# Optimizing SSVEP-based BCI training through Adversarial Generative Neural Networks

**Guilherme R. Figueiredo[1], Sarah N. Carvalho[2], Guilherme V. Vargas[3], Vitor M. Barbosa[4], Cecilia S. A. Peixoto[5], Harlei M. A. Leite[2,*]**

[1] Institute of Exact and Applied Sciences, Federal University of Ouro, Brazil,
*Email: guilherme.rf@aluno.ufop.edu.br*
[2] Electronic Engineering Division, Aeronautics Institute of Technology, Brazil,
*Email: sarahnc@ita.br, harlei@ita.br*
[3]Faculty of Electrical and Computer Engineering, University of Campinas, Brazil,
*Email: g229960@dac.unicamp.br*
[4]A3Data, Belo Horizonte, Brazil,
*Email: vitor_martinsb@hotmail.com*
[5] Department of Computing, Virtual University of São Paulo, Brazil.
*Email: cecilia.peixoto@univesp.br*
[*] *Corresponding author*

***Abstract:*** **Brain-computer interfaces (BCIs) based on steady-state visually evoked potential (SSVEP) use brain activity to control external devices, with applications ranging from assistive technologies to gaming. Typically, BCI systems are developed using supervised learning techniques that require labelled brain signals. However, acquiring these labelled signals can be tiring and time-consuming, especially for subjects with disabilities. In this study, we evaluated the performance impact of using synthetic brain signals to train and calibrate an SSVEP-based BCI system. Specifically, we used generative adversarial networks (GANs) to synthesize brain signals with SSVEP information, considering cases with two and four visual stimuli. Four scenarios with different proportions of real vs. synthetic brain signals were evaluated: Scenario 1 (baseline) using only real data and Scenarios 2-4 with 10%, 20% and 30% of real data replaced by synthetic data, respectively. Our results reveal that synthetic data can be used to train the BCI without a performance loss across the tested scenarios when two visual stimuli are used and with an average performance reduction compared to baseline of 7% (Scenario 2), 10,3% (Scenario 3) and 9,3% (Scenario 4) for four stimuli. Furthermore, considering each recording has duration of 2 seconds, by replacing 30% of real data with synthetic data, there is an immediate time-saving of 48 s and 96 s in the cases with two and four visual stimuli, respectively. This trade-off between accuracy and efficiency has significant implications for improving the usability and accessibility of SSVEP-based BCI, especially for assistive applications.**

***Keywords:*** **Brain-Computer Interface, Generative Adversarial Networks, Human-Computer Interface, Steady-State Visually Evoked Potential.**

## I. INTRODUCTION

Brain-computer interface (BCI) is a sophisticated technology that captures and translates brain signals into commands for devices and applications. The primary advantage of BCI systems lies in their ability to bypass traditional neuromuscular output pathways, rendering this mode of human-computer interaction highly desirable for the development of assistive technologies [1,2].

Subjects with physical impairments, such as spinal cord injuries, cerebral palsy, or amyotrophic lateral sclerosis can perform tasks and interact with technology in ways that were previously impossible. One example is the use of BCI technology to control robotic arms. This breakthrough allows individuals with paralysis to regain the ability to grasp and manipulate objects, significantly enhancing their overall quality of life [3]. However, BCI systems are still in the development stage. For their popularization, some challenges need to be overcome. Brain signal quality is critical in BCI systems, as accurate and reliable brain signals are necessary for effective human-computer interaction. However, the quality of brain signals can be impacted by a variety of factors, such as movement artifacts and electromagnetic interference [4].

Another challenge, it is the time for collecting brain signals exclusively for the training and calibration of the system [5]. In this work, we address precisely this issue, attempting to reduce the time required for collecting brain signals by substituting real data with synthetic data, and we assess how this impacts the final performance of the Steady-State Visually Evoked Potential (SSVEP)-based BCI. The synthetic brain signals were generated by a Vanilla Generative Adversarial Network (GAN) [6].

This manuscript is organized as follows: Section II presents a brief revision with the related work. Section III presents the four stages of an SSVEP-based BCI: acquisition, pre-processing, feature extraction and classification. Section IV presents the structure of a GAN and its application in the generation of SSVEP signals. Section V describes the experimental setup. Section VI presents the results and discussion, while Section VII contains our conclusions and final remarks.

## II. RELATED WORK

Currently, examples of GANs in generating EEG signals can be found in the literature. In [7], the authors propose the use of Deep Convolutional (DCGAN), Wasserstein GAN (WGAN), and Vibrational Auto-Encoders (VAE) for generating EEG signals during the training phase of SSVEP-based BCI systems. The study presents the entire GAN training process and the application of synthetic EEG signals in the training phase of the BCI system. The method improved the BCI system performance by 3% when using synthetic data in conjunction with real data during the BCI system training stage. As a future work, the authors suggest analyzing the influence of the quantity of synthetic data during the training and classification stages.

