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RESEARCH ARTICLE

# Attention and Concentration for Software Developers

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**ABSTRACT** Attention and concentration has been claimed as reasons for higher quality code and more productive development, also with some empirical evidence. In this paper we investigate the matter further. We present a systematic literature review focused on investigating the existing methods for measuring attention in the software development processes especially team meetings. Based on the research gap revealed by literature review, we conducted experiments measuring attention levels using portable electroencephalography (EEG) device. Attention was measured while the software developers took part in stand-up and sit-down meetings. The experimental results revealed that stand-up meetings foster higher level of attention compared to sit-down meetings.

**INDEX TERMS** Software engineering, software development, brainwaves, EEG, empirical studies.

## I. INTRODUCTION

Knowledge-based activities such as software development require selective or sustained attention. With increase in demand for high quality software and fast software development, it has become critically important to develop software development practices that promotes high level of concentration and attention to details. Over the years methods such as Agile and Scrum have been developed to keep up with the market demand in the information and communications technology (ICT) domain [1]. However to better understand if these approaches really increases the level of developers attention and concentration, it is important to measure accurately the levels of attention [2], [3].

Over the years researchers have tried to present the core aspects of nature and measurement of attention [4]. More often the attention has been defined in relation to concepts of working memory and executive function. There exist two components that appear in nearly all discussions of attentional processes: selective attention and sustained attention [4], [5]. Selectivity of attention is directing attention to a specific external or internal 'object' from among the potentially available myriad [6]. This selection involves not only the directing of attention to the relevant object but the suppression of attention to the irrelevant. Sustained attention is essentially synonymous with what other researchers refer to as the degree of concentration and duration of attention once an object has been selected [4], [7], [8].

There are numerous psychological measures that pertain to the broad domain of attention and concentration. The majority of these measures are solely based qualitative approaches. However quantitative serve as bases of solid research. It is no doubt that attention is one of the ingredients for good quality software and productivity [2]. Understanding the impact and influence of environment and software development processes to the software production is crucial. Therefore in this study we employ one technique from neuroscience called Electroencephalography (EEG) to measure level of attention in the software development domain. Our research is split into two parts.

Firstly, investigating the possibility of using EEG for attention measurement in software development. Specifically, we are aimed at investigating the possibility to detect the level of attention while coding using EEG and identification of correlations between levels and types of mental activity,

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assuming that the attention level is measured using EEG devices.

Secondly, we investigate whether is EEG a suitable technique to measure the attention levels during team meetings in Agile and to answer the question whether there is a relationship between meeting environment and a developer's attention during meetings. We conduct experiments whereby we measure the level of attention of software developers while in a stand-up meetings. A stand-up meeting attendees communicate and share knowledge while standing. Stand-up meetings are believed to be effective and short compared to sit-down meeting where attendees participate in a sitting position.

To the best of our knowledge this is the first paper measuring the variation of attention level during different kinds of software development process specifically stand-up meetings. Overall, our investigation is driven by the following research questions:

- **RQ1.** What methods exist to estimate the level of attention while programming?
- **RQ2.** Can the attention level change be measured using EEG?
- **RQ3.** Are there differences in level of attention as measured by EEG when people perform sit-down vs. stand up meetings?
- **RQ4.** Is there any possibility to identify correlation between attention levels and various types of mental activity related to programming, assuming that the attention level is measured using EEG devices?

The rest of this paper is organized as follows. Section II gives background information on EEG and related works. Section IV presents the methodology. Section V and V-B presents the results together with the experimentation results discussions. Threats to validity are presented in section VI. Lastly, section VII draws the conclusions and introduces future work.

## II. BACKGROUND

This section presents background on brain waves, electroencephalography analysis techniques, and studies related to attention measurement using EEG. It can be skipped by readers already familiar with the matter.

### A. BRAIN WAVES

Electroencephalography is a method of measuring electrical signals that causes neurons to activate in the brain. It is often applied as a technique for data analysis such as time and frequency series analysis [9]. The brain's neurons contain ionic current, which creates voltage fluctuations that EEG can measure. This electrical activity is spontaneous and recorded over a period of time from many scalp electrodes to form an EEG signal. Traditionally, EEG signals are taken on the surface of the scalp, but there also exists iEEG signals, which are taken inside the brain [10]. In this paper, we will be focusing primarily on conventional scalp EEG signals. There exist different brain signals and they are classified mainly based on their frequencies. The following subsections presents a brief descriptions of different brain signals and conventions used throughout the paper.

