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Research Article

A brain-computer interface for gamification in the Metaverse

Yaşar DAŞDEMİR[1*]

[1] Erzurum Technical University, Computer Engineering Department, yasar.dasdemir@erzurum.edu.tr, Orcid No: 0000-0002-9141-0229

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* Corresponding author

ABSTRACT

This study contributes to our understanding of the Metaverse by presenting a case study of the implementation of brain-computer interface supported game-based engagement in a Virtual Environment (VE). In VE, individuals can communicate with anyone, anywhere, anytime, without any limits. This situation will increase the barrier-free living standards of disabled people in a more accessible environment. A virtual world of well-being awaits these individuals, primarily through gamified applications thanks to Brain-Computer Interfaces. Virtual environments in the Metaverse can be infinitely large, but the user's movement in a virtual reality (VR) environment is constrained by the natural environment. Locomotion has become a popular motion interface as it allows for full exploration of VE. In this study, the teleport method from locomotion methods was used. To teleport, the user selects the intended location using brain signals before being instantly transported to that location. Brain signals were decomposed into alpha, beta, and gamma bands. The features of each band signal in Time, frequency, and time-frequency domains were extracted. In this proposed method, the highest performance of binary classification was obtained in the frequency domain and the Alpha band. Signals in the alpha band were tested in the Time, Frequency, and Time-Frequency domains. Teleport operations are faster in the time domain and more stable in the frequency domain. However, the Hilbert-Huang Transform (HHT) method using in the Time-Frequency domain could not respond adequately to real-time applications. All these analyses were experienced in the Erzurum Virtual Tour case study, which was prepared to promote cultural heritage for the gamification method.

Introduction

Metaverse provides a virtual environment to experiment, practice, and learn without the costly consequences of doing them in the real world. The Virtual Reality (VR) industry, which will enable us to enter this virtual world, is overgrowing as more powerful and versatile Head-Mounted Displays (HMD) and VR peripherals are developed. That's why technology-based companies are turning their attention to immersive VR as a strategic opportunity. So recognizing in the rapid growth and interest in the Metaverse, this study presented an exemplary study by analyzing VR research in BCI and related fields. Thus, the pros and cons of technologies such as Metaverse, Virtual Reality, Gamification, and Brain-Computer Interfaces in human life were investigated and the place of BCI in Metaverse was mentioned.

The Metaverse is a virtual world that users can experience from a first-person perspective. It can also be considered a navigable internet or social media platform. The Metaverse gained immense popularity after Facebook changed its name to Meta. Especially after the statement made by Mark Zuckerberg in 2021, everyone started to wonder what this technology is when it would come and what it includes.

The challenges of the Metaverse include sustainability, hardware and software constraints, difficulty in developing and preparing content, and cyber nuisances. The sustainability of Metaverse is essential. Because if the world population is kept at a certain level, it can grow and solve problems, but the world cannot be sustained when the number of users accessing the Metaverse decreases. Using episodic memory that effectively manages people's daily activities allows the user to feel the comfort and advantage of accessing the Metaverse for a long time. Storing all experiences in memory has usage and capacity limitations. Therefore, memory research is needed to find and reuse important parts effectively.

While the Metaverse is very similar to the real world in terms of sensors in hardware, some sensations are better felt in real life (e.g., daylight, smell, sticky, slippery, wind). However, as the program becomes more complex, it faces the limit of sophistication in a complex application. For example, if modals such as scent [1] are added to BCI applications, the immersive of the systems will increase even more.

Another challenge is the development phase. From a metaverse development perspective, there are very few online resources, especially for beginner developers. There is not enough information with practical details to make complex and realistic applications (e.g., object selection, conditional actions, user storyboards with scene flow, teleport-teleport between scenes, motion, and dialogue). Therefore, an individual developer must develop a standard system (i.e., a platform and a community of developers) together without designing the entire system. As for the framework, consider a commercial platform with proper maintenance (e.g., Roblox) and an open source-based platform with various possibilities (e.g., Unity3D).