In [8], the authors address the challenge of training SSVEP-based BCI systems, which require a large amount of data collection and can be cumbersome for the user. To optimize this stage, they propose the use of a GAN-based end-to-end signal transformation network for Time-window length Extension, termed TEGAN. The proposed augmentation method demonstrated a substantial improvement in the recognition accuracy of both traditional and deep learning methods. The authors highlight that optimizing the training stage of BCI systems remains a challenge, and the ultimate goal for BCI researchers is to develop a plug-and-play BCI system without the need for calibration and training.

In [9], the authors propose the use of WGAN for generating EEG signals for motor imagery tasks. It presents four models and evaluates them using the metrics Inception Score (IS), Frechet Inception Distance (FID), Euclidean Distance, and Sliced Wasserstein Distance (SWD). The model generated EEG signals similar to real ones, making it suitable for use in motor imagery tasks. As a future work, the authors suggest testing new network topologies and exploring the influence of network hyper parameters on performance.

In [10], the authors propose the use of the Source Aliasing Matrix Estimation (SAME) method to generate synthetic EEG data for the training stage of SSVEP-based BCI systems. The technique resulted in a 7.5% increase in the accuracy of the BCI system, demonstrating the effectiveness of the data generation technique.

A common viewpoint among the articles is the challenge of generating artificial EEG signals that resemble real signals. Despite the capabilities of GAN techniques to generate EEG signals, the studies acknowledge that this field is still in a developmental stage, requiring further efforts to reach a definitive model. The endeavour to develop algorithms for EEG signal generation is driven by the need to expedite the training phase of BCI systems and reduce susceptibility to errors. Only with a fast, reliable and secure calibration and training stage can BCI systems become a viable and realistic option for human-computer interface.

## III. SSVEP-BASED BCI

SSVEP-based BCI is a paradigm of BCI that relies on SSVEP to interpret the user's intention. SSVEP are rhythmic brain signals that are elicited when a user focuses on a visual stimulus that is flickering at a specific frequency. These signals can be detected using electroencephalography (EEG) electrodes placed on the user's scalp [11]. Figure 1 shows an SSVEP signal of a user exposed to a flickering stimulus at 10 Hz.

The process of translating brain signals into commands in an SSVEP-based BCI consists of 4 steps: acquisition, pre-processing, feature extraction and classification [12]. Figure 2 shows the architecture of a BCI system. In the following subsections, each step is described and the techniques used for the construction of the BCI system are presented.

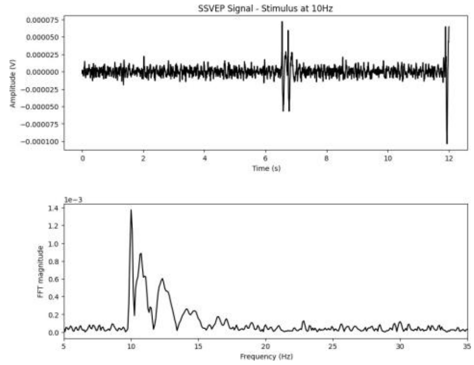


Fig.1. SSVEP signal from channel Oz in time and frequency domain.

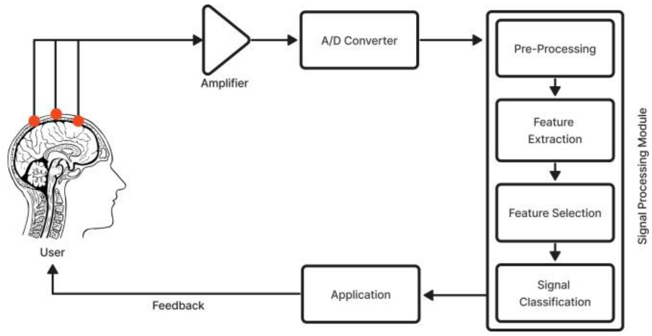


Fig.2. BCI system architecture.

### A. Acquisition

The acquisition is the first step in the process of building an SSVEP-based BCI system. It involves recording electrical signals from the user's brain using a set of electrodes placed on the scalp. The electrodes detect the small electrical potentials generated by the neurons in the brain, which are then amplified and digitized using an analog-to-digital converter (ADC) [2].

During acquisition, it is important to ensure that the electrical signals are not contaminated by external noise or artifacts, which can interfere with the analysis of the signals. To minimize these sources of interference is important to apply pre-processing techniques before the feature extraction step [13].

