Multimodal Data Integration and Processing Method for Brain-Computer Interface Research

Nikita Gordienko[1], Oleksandr Rokovyi[2], Kostiantyn Kostiukevych[3],
Oleg Alienin[4], Sergii Stirenko[5], Yuri Gordienko[6]
National Technical University of Ukraine "Igor Sikorsky Kyiv Polytechnic Institute"
Kyiv, Ukraine
[1]nik.gordiienko@gmail.com, [2]rokovoy@comsys.kpi.ua, [3]jjwpey@gmail.com,
[4]oleg.alenin@gmail.com, [5]sergii.stirenko@gmail.com, [6]yuri.gordienko@gmail.com

***Abstract*—Rapidly growing demand for investigations of human physical and mental activities is dictated by the necessity of online monitoring and immediate diagnosis of health conditions at home or in the field. Therefore, the need for a mobile system appears for online biometric data collection by different sensors in wearable electronics. A prototype system was developed to collect multimodal data from many sensors and several sources. The proposed system, based on the example of the integration of electroencephalography (EEG) data, makes it possible to capture such multimodal EEG data from the brain-computer interface (BCI), to control, automatically mark data and store them on the server. In this way, EEG data can be used later for further analysis and can greatly facilitate the work of researchers and health professionals. The main advantages of the developed system compared to the available systems are its openness, mobility, speed of collection, transmission, and security of personal health data.**

***Index Terms*—multimodal data, electroencephalography, brain-computer interface, mobile system, data acqusition.**

I. INTRODUCTION

Today, many researchers are dedicating their work to investigation of the brain activity using the electromagnetic waves that the brain produces during mental activity for practical purposes. Scientific research on brain activity requires the processing of a large variety of data from different types of sensors (such as electroencephalograph (EEG), tonometer, thermometer, etc.) corresponding to different types of activity (such as vision, sound, touch, smell, taste, etc.) at various temporal and spatial scales and practically in the current time. That is why the problem of collecting data from different types of sensors and storing data for further access naturally appears. The current integrated systems are usually very complex, accessible only to professionals, and stationary often, that makes complex their wide usage, especially in field conditions. In this context the current need is to develop and create means for recording, processing, analyzing, and interpreting all such multimodal data, i.e., methods and means for integrating multisensory (multimodal) data that will be accessible, easy to use and mobile to carry out measurements under any field conditions. The practical significance of the proposed work is to provide a way of collecting and accessing such data, which will facilitate the progress of the study and allow the accumulation of data from different parts of the world. In this way, researchers can share the collected data and conduct more extensive research, and professionals will be able to examine and collect patient data anywhere.

The work focuses on methods for collecting and processing multimodal data from different sensors for the brain-computer (BCI) use case. The main aim of the work is to systematize knowledge on the development of complex systems based on mobile application and cloud storage and to create proposals for solving the problem in BCI-context. To reach this aim the following task should be resolved:

- to consider the main practices used to build complex systems based on mobile applications and cloud storage,
- to select the best approaches to building a data collection system from different types of sensors,
- to create a multimodal data acqusition and processing system,
- to analyze the performance and security of the developed system and find ways to improve and optimize the presented solution.

II. BACKGROUND AND RELATED WORK

A. Basic Electroencephalography Terms and Notions

Electroencephalography (EEG) is a method of electrophysiological monitoring for recording brain electrical activity. It is usually non-invasive, that is, it does not enter the body of the examined person, with electrodes arranged along the skin of the head. EEG measures voltage oscillations resulting from ion currents in brain neurons [1]. The EEG is usually used in clinical settings to identify changes in brain activity that may be useful in diagnosing brain disorders, especially epilepsy or other seizure disorders. The EEG may also be useful for diagnosing or treating such disorders [2]:

- brain tumor,
- brain damage from a head injury,
- brain dysfunction, which can have various causes (encephalopathy),
- inflammation of the brain (encephalitis),
- stroke,
- sleep disorders.

Also, EEG is beginning to be used in various types of applications to measure brain activity at home, and research is underway to use data collected during the EEG as a method of controlling external devices [3]–[6].