Langbehn et al. [2] analyzed different methods of locomotion: Joystick, Teleport, and Redirected Walking. They conclude that Redirected Walking provides better spatial recognition compared to the other two. They also indicate that the Joystick is the locomotion method that produces more cybersickness. In this study, the participants did not observe cybersickness (such as dizziness and nausea) since locomotion was performed with direct brain signals. The negativities brought about by locomotion movements are somewhat eliminated by BCI applications.

A. Metaverse tools (AR, VR, MR, XR)

Virtual Reality (VR) and Augmented Reality (AR) were among the top ten emerging technologies in 2020. It is expected to be among the best developing technologies of 2021 in the field of information technologies. These systems, which have been widely used in education, training, entertainment, and marketing, and even in post-injury rehabilitation centers, have attracted the attention of the game industry.

With the growing popularity in VR and the introduction of new devices at relatively lower costs, more video games have been developed in this area recently. Most of these games provide a more natural and immersive environment with an HMD while also using more first-person interaction techniques.

It is essential to understand better the factors that promote learning through games. Therefore, VR offers new possibilities in education and vocational training. VR excels when real education is too expensive, and some lab applications are too dangerous.

In the VR environment, players often experience the feeling of "being there". This feeling is sometimes expressed with the concepts of "presence" and "immersive" for VR, which are used interchangeably.

In Figure 1, Milgram [3] presents descriptive terminology. Researches in different disciplines such as AR, Mixed Reality (MR), and Augmented Virtuality (AV) are classified.

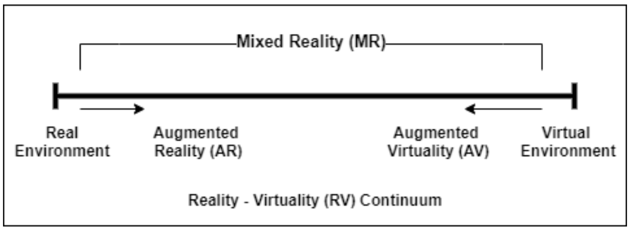

Figure 1. Augmented Reality in the Reality-Virtuality continuum (adapted from [3])

Burdea and Coiffet [4] define virtual reality with the “Virtual Reality Triangle (I^3)”: Immersion, Interaction, and Imagination (Figure *2*).

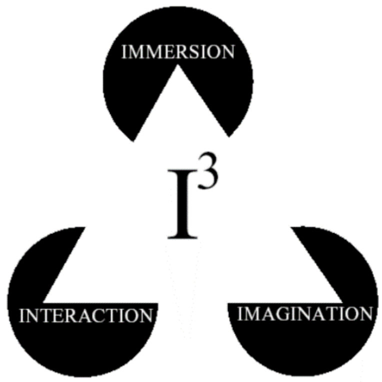

Figure 2. Virtual Reality Triangle

Immersion: This concept defines the immersive, inclusive, and inclusive effects of the virtually created world environment. This definition is divided into two subclasses: Mental and Physical Immersive. These two concepts are essential for the player to have a successful personal experience in the VR environment. Mental immersion shows the emotional state of the player and shows that he has deep anxiety and tension in the game. With its physically immersive feature, the actor shapes his physical behavior with visual, auditory, or tactile devices.

Interaction: This feature of the VR system provides real-time detection of the user's responses (user movements) to the activities in the game with the help of many sensors (visual, tactile, etc.).

Imagination: This feature, specified as imagination, expresses the capacity of the player's mind to perceive things that do not exist. VR supports the user to elaborate thoughts and engage in meaningful learning.

It is possible to classify VR Types as follows:

1. Textual VR (interaction, no inclusive)
2. Desktop VR (interaction, inclusive)
3. Immersive VR (interaction, high inclusive)
4. Augmented VR (interaction, no inclusive)

B. Locomotion

One of the most used interaction techniques in the VR environment is motion, which moves the user's perspective in virtual environments. Locomotion is an essential component of VR as it can substantially impact the user experience. Teleporting has become a popular locomotion interface as it allows VE to be fully explored. To teleport, the user selects the intended location using brain signals before being instantly transported to that location.

In recent years, many variable motion approaches have been used in research [5], [6] and in the game industry [7]. In particular, besides the techniques developed around the idea of natural walking in VR, there are also motion approaches that do not involve a physical movement of the player.

