The use of the Emotiv Epoc Flex kit in applications involving artificial intelligence

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Abstract

This article presents a wide, proprietary range of Emotiv Epoc Flex Gel headset applications for EEG signal measurement. It is about its use in systems involving artificial intelligence, such as artificial neural networks and expert systems. The constantly developing field of biomedical engineering as well as newer and more advanced BCI (brain-computer interface) systems require their designers to constantly develop and search for various innovative methods used in their creation. In response to practical requirements and the possibility of using the system in real conditions, the authors propose an advanced solution using EEG signal analysis (electroencephalography). An AI-based approach to designing the BCI system was used for advanced signal analysis. The article contains a detailed description of two applications based on artificial intelligence using EEG signals. The first one, for controlling a mobile robot using mental commands. The second one, on the other hand, for controlling a mobile robot with verification in the form of an EMG signal. This article provides a comprehensive overview of the integration of the Emotiv Epoc Flex Kit with proprietary AI systems and its significant impact on the field.

Keywords

EEG; Emotiv EPOC Flex Gel; neural networks; EMG; LEGO Mindstorms; brain–computer interface (BCI); motor imagery verification; signal classification; expert system; artificial intelligence

1. Introduction

Electroencephalography (EEG) is widely used in research involving biomedical engineering, neuroscience and others (e.g. Brain-Computer Interface, BCI), as well as in sleep analysis and detecting abnormal brain function. The reason is e.g. non-invasiveness and relatively low financial costs [1, 2].

An electroencephalogram (EEG) captures the electrical activity patterns emanating from the cerebral cortex. Due to the minute nature of these electrical signals, typically measured in microvolts, a substantial amplification, roughly on the order of a millionfold, is required for them to be visualized on a computer screen. The recorded signals primarily originate from the neurons, within which a multitude of bioelectric events occur. These encompass phenomena like action potentials, post-synaptic potentials (PSP), and the protracted depolarization of neurons over an extended period [36, 3, 4, 5].

Brain-computer interface (BCI) technology facilitates direct communication between the brain and external devices. The analysis of electroencephalogram (EEG) signals plays a pivotal role in the ongoing exploration of BCI capabilities. BCI technology emerged in the 1990s, and although it remains relatively new, its potential to transform the way people interact with computers and other devices is profound [6, 7, 8, 9].

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Currently, most widely adopted methods for computer interaction rely on muscular movements. In contrast, EEG-based brain-computer interfaces have been under scrutiny for numerous years as a means of communication and control for individuals with physical disabilities. Through training, individuals can learn to employ imagined motor actions as input data for computers or to control assistive technologies. This promises to enhance the accessibility and usability of technology for those with limited physical mobility [37, 10, 11, 12, 39].

Research on brain-computer interfaces, including research involving projects using artificial intelligence, was addressed in [13, 14, 15, 16, 17, 18, 19, 38]. The authors of these papers addressed various issues, from BCI systems, through classifiers and simulations, to various types of medical and biomedical applications.

Electromyography (EMG) is an electrophysiological test that captures the electrical impulses generated by muscle activity. In the realm of neuromodulation research, EMG is frequently employed to assess the diverse effects of stimulation within the brain's motor regions. In clinical settings, EMG serves as a valuable tool for diagnosing nervous and muscular disorders, allowing for the localization and characterization of pathologies [20, 21].

In clinical applications, EMG may necessitate the insertion of a small needle into muscles to record electrical activity accurately. However, in the field of biomedical engineering, researchers commonly opt for non-invasive methods, utilizing surface electrodes placed on the skin to detect muscle-generated electrical activity. This non-invasive approach eliminates health risks associated with invasive methods.

Myoelectric interfaces also find utility in rehabilitation technology as supportive devices. The EMG signal, a prominent biological signal, is often harnessed to predict human motor intentions and can be integrated into human-robot collaboration systems [22, 23, 24, 25, 26].

The Emotiv EPOC Flex Gel is an affordable, lightweight, wireless brain-computer interface (BCI) headset that offers reliable control and efficient measurement capabilities. Each sensor on this headset has the capability to capture real-time data from four distinct brainwave frequencies, including delta, theta, alpha, and beta [27, 28, 29, 30, 31, 32].

Despite its advanced features and accuracy, the utilization of this particular device (the Flex Gel version) in research remains relatively scarce. It's worth noting that this headset stands out as one of the manufacturer's most intricate and precise offerings. However, its adoption is steadily increasing, and its applications are expanding across various domains [14, 15, 16, 28, 33, 34, 35].

The first system revolves around research utilizing the Emotiv Epoc Flex kit, developed as a response to the quest for innovative solutions for controlling robotic components through user-generated mental commands. In this endeavor, the recorded signal, acquired through a 32-electrode apparatus, underwent preprocessing for classification. This involved a novel approach that integrated the EEG signal, thereby producing modified waveforms that could be identified not only by conventional proprietary software but also by an artificial neural network. Effective signal classification culminated in the generation of a control signal, which was subsequently employed to govern the actions of the LEGO EV3 Mindstorms robot.

The aim of the research included in the second project was to design an EEG signal classification system for controlling a mobile robot while verifying pure mental commands using a sensor that measures the EMG signal. This is crucial, because paralyzed people can control objects only by means of generated changes in the EEG signal, without any additional "support" by movements of the muscles of the limbs.