#### 1) DELTA BAND (1 - 4 Hz)

Delta ($\delta$) 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 [11].

#### 2) THETA BAND (4 - 8 Hz)

Theta ($\theta$) band waves range between 4 and 8 Hz. Researchers [11], [12] over the years have shown that the frontal $\theta$ waves are correlated to the high level of mental workload, attention and memorising. Klimesch et al. [13] presented evidence that higher levels of $\theta$ frequencies positively correlates with the task difficulty level. Theta waves are usually present and can be captured from all parts of the brain cortex. Theta is typically used for studying spatial navigation and monitoring brain activity in operational environments.

#### 3) ALPHA BAND (8 - 12 Hz)

Alpha ($\alpha$) band waves range from 8 to 12 Hz and were discovered in 1929 by Henry [11]. 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 [14]. On the other hand, alpha waves are decreased during mental or body activity, so they used as an indicator of mental workload [15]. The alpha band could be captured from posterior cortical lobes, such as occipital, parietal and posterior temporal.

#### 4) BETA BAND (12- 25 Hz)

Beta ($\beta$) band waves are in the range from 12 to 25 Hz. The beta band usually correlates with mental concentration and active thinking [11]. Beta power increases when the subject wants to execute movements and could be seen in central cortex. In addition, $\beta$ power increases when we observe movements of other subjects, because of activations in "mirror neuron system" [16]. Beta frequencies are generated in posterior and frontal regions.

#### 5) GAMMA BAND (above 25 Hz)

Gamma ($\gamma$) 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 [17], [18] and micro-saccades. On the other hand, other authors report that gamma waves are correlated with work of memory and attention, similar to theta [19], [20].

### *B. MEASURING ATTENTION*

Attention is the ability to actively process specific information in the environment while tuning out other details [21]. Attention is limited in terms of both capacity and duration, so it is important to have ways to effectively manage the attentional resources we have available in order to make sense of the world. Over the years researchers have proposed different techniques to measure the level attention and workload from brain signals. The following subsections presents the prominent approaches found in literature to measure levels of attention.

#### 1) ALPHA AND THETA WAVES

The first technique to measure attention is solely based on the analysis of the relationship between alpha and theta waves using mainly correlation. Gevins and Smith [6] analyzed attention using continuous performance tasks (N-back). The researchers [6] recorded electroencephalograms of 80 healthy young adults during spatial working memory task. From the analysis of the electroencephalograms, the researchers 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. These results confirmed the results presented in by Gevins et al. [22] 5 years earlier.

Sammer et al. [23] examined the relationship between regional brain activity and the occurrence of theta using EEG and fMRI. Having a conviction that theta increases with workload, the researchers [23] results revealed that theta values from EEG recordings were enhanced by mental arithmetic-induced work-load and theta band reflects comprehensive functional brain states (including attention).

#### 2) EVENT-RELATED DESYNCRONIZATION

The second popular attention measuring technique is Event-Related Desynchronization (ERD). ERD measures how many neuron populations no longer synchronously react after being triggered to perform the given task [24]. 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. Based on experiments, Rihs et al. [25] report the following conclusions about ERD:

- 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

#### 3) THETA/BETA RATIO

The last technique to measure attention we consider in this paper is called theta/beta ratio (TBR). TBR is a power of the slow theta band divided by the value of the fast beta frequency band. Elevated TBR has long been considered as an indicator for Attention Deficit Hyperactivity Disorder (ADHD), especially on children [26]. Judah et al. [27] and Putman et al. [28] present evidence that TBR negatively correlates with attentional control among healthy subjects.

Using TBR as bases for analysis Son et al. [29] conducted an experiment on twenty-six participants to investigate the ralationship between Mind Wondering (MW) related changes in frontal TBR and attentional control. The authors recorded baseline EEG, then the subjects had to do a 40-minute breath-counting task while EEG was recorded. The participants pressed a button when they experienced MW episodes during the session. After the experiments they concluded that the frontal TBR correlates with MW, which means a state of reduced control over thoughts and low level of attention.