Virtual worlds are hardly ever built in a linear way and players need the ability to change the walking direction. Hence, VR games require Omnidirectional treadmills [8]. Treadmills allow the players to move in a physical way. Combined with an HMD, players usually cannot distinguish such installations from real walking experiences (Figure 3).

Figure 3. The treadmill for real walking

C. Serious Game and Gamification

AR and VR play an important role in today's world, where we have started doing all our work online due to COVID-19. With these systems, new BCI designs are also reflected in the game world by adding brain signals to applications such as disabled people and distance education/therapy. With BCI, the information read from the brain is analyzed in response to the stimuli given in the immersive and inclusive environment of technologies such as virtual reality. It aims to develop a more immersive and instructive user experience by obtaining information about the player's physiological state during the game.

Digital games are generally perceived as a leisure activities. However, as a result of various studies, it has been observed that digital games positively affect cognitive activity. Some of these non-invasive studies have shown that games change brain dynamics, strengthen information processing and motor skills, and potentially reduce the time required for information processing. These studies show the mixture of different game-playing aspects that affect many factors such as attention, cognitive control, visuospatial skills, and cognitive workload arising from the mechanical nature of games [9]. For example, unlike strategy games, shooting games (like FPS) require different cognitive demands and different strategies. Different studies have shown that virtual reality design an interactive environment, increasing the participation and motivation of students and providing deeper learning [10].

Gamification and Serious Game are two e-learning strategies with similar aims. However, although they have similar purposes, they also have significant differences. The serious game is used to denote video games used in fields such as education, defense, health, simulation, and engineering instead of entertainment. Gamification, on the other hand, is the application of game-like elements to different fields (marketing, education, etc.) to change attitudes and behaviors and increase participation and effectiveness [11]. The main difference between serious gaming and gamification is that serious games involve structures that offer not only entertainment but also some form of educational value. Gamification, on the other hand, incorporates game elements into traditional e-learning programs to increase engagement. Gamification adds game-like elements to your education, while serious games add educational value to games.

D. Brain-Computer Interfaces

Brain-Computer Interface (BCI) is a system that provides a direct connection between the brain and the computer to control an external device. These systems are also called Brain-Machine Interface (BMI) systems. EEG-based BCI is characterized by using non-invasive EEG electrodes to measure brain activity and convert the recorded brain signals into commands.

In the literature, BCI is defined as a system that measures the brain's central nervous system activity and converts it into an artificial output, thus ensuring the interaction between the central nervous system and its internal and external environment [12]. A modern BCI system is a brain activity analyzer that takes complex brain signals, analyzes them, and translates them into a command for a machine (usually a computer, a robotic arm, game controllers, prosthesis, wheelchair, etc.) [13], [14].

There are basically three different types of BCI:

Active BCI: BCI is used to complete mental tasks. For this, motor signals or imagery completes these tasks. For example, a person raises one's leg to step on a stair step. It is independent of external events. The person provides direct cognitive control.

Reactive BCI: This BCI works based on a stimulus (like SSVEP). The P300 (event-related potential) signal further explains the basis of Reactive BCI. The P300 includes cognitive learning and decision-making processes dependent on a visual stimulus. Here, a stimulus is given to the person externally.

Passive BCI: BCI works without visual stimuli. The BCI mechanism only acts as an on/off switch. Passive BCI works willingly without the purpose of controlling, that is, with the outputs of spontaneous brain activity.

Brain Signal Acquisition Technologies

Advances in functional neuroimaging and inter-cranial spatial imagery have opened new doors in the fields of Cognitive Learning and Associated Neural Networks. BCI systems consist of a mixture of signals from the brain and nervous system. These signals are:

1. Electrical and magnetic signals
2. Intracortical electrode array-invasive method
3. Electrocorticography (Electrocorticography, ECoG or intracranial EEG, IEEEG)-invasive method
4. Electroencephalography (Electroencephalography)
5. Magneto-encephalography (Magnetoencephalography)
6. Metabolic signals
7. Functional magnetic resonance imaging (fMRI)
8. Functional near-infrared spectroscopy (fNIRS)

Signals that are not brain signals:

1. Electromyography (Electromyography, EMG)
2. Electrocardiography (Electrocardiography, ECG)
3. Electrooculography (Electrooculography, EOG)

BCI systems measure the electrical activity of the brain and evaluate it with different techniques. EEG method is widely used among non-invasive methods for measuring brain activity. EEG and BCI are currently the focus of research in this area.

