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A Brain-Computer Interface (BCI) for Silent Speech Prediction using Machine Learning

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Abstract— *This work describes the development and implementation of a brain-computer interface (BCI) designed for silent speech recognition using multichannel electroencephalographic (EEG) signals. EEG provides a non-invasive means of capturing cerebral electrical activity through scalp electrodes, allowing neural signal patterns associated with specific cognitive processes to be examined. In this study, EEG patterns related to the imagined words "Yes" and "No" were identified and classified through machine learning methods. The proposed acquisition system records 16 EEG channels by means of two cascaded Texas Instruments ADS1299 integrated circuits, enabling high-resolution and synchronized multichannel measurements. Experimental classification using the K-nearest neighbors (KNN) algorithm yielded an accuracy of 85.9% in distinguishing between the two target words.*

Keywords— Brain-Computer Interface, BCI, digital signal processing, silent speech, feature extraction, electroencephalogram, filtering.

I. INTRODUCTION

Brain-computer interfaces (BCIs) provide an alternative means of interaction in which neural activity is translated into information that can be used to operate or communicate with external systems. The present work addresses the development of a multichannel brain-signal acquisition platform designed as the hardware basis of a BCI. This approach is particularly relevant to assistive technologies because it may allow individuals with severe motor impairments or paralysis to interact with their environment without relying on voluntary muscle activity.

In addition to motor-assistance applications, BCI research has increasingly explored communication alternatives for individuals who are unable to produce conventional speech. One approach involves the analysis of silent speech, in which a person attempts to formulate or articulate words without generating an audible acoustic signal. Although no sound is produced, speech-related neural activity remains present during imagined articulation or during movements of the speech organs. Detecting and characterizing these patterns therefore provides a potential pathway for developing communication systems that do not depend on audible vocalization.

In this work, neural activity was recorded by means of electroencephalography (EEG) [1]. EEG provides a non-invasive method for measuring variations in electrical potentials associated with brain activity using electrodes distributed over the scalp. To standardize electrode positioning across experimental sessions and participants, the recording locations were established according to the international 10–20 electrode placement system [2].

Previous research has demonstrated the potential of neural-signal processing for silent and imagined speech applications. Ramirez [3], for example, developed a machine-learning-based methodology aimed at dual silent communication through silent-speech analysis. Sarmiento [4] examined the principal models associated with human language processing and their relationship to BCI systems, with particular emphasis on approaches for recognizing speech without audible production. More recently, Kunz [5] demonstrated real-time decoding of self-paced imagined sentences selected from a relatively broad vocabulary, illustrating the progress achieved in extracting linguistic information from inner-speech-related neural activity.

The acquisition hardware developed for this study is based on the Texas Instruments ADS1299, an integrated analog front end specifically intended for measuring electrophysiological and other low-amplitude biopotential signals, including EEG [6]. Its combination of high-resolution analog-to-digital conversion, low input-referred noise, and low-power operation makes this device suitable for multichannel neural recording systems and BCI implementations. The acquired EEG data were processed and evaluated using different supervised machine-learning methods to investigate their ability to discriminate the recorded patterns. Among the evaluated classification techniques, the k-nearest neighbors (KNN) method provided the highest performance.

The remainder of this work presents the architecture and implementation of the proposed acquisition platform, including the electronic design and the main hardware components required for EEG recording and subsequent signal analysis.

II. MATERIALS AND METHODS

2.1 Silent Speech

Silent speech describes a communication process in which linguistic information is generated without producing an audible voice signal. Rather than relying on conventional acoustic speech, this type of communication can be identified through physiological activity or physical responses associated with the intention to speak [7]. Consequently, silent-speech approaches provide a potential means of extracting verbal information even when no detectable sound is emitted.

