ЕЛЕКТРООБЛАДНАННЯ ТА РАЦІОНАЛЬНЕ ВИКОРИСТАННЯ ЕЛЕКТРИЧНОЇ ЕНЕРГІЇ В АПК

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H28: A PORTABLE LOW-COST SSVEP-BASED EEG SIGNAL PROCESSING UNIT ALONG WITH VISUAL STIMULI

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A brain-computer interface (BCI) yields a communication between the human brain and other devices without getting the peripheral muscles involved. One common method to fulfill this objective is to analyze the evoked responses from the brain's visual cortex (SSVEP) caused by gazing at a constantly flickering target, i.e., the visual stimulus. Most of the current SSVEP-based BCI systems are not able to concurrently satisfy the criteria of portability, cost-efficiency and accuracy. In this paper, a portable inexpensive device is presented and evaluated. This device is capable of recording and processing the electroencephalography (EEG) signals simultaneously with the help of a 32-bit STM32 F429 Cortex-M4 microcontroller. Amplitude spectral density analysis is implemented to classify the recorded data using the Goertzel algorithm instead of the widely used fast Fourier transform (FFT). This is a key feature which enables microcontrollers to be used as signal acquisition and processing units. The developed system performs the classification procedure on 4 channels of EEG data in less than 100 ^s immediately after it receives the necessary amount of data. A mean accuracy of 89.40% and a mean information transfer rate (ITR) of 20.83 bits/min were achieved.

Index Terms—**Brain-Computer Interface (BCI), Electroencephalogram (EEG), Steady-State Visually Evoked Potential (SSVEP), Digital Signal Processing, Microcontroller.**

I. INTRODUCTION

A Brain-Computer Interface comes up with a type of communication between the human brain and other electronic devices which does not rely on the brain's normal output pathways of peripheral nerves and muscles. One of the principal goals of the BCIs is to assist people suffering from motor impairments and disabilities in their everyday lives [1], [2]. Mind spelling [3], wheelchair [4] or robot control and gaming [5] are only a few possible applications of the BCI systems.

These systems are built on the basis of recording and analyzing the electrical signals from the human brain. Lately, the vast majority of BCI studies prefer to put focus on noninvasive EEG-based methods. The steady-state visually-evoked potential (SSVEP), motor imagery (MI) and P300 are some instances of the EEG-based interfaces [2]. The SSVEP refers to a BCI paradigm which measures the brain responses elicited by a visual stimulus flickering at a specific constant frequency usually ranging from 6 up to 60 Hz [6].

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Most of the SSVEP-based BCI systems are confined in terms of portability and cost-effectiveness. With the recent advances in embedded systems and digital signal processing, there has been a growing tendency towards portable and low- cost BCI devices. As for instance, Wang *et al.* conducted a study on the basis of a cell phone-based BCI [7]. They applied the FFT on four EEG channels using a 4-second moving window. The processing unit was a Nokia N97 cell phone. Lin *et al.* developed a wireless BCI [8]. Their system consisted of a four-channel biosignal acquisition/amplification module. A dual-core processor integrating a digital signal processor (DSP) together with an ARM processor was responsible for processing the EEG data. Feng *et al.* developed an embedded device for brain signal acquisition [9]. A DAQ board containing an ADS1299 and a BeagleBone Black were handling the acquisition and processing part respectively. Ribeiro *et al.* developed an EEG standalone device for BCI [10]. They made use of a PIC18F4550 for data acquisition, a dsPIC for signal processing and a PIC18F458 for the generation of visual stimuli.

This paper offers an economical and portable signal processing unit for BCIs which particularly targets the ordinary microcontrollers. It is worth mentioning that the proposed system is an initial step towards an entirely portable BCI device, and was merely developed to examine the concept. The professional EEG amplifier LiveAmp from Brain Products (Gliching, Germany) was used for signal amplification and acquisition since it could provide an exceptionally good signal quality and satisfy the need for portability. Due to the fact that the provided software SDK required an operating system e.g. Windows or Linux to transmit the data, the use of a portable computer acting as a relay was inevitable.

The system makes use of the Goertzel algorithm for the classification, which in fact gives the identical result as the fast Fourier transform (FFT) under specific conditions. The algorithm was applied on four filtered EEG channels. Several studies have already highlighted the differences between the canonical correlation analysis (CCA), minimum energy combination (MEC) and power spectral density analysis (PSDA) [11], [12]. Requiring significantly less amount of memory and processing power in comparison to other feature extraction techniques makes the Goertzel algorithm a flawless solution to the issues of portability and budget-friendliness.