The electrical charge of the brain is maintained by billions of neurons. Neurons are electrically charged (or "polarized") by membrane transport proteins that pump ions across their membranes. Neurons constantly exchange ions with the extracellular environment, for example, to maintain resting potential and to spread the action potential. Ions of this charge repel each other, and when many ions are ejected from many neurons at the same time, they can push their neighbors with a wave, push their neighbors, and so on. This process is called bulk conductivity. When the ion wave reaches the electrodes on the scalp, they can push or pull electrons on the metal in the electrodes. Because metal easily conducts current, that is, it picks up or gives off electrons, the voltage difference between any two electrodes can be measured with a voltmeter. Recording these voltages over time from different electrodes installed on the body and creates an EEG result [7]. The electrical potential generated by a single neuron is too small to be recorded. Therefore, EEG activity always reflects the result of the synchronous activity of thousands or millions of neurons that have a similar spatial orientation. If the cells do not have a similar spatial orientation, their ions do not align and do not create waves that can be detected by the electrodes. It is believed that the pyramidal neurons of the cortex create the most significant, and therefore noticeable, an activity that can be recorded by EEG. The main explanation for this feature is the location of neurons and their simultaneous and cooperative work. Because voltage field gradients fall with the square of the distance, activity from deep sources is harder to detect than currents near the skull [8]. The EEG of the scalp activity shows oscillations at different frequencies. Some of these oscillations have characteristic frequency ranges, spatial distribution, and are associated with different states of brain functioning (e.g., awakening and different stages of sleep). These oscillations represent synchronized activity across a network of neurons. The neural networks underlying some of these oscillations are already well researched and understandable to doctors and specialists. On the other hand, the nature of many others is not clear and is still being studied.

Our brainwaves change according to what we do and feel. When dominant slow brain waves, we can feel fatigued, slow, or dreamy. Higher frequencies are dominant when we feel tension or anxiety. Brain processes are a complex phenomenon but can be divided into certain groups. The brainwave velocity is measured in hertz (cycles per second) and divided into groups that define certain wave types, such as slow, moderate and fast waves [9] [10].

B. Equipment

Several BCI devices are accessible now to a wide audience and they are intensively used in research in various innovative areas, such as information technology and so on. One of the devices is MindFlex [11] [12]. This is an EEG-based device whose main task is to train the brain based on ThinkGear technology developed by NeuroSky. The device includes a control unit and a wireless EEG headset. Brain signals are detected by a metal electrode, narrowed to the forehead by the monopolar method, and the zero point is the electrode clamped on the earlobe. The signal processing unit, also developed using ThinkGear NeuroSky technology using a special analysis of brain activity, can determine the value of concentration or attention. The NeuroSky MindFlex EEG headset transmits the processed signals to the controlled unit via a wireless network [13]–[15].

There are other analogs that have been used in other studies. For example, one of the works considered uses a mobile system that can run between 8 and 16 channels simultaneously. This is the Ultracortex Mark 4 system with the extension of Cyton Board and Daisy from OpenBCI [16] [17]. This allows measurements to be made using either 8 channels with a frequency of 250 GHz EEG data, or 16 channels with a frequency of 125 GHz. The main advantages of the system are its low cost, the ability to perform measurements from 16 channels, accuracy, and ease of measurement. The Bluetooth data transfer protocol used in this device provides the ability to collect data remotely without using additional wires. Another advantage is the use of dry electrodes, which reduce the adjustment time to a few minutes. As a result, data quality deteriorates due to high sensitivity to movement artifacts and higher resistance.

C. Methods

There are different methods for analyzing EEG data. This section will look at different types from the simplest ones that have been used and are obsolete to the use of the latest technologies for data analysis, such as machine learning:

1) Multimodal data: Sensor fusion is a combination of sensory data or data from different sources so that the information obtained is less uncertain than would be possible if these sources were used separately. Data collected from several different sources can be defined as multimodal because they have different natures and complement each other. You can distinguish a straight line synthesis, indirect synthesis, and synthesis of outputs of the previous two. Direct synthesis is the merging of sensor data from a set of heterogeneous or homogeneous sensors, soft sensors, and sensory data history values, while indirect synthesis uses sources of information such as a priori knowledge of the environment and human input. Sensor fusion is also known as (multisensory) data synthesis and is a subset of information synthesis.