The acquisition stage typically involves the use of a visual stimulus, such as a flashing light, to elicit SSVEP responses in the user's brain [14]. The stimulus is presented at a specific frequency, which is known as the target frequency. The user is instructed to focus their attention on a flickering square projected on the LCD monitor, and the resulting SSVEP signals are recorded by the electrodes.

This study utilized a database of EEG brain signals of 32 subjects collected with 16 electrodes (O1, O2, Oz, POz, Pz, PO3, PO4, PO7, PO8, P1, P2, Cz, C1, C2, CPz, and FCz) following the 10-10 system. The signals were sampled at a rate of 250 Hz and included 8 acquisitions of 12 seconds for 4 frequencies (6, 10, 12, and 15 Hz), resulting in a total of

32 acquisitions per subject. The EEG equipment used was a g®.SAHARAsys dry-electrode cap with 16 channels and a g®.USBamp biosignal amplifier [15].

The four frequencies employed were selected for their ability to evoke a robust SSVEP signal and their distinctiveness due to not being sub-multiples of one another. By using these four frequencies, it is feasible to construct SSVEP-based BCI systems with four commands, which are adequate for controlling applications of moderate to high complexity.

In this study, only channel Oz was considered to assess the capability of the GAN in generating synthetic data that follows the same pattern as a specific channel, without the influence of other channel data. This approach allowed us to examine the impact of synthetic data solely on channel Oz, in addition to this channel being demonstrated to exhibit clear SSVEP peaks [16].

### *B. Pre-processing*

During the pre-processing, the EEG signal undergoes conditioning to prepare it for subsequent analysis. Various techniques are employed to remove artifacts, interference, and signal noise that may be present in the raw data. These pre-processing methods aim to enhance the quality and reliability of the EEG signal, ensuring that accurate and meaningful information can be extracted [12, 17].

In this work, the pre-processing stage performed an analogic bandpass filter from 5 to 30 Hz and the signal was segmented into 2-second windows. No other typical filters for artifacts extraction were applied since the goal was to evaluate the performance of the BCI system trained with real and synthetic samples, and the application of filtering techniques could mask the true influence of synthetic data on the BCI system training stage.

### *C. Feature extraction*

Feature extraction involves the computation of relevant information from the raw EEG signals that correspond to the user’s visual response to each flickering stimulus. In this process, the goal is to extract robust and discriminative features that can be used to distinguish between different frequencies of visual stimuli [18].

There are different methods for feature extraction, including time-domain, frequency-domain, and time-frequency analysis. Time-domain features can be based on statistical moments, such as mean, variance, skewness, and kurtosis, or on wavelet coefficients. Frequency domain features can be obtained from the Fourier transform, such as spectral power, phase coherence, or the amplitude of specific frequency bands. Time-frequency analysis can also be used to extract features that capture changes in the signal over time and across different frequency bands.

In this study, we used the Fast Fourier Transform (FFT) [19] to obtain information on the spectral content of the EEG signal and to extract features that correspond to the user’s response at different frequencies associated with the visual stimuli. The extracted features were defined as the amplitude of the power spectral density (PSD) estimate with the FFT algorithm at the frequencies of interest (i.e., 6, 10, 12 and 15 Hz) in each 2 s window of the EEG signal. This technique is extensively utilized in feature extraction for SSVEP-based BCI systems due to its inherent simplicity and minimal computational demands. Its efficiency enables the possibility of deploying the BCI system on a microcontroller if required, while also serving as an immediate method for identifying SSVEP signals [20].

### *D. Classification*

Classification refers to the process of identifying the user’s intended target based on the features extracted from the EEG signals in response to different frequencies of visual stimuli [21].

The classification operates in two modes. First, in training mode, the classifier is trained to recognize the user’s brain signal pattern. The system then, in the online mode, receives new brain signals and classifies them [2].

There are various methods for classification in SSVEP-based BCI systems, including linear discriminant analysis (LDA), support vector machines (SVM) and neural networks. In this study, we used LDA [18]. LDA is a linear method that finds a hyperplane in the feature space that best separates the data into different classes. The performance of the classification algorithm is typically evaluated using metrics such as accuracy [22].

## IV. EEG-SSVEP SIGNAL GENERATION USING GAN

GANs are a type of deep learning architecture formed by two neural networks: a generator and a discriminator. The goal of a GAN is to generate new data that are similar to a set of training data, without having explicit access to the data distribution [6].