Electroencephalography (EEG)

EEG is a non-invasive method that allows electrical recording activity from the scalp surface [15], [16]. The recording process is made by measuring the voltage fluctuations coming from the brain with various numbers of electrodes placed on the scalp surface. Hans Berger first made this measurement from the scalp surface in 1929 [17]. The electrical activity recorded from the brain is measured in microVolts (μV). The rhythmic activity recorded from the brain is classified into five frequency bands (Table 1): Delta (0.5-4 Hz), Theta (4-8 Hz), Alpha (8-13 Hz), Beta (13-25 Hz), Gamma (25-100Hz). These frequency band ranges are used in various studies with slight differences in different fields [18].

Table 1. Frequency band ranges

Bands	Range(Hz)	Location	Activity
Delta	1.3 – 3.5	Frontal	Deep sleep.
Theta	4 – 7.5	Various	Theta activity is a slow-wave activity seen in drowsiness and often during meditation. Increased theta frequencies are associated with relaxed and creative states, as well as memory recall and ‘flow’ states.
Alpha	8 – 13	Back of the head	Alpha waves are the default ‘relaxed and alert’ mode of your brain. Alpha activity is often observed when the eyes are closed, indicating that the visual system is ready and awaiting input. Decreases in alpha activity can also be seen in other parts of the brain when that part of the brain is activated.
Beta	12.5 – 30	Symmetrically distributed in the left and right hemispheres, mostly anterior	Beta frequencies are associated with active, task-oriented, busy, or anxious thinking and active concentration.
Gamma	30 – 40	Somatosensory cortex	Gamma activity is the high-frequency activity that occurs during demanding mental or motor functions. Gamma waves can be observed, especially in the frontal lobes, when you switch activities during multi-tasking.

Material and Method

BCI software can translate mental commands from EEG data into commands in a video game. In BCI-based games, subjects wear an EEG headset while playing VR games designed to control virtual objects. Instead of using a traditional game controller, the subject uses mental commands to activate motion-based actions such as "push", "pull" or "jump" in the game. In this study, navigation was made between teleport points with the "push" command, and the "pull" command action was used to open the door of the historic building. BCI processed these mental commands from the EEG and triggered the corresponding movement in the VR game. As gamification, interaction with teleport and Non-Player Character (NPC) corresponding to navigation from game mechanics were used in the study.

A total of 11 subjects (right-handed) without prior experience in the BCI and not diagnosed with any neurological or psychiatric disorder were recruited for the study. Participants ages ranging from 18 to 29 (M = 20.25 years, SD = 2.43). The sample was selected from the university student population. Participants of the study hold a Bachelor of Science degree in different disciplines related to computer engineering, electrical-electronics, computer science, and others without BCI experience.

All tasks were performed with the same group of participants and devices. The experiment was performed in a quiet room, with a 3m×2.5m space to set up two HTC-

Vive Lighthouses. The VR device was connected to a desktop computer with 64 GB RAM and an Intel Core i7-9700K processor running at 3.60 GHz. The Emotiv Epoc Flex device was wirelessly connected to a laptop with 32 GB RAM and an Intel Core i7-11800H processor running at 2.30 GHz. The desktop computer had Nvidia GeForce RTX 2080 Super GPU (8 GB), while the laptop had Nvidia GeForce RTX 3070 GPU (8 GB) graphics card. It has been used HTC Vive Pro Eye's HMD to display the pre-built virtual scene by Erzurum Virtual City project.

Emotiv Epoc Flex with 32 channels was used as an EEG acquisition device (Figure 4-a). Channels:

Cz, Fz, Fp1, F7, F3, FC1, C3, FC5, FT9, T7, TP9, CP5, CP1, P3, P7, O1, Pz, Oz, O2, P8, P4, CP2, CP6, TP10, T8, FT10, FC6, C4, FC2, F4, F8, Fp2.