2. Emotiv device and software

The Emotiv EPOC Flex is a wearable electroencephalography (EEG) headset designed for capturing and interpreting brain activity. It's a product of Emotiv, a company specializing in brain-computer interface (BCI) technologies. The EPOC Flex is known for its flexibility and adaptability, making it suitable for various applications, including brain research, human-computer interaction, and neurofeedback. An example EEG signal waveform in the Emotiv PRO environment is presented in Figure 1.

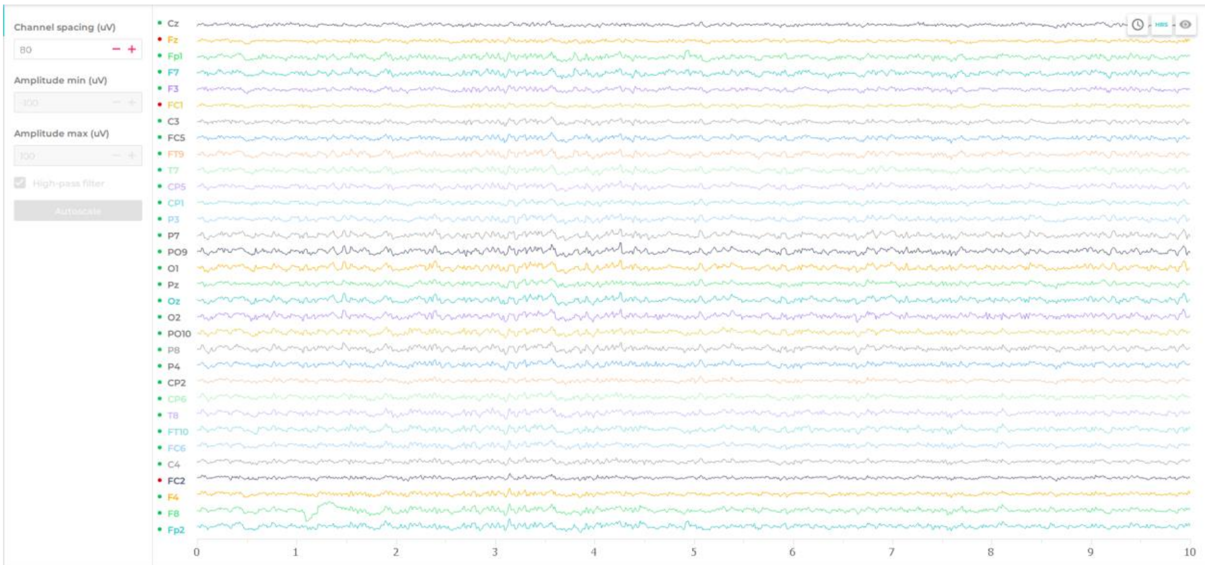


Figure 1: Presentation of electrodes configuration and LEGO Mindstorms EV3 [16]

An equally important issue is the arrangement of electrodes and their nomenclature. This is described in Table 1.

Table 1
Names of electrodes

Electrodes			
LH-Fp1	LD-FC5	RA-C4	LJ-Pz
RH-Fp2	LC-FC1	RB-T8	RN-P4
LG-F7	RC-FC2	LQ-CP5	RO-P8
LF-F3	RD-FC6	LP-CP1	LM-PO9
RK-Fz	RE-FT10	RP-CP2	LL-O1
F-F4	LB-T7	RQ-CP6	RJ-Oz
RG-F8	LA-C3	LO-P7	RL-O2
LE-FT9	LK-Cz	LN-P3	RM-PO10

The data in Table 1 are crucial for the systems described in the following sections. These sections effectively outline the scope and possibilities of the authors' projects using Emotiv Epoc Flex Gel.

