Towards analyzing user attention using electroencephalography in immersive multisensory virtual environments

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Abstract

This study explores attention detection using EEG signals and its application in immersive environments, combining insights from different approaches. We assessed the attention levels of 12 participants through 2D digital games, highlighting that tasks without time limits were more effective in maintaining user engagement. We intend to run another experiment with PhysioDrum, a multisensory drum system that combines physical and digital elements for immersive musical experiences. Equipped with sensors and actuators, PhysioDrum ensures real-time synchronization and multimodal feedback, demonstrating potential for creative and educational uses. Future research aims to analyze the interaction between attention and immersive environments, focusing on the differences in engagement between neurotypical and neurodivergent users, and promoting the development of therapeutic tools for cognitive and emotional enrichment.

Keywords

Attention detection, physiological signals, Wavelet transform, Io3MT, virtual drum

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1 Introduction

Attention plays a vital role in our daily lives, being essential for effective performance in academic, professional, and personal activities. Attention disorders, such as Attention Deficit Hyperactivity Disorder (ADHD), affect millions of people worldwide. Traditional methods of attention assessment, although effective, often face challenges such as limited accessibility and complexity of procedures [4].

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In recent years, the field of brain-computer interface (BCI) has advanced considerably with the use of neural networks and deep learning techniques, which allow the classification of cognitive states, such as attention levels, with high accuracy. These tools demonstrate great potential in identifying complex patterns in brain activity, being widely used for tasks such as attention classification and analysis of cognitive functions. Examples include the use of hybrid models, such as CNN (Convolutional Neural Network) and LSTM (Long Short-Term Memory), which achieve high levels of accuracy when processing EEG (electroencephalogram) signals [7]. Feature extraction methods, such as the Wavelet Transform, have also been explored in conjunction with machine learning algorithms, as demonstrated in [8], optimizing classification in various contexts.

Although there are few recent works that address attention detection using exclusively signal processing techniques, it is possible that older studies have explored this approach. However, the current trend seems to favor the use of neural networks for classification. In this context, this work aims to detect the attention of individuals through their brain waves using only the Fp1 channel of the 10-20 system [10] connected to the Bitalino device [13], without the use of neural networks. To understand, analyze and explain how this pattern can be found, we developed four 2D digital games to stimulate the attention of participants while their brain waves were recorded. In addition, individuals who used *mouse* and individuals who used *touchpad* to interact with the games were also analyzed. The proposed approach makes use of Wavelet decompositions and spectrogram analysis to detect the level of attention. The main contributions of this paper include:

- Generation of a public database for attention levels.;
- Detection of attention levels using a low-cost device;
- Facilitating the development of future brain-computer interactions by making the data from this study available to the public.

We intend to apply the methodology we used for analyzing 2D games to understand EEG signals during immersive multisensory experiences. To achieve this goal, we intend to use PhysioDrum [22], a multisensory drum system that combines physical and digital elements for immersive musical experiences. Equipped with sensors and actuators, PhysioDrum ensures real-time synchronization and multimodal feedback, demonstrating potential for creative and educational uses. Future research aims to analyze the interaction between attention and immersive environments, focusing on the differences in engagement between neurotypical and neurodivergent users, and promoting the development of therapeutic tools for cognitive and emotional enrichment.

This paper is organized as follows. Section 2 presents the literature review, covering fundamental concepts and works related to attention detection, with emphasis on the differences between methods based on artificial intelligence, different from the approach of this study, which exclusively uses signal processing and pattern analysis. Section 3 discusses our study results including the description of the games used, the associated attention tests, the data collection procedure and the processing and analysis of the signals for the detection of the attention pattern. Section 4 discusses PhysioDrum, which will be used as an immersive multisensory system for our future experiments. Finally, Section 6 brings the conclusion, where contributions and future work are discussed, proposing possible developments to improve research in the area.

2 Literature review

Attention is a central cognitive ability, widely studied in various contexts due to its importance in academic, professional and interactive activities. Methods based on EEG signals have been widely explored for the detection of attention levels, combining classical and modern approaches. The authors of [7] developed a system to recognize human attention levels from EEG signals. The attention levels were: attentive, neutral, happy and bored state. The authors proposed a CNN (Convolutional Neural Network) together with an LSTM network, that is, a hybrid model, to classify the cognitive functions of individuals. 89% accuracy was achieved, where individuals watched videos and performed mathematical calculations.

