Design of EEG Experiments for Motor Imagery Mental Task Classification

Ivaylo Ivaylov, Agata Manolova, Milena Lazarova

***Abstract*—The research of Brain–Computer Interface (BCI) and its utilization has significantly raised in the last years. A BCI system perceives and processes brain signals following five data processing stages: signal acquisition, signal preprocessing, data extraction and data classification and generation of control signals. Brain activity data to be used for BCI systems can be achieved through measurements of induced as well as evoked neuronal activity of the cortex. Motor imagery based BCI is a system wherein a person can generate prompted brain activity with the aid of imagining motor movements. In order to design and develop BCI system a relevant dataset is used. The acquisition of a dataset on which the BCI system is based is very important for the overall system performance. Many BCI datasets are available and can be used either for research purposes or for development of certain BCI system. The paper presents a procedure for design and conduction of EEG data acquisition for motor imagery mental tasks classification as well experimental results for usage of the data acquired using different classification approaches.**

***Index Terms*— Brain-computer interface, Classification, Electroencephalography, Motor imagery tasks**

I. INTRODUCTION

A Brain–Computer Interface (BCI) based system allows human-computer interaction to be established using control signals produced from cerebrum activities without the interference of any nerves and muscles. Electroencephalography (EEG) is an approach for recording the cerebrum electrical activity through the scalp due to measurements of the activity of the neurons and thus the recorded EEG signals represent the electrical neural activity of the brain. EEG is considered as the most widely utilized approach for recording of cerebrum signals and has several important advantages: high temporal resolution, noninvasive, simple, easy and safely applied, portable and inexpensive [1, 2]. EEG is the most common approach used for gathering brain signals for research and clinical studies of some of the brain functionalities as memory, vision, intelligence, motor imagery, emotion, perception and recognition, as well as for detection and diagnosis of some brain disorders and abnormalities such as epilepsy, stroke, dementia, sleep disorders, depression and trauma [3].

The study of the cerebrum oscillations of the recorded EEG data and the association with the brain functionalities is widely studied research problem. The EEG brain oscillations are categorized in frequency bands (alpha, beta, gamma, delta, mu, theta) and are connected to several brain states or abilities [2]: alpha waves are connected to the states of relaxation, concentration, and in some cases attention; beta waves are connected to the states of alert, thinking and active concentration, gamma waves are associated with short term memory and identification of visual objects, sounds, or tactile sensitivity, delta waves are associated with deep sleep stages as well as with cortical plasticity in awake state, mu waves are detected as part of the range of the alpha wave and correspond to high motor neuronal activity, theta waves are recorded during a sleepy state and are usually observed for youngsters than in grown-ups brain activity and are associated with states of idling, creative inspiration, drowsiness, and deep meditation.

The general EEG data processing for BCI systems can be summarized as comprising three main data processing stages: preprocessing stage aimed at the enhancement of the recorded raw data of the cerebrum activity through data normalization, noise and artifact filtering; feature extraction stage aimed at selection of low-dimensional set of discriminative features from the filtered data that adequately represent certain neuronal activities; classification stage aimed to assign certain category to the defined set of features and to convert them accordingly into control signals for given operation.

The classification stage is actually responsible for identification of the correspondence between the recorded cerebrum neural activities to activity category based on differences and similarities of the captured signals. Different classification techniques are used for BCI data classification that can be categorized according to various criteria as generative and discriminative classifiers, static and dynamic classifiers, stable and unstable classifiers [1]. Despite the classification approach for the EEG data processing a relevant dataset is required and used. Many BCI datasets exists that are acquired and published for research and development of BCI systems targeted at research and clinical studies of brain functions and related activities.

This paragraph of the first footnote will contain the date on which you submitted your paper for review.

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Motor imagery based BCI is a system wherein a person can generate prompted brain activity with the aid of imagining motor movements. The design and the acquisition of an EEG dataset for motor imagery tasks is a long process that requires special attention at each of the steps including the recording devices and software, the experimental environment for data measurements, as well as the next stages of data processing.

The paper presents a procedure for design and conduction of EEG data acquisition for motor imagery mental tasks classification as well experimental results for usage of the data acquired using several classification approaches.

II. Related Work

The design of EEG experiments is targeted at supporting certain research question or studying certain aspects of brain function or malfunction. The experimental question in hand is the base for definition of a research hypothesis to be tested by the experimental data. Thus the design of an experiment is aimed at controlled manipulation of certain aspect of the research problem and measurement of the outcome of that manipulation to support the investigation of the research question.

As suggested in [3] several important features characterize well-designed experiments:

- The experiment should be as simple as possible to be carried out for the experimenter and easy to later reproduction by other researchers.
- The experiment should test certain hypothesis and should provide fair estimates of the factor effects and associated risks.
- The experiment should require minimum cost of running and should enable significant differences to be detected.
- The experiment should include planning for data analysis and results interpretation.
- The experiment should allow conclusions to be made that have wide validity.