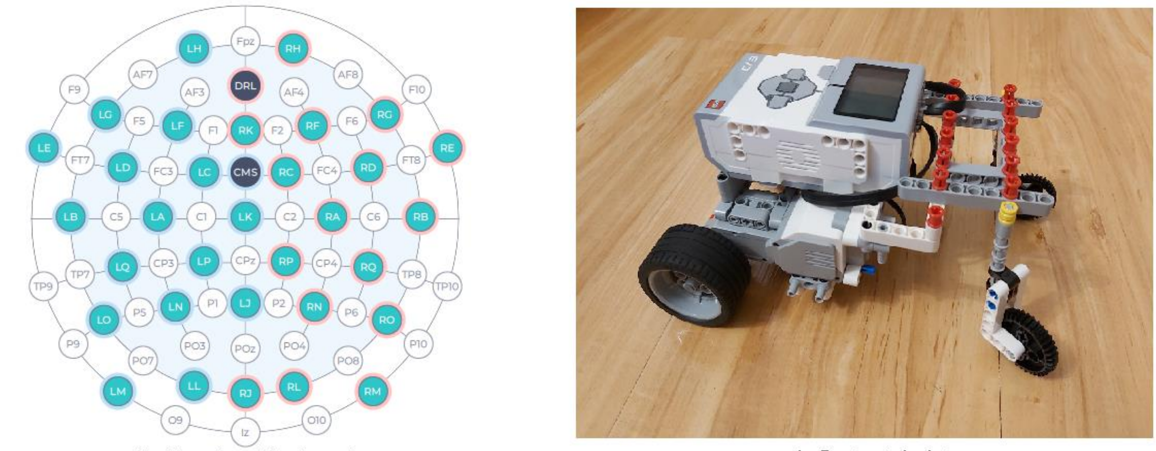
3. First system

This chapter introduces an intriguing approach to the task of recognizing and categorizing electroencephalographic (EEG) signals. The scarcity of studies utilizing the Emotiv Epoc Flex kit prompted the pursuit of original solutions, particularly in the realm of controlling robotic components through user-issued mental commands. The measured signal, acquired through a 32–electrode device, underwent preparation for classification via a novel technique involving the integration of the EEG signal. This transformation led to the generation of new waveforms, which could subsequently be recognized by an artificial neural network. Through the appropriate classification of the signal, a control signal was generated, facilitating the manipulation of the LEGO EV3 Mindstorms robot [16].

3.1. Presentation of methodology, data acquisition and system

The construction of the EEG signal analysis and classification system described in this article comprises several components. The raw EEG signal was recorded using an Emotiv EPOC Flex device, and measurements were acquired using the dedicated EmotivPRO software. In Figure 2, you can observe the electrode configuration on the headset, along with a vehicle designed by the authors, which is based on the LEGO EV3 cube.

The electrodes in the set are designated by the following channel names: Cz, Fz, Fp1, F7, F3, FC1, C3, FC5, FT9, T7, TP9, CP5, CP1, P3, P7, O1, Pz, Oz, O2, P8, P4, CP2, CP6, TP10, FC6, C4, FC2, F4, F8, and Fp2 [16].



a. Configuration of the electrodes

b. Constructed robot

Figure 2: Presentation of electrodes configuration and LEGO Mindstorms EV3 [16]

Two individuals participated in this study, during which several hundred tests were conducted. Signals were recorded both during resting states and when commands to move forward, backward, right, and left were triggered. An essential factor influencing the study's outcomes is the level of focus. It is imperative that the participants maintain a state of deep concentration, as the absence of focus can disrupt the test process, potentially leading to inaccurate results. After collecting a substantial number of measurements, further processing and classification were performed using various methods [16].

In this research endeavor, all analyses and classification methodologies were executed using Matlab, a platform for programming and numerical calculations. The system's operational flow is depicted in Figure 3. Within this program, it is possible to appropriately filter the signals, followed by the execution of relevant analyses and classification procedures. In the subsequent stage, the signal is integrated over time for each of the 32 electrodes individually, spanning one second for the entire signal duration. This process yields one–second integrated samples, which serve as a foundation for the precise determination and classification of signal types based on the integrated potentials [16].

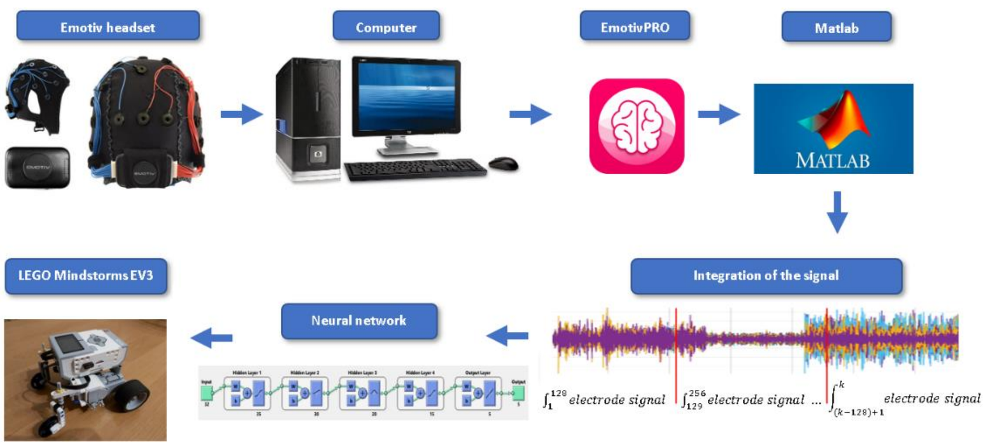


Figure 3: Scheme of system (based on [16])

These obtained samples, containing the signal integrated over time, can then undergo an appropriate classification algorithm. The proposed algorithm for classifying integrated EEG signal samples from the electrodes is grounded in a multi–layer neural network. Recognized signals, such as commands to move forward, backward, or right and left, can subsequently be transmitted to a robot for the execution of the desired commands, as demonstrated in Figure 3.

3.2. EEG signal integration and filtration method

The EEG signal obtained from the headset undergoes a crucial filtering process. The raw signal received from the 22 most essential electrodes is not directly subjected to classification by the designed system. This decision was made to simplify the algorithm's development process, as unfiltered waveforms exhibit prolonged stabilization and transient times when voltage measured by the sensors increases. Consequently, a high–pass filter with a sampling frequency of f_s= 1000 Hz and a bandwidth of f_p= 200 Hz was employed [14].

