Incremental EEG Analysis using Goertzel Transform for SSVEP-based HMI

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Abstract:
This work presents a Human-Machine Interface (HMI) development based on Steady-State Visual Evoked Potentials (SSVEPs). The Goertzel transform was used in this proposal to identify the stimulus frequencies present in electroencephalogram (EEG) signals. A maze game was created as a mobile application to relate the stimuli to navigation commands. The preliminary results show a hit rate above 85%. Besides, the system is structured to insert Augmented Reality (AR) tools.

Resumo:
Este trabalho apresenta um desenvolvimento de Interface Homem-Máquina (HMI) baseado em Potenciais Evocados Visuais de Estado Estável (SSVEPs). A transformada de Goertzel foi utilizada nesta proposta para identificar as frequências de estímulo presentes em sinais de eletroencefalograma (EEG). Um jogo labirinto foi criado como um aplicativo móvel para relacionar os estímulos aos comandos de navegação. Os resultados preliminares mostram uma taxa de acerto acima de 85%. Além disso, o sistema está estruturado para inserir ferramentas de Realidade Aumentada (AR).

Keywords: EEG; SSVEP; HMI; Goertzel Transform.
Palavras-chaves: EEG; SSVEP; IHM; Transformada de Goertzel.

1. INTRODUCTION

The brain is known as the most complex organ in the human body controlling the senses and emotions and promoting human interaction with the environment. Then, Human Machine Interfaces (HMIs) arose from the idea that the reading of individual brain activities can set an external device (LEVINE et al., 2000), (STAWICKI et al., 2016).

Steady-State Visual Evoked Potentials (SSVEPs) are brain responses well-measured in the visual and parietal cortical areas considering flickering visual stimulation (VIALATTE et al., 2010). The SSVEPs are used as basis in Brain Computer-Interfaces (BCIs), as well as other kinds of Human-Machine Interfaces (HMI) which allows its user to choose commands associated with different stimulus frequencies. For example, SSVEP-based HMI could be used to give autonomy to people with motor disabilities or even be used for immersion applications and digital games (MASON et al., 2004), (BAYLISS, 2003).

The SSVEPs contain stationary periodic oscillations with observable peaks in the frequency spectrum (VIALATTE et al., 2010). In many cases, a non-parametric technique is employed to estimate the spectrum, such as the periodogram (MANOLAKIS et al., 2005). However, according to Oikonomou et al. (2016) the periodogram method has problems related to spectral leakage and frequency resolution. Furthermore, from a statistical point of view, the periodogram befalls an inconsistent estimator.

The Goertzel transform is another method for calculating the discrete Fourier transform coefficients. This transform uses arithmetic operations to determine a unique value in each iteration, calculating these coefficients is a less complex, numerically more efficient, and computationally less expensive operation. These are necessary characteristics for the implementation of an HMI in an embedded system. Among the possible SSVEP-based HMI, this work chose the development of a maze game for cell phones, in which the stimulus frequency identification is associated with the player movement.

The remainder of this paper is organized as follows. Section 2 refers to the methodology for signal processing and mobile game development. Section 3 describes the results from the Goertzel transform and the reliability of stimulus frequencies. Section 4 provides the concluding remarks.

2. MATERIALS AND METHODS

2.1 Signal Database

In the initial step, the Goertzel transform was applied in an SSVEP database acquired in (MüLLER, 2012). The experiments were performed according to the rules of the Ethics Committee of the Federal University of Espirito Santo, under registration number CEP-048/08. This database is composed of EEG signals from 12 EEG channels of 9 volunteers with a stimulus sampling rate of 600 samples per second. All the volunteers are male ones with an average age of 27.3 years and a standard deviation of 4.2. The 12 EEG channels correspond to P7, PO7, P5, PO3, POz, PO4, P6, PO8, P8, O1, O2 and Oz electrodes, as shown in Fig. 1.