Sensor cables are color-coded. Blue is used for the left, red for the right, and black for the references. In addition, each sensor is individually labeled with the channel name to which it is connected to the EPOC Flex. With this color coding, the channel name can be defined quickly in the software, and the appropriate electrode location can be found quickly. For example, if the contact quality is poor in the LA (Left-A) channel, it corresponds to the blue A wire.

Data were obtained from all channels (32 channels), but only the channels in Figure 4-b were used in the BCI software. The channels used in the study are: FC3-FC4 [19], C3, C4, P3, P4 [20], FC5, FC6, P7, P8 [21], Fz, Cz, Pz, Oz.

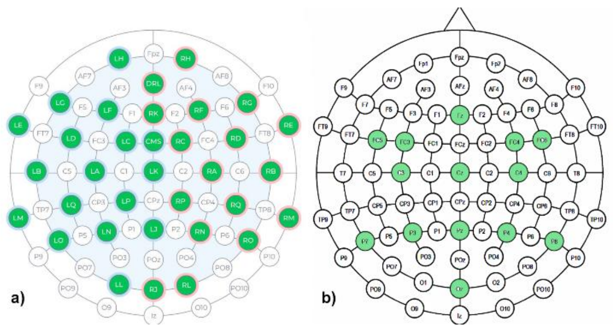

Figure 4. a) EEG electrode placement b) selected electrodes

The flow chart of the study is presented in Figure 5. The signals obtained with the EEG device are transferred to the developed machine learning module (Control Module) with Cortex-V2 (C# programming). Brain signals are converted into commands by the module, and these commands are classified. Among the classification algorithms, two different algorithms were used: Random Forest (RF) and Naive Bayes (NB). The output of the RF classifier was sent to the Unity3D game engine because it gave better accuracy values (Figure 6).

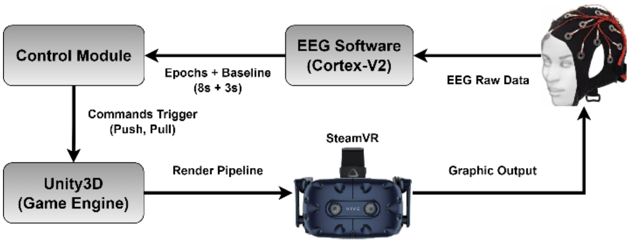

Figure 5. The flowchart of the study

The experimental protocol was determined as follows:

1. Preliminary information was given to the participant. EEG and VR devices were then mounted to the user (Figure 7).
2. Three seconds baseline signal received.
3. Eight seconds teleport signal received.
4. Steps 2 and 3 were repeated five times for training.

The same steps were repeated for the door opening task. A total of 10 training signals were obtained from one subject.

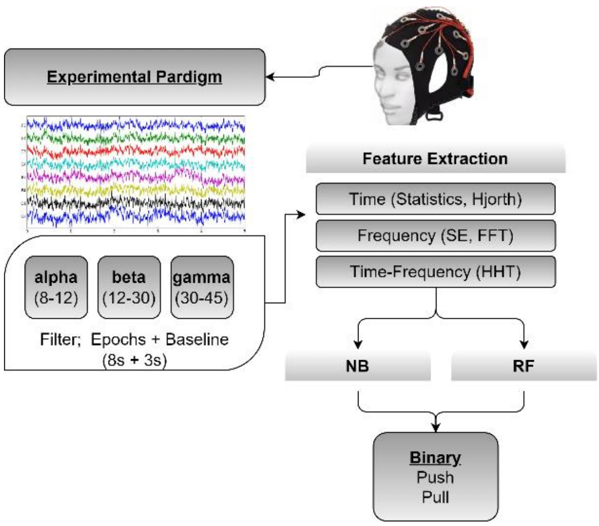

Figure 6. Control module

Erzurum Virtual City, which was prepared with another project as VE, was used on the game engine side. Erzurum Virtual City (Figure 8) virtual elements were modeled with Autodesk Maya, and the characters were rigged. The materials of the virtual items were obtained with Substance Painter. SteamVR v2 framework was used for the VR environment. Gamification was developed in the Unity 3D game engine with the C# programming language. Brain signals obtained with Emotiv Epoc Flex were processed and translated into commands in Unity3D, depending on two mental tasks.