The dedicated application facilitates EEG signal sampling at a frequency of f_e= 128 Hz. With this knowledge in mind, the authors proposed an innovative approach that involves the rolling integration of the signal from each electrode for a one–second duration. This approach is unique in the context of pre–classifying biomedical signals such as electroencephalograms. In terms of methodology, this can be effectively represented analytically. The variable *M* represents the number of samples within the signal, while *k* signifies the count of full one–second periods in the signal. Given the information about the sampling frequency f_e, it's understood that, for instance, a 5–second EEG signal comprises *M*= 640 samples. Utilizing the calculations in Equation 1, it is determined that there will be *k*= 5 full one–second periods available for classification. Importantly, in the case of a 10.5–second signal, only the first 10 seconds will be considered, amounting to a total of *M*= 1280 samples, which yields *k*= 10 integrated signal samples. This approach is implemented to ensure efficiency and clarity in the interpretation of each waveform [16].

$$k = \frac{M}{128} \tag{1}$$

The variable *S* is individually defined for each electrode and is represented as S_1 to S_{22}, as demonstrated in Equation 2 below.

$$S_{1\dots22}^{(1\dots k)} = \left[\int_{(((1\dots k)-1)\cdot128)+1}^{(1\dots k)\cdot128} |E_{1\dots22}^{EEG}|\right] \tag{2}$$

Each of these 22 variables, namely S_1 to S_{22}, is an array that accumulates values derived from the rolling integration of one–second segments of the EEG signal for each respective electrode. The upper index of each array corresponds to a specific sample within the integrated value. To illustrate, for a 10–second signal from the second electrode, where *k*= 10, the *S* variable takes the form of $S_2^{(1\dots k)}$. Organizing data in this tabular manner proves to be both convenient and efficient for applications of this nature [16].

The EEG variable represents the signal obtained from individual electrodes within the set. As outlined in Equation 2, it is evident that the absolute value of the signal from each channel is integrated over a span of 128 samples. This integration approach facilitates the utilization of the rolling integration method and enables the recording of these integrated values into the *S* variables [16].

3.3. Signal classification by the designed neural network

In this section, we will delve into an advanced approach that incorporates a neural network algorithm. Specifically, a feed–forward neural network has been put forth for analysis. The determination of the number of layers, the choice of activation functions, and the allocation of neurons in each layer were made through a process of trial and error, guided by an expert approach.

To conduct the neural network training procedure, it was essential to prepare a training dataset comprising both input and output data. In the training process, the training input set *U* was employed, which utilized a pattern matrix *u* with a total of *i*= 32 rows. These input values were derived from integrated one–second segments of the EEG signal, and the number of rows in the matrix depended on the number of electrodes in the set [16].

For the neural network training, an output set Y was also imperative. This set consisted of an input pattern matrix y with j= 5 rows, reflecting the recognition of 5 distinct signal types: neutral state, forward movement, backward movement, right movement, and left movement. It's noteworthy that both the input and output training patterns comprised an equal number of elements, totaling n= 250. The presentation of the data can be substantiated using the following formulas [16]:

$$U = \begin{bmatrix} u^{(1)} \\ \vdots \\ u^{(i)} \end{bmatrix} = \begin{bmatrix} u_1^{(1)} & \cdots & u_n^{(1)} \\ \vdots & \ddots & \vdots \\ u_1^{(32)} & \cdots & u_n^{(32)} \end{bmatrix}, \tag{3}$$

In turn, the set of output patterns follows the relationship:

$$Y = \begin{bmatrix} y^{(1)} \\ \vdots \\ y^{(i)} \end{bmatrix} = \begin{bmatrix} t_1^{(1)} & \cdots & t_n^{(1)} \\ \vdots & \ddots & \vdots \\ t_1^{(5)} & \cdots & t_n^{(5)} \end{bmatrix}, \tag{4}$$

The chosen neural network architecture incorporates 4 hidden layers. In the first hidden layer, the tangent function *tansig* is employed with 35 neurons. The second layer utilizes the logistic sigmoid activation function *logsig* and comprises 30 neurons. Moving on to the third layer, it incorporates the radial basis function *radbas* with 20 neurons. Finally, the last hidden layer once again employs the tangent function *tansig* and is composed of 15 neurons.

The concluding segment of this feed-forward neural network consists of a single layer containing 5 neurons, each utilizing a linear activation function *purelin*. This linear layer plays a pivotal role in summing up the outputs from the non-linear neuron activation functions situated in the preceding layers [16].