The generator network takes as input a random noise vector and generates a new sample that is intended to be similar to the training data. The discriminator network takes both real and generated samples as input and is trained to distinguish between them. The two networks are trained simultaneously, with the generator trying to produce samples that are realistic enough to fool the discriminator, while the discriminator tries to correctly classify real and generated samples.

The GAN training process is iterative and adversarial, which means that the generator and the discriminator are in a constant battle, each trying to out-smart the other. As training progresses, the generator learns to generate more realistic samples, while the discriminator becomes better at distinguishing between real and generated data. Ideally, the training process reaches a point where the generator produces samples that are indistinguishable from the real data. Figure 3 shows the architecture of a GAN.

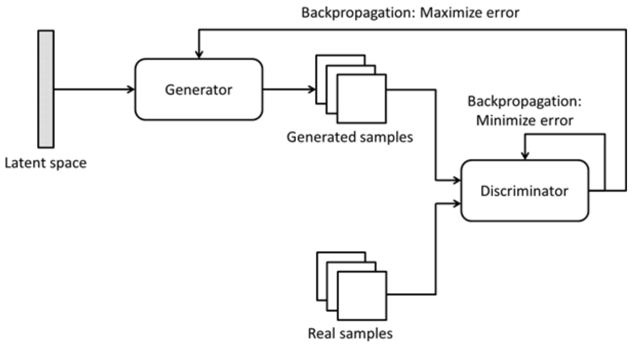


Fig.3. Generative Adversarial Network architecture.

GANs have been increasingly used in the field of neuroscience to generate realistic EEG signals [23]. One of the key challenges in using GANs for EEG signal generation is ensuring that the generated signals are realistic and physiologically plausible. Several techniques have been proposed to ensure that the generated signals have the desired properties [24].

In this study, we developed a GAN to generate EEG-SSVEP signals to train the linear classifier of an SSVEP-based BCI system, intending to reduce the amount of brain signal collection required during the training stage of a BCI system.

Figure 4 shows the generator network, which is composed of 6 layers with a total of 1,207,552 trainable parameters. The binary cross-entropy loss function was used, and the Adam optimization method was adopted.

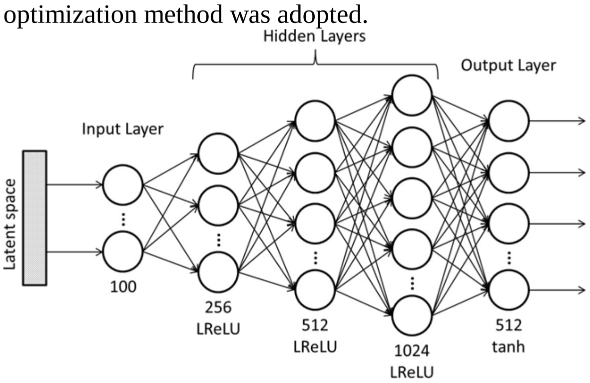


Fig. 4. Generator architecture.

Figure 5 shows the discriminator, composed of 7 layers, totalling 1,181,697 trainable parameters. The binary cross-entropy loss function was used, and the Adam optimization method was adopted.

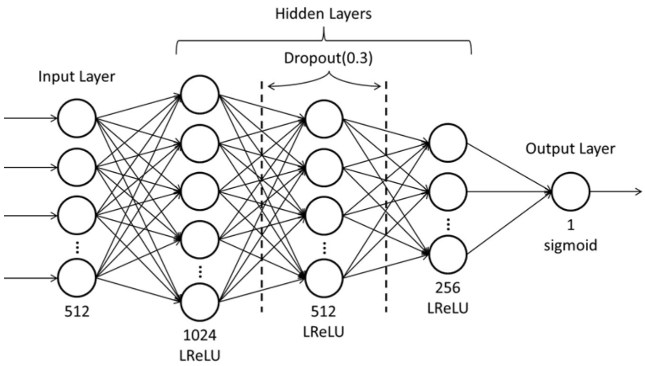


Fig. 5. Discriminator architecture.

The choice of the number of neurons, layers and hyper parameters in a neural network is a crucial factor in determining its performance, but it is done empirically.

## V. EXPERIMENTAL SETUP

For each of the 32 subjects, four GANs were trained, one for each frequency (6, 10, 12 and 15 Hz), to generate the synthetic database. For the GAN training phase, the dataset of each subject was partitioned. Initially, the 32 acquisitions of each subject (8 for each frequency) were windowed into 2 seconds, resulting in a total of 48 windows for each frequency. Subsequently, for each frequency, 10 windows (20%) were selected for the BCI validation stage, while the remaining 38 windows (80%) were chosen for the GAN training phase.