2.2 ADS1299-Based Signal Acquisition

The acquisition hardware was implemented around the ADS1299 analog front end from Texas Instruments. This device is intended for the measurement of low-amplitude electrophysiological signals and is suitable for applications involving EEG, ECG, ECoG, and other biopotentials. A single ADS1299 provides eight simultaneous acquisition channels. Therefore, multiple devices can be interconnected when a larger number of recording channels is required; in the system presented here, two devices were used to implement a 16-channel architecture. An integrated 24-bit analog-to-digital conversion stage provides the resolution required for measuring signals with amplitudes in the microvolt range, as typically encountered in EEG recordings [6].

2.3 Classification Methods Based on Machine Learning

Machine-learning algorithms offer computational methods for identifying relationships within measured data and assigning observations to predefined categories based on representative signal characteristics. Different supervised approaches can be applied to EEG analysis, including k-Nearest Neighbors (KNN), Support Vector Machines (SVM), Random Forest models, and Artificial Neural Networks (ANN). In BCI applications, these algorithms provide a mechanism for converting features obtained from complex electrophysiological recordings into discrete outputs that can subsequently be interpreted by the system.

2.4 System Development Methodology

The implementation strategy was organized as a sequence of three major stages covering signal acquisition, data visualization, and preliminary EEG classification.

The initial stage addressed the electronic architecture of the acquisition subsystem. Two ADS1299 devices were configured to obtain 16 differential EEG channels. Communication between the acquisition electronics and the processing system was first established and tested to verify proper device configuration and data transfer. Once the required functionality had been confirmed, a dedicated printed circuit board was developed using KiCad. PCB design decisions were made according to the

electrical and layout considerations recommended by the device manufacturer, with particular attention to maintaining appropriate conditions for acquiring low-amplitude electrophysiological signals.

The next stage focused on the software environment required to observe and handle the information delivered by the acquisition hardware. An interface was implemented to display the recorded waveforms and provide access to the EEG data generated by the multichannel system.

The final stage was conceived as an experimental proof of concept rather than as a comprehensive silent-speech recognition system. EEG recordings obtained with the developed platform were used in a binary classification experiment involving the keywords "Yes" and "No." This experiment provided an initial assessment of the complete acquisition and processing chain, from the measurement of brain activity to the generation of a classification output.

Figure 1 summarizes the methodological workflow adopted in this study. The diagram presents the progression from the implementation of the EEG acquisition hardware through signal visualization and, finally, to the proof-of-concept classification experiment. This sequential organization allowed each subsystem to be implemented and evaluated before its integration into the complete BCI platform.



FIGURE 1: Overview of the three-stage methodology followed for system development and experimental evaluation

2.5 Circuit Design and Implementation

The initial stage of the hardware development involved analyzing the operating requirements and relevant specifications of the ADS1299. Particular attention was given to its simultaneous multichannel acquisition capabilities for differential biopotential measurements, 24-bit analog-to-digital conversion at a 500 Hz sampling rate, low-noise performance, and SPI-based communication with the processing unit.

Based on these design requirements, the acquisition electronics were subsequently implemented as a custom printed circuit board using KiCad. The PCB layout was organized into two main functional sections to facilitate the integration and interconnection of the system components. The first section incorporates the 64-pin interface associated with the ADS1299 circuitry, as illustrated in Figure 2.

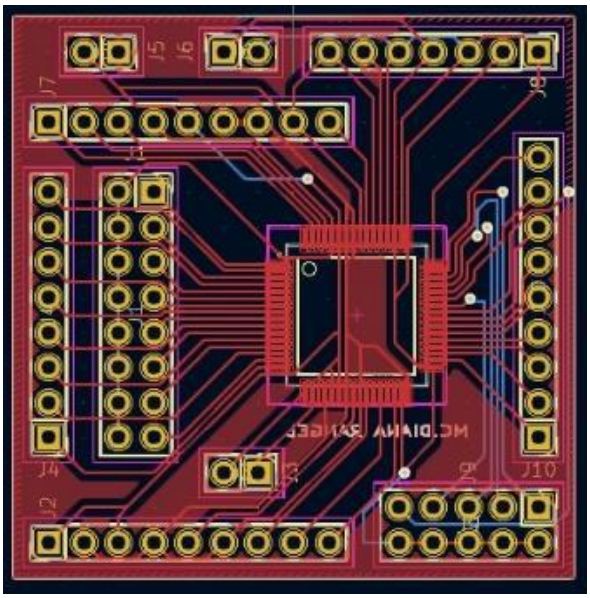


FIGURE 2: Connector board for the ADS1299 integrated circuit

The second section of the PCB incorporates the complementary circuitry required for simultaneous 16-channel EEG acquisition. This part of the design includes the connections associated with electrode interfacing, signal routing, and the communication paths necessary for data transfer between the acquisition electronics and the processing system, as illustrated in Figure 3.

