SSRG International Journal of Electrical and Electronics Engineering
ISSN: 2348-8379/ https://doi.org/10.14445/23488379/IJEEE-V11I3P104

Volume 11 Issue 3, 42-64, March 2024

Original Article

Analyzing and Monitoring of People's Attention from EEG Signals

T. Manoj Prasath[1], R. Vasuki[2]

[1,2]*Department of Biomedical Engineering, Bharath Institute of Higher Education and Research, Tamilnadu, India.*

[1]*Corresponding Author : mprasath.t@gmail.com*

Received: 03 January 2024 Revised: 03 February 2024 Accepted: 02 March 2024 Published: 25 March 2024

Abstract - *The human brain is made up of millions of neurons which are responsible for the regulation of motor and sensory events. Analyzing brain signals or images can help one understand the cognitive behaviour of the brain. On earth, psychologists often think about reading EEG signals in order to get a typical analysis of an individual. Yet, it can be pretty challenging and varies from person to person to comprehend how an individual behaves and responds to the numerous orders set up for them. This research is prone to an experimental take away of the personage's electroencephalographic waveform, retrieving the unusually fluctuating curves over suspected guidelines during the complete examination. EEG fluctuations play a significant role in this procedure because it is possible to distinguish crucial details specifically from the waveform. With the assistance of a connected set of probes, an impotent lead, an EEG kit, and the patient being evaluated, this intervention is carried out automatically. This work analyses the attention from EEG signals obtained. A proprietary eSense algorithm was designed to calculate attention. To verify the proposed algorithm, an application was created, which was used in the experiment itself. Next, an analysis of the results and progress of the different phases was carried out based on the data obtained from the measurements. Finally, the overall success of the proposed algorithm was evaluated, and the strengths and weaknesses of the chosen approach were discussed. The calculated values were compared with those from the headband to check whether the "eSense" algorithm matches methods based on traditional techniques.*

Keywords - *Brain states, Electroencephalogram (EEG), Fluctuating curves, Nervous system, eSense algorithm.*

1. Introduction

Attention can be defined as focusing on a specific object, activity or phenomenon. Without a doubt, there is a connection between attention and some of the human senses, primarily hearing and sight. In general, it can be argued that attention depends on the perceived subject and also on the environment in which the person is located. In humans, this is a significant factor that significantly affects the consciousness.

The most famous and quite traditional tool used to measure EEG signals is a unique EEG cap with many. However, for electrodes, the practical use of this cap in applications dealing with the user's attention is minimal, not to mention lower comfort. For this work and the related experiment, a more modern device was used the Mind Wave EEG headband from the NeuroSky company, containing a single electrode with which the EEG activity of the brain is also recorded.

In this case, the use is easier, faster and more user-friendly. The headband calculates attention itself based on raw EEG data, but the way in which the results are achieved is not entirely known. This is the patented "eSense" approach. This product also outlines the direction in which the development of technology in this area is going while also becoming more accessible to more users. However, the price for easier use and greater user comfort is lower accuracy compared to an EEG cap containing around twenty or more electrodes spread over the entire head [1-3].

This work aims to study the literature related to the issue of brain activity signal processing, mainly by means of frequency analysis, as well as to investigate the relationship between EEG waves and the resulting attention of a person. An essential aspect of the work is also the comparison of the values calculated directly by the headband with the results of the designed algorithm, thus comparing the patented "eSense" algorithm with methods based on traditional approaches [4].

1.1. Human Attention

Different activities can be assigned different frequency bands depending on brain activity. When you close your eyes and calm down, for example, alpha activity in the back of the head (area of the visual centre) increases, and beta decreases. Attention can be defined as the concentration of mental activity on a certain activity, event or object.

It is absolutely indispensable for humans. It represents the prerequisite for sensory perception that enters consciousness. It is also one of the essential components of intelligence. Attention or concentration depends on the perceiving person and also on the environment in which the subject is found. Weakening of attention can occur when tired, the originality of the object can cause strengthening, the unexpectedness of the phenomenon, and imagination. At the same time, consciousness is protected from being overwhelmed by too much information [5].

Attention can be divided into intentional and unintentional. When deliberate, the subject perceives stimuli or events in a purposeful way, and a certain amount of effort is needed to maintain it. It participates in two mental activities - vigilance (the attempt to observe the entire perceptual field for a more extended period of concentration) and search (the active activity itself).

In the case of the involuntary, perception occurs arbitrarily and unintentionally. Stimuli that attract attention unintentionally are, for example, intense, moving events, new and unusual stimuli, and those associated with danger or contrast with the surroundings.

If the attention is focused on one specific event, it can be described as selective, otherwise also called concentration. The opposite is then distracted attention. One can maintain 100% attention for one to two minutes, after which it is distracted, and one has to start concentrating more intensively. The ideal length of concentration is around 15-20 minutes, followed by a few-minute rest break [5, 6].

Specific properties can be defined for attention. It is for example:

- Depth: Degree of concentration - indicates how clearly a person processes incoming stimuli from the environment.
- Scope: It is the amount of stimuli that a person is able to perceive at once. For an adult, it is usually around four to five stimuli. The range is inversely proportional to depth the more stimuli to focus on, the less to focus on them.
- Permanence: Fixation of concentration on the same stimulus occurs for a short period of time. Volatility occurs when disturbed by another stimulus.

People can have a variety of attention deficit disorders. The most serious condition is a complete loss of attention (aprosexia). This does not occur under normal circumstances, it occurs in severely melancholic and demented states or strong psychoses.

Less serious is a reduction in the quality of attention (hyperprosexia), which can occur as a result of fatigue, exhaustion or depression or under the influence of medication. It can manifest as distraction and unsteadiness of concentration. The opposite is then increased concentration of attention (hyperprosexia), which can occur under the influence of psycho-stimulants. A person concentrates on too many stimuli and cannot perceive them with sufficient quality. In psychoses, paraprosexia can occur, which means incorrect focus of attention, when concentration is disturbed by external influences and internal tension often appears in a person.

Attention-Deficit/Hyperactivity Disorder (ADHD) can manifest itself in children, especially at school age, which results in inner restlessness, impulsivity and impaired concentration. In 75% of cases, heredity is involved in the occurrence; other stimuli are still being analyzed and investigated [6].

Various studies on the topic of human attention have confirmed that this ability can be trained to some extent. It follows from the materials [7] that the EEG signal in the frontal region in a trained preschool child is similar to that measured in an adult.

In addition, the results show that the effectiveness of attention training increases with increasing education despite the presence of negative innate factors. A common opinion in professional circles is the claim that improving attention can also improve other cognitive functions, including intelligence.

The scientific branch of human attention in relation to brain waves and EEG activity in general has received much attention in recent years. There are countless practical uses in the field of device control or communication using only the interface created between the human brain and the computer (so-called BCI) [7].

2. Literature Review

The use of electroencephalography, both in medical applications and for Brain-Computer Interface (BCI) systems, advances according to processing methods. From these signals, research in biomedical instrumentation and knowledge about the functioning of the brain evolve [8-10].

Furthermore, in [11], brain activities are compared using high-density EEG for recordings of individuals sedated with anaesthesia using Propofol and individuals in a sleep state. Eight healthy individuals were analyzed, and the results showed that the state of anaesthesia with Propofol is similar to the state of sleep, where there is the appearance of slow waves associated with decreased consciousness. However, in the state of anaesthesia, there was still a presence of great activity in the gamma waves.

In [12], a study was carried out with motor responses of the EEG signal during changes in the state of consciousness based on different dosages of the drug Propofol. The objective of this work was to verify a possible attempt at a motor reaction during a procedure using the anaesthetic Propofol, where the individual would be aware of the procedure but would be unable to perform the movement due to neuromuscular blockers. In this work, 12 healthy subjects were evaluated.

Firstly, preliminary tests are carried out with each volunteer, where they are asked to move without any Propofol application. From this test, classifiers based on logistic regression are created, classifying non-motion and movement and the characteristics used are based on Power Spectral Density (PSD) using the Welch method. Subsequently, the same test is carried out with each volunteer, but with two dosages of Propofol, 0.5 and 1.0 ug/ml.

In the protocol by [13], The study proposes acquisition during different sections over a period of up to one month per individual - including a period for training to experiment, with 50 trials per type of task, divided into trails with predetermined times for carrying out a task and a rest period. At the time of publication, the recruitment of volunteers had begun, but the signals had not yet been acquired, and there were no results.

A study protocol is presented to investigate brain activities during sedation with protocol, with the aim of studying EEG signals to develop a BCI system that helps in the identification of Accidental Awareness during General Anaesthesia (AAGA). AAGA occurs in approximately 0.1% to 0.2% of surgical procedures with anaesthesia, but this rate increases to up to 1% in high-risk patients.

Literature [14] analyzes a review of numerous articles related to EEG signal processing. The survey encompassed the entire process of EEG signal processing, from acquisition and pretreatment (denoising) to feature extraction, classification, and application. They present a detailed discussion and comparison of various methods and techniques used for EEG signal processing.

The work developed by [15] makes use of the IEMOCAP, Emu-DB and RAVDESS datasets. The author uses five methods for feature extraction that are provided as input to the proposed convolution neural network, the methods are MFCC, Honey-scaled spectrogram, Chromagram, Spectral contrast feature and Tonnetz representation.

The author also compared the result of the model with the result of the validation carried out by the authors of the set [16], getting just above human recognition, 71.61% of the author against 67% of human validation. In the work presented by [17], it is demonstrated how it is possible to use CNN to analyze the spectrogram image. This methodology is presented aiming to escape the standard pipeline of emotion recognition through speech. The spectrogram is formed by an x-axis denoting time and a y-axis denoting frequency. In this graph created by the spectrogram, the amplitude of the frequency is indicated by the intensity of the colours; the coldest represents the lowest intensity and the hottest the highest.

3. Frequency Analysis

Every signal carries information, but not every piece of information is relevant to the end user. The useless signal is then referred to as noise. By the term frequency analysis means the application of various methods in order to find the frequency components of the input signal, of which it is composed. It can be a continuous or discrete signal and is typically characterized by its amplitude and frequency, as well as the beginning and end in terms of time.

For frequency analysis, the main goal is to determine the amplitude and frequency magnitude of individual signal components. While in temporal analysis it is important to decide on the occurrence of the signal component within the time axis. Both criteria cannot be achieved at the same time, but it is always possible to find a suitable compromise solution with regard to the use.

The most frequently used apparatus for identifying one or another component is the so-called transformation. They can be divided from several points of view; one of the basic divisions is for continuous or discrete signal processing [18-20]. The most straightforward approach to characterizing waves is to find the frequency of intersection of the imaginary x-axis (e.g. when plotting the time course of the wave). If a measurement time of 60 seconds and count is considered, for example, 800 transitions, with this methodology, the wave would be included in the theta level.

However, additional analysis of the amplitudes of the frequency spectrum can provide additional essential information, for example, that the dominant frequencies are in the alpha region. This is precisely what Fourier analysis is all about, which provides much more detailed information about the dynamic properties of the signal.

In addition, if the obtained amplitude values are multiplied by the square, an overview of the power spectrum is received, which will provide us with information about the energies in the signal. The monotony of the frequency course is modulated by a change in the state of the brain (e.g. sleep versus concentration), stimulation of perceptions, etc. [18].

3.1. Continuous Signal

The basic property of a continuous signal is its continuity. It must be uniquely defined for both amplitude and phase at each moment of the waveform, so it must not contain any spaces. Such a signal can be described, for example, by a mathematical function, or in the computing world, a large amount of data can be used, and those missing between them can be approximated.

3.2. Discrete Signal

A discrete signal consists of amplitude values spread over time. It can be obtained by sampling the input signal, but a certain limitation applies here - the so-called Nyquist-Shannon theorem [21]. In simplified form, it says that:

"The sampling frequency must be at least twice as high as the highest harmonic component contained in the signal samples."

If this rule is not taken into account, a phenomenon called aliasing occurs. It occurs when the signal is sampled to an insufficient extent, which cannot capture the changes in the waveform. Mathematically, this limitation can be expressed by Equation 1.

$$f_S \geq 2f_C \tag{1}$$

Where f_S is the sampling frequency - how often the signal values are recorded per unit of time and f_C is the highest frequency contained in the signal.

