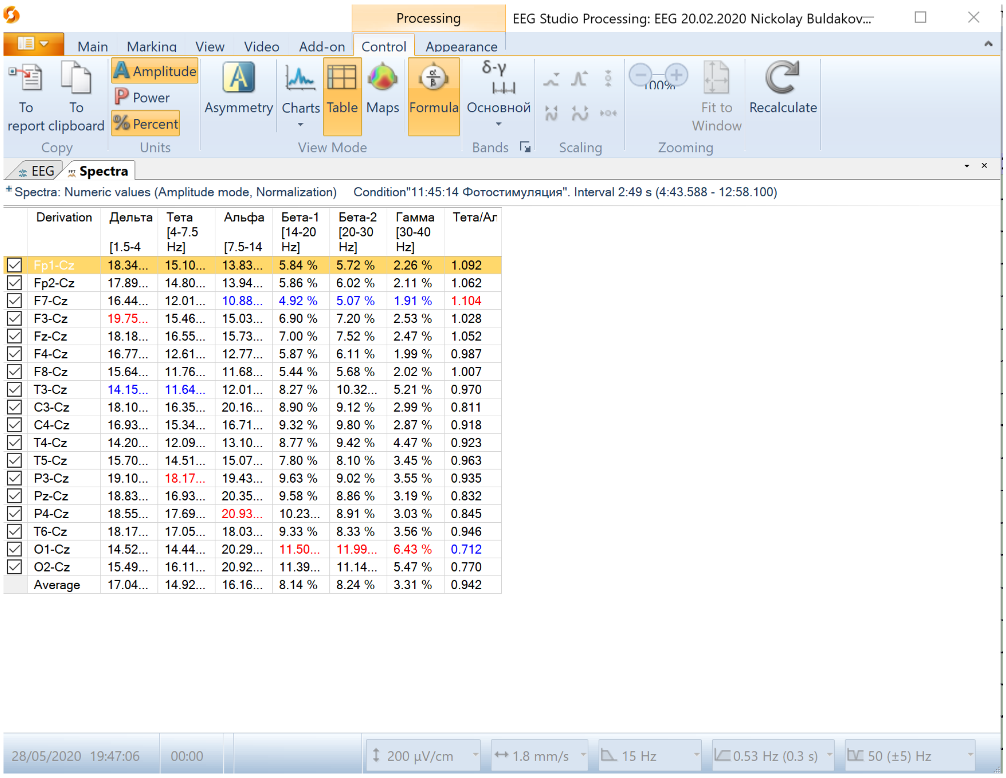

Figure 4.8: EEG spectra analysis

For that, first of all, we opened samples in EEG studio, then divided the experimentation part by marking it as two epochs using "Markers" pannel and "Manual marking" tab. After that, we used the Analysis Wizard to perform spectral analysis to quantify the amount of oscillatory activity of different frequency bands in the recording. After that, we obtained the table with spectral values of the corresponding part of the recording for further analysis. We performed these steps for both halves of experimentation for all of the participants. Then we compared halves, the example of the results is shown in Table 4.2

Analysis of Types of Brain Activity

To compare programming with another type of activity, we decided to pick mean values of Alpha and Theta bands, dividing theta to three sub-bands: lower 1 alpha, lower 2 alpha and upper alpha. First of all, we picked channels