## III. REVIEWING EXISTING WORK ON THE SUBJECT

To understand the state of the art of research with respect to our research questions we have conducted a literature review, following the guidelines proposed by Kitchenham et al. [30]. The research questions were same as defined in section I (**RQ1, RQ2, RQ3** and **RQ4**). The electronic data sources we used are the ACM Digital Library and the IEEE Xplore Digital Library. The query used for retrieving the studies where created using the keywords presented below in Table 1. For each RQ, the search queries were defined using boolean expressions and the corresponding keywords presented in Table 1

**TABLE 1. Identified keywords.**

| RQ | Keywords |
|---|---|
| RQ1. | biophysical signals, biological signals, EEG, MRI, fMRI, HRV, brain waves, attention, measures, conditions, environment, IT, software developers, programmers |
| RQ2. | EEG, signals, data, information, measures, conditions, environment, IT, developers, programmers, work, work environment, attention, comfort level, stress, stress response |
| RQ3. | EEG, analysis, attention levels, concentration, interpretation, agile meetings, stand-up, sit-down, retrospective |
| RQ4. | concentration, productivity, team, meeting, team meeting, brain signals, correlation, agile meetings, attention levels, EEG |

The inclusion and exclusion criteria during the review process:

- 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 (papers, books, thesis, posts, videos)
- Methods description and approaches of brain activity and biophysical signal analysis
- Focus on studies of work environment
- Written in English

All found publications were distributed among authors who carefully reviewed each publication article titles and abstracts before being considered as part of the SLR. The publications that did not comply with the inclusion criteria and satisfied the exclusion criteria were immediately discarded. During the scanning process, all the publications were marked as "exclude", "maybe" and "include". Some of the gray literature was marked with the tag "maybe". The results and the answers to the research questions are presented in the next subsections.

### A. ABOUT RQ1 – MEASURING ATTENTION DURING CODING

Measuring attention is very important in many fields, such as detecting drivers' drowsiness and workers' fatigue. After analyzing all the studies we gathered from ACM Digital Library and IEEE Xplore Digital Library we found out that attention could be measured using: heart rate variability, galvanic skin response, pupil diameter, eye blink frequency [31], brain activity measurement (Magnetoencephalogram, functional near-infrared spectroscopy, electrocorticogram, functional magnetic resonance imaging, positron emission tomography, transcranial magnetic stimulation) [32], [32] and Conner's Continuous Performance Test [32], [33], [34].

Bi et al. [33] first proposed to use EEG to estimate alertness in real time. Then, Li et al. [35] have used EEG signals for attention recognition, extending the existing approaches based on eye-gaze, face-detection, head pose, and distance from the monitor. Ko et al. [36] has shown that even a simple and cheap single channel wireless EEG device can detect driver's fatigue level in real-time on a mobile device such as smartphone or tablet. In the followup work of Hu et al. [37] the EEG has been used to determine the attention level while the subject was performing a learning task.

In light of the aforementioned research we see that there is limited research in understanding attention levels during software development processes such as coding and team meetings. However we can see that the EEG is being used and can accurately measure mental states such as attention levels.

### B. ABOUT RQ2 – MEASURING ATTENTION VARIATION USING EEG

Based on the reviewed literature, we conclude that it is possible to measure level of attention using EEG. There has also been studies showing that collecting EEG data can help in creating effective and comprehensive BCI systems to monitor behaviour and well-being at work, such as Aljuaid [38]. There is also a growing and noticeable interest of the research community in this area – see for instance [35], [39], [40], [41], [42]. However, studies on capturing variations of level of attentions are limited. Moreover, there are few researchers using EEG to measure attention while developing software.

### C. ABOUT RQ3 – DIFFERENCES IN ATTENTION AS MEASURED BY EEG FOR SIT-DOWN VS. STAND UP MEETINGS

From the studies that we retrieved from the digital libraries we could not find anything addressing the subject of measuring the different of attention levels between sit-down and stand-up meetings. However Sillitti et al. [2] tried to address the subject of importance of attention in software development process [2]. The authors presented a case study aimed in understanding the impact of pair programming on developers attention. This study is aligned to our research goals. To the best of our knowledge there exist no study that has conducted experiments using EEG to measure developers attention in stand-up and sit-down meetings. This is a an indication of a research gap. For this reason we decided to conduct experiments in this direction.