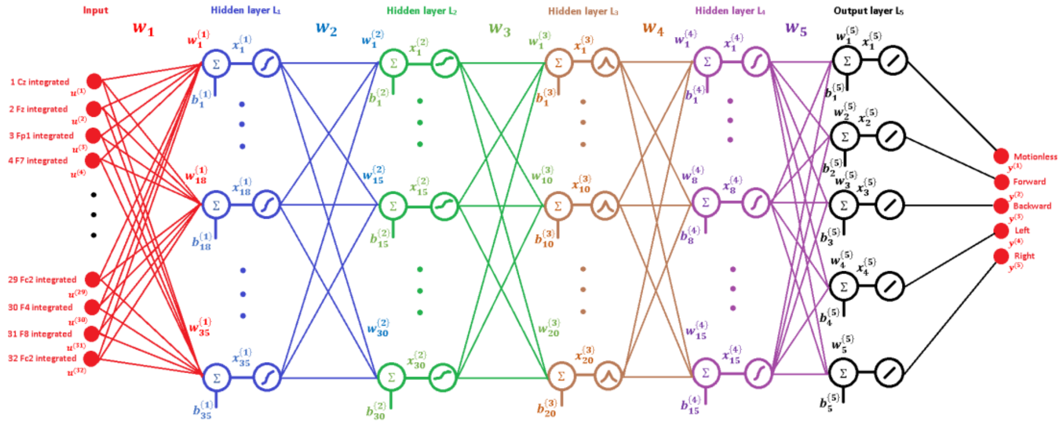
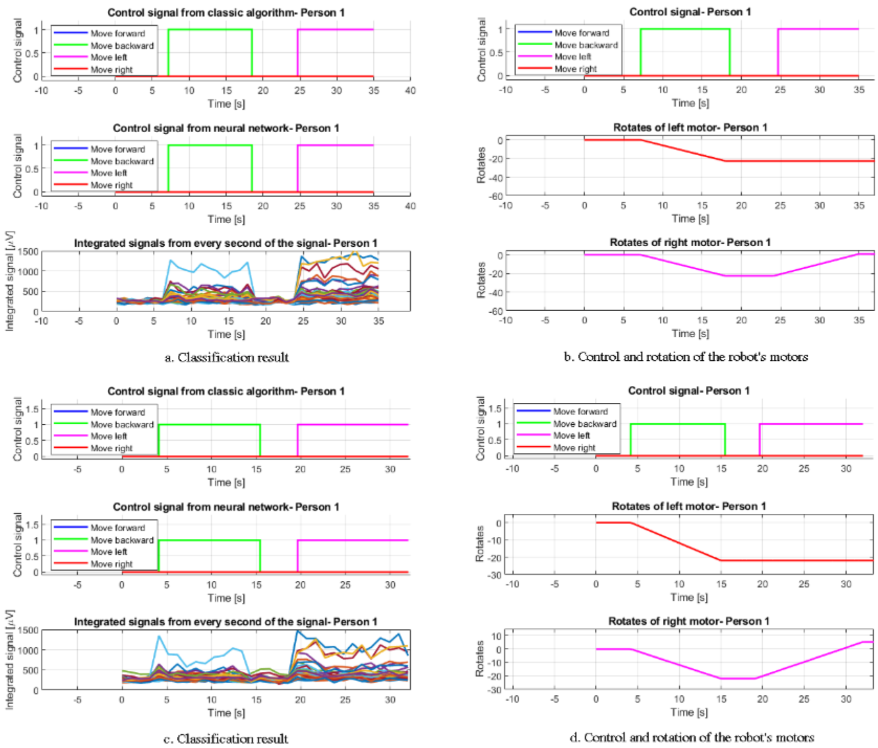


Figure 4: The structure of the feed-forward neural network [16]

In the network diagram (Figure 4), the output data vector is denoted as y, while the network inputs, which represent the integrated values of the EEG signal from the 32 electrodes, are indicated as u [16].

3.4. Selected examples of results

The ultimate phase of this research involves validating the functionality of the developed classification system. To accomplish this, both the performance of the classical algorithm and artificial intelligence solutions were assessed. These tests were conducted using pre–processed EEG signals from the archive. The outcomes of signal recognition pertaining to the study participants are illustrated in Figures 5 and 6.



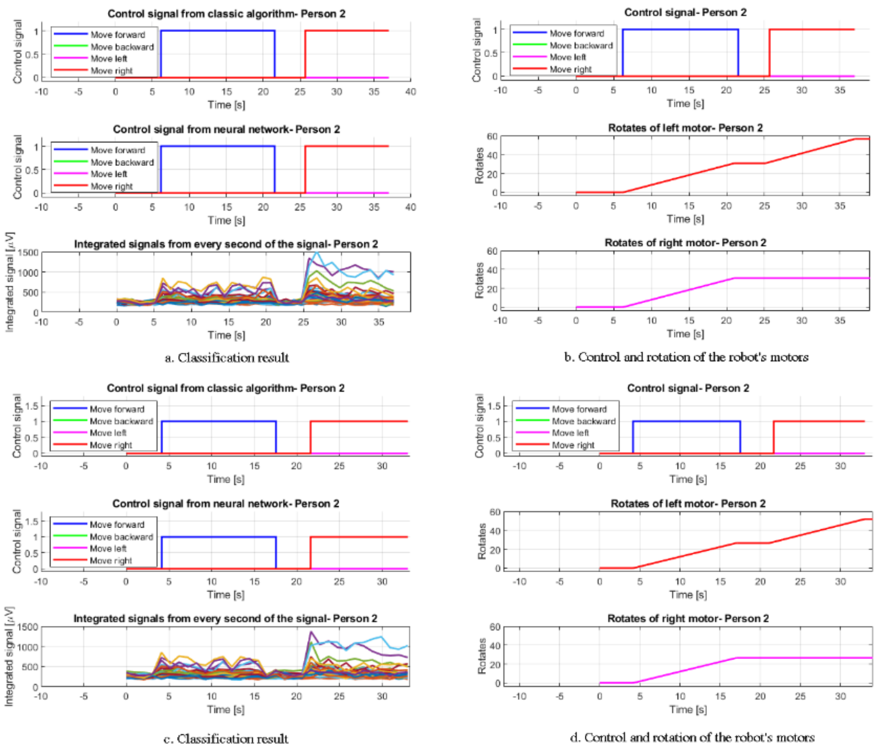
a. Classification result

b. Control and rotation of the robot's motors

c. Classification result

d. Control and rotation of the robot's motors

Figure 5: Observation of signal classification and verification results on a mobile robot [16]



a. Classification result

b. Control and rotation of the robot's motors

c. Classification result

d. Control and rotation of the robot's motors

Figure 6: Observation of signal classification and verification results on a mobile robot [16]

4. Second system

This chapter will present issues related to the second designed system. The authors will present the methodology, data acquisition and system. In addition, a method of preparing the EMG signal for classification will be shown. Then the classification system is described, and the chapter ends with examples of results.