Figure 7. A subject preparing to participate in the experiment (left: EEG device deployment, right: VR device deployment)

Figure 8. Ottoman Era Erzurum Virtual City

Two mental tasks were tested in each historical building in the Erzurum Virtual City tour, both to teleport to specific locations and to open the door of the historic building. Navigation between Teleport Points was performed with the "Push" command. Only the "Pull" command has been applied from the Teleport Point position in front of the door (Figure 9).

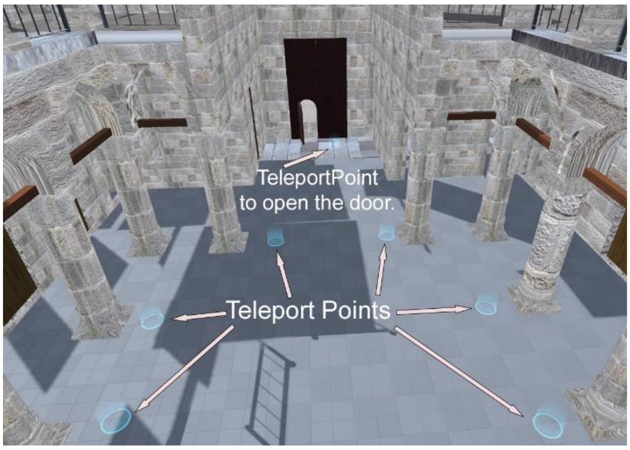

Figure 9. Teleport locations used in BCI

Time features

Both statistical and Hjorth parameters are used in the time domain. Statistical estimates of the temporal signals, such as mean, variance, standard deviation, and first/second differences, are usually taken to reduce the effect of temporal variations on signals. Statistics of the signals are given in Table 2. Hjorth, on the other hand, provides a set of three parameters (Table 2) to analyze the EEG signal in the time domain [22]. The Hjorth algorithm, which has the advantage of low computational cost, is based on variance calculation.

Table 2. Time features (1..5:statistical, 6..8:Hjorth parameters)

No	Measures	Formula
1	Power	$P = \frac{1}{N}\sum_{-\infty}^{\infty} \lvert x(t)\rvert^2$
2	Mean	$\mu = \frac{1}{N}\sum_{t=1}^{N} x(t)$
3	Standard deviation	$\sigma = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(x(t)-\mu)^2}$
4	Normalized first difference	$d_{1n} = \frac{\frac{1}{N-1}\sum_{t=1}^{N-1}\lvert x(t+1)-x(t)\rvert}{\sigma_x}$
5	Normalized second difference	$d_{2n} = \frac{\frac{1}{N-2}\sum_{t=1}^{N-2}\lvert x(t+2)-x(t)\rvert}{\sigma_x}$
6	Activity	$A = \frac{\sum_{i=1}^{N}(x(t)-\mu)^2}{N}$
7	Mobility	$M = \sqrt{\frac{\mathrm{var}\left(\frac{dx(t)}{dt}\right)}{\mathrm{var}\,(x(t))}}$
8	Complexity	$C = \frac{M\left(\frac{dx(t)}{dt}\right)}{M(x(t))}$

Frequency features

In frequency domain, we used Spectral Entropy (SE) and Fast Fourier Transform (FFT). Spectral Entropy (SE) gives information about the non-linearity situation of an EEG signal (Eq. 1). FFT can be used to show various types of frequency activity in useful ways (Eq. 2).

$$H(x) = \sum_{x \subset X} x_i \cdot log_2\ x_i \tag{1}$$

$$X_k = \sum_{n=0}^{N-1} x_n e^{-i2\pi k \frac{n}{N}}\ k = 0,1,2,\dots,N-1 \tag{2}$$

Time-Frequency features

Hilbert Huang Transform (HHT) presents momentary energy and frequency values of a signal, unlike Fourier spectral analysis which presents global energy and frequency. Since EEG signals contain more then one frequency content, HHT can't be directly used on EEG signals. To solve this problem, Huang proposed Intrinsic Mode Functions (IMF), which considers momentary EEG signals as a sum of single frequency functions. Empirical Mode Decomposition (EMD) is used to separate data into IMFs (Eq. 3). After decomposition, Hilbert transform (Eq. 4) is applied and energy-frequency-time distribution is obtained, this is also known as Hilbert spectrum.

$$x(t) = \sum_{i=1}^{n} c_i(t) + r_n(t) \tag{3}$$

$$y(t) = \frac{1}{\pi} PV \int_{-\infty}^{\infty} \frac{x(t')}{t - t'} dt' \quad (4)$$

where $c_i(t)$ is the nth extracted IMF and $r_n(t)$ is a residual function. HHT is represented by Eq. 4 to find the instantaneous frequency from the IMF, where the PV denotes the Cauchy Principal Value of the singular integral.