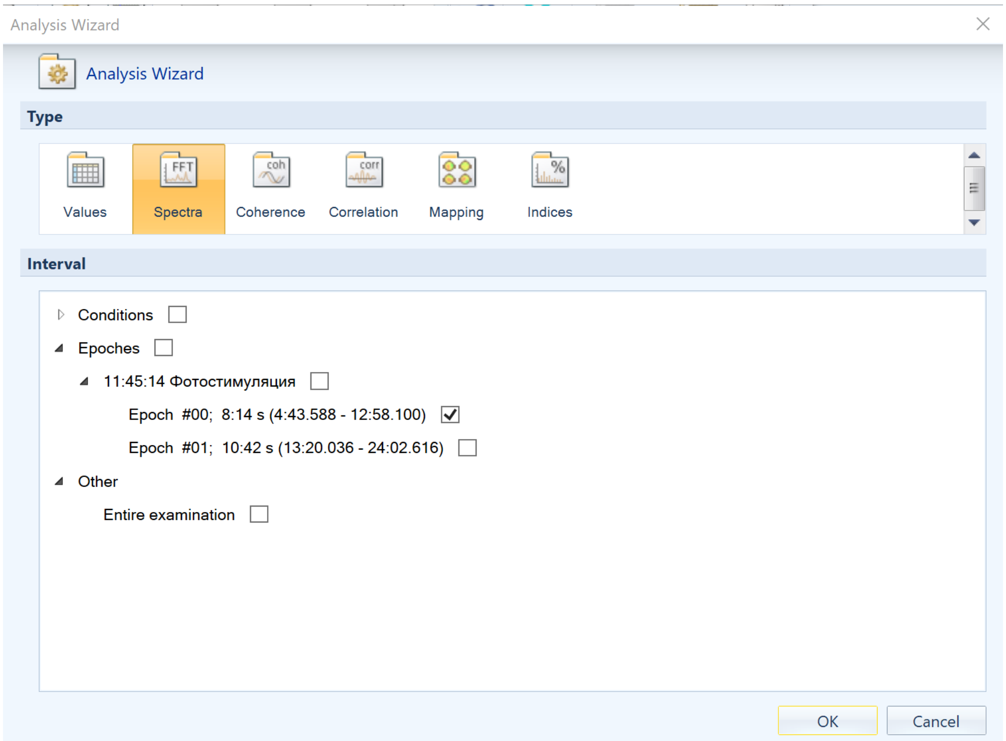

Figure 4.9: Analysis Wizard

Band	**Participant 1**	
	Theta difference	Alpha Difference
F3-Cz	0,27	1,83
Fz-Cz	-1,32	1,02
F4-Cz	1,44	2,86
C3-Cz	-2,01	-0,27
C4-Cz	-0,69	0,94
P3-Cz	-2,22	7,01
Pz-Cz	-2,13	6,13
P4-Cz	-2,69	6,07

Table 4.2: Comparison of mean band values for the beginning and ending of the session

of interest listed in Section 3.5.3 using the following method from the MNE library:

```
data = raw.pick_channels(ch_names=electrodes_list)
```

Then we computed the average value for each sub-band as it was described in Section 4.3.2 and averaged it between selected channels. Averaging, in that case, is acceptable because selected electrodes were from one zone. After that, we calculated the average value for each sub-band between the subjects from all of the two mental states: Programming and Driving.

Chapter 5

Analysis and Discussion

This chapter presents the analysis of the obtained results with the discussion of its validity and applications. It starts with a review of the possibility of attention tracking of programmers, then proceeds with a comparison of the mental workload between programming and driving in order to discuss the possibility to compare the mental workload between programming and other types of mental activities.

5.1 Attention Control

During studying the EEG dataset collected by ourselves with samples recorded during programming, we found an interesting pattern. In the majority of the samples, we found that mean values of Theta and Alpha varied between the first and second half of the recordings. In particular, Alpha decreased, and Theta increased. The example of data is presented in Figure 5.1 Positive Alpha difference means that in the first half of the recording, the mean value of the Alpha band was higher than in the second, which means that the Fatigue was lower and then increased. Negative Theta difference means that in

	Participant 1		Participant 2		Participant 3		Participant 4	
	Theta difference	Alpha Difference	Theta difference	Alpha Difference	Theta difference	Alpha Difference	Theta difference	Alpha Difference
F3-Cz	0,27	1,83	-7,1	-5,24	-5,41	0,35	-1,07	-0,22
Fz-Cz	-1,32	1,02	-1,8	3,95	-4,34	1,7	-0,29	1,37
F4-Cz	1,44	2,86	-3,5	0,18	-3,98	0,68	0,01	0,89
C3-Cz	-2,01	-0,27	-3,16	-0,17	-1,27	1,2	-0,68	5,39
C4-Cz	-0,69	0,94	-2,19	1,99	-1,97	1,32	0,36	4,08
P3-Cz	-2,22	7,01	-2,54	2,72	-2,62	9,2	0,42	3,95
Pz-Cz	-2,13	6,13	-3,89	6,09	-3,73	10,55	-0,43	2,87
P4-Cz	-2,69	6,07	-2,97	7,08	-4,88	11,42	-0,68	5,6
Mean	-1,16875	3,19875	-3,39375	2,075	-3,525	4,5525	-0,295	2,99125

Figure 5.1: Comparison of Alpha and Theta band values for the halves of the recordings

the first half of the recording mean Theta value was lower than in the second, which means that the Attention was higher and then decreased. This pattern could be explained in the following way: during the first half of the experimentation session, the participants felt slightly detached, but by the end of the experiment they gathered their attention to solving the problem as soon as possible. This is only a primary assumption, which cannot be considered as a conclusion. However, with full confidence, we can argue that changes in the level of attention can be analyzed using EEG. This information can be useful for improving the quality and productivity of work, as well as building online systems for controlling the level of attention.