4.1. Presentation of methodology, data acquisition and system

The EEG and EMG signal analysis and classification system described in this paper comprises several interconnected components. Initially, the raw EEG signals were captured using the Emotiv EPOC Flex Gel headset, and the data acquisition was facilitated by the dedicated EmotivPRO software. On the other hand, the EMG signals were acquired using the MyoWare Muscle Sensor device, which was connected to an Arduino UNO microcontroller. This setup was then synchronized with the Matlab program, where the acquired data was collected and subjected to analysis. Both the EEG and EMG signals underwent assessment through an expert system that incorporates artificial intelligence algorithms in the form of a neural network. Additionally, a conventional algorithm for artifact detection and activation of the arm muscles was integrated into the system. The schematic representation of this system can be observed in Figure 7.

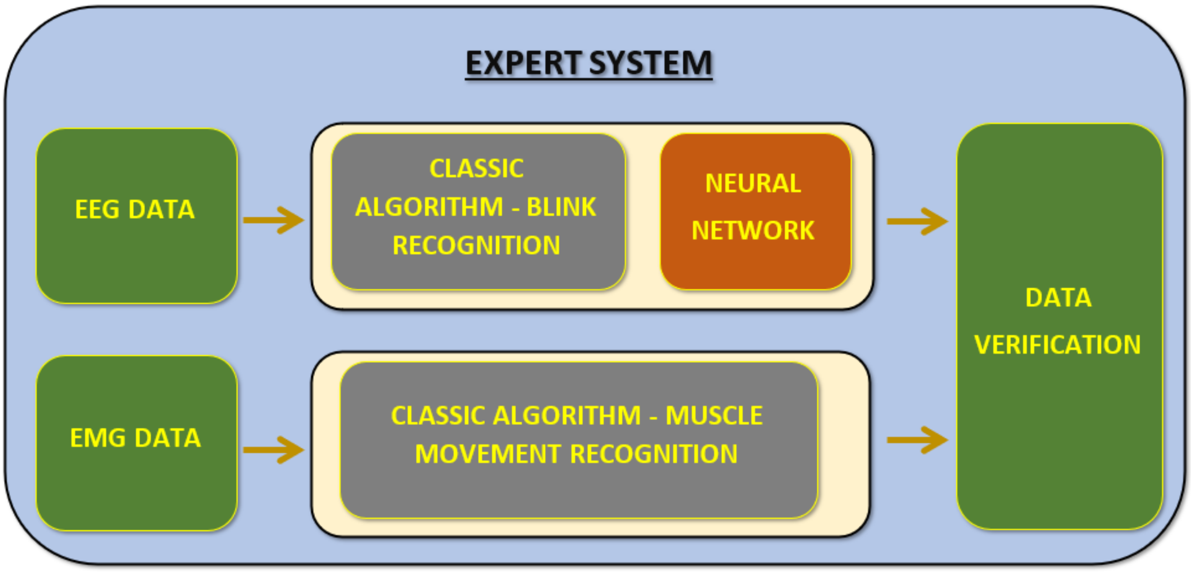


Figure 7: Scheme of the expert system

An illustrative example of the research approach is depicted in Figure 8, showcasing the moment when EEG and EMG signals were recorded from two study participants. In total, a cohort of 10 individuals underwent testing. This sample size was chosen to enable a robust evaluation of the algorithm's effectiveness and, notably, to design it with a degree of resilience to variations in measurement values that can be attributed to individual differences.

The Emotiv EPOC Flex Gel device utilized in the study features 22 electrodes, each designated with specific channel names: Cz, Fz, Fp1, F7, F3, FC1, C3, FC5, FT7, T7, CP5, CP1, CP2, CP6, FT8, FC6, C4, T8, FC2, F4, F8, and Fp2.

Figure 8: The process of collecting measurements [14]

Each participant in the study conducted a series of 15 measurements, involving the repetition of specific mental command sequences. These sequences, each lasting a few seconds, encompassed the following steps:

1. A neutral state.
2. Imagining an arm movement (mentally commanding the mobile robot's movement).
3. Blinking the right eye (a switch that causes the next move command to move the robot to the right).
4. Imagining an arm movement.
5. Blinking the left eye (a switch that causes the next move command to move the robot to the left).
6. Imagining an arm movement.
7. Blinking both eyes (returning the system to the initial state, with subsequent arm movement imaginings directing the robot forward).
8. Imagining an arm movement.

This carefully orchestrated sequence of activities resulted in measurement signals that extended over approximately 45 seconds.

Concurrently with the EEG measurements, participants also wore the MyoWare Muscle Sensor device on their biceps brachii muscles. This allowed for the effective collection of the EMG signal, which later facilitated the verification of pure mental commands, excluding any reliance on additional muscle movements. This aspect is of paramount importance, particularly for individuals with paralysis, as it enables research on systems exclusively reliant on mental commands for controlling arm movements.