### D. ABOUT RQ4 – CORRELATION OF ATTENTION LEVELS ACROSS DIFFERENT MENTAL ACTIVITIES

There are studies evidencing that it is possible to estimate the correlations between attention levels and types of mental activity with the help of EEG devices. For instance, Bi et al. [33] conducted the research on the use of EEG signals to estimate the alertness level and by recording the response time for the Test Of Variables Of Attention (TOVA) [33]. The correlation between those two measures was then studied. The results of the experiment showed that EEG can be used in real-time systems that estimate human alertness.

In the same spirit, Saidatul et al. [43] conducted experiments to understand the relationship between specific mental tasks and stress levels [43]. In their study the subjects were given arithmetic tasks to solve, while their brain activity data were recorded with an EEG, showing that with EEG it was possible to detect when the mental activity was more intense. Shou and Ding [44] presented an approach for analysing the growth of mental fatigue in a Stroop task with a help of EEG using independent component analysis (ICA). Particularly, the authors [44] 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.

Despite the great effort expressed by the aforementioned studies, all the experiments did not include analysis of correlation between attention levels and activities related software development processes using EEG.

## IV. METHODOLOGY

This section presents the design and the approach used for conducting the experiments. The experimental design is crafted to resemble the environment in which software developers work. Stand-up and sit-down meetings are components of several Agile software development life-cycle [45]. The building blocks of our experimental procedure are outlined in the following subsections.

### A. PROFILING THE PARTICIPANTS

For the first part of the experiments we conducted a survey which helped us to better understand the participants and the software development strategy employed/familiar to the participants. The recruited participants were students from Innopolis university and software developers working in different companies located in the Special Economic Zone (SEZ) of Innopolis. The experiment subjects men and woman in their 20s who had no neurological illnesses.

### B. EXPERIMENTAL PROCEDURE

The experiments were split into two sessions: (1) sit-down meeting session and (2) stand-up meeting session. Each session took took fifteen to thirty minutes. Before the start of the experiments the participants and the meeting participants were introduced to EEG, EEG recording devices, and the nature of the experimental tasks. During sit-down meetings, the participant was then seated on a comfortable chair. The participants were also asked to put their phones into silent mode and take them away to avoid unexpected disturbances.

During the first twenty minutes, the experimenters wirelessly connected the EEG cap a computer and put the EEG cap to the participant's head, applying gel on the electrodes when necessary. Electrodes which did not function properly after application of gel, were hidden. To calibrate the EEG cap, the participants spent two minutes with their eyes open and two minutes with their eyes closed before start of each an every meeting (either stand-up or sit-down meeting). At the end of the meeting (session), the EEG cap was removed and experiments were asked to give feedback on their attention levels during the meeting. All the information about the sessions time and duration were noted down.

### C. DATA RETRIEVAL

Mitsar 32-channel SmartBCI with international 10-20 system montage was used to record the brain signals during the experiments. EEG Studio software by Mitsar was used to interpret the collected data. The software consists of two independent blocks: the data recording block and data analysis block. The latter is used for capturing brain biological parameters by placing multiple electrodes on a participant's head. Data analysis block is used for a detailed interpretation of acquired data and for performing different mathematical operations for further analysis of this data. The biological parameters that are recorded as EEG signals that contain spontaneous brain oscillations as well as reactions to the caused potentials.

EEG data is usually interpreted as wavebands. The possible bands and their frequencies are presented in the background section (section II). After the meeting ended, and the data was collected, a participant was required to fill a post-experiment questionnaire. The post-experiment questionnaire assesses participants subjective feelings about their level of concentration and attention during the attended meeting.

### D. CHANNEL SELECTION

First, we selected a subset of channels (EEG electrodes) which we will use for further analysis. Duration for each experiment session varied from 15 minutes to 40 minutes, hence resulting in a lot of samples for collected for analysis per session. To optimise the performance and reduce the computational complexity of the processing phase, we decided to select the relevant channels and extract the features of significant importance. Since our experiments are focused on detecting attention and concentration, not all brain regions activations are necessary to characterise attention levels, therefore, we decided to stick specific bands which are associated with attention. The selected bands: Alpha band [46], Theta band [47] and Beta band [48].