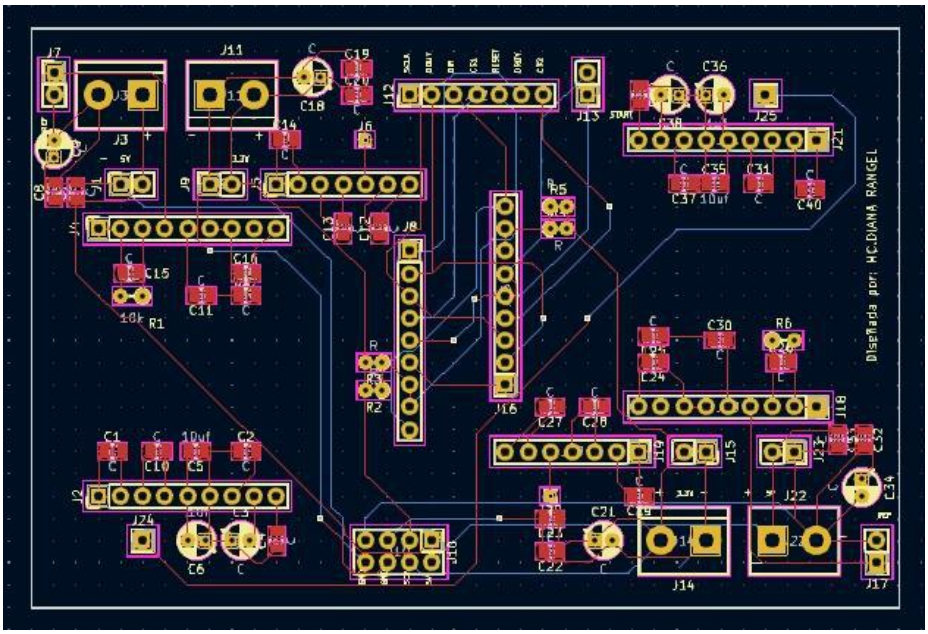


FIGURE 3: Complete PCB design for the 16-channel EEG system

EEG electrodes were used for signal acquisition. The international 10–20 system was adopted for non-invasive electrode placement, as shown in Figure 4.