2) Frequency analysis: The signals are recorded from the surface electrodes of the EEG of the scalp, which can be represented in time or in terms of their decomposition into sines and cosines in frequency measurement. The purpose of frequency measurement is to describe the signal by decomposition into sinusoids of different frequencies by the Fourier transformation. That is, any signal can be considered as a superposition of three sinusoids of different frequencies.

3) Time-frequency analysis: One of the main limitations of the Fourier transform is that it does not use time as a characteristic of the collected data. To calculate the Fourier transform, the signal is considered to be stationary, and therefore the activity at different frequencies is constant throughout the signal. In many cases, however, signals have different functions that cannot be determined by the Fourier transform. It is possible to overcome the lack of time resolution of the Fourier transformation by breaking the data into pieces and then calculating the power spectrum for each part or, even better, using a time-evolving window to focus on different segments of data. This procedure is called a short-term Fourier transform (STFT) or window Fourier transform. To quantify the frequency distribution at a given point in time and, especially to see its evolution, we can calculate the entropy of the power spectrum. Entropy is a measure of randomness or, in other words, the information content of a signal. Random signals are unpredictable, and each new data point provides new information. On the contrary, according to the ordered signals, new data points can be predicted from previous values and, therefore, carry less information [18].

4) Wavelets: Wavelet is a mathematical function that allows the analysis of different frequency components of data. The thus obtained wavelet spectrograms differ fundamentally from the usual Fourier spectra in that they give a clear indication of the spectrum of different characteristics of the signals over time. A wavelet transform is a transformation that views a function (taken as a function from the time) in terms of oscillations localized in time and frequency.

5) Artificial intelligence techniques.: Most modern EEG of the brain is based on or uses machine learning algorithms for data analysis. There is a wide variety of types of classifiers used in this area. Over the years, many different techniques and approaches to data processing have been developed and discussed in various materials [19].

In recent years, the methods and techniques of machine learning (ML) and in-depth learning or deep learning (DL) [20], are gaining popularity and are used in various fields, such as data analysis, machine vision, and so on. These data analysis techniques have the very big potential and can replace human EEG data analysis in the nearest future [21].

III. System Design and Development

A. Development Tools

For effective processing and monitoring of multimodal data, it is extremely important to use some of the most appropriate and carefully selected software, such as operating systems, programming languages, development environments, libraries, etc., to organize the collection, storage, and analysis of such multimodal data. Java was chosen for the development of the system due to its wide application in various fields and large community, which can help solve problems during development. Using a wide range of existing libraries it is easy to create a mobile application for the system. Java will also be used to write server service software. The selected REST server software architecture allows efficient distribution of functionality and workload, making the server part efficient and scalable. The selected Spring framework provides a set of libraries and approaches that facilitate the process of software development and its subsequent maintenance and modification. The considered HTTPS and Bluetooth data transfer protocols allow secure and easy data exchange on the Internet and wirelessly over short distances, which will make the developed system mobile, convenient and cheap. Different types of databases and approaches to storing large data sets were considered and a data storage model for the project was chosen. For the development of a small system, PostgreSQL was chosen because of its highest data read speed, as fast data access is an extremely important criterion for the system. Among the various methods of authorization and authentication, the JSON Web Token was chosen. Because, it can be supported by various types of front-ends on different devices (browsers via personal computers, mobile applications on different platforms) and has a sufficient level of security to ensure the security of user data.

B. Multimodal Data Acquisition System

The system consists of the following main components (Fig. 1):

- server (cloud storage),
- mobile application,
- sensors and device controller in BCI device that collects information from sensors to measure the brain activity.

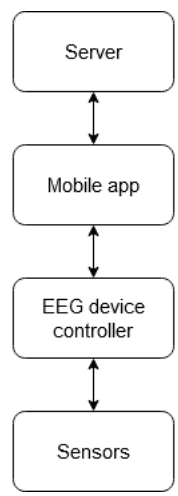


Fig. 1. Diagram of the integrated EEG data acquisition and storage system.