Since our experimental environment is very close to real meetings, there is a higher possibility of noise and movements which can interfere with signal capturing thus degrading the quality of the captured data. We decided to analyse the electrodes placed in the specific regions of the brain. The specific electrodes are as follows:

- frontal lobe – F7, F3, Fz, F4, F8
- occipital lobe – O1, O2
- parietal lobe – P3, Pz, P4
- posterior temporal lobe – T6, T5

Electrode Cz was also included to the analysis, since it was chosen as a reference electrode for EEG recording. The placement of the selected electrodes are presented on Figure 1 and highligted in red.

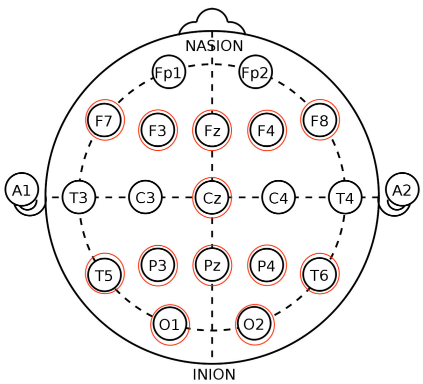


**FIGURE 1. Selected channels: Figure taken from [49] with modifications.**

### E. FILTERING

As a first step towards extracting meaning from the recorded EEG raw data, we applied three specific filters. The three selected filters are:

1) low-pass filter – all frequencies below 31 Hz (a frequency 1 Hz higher than maximum Beta frequency) were passed, and all frequencies above this limit were rejected
2) high-pass filter – the inverse of the low-pass filter in which all frequencies above 3 Hz (one Hz lower than

a minimum Theta frequency) limit are passed, and all below are rejected.
3) amplitude filter – was used to detect and remove artefacts from the raw data.

We did not apply more filters, due to the fact that using more filters introduces a risk of changing the initial data. All the filters we selected were are implemented using MNE Python library.

### F. FEATURE EXTRACTION

One of the most important parts of the experiment was the selection of the features we wanted to extract for further analysis. EEG data is hard to analyse with the naked eye, so for the current experiment, we chose the following features:

1) Mean $\alpha$, $\theta$ and $\beta$ signal of the selected channels
2) $\alpha$ wave coherence
3) Changes in $\alpha$, $\theta$ and $\beta$ waves in different epochs

The overall feature extraction process is visualized in Figure 2.

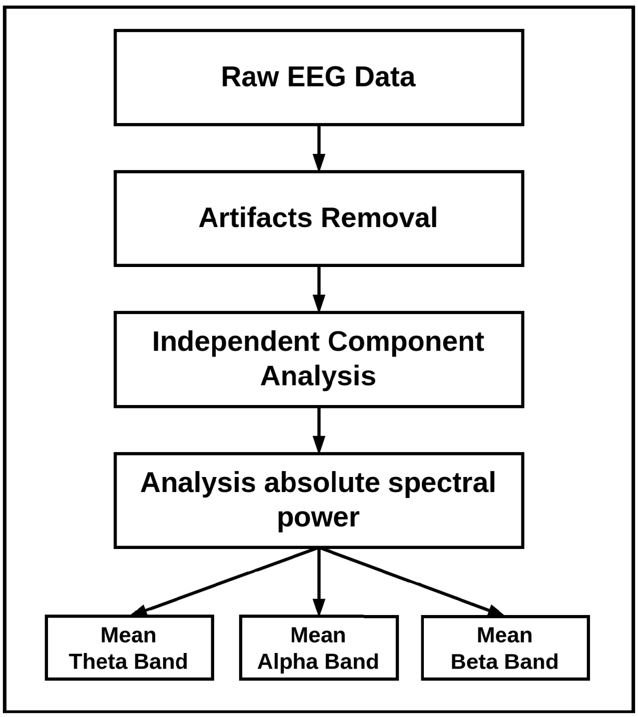


**FIGURE 2. Data processing and feature extraction pipeline.**

An important step that was included in the extraction of the first feature was the calculation division the $\alpha$ band to subbands namely:

- lower-1 $\alpha$ (L1A)
- lower-2 $\alpha$ (L2A)
- upper $\alpha$ (UA)

For example, the changes of L1A and L2A sub-bands can indicate task-related attention, including both components of attention and alertness whereas changes in UA correlate with semantic memory processing and synchronisation with the theta band [12].