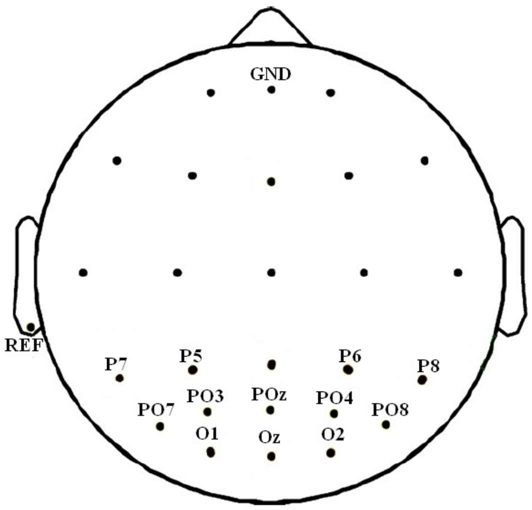

Figure 1. Electrode placement for recording EEG signal (MüLLER, 2012)

The EEG acquisition equipment was the BrainNet36, from Lynx Ltda. The reference and ground electrodes were positioned in the left ear and the forehead, respectively. For data acquisition, each volunteer was accommodated comfortably in a chair while observing a 17"LCD monitor placed at 70 cm from the chair. In the center of the screen, there was a stripe composed of black and white reverse patterns as on a chessboard. The volunteers were exposed to the stimuli flickering at frequencies of 5.6 Hz, 6.4 Hz, 6.9 Hz, and 8.0 Hz one at a time. Each trial lasted 2 minutes without rest between them. Thus, considering the sampling of 600 Hz, each trial generated a signal composed of 72000 samples per channel.

Moreover, the signals were analyzed in intervals of 2, 3, and 4 seconds, which correspond to 1200, 1800, and 2400 samples, respectively. The overlap window was defined to 1 second or 600 samples, aiming to obtain a new response for every new second of the recorded signal.

The limit of 2400 samples, 4 seconds, represents a maximum response time tolerable for this application type. When using more samples, the response time would increase. Besides, the more samples used in the algorithm, the higher the computational cost. Since the proposal is to optimize the system, taking all the processing to a microcontroller, it becomes unfeasible to increase the number of samples due to these two factors. For the database, no artifact removal was performed, only temporal and spatial filtering. Therefore, the maximum delay for the system is approximately 4 seconds, even though the system produces one response every second due to the 75% of window overlap.

2.2 Filtering Procedure

Initially, the raw EEG signal, $signal_c$, was filtered from continuous components. The mean value μ was determined for each channel and the resulting signal, $signal_s$, was calculated such as presented in Equation(1).

$$signal_s = signal_c - \mu \tag{1}$$

Then, a Common Average Reference (CAR) was applied as spatial filtering. For that, the mean value ρ was determined for each sample considering all the twelve EEG channels. The resulting signal, $signal_f$, was calculated for each sample and each channel such as presented in Equation(2).

$$signal_f = signal_s - \rho \tag{2}$$

The final filtering operation was to apply a 5-order elliptic IIR filter to the $signal_f$ over a frequency range of 3 to 50 Hz. Even though 12 EEG channels were used for the filtering procedure, only three channels were used in the further feature extraction and classification steps. They are O1, O2, and OZ electrodes since the signals recorded in these channels are the most relevant as shown in (Müller et al., 2015) and corroborated in Section 3.2.The flowchart in Fig. 2 illustrates the pre-processing steps, filtering the signals temporally and spatially.

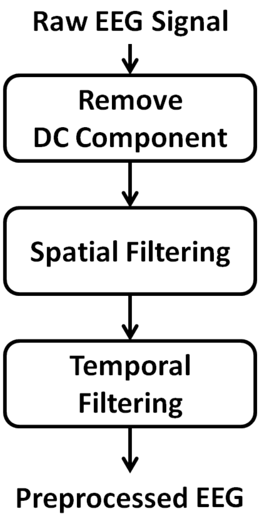

Figure 2. Preprocessing Steps

2.3 Goertzel Transform

The Goertzel transform is a signal processing technique that provides a means for evaluating individual terms of the Discrete Fourier Transform (DFT) (SUNDARARAJAN et al., 2020). This filter operates on a two-steps proceeding. The first step acts as a second-order IIR filter to calculate an intermediate sequence $z[n]$ from the discrete sequence $x[n]$ corresponding to the signal to be processed ($signal_f$), as described in Equations 3 and 4:

$$z[n] = x[n] + 2 \cdot \cos{(2\pi \frac{k}{N})} \cdot z[n-1] - z[n-2] \tag{3}$$

$$k = \frac{F_i}{F_s} \cdot N \tag{4}$$

where $z[n-m]$ is the intermediate sequence delayed of m samples, N is the total number of samples used in the calculation, F_i is the desired frequency, and F_s is the sampling frequency. In Equation (4), k is the ratio of the desired frequency by the sample frequency, multiplied by the number of samples.