In the study by [8], the authors investigated the effectiveness of different machine learning algorithms in classifying the joint attention of individuals with Autism Spectrum Disorder (ASD) using EEG data. Initiated Joint Attention (IJA) refers to the ability of a person to direct another person's attention to an object or event. And Responded Joint Attention (RJA) refers to the ability of a person to respond to another person's attention. The results showed that the Generalized Relevance Learning Vector Quantization (GRLVQ) method performed best, outperforming other algorithms such as SVM and Random Forest, especially when combined with feature extraction via Wavelet Transform.

The study by [1] aimed to develop and evaluate the feasibility of a new BCI paradigm, based on the P300 response and integrated into a virtual reality environment, to train joint attention skills in individuals with ASD. Three EEG systems were tested (g.Mobilab+, g.Nautilus and V-Amp with actiCAP Xpress), with g.Nautilus standing out in accuracy, comfort and speed. The study used a paradigm divided into two phases: identification of the focus of attention with the Naive-Bayes classifier used to classify joint attention events based on the detected P300 signals. And interaction with a virtual avatar using an automatic component of the BCI that identifies the presence of P300 signals during the interaction, providing real-time feedback and demonstrating effectiveness in classifying joint attention.

The differential of the present work is the use of Bitalino, a low-cost, accessible and widely applicable device in different contexts, especially in academic research. In contrast to previous studies, which used conventional hospital EEG systems, such as Neurocom or g.Nautilus, these devices are significantly more expensive, have multiple collection channels and require a complex infrastructure. On the other hand, this work adopts a more simplified approach, employing only one collection channel to perform the analysis of attention patterns, without relying on sophisticated equipment.

Regarding PhysioDrum, since its device explores cyberphysical interactions in a dynamic and multisensory environment, the cognitive investigation will be unprecedented in this domain and it is important to highlight relevant points about the attention used and the cognitive behavior related to the use of this application.

3 Analyzing User Attention when playing 2D Games

3.1 Detecting user attention

3.1.1 Participants and Data Collection. The study included 12 participants, 2 women and 10 men, with an average age of $\bar{x} = 23$ years and standard deviation $\sigma = 2.45$. The volunteers were recruited at the Institute of Computing, including undergraduate and master's students and a History student. The EEG signals were collected in a controlled environment, using the Bitalino device configured to record data on the Fp1 channel of the 10–20 system [10] with a sampling rate of 1000 Hz. Participants were divided into two groups: one used a *mouse*, and the other a *touchpad* (*notebook mouse*) to play the four games we created shown in Figure 1.

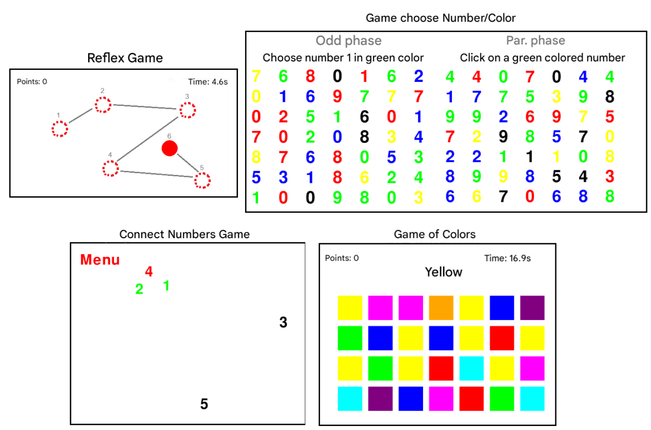

Figure 1: Games developed to assess attention.

Each game created is associated with a psychological test of attention. The reflex game consists of clicking on as many red dots as possible on the screen in 10 seconds, associated with the **selective attention test** [11]. The choose number/color game involves clicking on a number of the given color, or on any number of the given color, associated with the **Stroop test** [18]. The connect numbers game involves clicking in ascending order on the numbers that appear on the screen, associated with the **colored trails test** (***Trail Making Test***) [15]. Finally, the choose color game involves clicking on as many colors as possible according to the indicated color in 20 seconds. This game is associated with the ***Symbol Digit Modalities Test*** [17].