Participants were instructed to maintain high levels of concentration throughout the experiments, as lapses in focus could disrupt the research process and lead to erroneous results. Once a sufficient number of measurements were obtained, subsequent processing and classification were carried out using a combination of artificial intelligence and conventional algorithms [14].

4.2. Method of preparing the EMG signal for classification

The MyoWare Muscle Sensor (EMG) device is a distinct kit and operates independently from the Emotiv EPOC Flex Gel (EEG) kit. Consequently, synchronization between these two systems is not seamless. This disparity impacts the chosen sampling time, which was arbitrarily determined by the system designers. It's essential to acknowledge that EMG measurement devices are not obligated to produce signals sampled in identical fashion to an electroencephalograph (EEG). In this context, the emphasis is not on prolonged signal analysis; rather, the priority lies in promptly and effectively detecting muscle activation [14].

$$h = \frac{N}{k} \tag{1}$$

The approach for segmenting the collected samples was based on the formulation provided in Equation 1. For instance, given a 10–second EEG signal with a parameter value of $k = 10$, and an EMG signal consisting of $N= 100$ samples, it can be computed that for every second of the electroencephalographic signal, there will be $h = 10$ samples of the EMG waveform [14].

$$L^{(1\ldots k)} = \begin{cases} 1, dla\ E^{EMG}_{(1\ldots h)\ldots(N-h\ldots N)} \geq V_{max} \\ 0, dla\ E^{EMG}_{(1\ldots h)\ldots(N-h\ldots N)} < V_{max} \end{cases} \tag{2}$$

The electromyographic signal will be assessed in a binary manner, as outlined in Equation 2. The variable L will store a sequence of binary values, where 0 signifies no muscle movement ($E^{EMG} < V_{max}$), and 1 indicates muscle activity ($E^{EMG} \geq V_{max}$). Here, V_{max} represents the maximum tension level, determined through observations of the system when the arm muscles are deemed to be at rest, set at 4.5 V.

To illustrate, suppose that within the 40–50 range of the EMG signal, at least one of the samples registers a value greater than the specified voltage, i.e., $E^{EMG}_{(40\ldots50)} >= V_{max}$, then $L(5)$ will be set to 1. This will unequivocally halt any commands to control the robot, even if the conditions for imagining arm movement are met [14].

This approach offers distinct advantages, with the primary one being its independence from the sampling rate of the MyoWare Muscle Sensor. The method employed allows for arbitrary sampling of the sensor, as it hinges on the variable k, which governs the range of samples h per second of the EEG signal [14].

4.3. The functioning of the designed neural network

The neural network was trained using two primary datasets: I (input) and O (output). The first dataset, denoted as the input training set, comprises 22 network inputs corresponding to the measurement channels of the EEG signal. These inputs were organized as a pattern matrix with a total of a= 22 rows, each representing integrated one–second segments of the EEG signal. The ouput training data was stored in a separate matrix, which had b= 2 rows. This specific data structure aligns with the requirements of the neural network used, which was designed for recognizing binary 0–1 signals, specifically related to the imagination of arm movement or its absence [14].

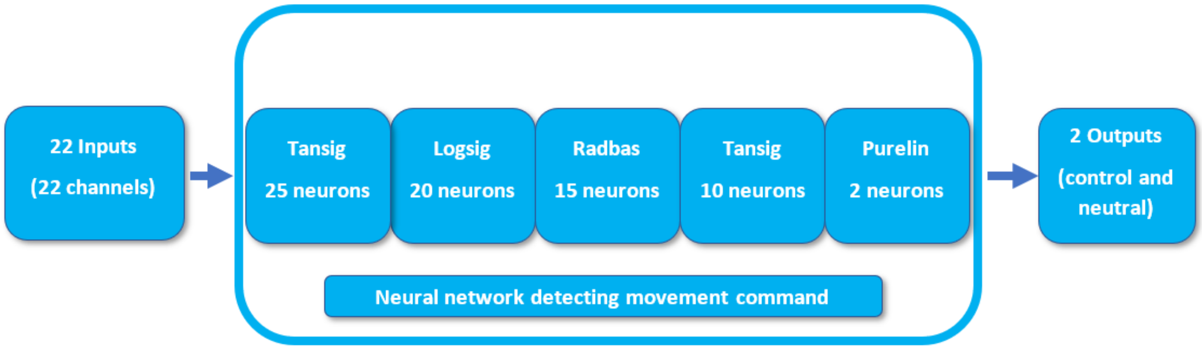


Figure 9: The structure of a neural network

The input and output training patterns were determined through an iterative process, and it was determined that a satisfactory set size was n= 450. In Figure 9, you can see the architecture of the feed–forward neural network employed for classifying periodically integrated EEG signals.

This feed–forward network utilized in the research comprises 4 hidden layers and one output layer. The first layer is equipped with a tangential activation function and consists of 25 neurons. The second layer employs a logarithmic sigmoid activation function with 20 neurons. The third layer, featuring 15 neurons, employs a radial activation function. Moving further, the penultimate fourth layer, comprising 10 neurons, employs the tangential activation function. Finally, the output layer contains a linear activation function and consists of 2 neurons, which aligns with the number of neural network outputs. The primary role of this output layer is to aggregate the outputs of the non–linear neuron activation functions [14].