The main purpose of the system is to collect data from sensors through the BCI and accumulate them on a mobile device for further use and analysis. At the end of the measurement session, the data can be supplemented by a user comment or additional data such as geolocation, etc. and should be stored in the cloud storage for further use and analysis. That is, the data of each session will be multimodal and supplemented not only by various sensors but also by user-entered data. For the convenience of data transfer from BCI sensors to a mobile device, the Bluetooth wireless protocol is used. The mobile application for communication and messaging with the server will use the HTTP / HTTPS protocol at the application level. For authentication and authorization, the mobile application will use JWT technology, which ensures the security of user data. The mobile application will act as a end user interface. The application will allow you to monitor the recording process and view sessions stored in the cloud storage. To choose the right device, you should review the technical specifications and the research conducted with them. The review of these works gives the chance to compare 2 systems. Because the OpenBCI system offers 16 channels, more electrode placement capabilities, and mobility (that can be a significant advantage when designing a mobile system), the Ultracortex Mark 4 system from Cyton Board was chosen.

C. Application and Controller Software for Data Acquisition

1) Transfer format with OpenBCI Cyton: The data is transmitted to the device in the form of a stream of bytes, which are divided into packets. Because each packet has a specific format, the mobile application must read the byte stream and divide it into packets. Each packet contains a header, a sample counter, data from 8 channels, and then three values of the accelerometer axis followed by a footer. Accelerometer data is optional and does not need to be sent with each packet in use. If not used, the bytes will be 0. This allows user-defined auxiliary data to be sent to the last six bytes before the footer.

2) Read and store data in the mobile application: The data is read from a connected USB transmitter, as if from a standard serial port running at 115200 Baud. To optimize the reading and processing process, the received packets are processed in groups of more than X packets. During data processing, subsequent packets continue to accumulate on the port. Each group of packets is divided into separate packets based on the value of the stop byte. The data from each packet is sequentially processed and written to a file in CSV format for further convenient processing. After the data collection session is completed, all information is sent to the server for further storage.

3) Mobile application interface: The interface of the mobile application is based on several main screens, such as the login screen, the main menu, the screen for reading and writing data, and the screen for viewing the collected data.

D. Server Software

1) Registration, authentication, and authorization: The registration process involves filling out forms. Validation takes place both from the front end (user interface to indicate the wrong format or possible errors) and from the back end (server software that rejects requests with incomplete or incorrect information). The saved information is stored in the database after successful validation. The user can then log in to their account. The authorization and authentication process uses a Spring mechanism such as The Security Filter Chain [22]. Because JWT technology is used for authorization and authentication, a proprietary filter has been developed that reads the token from the JWT header and validates it. As a result of successful validation, user information is added to the context, which allows it to be used during query processing. This allows you to build a RESTful service without remembering the state and makes it easier to use the service in the application.

2) Web service architecture: The web service uses the REST architecture and therefore accepts 4 types of basic queries with parameters. Queries with the GET method provide data to the user by checking whether the user has access to them. All data is provided in JSON format and the data in the form of a list is transmitted by pages on which a certain number of objects are placed. The front end, which displays data to the user, manages pages and requests for new information. This helps to manage the list and not make unnecessary requests by overloading the server and network. Queries with the POST method pass information in the body of the query for use or storage in the database. Queries with the PUT method are used to edit the database and in this application are available only to administrators and developers. Queries with the DELETE method are used to delete database records and are only available to administrators and developers in this application.

3) Data acquisition and storage: The data is stored in a database, which has several basic entities: user, session, available sensors, data of each sensor.

- The user saves basic user information that is used in the application and collected during registration.
- A session stores information about the session, the device that was used to collect the information, the duration of the information collection, the start and end dates of the measurement, and so on.
- Sensor data uses the session ID to establish the session during which it was collected.
- Available sensors store information about the name of the data table, a brief description of the data and units of measurement. Used to describe data on the user interface.