The need to extract alpha subbands comes from the fact that each of them can indicate districts behaviours. Also, the use of adjusted bands improves the precision of measures and allows to determine the patterns, which otherwise can be obscured by inaccurate band boundaries definition. One of the ways to adjust the bands is the use of a Peak alpha Frequency (PAF). PAF is correlated with cognitive performance and varies among individuals of different physiological states and different cognitive tasks. PAF indicates a state of cognitive preparedness [50]. In our study, we chose to omit the calculation of PAF because the age of the participants did not vary much (21-30 years).

### G. DATA ANALYSIS

To extract meaning from the collected data, we analyze the wavebands statistics and alpha band coherence. Different wavebands are associated with different mental activity.

The increase in $\alpha$ band levels can be seen throughout mental and physical rest with eyes closed. On the other hand, alpha power is reduced, or suppressed, during mental or physical activity with eyes open. Alpha suppression suggests states of mental activity and engagement, for example, during focused attention towards any stimulus [51]. Alpha suppression also indicates that the brain is preparing to pick up information from multiple senses, coordinates resources of attention and focuses on what matters in that particular moment. Hence, we can track the variations in $\alpha$ bands, which can indicate concentration during the meeting and focus towards its contents.

We focused on the detection of variation of $\theta$ and $\alpha$ frequency bands, as they generally indicate a change in focus and attention. The following variations in frequencies are what we assume will help us detect the drop or rise in the level of attention or concentration: (1) theta frequency all over the cortex, but mainly in the frontal lobe, (2) suppression of $\alpha$ band in occipital, parietal and posterior temporal brain regions

The second approach to analyse our experimental data is band coherence. Coherence analysis can show how two or more EEG electrodes relate to each other and synchronisation of activation the EEG electrodes. Kelly et al. [52] investigated the coherence of Alpha activity during a sustained attention to response task. Sustained attention can be characterised as a physiological state that describes the readiness to detect or respond to rear signals over a long time period. In our opinion, the task of a meeting participant is quite close to this definition – a participant must follow the contents of the meeting and be ready to react when a suitable moment arrives. In [8], and [53] authors performed imaging studies which showed that the activation of frontal and parietal lobes mostly on the right hemisphere indicate sustained attention performance.

**TABLE 2. Demographics of the participants in our study.**

| Demographic Variables | Category | # Participants |
|---|---|---|
| Sex | Male | 4 |
| | Female | 2 |
| Education | Bachelors | 3 |
| | Masters | 3 |
| Occupation | Student | 4 |
| | Software Developer | 4 |

**TABLE 3. Mean band values for sit-down meetings.**

| Participant | Mean Theta | Mean Alpha | Mean Beta-1 | Mean Beta-2 | Theta / Alpha |
|---|---|---|---|---|---|
| **Participant 1** | 5,69 | 5,18 | 1,8 | 1,9 | 1,28 |
| **Participant 2** | 5,6 | 9,53 | 3,66 | 3,17 | 1 |
| **Participant 3** | 6,61 | 4,72 | 3,04 | 5,22 | 1,9 |
| **Participant 4** | 8,34 | 13,23 | 2,42 | 2,3 | 1,46 |
| **Participant 5** | 6,3 | 7,4 | 2,6 | 2,1 | 0,94 |
| **Participant 6** | 15,0 | 21,7 | 7,9 | 10,4 | 0,82 |
| **Mean** | 7,93 | 10,31 | 3,57 | 4,18 | 1,23 |

**TABLE 4. Mean band values for stand-up meetings.**

| Participant | Mean Theta | Mean Alpha | Mean Beta-1 | Mean Beta-2 | Theta / Alpha |
|---|---|---|---|---|---|
| **Participant 1** | 5,72 | 2,46 | 1,04 | 1,54 | 2,32 |
| **Participant 2** | 3,7 | 6,6 | 1,73 | 1,57 | 1,16 |
| **Participant 3** | 6,72 | 6,33 | 4,37 | 7,5 | 1,06 |
| **Participant 4** | 10,28 | 8,48 | 1,68 | 1,85 | 1,21 |
| **Participant 5** | 7,2 | 9,0 | 5,2 | 2,7 | 1,0 |
| **Participant 6** | 23,6 | 16,7 | 8,5 | 5,9 | 1,8 |
| **Mean** | 9,54 | 8,26 | 3,30 | 3,54 | 1,43 |