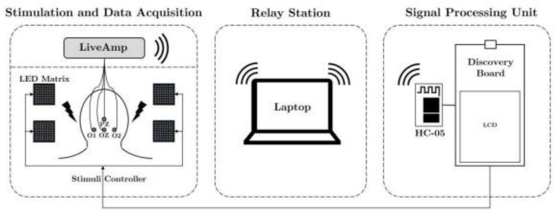

Figure 1 – Overview of the experimental setup. The LiveAmp was clipped onto the participants' clothes while the Discovery board (signal processing unit) was placed near the laptop. The participants were asked to gaze at the prepared visual stimuli i.e. LED matrices which were positioned in a distance of about 30 to 40 cm from the user. The minimum time for gazing at each LED matrix was 4 seconds depending on the classification. As can be seen, four EEG electrodes P_z, O_1, O_z and O_2 were used.

II. Methods and Materials

A. Desired System

Our ultimate goal is to develop a standalone EEG signal processing unit which has the ability to talk to the EEG amplifier in the absence of a laptop or any kind of additional computer, and process the EEG data in real time. It is obvious that such an interface could be either installed on the user's wheelchair or carried in the user's hands, pocket, bag, etc. As the first step, the signal processing unit for such a system was introduced in reliance on a laptop acting as a relay.

The proposed system will be supplied by a portable power bank. The structure of such a system could result in a lightweight interface which could be employed in cost-sensitive applications.

B. Participants

All participants gave written informed consent in accordance with the Declaration of Helsinki. Seven healthy subjects with a mean age (SD) of 24.29 (4.07) years ranging from 20 to 31 participated in this study. The information required for the analysis of the experiments was stored anonymously, thus the results cannot be traced back to the participants. This research was approved by the Ethical Review Board of the Medical Faculty of the University of Duisburg-Essen. Subjects did not receive any financial reward for participation in this study.

C. Experimental Setup

As demonstrated in the Figure 1, the experimental setup was composed of the following elements. More specific information is provided subsequently.

•LiveAmp (Brain Products, Gilching, Germany; Model No.: LiveAmp 8 (BP-200-3020)) - high accuracy compact wireless 8 channel amplifier and acquisition system together with active electrodes,

•Discovery board (STMicroelectronics, Geneva, Switzerland) featuring STM32F429 high-performance microcontroller,

•HC-05 - a serial port protocol (SPP) Bluetooth module,

•Bi-color (Red/Green) LED matrices (Adafruit Industries, New York City, NY, US; Product ID: 902),

•a gaming series laptop (MSI, New Taipei City, Taiwan; Model No.: MS-17A1) running on Windows 10 used as a relay station to exchange data between the LiveAmp and Discovery board.

LiveAmp: The ultra-lightweight, wearable 8-channel 24- bit LiveAmp was used for EEG signal amplification and acquisition. A minimum input impedance of 200 MO, least common-mode rejection ratio of 80 dB and a resolution of approximately 40.7 nV/bit are some of the most important features of the LiveAmp. The amplifier's input range is ±341.6 mV. It was set to sample the input signals at the frequency of 250 Hz.

Discovery board: The 32F429IDISCOVERY kit (a development board from STMicroelectronics) was used for signal processing, classification and other operational scenarios. It consisted of a 2.4" QVGA TFT LCD used for the graphical user interface representation. It featured an STM32F429 microcontroller with ARM 32-bit Cortex-M4 core accompanied by a single precision floating point unit (FPU), running at 168 MHz and containing 2 MB of flash memory, 256 KB of internal SRAM and a 64-Mbit external SDRAM.

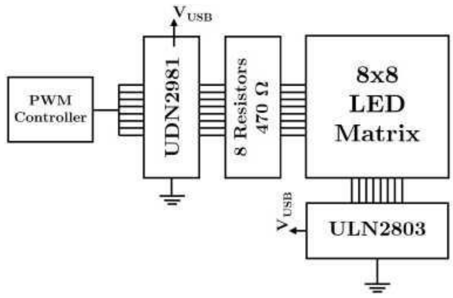

Figure 2 –The schematic diagram of the LED matrix driver. The UDN2981 was set to source roughly 350 mA and the ULN2803 was able to sink the same amount of current.