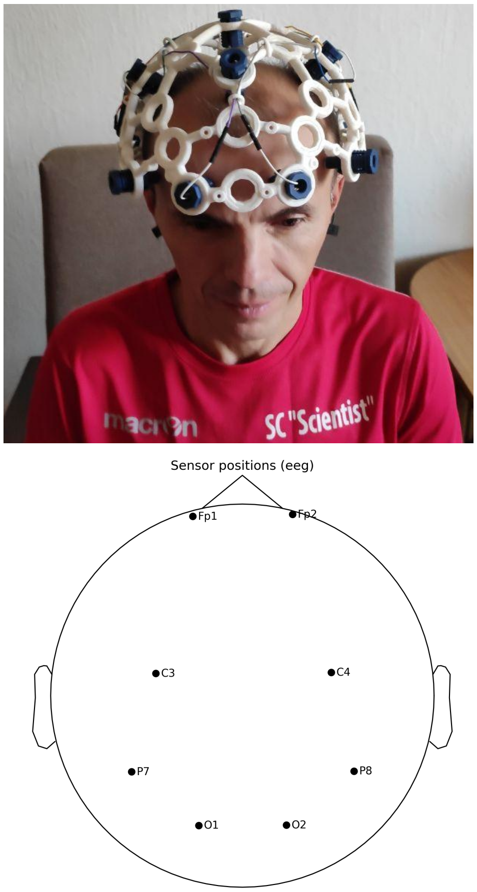
In this way, you can add new sensors and assemble and store them without modifying the existing database architecture.

IV. Experimental Results

EEG data were collected from the BCI device, namely OpenBCI with Cyton Board (Fig. 2a) with 8 electrodes ("EEG channels"): Fp1, Fp2, C3, C4, P7, P8, O1, O2. These channels are defined by international standards [23] (Fig. 2b).

To test the performance, you should check how the data is collected and displayed in the user interface. As an example of measurements, the set of actions and data acquisition algorithm used in the standard grasp-type experiment was chosen [24]. Thus, one data collection session is divided into 6 stages during which the activity of the brain during various actions is recorded. In this example, the person must perform the following movements:

- HandStart - the beginning of the movement of the hand to the object, such as the smartphone on the table,
- FirstDigitTouch - the researched person has to touch the object, for example, a smartphone,
- BothStartLoadPhase - the subject should squeeze an object, such as a smartphone on the table, with two fingers,



a)

b)

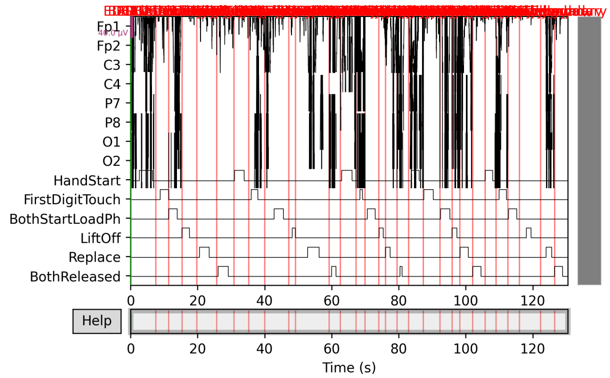
Fig. 2. The BCI device OpenBCI with Cyton Board used in the work (a) and the scheme of EEG electrode locations on the human scalp (b).

- LiftOff - the subject lifts an object into the air with two fingers, for example, a smartphone from a table to a certain height,
- Replace - the subject rotates the object with two fingers back, for example, returns the smartphone to the table,
- BothReleased - the subject releases two fingers, for example, releases the smartphone on the table.

Continuous EEG raw data from the above mentioned actions as time series are shown in Fig.3, where the EEG sensors ("EEG channels") are located equally along the vertical axis, and the timeline is located along the horizontal axis.

At least two persons with different roles should be involved in the data collection for the study. One person would be a warden and would use the interface to start the data collection, while the other person would perform certain actions according to the wardens commands. This division of roles is necessary to ensure that the results of the measurements are not distorted by other brain activities and that the observed face is not distracted by other activities. In addition, data on the calm state of the subject was collected to measure the background level.