However, it is essential to mention that aliasing does not only result in the loss of information, but directly in its overall distortion. The result is an incorrect frequency determination. Without awareness of the original signal, its misleading interpretation may occur without the possibility of detecting a miscalculation.

For a complete idea of this effect, one example from the field of video processing can be given. Aliasing can occur quite often, for instance, in images where a rapidly rotating wheel or propeller can be seen.

The human brain is confused and does not know how to correctly interpret this movement since there are two ways to get from the initial state to the target state by rotating clockwise as well as counter-clockwise. To the eye of the observer, it may appear that the blades of the propeller or wheelbar are turning much more slowly or even in the opposite direction than it actually is.

3.2.1. Discrete Fourier Transform (DFT)

The initial data source is a digitized signal in the form of N discrete values with regular time intervals in the interval T. The basic Equation 2 between the sample length T, the number of discrete values N, the sampling frequency f_S and the range of the frequency spectrum is as follows [14]:

$$f_{max} = \frac{f_S}{2} = \frac{N}{2T} \tag{2}$$

The obtained frequency value f_{max} is also called the Nyquist frequency; it means the highest possible detectable frequency value. The total frequency range of the obtained spectrum can be described by the interval $<0;f_{max}>$.

The following Equation 3 applies to the DFT relation of N discrete signal points [18, 22].

$$X_{DFT}[k] = \sum_{n=0}^{N-1} x(n)e^{\frac{-j2\pi nk}{N}} \quad k = 0.1, \dots N - 1 \tag{3}$$

Due to the fact that the function $e^{\frac{-j2\pi nk}{N}}$ is periodic (there is a trigonometric shape composed of sines and cosines that cause periodicity), the DFT itself has the same property [20].

Based on the calculated DFT, the frequency range can be estimated by determining the Power Spectral Density (PSD) [7]. This will allow us to detect better those frequency spectra that are strong from the point of view of energy and can be assumed to be of greater importance than weak ones. The result of the PSD process is the so-called period gram [20] and is defined according to Equation 4.

$$P[k] = \frac{1}{N} |X_{DFT}[k]|^2 \quad k = 0.1, \dots N - 1 \tag{4}$$

3.2.2. Fast Fourier Transform (FFT)

However, the Discrete Fourier Transform itself has one significant drawback - and that is its complexity (N^2). Using the very efficient Cooley-Tukey algorithm, however, that complexity can be reduced to ($NlogN$). This improvement was already known to the famous mathematician and physicist Friedrich Gauss around 1805; over time, the algorithm was rediscovered several times.

Cooley and Tukey contributed to its global popularization in their work in 1965. The principle of efficiency is the recursive division of the DFT into smaller and smaller parts, most often on $N/2$ in each iteration - hence the limitation on the total length of processed data, which must be a power of two (in general, any factorization can be used) [23].

In addition to the Cooley-Tukey modification of the FFT algorithm, others are based on more or less different approaches. Only by enumeration are the algorithms Bruun's FFT algorithm, Rader's FFT algorithm, Bluestein's FFT algorithm, hexagonal fast Fourier transformation or Prime Factor FFT algorithm using odd numbers.

4. Description of the Experiment

After studying the materials dealing with human attention and its stimulation with specific stimuli that can affect it either positively or negatively, the creation of measurement scenarios was started. The recommended number of test subjects for similar work is between 13-16 volunteers. These must be people who do not suffer from any of the attention disorders or other similar limitations of concentration.

All measurement participants were given a short questionnaire to fill out in order to map their current mental and health status and collect personal data. It also included permission to measure, subsequently process and store data and provide anonymized data for future work dealing with this topic.

The template for this document was a pattern commonly used for similar measurements on the occasion of the Open Door Day at the Faculty of Applied Sciences (it is part of the appendix on the CD). Due to the protection of personal data, all participants in this work will be referred to by their initials, which are sufficient for precise identification of the needs of this work.

4.1. Health Status Mapping

In addition to personal data, the following values were also measured or determined:

- Blood pressure before measurement
- Mass
- Height
- Flexibility
- Color perception
- Blood pressure after measurement

Classic color pictures with numbers (Figure 1), which are standard used to examine color sensitivity [24], were used to test color perception. In total, it was necessary to recognize eight digits on differently colored pictures. The order of the displayed tables was the same for all test subjects.

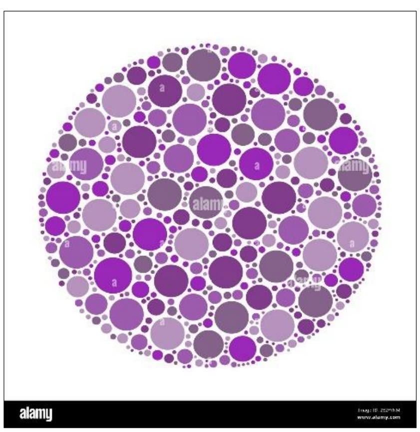

Fig. 1 Sample from the color perception test; digit 45

4.2. Measurement Scenarios

Each volunteer was subjected to a total of three different measurements in a fixed order. The scenario was identical for all participants to ensure as similar conditions as possible. All participants were always explained the course and individual phases of the measurement before the very beginning, so that it was not necessary to interrupt the experiment during them and deal with explanations. After any questions were answered, it was possible to proceed to the first part. In all three phases, a Lenovo Tab 2 Android tablet was used for the experiment.

To carry out this work, it was sufficient to store only the values obtained by attention. The reason for storing all brain wave data is, on the one hand, the possibility to analyze the EEG course afterwards in case of any exciting or surprising fluctuations in concentration, and, on the other hand, the obtained data sets are available to other colleagues dealing with similar topics. They can also use them for their work.

4.2.1. Focus on Listening

The first scenario was focused on listening. The used video document [25] was set to precisely 0:07:00 minutes, and from this position, the measurement itself began, during which the participant performed the assigned task. Headphones were used to eliminate possible distractions from the surroundings. The active part lasted 5 minutes. After this time, the participant played relaxing music [26] for two minutes while the measurement continued. Once the seventh minute was completed, the measurement was automatically interrupted, and the scenario ended.

At the turn after the fifth minute of measurement, a general decrease in attention and beta brain wave activity is expected. Ideally, an increase in alpha activity should also be observable, especially if the participant had their eyes closed and was effectively resting.

The expected result of the degree of concentration in this case was the lowest of all three measurements. The reason for this assumption was the fact that, compared to visual sensations, auditory ones are much less important for a person, so focusing on sound stimuli requires a little less concentration than it does when perceiving the surroundings by sight. Additionally, the auditory centre in the brain is located on the sides of the head. Sensing EEG activity with a single electrode on the forehead will undoubtedly provide less accurate data than would be the case with the use of multiple electrodes.

The Task of the Experiment 1

In the first scenario, the participant was tasked with counting the occurrences of proper names that were mentioned in the document and could be picked up by hearing. According to the analysis, a total of 32 proper names appeared in the referenced section of the video. Several iterations are made of this check to ensure accuracy.

In the final, the result that the participant worked towards is irrelevant to the purpose of this work. Of course, this was not disclosed in advance in order not to demotivate the volunteer with the possible consequence of distorting the attention results.

4.2.2. Visual Attention

The second phase of the experiment was devoted to visual stimuli and the need to concentrate with the eyes. Participants were then shown the video from the point where it left off the last time. So, the measurement started at the time of the video, 0:12:00 minutes and lasted until 0:17:00 minutes, when the relaxation phase resumed. Again, the exact number to which the measured subject worked is not important for this experiment. The goal was to focus continuously and deeply on the video, as it often happened that several attention stimuli could be seen within one film frame. After five minutes of playing the document, there was a relaxation phase again, the same length as in the previous case, when the participant was supposed to calm down and let the mind rest. The total time of concentration and rest was the same as in the previous case, 7 minutes, of which 2 minutes were for rest.

Given that a person perceives approximately 80% of all information around him with his eyes, the efficiency and success of this phase were expected to be much higher than in the first case. More significant beta activity with higher attention values was expected during active focus, especially during times of occurrence of attention stimuli. However, this assumption cannot be generalized because each individual has their sensory perception differently developed and set up in their way.

The Task of the Experiment 2

In the video scenario, the task was similar to the previous measurement. This time, however, it was necessary to notice all possible inscriptions or names that contained any number, whether it was a chapter number, a reference number on a building or a car registration number. For each finding of such a chain within one shot of the film, even if it was an occurrence already recorded, a point was added.

The scenario was slightly more complex than the previous one, especially in that it required much higher concentration and more thorough tracking of shots. Strings with numbers could appear anywhere on the scene, and multiple occurrences were also widespread (e.g. when shooting a chapter in a book, the chapter itself is usually numbered, the page number can also be seen, and the number often appears in the text as well).

4.2.3. Concentration while Playing

The activity requiring continuous focus and concentration was chosen as the last one. As this was the previous scenario of the experiment, there was no longer a relaxation phase, which served, among other things, to separate the individual scenarios logically.

In this case, too, vision played a significant role, but the degree of concentration was much higher because the game situation was changing rapidly. After each turn, it was necessary to explore most of the loose stones and find new connections with previously revealed stones that one remembered. If the participant were to concentrate really intensely, the range of attention should narrow, and its depth should increase.

Of all the three proposed scenarios, this one was considered the most promising in terms of accurate results, as it required constant focus and evaluation of the situation.

The Task of the Experiment 3

The participant was tasked with playing Mahjong throughout the measurement in order to complete the level. Now, it was also necessary to think, evaluate the overall situation of the game and compare more or less favourable combinations because by removing an unsuitable pair of stones, a problem could arise when no two identical stones were available. They had to be shuffled (this is done by automatic detection on the part of the game).

This game was chosen for its relatively simple rules [27], similar to the well-known Pexeso game. Alternative activities requiring a combination of concentration and thinking, such as solving complex mathematical equations or other examples, were subsequently abandoned due to the need for specific knowledge of the participants. Although roughly a third of those measured had never played Mahjong before and did not know the principles of the game, the explanation of the rules in the order of a few minutes was sufficient.

Unfortunately, in this scenario, the conditions were not entirely identical for all participants since the initial state of the game is always newly generated, and the stones are distributed randomly. The most similar conditions were ensured, at least by the fact that everyone had the same initial stone formation.

Specifically, it was level 5 in Mahjong Masters in the category “Traditional” [28]. A comparison of the attention values of individual measurement participants during all scenarios can be found below.

Mahjong is a traditional Chinese game with rectangular stones, whose origin is attributed to the famous philosopher Confucius. Four players usually play it, but throughout its existence, various versions and mutations of the game have been created, and today, it is one of the most famous versions of the single-player mod. According to the original rules, the stones have different functions and effects in the game mechanics, but for this work, a much simpler variant was chosen.

Fig. 2 Mahjong solitaire; "turtle" formation

In it, the stones are arranged in a specific shape (e.g. pyramid, turtle - Figure 2). The game aims to remove those stones that are available on the surface and bear the same symbol, thereby revealing the ones hidden below; these can be used in new combinations [27]. In a very loose interpretation, the rules can be compared to the game Pexeso. The game used for this experiment was freely downloaded from the source [28]. All participants had the same dice formation at the start of the game, but as mentioned, the layout of the game stones is randomly generated.

4.2.4. Relaxation Phase

The first and second scenarios were always followed by a two-minute relaxation phase so that the measurement participant could rest, calm down and prepare for the next part. Music from the source [26] was used to stimulate relaxation. Participants were advised to sit comfortably, close their eyes and relax, not thinking about anything.

Even during this part, attention was continuously measured, and EEG activity was recorded, so it was possible to observe from the currently provided data whether the subject was really resting or not. Of course, the expected concentration values in this phase were low and ideally stable but undoubtedly highly individual, differing for each participant.