Bluetooth Module HC-05: It is fully qualified Bluetooth V2.0 + EDR (Enhanced Data Rate) with complete 2.4 GHz radio transceiver and baseband together with the AFH (Adaptive Frequency Hopping). It has a -80 dBm sensitivity and up to +4 dBm RF transmit power. It runs on 3.3V and has an UART interface with programmable baud rate.

LED Matrices: Four Adafruit 1.2" 8 x 8 bi-color square LED matrices (33 mm x 41 mm x 4 mm) were mounted on corners of an extension 2-layer custom-designed printed circuit board in order to be used as visual stimuli which then could be controlled by four 32-bit timer channels of the main board; however, the red color was only used. Each LED matrix was driven by a UDN2981 high-side and a ULN2803 low-side driver in order to be able to source and sink the necessary amount of current. The board could be fed by any 5V/2A output power adapter. More information regarding the circuitry is provided in the Figure 2. Handling the stimulation frequencies in this type of visual stimulation was more reliable and the generated frequencies were very precise and close to the desired ones, since all the LEDs on the LED matrix flickered synchronously and at the same time.

D. Experimental Protocol

As mentioned before, this experiment was conducted to evaluate the accuracy and performance reliability of the developed signal processing unit. For this reason, our SSVEP- based BCI device could not be categorized into real-life applications since the classifications were not followed by any kind of operation e.g. wheelchair movement, spelling, etc. Each participant was asked to gaze at the visual stimulation frequencies on the LED matrices for at least 4 seconds. The order in which the user was asked to gaze at specific LED matrices was chosen randomly. If the classification could be performed according to our prerequisites and factors, the flickering of the visual stimulation device would stop and another random frequency was set to flicker. Otherwise, the time for which the participant was asked to gaze at the target would increase until the classification, which could either be correct or wrong, was performed.

E. Signal Processing

The Goertzel algorithm [13], [14] was implemented to analyze the amplitude spectral density and classify the recorded EEG data. It is capable of performing single tone detection, i.e. detecting a specific frequency from a signal which most probably contains different frequencies, and is utilized in many applications [15], some of which are: dual-tone multi-frequency (DTMF) decoding, frequency response measurement, etc. The algorithm is implemented in the form of a second-order infinite impulse response (IIR) filter to compute the single-bin discrete Fourier transform (DFT) more effectively. Considering the number of samples for each input channel N, sampling frequency f_s and visual stimulus' flickering frequency f_{vs};

$$k \equiv \frac{f_{vs} \cdot N}{f_s} \quad (1)$$

where k (frequency-domain index) must take an integer value. The Goertzel filter can then be described by the following time-domain difference equations:

$$w(n) = x(n) + 2\cos\left(\frac{2\pi k}{N}\right)w(n-1) - w(n-2), \qquad (2)$$

$$y(n) = w(n) - e^{-j2\pi k/N}w(n-1) \qquad (3)$$

The output of the filter y(n) is equal to the DFT output X (k) only if n = N iterations of the Equation 2 are performed. Equation 3 needs to be executed once the previous step is completed. As an illustration, the block diagram together with parameters and coefficients of the used system for a specific frequency-domain index k = 6 are presented in the Figure 3 where,

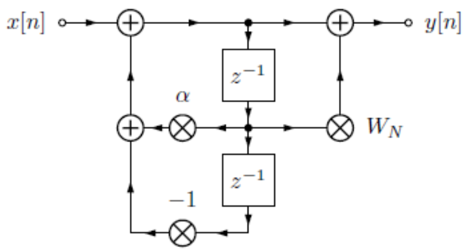

Figure 3 – Block diagram of the used Goertzel algorithm

$$\alpha = 2\cos\left(\frac{2\pi k}{N}\right) = 2\cos\left(\frac{2\pi \times 6}{250}\right), \quad (4)$$

$$W(n) = -e^{-j2\pi k/N} = -e^{2\pi \times 6/250} \quad (5)$$

A pseudocode is provided in the Algorithm 1 for the sake of clarification.