5.2 Mental Workload types

We can see that results for driving lower because data collected for driving dataset was recorded by another type of device as presented in Table 5.1. However, we can see that Theta band for both programming and driving is higher than alpha, which is a signal of a high level of mental concentration. For programming, the difference between theta and alpha is much higher than for driving, which means a higher level of mental workload, attention and task

Band	Programming	Driving
L1A	38046083.85489248	1971244.8703139534
L2A	30690901.415404692	1911859.340372675
UA	25460400.87148648	1866851.002737085
Th	53956243.903502904	2123524.258705829

Table 5.1: Mean values of bands for different types of mental activity

difficulty, according to [61]. The relative value of UA for driving is higher than for programming, which is a signal of higher semantic memory process [82].

Chapter 6

Conclusion

Current work aimed to report about methods of detection attention for programmers. First of all, it reviews current methodologies of studying human brain biophysical signals. To provide an extensive review of state of the art, a Systematic Literature Review performed. Then research focuses on investigating the possibility to detect the level of attention while coding using EEG and identification of correlations between levels and types of mental activity, assuming that the attention level is measured using EEG devices. An experiment was conducted to investigate these aspects. It was crucial to identify and adhere to a precise protocol. To compare programming with other mental activities, we used driving open-source dataset. Then the data was analyzed, and the following conclusions are drowned. First of all, the level of attention could be measured using EEG based on the data collected from central electrodes (F3, Fz, F4, C3, C4, P3, Pz, P4 with Cz as a reference) by tracking in changes of Alpha and Theta bands. Regarding the comparison types of mental activities, for programming, the difference between theta and alpha is much higher than for driving, which means a higher level of mental workload, attention and task difficulty, according to [61]. The relative value of UA for driving is higher than for programming, which is a signal of higher semantic memory process [82]. As a result, we can conclude that with the help of EEG, it is possible to study changes in the level of attention using alpha and theta waves. This fact in the future allows us to build a system for monitoring the level of attention, which can be used to improve the quality of work and detect fatigue. It could help to prevent diseases associated with overwork. A deeper study of specific neuron activation patterns can be used to build human-machine interfaces.

Bibliography cited

[1] D. Graziotin, F. Fagerholm, X. Wang, and P. Abrahamsson, "On the unhappiness of software developers", *CoRR*, vol. abs/1703.04993, 2017. arXiv: 1703.04993. [Online]. Available: http://arxiv.org/abs/1703.04993.

[2] ——, "What happens when software developers are (un)happy", *Journal of Systems and Software*, vol. 140, pp. 32–47, 2018, ISSN: 0164-1212. DOI: https://doi.org/10.1016/j.jss.2018.02.041. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0164121218300323.

[3] R. Layard, D. Chisholm, V. Patel, and S. Saxena, "Mental Illness and Unhappiness", DIW Berlin, The German Socio-Economic Panel (SOEP), SOEPpapers on Multidisciplinary Panel Data Research 600, 2013. [Online]. Available: https://ideas.repec.org/p/diw/diwsop/diw_sp600.html.

[4] A. Rozaliya, R. Anastasiia, T. Herman, A. Kruglov, and S. Busechian, "Attention and vigilance detection based on electroencephalography - a summary of a literature review", Innopolis University, Tech. Rep., 2019.

[5] A. P. Siddaway, A. M. Wood, and L. V. Hedges, "How to do a systematic review: A best practice guide for conducting and reporting narrative reviews, meta-analyses, and meta-syntheses", *Annual Review of Psychology*, vol. 70, no. 1, pp. 747–770, 2019, PMID: 30089228. DOI: 10.1146/annurev-

psych-010418-102803. eprint: https://doi.org/10.1146/annurev-psych-010418-102803. [Online]. Available: https://doi.org/10.1146/annurev-psych-010418-102803.

[6] B. Kitchenham, O. P. Brereton, D. Budgen, M. Turner, J. Bailey, and S. Linkman, "Systematic literature reviews in software engineering – a systematic literature review", *Information and Software Technology*, vol. 51, no. 1, pp. 7–15, 2009, Special Section - Most Cited Articles in 2002 and Regular Research Papers, ISSN: 0950-5849. DOI: https://doi.org/10.1016/j.infsof.2008.09.009. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0950584908001390.

[7] G. Succi, L. Benedicenti, and T. Vernazza, "Analysis of the effects of software reuse on customer satisfaction in an RPG environment", *IEEE Transactions on Software Engineering*, vol. 27, no. 5, pp. 473–479, 2001.

[8] G. Succi, W. Pedrycz, M. Marchesi, and L. Williams, "Preliminary analysis of the effects of pair programming on job satisfaction", in *Proceedings of the 3rd International Conference on Extreme Programming (XP)*, Alghero, Italy, May 2002, pp. 212–215.