The second step corresponds to the FIR filter of the output sequence $y[n]$ ($signal_g$). This output represents the amplitude of the signal spectrum at the desired frequency and considers the intermediate sequence $z[n]$ according to Equation (5):

$$y[n] = z[n] - z[n-1] \cdot e^{-j2\pi \frac{k}{N}} \tag{5}$$

The procedure of extracting characteristics by the Goertzel transform depends on the choice of some parameters, such as:

- the frequency interval, k, which is related to the number of samples, N, in each sequence $x[n]$;
- the chosen EEG channels, whose preference most be the parieto-occipital channels;
- the window overlap percentage, since it influences the speed of stimulus changes identification enabling faster responses to command external devices.

2.4 Classification

The Goertzel transform output, $signal_g$, is examined to identify the frequency stimulus that the user was submitted. The spectral amplitude at each known stimulus frequency is used to classify stimuli. The Goertzel algorithm is applied to each signal window in the database for the three occipital channels (C_j) and the four stimulus frequencies (F_i).The Equation (6) shows how to obtain this value.

$$F_e = F_i | i -> A_{max} = max(A_{i,j}), \tag{6}$$

where F_e is the stimulus frequency identified; F_i is the i-th stimulus frequency of interest; A_{max} is the maximum spectral amplitude and $A_{i,j}$ is the spectral amplitude corresponding to the stimulus frequency F_i in the channel C_j.

2.5 Maze Mobile Game

In an SSVEP-based HMI, the stimulation system is typically implemented using LEDs or conventional monitors. This work, on the other hand, created a game application for cell phones. Then, even for the development of the visual stimuli system and the game itself, it was necessary to select a game engine. The Unity game engine was chosen for its ease of use and practicality, and the visual stimuli system was created in the C# programming language using threads.

The game application uses green and black frames alternately on the borders of its interface. The green color was chosen since the contrast of green and black color making the stimulation more pleasant (Tello et al., 2015). The frames positioned in the center of each border alternated on different frequencies to represent four distinct commands to the game. The game itself is a labyrinth game on which a digital robot can move according to the stimulus selection. The game layout was based on a maze proposed by (VOLOSYAK, 2011). Fig. 3 shows the interface developed in the Unity game engine for cell phones.

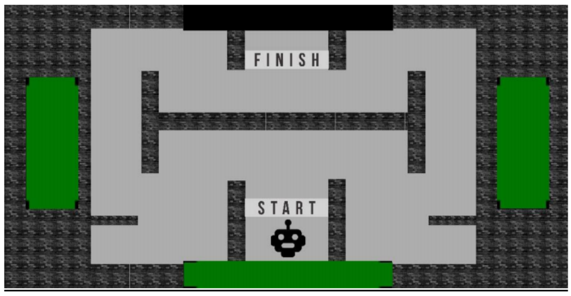

Figure 3. Maze game layout.

The use of threads increased processing capacity while also improving stimulus flickering frequency precision. A circuit with a Light-Dependent Resistor (LDR) attached to the screen stimulus region was used to test the precision of the stimulus frequencies on the game application. The voltage signal on the LDR was measured and processed to identify the peak of the power spectrum on the region between the stimulation frequencies (between 3 and 18 Hz). It is expected that the error in this measurement process does not exceed 5%.

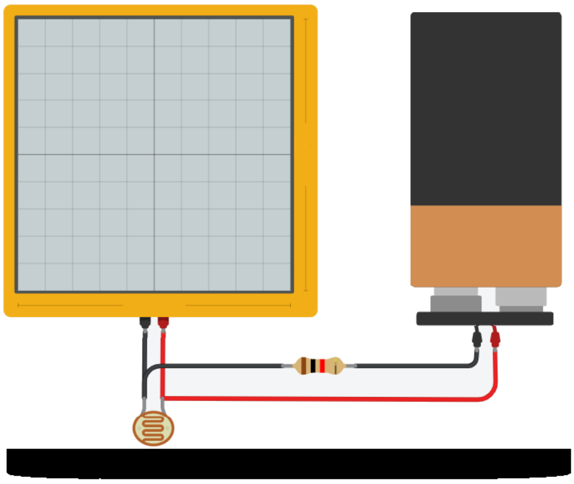

Figure 4. Schematic for stimulus frequency measurement

The new stimulus frequencies chosen for the mobile game were 6.4 Hz, 8.9 Hz, 12.5 Hz, and 14.9 Hz corresponding to the upper, right, lower, and left stimulus, respectively. These are different frequencies from those in the database presented in Section 2.1, as the choice of these new frequencies is according to some criteria as follow:

- more widely spaced frequencies reduce interference from adjacent frequencies, allow for the evaluation of shorter windows, and are less susceptible to inaccuracies in stimulus frequencies;
- the region near 10 Hz should be avoided due to possible confusion in SSVEP identification since it is more prone to the appearance of the alpha rhythm;
- gradual frequencies (such as 6.0, 12.0, 18.0, etc.) should be avoided to reduce aliasing and avoid overlapping harmonics from one stimulus on the another.