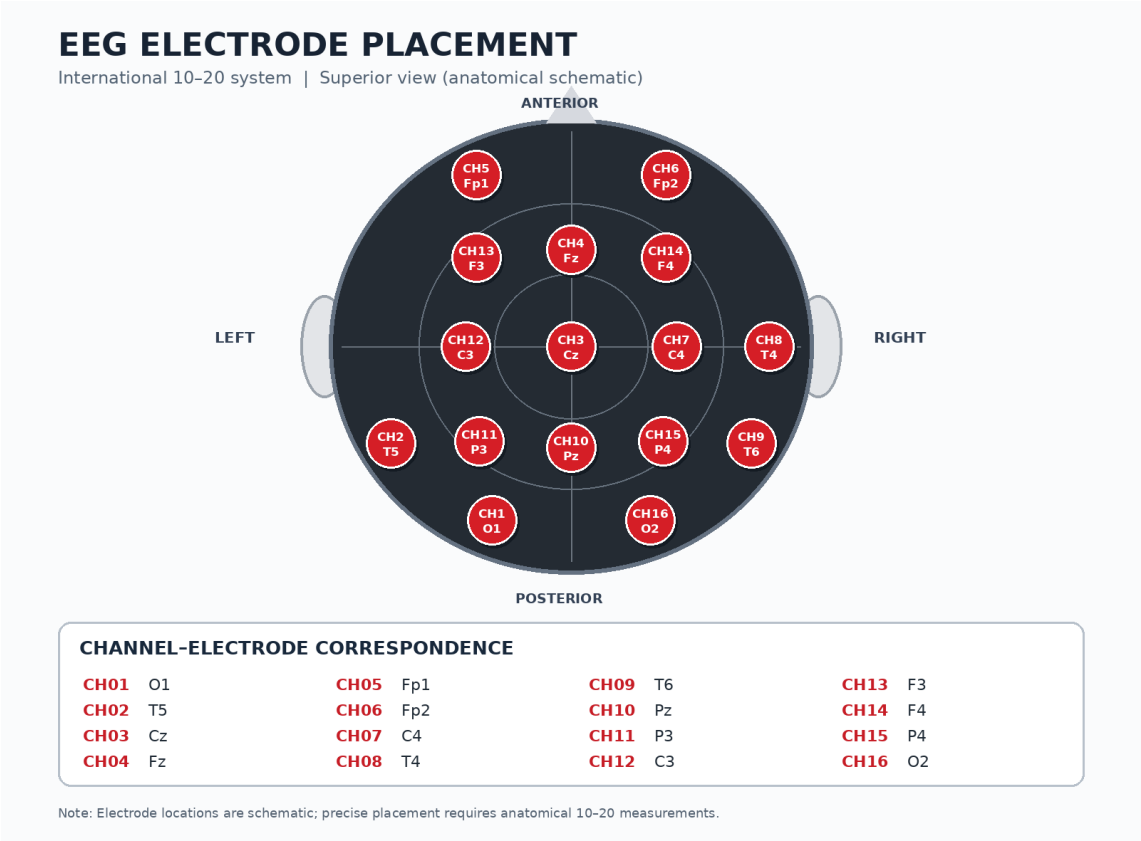


FIGURE 4: Electrode placement according to the 10–20 system

2.6 GUI and Tools Development

For the second phase, a graphical interface was developed in MATLAB to process and manage the acquired EEG signals. The interface applies band-pass filtering to attenuate unwanted frequencies. The EEG acquisition considered a bandwidth from 1 Hz to 100 Hz, while the brain rhythms of interest are commonly divided into frequency sub-bands: delta (1–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), and beta (13–30 Hz) [8].

It was also important to map the average value of each channel to identify whether the electrodes were correctly positioned on the scalp. Figure 5 compares a test with the system connected against a test with the system disconnected. With an active connection, the signals show greater definition and amplitude, indicating more effective acquisition than in the disconnected condition.