[9] I. Fronza, A. Sillitti, and G. Succi, "An Interpretation of the Results of the Analysis of Pair Programming During Novices Integration in a Team", in *Proceedings of the 2009 3rd International Symposium on Empirical Software Engineering and Measurement*, ser. ESEM '09, IEEE Computer Society, 2009, pp. 225–235, ISBN: 978-1-4244-4842-5. DOI: 10.1109/ESEM.2009.5315998. [Online]. Available: http://dx.doi.org/10.1109/ESEM.2009.5315998.

[10] I. Fronza, A. Sillitti, G. Succi, and J. Vlasenko, “Understanding How Novices Are Integrated in a Team Analysing Their Tool Usage”, in *Proceedings of the 2011 International Conference on Software and Systems Process*, ser. ICSSP ’11, Waikiki, Honolulu, HI, USA: ACM, 2011, pp. 204–207, ISBN: 978-1-4503-0730-7. DOI: 10.1145/1987875.1987910. [Online]. Available: http://doi.acm.org/10.1145/1987875.1987910.

[11] W. Pedrycz, B. Russo, and G. Succi, “A model of job satisfaction for collaborative development processes”, *Journal of Systems and Software*, vol. 84, no. 5, pp. 739–752, 2011. DOI: 10.1016/j.jss.2010.12.018. [Online]. Available: http://dx.doi.org/10.1016/j.jss.2010.12.018.

[12] A. Sillitti, G. Succi, and J. Vlasenko, “Understanding the Impact of Pair Programming on Developers Attention: A Case Study on a Large Industrial Experimentation”, in *Proceedings of the 34th International Conference on Software Engineering*, ser. ICSE ’12, Zurich, Switzerland: IEEE Press, Jun. 2012, pp. 1094–1101, ISBN: 978-1-4673-1067-3. DOI: 10.1109/ICSE.2012.6227110. [Online]. Available: http://dl.acm.org/citation.cfm?id=2337223.2337366.

[13] E. Di Bella, A. Sillitti, and G. Succi, “A multivariate classification of open source developers”, *Information Sciences*, vol. 221, pp. 72–83, 2013.

[14] A. Janes and G. Succi, *Lean Software Development in Action.* Heidelberg, Germany: Springer, 2014, ISBN: 978-3-662-44178-7. DOI: 10.1007/978-3-642-00503-9. [Online]. Available: http://dx.doi.org/10.1007/978-3-642-00503-9.

[15] V. Ivanov, M. Mazzara, W. Pedrycz, A. Sillitti, and G. Succi, “Assessing the Process of an Eastern European Software SME Using Systemic Analy-

sis, GQM, and Reliability Growth Models: A Case Study", in *Proceedings of the 38th International Conference on Software Engineering Companion (ICSE 2016)*, Austin, Texas: ACM, May 2016, pp. 251–259, ISBN: 978-1-4503-4205-6. DOI: 10.1145/2889160.2889250. [Online]. Available: http://doi.acm.org/10.1145/2889160.2889250.

[16] S. Livinov, M. Mingazov, V. Myachikov, V. Ivanov, Y. Palamarchuk, P. Sozonov, and G. Succi, "A tool for visualizing the execution of programs and stack traces especially suited for novice programmers", in *Proceedings of the 12th International Conference on Evaluation of Novel Approaches to Software Engineering (ENASE 2017)*, Porto, Portugal, Apr. 2017.

[17] M. Ouzzani, H. Hammady, Z. Fedorowicz, and A. Elmagarmid, "Rayyan—a web and mobile app for systematic reviews", *Systematic Reviews*, vol. 5, no. 1, p. 210, 2016, ISSN: 2046-4053. DOI: 10.1186/s13643-016-0384-4. [Online]. Available: http://dx.doi.org/10.1186/s13643-016-0384-4.

[18] X. Li, B. Hu, Q. Dong, W. Campbell, P. Moore, and H. Peng, "Eeg-based attention recognition", in *2011 6th International Conference on Pervasive Computing and Applications*, IEEE, 2011, pp. 196–201.

[19] B. Hu, X. Li, S. Sun, and M. Ratcliffe, "Attention recognition in eeg-based affective learning research using cfs+knn algorithm", *IEEE/ACM Transactions on Computational Biology and Bioinformatics*, vol. 15, no. 1, pp. 38–45, 2018, ISSN: VO - 15.

[20] L. Bi, R. Zhang, and Z. Chen, "Study on real-time detection of alertness based on eeg", in *2007 IEEE/ICME International Conference on Complex Medical Engineering*, IEEE, 2007, pp. 1490–1493.

[21] L.-W. Ko, W.-K. Lai, W.-G. Liang, C.-H. Chuang, S.-W. Lu, Y.-C. Lu, T.-Y. Hsiung, H.-H. Wu, and C.-T. Lin, "Single channel wireless eeg device for real-time fatigue level detection", 2015.