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2.6 Augmented Reality

This work was developed as part of an app using the Augmented Reality (AR) system, as shown in Fig. 5. Virtual Reality (VR) glasses increase the mobility of the HMI and allow the experience of immersion in a virtual environment. The AR system shown in Fig. 5 represents the complete arrangement and is a proposal for future work that includes active electrodes for the acquisition of EEG signals rather than using an electrode cap. Therefore, the SSVEP-based HMI would be portable in the glasses.

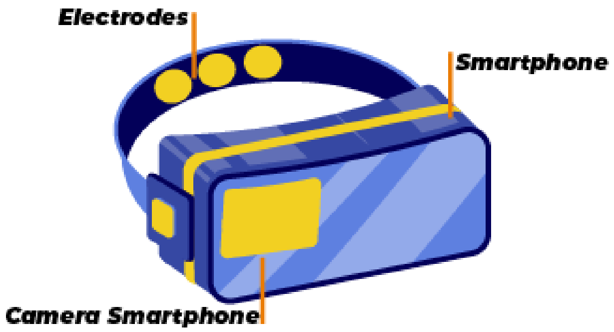

Figure 5. Glasses prototype with attached electrodes

3. RESULTS AND DISCUSSIONS

This section presents the results from Goertzel Transform applied to the EGG signals from the database described in Section 2.1. The first scenery sought to evaluate the best window size for SSVEP identification. Once defined $N = 2400$ samples as the most appropriate window, the Feature Extraction and Classification steps allowed identify the most relevant occipital channel.

3.1 Window Size Analysis

The EEG signals from 9 volunteers according to Section 2.1 were analyzed. The stimulus frequencies are 5.6 Hz, 6.4 Hz, 6.9 Hz, and 8.0, the sampling frequency is 600 samples/s and each trial lasted 2 minutes. Then, the total number of samples from each channel per frequency was 72000 samples. Thus, the data were organized in a multi-dimensional structure of 9 (volunteers) x 4 (frequencies) x 12 (channels) x 72000 (samples).

The window size used in Goertzel transform parameters directly affects the interval between two frequencies in the frequency vector and thus it influences the accuracy of the stimulus frequency identification. For example, considering a sampling frequency of 600 Hz, a two-second window (1200 samples) corresponds to a 0.5 Hz interval between adjacent frequencies, 2400 samples corresponds to a 0.25 Hz spacing, and so on.

Three N values were evaluated to determine the most relevant window size for SSVEP identification: 1200, 1800, and 2400 samples, which correspond to 2, 3, and 4-second windows of EEG signal, respectively. An overlapping window was used to obtain the system response every second. Thus, the overlap was performed by window sliding of 600 samples.

The Goertzel algorithm was applied to identify the frequency corresponding to the sample with the highest power spectral for all possible values of stimulus frequencies and all windows. Table 1 lists the hit rate for each frequency considering the three window sizes analyzed. The rate shown is not the average from the three channels (O1, O2, and OZ), but the highest maximum value among these three channels.

Table 1. Maximum hit rate per volunteer for different window size.