With both real and synthetic data for each subject in the database, two SSVEP-based BCIs were employed, where the first one discriminated between two classes (10 and 15 Hz), and the second one discriminated among four classes (6, 10, 12, and 15 Hz). For each BCI, four scenarios were simulated, as depicted in Table 1.

TABLE I. PROPORTION OF REAL AND SYNTHETIC DATA FOR EACH SCENARIO AND THE MINIMAL TIME-SAVING.

| Scenario | Real Data | | Synthetic Data | | Time-saving (s) | |
|---|---|---|---|---|---|---|
| | Percent | Samples | Percent | Samples | 2 stimuli | 4 stimuli |
| 1 | 100% | 38 | 0% | 0 | 0 | 0 |
| 2 | 90% | 34 | 10% | 4 | 8 | 16 |
| 3 | 80% | 30 | 20% | 8 | 16 | 32 |
| 4 | 70% | 26 | 30% | 12 | 24 | 96 |

The first scenario was proposed to obtain the performance of the BCI trained solely with real data for each subject. This information is crucial to enable a comparison with scenarios involving the use of synthetic data. Scenarios 2-4 use 10%, 20%, and 30% of synthetic data, respectively, to understand how the quantity of synthetic data impacts the BCI system training stage. In all cases, a 20-fold cross-validation was performed, and the average accuracy was used as the performance metric for the system.

Figure 6 illustrates the process of blending real and synthetic data. For each frequency, a variable number of windows, depending on the scenario, are randomly selected for replacement with synthetic data of the corresponding frequency. The synthetic data is randomly chosen from the synthetic database.

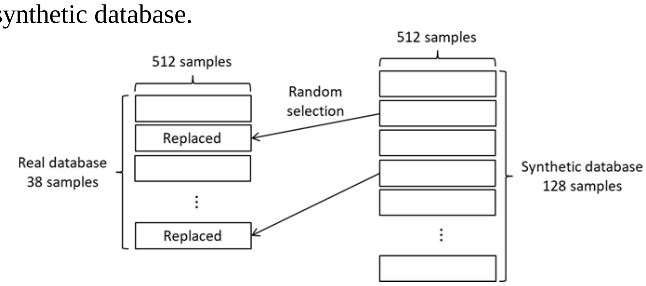


Fig. 6. Process of blending real and synthetic data.

## VI. RESULTS AND DISCUSSION

Our results have provided valuable insights into the performance of an SSVEP-based BCI system concerning the composition of training data. Table 2 presents the results of the BCI simulation distinguishing two commands for four distinct scenarios. In Scenario 1, using only real data in the training phase, an average accuracy of 59.6%±6.2% was observed. Remarkably, Subject 8 achieved the highest average performance, with 95.3%±4.7%, whereas Subject 2 exhibited the lowest average performance, at 45.5%±7.6%. These results indicate significant variability in accuracy among the subjects, due to various factors, such as differences in brain activity, concentration skills, tolerance to noise, and adaptation to the BCI operating principle. Additionally, variability may arise due to natural variations in brain responses to the visual stimulations used in SSVEP paradigms.

Upon incorporating 10% of synthetic data (Scenario 2), a slight decrease in accuracy to 58.9% ±5.1% was observed. This decline was gradual as the proportion of synthetic data increased. With 20% synthetic data (Scenario 3), accuracy dropped to 57.3%±5.9%, and with 30% synthetic data, accuracy decreased to 55.8% ±6.7%. Although the decrease in accuracy indicates a negative correlation between BCI precision and the inclusion of synthetic data, the difference between the mean of Scenario 1 (100% real data) and the mean of Scenario 3 (30% synthetic data) was only 3.8%, falling within the standard deviation of Scenario 1. The ANOVA analysis revealed no statistically significant difference ($p > 0.05$) in accuracy among the four considered scenarios.

Table 3 shows the results for an SSVEP-based BCI with four visual stimuli. In Scenario 1, with 100% real data, the accuracy was 37.1% ±5.1%. The introduction of synthetic data negatively impacted the performance, leading to a decrease in accuracy to 30.1% ±5.0% with 10% synthetic data, 27.4%±5.0% with 20% synthetic data, and 26.4%± 4.8% with 30% synthetic data. For all scenarios, the accuracy of the BCI distinguishing 4 frequencies was lower than the accuracy of the BCI distinguishing 2 frequencies, as expected, since the complexity of the classification task is related to the number of classes to be distinguished. The ANOVA test revealed a statistically significant difference ($p < 0.05$) between the baseline and Scenarios 2-4.