**TABLE 5. Differences if the mean values among all participants.**

| Band | Stand-up | Sit-down | Sit down - Stand up |
|---|---|---|---|
| **Theta** | 9,537 | 7,925 | 1,61 |
| **Alpha** | 8,262 | 10,313 | -2,05 |
| **Beta 1** | 3,303 | 3,570 | 0,27 |
| **Beta 2** | 3,540 | 4,182 | -0,64 |
| **Theta / Alpha** | 1,425 | 1,233 | 0,19 |

## V. RESULTS FROM THE EXPERIMENTATION

In this section we present the experimental results analysis and discussions. Table 2 summarizes demographic information for our experiments participants. The experimental results and data analysis for stand up meeting are presented in Table 3, for sit-down meetings in Table 4 and overall analysis in Table 4.

### A. ANALYSIS OF THE DATA

#### 1) WAVE BANDS SPECTRAL ANALYSIS

To analyse how the level of attention differs during stand up and sit down meetings, we analysed the mean values of Alpha, Beta and Theta wavebands. We performed a spectral analysis of the power of each band. The spectral analysis shows the amount of rhythmic (power) frequency band included in the signal. Alpha, Beta and Theta waves bands were used as metrics for calculating average differences in brain activity in stand-up or sit-down meetings. The selected electrodes for calculating the mean band values for each participant presented in Figure 1. The results of stand-up and sit-down meetings are shown in Table 4 and Table 3 respectively. Overall comparison of sit-down and stand-up meetings is presented in Table 4.

The experimental data presented in Table 3 and Table 4, illustrates that there was a higher $\alpha$ for most of the participants during stand-ups than on sit down meetings. The higher $\alpha$ can indicate that the participants were more mentally active and focused.

To verify this claim we also divided the EEG recordings to epochs and compared them. The Theta waves were not very representative. In contrast to sit-down meeting, in stand-up meeting the $\alpha$ waves were higher at the beginning as well as at the end of the meeting, which can mean that there was sustained high level of concentration from the start to the end of the meeting.

Moreover, with the help of coherence analysis, we looked for alpha activation patters which are also used to indicate attention. We found out that some participants had a pattern that can be associated with greater sustained attention during stand-ups than sit-downs.

#### 2) ALPHA BAND COHERENCE

We further analysed the experimental data using alpha coherence analysis. Coherence analysis detects the interrelationships between different parts of the brain by capturing the synchronization of electrical activity in the brain and between different electrodes [54]. The metric for coherence measurement is called Coherence Coefficient (CC) and it ranges between 0 and 1 [55]. The highest value of CC indicates very high coordination of brain regions.

The analysis was also done in EEG Studio with the help of Analysis Wizard. For each participants CC was visualized and analysed with the help of coherence map. An example of a Coherence map for stand up meeting and for a sit-down meeting is presented in Figure 3 and Figure 3 respectively.

The main goal for using coherence analysis was to detect pattern of $\alpha$ activity in frontal and parietal lobes of the right hemisphere. As a result of the coherence map and CC we observed the following:

1) Most of the experiments showed cohesion of $\alpha$ band in parietal, occipital and temporal lobe
2) During stand up meetings, the participants brain activity data showed higher CC in the frontal lobe.