5. Program Design

5.1. Application Description

The application was created for the purpose of monitoring EEG signals with a focus on calculating and monitoring attention (Attention Monitor). It enables the following:

- Connection with the Think Gear headband via the Bluetooth interface
- Plotting the measured EEG activity
- Rendering of attention calculated by the headband and the designed algorithm
- Save the measured data in the given format
- Tracking the measurement time
- Automatic termination of measurement after the set time has elapsed

The primary requirement for the application was to be able to determine the attention of the subject being measured in real-time in an ongoing experiment. For this, of course, it was also necessary to be able to connect to the headset and read the data being sent. Other functions and options are somewhat additional, they were added over time while tuning the application to achieve a certain level of user-friendliness. A more detailed description and control of the application are explained in the user documentation in the appendix at the end of the thesis.

Depending on the information about the supported systems and the requirements of the Mind Wave headband [29], the Windows operating system and Visual Studio were chosen as the development environment. The programming language was C#. Two third-party libraries were used during development. The advantage was the use of already debugged and verified algorithms, which guaranteed the correctness and efficiency of running the computational part of the program.

5.2. Algorithm for Calculation of Attention

After studying the materials dealing with EEG signals and their processing (e.g. [30-32]) and after consultation with the client, an attention calculation algorithm based on frequency analysis was chosen. The data source for this approach was, of course, the data sent by the Mind Wave headband, specifically the "RAW" data (raw data of one wave sample) provided by it. The values of individual frequencies that the headband itself calculates and also sends were only drawn to better illustrate the current state of the tested subject. In the same way, the value of the measured person's attention calculated by the headband was used only as a reference for comparison with the results and evaluation of the experiment.

As discussed in the section on brain waves and their characteristics, higher beta activity is evident during concentration. The upper limit of the frequency range is related to more complex tasks when the waves can already fall into the gamma band.

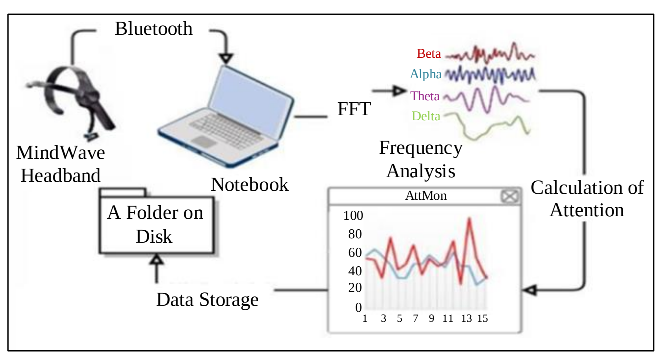

Fig. 3 Flow of data analysis and processing

Based on these findings, a custom algorithm was designed, mainly using frequencies from the beta band. In order to perform such a calculation, it is necessary to have a frequency analysis of the waves available, from which the essential values can be selected. The previously described Discrete Fourier transform, and PSD will be used for this purpose. The process of data processing from the beginning of measuring the EEG values with the headband to the resulting calculation of the attention stored in the file is outlined in the diagram above (Figure 3).

5.3. Implementation Specifics

5.3.1. Libraries Used

Two third-party libraries were used for the actual implementation of the proposed algorithm. One was from NeuroSky and was used to mediate communication, transfer and data processing between the headset and the computer. Developer tools for various platforms (Windows, Android, IOS, Mac) can be downloaded from the manufacturer's website [29]. For this work, the Windows version is used.

The second library used was the set of Math.NET Iridium functions [33]. It is a collection of libraries containing mathematical operations for the C# programming language. Among countless other functions, it also includes various implementations of the FFT algorithm, which are already debugged and verified.

5.3.2. Data Collection

As already mentioned in the theoretical part above, applying the Fast Fourier Transform is possible to data with a magnitude of power of two. The headband sends data about EEG activity in specific doses, but their size usually does not correspond to a power of two. Moreover, during the implementation, it was found that the size of the data field sent varies very often and is not fixed.

This was observed while debugging the application when stepping in the program caused more delay between two received bursts, and the data was enough "to accumulate". The sizes were always the same -the maximum, but during normal program running, the length varied and was usually smaller. After filling the field of the set length to 512 (which corresponds to the sampling frequency of the headband [29]), the algorithm continued with the Fourier transformation step and then the calculation of the attention itself on the thus accumulated data.

5.3.3. Fourier Transform and Power Spectral Density

The already mentioned Math.NET Iridium library provided the Fourier transformation. During the calculation, the Nyquist theorem was taken into account when only half the frequency field, which was obtained as the output of the transformation, was worked on. For this work, frequencies in the range of 0-40 Hz were anyway important, higher values for the calculation of attention were neither interesting nor necessary. The second step of this phase was to determine the PSD values. Subsequently, it was possible to move on to deciding the attention itself.

5.3.4. Calculation of Attention and Its Normalization

The attention calculation is based on the data coming out of the PSD algorithm. This is a field of real values where the calculated data can be interpreted as a measure of the representation of individual frequencies. For this work, in the context of determining attention, significant frequencies are only up to 40 Hz, that is, for subsequent calculations, one can only work with a part of the field with indices 1 to 40. This restriction can be further extended to those frequencies that are, from the point of view of attention, somehow interesting and significant.

In the theoretical part, it was already mentioned that the beta activity of the brain increases during concentration. Beta is characterized by its occurrence in the frequency range roughly between 13-30 Hz. In the case of analytical thinking; gamma activity also begins to manifest itself. The proposed algorithm works with data from both areas. First, the largest value of the frequency power within the examined field is found for a given iteration of the calculations. The search is chosen traditionally by traversing the field and comparing the values against the maximum found so far.

If a higher value is found, the local maximum is overwritten by this newly identified one. Based on the global maximum, a coefficient for the overall normalization of the magnitudes is then calculated to maintain the ratio of the rate of beta activity to the others. However, coefficients of two are used for normalization purposes. One is dynamic, always calculated according to the maximum frequency power, and the other is constant, fixed for each calculation cycle. The second parameter to the overall normalization coefficient was obtained by the experimental method in such a way that it corresponds to the mapping of the final result of attention to the interval 0 to 100.

By performing several different measurements, it was determined to be 215. To determine the final attention, the arithmetic mean of the magnitudes is finally calculated across all frequencies from 1 to 40 Hz. When traversing the data field, the frequency powers are adjusted by the final normalization coefficient.

The last modification in the calculation of attention is the inclusion of a weight coefficient for those frequencies that have a more significant share in concentration. Specifically, this is beta activity in the frequency range of 15-22 Hz. The magnitudes of these frequencies are additionally multiplied by a factor of 1.5 compared to all others, which enters the calculation unchanged.

5.3.5. Modification of Attention

After performing several tests of the application running in an actual situation, a considerable fluctuating course of the resulting attention compared to the reference one from the headband was observed. In an effort to improve the performance results, two attempts were made to eliminate this undesirable aspect.

Damping of Large Fluctuations

The idea of the modification was based on the fact that I did not consider it very realistic that after 1 second, the attention of the test subject would change rapidly. To put it simply, if at time tx attention comes out at 85, at time tx+1, it is unlikely to drop to 10 (normally consider a range of 0-100).

In this case, it was also necessary to monitor and remember the attention value calculated in the previous cycle. If the absolute value of the difference between these two data was more significant than the specified limit, the newly computed attention was set to this extreme value. When testing this modification, two limit values of the difference of two consecutive attentions were tested - 20 and 30. The expected result was a smoother and less fluctuating course of attention calculation.

Averaging the Counted Attention

When debugging the program, it was found that the second changes of the application, in which the data is rendered, do not entirely correspond to the frequency with which the headband sends the data to the receiver. In the final the attention result is obtained from this data. On the basis of this observation, an approach was tried that also uses attention values, which can be calculated between individual cycles of redrawing the application. This number is not constant; it varies by unit. The main idea was that the calculated probabilities were stored in a list, and when the application redrew the individual graphs, an attention equal to the arithmetic average of those calculated so far was recorded. With a new cycle, the list is emptied, and new values are stored.

5.3.6. Output Data Format

Processed and calculated measurement data can be saved in a CSV file. Individual data are stored in a fixed order and separated from each other by semicolons. This format is inserted into the header of each data file to make subsequent processing and analysis more user-friendly. The specified format can be seen below (Table 1).

The values of alpha, beta and gamma waves are divided according to frequency into two areas. The "Time" value indicates the number of seconds that have passed since the start of the measurement. The "att" and "calc_att" data are attention values. The first is the reference provided by the NeuroSky headband; the second is the calculation according to the implemented approach.

6. Experimental Results

In this section, the achieved results will be discussed in detail, and the overall success of the proposed algorithm for determining attention and the effectiveness of designing test scenarios will be evaluated. In total, the experiment was carried out on 15 volunteers, each of whom was measured according to three different scenarios.

For all participants, the scenarios were identical, and the conditions were as similar as possible. Unfortunately, this was more difficult due to the time-consuming nature of the measurements, as the measurements had to be performed over several days. Five women and ten men participated in the age range of 22-37 years; the vast majority were around 30 years old.

6.1. Calculation of the Error Rate

A total of 15 participants were measured in 3 scenarios, each for 19 minutes. This provided a total of 17,100 attention recordings of reference, calculated, and also all types of EEG waves.

In the following sections, the achieved results will be analyzed in detail from different perspectives and in different comparisons. In order to be able to compare The measurement is necessary to express its success in some way. For these purposes, absolute and relative measurement error quantities and their relationship to the defined success classes will be used.

6.1.1. Absolute Mistake

It is the simple algebraic difference between the actual and the measured value. In this case, it will be the difference between the reference attention provided by the headband and the attention calculated by the proposed algorithm. The relationship can be expressed in Equation 5:

$$\mathrm{A_i} = \left[\mathrm{Att_i^{ref}} - \mathrm{Att_i^{calc}}\right] \tag{5}$$

Table 1. Data storage format

Time	Att	Calc_Att	Delta	Theta	Alpha1	Alpha2	Beta1	Beta2	Gamma1	Gamma2

Table 2. Success classes for determining attention

	Acceptable Error	Major Deviation	Totally Incorrect Result
Absolute Error	Range 0-10	Range 11-30	Range 31 and Above

Table 3. The success of determining attention - the first scenario

Participant	Absolute Error	Relative Error	Deviation Up to 10%	Deviation 10-30%	Deviation Above 30%
P1	16.221	0.809	42%	44%	14%
P2	23.093	1.457	29%	43%	28%
P3	18.588	0.339	34%	47%	19%
P4	24.148	1.411	25%	40%	35%
P5	16.638	0.524	40%	45%	15%
P6	26.557	0.434	22%	40%	38%
P7	21.460	1.232	31%	44%	25%
P8	16.531	0.704	40%	45%	15%
P9	14.731	0.286	42%	48%	10%
P10	16.904	0.548	39%	48%	13%
P11	19.695	0.386	35%	42%	23%
P12	29.760	0.420	21%	35%	44%
P13	17.967	0.477	34%	49%	17%
P14	30.076	1.331	17%	39%	44%
P15	21.693	1.771	30%	45%	25%
Average	20.937	0.809	32%	44%	24%

This allows you to determine the success rate for each calculation in each second. As part of the measurement of the entire scenario for one participant, the values can then be averaged, and the resulting absolute error value for each measurement can be obtained according to Equation 6:

$$\overline{\mathrm{A}} = \frac{1}{\mathrm{n}}\sum_{\mathrm{i}=1}^{\mathrm{n}} \mathrm{A_i} = \frac{1}{\mathrm{n}}\sum_{\mathrm{i}=1}^{\mathrm{n}} \left|\mathrm{Att_i^{ref}} - \mathrm{Att_i^{calc}}\right| \quad (6)$$

6.1.2. Relative Error

Relative measurement error can also be a similar indicator. Equation 7 applies to it:

$$\mathrm{R_i} = \frac{\mathrm{A_i}}{\mathrm{A_i^{ref}}} \quad (7)$$

Again, even in this case, the relative error can be calculated for each measurement record and then averaged according to Equation 8:

$$\overline{\mathrm{R}} = \frac{1}{\mathrm{n}}\sum_{\mathrm{i}=1}^{\mathrm{n}} \mathrm{R_i} = \frac{1}{\mathrm{n}}\sum_{\mathrm{i}=1}^{\mathrm{n}} \frac{\mathrm{A_i}}{\mathrm{A_i^{ref}}} \quad (8)$$

6.1.3. Overall Success Rate

For a comprehensive overview of the error rate, it is always added graphically and numerically how many values of the calculated attention fell into one or another class of success. The three of these classes are defined (Table 2).