Volunteer #	window Size	Stimulus Frequency 5.6	6.4	6.9	8.0	Average (%)
Vol1	1200	100	100	97.5	94.1	97.9
	1800	100	100	99.2	97.5	99.2
	2400	100	100	100	99.2	99.8
Vol2	1200	59.7	51.3	35.3	45.4	47.9
	1800	65.3	55.1	39.0	55.9	53.8
	2400	79.5	64.1	46.2	65.0	63.7
Vol3	1200	86.6	88.2	94.1	94.1	90.8
	1800	92.4	96.6	97.5	97.5	96.0
	2400	97.4	99.2	99.2	98.3	98.5
Vol4	1200	55.5	74.8	79.8	97.5	76.9
	1800	61.9	78.8	78.8	100	79.9
	2400	66.7	79.5	85.5	100	82.9
Vol5	1200	37.8	44.5	52.9	63.0	49.6
	1800	41.5	56.8	59.3	72.0	57.4
	2400	57.3	65.8	70.1	80.3	68.4
Vol6	1200	89.9	81.5	77.3	90.8	84.9
	1800	96.6	90.7	85.6	96.6	92.4
	2400	99.2	93.2	92.3	95.7	95.1
Vol7	1200	94.1	100	100	100	98.5
	1800	99.2	100	100	100	99.8
	2400	100	100	100	100	100
Vol8	1200	63.9	73.1	65.6	84.0	71.6
	1800	76.3	77.1	78.0	89.8	80.3
	2400	77.8	78.6	85.5	95.7	84.4
Vol9	1200	83.9	94.9	88.1	70.3	84.3
	1800	92.3	100	90.6	78.6	90.4
	2400	95.7	100	94.0	84.5	93.5

Table 1 shows that the window size of $N = 2400$ samples (4 s) produced the highest hit rates. Considering $F_i/F_s = k/N$, then k is the integer value closest to $N \cdot F_i/F_s$. Thus, the greater the value of N, the narrower the frequency streaks will be. It allows a greater accuracy of power spectral density measurement corresponding to F_i. Therefore, this accuracy improves as you increase N.

However, the window size, N, can not increase indefinitely once it increases the processing delay for system response. It is only necessary to guarantee a minimum distance between the frequencies of interest to avoid the spectrum of one contributes to the other.

3.2 Channel Relevance Analysis

Once the best window size was determined as 2400 samples (4 s), it was necessary to investigate the most occipital relevant channel. For that, the hit rate for each stimulus frequency and volunteer was evaluated considering 2400 samples and shown in Table 2.

Table 2 also shows the average hit rate for each volunteer and channel. Even though the Oz channel has achieved the best result for four among nine volunteers, it was necessary to make an individual assessment, since there were some

Table 2. Hit rate for each stimulus frequency and channel, considering 2400 samples.

Volunteer #	Channel	Stimulus Frequency 5.6	6.4	6.9	8.0	Average %
Vol1	O1	100	100	100	98.3	99.6
	O2	100	100	100	98.3	99.6
	Oz	100	100	100	98.3	99.6
Vol2	O1	61.5	42.7	39.3	59.8	50.9
	O2	55.6	42.7	53.0	23.1	43.6
	Oz	73.5	77.8	57.3	66.7	68.8
Vol3	O1	94.9	99.2	100	87.2	95.3
	O2	93.2	94.0	84.6	97.4	92.3
	Oz	98.3	98.3	94.9	94.9	96.6
Vol4	O1	35.0	47.0	47.0	76.1	51.3
	O2	67.5	80.3	86.3	100	83.5
	Oz	51.3	77.8	75.2	100	76.1
Vol5	O1	49.6	65.0	75.2	73.5	65.8
	O2	39.3	56.4	35.0	52.1	45.7
	Oz	60.7	51.3	60.7	65.0	59.4
Vol6	O1	77.8	88.9	90.6	100	89.3
	O2	76.9	75.2	67.5	75.2	73.7
	Oz	98.3	95.7	91.5	100	96.4
Vol7	O1	49.6	75.2	80.3	82.9	72.0
	O2	100	100	100	100	100
	Oz	95.7	100	100	100	98.9
Vol8	O1	64.1	76.1	65.8	73.5	69.9
	O2	68.4	75.2	82.1	96.6	80.6
	Oz	50.4	71.8	61.5	65.0	62.2
Vol9	O1	71.6	89.7	80.2	75.0	79.1
	O2	96.6	100	80.2	77.6	88.6
	Oz	100	100	92.2	85.3	94.4

tie cases. Thus, in Table 3 the Oz channel presents itself as the majority in the choice of the most relevant channel, which is reinforced if it goes chosen in the tie cases in which it is a part.

Another way to evaluate the results is by calculating the overall hit rate per channel, which means the mean value was determined for each channel considering all volunteers and all stimulus frequencies. Table 4 presents these results.

Table 3. Occipital channel with higher hit rate per stimulus frequency.