Algorithm 1 The Goertzel algorithm

```
function GOERTZEL(x, W_N)
    W_1 = 0
    W_2 = 0                                          ▷ Two initial values.
    α = 2cos(2πk/N)
    for counter = 0 to counter = 249 do              ▷ 250 data samples.
        W_0 = α · W_1 − W_2 + x(counter)
        W_2 = W_1
        W_1 = W_0
    Re = W_1 − W_2 · cos(2πk/N)                      ▷ The cosine term is the real part of W_N.
    Im = W_2 · sin(2πk/N)                            ▷ The sine term is the imaginary part of W_N.
    y = √(Re² + Im²)                                 ▷ y is the output of the filter.
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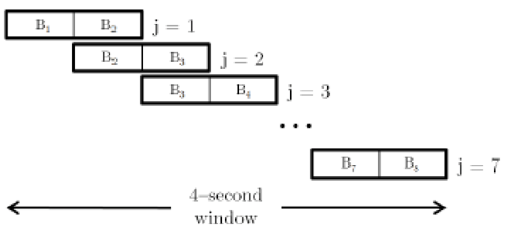

Figure 4 - Structure of the sliding window. In this figure, j represents a counter which is incremented each time a new data block arrives. As indicated earlier, Bj refers to a block of data which contains 125 data samples (approximately 0.5 seconds).

For the realization of the system in this paper, the sampling frequency (f_s) of 250 Hz, first 4 data channels from the LiveAmp, 250 data samples (N) per channel and four frequency-domain indexes (k) 6, 7, 8 and 10 were used. It is worthy of note that the system was set to receive the data samples in two parts, called blocks, each containing 125 points. Once the first two blocks of data points were received, the system could perform the aforementioned algorithm. Receiving the next 125 data points was followed by performing the same algorithm on the received block together with the most recent block from the previous data set. Simple moving average was run afterward on the computed DFT magnitudes of all channels for each frequency each time the algorithm was executed:

$$y_{av,k} = \frac{1}{4}\sum_{i=1}^{4}\left|y_{i,k}\right| \quad k = 6, 7, 8, 10. \qquad (6)$$

In order to attain a high accuracy, the calculated $y_{av,k}$'s were averaged over a minimum 4-second time window,

$$Y_k = \frac{1}{7}\sum_{j=1}^{7} y_{av,k_j} \quad k = 6, 7, 8, 10. \tag{7}$$

Figure 4 illustrates the sliding window behavior on 4 seconds of data.

The system was able to go through the classification procedure when the predefined time window was analyzed and a certain threshold was exceeded for the obtained Y_k's.

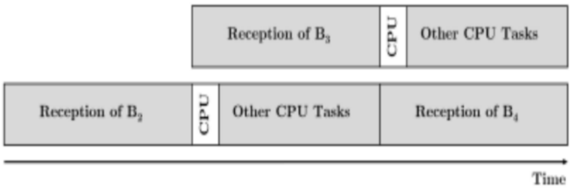

Figure 5 - Task scheduling. The DMA controller let the processor perform other operations while the data were being received. The block notation refers to the one used in the Figure 4.

The threshold was determined and set manually by considering the amplitude of the evoked responses for each participant.

$$\hat{C}_n = \max\{Y_1, \ldots Y_4\}, \tag{8}$$

Equation 8 refers to the final classification step where the maximum obtained Y_k was being found. Since only four stimulation frequencies were used, only four Y_k's were expected; Y_1 to Y_4. where C_n denotes the classified command.

F *Software*

System Workbench for STM32 integrated development environment equipped with the ARM GCC compiler was used for source code editing, building and debugging. STM32F4 HAL, BSP and CMSIS APIs were exerted for the program development. The HAL driver was in control of working with peripherals like UART, initializing the flash interface and the System Tick Time (SysTick), setting the direct memory access controller, etc. Setting the touchscreen LCD for the graphical user interface was carried out by the BSP driver. In addition, CMSIS provides a useful optimized floatingpoint enabled DSP library for use on Cortex-M based devices.

Realization of Flickering Targets: LED matrices were controlled by four 32-bit timer channels of the microcontroller. Four used flickering frequencies 6 Hz, 7 Hz, 8 Hz and 10 Hz were generated by the PWM channels running in parallel, where PA0, PA1, PA2 and PA3 represent the respective pins on the Discovery board.

Data Acquisition: In the first step, the amplified and digitized EEG signals were transmitted to the laptop via Bluetooth with the help of the Lab Streaming Layer (LSL) [16] API.

Table 1 – Results for 7 participants the task as to gaze at a specific led matrix which was selected randomly and shown to the participants the time parameter refers to the total time it took for the user to accomplish the task

Participants	Total No. of Classifications ($\hat{C}_n$)	Accuracy [%]	Time [s]	ITR [bits/min]
1	10	100	40	30
2	12	91.67	48	21.81
3	16	75	64	11.89
4	13	92.31	52	22.30
5	14	92.86	56	22.74
6	14	85.71	56	17.73
7	17	88.23	68	19.36
Mean	13.71	89.40	54.86	20.83