The proposed metric can be applied by comparing the absolute error against the criteria of individual classes, whether it meets the given intervals and quantifying the frequencies of individual groups. In the accompanying graphs where the results are discussed, the frequencies of these classes are usually expressed as a percentage of the total set of all calculations of the given scenario and participant (usually 420 or 300 value. The importance of individual groups is as follows:

- Acceptable error - deviation up to 10%: Calculations that differed from the reference value by less than ten from the point of view of attention (i.e. absolute error less than or equal to 10) were included in this category. For example, if the attention from the headband was 57 and the calculated 65 (or even lower, for example, 49), such a calculation was considered successful and fell into this category.

- Serious deviation - 10-30% deviation: In this case, the absolute error of the calculated attention compared to the reference one at the given time was already higher than 11 but less than 30. Practically, this means, for example, a reference value of attention of 60, but the actual calculation reached a value of 40, which is a considerable difference.
- Totally incorrect result - deviation above 30%: Here, there was a completely different calculation with a very high deviation of more than 31.

6.2. Analysis of Individual Scenarios

In this part, the results achieved by the measurement participants will be evaluated from the point of view of individual scenarios. The assumption is that the lowest degree of centrality was needed for the first listening scenario and the highest, on the contrary, for the third last one. At the same time, the degree of success in determining attention by the designed algorithm against the reference value from the headband will be illustrated using the metrics.

6.2.1. Listening Scenario

Below is an overview of the success of determining attention values across all participants for the first measured scenario (Table 3). For a greater overview, the identical results of the categorization of the accuracy of the attention calculation are still graphical (Figure 4).

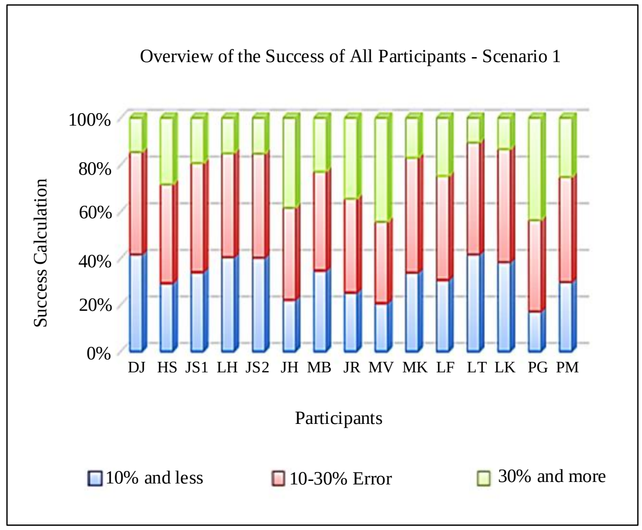

Fig. 4 Success of determining attention - first scenario graphically

From the results of the first scenario, it is quite clearly visible that the overall success rate of calculating attention from raw data is relatively small - around 32%, and the absolute error is, on average, 21, which means relatively poor efficiency of attention calculation.

The correct value then lies in the range ±21 from the calculated one, which is very imprecise. In a quarter of the cases, on average, the attention was determined with a significant deviation, with a difference greater than 30. Graphically, these proportions are shown in a pie chart (Figure 5).

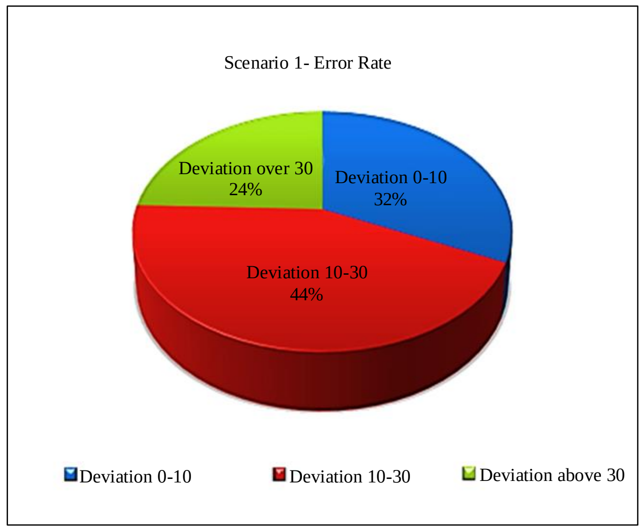

Fig. 5 Error rate of listening scenario

The most successful measurement took place with the P9 participant when the average absolute error reached a value of 14.731 more than half lower than the maximum, and 42% of the calculations were in the first category of deviation up to 10%. However, even this is not very efficient in determining attention. The progress of both attentions can be seen on the graph (Figure 6) below, which is a section of part of the first scenario. From the graph, it can be seen at first glance that the reference and calculated values, in many cases, approach and remain relatively close to each other. The worst achieved result of a P14 participant is also worth analyzing.

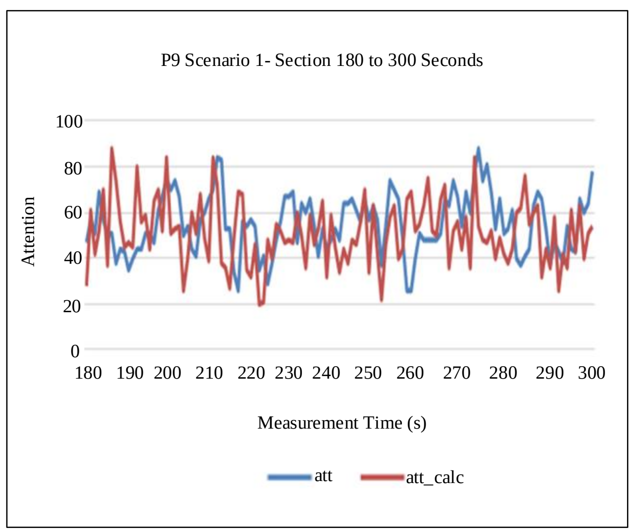

Fig. 6 Attention in the third to fifth-minute section, participant LT

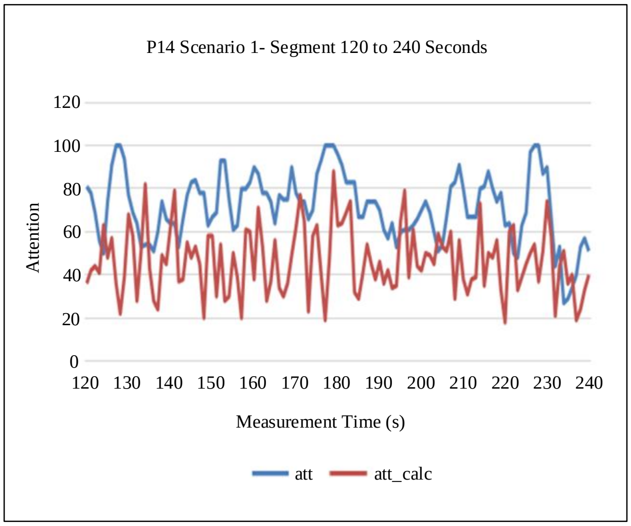

Fig. 7 Attention in the second to fourth-minute section

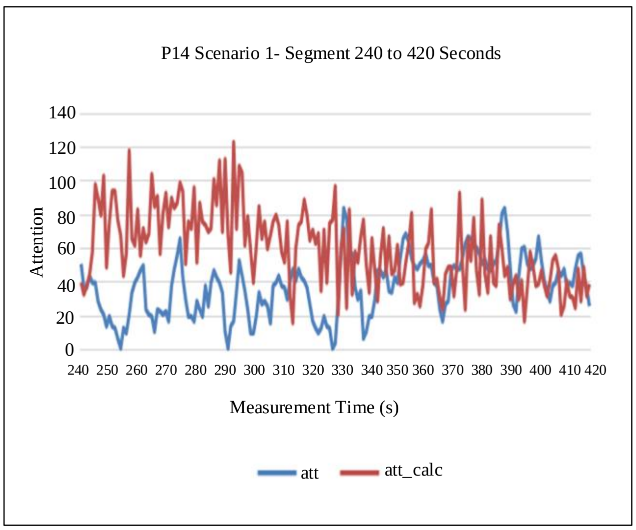

Fig. 8 Attention in the fourth to seventh-minute section

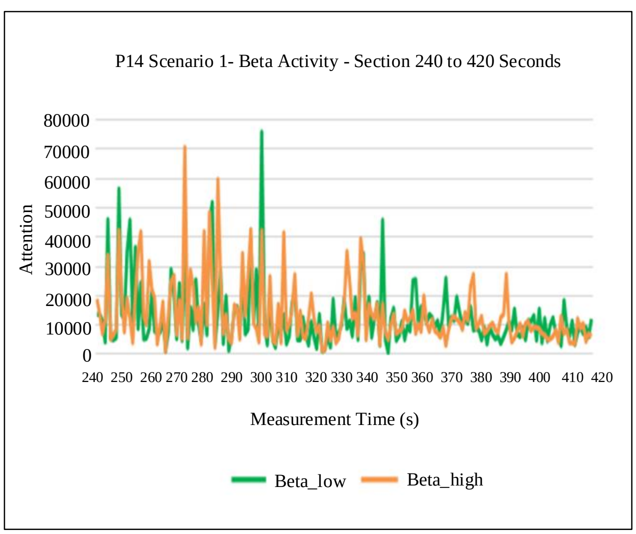

Fig. 9 Beta activity in the fourth to seventh-minute section

Upon closer analysis, it can be seen that, essentially, the entire course of the measurement of attention was shifted by a value of several tens lower than the reference. The first part of the measurement process is shown on the graph (Figure 7).

The attention of subject P14 had a similar course in the second part of the measurement. Still, the values were essentially reversed (Figure 8). A specific stabilization and a more significant meeting of both values by attention occurred only at the moment when the active part of the measurement was finished. The relaxation phase started from the fifth minute.

These very inconsistent results seem to be at least partly caused by the position of the participant's head or his headband during the measurement. He was the only one who sat down in a forward bending position, supported his head, and remained that way for most of the experiment. During the relaxation phase, he then settled into a slight lean, which is a fairly typical position for this activity. After this change in position, the two calculated values have already come closer together. This adverse effect is discussed below.

Upon closer examination of the course of beta activity on the graph, when the "Beta_low" component is the most significant for calculated attention (Figure 9), at the same time as in the previous graph, the overall attenuation of this component of EEG waves towards the end of the measurement is quite clear, from about the fifth minute onwards.

This corresponds well with the set scenario, where the relaxation part started at precisely this time. So it can be said that the subject really and effectively rested. Similarly, a clear conclusion cannot be drawn from the course of attention. However, as already stated, a certain alignment of the two monitored variables came to an end there as well. However, even from the reference value of the attention sent by the headband, which ranged between 20 and 80 in this time interval, the relaxation of the participant is not clearly visible.

An overview graph (Figure 10) illustrates the progress of the attention of the individual sections of the measurement at minute intervals. The values given are the averages of all participants. The graph shows a slight decrease in attention toward the end of the scenario, but the difference was expected to be much more pronounced. Although participants were instructed not to think or concentrate on anything while resting, it wasn't easy to enforce such a state. By using relaxing music, I tried to create a comfortable atmosphere, at least as much as possible, but several volunteers described the music as rather distracting.

6.2.2. Visual Scenario

In this case, too present an overall overview of the success rate and error rate of attention calculation across all participants (Figure 11 and Table 4).