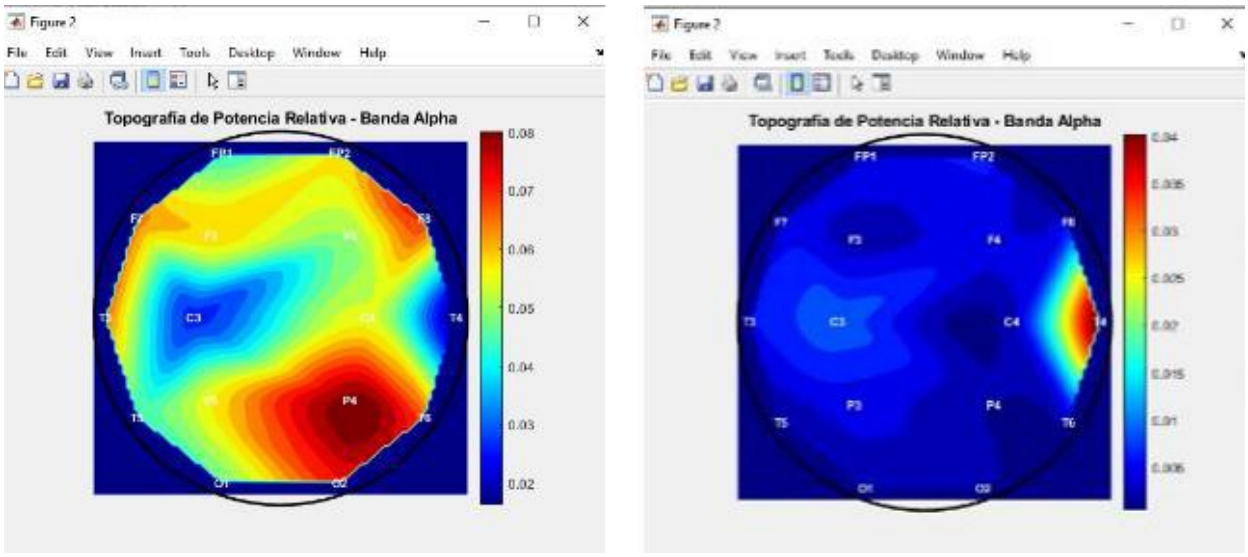


FIGURE 5: Comparison between the disconnected and connected device conditions

Real-time visualization and storage of electroencephalographic data in formats suitable for subsequent analysis were also incorporated. Figure 6 shows the acquisition of the 16 EEG channels.

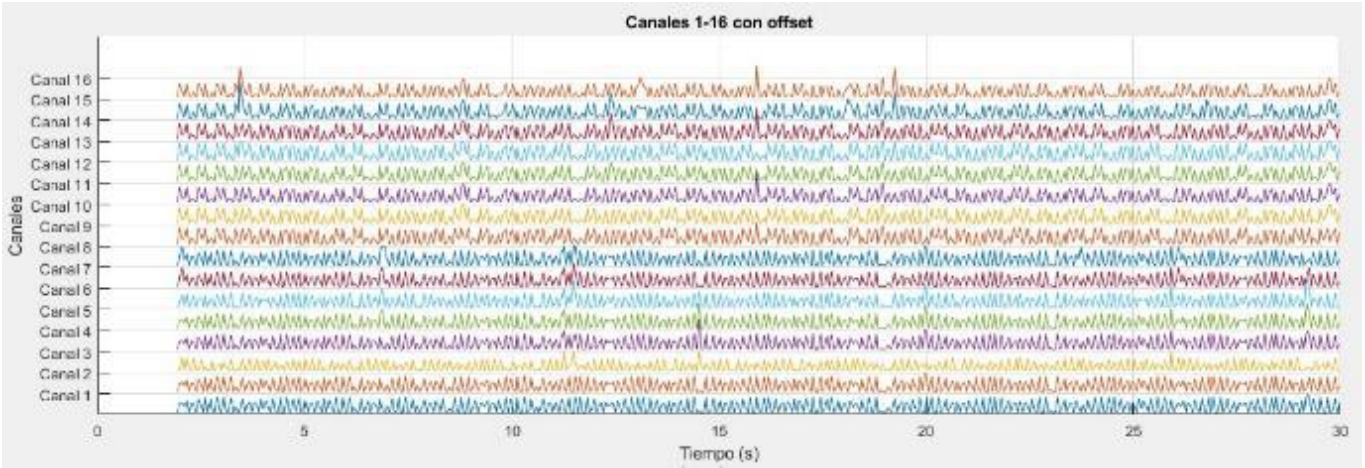


FIGURE 6: Visualization of EEG signals from the 16 channels

For signal collection, the developed device was used to acquire one-second EEG segments, corresponding to 500 samples. Five participants were asked to think of the indicated word. The experiment was repeated 20 times for each word, producing a total of 200 records of 500 samples each.

After the database was obtained, several machine-learning classifiers were applied to compare electrode performance and determine which channels contributed most significantly to prediction accuracy. This evaluation made it possible to identify the most relevant electrode locations for future applications of the system.

III. RESULT AND DISCUSSION

3.1 System Validation

After the accuracy of the different channels was evaluated, the K-nearest neighbors (KNN) classifier was found to provide the best performance, reaching an average accuracy of 85.9% across the 16 channels. The other classifiers produced prediction accuracy below 80%. After the model was trained and validated, a practical test was implemented to evaluate its real-time prediction capability.