[22] S. Samima, M. Sarma, and D. Samanta, "Detecting vigilance in people performing continual monitoring task", Dec. 2017, pp. 202–214, ISBN: 978-3-319-72037-1. DOI: 10.1007/978-3-319-72038-8_16.

[23] J. Katona, "Examination and comparison of the eeg based attention test with cpt and t.o.v.a.", 2014.

[24] C. K. C. et al., "Continuous performance test performance in a normative epidemiological sample", *Journal of Abnormal Child Psychology*, 2003.

[25] G. B. Forbes, "Clinical utility of the test of variables of attention (tova) in the diagnosis of attention- deficit/hyperactivity disordere", *Journal Of Clinical Psychology*, 1998.

[26] M. Andersson, A. Avamini, A. Colosimo, A. D'Amico, F. Davide, C. Di Natale, S. Ganci, M. Gutknecht, M. Holmberg, E. Mazzone, *et al.*, "Angelo evaluation: Application of a multisensor system for psychophysiological stress detection in working environments", in *ICECS 2001. 8th IEEE International Conference on Electronics, Circuits and Systems (Cat. No. 01EX483)*, IEEE, vol. 3, 2001, pp. 1509–1512.

[27] A. M. Aljuaid, "Theoretical design of eeg-based neuroergonomics integrated portable system, applying direct psychophysiological indicators", in *2019 Industrial & Systems Engineering Conference (ISEC)*, IEEE, 2019, pp. 1–6.

[28] J. Amores, R. Richer, N. Zhao, P. Maes, and B. M. Eskofier, "Promoting relaxation using virtual reality, olfactory interfaces and wearable eeg",

2018 IEEE 15th International Conference on Wearable and Implantable Body Sensor Networks (BSN), pp. 98–101, 2018, ISSN: VO -.

[29] A. Saidatul, M. P. Paulraj, S. Yaacob, and M. A. Yusnita, "Analysis of eeg signals during relaxation and mental stress condition using ar modeling techniques", *2011 IEEE International Conference on Control System, Computing and Engineering*, pp. 477–481, 2011, ISSN: VO -.

[30] A. Duraisingam, R. Palaniappan, and S. Andrews, "Cognitive task difficulty analysis using eeg and data mining", *2017 Conference on Emerging Devices and Smart Systems (ICEDSS)*, pp. 52–57, 2017, ISSN: VO -.

[31] H. Sun, L. Bi, X. Lu, B. Fan, and Y. Guo, "Vigilance analysis based on eeg band power using support vector machine", *2015 8th International Congress on Image and Signal Processing (CISP)*, pp. 1090–1094, 2015, ISSN: VO -.

[32] S.-i. Ito, Y. Mitsukura, M. Fukumi, and J. Cao, "Detecting method of music to match the user's mood in prefrontal cortex eeg activity using the ga", *2007 International Conference on Control, Automation and Systems*, pp. 2142–2145, 2007, ISSN: VO -.

[33] S. Ito, M. Ito, and M. Fukumi, "Method to detect impression evaluation patterns on music listened to using eeg analysis technique", *2015 10th Asian Control Conference (ASCC)*, pp. 1–6, 2015, ISSN: VO -.

[34] J. A. Miranda-Correa and I. Patras, "A multi-task cascaded network for prediction of affect, personality, mood and social context using eeg signals", *2018 13th IEEE International Conference on Automatic Face & Gesture Recognition (FG 2018)*, pp. 373–380, 2018, ISSN: VO -.

[35] K. Guo, H. Mei, X. Xie, and X. Xu, “A convolutional neural network feature fusion framework with ensemble learning for eeg-based emotion classification”, *2019 IEEE MTT-S International Microwave Biomedical Conference (IMBioC)*, vol. 1, pp. 1–4, 2019, ISSN: VO - 1.

[36] K. Li, X. Li, Y. Zhang, and A. Zhang, “Affective state recognition from eeg with deep belief networks”, *2013 IEEE International Conference on Bioinformatics and Biomedicine*, pp. 305–310, 2013, ISSN: VO -.

[37] P. Keelawat, N. Thammasan, B. Kijsirikul, and M. Numao, “Subject-independent emotion recognition during music listening based on eeg using deep convolutional neural networks”, *2019 IEEE 15th International Colloquium on Signal Processing & Its Applications (CSPA)*, pp. 21–26, 2019, ISSN: VO -.

[38] T. Ogawa, S. Karungaru, Y. Mitsukura, M. Fukumi, and N. Akamatsu, “Feature extraction in listen’ng to music using statistical analystis of the eeg”, *2006 SICE-ICASE International Joint Conference*, pp. 5120–5123, 2006, ISSN: VO -.