Rest intervals of 10 seconds before and after the games were recorded as a baseline for comparison with attention spans during the experiment. Data collection followed all ethical guidelines, including informed consent, with guaranteed data anonymization.

3.1.2 Data Processing. The processing of the EEG signals involved several structured steps (Figure 2):

- **Channel selection**: Only the frontal channel Fp1 was analyzed to ensure consistency with open databases [10].
- **Segmentation**: The data were divided into 200 millisecond intervals.
- **Filters**: High-pass and low-pass filters were applied to reduce noise [5].
- **Independent Component Analysis (ICA)**: Eye and muscle movement artifacts were removed [3].
- **Wavelet Transform**: The Daubechies Db 10 family was used to decompose the signals into temporal and frequency components [14].
- **Continuous Wavelet Transform (CWT)**: Applied to identify detailed characteristics of the signals [19].
- **Spectrograms**: Generated to visualize the power distribution over time, with normalized values[12].

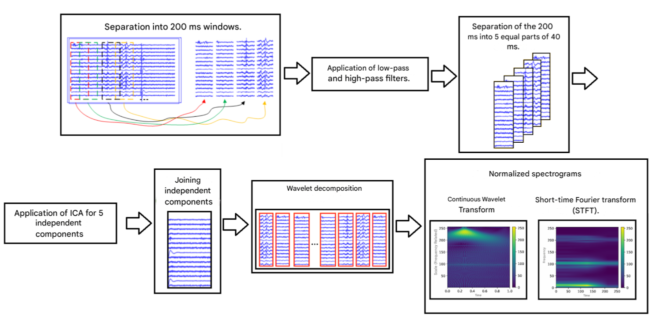

Figure 2: Processing applied to electroencephalogram (EEG) data.

3.1.3 Detection of Attention Patterns. Spectrograms were generated for the approximation and detail coefficients for all wavelet decompositions. It was decided to use the approximation coefficients and the first decomposition that represents the Gamma waves (30-100 Hz). This stronger pattern of signal change is present in all 9 Wavelet decompositions, in the continuous transform in yellow and in the STFT transform in dark blue. See Figure 3 which presents this attention pattern and which presents a normal state with no signs of attention. Comparing these decompositions and based on the literature, we decided to use only the first Wavelet decomposition which represents the Gamma wave, where the state of attention is defined.

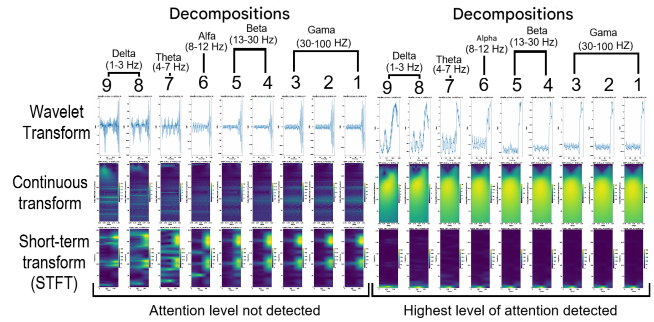

Figure 3: Comparison between attention and distraction in continuous wavelet decomposition and short-time transform.

To define attention, it was noticed that the pattern in the time series in Figure 4 presents a larger blue area in the Daubechies Wavelet spectrogram and an intense yellow in the CWT Wavelet spectrogram (continuous transform). There are cases where there is a bluish pattern in the Daubechies Wavelet spectrogram (short-time transform), but there is no presence of the yellow hyper signal in the CWT Wavelet spectrogram. Thus, attention was defined as,

$$A = Espec_{\text{cwt}} \times 0.70 + Espec_{\text{Daubechies}} \times 0.30 \tag{1}$$

where, $Espec_{\text{cwt}}$ is the proportion of the area of the CWT Wavelet spectrogram above band 3, ranging between [76, 256], and $Espec_{\text{Daubechies}}$ is the proportion of the blue area of the Daubechies Wavelet spectrogram, represented by band 1, ranging between [0, 31].