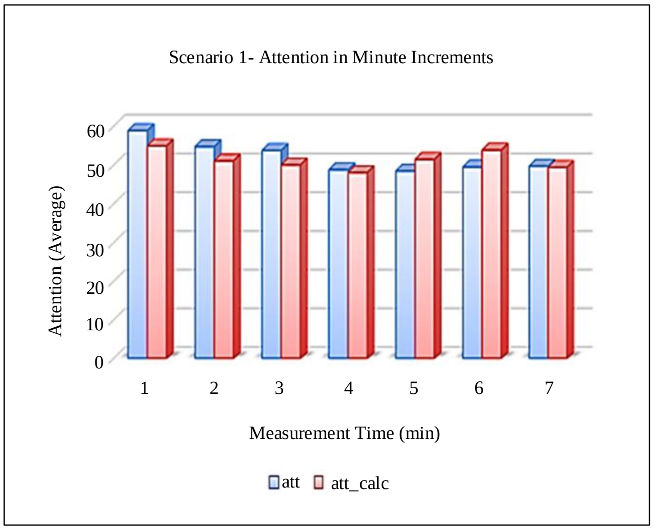

Fig. 10 Average attention of participants in minute segments of the scenario

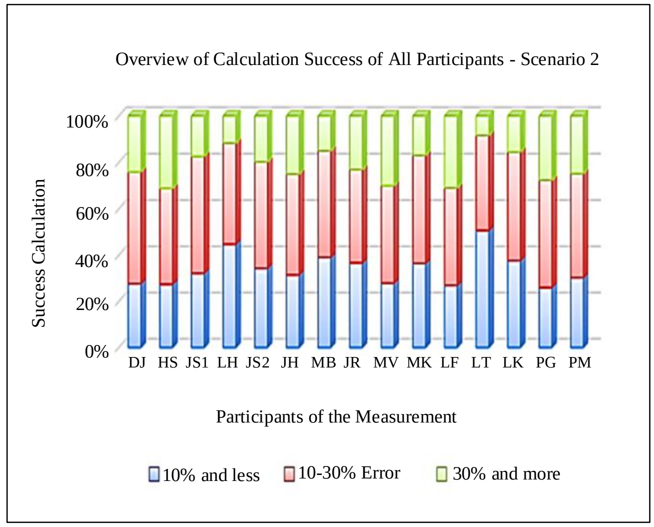

Fig. 11 Success of determining attention - second scenario graphically

Table 4. The success of determining attention - second scenario

Participant	Absolute Error	Relative Error	Deviation up to 10%	Deviation 10-30%	Deviation above 30%
P1	21.573	1.209	30%	45%	25%
P2	24.886	3.019	27%	42%	31%
P3	18.095	0.324	32%	51%	17%
P4	19.453	0.477	37%	40%	23%
P5	19.445	0.932	34%	46%	20%
P6	21.702	0.545	31%	44%	25%
P7	24.462	2.903	27%	42%	31%
P8	15.286	0.420	45%	43%	12%
P9	13.398	0.418	51%	41%	8%
P10	17.347	0.918	38%	47%	15%
P11	16.671	0.398	39%	46%	15%
P12	22.507	0.407	28%	42%	30%
P13	18.193	0.336	36%	47%	17%
P14	22.836	1.130	26%	46%	28%
P15	21.574	1.209	30%	45%	25%
Average	19.788	0.926	34%	45%	21%

The results are basically comparable to those of the first scenario. There was a slight improvement of a few per cent in the category of determining attention with an error of up to 10%, but nothing significant. Let me illustrate the overall success rate again using the pie chart shown below (Figure 12). As with the first scenario, the most accurate determination of attention occurred for the P9 participant.

Now, however, a higher frequency of calculating the correct values was achieved in roughly a tenth of cases - in the previous scenario, in the category "deviation up to 10%", his attention was determined in 42%; now it was up to 51% of cases. It is a slightly better result, but overall still not dizzying and still far from the imaginary target of around 85% success rate.

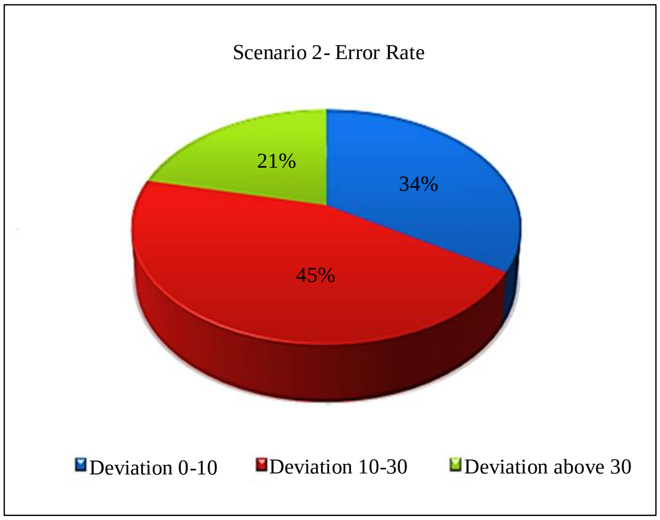

Fig. 12 Error rate of visual scenario

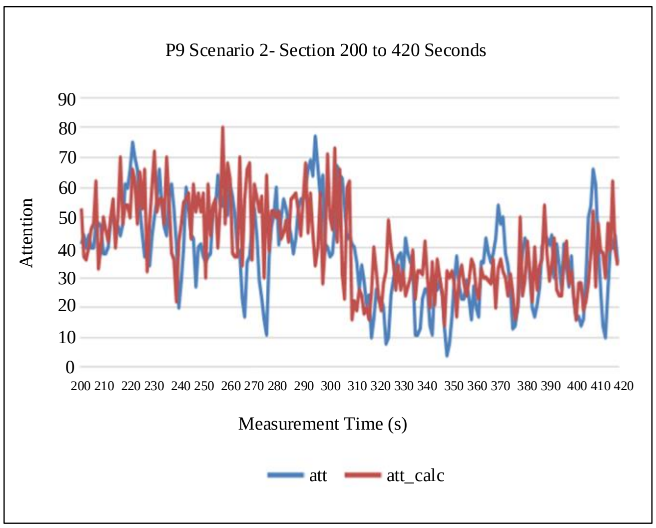

Fig. 13 Attention in the section between the third and seventh minutes, participant P9

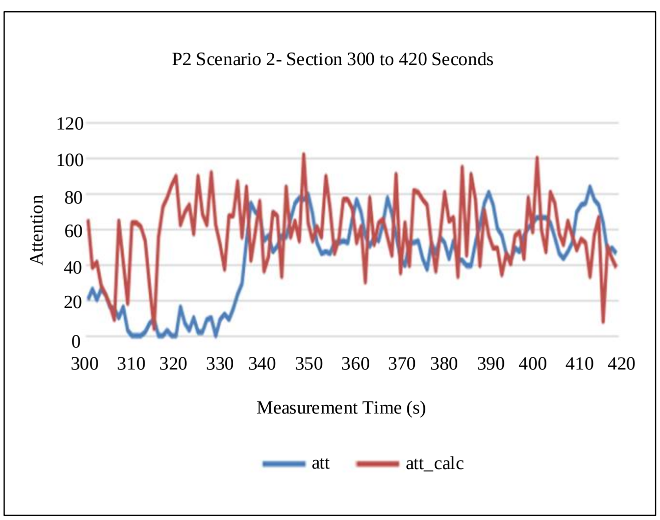

Fig. 14 Attention in the fifth to seventh-minute section, P2 participant

Even now, look at a part of the course of attention of that one, the "best" participant. It outlines the course of the following graph (Figure 13). The captured section shows quite well that even in this case, the values were referenced and calculated attention relatively close to each other, but even this time, the course of both values did not match.

It is also worth noting, at first glance, a noticeable decrease in both monitored attentions after approximately the fifth minute, when the scenario requiring increased attention came to an end and smoothly transitioned into the relaxation phase.

Although there seems to be a certain distraction towards the end of the rest, the two phases are clearly distinguishable. The P9 participant rested in a comfortable position with his eyes closed and described the music as soothing and pleasant, which undoubtedly played a part in the result achieved.

A look at the progress of the measurement of the worst participants, with the designation of P2 and P7, is considered. For both, essentially identical results were achieved in terms of the success of calculating attention in the second scenario. Still, from the point of view of analysis, the first mentioned candidate is more interesting.

The fifth minute was when the transition to the relaxation phase occurred, as the critical section in the case of the P2 participant (Figure 14). Here, the reference value of attention was really low, as expected, below 20, even if only for a short time interval. However, the calculated attention was still very high, which significantly contributed to the increase in the frequency of results in the most error category, "error over 30%". After about half a minute, the participant's thoughts were probably distracted and diverted. It will undoubtedly be interesting to examine this section also from the point of view of brain activity.

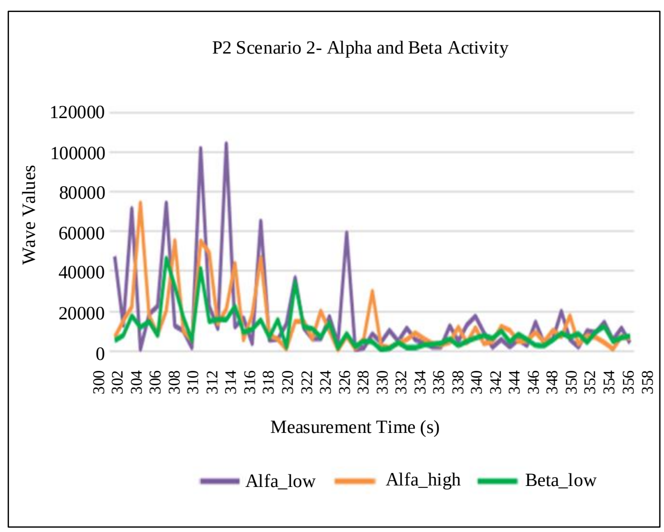

Fig. 15 Alpha and beta activity during rest

This is partially shown in the graph (Figure 15), where the course of crucial EEG waves can be seen. It is clear at first sight that at the beginning of the relaxation phase the alpha activity was indeed significant. This corresponds very well with the level of attention provided by the headband when it was essentially minimal.

Beta activity was also noticeable but did not reach such fluctuations. The alpha and beta activity were gradually dampened, which I dare say is a weak point of the algorithm used for calculating attention. After performing the frequency analysis, the algorithm normalizes the obtained values and recalculates the performance spectrum with respect to the surrounding values in the frequency band 1 - 40 Hz.

In practice, this means that in the case of insignificant brain activity, or when alpha activity is comparable to the intensity of beta activity, similarly significant values will be obtained for both types of waves. However, only beta values are used to calculate attention. In the case of higher alpha activity, these would be low compared to it, and the computed attention would be the same. However, the comparable waveform seen in the image above will incorrectly identify beta waves as dominant because alpha activity is not taken into account in the calculation.

This deficiency will eventually manifest itself when neither alpha nor beta is significant, but the calculated attention will come out in higher numbers. An overview of the course of attention of the individual minute intervals of the scenario measurement is seen in Figure 16. In the case of the second scenario, it is evident that the relaxation phase did not go very well. Averages reference attention even increased at the last minute. Here, slightly better results were achieved using the designed algorithm, although even so, the average value of attention around 45 is still too high for the relaxation phase. Compared to the listening scenario, slightly better results were achieved in terms of comparison of attention calculations; however, the overall course of attention from the point of view of stimulation and attenuation was not significant.

6.2.3. Game Scenario

The third and last scenario was two minutes shorter, as it no longer contained the relaxation part. However, the level of concentration needed was considerably higher than it had been in previous cases. This stimulated beta activity and thereby increased the overall chance of the proposed algorithm to more accurately determine the value of attention at a given moment in time. The results according to individual participants are shown again in the table below (Table 5).