[39] V. Alizadeh1 and O. Dehzangi, “The impact of secondary tasks on drivers during naturalistic driving: Analysis of eeg dynamics”, 2016.

[40] M. I. Guofa Shou and L. Ding, “Ongoung eeg oscillatory dynamics suggesting evolution of mental fatigue in a color-word matching stroop task”, 2013.

[41] M. Mohammadpour and S. Mozaffari, “Classification of eeg-based attention for brain computer interface”, in *2017 3rd Iranian Conference on Intelligent Systems and Signal Processing (ICSPIS)*, IEEE, 2017, pp. 34–37.

[42] T.-P. Jung, S. Makeig, M. Stensmo, and T. J. Sejnowski, "Estimating alertness from the eeg power spectrum", *IEEE transactions on biomedical engineering*, vol. 44, no. 1, pp. 60–69, 1997.

[43] J. He, D. Liu, Z. Wan, and C. Hu, "A noninvasive real-time driving fatigue detection technology based on left prefrontal attention and meditation eeg",

[44] R. W. E. Donchin K. M. Spencer, "The mental prosthesis: Assessing the speed of a p300-based brain-computer interface", *IEEE transactions on rehabilitation engineering, vol. 8, no. 2*, 2000.

[45] A. S. M. Donnerer, "Using a p300 brain-computer interface in an immersive virtual environment", *Presence: Teleoperators and Virtual Environments, vol. 19, no. 1*, 2010.

[46] J. A. O'Sullivan, R. B. Reilly, and E. C. Lalor, "Improved decoding of attentional selection in a cocktail party environment with eeg via automatic selection of relevant independent components", in *2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, IEEE, 2015, pp. 5740–5743.

[47] A. Kołakowska, "Towards detecting programmers' stress on the basis of keystroke dynamics", in *2016 Federated Conference on Computer Science and Information Systems (FedCSIS)*, Oct. 2016, pp. 1621–1626.

[48] R. Couceiro, G. Duarte, J. Durães, J. Castelhano, C. Duarte, C. Teixeira, M. Castelo Branco, P. Carvalho, and H. Madeira, "Pupillography as indicator of programmers' mental effort and cognitive overload", in *2019 49th Annual IEEE/IFIP International Conference on Dependable Systems and Networks (DSN)*, Jun. 2019, pp. 638–644. DOI: 10.1109/DSN.2019.00069.

[49] A. Sillitti, G. Succi, and J. Vlasenko, "Understanding the impact of pair programming on developers attention: A case study on a large industrial experimentation", in *2012 34th International Conference on Software Engineering (ICSE)*, Jun. 2012, pp. 1094–1101. DOI: 10.1109/ICSE.2012.6227110.

[50] A. Sillitti, A. Janes, G. Succi, and T. Vernazza, "Collecting, integrating and analyzing software metrics and personal software process data", Oct. 2003, pp. 336–342, ISBN: 0-7695-1996-2. DOI: 10.1109/EURMIC.2003.1231611.

[51] S. Busechian, V. Ivanov, A. Rogers, I. Sirazitdinov, G. Succi, A. Tormasov, and J. Yi, "Understanding the impact of pair programming on the minds of developers", in *2018 IEEE/ACM 40th International Conference on Software Engineering: New Ideas and Emerging Technologies Results (ICSE-NIER)*, IEEE, 2018, pp. 85–88.

[52] S. Lee, A. Matteson, D. Hooshyar, S. Kim, J. Jung, G. Nam, and H. Lim, "Comparing programming language comprehension between novice and expert programmers using eeg analysis", in *2016 IEEE 16th International Conference on Bioinformatics and Bioengineering (BIBE)*, IEEE, 2016, pp. 350–355.

[53] S. Koelstra, C. Muhl, M. Soleymani, J. Lee, A. Yazdani, T. Ebrahimi, T. Pun, A. Nijholt, and I. Patras, "Deap: A database for emotion analysis ;using physiological signals", *IEEE Transactions on Affective Computing*, vol. 3, no. 1, pp. 18–31, Jan. 2012. DOI: 10.1109/T-AFFC.2011.15.

[54] J. A. Miranda-Correa, M. K. Abadi, N. Sebe, and I. Patras, "Amigos: A dataset for affect, personality and mood research on individuals and groups", 2017.

[55] A. Sillitti, A. Janes, G. Succi, and T. Vernazza, "Measures for mobile users: An architecture", *Journal of Systems Architecture*, vol. 50, no. 7, pp. 393–405, 2004. DOI: 10.1016/j.sysarc.2003.09.005. [Online]. Available: http://dx.doi.org/10.1016/j.sysarc.2003.09.005.