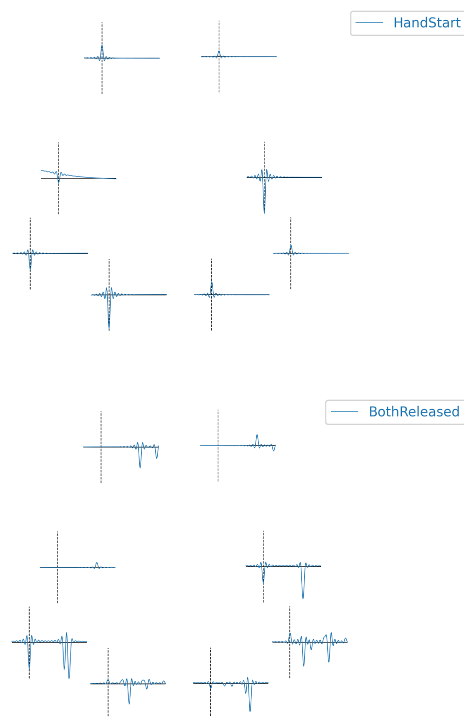
Usually, for analysis of channel-level data representation, the response at each sensor in a topographical layout is very



b)

Fig. 3. Time sequence of EEG raw signals by channels ("EEG channels") with graphical representation of the above mentioned actions labeled in the additional stimulo channels ("STIM channels").

useful like it is shown in Fig.4, where 2D scalp topography of evoked responses at sensor locations (EEG channels) is presented for HandStart (Fig.4a) and BothReleased (Fig.4b) actions. The locations of the evoked responses shown in Fig.4 correspond to EEG electrode locations (EEG channels) in Fig.3.



a)

b)

Fig. 4. 2D scalp topography of the evoked responses at sensor locations (EEG channels) for: a) HandStart and b) BothReleased actions.

Finally, such channel-level data representation allow to construct and monitor the temporal dependence of the power spectral density (PSD) that describes the distribution of power into frequency components composing the signal across sensor locations (eeg channels) for HandStart (Fig.5a) and BothReleased (Fig.5b) actions.

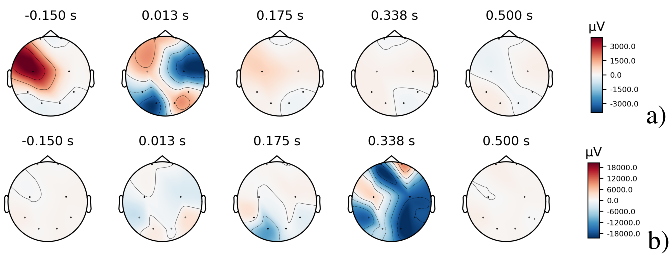


Fig. 5. 2D scalp topography of the power spectral density (PSD) for the evoked responses at sensor locations (eeg channels) for: a) HandStart and b) BothReleased actions.

For the more detailed analysis and visual representation of the above mentioned time sequences, their 2D channel-level data representation is shown as 2D plots for HandStart (Fig.6a) and BothReleased (Fig.6b) actions. From the qualitative point of view, these time sequences are quite different for the different actions (for example, for HandStart (Fig.6a) and BothReleased (Fig.6b) here) and are widely used by medical experts for the further analysis. But the characterization of these data from the quantitative point of view is the big current challennge due to variety and complexity of the data obtained by BCIs, their dependence on many external factors (even under such simple action scenarios), and absence of the generally accepted strict and precise quantitative relationships between actions and responses. But the current fast development of artificial intelligence (AI) approaches, including ML and DL methods, and their successful application for human activity analysis by wearable electronics including BCI in everyday activities [13], sport [14], [25], [26], health [15] and, especially, elderly care [27], allows to leverage potential of AI in BCI research also.

This difference is more pronounced when the same data are plotted as the intensity image plots (Fig.7), where the time runs along the horizontal axis, the channels go along the vertical axis, and the amplitudes are shown by the color notation where the amplitude values run from negative to positive and it corresponds to shift from blue to red colors for HandStart (Fig.7a) and BothReleased (Fig.7b) actions.

The developed application interface can potentially facilitate the progress of the BCI-related research so that the observer could control the data collection via a mobile device without distraction. Since the data must be labeled for the successful application of ML/DL methods, adding a state change function to the application was very useful.