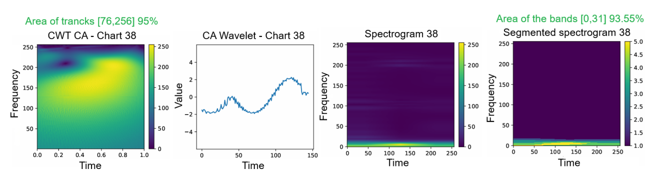

Figure 4: Spectrograms of the first decomposition of the Continuous Wavelet Transform (CWT) and its approximation coefficients (cA), using the Daubeuchies family. Includes the complete analysis (a, b) and segmented into bands (c, d).

3.2 Results of attention detection in participants

In summary, our experiment involved 12 participants, using EEG signals recorded on the Fp1 channel with the Bitalino device. Pattern recognition techniques were applied to detect and analyze the participants' attention levels, focusing on changes during the games compared to resting states. An ANOVA test was performed with the participants' resting data to estimate a baseline of the participant's current state before the stimuli. This value by the ANOVA method was 55% to differentiate resting states and heightened attention, with confidence intervals that provide a solid reference for future individual analyses.

However, the time-limited games: "Reflex Game" and "Choose Number/Color" presented fluctuating attention patterns, with less impact on maintaining engagement. However, games without time limits, such as "Connect Numbers" and "Color Game", demonstrated greater stimulation of attention over time, regardless of mouse use, these results are presented in Figure 5. The observed patterns reveal the importance of exploring different game configurations, immersive environments, and other applications to stimulate user attention and concentration. Thus, the results highlight the importance of designing interactive games that consider time and task structure, which have a direct impact on attention patterns. Games without time limits proved to be more effective in maintaining focus throughout the experiment.

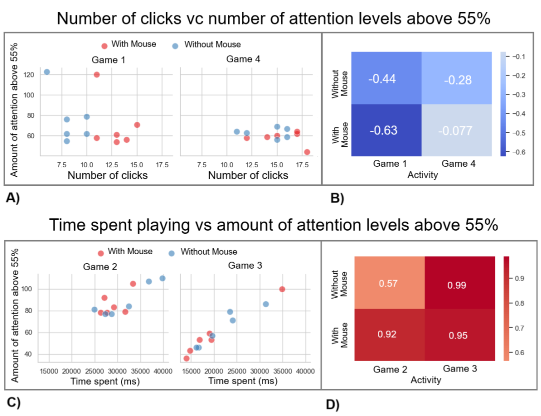

Figure 5: A) and B) - relationship between clicks and attention levels of each participant using or not the *mouse* in Game 1 (Reflection) and in Game 4 (Colors), which had a time limit and a greater need for clicks. C) and D) - relationship between the time spent and attention levels of each participant using or not the *mouse* in Game 2 (Choose Number/Color) and Game 3 (Connect Numbers), with no defined time limit, but with the same number of clicks.

4 PhysioDrum Immersive Experience

Based on the results obtained with 2D games, which identified clear attention patterns in different conditions, the present study expands this approach, proposing the application of the methodology in immersive environments. To this end, a series of 360° environments that simulate interactive scenarios and a virtual drum kit, called PhysioDrum, will be used, which allows the analysis of stimuli in more dynamic and realistic conditions.

PhysioDrum [22] is a virtual drum kit developed from the convergence between the concepts of the Internet of Multisensory, Multimedia and Musical Things (Io3MT) [21] and the field of the Musical Metaverse (MM) [20], with the purpose of creating immersive, multimodal and interoperable musical experiences. The application consists of a digital drum kit running on a Head-Mounted Display (HMD), which integrates inputs from physical drumsticks and pedals. The drumsticks are equipped with colored spheres tracked by a computer vision algorithm, allowing their movements to be mapped in the virtual environment to act as input objects, responsible for striking the drums and generating sound. In addition, each drumstick contains a touch sensor, which can be used to trigger pre-recorded soundtracks in environments such as Pure Data or Digital Audio Workstations (DAWs). An accelerometer is also incorporated, enabling control of the properties of these musical tracks, such as volume and effects, or even the manipulation of parameters in visual elements, such as the speed of movement and the color pattern of a given graphic art.