[56] E. Petrinja, A. Sillitti, and G. Succi, "Comparing OpenBRR, QSOS, and OMM assessment models", in *Open Source Software: New Horizons - Proceedings of the 6th International IFIP WG 2.13 Conference on Open Source Systems, OSS 2010*, Notre Dame, IN, USA: Springer, Heidelberg, May 2010, pp. 224–238, ISBN: 978-3-642-13243-8. DOI: 10.1007/978-3-642-13244-5_18. [Online]. Available: http://dx.doi.org/10.1007/978-3-642-13244-5_18.

[57] B. Rossi, B. Russo, and G. Succi, "Modelling Failures Occurrences of Open Source Software with Reliability Growth", in *Open Source Software: New Horizons - Proceedings of the 6th International IFIP WG 2.13 Conference on Open Source Systems, OSS 2010*, Notre Dame, IN, USA: Springer, Heidelberg, May 2010, pp. 268–280, ISBN: 978-3-642-13244-5. DOI: 10.1007/978-3-642-13244-5_21. [Online]. Available: http://dx.doi.org/10.1007/978-3-642-13244-5_21.

[58] I. D. Coman, P. N. Robillard, A. Sillitti, and G. Succi, "Cooperation, collaboration and pair-programming: Field studies on backup behavior", *Journal of Systems and Software*, vol. 91, pp. 124–134, 2014. DOI: 10.

1016/j.jss.2013.12.037. [Online]. Available: http://dx.doi.org/10.1016/j.jss.2013.12.037.

[59] 1. Niedermeyer Ernst, 1. Lopes da Silva F. H., and I. Ovid Technologies, *Electroencephalography : basic principles, clinical applications, and related fields*, English, 5th ed. Philadelphia ; London : Lippincott Williams & Wilkins, 2005, ISBN: 0781751268.

[60] W. Klimesch, "Eeg alpha and theta oscillations reflect cognitive and memory performance: A review and analysis", *Brain Research Reviews*, vol. 29, no. 2, pp. 169–195, 1999, ISSN: 0165-0173. DOI: https://doi.org/10.1016/S0165-0173(98)00056-3. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0165017398000563.

[61] W. Klimesch, B. Schack, and P. Sauseng, "The functional significance of theta and upper alpha oscillations", *Experimental psychology*, vol. 52, pp. 99–108, Feb. 2005. DOI: 10.1027/1618-3169.52.2.99.

[62] O. Klimecki and T. Singer, "Compassion", in. Dec. 2015, vol. 3, pp. 195–199. DOI: 10.1016/B978-0-12-397025-1.00178-0.

[63] G. Pfurtscheller and A. Aranibar, "Evaluation of event-related desynchronization (erd) preceding and following voluntary self-paced movement", *Electroencephalography and Clinical Neurophysiology*, vol. 46, no. 2, pp. 138–146, 1979, ISSN: 0013-4694. DOI: https://doi.org/10.1016/0013-4694(79)90063-4. [Online]. Available: http://www.sciencedirect.com/science/article/pii/0013469479900634.

[64] J. Zhang, K. Fong, N. Welage, and K. P. Liu, "The activation of the mirror neuron system during action observation and action execution with

mirror visual feedback in stroke: A systematic review", *Neural Plasticity*, vol. 2018, pp. 1–14, Apr. 2018. DOI: 10.1155/2018/2321045.

[65] O. Dimigen, M. Valsecchi, W. Sommer, and R. Kliegl, "Human microsaccade-related visual brain responses", *The Journal of neuroscience : the official journal of the Society for Neuroscience*, vol. 29, pp. 12 321–31, Sep. 2009. DOI: 10.1523/JNEUROSCI.0911-09.2009.

[66] P. Adjamian, I. E. Holliday, G. R. Barnes, A. Hillebrand, A. Hadjipapas, and K. D. Singh, "Induced visual illusions and gamma oscillations in human primary visual cortex", *European Journal of Neuroscience*, vol. 20, no. 2, pp. 587–592, DOI: 10.1111/j.1460-9568.2004.03495.x.

[67] A. Lutz, L. Greischar, N. Rawlings, M. Ricard, and R. Davidson, "Long-term meditators self-induce high-amplitude gamma synchrony during mental practice", *Proceedings of the National Academy of Sciences of the United States of America*, vol. 101, pp. 16 369–73, Dec. 2004. DOI: 10.1073/pnas.0407401101.

[68] B. McDermott, E. Porter, D. Hughes, B. Mc Ginley, M. Lang, M. Halloran, and M. Jones, "Gamma band neural stimulation in humans and the promise of a new modality to prevent and treat alzheimer's disease", *Journal of Alzheimer's Disease*, vol. 65, pp. 1–30, Jul. 2018. DOI: 10.3233/JAD-180391.