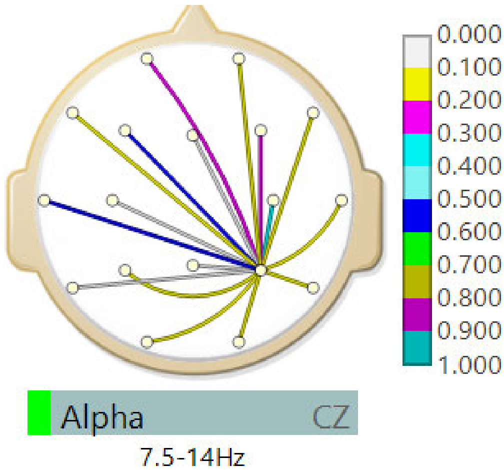


**FIGURE 3.** Example of Coherence in stand-up meeting.

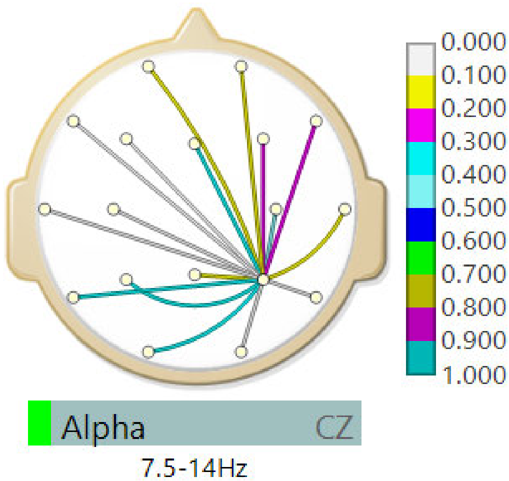


**FIGURE 4.** Example of Coherence in sit-down meeting.

3) Lower coherence of parietal to temporal lobe during stand up meetings

Based on the aforementioned observations we are inclined to conclude that stand-up meetings results in higher sustained attention compared to sit-down meetings. As general observation, the participants in stand-up meetings we able to better respond to the contents of the meeting.

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. In addition this serve as starting point to help prevent diseases associated with overwork. A deeper study of specific neuron activation patterns can be used to build human-machine interfaces.

### *B. CONSIDERING THE RESEARCH QUESTIONS*

With respect to **RQ1.**, we have found that EEG is one of the tools that can be used to estimate the level of attention while programming and we moved on to validate the claim by conducting experiments. Moving to **RQ2.**, previously conducted experiments (i.e [38]) provides evidence by using EEG change in attention level can be measured. Considering the attention differences measurement using EEG while performing sit-down and stand-up meeting (addressed by **RQ3.**), there was insufficient evidence from the literature. For this reason we decided to conduct experiments. Finally, about **RQ4.**, the literature did not present sufficient evidence to answer this research question. However from the experiments we conducted, we came to a conclusion that there exist correlation between attention level and types of meetings in software development (specifically stand-up and sit-down meetings).

We have put a synoptical view of our finding for each research question and of the associated experiments (Table 6).

**TABLE 6.** Results summary.

| | RQ1. | RQ2. | RQ3. | RQ4. |
|---|---|---|---|---|
| **Literature Review** | YES | YES | NO EVIDENCE FOUND | NO EVIDENCE FOUND |
| **Experiment** | YES | YES | YES | YES |

## VI. THREATS TO VALIDITY

Despite following the guidelines for performing a systematic literature review and conducting experiments, our study has several limitations:

- The number of participants in the experiments is very low to draw a solid conclusion.
- The environment and the nature of the software project can have a significant impact on the level of attention and brain signals collection. The environment can induce noise which can be removed, however the existing artifact and noise removal techniques do not guarantee 100 percent data cleaning.
- Our experiments mainly focus on selectivity of attention other than sustained attention.

It is worth mentioning that it is quite challenging to get volunteers for experiments and some volunteers get skeptical about committing due to the procedure of applying gel which is not yet familiar to many. However, our research can be recognized as a stepping stone since till now to the best of our knowledge we are the first to try with the hope to increase the number of participants in the near future.

## VII. CONCLUSION

In this study we presented a case of using EGG to measure software developers attention in agile development. Firstly we conducted a review of the existing attention measurement techniques. The literature review was conducted using guidelines proposed by Kitchenham et al. [30]. The SLR reveled a research gap on measuring software developers attention levels. Secondly, we conducted experiments to measure programmers attention in sit-down and stand-up meetings using EEG. The experiments were also aimed at finding out if there exists a relationship between the meeting environment and a developer's attention during meetings. Based on the analysis of the data gathered during the experiment, EEG appears to provide mechanisms to measure the different levels of attention and also that there are specific physical conditions, such as stand-up meetings, that foster higher levels of attention, and this explains why they are successfully applied in agile methods and other development approaches. For the future, we are aimed at increasing the number of experiment participants and also use the EEG to measure stress levels in the software development process such as code review or code writing.

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