Discussion and results

Feature extraction from the EEG signal is one of the basic steps of classification. The features can be obtained from different domains. In this process, extracting the more dominant features from the EEG signal is important. EEG signals have a complex, nonlinear and Spatio-temporal structure. Therefore, features in the time, frequency, and time-frequency domains were searched to find the most distinctive features. All of these domains were used in this study. In addition, the features were extracted by considering the alpha, beta, and gamma bands of the EEG signals [23], [24].

The results obtained with RF and NB algorithms are given in Table 3. The extracted features for Time, Frequency and Time-Frequency are 140, 942, and 588, respectively.

Table 3. Binary task classification results (NB:Naïve Bayes, RF:Random Forest)

Push/Pull Tasks		Alpha	Beta	Gamma
Time	**NB**	69.091	58.182	60.909
	RF	81.818	76.364	80.000
Frequency	**NB**	59.091	70.909	62.727
	RF	**82.727**	80.000	65.455
Time-Frequency	**NB**	64.546	66.364	69.091
	RF	80.000	77.273	79.091

In general, the alpha channel has shown higher success. On the domain basis, the frequency domain stands out (Figure 10).

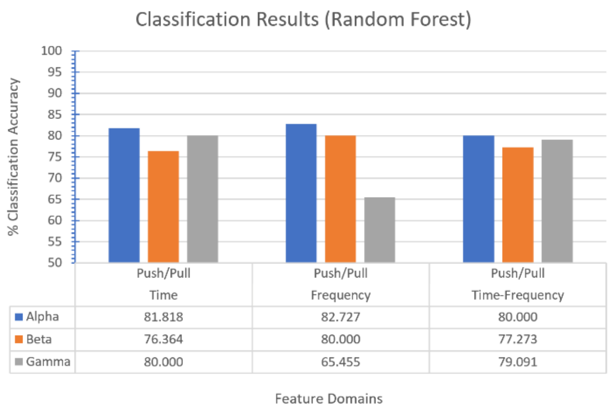

Figure 10. Binary (Push/Pull) classification results for Random Forest

Conclusion

As a result, the Metaverse can transport you to an entirely different imaginary world where you don't have constraints (as mentioned in Neal Stephenson's 1992 novel Snow Crash). With BCI, it will ensure the unlimited participation of people with disabilities in this imaginary world.

With the development of technology, digital gaming has become a more holistic and realistic experience that activates all the senses. Game-based learning and serious games often need to be viewed in the light of technology and E-Learning. Also, supporting such designs with BCI will make it a more sustainable environment for Metaverse.

BCI provides the possibility of life-changing for subjects with motor impairments. Because this system allows them to perform physical actions that they would not otherwise be able to do. Since BCI converts brain signals to command results using artificial intelligence algorithms, these commands can be encoded as commands that will provide unlimited control in the Metaverse environment.

Cyber-discomfort in the virtual environment is a relatively common, undesirable side effect of immersive interfaces that causes various irritating symptoms, such as nausea, headaches, disorientation, and fatigue. Although less common, more severe symptoms, such as postural instability, can also result from prolonged exposure to virtual interfaces. Improvements in the direction of eliminating these discomforts by making locomotion movements more natural can be done in future studies.

Data availability

The dataset will be published at https://eegdatasets.erzurum.edu.tr

Ethics committee approval and conflict of interest statement

This study, which included human participants, was reviewed and approved by the Scientific Research and Publication Ethics Committee of Erzurum Technical University-ETU (11-2-20052021), Erzurum, TUR. The patients/participants provided their written informed consent to participate in this study. There is no conflict of interest with any person / institution in the article prepared.

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