Figure 6: Structural composition and practical application of PhysioDrum [22].

The pedals, in turn, work in a similar way to those of traditional acoustic drums, being responsible for triggering the sounds of the bass drum and hi-hat. This approach aims to increase the physicality of the virtual experience, as well as to use mechanical and motor actions inherent to the practice of percussion for the virtual environment, reducing the learning curve of the proposed application and also the mental effort required to use it. Thus, the combination of auditory, visual and tactile stimuli becomes especially suitable for investigations on attention in realistic contexts.

We intend to run user experiments with PhysioDrum and Bitalino sensors to analyze EEG signals and the user attention when playing in immersive multisensory environments. In addition to the collection of physiological data, the experiments with PhysioDrum include both quantitative and qualitative evaluations. For the quantitative assessment, a user experience (UX) protocol was developed by the authors based on a systematic review of the scientific literature, which identified the most common techniques for evaluating immersive musical performances and/or technology-mediated artistic experiences. Based on this review, the following instruments are employed: Presence Questionnaire (PQ) [23] and the Simulator Sickness Questionnaire (SSQ) [9], used to assess the degree of immersion and the overall quality of the virtual reality experience; System Usability Scale (SUS) [2], which evaluates the usability of the system as a whole, including both the virtual application and the hardware components; NASA Task Load Index (TLX) [6], which measures the mental workload required to use the application; and the Haptic Questionnaire [16], which provides insights into how haptic feedback integrates with the rest of the system.

Qualitative evaluation is conducted through semi-structured interviews in which users respond to and reflect on various aspects of their experience, including comfort in using the hardware elements, overall satisfaction, and the artistic and creative value of the

PhysioDrum. Participants are also encouraged to suggest features they believe should be added or improved.

Following the data collection, the aim is to explore correlations between the captured physiological responses and user feedback concerning the diverse aspects of the PhysioDrum experience. For instance, it seeks to determine whether users who reported high mental workload or usability issues exhibited similar physiological patterns, and whether these differed from those who rated the system more positively. In addition to offering valuable insights into user experience, this methodology allows for a more comprehensive and objective evaluation of the system's effectiveness. Unlike traditional approaches that rely solely on questionnaires and interviews, which are predominantly subjective, the integration of physiological data yields more robust results. These insights are particularly valuable for developers and researchers, contributing to the advancement and broader dissemination of the emerging fields of the Io3MT and the Musical Metaverse.

5 Limitations

This study has some limitations. There was no explicit marking of the participants' attention moments, either in open databases or in our data capture, preventing the use of neural networks (supervised learning). We therefore opted for an exploratory approach, identifying recurring patterns after the game stimuli. Despite the small sample of 12 participants, the results demonstrated a consistent pattern for both participants. Future studies with larger and more diverse groups could expand and validate these findings.

6 Final Remarks

The purpose of this work is to integrate research on attention with the immersive environment provided by PhysioDrum, exploring how multisensory stimuli can influence users' focus, engagement, and relaxation in musical experiences. This integration aims to analyze how the visual, sound, and tactile elements present in PhysioDrum contribute to user immersion and promote an enriching experience, both in creative and therapeutic contexts.

In addition, this work aims to evaluate the profile differences between neurotypical and neurodivergent users when interacting with the PhysioDrum environment. In this way, it will be possible to understand the response of these groups to sensory stimuli and musical interactions, providing useful data on their levels of attention and engagement. If the results demonstrate positive impacts, then PhysioDrum is a useful tool for application in therapeutic environments in conducting activities related to relaxation, concentration, and emotional expression.

According to these studies, opportunities to adjust and improve PhysioDrum emerge, thus strengthening the application of the tool in educational and therapeutic contexts. The system can be modified to include specific training modes or personalized exercises designed to adequately develop the motor, cognitive and emotional skills of users. The implementation of these solutions will allow PhysioDrum to be used as a multifaceted tool, serving not only to train musicians but also to be used in therapeutic processes.

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