The gradual decrease in accuracy was accompanied by a significant reduction in the time and resources required to train the BCI. The incorporation of synthetic data provided a more efficient approach, allowing the training process to be faster and less labor-intensive. In scenarios where real data availability is limited, the inclusion of synthetic data in the training stage can be a viable solution. It is essential to recognize that while accuracy decreased with the use of synthetic data, this decline does not render the use of synthetic data in BCI system training impractical. There is a need to balance the desired accuracy and the time required for the training stage for each type of user, considering their limitations.

TABLE II. SSVEP-BASED BCI PERFORMANCE FOR 2 VISUAL STIMULI USING REAL AND SYNTHETIC BRAIN DATA.

| Subject | 100% real | | 10% synthetic | | 20% synthetic | | 30% synthetic | |
|---|---|---|---|---|---|---|---|---|
| | Acc. | Std. | Acc. | Std. | Acc. | Std. | Acc. | Std. |
| SUBJ1 | 52.8 | 5.3 | 50.0 | 0.0 | 50.0 | 0.0 | 50.0 | 0.0 |
| SUBJ2 | 45.5 | 7.6 | 49.5 | 3.2 | 50.3 | 3.4 | 50.0 | 2.8 |
| SUBJ3 | 48.5 | 5.2 | 47.0 | 4.4 | 47.0 | 2,5 | 46.3 | 2.2 |
| SUBJ4 | 48.0 | 4.1 | 46.0 | 6.2 | 42.8 | 7.3 | 45.5 | 6.3 |
| SUBJ5 | 48.8 | 7.0 | 42.8 | 4.7 | 46.3 | 5.6 | 44.8 | 4.7 |
| SUBJ6 | 50.5 | 7.1 | 52.0 | 7.7 | 51.5 | 2.9 | 50.8 | 3.7 |
| SUBJ7 | 51.5 | 6.7 | 50.0 | 0.0 | 52.8 | 8.5 | 57.3 | 12.9 |
| SUBJ8 | 95.3 | 4.7 | 94.3 | 5.7 | 58.5 | 21.0 | 34.3 | 20.5 |
| SUBJ9 | 49.8 | 1.1 | 52.8 | 5.3 | 52.3 | 3.4 | 51.8 | 4.7 |
| SUBJ10 | 60.0 | 7.1 | 57.8 | 8.0 | 56.0 | 8.0 | 57.8 | 12.3 |
| SUBJ11 | 83.5 | 11.4 | 82.0 | 2.5 | 81.3 | 2.8 | 79.8 | 3.8 |
| SUBJ12 | 82.8 | 6.6 | 90.3 | 5.5 | 90.8 | 1.8 | 80.3 | 17.4 |
| SUBJ13 | 48.5 | 8.1 | 50.0 | 5.6 | 49.5 | 5.1 | 50.8 | 3.4 |
| SUBJ14 | 49.0 | 4.5 | 35.0 | 4.9 | 37.8 | 3.4 | 38.0 | 3.0 |
| SUBJ15 | 48.8 | 3.9 | 50.5 | 5.6 | 50.8 | 3.7 | 49.3 | 5.2 |
| SUBJ16 | 48.0 | 4.7 | 50.3 | 7.9 | 52.3 | 5.7 | 50.8 | 6.7 |
| SUBJ17 | 72.5 | 8.0 | 67.8 | 13.0 | 72.3 | 9.2 | 73.3 | 8.5 |
| SUBJ18 | 57.5 | 9.0 | 54.5 | 7.2 | 56.8 | 6.5 | 58.5 | 3.7 |
| SUBJ19 | 84.5 | 7.4 | 87.8 | 7.0 | 87.5 | 6.6 | 88.5 | 7.3 |
| SUBJ20 | 50.3 | 4.1 | 48.8 | 3.2 | 48.5 | 3.7 | 50.0 | 0.0 |
| SUBJ21 | 75.0 | 5.8 | 77.3 | 3.8 | 72.8 | 11.6 | 65.5 | 13.0 |
| SUBJ22 | 47.8 | 5.5 | 45.0 | 9.2 | 44.8 | 6.6 | 43.5 | 6.1 |
| SUBJ23 | 50.0 | 0,0 | 47.5 | 4.7 | 48.5 | 6.5 | 44.5 | 3.2 |
| SUBJ24 | 49.5 | 4.8 | 51.3 | 2.8 | 50.5 | 1.5 | 50.0 | 0.0 |
| SUBJ25 | 47.5 | 12.7 | 57.0 | 5.5 | 54.3 | 6.1 | 51.5 | 4.0 |
| SUBJ26 | 49.0 | 3.5 | 43.0 | 7.1 | 43.5 | 5.6 | 47.3 | 6.6 |
| SUBJ27 | 63.5 | 13.6 | 65.5 | 3.9 | 64.0 | 6.2 | 61.5 | 8.1 |
| SUBJ28 | 81.0 | 9.3 | 60.3 | 11.6 | 47.5 | 10.7 | 44.3 | 7.5 |
| SUBJ29 | 50.5 | 1.5 | 60.0 | 0.0 | 62.3 | 3.8 | 61.8 | 2.9 |
| SUBJ30 | 91.0 | 5.8 | 99.3 | 1.8 | 99.3 | 1.8 | 94.5 | 11.5 |
| SUBJ31 | 51.0 | 4.5 | 50.0 | 0.0 | 52.0 | 8.9 | 60.3 | 16.3 |
| SUBJ32 | 75.0 | 9.3 | 69.0 | 5.5 | 58.5 | 9.0 | 52.3 | 6.4 |
| Mean | 59.6 | 6.2 | 58.9 | 5.1 | 57.3 | 5.9 | 55.8 | 6.7 |