Table 5. Success of attention determination - third scenario for better clarity, the same results in graphic form Figure 17

Participant	Absolute Error	Relative Error	Deviation up to 10%	Deviation 10-30%	Deviation above 30%
P1	17.680	0.330	42%	38%	20%
P2	17.687	0.416	36%	47%	17%
P3	21.533	0.905	24%	50%	26%
P4	18.447	0.387	38%	41%	21%
P5	13.483	0.361	52%	41%	7%
P6	15.647	0.700	42%	47%	11%
P7	26.397	0.938	21%	45%	34%
P8	24.377	0.521	24%	43%	33%
P9	25.240	2.148	28%	38%	34%
P10	16.810	0.567	40%	43%	17%
P11	34.653	3.434	15%	26%	60%
P12	19.777	0.347	30%	46%	24%
P13	16.570	0.354	39%	45%	16%
P14	18.613	1.533	36%	47%	17%
P15	18.967	0.538	38%	40%	22%
Average	19.375	0.926	35%	44%	21%

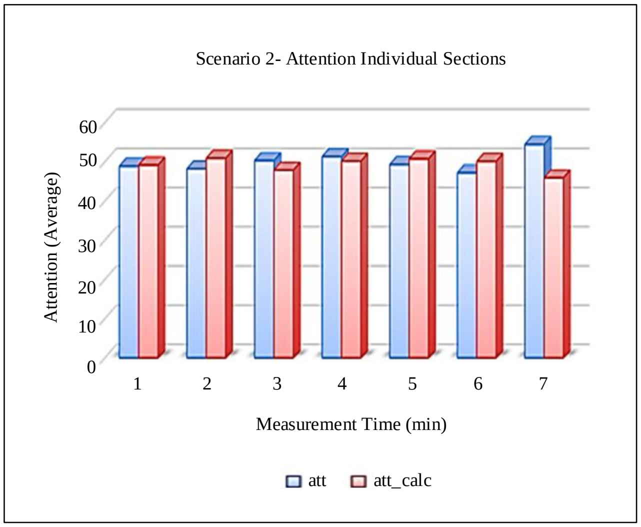

Fig. 16 Average attention spans in minute segments across all participants

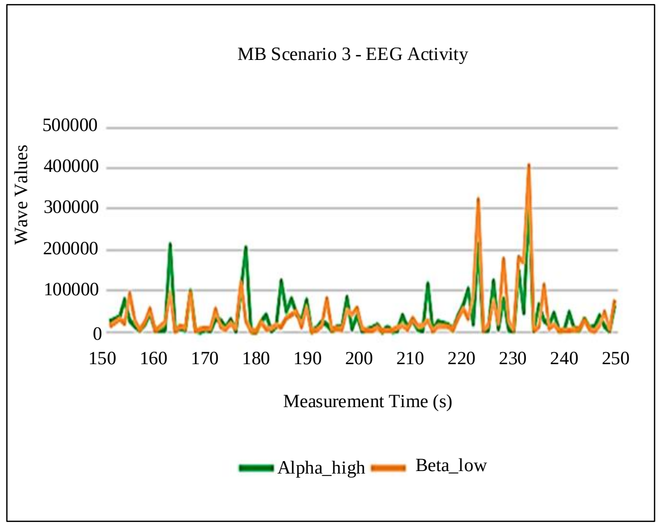

Fig. 19 Alpha and beta activity in the middle of the measurement

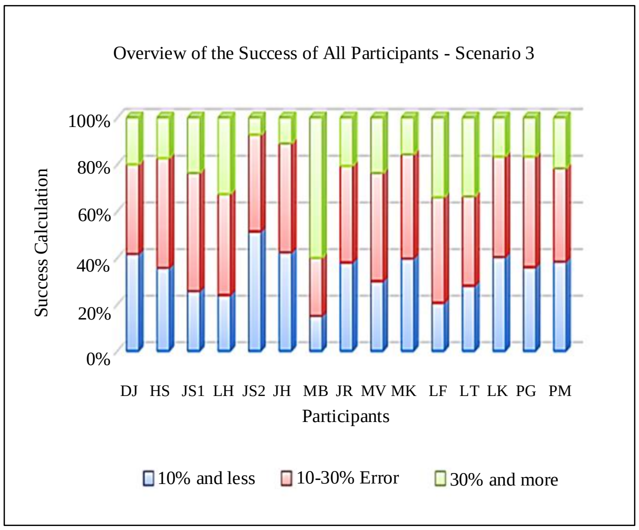

Fig. 17 Success of determining attention - third scenario graphically

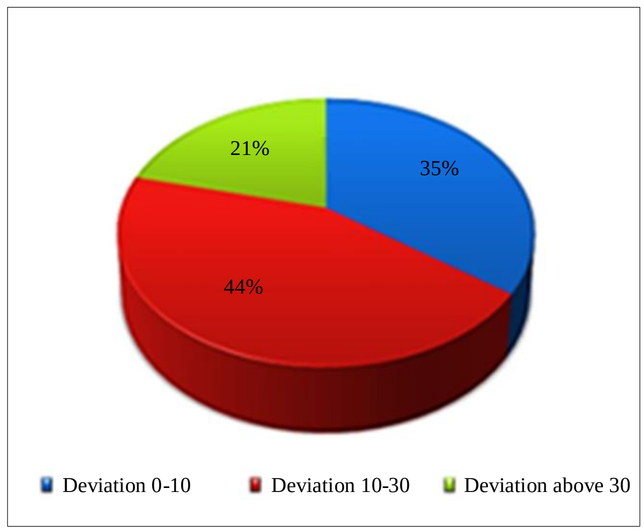

Fig. 20 Concentration scenario error rate

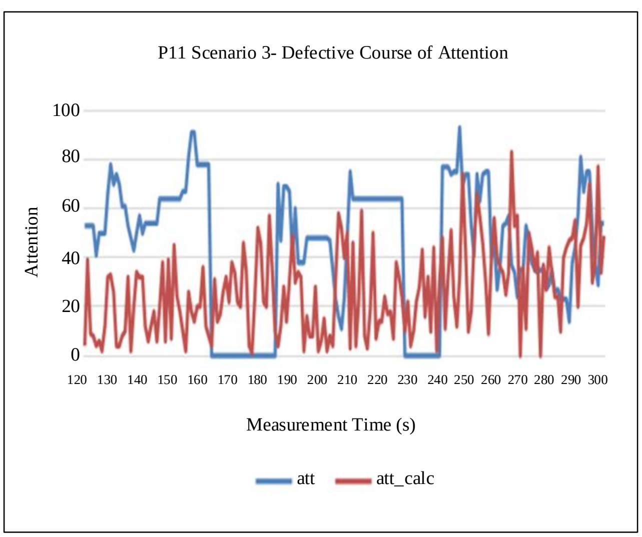

Fig. 18 Faulty course of attention

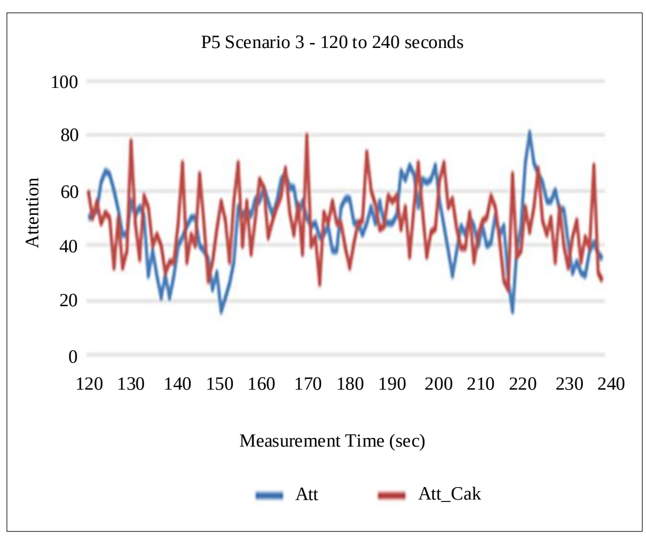

Fig. 21 Attention during the second to fourth minutes

In the case of evaluating the results of the third scenario, it was necessary to make a minor correction. Participant P11 was removed from the statistics due to damaged data. During the measurement, there must have been a break in the contact of the electrode on the forehead with the skin or some other event that caused a loss of the sent attention. This was manifested in two time periods when the reference attention was zero or constant (Figure 18), but the EEG activity was still coming; therefore, the resulting attention values of the designed algorithm were still non-zero.

When analyzing the two graphs above in more detail, a specific correlation of significant local maxima (the peak) can be observed in the time of approx. 160 to 180 seconds and 220 to 240 as well (Figure 19). At these times, the attention provided by the headband showed rather significant fluctuations, and for several tens of seconds, it dropped entirely to the value of 0. However, since the application was still receiving EEG data and its values were calculated, the results were much distorted. If this corrupted measurement is removed, the overall success rate then looks as follows (Figure 20).

Globally, the achieved results are again a tiny bit better than in the previous case. However, what is worth noting are the individual statistics of participants P5 and P6, who achieved a very respectable value of 7% and 11% for the third category of attention determination with an error greater than 30%.

In addition, for participant P5, the proposed algorithm for calculating attention was significantly more successful than for the others, where it was possible to determine attention with an acceptable deviation of up to 10% in more than half of the cases. The course of attention during the scenario on the graph below (Figure 21), where the data part of the attention is shown.

When analyzing the course of attention not only of this but also of the other participants from the perspective of the third measured scenario, Compared to the first two scenarios, this one was more demanding on overall concentration, but it also required additional activity in the form of moving hands and controlling the tablet. Although the person concentrated on one activity - playing the game, he had to constantly move his eyes around the display in order to find suitable pairs of stones. This instability in focus or distraction is most likely the cause of the more fluctuating flow of attention overall for the third scenario.

At the end of this section, a traditional overview of the course of attention across all participants divided by minute intervals (Figure 22) is presented. The data show that, on average, for all participants, the possession scenario was more demanding on concentration, especially in the first two minutes.

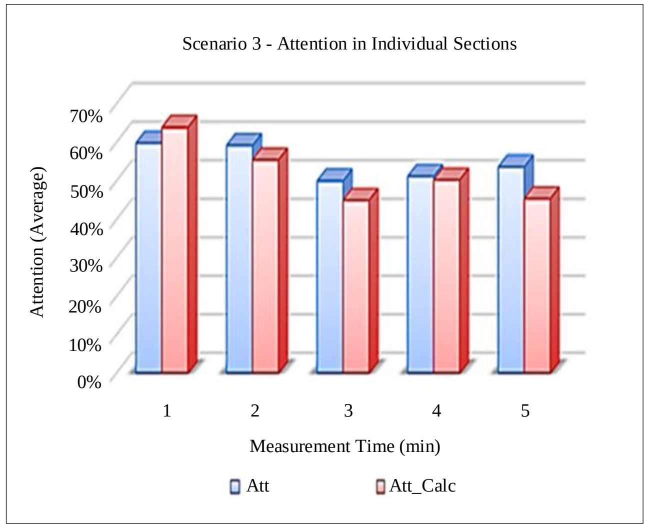

Fig. 22 Average attention in minute segments

Gradually, the overall concentration decreased, which could be explained by the nature of the activity being performed - in the beginning, one needs to concentrate more because there are more stones in the game. It is necessary to check more options with the eye before finding a suitable pair. As the game progresses, the number of available combinations decreases, and the player also remembers the position of some stones, which reduces the demands on thinking and concentration, and the game becomes easier.

6.2.4. Evaluation of Results

From the point of view of stimulating attention across different scenarios, the results turned out as expected. The first listening scenario offered the weakest stimulation - although hearing is a very useful sense, it is not very well developed in humans, and its role is less significant compared to sight. At the same time, auditory sensations are not able to attract human attention so much. Moreover, in everyday life, excessive attention is not needed for a person to perceive what he hears around him.

The second place for the visual scenario is also adequate, in my opinion. It was also necessary to concentrate more when looking for strings with numbers within the shot, which was only offered for a few seconds. If the conditions with listening are compared, there the counted words were provided directly to the participant, all that was needed was to realize that it was one’s name.

The third scenario also involved motor skills and emphasized attentiveness and agility of observation accompanied by a certain amount of memorization. The primary sense that was used was sight again, but it was through involvement and thinking that different demands were placed on the activity. The third scenario was the favourite from the point of view of intentional demands, and the highest measured attention values of all three scenarios were expected. The results, as seen in the graphs at the end of each section, ended up being as predicted, but the differences between the scenarios are minor.

Also, the rest phase did not take place from the point of view of attenuation of attention, as expected, but this part was strongly individual and subjective from the point of view of the participants. The relaxing music didn't help too much either, as many volunteers found it ineffective and described it as rather distracting. After all, this phase was not even the goal of the measurement, it was included instead for the logical separation of individual scenarios and the possible rest and calming down of the participants, if necessary. Everyone uses it in their way; after all, the course of rest is highly subjective, which is why it isn't easy to compare results.

6.3. Success of Individual Participants

The subject of this section will be the analysis of the results achieved and the course of individual measurements from the point of view of all participants. An overall overview of how successful the attention value calculation was for each participant from all three scenarios is shown in the graph below (Figure 23).