The buffered data on the laptop were then transmitted to the main board via Bluetooth with the baud rate of 115.2 kbits/s. The UART on the board was set to function in non-blocking circular double buffer mode, thanks to the DMA controller on the F429 microcontroller.

Data Processing: Two interrupt service routines, each being called by the end of the block transfer, were responsible for processing the received data. The first interrupt flag was set when 125 data samples were already in one of the double buffers. The classification process started immediately after the interrupt, while the other buffer was being filled by another set of 125 data samples. Figure 5 highlights the aforementioned functionality in a detailed manner.

III. Results

Table I represents the results for all participants. The overall performance of the system was evaluated by calculating the information transfer rate (ITR) in bits/min [2]:

$$B_t = \log_2 N' + P\log_2 P + (1-P)\log_2\left(\frac{1-P}{N'-1}\right), \tag{9}$$

$$B = B_t \cdot C_n \cdot \frac{60}{T} \tag{10}$$

where N', P, C_n and T refer to the total number of possible choices, accuracy, total number of classified commands and the total classification time respectively. Accuracy ($0 < P < 1$) was calculated by dividing the number of correct classifications by the total number of classified commands. Table II put focus on the accuracy of the classifier for each specific stimulation frequency separately. The second column refers to the total number of times the classification procedure of a specific frequency was performed for all users regardless of its correctness, while the third column counts only the correct classified commands. Accuracy was calculated by dividing the elements of the third column by the ones in the second column.

IV. Discussion

As previously stated, this system was solely developed to assess the reliability of the idea. Using the Goertzel algorithm to realize the classification had several significant advantages over the widely used fast Fourier transform (FFT):

•A radix-2 FFT requires 2N $\log_2$ N real multiplications, whereas the Goertzel calculates N + 2 real multiplications. This might not be a big deal for high-performance microprocessors, however by increasing the number of input channels it could play a crucial role in microcontrollers. In order to get the most out of the algorithm, the number of frequencies to be classified should be kept less than $\log_2$ N. Since N was 250 for each input channel in our case, the number of frequencies to be classified should be less than 7.

Table 2 – Classification accuracy the of the signal processing unit based on the total number of classifications for all the participants for the used frequencies on the visual stimuli**.**

Frequency [Hz]	No. of $\hat{C}_n$'s	No. of Correct $\hat{C}_n$'s	Accuracy
6	21	21	100 %
7	23	23	100 %
8	23	20	86.96 %
10	29	21	72.41 %

•A Goertzel filter incorporates a second-order digital resonator. This gives the freedom to choose any resonance frequency between zero and f_s. In this case, the final result will not be the same as the FFT.

•N does not need to be a power of 2 in the used algorithm whilst the FFT processes a block of data, of which the length has to be a power of 2.

•It does not require a block of data for the processing to be started. This indeed is the most important advantage of this technique which enables the cheap microcontrollers to come into play.

Furthermore, using the high-performance STM23F429 microcontroller had several benefits:

•It featured 2 MBytes of flash memory which could be loaded with a very thorough BcI classifier.

•Being equipped with 256 KBytes of fast SRAM could help us save more temporary variables without the need to worry about RAM management.

•The 32-bit timers could provide a very precise pulse width modulated waveform in order to be used on the visual stimulation devices.

•Having the capability to be clocked at 168 MHz, resulting in 210 Dhrystone Million Instructions per Second (DMIPS) could lead to a very fast signal processing unit.

•Coming up with special DSP instructions and benefiting from the floating point unit (FPU) could lead to an even faster processing unit.

•Last but not least, the above mentioned microcontroller was able to deliver such a great performance in exchange for an absolutely reasonable price.

Besides, using the 8-channel LiveAmp amplifier could provide us with a very well-filtered high-quality EEG data, which highly influenced the accuracy of the classifier.