Volunteer #	Stimulus Frequency 5.6	6.4	6.9	8.0
Vol1	O1-O2-Oz	O1-O2-Oz	O1-O2-Oz	O1-O2-Oz
Vol2	Oz	Oz	Oz	Oz
Vol3	Oz	O1	O1	O2
Vol4	O2	O2	O2	O2-Oz
Vol5	Oz	O1	O1	O1
Vol6	Oz	Oz	Oz	Oz
Vol7	O2	O2-Oz	O2-Oz	O2-Oz
Vol8	O2	O1	O2	O2
Vol9	Oz	Oz	Oz	Oz
Majority	Oz	Oz	Oz	Oz

Table 4. Overall hit rate per channel

Channel	Overall Hit Rate
O1	77.8 %
O2	83.0 %
Oz	85.4 %

Based on Table 2, the occipital channel chosen for performing the next steps will be Oz (higher hit rate in 5 out of nine volunteers), followed by channel O2 (3 volunteers), and channel O1 (1 volunteer). This finding is consistent with that reported in Müller et al. (2015), which shows that Oz is the most relevant individual occipital channel.

All of these results indicate that the Oz channel is the most relevant occipital channel. Another possibility is to develop an algorithm that combines the decision from each occipital channel using specific weights.

3.3 Validation of Game Stimulus Frequencies

A very important parameter in an SSVEP-based HMI is the reliability of the frequencies that make up the interface. In this case, it is necessary to check up the flickering frequencies in the cell phone screen. The frequency precision evaluation was performed by capturing the voltage signal over an LDR for 2 seconds, as shown by Fig 4 in Section 2.5. This signal was used as input to calculate the Fast Fourier Transform in the Matlab environment. The peak frequency was identified and the frequency corresponding to the greater peak bellow than 20 Hz was considered.

Table 5. Verification of stimulus frequencies

	Stimulus Frequency (Hz) 6.4	8.9	12.5	14.9
	6.4	8.5	12.3	14.8
	6.5	8.6	12.5	14.7
	6.5	8.6	12.3	15.0
	6.6	9.2	12.0	15.0
	6.2	9.2	12.7	14.9
	6.1	9.0	12.6	14.6
	6.7	8.7	12.8	14.5
	6.6	8.9	12.6	15.2
	6.2	9.1	12.4	15.0
	6.5	8.8	12.5	15.1
Average	6.43	8.86	12.47	14.88
Std. Dev.	0.2003	0.2591	0.2312	0.2251

Table 5 displays the average values that are close to the expected values and have low standard deviations. A worst-case metric is to calculate the maximum value by dividing the difference between the expected and measured values by the expected value.

In Table 5, the worst case is for $f_{expected} = 6.4Hz$ and $f_{measured} = 6.7Hz$. This leads to an error of $0.3/6.4 = 4.7\%$, which is within the margin of error of 5% proposed by the authors in Section 2.5. This margin of error is justified by the use of more spaced frequency streaks.

It emphasizes that the tests performed to verify the game frequencies were performed only using LDR for 2 seconds, so the system was not tested in the HMI configuration, using volunteers for data acquisition.

4. CONCLUSION

The work presented in this paper analyzed and evaluated results from the Goertzel transform applied to an SSVEP-based HMI. These results showed hit rates above 85% considering maximum spectral on the Oz channel and relating them to the stimulus frequencies.

Moreover, the results proved that a 2400-samples window size (4 s) with an overlap of 1 s is sufficient to identify the stimulus frequencies. Even more, the results considering the three occipital channels together (Table 1) can have higher or lower hit rates when they are considered individually (Table 2). This allows the development of an adaptive channel selection system from a previous signal acquisition step.

Another SSVEP identification approach is to evaluate which stimulus frequency is the most identified among all channels. It can be done by calculating the maximum spectral amplitude per channel and analyzing the resulting mode, which is the most frequent frequency considering all channels. Moreover, it is possible to develop a hybrid decision process on which more than one processing technique could be applied to the EEG signal. For example, a switching system between two or more algorithms can be used to choose the one with the highest hit rate for a given volunteer. This would allow a raise in the SSVEP hit rate.

The smartphone game proved to be effective for carrying out the flickering visual stimulation since the margin of error will not influence the result of the captured data. Furthermore, active electrodes should be coupled to the augmented reality glasses to capture EEG signals in the new stimulus frequencies as shown in Section 2.5.

To complete the system, a tiny and affordable computer Raspberry Pi has already been purchased to embed the SSVEP-based HMI. It will be responsible for acquiring and processing the EEG signals, generating a command signal for an external device, or a decision for a virtual navigation system.

Therefore, the Goertzel transform was presented as a viable tool for stimulus frequency identification in an SSVEP-based HMI.

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