The test associated keyword detection with a physical response using an RGB LED. When the system predicted the word "Yes," the LED was illuminated in blue; when the word "No" was detected, the LED was illuminated in green.

As shown in Figure 7, the system activates the corresponding LED according to the word recognized from brain activity during silent-speech execution.

The performance of the classification algorithms was assessed using the EEG data obtained from the 16 acquisition channels. Among the evaluated approaches, the k-nearest neighbors (KNN) algorithm achieved the highest overall performance, with a mean classification accuracy of 85.9% across the complete channel set. In comparison, none of the remaining classifiers reached an accuracy of 80%. Based on these results, KNN was selected for the subsequent experimental implementation. Once the classification model had been trained and evaluated, its ability to generate predictions during system operation was examined through a real-time proof-of-concept experiment.

To provide an observable representation of the classifier output, the predicted silent-speech commands were mapped to different states of an RGB LED. A classification corresponding to the keyword "Yes" produced blue illumination, whereas recognition of the keyword "No" resulted in green illumination. In this manner, the classifier output was translated into an immediate physical response from an external device.

Figure 7 illustrates the experimental implementation of this procedure. The RGB LED changes its illumination according to the class assigned to the EEG pattern recorded during the silent-speech task, thereby providing a visual indication of the system's real-time classification output.

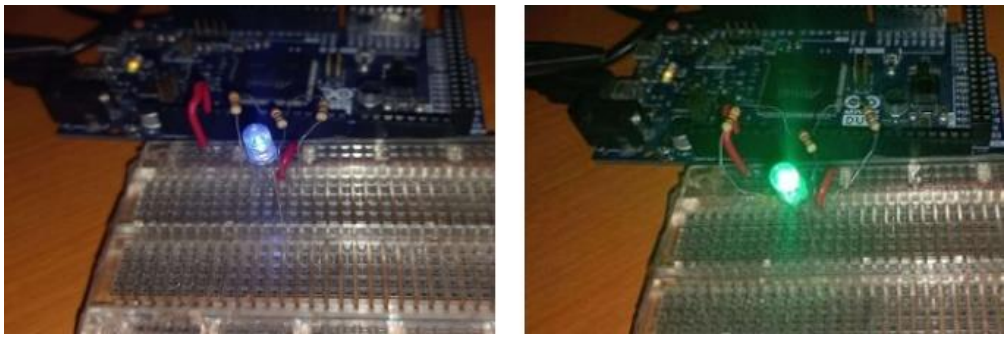


FIGURE 7: Experimental representation of the real-time classifier output using an RGB LED

IV. CONCLUSION

The proposed platform demonstrates the feasibility of integrating multichannel EEG acquisition, signal visualization, and computational classification within a single BCI-oriented system. The ADS1299-based hardware provided the electrophysiological recordings required for subsequent processing, while the developed software interface enabled signal monitoring and data management. The complete acquisition and processing chain was evaluated through a proof-of-concept silent-speech classification experiment using machine-learning algorithms. Among the evaluated methods, KNN yielded the highest classification performance, reaching an accuracy of 85.9% for the experimental conditions considered in this study.

In a practical sense, this means that the developed system can translate imagined speech-related neural activity into discrete outputs that can be used to control external devices, demonstrating the viability of the proposed architecture for future assistive communication applications.

These findings indicate that the developed architecture can serve as a practical experimental platform for investigating non-invasive EEG-based communication strategies. Rather than representing a complete assistive solution, the present

implementation establishes a technological foundation upon which more advanced BCI capabilities can be developed. Further work should include evaluation with larger datasets and participant groups, optimization of signal-processing and classification methods, and assessment under less controlled operating conditions. Such developments would help determine the robustness and generalizability of the system and its suitability for future assistive-technology applications.

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CONFLICT OF INTEREST

The authors declare that they have no known financial, professional, or personal conflicts of interest that could have influenced the research, results, interpretation, or conclusions presented in this work.

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