The results show that these are generally inconsistent measurement outputs. In about half of the cases, one of the scenarios is always dominant, which means a more accurate approximation of the results of the algorithm for calculating attention to the reference values. However, it is rarely the first listening scenario; more often, the video or gaming scenario prevails. As already mentioned several times, it is assumed that listening does not require such a degree of concentration due to the nature of the calculation of attention by the proposed algorithm, which places the main emphasis on the occurrence of beta brain waves during concentration. These will be more pronounced in the second two scenarios, providing more suitable data for calculations.

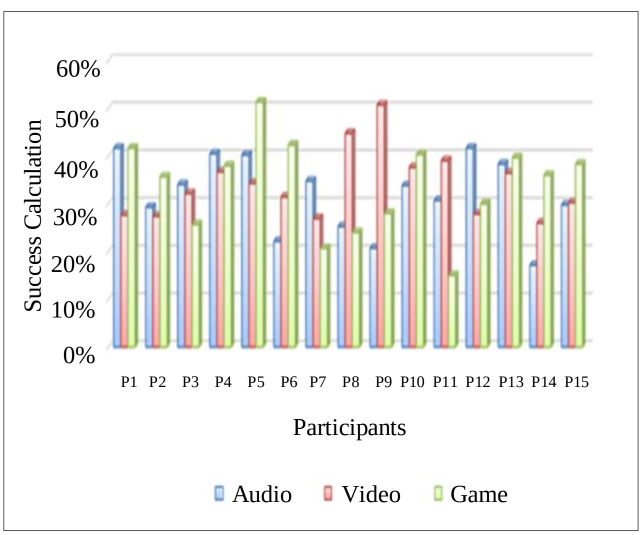

Fig. 23 Error rate within 10% for all participants scenarios

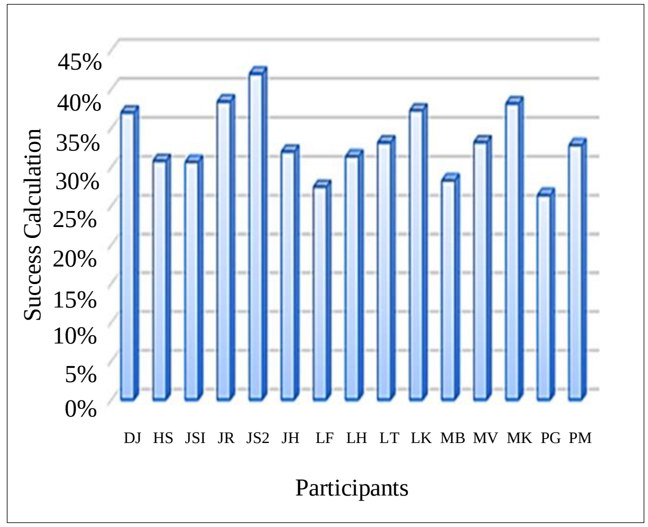

Fig. 24 Average attention calculation success, all scenarios

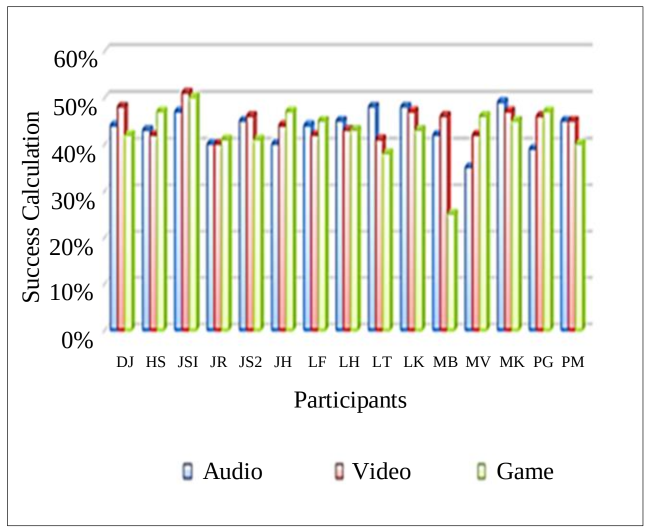

Fig. 25 Second error category across all participants and scenarios

About two participants managed to obtain a stable result across all three scenarios, although only less than 40% more accurate calculations were achieved. The most successful determination of attention took place within one scenario with the two participants, P9 and P5, when the 50% threshold was exceeded.

The graph above (Figure 24) illustrates the overall success rate of the proposed algorithm for all participants averaged across all scenarios. Only the results of the first group with an error of up to 10% are displayed. The results are pretty different; the worst were achieved in P7, P11 and P14 participants, in slightly more than a quarter of the cases. On the contrary, the values closest to the reference came out for participants P5, P4 and P13, around 40%. However, even this is not a very good value and indicates that the algorithm as implemented is not sufficient to determine attention reliably. One of the main possibilities for improvement would be to refine the results that fell into the middle group with an error between 10-30%, as these were prevalent in all measurement cases. Partial representation again averaged across all scenarios, and participants can be found on the graph (Figure 25). The results in less than half of the calculations and essentially equally in all scenarios were included in this group. The exception is participant MB, for whom this category was only represented in a quarter of the calculations in the third scenario. However, this was due to a break in the connection of the headband to the skin, placing most of the results in the most error group.

7. Discussion of Results

As can be seen from the obtained results of the calculated and reference data of the attention provided by the headband, the proposed algorithm is not sufficient in the form in which it was implemented to determine the concentration values unambiguously. The achieved results of the success of determining attention differ both between individual participants and also between the applied stimulation scenarios.

The range of effectiveness is from the most successful 52% to the worst result, providing only 21% agreement with the reference values, considering the tolerable error rate of up to 10%. In addition, in some sections, the measurement comes very close to the results from the “eSense” sensor, which indicates a certain degree of correctness of the approach. The results clearly show that the direct processing of EEG signal data by Fourier transformation is not very reliable in this case and that later adjustments of the calculated attention are not sufficient.

Preprocessing of the EEG data obtained by the headband (various filtering or other modifications) seems to be a much more effective method. It would certainly be worth a more profound investigation before proceeding to the frequency analysis itself or to use, e.g. Welch’s algorithm for PSD calculation. Also, when calculating the final attention, it would be advisable to include more frequency areas or types of EEG waves that are directly or indirectly related to human attention, especially alpha activity.

7.1. Efficiency of Attention Calculation

Finally, the obtained results are analysed from the point of view of the effectiveness of the proposed algorithm. As already discussed in the previous sections devoted to the analysis of results from other perspectives, the overall error rate of the algorithm is relatively high. Even if to consider the best achieved result, we arrive at a success rate of only 52% (Figure 26), which in itself is not very reliable. On the contrary, when considering the worst objectively achieved result (Figure 27), the success rate is only 21%; less than half of all results ended up entirely outside, with a very high deviation from the reference value of attention.

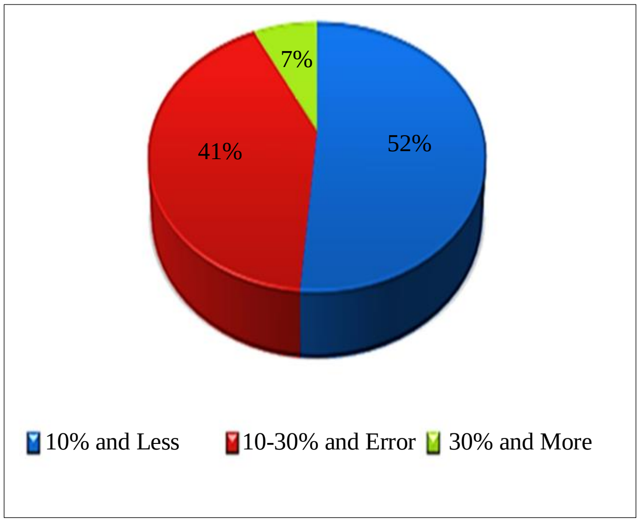

Fig. 26 Scenario 3, participant P3, P5 - the lowest error rate of the algorithm

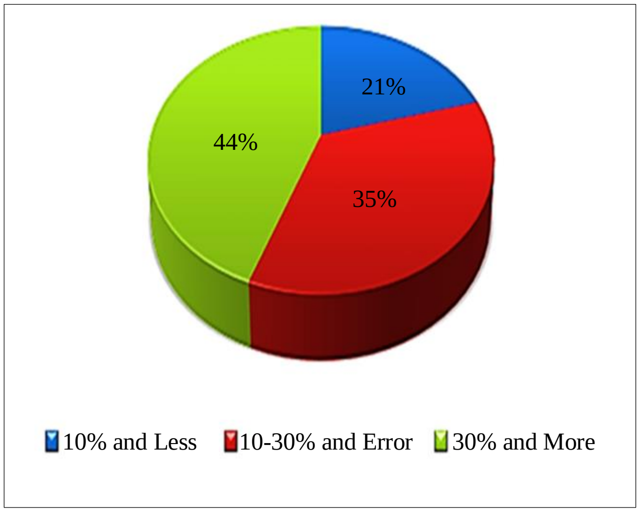

Fig. 27 Scenario 1, P12 participant - highest error rate

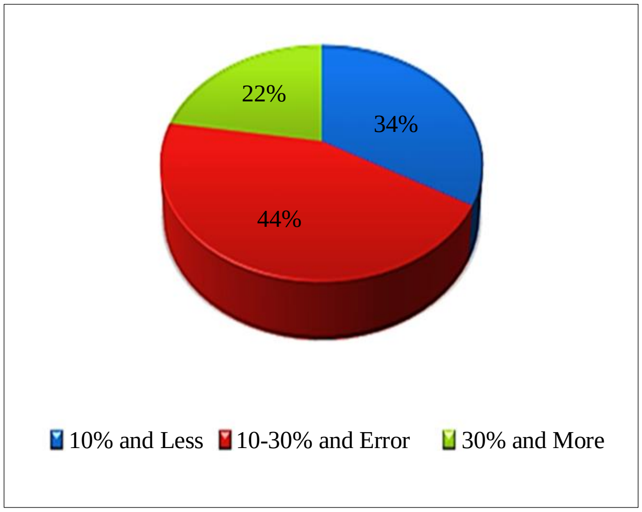

Fig. 28 Average success rate across all scenarios and participants

A general graph (Figure 28) illustrates individual success rates for all participants and scenarios from the point of view of the implemented algorithm for calculating attention. The average success rate is around 34%, which means that every third calculation reached an acceptable deviation. Conversely, the highest error rate was 22%.

As already mentioned, the middle most numerous category - less than half of the results - ended up with a higher than acceptable error if it were possible to improve the algorithm to such an extent that these results would be included in a class better group, relatively decent overall results would be achieved, offering further possibilities for use and development.

7.2. Tested Modifications

After implementing the basic version of the attention calculation algorithm, two modifications were tried. Both consisted of post-processing the attention data before rendering.

Unfortunately, none of the mentioned ideas gave better results at first glance. Therefore, the participants undergoing the individual scenarios of the experiment were measured using the classic, unmodified version of the algorithm, on the one hand, so that everyone had the same conditions and the data was comparable (modifications were tried only after the first measurements were taken) and, on the other hand, to create a kind of base on which to base eventually, they will be able to build future experiments of a similar nature, so that artificial corrections do not distort the results.

7.2.1. Damping of Large Fluctuations

In its essence, this adjustment is not very useful for streamlining the results calculated by attention. The idea that attention does not change too rapidly in a short period may seem valid, but it does not improve the data in any way from the point of view of the calculation, nor does it make it more efficient. This is only an artificial correction for obtaining very improbable results, and with a high chance, an even greater error compared to the actual values would be introduced into the entire course of attention.

Also, this approach could cause complications in the event of a disconnection between any of the headband wiring parts (when the values would suddenly drop to 0). If this were to happen at high attention values, it would take several ticks (according to the set limit value of the allowed difference of consecutive results) before the program’s response to the interrupt would be noticeable, which is not desirable. If the permitted threshold is set too low for two consecutive attention values, then there would be an artificial slowing down of the growth or decrease of attention, which can completely distort the progress compared to the correct values. In the extreme case, with a steep change and a return to the original value, the calculated attention would not be able to capture the degree of change in a realistic form, as its progress would be dampened. This could lead to the omission of a local extreme at a given moment.