[69] W. Ray and H. Cole, "Eeg alpha activity reflects emotional and cognitive processes", *Science (New York, N.Y.)*, vol. 228, pp. 750–2, Jun. 1985. DOI: 10.1126/science.3992243.

[70] A. Gevins and M. Smith, "Neurophysiological measures of working memory and individual differences in cognitive ability and cognitive style",

Cerebral cortex (New York, N.Y. : 1991), vol. 10, pp. 829–39, Oct. 2000. DOI: 10.1093/cercor/10.9.829.

[71] A. Gevins, H. Leong, R. Du, M. E. Smith, J. Le, D. DuRousseau, J. Zhang, and J. Libove, "Towards measurement of brain function in operational environments", *Biological Psychology*, vol. 40, no. 1, pp. 169–186, 1995, EEG in Basic and Applied Settings, ISSN: 0301-0511. DOI: https://doi.org/10.1016/0301-0511(95)05105-8. [Online]. Available: http://www.sciencedirect.com/science/article/pii/0301051195051058.

[72] K. Smith and W. Ferrier, "Competitive dynamics research: Critique and future directions", Jan. 2001.

[73] Comstock, J. Raymond, and R. Arnegard, "The multi-attribute task battery for human operator workload and strategic behavior research", Feb. 1992.

[74] G. Sammer, C. Blecker, H. Gebhardt, M. Bischoff, R. Stark, K. Morgen, and D. Vaitl, "Relationship between regional hemodynamic activity and simultaneously recorded eeg-theta associated with mental arithmetic-induced workload", *Human brain mapping*, vol. 28, pp. 793–803, Aug. 2007. DOI: 10.1002/hbm.20309.

[75] I. Crk, T. Kluthe, and A. Stefik, "Understanding programming expertise: An empirical study of phasic brain wave changes", *ACM Trans. Comput.-Hum. Interact.*, vol. 23, no. 1, Dec. 2016, ISSN: 1073-0516. DOI: 10.1145/2829945. [Online]. Available: https://doi.org/10.1145/2829945.

[76] T. Rihs, C. Michel, and G. Thut, "Mechanisms of selective inhibition in visual spatial attention are indexed by ?-band eeg synchronization", *The*

European journal of neuroscience, vol. 25, pp. 603–10, Feb. 2007. DOI: 10.1111/j.1460-9568.2007.05278.x.

[77] M. Judah, D. Grant, A. Mills, and W. Lechner, "Factor structure and validation of the attentional control scale", *Cognition and Emotion*, vol. 28, Sep. 2013. DOI: 10.1080/02699931.2013.835254.

[78] P. Putman, J. Van Peer, I. Maimari, and S. Van der Werff, "Eeg theta/-beta ratio in relation to fear-modulated response-inhibition, attentional control, and affective traits", *Biological psychology*, vol. 83, pp. 73–8, Nov. 2009. DOI: 10.1016/j.biopsycho.2009.10.008.

[79] D. [Son], F. M. [Blasio], J. S. Fogarty, A. Angelidis, R. J. Barry, and P. Putman, "Frontal eeg theta/beta ratio during mind wandering episodes", *Biological Psychology*, vol. 140, pp. 19–27, 2019, ISSN: 0301-0511. DOI: https://doi.org/10.1016/j.biopsycho.2018.11.003. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S030105111830560X.

[80] J. Min, P. Wang, and J. Hu, "The original EEG data for driver fatigue detection", Jul. 2017. DOI: 10.6084/m9.figshare.5202739.v1. [Online]. Available: https://figshare.com/articles/The_original_EEG_data_for_driver_fatigue_detection/5202739.

[81] G. H. Klem, H. Lüders, H. H. Jasper, and C. Elger, "The ten-twenty electrode system of the international federation. the international federation of clinical neurophysiology.", *Electroencephalography and clinical neurophysiology. Supplement*, vol. 52, pp. 3–6, 1958.

[82] W. Klimesch, M. Doppelmayr, T. Pachinger, and B. Ripper, "Brain oscillations and human memory: Eeg correlates in the upper alpha and theta band", *Neuroscience letters*, vol. 238, no. 1-2, pp. 9–12, Nov. 1997, ISSN:

0304-3940. DOI: 10.1016/s0304-3940(97)00771-4. [Online]. Available: https://doi.org/10.1016/s0304-3940(97)00771-4.

[83] W. Klimesch, "Eeg alpha and theta oscillations reflect cognitive and memory performance: A review and analysis", *Brain Research Reviews*, vol. 29, no. 2, pp. 169–195, 1999, ISSN: 0165-0173. DOI: https://doi.org/10.1016/S0165-0173(98)00056-3. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0165017398000563.