From the human-computer interface perspective, this study holds significant implications by exploring the intersection between real data, synthetic data, and brain-computer interface performance. Understanding the feasibility of employing synthetic data to expedite the training stage, BCIs can be developed with a user-centered design approach. This approach considers not only the classifier accuracy but also the user experience. User acceptability while interacting with a BCI system is a crucial factor in the acceptance and adoption of this technology.

TABLE III. SSVEP-BASED BCI PERFORMANCE FOR 4 VISUAL STIMULI USING REAL AND SYNTHETIC BRAIN DATA.

| Subject | 100% real | | 10% synthetic | | 20% synthetic | | 30% synthetic | |
|---|---|---|---|---|---|---|---|---|
| | Acc. | Std. | Acc. | Std. | Acc. | Std. | Acc. | Std. |
| SUBJ1 | 47.6 | 5.1 | 21.1 | 5.7 | 22.1 | 4.7 | 21.4 | 3.0 |
| SUBJ2 | 23.4 | 5.0 | 17.9 | 5.5 | 14.3 | 4.6 | 15.4 | 3.7 |
| SUBJ3 | 24.4 | 5.0 | 20.1 | 4.4 | 16.5 | 5.3 | 17.3 | 4.7 |
| SUBJ4 | 22.8 | 6.2 | 24.0 | 3.4 | 25.9 | 3.7 | 26.6 | 3.8 |
| SUBJ5 | 24.4 | 4.5 | 29.3 | 5.0 | 30.8 | 4.8 | 30.3 | 6.0 |
| SUBJ6 | 28.4 | 6.0 | 27.5 | 5.6 | 33.1 | 4.4 | 29.5 | 4.8 |
| SUBJ7 | 25.5 | 1.5 | 25.0 | 0.0 | 25.0 | 0.0 | 24.9 | 0.6 |
| SUBJ8 | 86.4 | 3.6 | 38.5 | 6.8 | 18.3 | 8.6 | 8.1 | 5.7 |
| SUBJ9 | 24.3 | 5.8 | 24.9 | 5.4 | 23.4 | 2.8 | 25.5 | 3.9 |
| SUBJ10 | 40.4 | 3.8 | 24.5 | 5.2 | 19.0 | 3.2 | 18.8 | 2.2 |
| SUBJ11 | 57.1 | 6.0 | 42.9 | 7.1 | 39.5 | 7.8 | 36.0 | 10.7 |
| SUBJ12 | 74.6 | 7.9 | 68.4 | 7.0 | 55.5 | 12.2 | 46.0 | 13.0 |
| SUBJ13 | 23.5 | 3.3 | 27.4 | 5.2 | 28.5 | 4.2 | 29.3 | 3.6 |
| SUBJ14 | 26.4 | 3.2 | 22.5 | 4.2 | 23.6 | 3.6 | 22.9 | 4.7 |
| SUBJ15 | 27.9 | 5.6 | 21.8 | 3.6 | 20.8 | 5.0 | 19.1 | 3.8 |
| SUBJ16 | 24.5 | 4.1 | 23.9 | 4.8 | 25.1 | 4.6 | 27.0 | 3.1 |
| SUBJ17 | 41.3 | 7.3 | 25.4 | 5.4 | 26.4 | 4.0 | 24.8 | 2.8 |
| SUBJ18 | 27.5 | 5.9 | 32.3 | 2.7 | 29.9 | 4.3 | 30.4 | 3.3 |
| SUBJ19 | 61.3 | 3.8 | 43.1 | 5.6 | 43.5 | 5.9 | 43.1 | 5.1 |
| SUBJ20 | 26.9 | 4.6 | 27.8 | 5.4 | 29.3 | 4.6 | 29.0 | 4.2 |
| SUBJ21 | 53.5 | 4.9 | 41.4 | 5.3 | 39.8 | 4.9 | 39.9 | 6.0 |
| SUBJ22 | 19.4 | 5.1 | 19.9 | 4.4 | 18.4 | 3.8 | 18.4 | 4.7 |
| SUBJ23 | 27.5 | 5.2 | 23.6 | 4.3 | 27.0 | 6.1 | 31.8 | 6.0 |
| SUBJ24 | 25.9 | 4.7 | 30.0 | 6.2 | 31.9 | 4.7 | 31.0 | 3.6 |
| SUBJ25 | 20.9 | 4.5 | 21.9 | 4.2 | 17.3 | 2.4 | 15.9 | 3.1 |
| SUBJ26 | 23.9 | 6.5 | 25.8 | 3.0 | 24.0 | 3.2 | 23.6 | 4.4 |
| SUBJ27 | 43.1 | 6.6 | 37.8 | 6.2 | 40.1 | 3.6 | 40.0 | 3.7 |
| SUBJ28 | 50.5 | 6.5 | 26.6 | 5.3 | 22.3 | 5.7 | 22.5 | 5.1 |
| SUBJ29 | 24.4 | 4.3 | 29.1 | 3.5 | 28.5 | 3.8 | 29.4 | 3.3 |
| SUBJ30 | 84.1 | 4.2 | 67.9 | 11.0 | 34.6 | 12.4 | 24.9 | 6.5 |
| SUBJ31 | 23.3 | 6.9 | 21.4 | 4.7 | 19.6 | 7.6 | 22.5 | 8.3 |
| SUBJ32 | 52.5 | 6.3 | 29.9 | 5.2 | 23.3 | 4.8 | 20.8 | 4.9 |
| Mean | 37.1 | 5.1 | 30.1 | 5.0 | 27.4 | 5.0 | 26.4 | 4.8 |