From the analysis of the reference data, it was observed that the maximum “jump” in the immediately following concentration values occurs by a value of 30 attention points, which in itself is quite a significant change. This means that the correction would make sense when the difference between consecutive calculations is higher than 30. This is not such a frequent phenomenon, at least not so much that it has a significant effect on the overall result by more than a few percentage points.

The second pitfall is that an artificial change is introduced into the results, which is in no way based on the initial data. It cannot be clearly determined if consecutive attention values of 85 and 20 come out, whether the first, second, both, or neither is correct. As a pair, they are suspect as there is too much difference between them, but it does not mean that the first is correct and the second should be 55.

The discussed approach always takes the first as valid, and the next adjusts the previous one, which can introduce considerable error into the whole process with a spiral effect where eventually all the resulting values come out completely wrong and do not correspond to brain activity.

When this correction was implemented, no significant improvement was achieved. The obtained data looked very similar in terms of the course of the resulting attention, even when reducing the marginal allowed difference to 25 points.

7.2.2. Averaging the Counted Attention

This approach was also worth trying, but it did not provide any significant change for the better. It was based on the fact that due to the fact that the headband sends data at a higher frequency than the application tick (i.e. 1 second), the accumulated data can somehow be used. Unfortunately, experimentally it was found that the amount of data sent varies and is not always constant, so it is not possible to count on a fixed number of data.

Thus, the tested modification counted attention whenever the field for data sent to the attention calculation algorithm was filled, the initial data went through the FFT and PSD transformation, and the attention value was calculated from them, which was stored in the list. In this way, several values were calculated, from which a new value of attention was determined with the help of an arithmetic average for a new tick, which was then plotted in a graph following the reference one.

If there were small fluctuations in attention values, this approach would be able to smooth out the course slightly by approximation. In the same way, if either a measurement error or an imperfect calculation results in a completely wrong result. However, in practice, it does not happen very often that a sharp change in attention occurs in a short moment - within one second or even less. And it is also not very likely that only one of several values is wrong.

When the results are entirely different with significant deviations from each other, it isn't easy to know which of the results is correct, and pure approximation will not help us much. In case the averaged values are very similar to each other, the resulting attention will be approximately the same as if any of these values. So it doesn't offer much improvement either. Thus, this approach only corrects a small number of cases.

The idea of approximation can, of course, be modified in various ways, e.g. discarding the highest and lowest values (where one of them is most likely to be in error if there is such a striking difference) and then calculating the average of the rest, and so on.

8. Conclusion

The goal of the work was to design an algorithm based on frequency analysis and studied materials dealing with this issue and to compare the results with the values that the headband itself calculates.

For this purpose, it was necessary to create an application where this attention calculation algorithm was implemented and then verify the effectiveness of the proposed approach on a given number of volunteers. The last task of the work was to finally evaluate the course of the measurement and the results obtained with regard to the degree of success in determining attention across all participants.

A Mind Wave headband from NeuroSky was used as a tool for measuring brain activity. It is a relatively new device that communicates via a Bluetooth interface and has only one reference electrode, which is placed on the participant's forehead during measurement. The headband has an "eSense" sensor, which enables self-calculation of attention. As this is a proprietary technology, the details of the implementation of the calculation are unknown. For measurements in connection with this work, one of the headbands was borrowed from the EEG laboratory of the Department of Informatics and Computer Technology of the University of West Bohemia in Pilsner.

After studying the documents related to the stimulation of a person's attention, a total of three different scenarios were proposed for the actual measurement of attention with different activities performed during the measurement. The first scenario focused on auditory stimulation, the second used sight as the main sense to obtain the necessary information, and the last one was to measure concentration while playing a logic-oriented game.

Furthermore, based on the approaches to processing EEG signals and the characteristics of different brain waves, an algorithm is designed based on frequency analysis, using Fourier transformation and power spectral density in the form of a period gram. The algorithm was implemented as part of the created application, used to monitor and process the raw EEG data sent by the headband. Part of the program was the possibility of saving data in the appropriate format for further analysis and processing. All measurement data, including stimulation documents, are available on the attached disc.

All three suggested attention stimulation scenarios were tested on a total of 15 participants. Due to the relatively large, time-consuming nature of the measurements, which also included mapping the health status of each volunteer as additional data for the measured collections, the experiments were carried out over several days with approximately two to four people.

The measurements took place on the same premises, and there was an effort to ensure optimal conditions, as similar as possible for everyone, in order to minimize possible external influences on the course of the measurements. The obtained results of attention and EEG activity courses were subsequently analyzed from several different perspectives in order to draw conclusions and evaluate the success of the proposed algorithm.

References

[1] Yongjae Park et al., "A Real-Time Depth of Anesthesia Monitoring System Based on Deep Neural Network with Large EDO Tolerant EEG Analog Front-End," *IEEE Transactions on Biomedical Circuits and Systems*, vol. 14, no. 4, pp. 825-837, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[2] Yongcheng Li et al., "Electromyogram (EMG) Removal by Adding Sources of EMG (ERASE)-A Novel ICA-Based Algorithm for Removing Myoelectric Artifacts from EEG," *Frontiers in Neuroscience*, vol. 14, pp. 1-16, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[3] Jiahui Xu, and Baichang Zhong, "Review on Portable EEG Technology in Educational Research," *Computers in Human Behavior*, vol. 81, pp. 340-349, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[4] Chi-Yuan Chang et al., "Evaluation of Artifact Subspace Reconstruction for Automatic Artifact Components Removal in Multi-Channel EEG Recordings," *IEEE Transactions on Biomedical Engineering*, vol. 67, no. 4, pp. 1114-1121, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[5] Rumen Pozharliev et al., "Merely being with you Increases my Attention to Luxury Products: Using EEG to Understand Consumers' Emotional Experience with Luxury Branded Products," *Journal of Marketing Research*, vol. 52, no. 4, pp. 546-558, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[6] Marie-Pierre Deiber et al., "Linking Alpha Oscillations, Attention and Inhibitory Control in Adult ADHD with EEG Neurofeedback," *NeuroImage: Clinical*, vol. 25, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[7] Zehong Cao et al., "Multi-Channel EEG Recordings during a Sustained-Attention Driving Task," *Scientific Data*, vol. 6, pp. 1-8, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[8] F. Lotte et al., "A Review of Classification Algorithms for EEG-Based Brain-Computer Interfaces: A 10 Year Update," *Journal of Neural Engineering*, vol. 15, pp. 1-28, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[9] Alexander Craik, Yongtian He, and Jose L. Contreras-Vidal, "Deep Learning for Electroencephalogram (EEG) Classification Tasks: A Review," *Journal of Neural Engineering*, vol. 16, pp. 1-28, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[10] Mohammad-Parsa Hosseini, Amin Hosseini, and Kiarash Ahi, "A Review on Machine Learning for EEG Signal Processing in Bioengineering," *IEEE Reviews in Biomedical Engineering*, vol. 14, pp. 204-218, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[11] Michael Murphy et al., "Propofol Anesthesia and Sleep: A High-Density EEG Study," *Sleep*, vol. 34, no. 3, pp. 283-291, 2011. [CrossRef] [Google Scholar] [Publisher Link]

[12] Yvonne Blokland et al., "Decoding Motor Responses from the EEG during Altered States of Consciousness Induced by Propofol," *Journal of Neural Engineering*, vol. 13, pp. 1-9, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[13] Sébastien Rimbert et al., "MOTANA: Study Protocol to Investigate Motor Cerebral Activity during A Propofol Sedation," *Trials*, vol. 20, pp. 1-9, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[14] Ahmad Chaddad et al., "Electroencephalography Signal Processing: A Comprehensive Review and Analysis of Methods and Techniques," *Sensors*, vol. 23, no. 14, pp. 1-27, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[15] Dias Issa, M. Fatih Demirci, and Adnan Yazici, "Speech Emotion Recognition with Deep Convolutional Neural Networks," *Biomedical Signal Processing and Control*, vol. 59, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[16] Steven R. Livingstone, and Frank A. Russo et al., "The Ryerson Audio-Visual Database of Emotional Speech and Song (RAVDESS): A Dynamic, Multimodal Set of Facial and Vocal Expressions in North American English," *PLOS ONE*, vol. 13, no. 5, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[17] Abdul Malik Badshah et al., "Speech Emotion Recognition from Spectrograms with Deep Convolutional Neural Network," *2017 International Conference on Platform Technology and Service (PlatCon)*, Busan, Korea, pp. 1-5, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[18] Paul L. Nunez, and Ramesh Srinivasan, *Electric Fields of the Brain: The Neurophysics of EEG*, 2nd ed., New York: Oxford University Press, 2006. [CrossRef] [Google Scholar] [Publisher Link]

[19] Yuneisy Garcia Guzman, and Michael Lunglmayr, "Sparse Cyclic Coordinate Descent for Efficient Frequency Estimation," *2019 IEEE 8th International Workshop on Computational Advances in Multi-Sensor Adaptive Processing (CAMSAP)*, Le gosier, Guadeloupe, pp. 440-444, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[20] Gui-Lin Chen, Shang-Ho Tsai, and Kai-Jiun Yang, "On Performance of Sparse Fast Fourier Transform and Enhancement Algorithm," *IEEE Transactions on Signal Processing*, vol. 65, no. 21, pp. 5716-5729, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[21] Bin Li, Zhikang Jiang, and Jie Chen, "On Performance of Sparse Fast Fourier Transform Algorithms Using the Aliasing Filter," *Electronics*, vol. 10, no. 9, pp. 1-27, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[22] Hau-Tieng Wu, "Current State of Nonlinear-Type Time-Frequency Analysis and Applications to High-Frequency Biomedical Signals," *Current Opinion in Structural Biology*, vol. 23, pp. 8-21, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[23] Harshit Bhardwaj et al., "EEG-Based Personality Prediction Using Fast Fourier Transform and DeepLSTM Model," *Computational Intelligence and Neuroscience*, vol. 2021, pp. 1-10, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[24] Dhiran Kumar Mahto, and A.K. Singh, "A Survey of Color Image Watermarking: State-of-the-Art and Research Directions," *Computers & Electrical Engineering*, vol. 93, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[25] Lauer C., (Prod.), Hangar 1 - The UFO Files (Own Recording), Prima ZOOM, A&E Television Networks, 2014.

[26] G.E. Berrios, "Musical Hallucinations - A Historical and Clinical Study," *The British Journal of Psychiatry*, vol. 156, no. 2, pp. 188-194, 1990. [CrossRef] [Google Scholar] [Publisher Link]

[27] Noam Brown, and Tuomas Sandholm, "Superhuman AI for Heads-Up No-Limit Poker: Libratus Beats Top Professionals," *Science*, vol. 359, no. 6374, pp. 418-424, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[28] Moyuru Kurita, and Kunihito Hoki, "Method for Constructing Artificial Intelligence Player with Abstractions to Markov Decision Processes in Multiplayer Game of Mahjong," *IEEE Transactions on Games*, vol. 13, no. 1, pp. 99-110, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[29] Genaro Rebolledo-Mendez et al., "Assessing NeuroSky's Usability to Detect Attention Levels in an Assessment Exercise," *Human-Computer Interaction. New Trends*, pp. 149-158, 2009. [CrossRef] [Google Scholar] [Publisher Link]

[30] Thomas H. Budzynski et al., *Introduction to Quantitative EEG and Neurofeedback: Advanced Theory and Applications*, 2nd ed., Academic Press, 2009. [CrossRef] [Google Scholar] [Publisher Link]

[31] Mengxi Dai et al., "EEG Classification of Motor Imagery Using a Novel Deep Learning Framework," *Sensors*, vol. 19, no. 3, pp. 1-16, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[32] Md. Kafiul Islam, and Amir Rastegarnia, "Recent Advances in EEG (Non-Invasive) Based BCI Applications," *Frontiers in Computational Neuroscience*, vol. 17, pp. 1-3, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[33] Szymon Fiałek, and Fotis Liarokapis, "Comparing Two Commercial Brain Computer Interfaces for Serious Games and Virtual Environments," *Emotion in Games*, pp. 103-117, 2016. [CrossRef] [Google Scholar] [Publisher Link]