As can be seen in Table II, there exists a noticeable accuracy decrease in frequencies 8 and 10 Hz. This might be linked to the differences in the SSVEP amplitudes for different frequencies, the used signal processing algorithms as well as to the fatigue of the user, concentration loss, etc.

V. Conclusion

In this paper, it was intended to overcome the most important challenges of a BCI system including the ability to be easily carried. To this end, a signal processing unit was developed with the help of a well-known algorithm in communication systems, the Goertzel algorithm, in a way that suits mainstream microcontrollers. The accuracy of the system is dependent on numerous factors e.g. choosing an adequate stimulation frequency set, making use of a low- noise amplification/acquisition device, establishing a proper algorithm for the classification, etc. All the frequencies applied in this research belonged to the range of 5 to 10 Hz, since it has been shown that lower frequencies yield higher accuracies [17].

The obtained results, especially the accuracies which were mentioned in the results section, imply that the performance of the proposed signal processing unit was absolutely reliable and promising in the presence of the high-quality and high- priced amplification/acquisition device, LiveAmp. Although the implemented classification method on the microcontroller may not outperform the CCA, minimum energy combination and other classification techniques, in conjunction with the limited computational power on the MCU boards, it connotes that this concept could be introduced in many low-price BCI applications and could be a fundamental step towards entirely portable, as well as inexpensive BCI interfaces.

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Анотація

H28: ПОРТАТИВНЕ НЕДОРОГЕ ОБЛАШТУВАННЯ ОБРОБКИ СИГНАЛІВ ЕЛЕКТРОЕНЦЕФАЛОГРАМИ НА ОСНОВІ SSVEP БЛОКА ЗА ДОПОМОГОЮ ВІЗУАЛЬНИХ СТИМУЛІВ

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Інтерфейс нейро-комп'ютер (ІНК) забезпечує зв'язок між людським мозком і іншими пристроями, не залучаючи периферійні м'язи. Одним з поширених методів для досягнення цієї мети є аналіз викликаних зорових реакцій кори головного мозку (SSVEP), викликаних наглядом за постійно мерехтливою мішенню, тобто візуальним стимулом. Більшість сучасних систем ІНК на основі SSVEP не можуть одночасно задовольняти критеріям мобільності, рентабельності і точності. У цій статті представлений і оцінений портативний недорогий пристрій. Цей пристрій здатний одночасно реєструвати і обробляти сигнали електроенцефалографії (ЕЕГ) за допомогою 32-розрядного мікроконтролера STM32 F429 Cortex-M4. Амплітудний спектральний аналіз щільності використовується для класифікації записаних даних з використанням алгоритму Герцеля замість широко використовуваного швидкого перетворення Фур'є (ШПФ). Це ключова функція, яка дозволяє використовувати мікроконтролери в якості блоків збору і обробки сигналів. Розроблена система виконує процедуру класифікації по 4 каналам даних ЕЕГ менш ніж за 100 мкс відразу ж після отримання необхідної кількості даних. Досягнуто середня точність 89,40% і середня швидкість передачі інформації (ITR) 20,83 біт / хв.

Аннотация

H28: ПОРТАТИВНОЕ НЕДОРОГОЕ УСТРОЙСТВО ОБРАБОТКИ СИГНАЛОВ ЭЛЕКТРОЭНЦЕФАЛОГРАММЫ НА ОСНОВЕ SSVEP БЛОКА ПРИ ПОМОЩИ ВИЗУАЛЬНЫХ СТИМУЛОВ

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Интерфейс нейро-компьютер (ИНК) обеспечивает связь между человеческим мозгом и другими устройствами, не вовлекая периферийные мышцы. Одним из распространенных методов для достижения этой цели является анализ вызваемых зрительных реакций коры головного мозга (SSVEP), вызванных наблюдением за постоянно мерцающей мишенью, т. е. визуальным стимулом. Большинство современных систем ИМК на основе SSVEP не могут одновременно удовлетворять критериям мобильности, рентабельности и точности. В этой статье представлено и оценено портативное недорогое устройство. Это устройство способно одновременно регистрировать и обрабатывать сигналы электроэнцефалографии (ЭЭГ) с помощью 32-разрядного микроконтроллера STM32 F429 Cortex-M4. Амплитудный спектральный анализ плотности используется для классификации записанных данных с использованием алгоритма Герцеля вместо широко используемого быстрого преобразования Фурье (БПФ). Это ключевая функция, которая позволяет использовать микроконтроллеры в качестве блоков сбора и обработки сигналов. Разработанная система выполняет процедуру классификации по 4 каналам данных ЭЭГ менее чем за 100 мкс сразу же после получения необходимого количества данных. Достигнута средняя точность 89,40% и средняя скорость передачи информации (ITR) 20,83 бит / мин.