4.4. Selected examples of results

In this section, the authors provide an illustrative test of the designed classification system, which encompasses the classification and validation of both EEG and EMG signals. This evaluation utilizes an expert system that combines classical algorithms with artificial intelligence techniques.

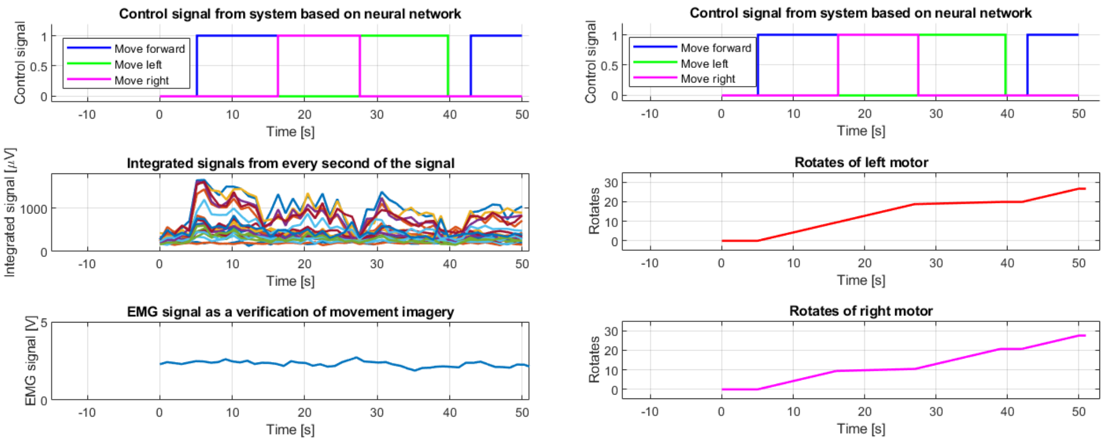


Figure 10: Observation of signal classification and verification results on a mobile robot [14]

Figures 10 and 11 showcase exemplary classification outcomes, accompanied by resultant control signals. Figure 10 displays the integrated EEG signal for each second of the measurement run across all channels. Additionally, it reveals the classification outcome in the form of control signals for maneuvering a mobile robot (e.g., move forward, move left, move right). The behavior of the EMG signal is intimately linked with the classification result, serving the purpose of confirming the absence of arm muscle movement. Figure 11, on the other hand, provides an instance where the system negatively verifies the signals, triggered by the detection of arm muscle activity based on EMG signal evaluation.

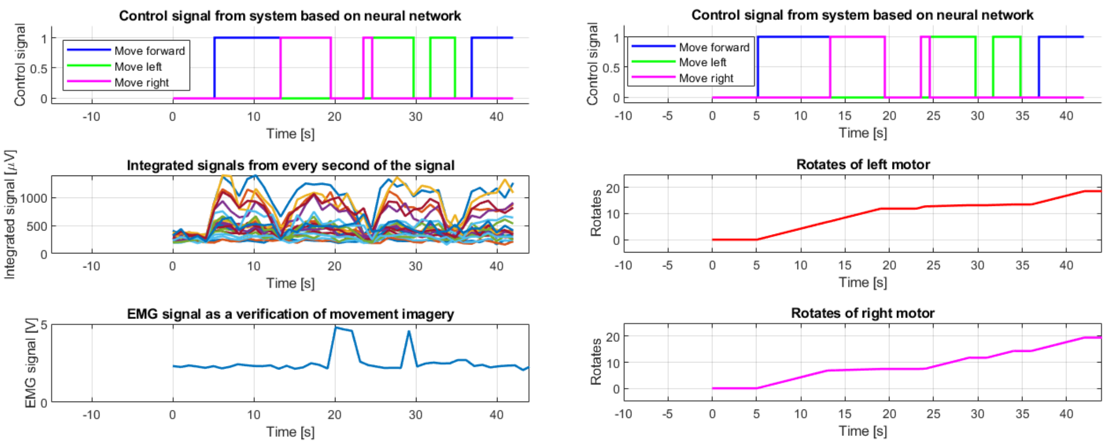


Figure 11: Interruption of robot control when arm muscle movement is detected [14]

5. Discussion and conclusions

The first system under investigation focuses on the Emotiv EPOC Flex headset, which is relatively uncommon compared to other products from the same manufacturer. In considering its potential applications in controlling robotic components, it becomes evident that the EEG signal classification methods outlined in this paper open up new avenues for research in this domain. It's noteworthy that the research employs a novel approach to EEG signal analysis, revolving around periodic signal integration. Furthermore, it incorporates artificial intelligence techniques and an expert–driven approach to signal classification. An additional factor contributing to the innovative nature of this study is the utilization of the Emotiv Epoc Flex Gel headset.

The second system detailed in this paper offers numerous prospects for further development and is well–suited for subsequent research catering to individuals with disabilities. The validation of the EMG signal serves as a means to assess the algorithm's performance in scenarios where mental commands are issued without concurrent muscle activation, as is often the case with paralyzed individuals who lack limb mobility. The results obtained in this experiment conclusively demonstrate the system's ability to classify integrated EEG signals and verify muscle movements, thereby achieving its intended objectives.

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