The observer had a choice of one of three potential states: before a certain action, during a certain action and after a certain action. Each time the mobile device received data from the EEG device, the application checked the state selected by the observer and added this information to the data collected from each sensor. Thus, the data from the EEG device was supplemented by user data, the selected state and sensor, and data from the mobile device, such as exact time and location, merging into one session and becoming multimodal. When using available methods of collecting information, the observer would have to use a personal computer, which may be absent under certain conditions, and independently notice the collected data using special software or manually.

Also, since the data has been transmitted and stored on the server, it can be retrieved at any time and in any place, provided that it is connected to the network. Additionally, clients can be developed for other platforms that will make it possible to collect data from more devices. The browser client will make it easier to get the collected data for further processing.

V. Discussion and Conclusions

Our previous attempts to characterize the single channel BCI signals by statistical and ML/DL methods demonstrated the limits of such characterization due to the small number of data channels and very complex nature of brain activity [14], [15], [25]–[27]. Moreover, the numerous current research cases shown that increase of the number of channels is the critical

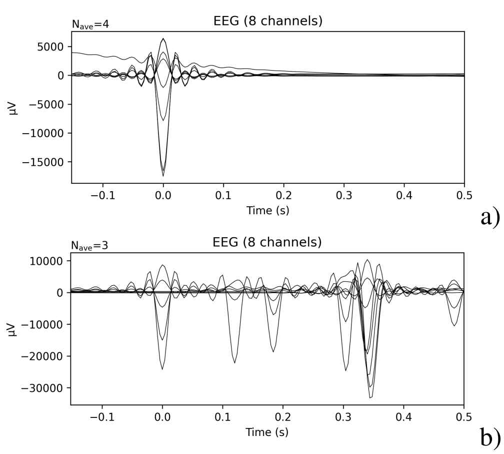


Fig. 6. The averaged time sequences for the evoked responses at sensor locations (EEG channels) for: a) HandStart and b) BothReleased actions.

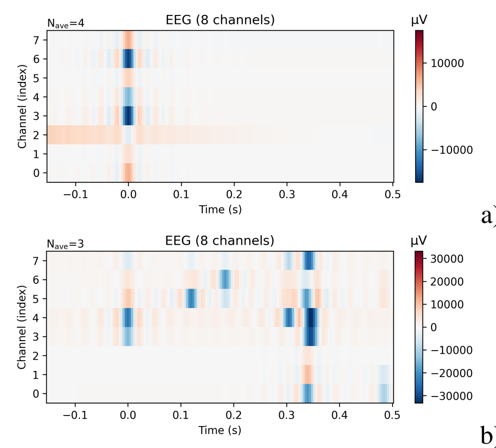


Fig. 7. The intensity image plots for the evoked responses at sensor locations (eeg channels) for: a) HandStart and b) BothReleased actions.

condition for obtaining the reliable and reproducible results [3]–[6], [28]–[31]. That is why the increase of the number of BCI channels and the statistically representable number of measurements are the critical conditions to reach the aim, namely, the reliable and reproducible results in the our future research.

In this paper, the problem of collecting and storing multi-modal data from many different sources was considered in the BCI use case. A solution to this problem has been proposed in the form of a mobile system for collecting data from several main components: a EEG data acquisition device, a mobile device with an installed application, and server software.

The main methods of EEG data acquisition and analysis and the main BCI-devices for EEG data collection available on the market were analyzed. To create a convenient mobile data collection system for BCI research, the Ultracortex Mark 4 system with a Cyton Board controller, a mobile device with Android OS and server software developed in Java using a set of Spring libraries were chosen. Bluetooth wireless technology was used for data transfer, and a relational database was used for data storage. To build the architecture of the server software, the basic rules of building REST web services were used. A JWT-based access system has been developed for authorization and authentication. The result is a prototype data collection system through which a user can collect data from the EEG of an Ultracortex Mark 4 device and access them on any device using a mobile application.

The developed system can be potentially used both by researchers and healthcare professionals to perform monitoring and diagnostics at home or under any field conditions.

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