## VII. CONCLUSIONS

Currently, there are several types of human-computer interaction devices, such as keyboards, mouse, virtual reality glasses, touchscreens, motion detectors, eye-tracking, among others. These devices have evolved over time, becoming more precise and anatomically better, improving the user experience. From the perspective of a user without physical limitations, it can be said that current interaction technologies are efficient and adequate. However, when analyzing from the perspective of users with physical limitations, a series of challenges need to be overcome.

BCI system is a technology that enables interaction without the need for muscle movement, making it possible for people with severe physical limitations to communicate. Due to its operation depending on the processing and classification of brain signals, the accuracy provided by the BCI system can vary significantly depending on the user and usage conditions. This variance in accuracy makes the adoption of the technology a challenge, especially in the context of assistive technology, which requires high accuracy and predictability.

Another characteristic that hinders the popularization of BCI systems is the difficulty in using EEG equipment, electrode placement, and system training, which requires the assistance of experts for proper operation. In addition to this, the high cost of these devices also inhibits potential users. Currently, several works attempt to overcome these challenges, either by building cheaper and easier-to-use equipment or by developing techniques for processing biological signals and classification.

This study proposed the use of a generative adversarial network to reduce the time required for the training stage of an SSVEP-based BCI system. For an SSVEP-based BCI with two visual stimuli, there was no statistically significant difference in mean accuracies between the scenario baseline (with real data) and the other scenarios involving synthetic data in different amounts. For a BCI with four visual stimuli, a decrease of 10.3% in the worst-case in average accuracy was observed with the inclusion of synthetic data, this decrease was accompanied by a reduction of the training process time of about 1 minute. This trade-off between accuracy and efficiency is important, especially in contexts with users that have a disability and belong to either the elderly or pediatric populations.

Furthermore, this study emphasizes the importance of a user-centered approach when developing BCI systems. User acceptability while interacting with a BCI system, even with a slight decrease in accuracy, is crucial for the successful adoption of this technology. Given the potential user base of individuals with physical limitations, the human factor is amplified.

As future work, we suggest the study of other topologies of generative adversarial networks in the context of EEG signal generation, as well as the search for combinations of feature extraction and classification techniques for BCI systems that make use of synthetic data in the training stage. Another approach that can be further analysed is the use of GANs with more sources, considering the spatial combination of electrodes on the scalp.

## VIII. DECLARATIONS

Data availability: The data that support the findings of this study are not openly available due to reasons of sensitivity and are available from the corresponding author upon reasonable request. Data are located in controlled access data storage at Aeronautics Institute of Technology.

Ethics Approval: The acquisition protocol was approved by the Ethics Committee of the University of Campinas (n. 791/2010).

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