In order to prepare and conduct a well-designed EEG experiment all of the related aspects of the research problem in question as well as all various parameters with respect to the research hypothesis should be carefully considered.

Many examples of EGG experiments designed to support given research hypothesis and BCI problems are described in the research studies.

In [4] a system is designed to explicitly accommodate EEG data acquisition with participants having coarse and curly hair and the experimental results demonstrate that the designed system provides better measurements than other state-of-the-art systems. Speech activity detection using EEG data is the research problem presented in [5] and the EEG experimental design is based on utilization of visual stimuli, such as reading and color naming as well as EEG signal measurements for speech activity detection. The research hypothesis in [6] is aimed at the investigation of the EEGtoText problem, i.e. the possibility for direct automatic generation of text reports based on EEG data. In [7] a EEG recording using polymer electrodes is studied and compared to a standard EEG based on experimental dataset. A hybrid stimulation recording approach based on new combined electrode for measurement of neuronal activity of transcranial electrical stimulation induced electric field distributions is described and experimentally evaluated in [8]. A wireless neural recording platform for sensing EEG data using an ear canal based equipment is suggested in [9]. The experimental evaluation based on the acquired EEG dataset demonstrates that the performance of the described system is better than several other systems used for detection of eye blinks and auditory steady-state response. A system that utilizes simultaneous scalp and ear-EEG recordings with common reference is proposed and experimentally evaluated in [10] based on 32 conventional scalp electrodes and 12 ear electrodes. The experimental dataset allows comparison to be made between conventional and ear electrodes and the analyses show that auditory steady-state responses and alpha-band modulation measurements using ear-EEG modality are reliable for sensing cortex activity from regions located close to the ears. In [11] the experimentally evaluated research hypothesis is aimed at utilization of subcutaneous recording system for study of epilepsy and sleep-related disorders and compared to the possibilities provided by scalp EEG recordings. EEG-based long short-term memory network model is used in [12] for human emotion recognition and the suggested approach is experimentally evaluated for recognition of user preferences toward architectural design images based on EEG records of the cerebrum electrical activity.

Even if the above mentioned studies are aimed at investigation of different research questions connected with BCI systems and are targeted to different stages of BCI data acquisition and processing, they all evaluate a research hypothesis based on carefully designed BCI experiments. In all of the provided research works EEG data acquisition is extremely important for the successful evaluation of the research hypothesis and the experimental assessment for the defined research question is highly dependent on the BCI dataset used and the quality of the recorded data. On the other hand, EEG data acquisition is very specific experiment that should be carefully designed and conducted as it includes usage of specialized hardware and software and is sensitive to both the environment as well as the participants in the experiment.

III. EEG Datasets for Motor Imagery Mental Tasks

Motor imagery in view of the BCI systems is considered as imaginary motor movement without any physical movement of the person’s body. Many research studies are aimed at analyses of the recorded brain activity during the motor imagery task in an attempt to disclose the mental action based on the sensed data [13, 14, 15]. Various application areas can benefit from automatic detection and recognition of motor imagery mental tasks based on brain activity data including medicine, rehabilitation and sports [16, 17, 18, 19], robotics [20, 21, 22, 23], smart environment [24, 25], entertainment [26, 27, 28].

Among the different methods for recording the brain activity, EEG based BCI systems that utilize motor imagery mental tasks are most intensively studied and adopted in practical applications since EEG data provide sufficient measurement accuracy and are noninvasive and low cost approach for sensing neuronal activity of the cortex.

The challenges and critical issues for successful commercial usage of motor imagery EEG based BCI systems are connected with providing highly responsive and consistent BCI systems that require enhancements of the methodologies and algorithms used at each of the processing stages: data acquisition, data filtering, feature extraction, channel and feature selection, motor imagery training and classification [29]. The processing of EEG data requires relevant EEG dataset to be used. Comprehensive collections of some of the publicly available EEG datasets are listed at [30, 31, 32]. The collection of open access BCI datasets available at [33] developed under BNCI Horizon 2020 project comprises a list and provides access to 28 BCI datasets. BCI Competition datasets [34, 35, 36] comprise 13 datasets collected and provided by the Berlin Brain-Computer Interface team as part of their activities for organizing four issues of BCI Competitions between 2000 and 2008. The EEG datasets available at [37] is used for the research studies of motor imagery BCI described in [38] and is one of the largest publicly available EEG dataset consisting of EEG data from 52 subjects as well as EMG datasets and EEG data for non-task-related states. In [39] a very big EEG BCI dataset is described containing EEG recordings and mental imageries for 4 BCI interaction paradigms. A BCI dataset with multiple distractor conditions is also available for public access [40]. As part of the Brain Imaging Data Structure (BIDS) standard for the organization of neuroimaging data, 64 public EEG datasets are available at OpenNEURO web site [41] that can be used for different studies including motor imagery tasks. Several BCI datasets for motor imagery tasks are also available as part of the software platform OpenVibe for designing, testing and using BCI [42].

IV. Design of EEG Experiments for Motor Imagery Mental Task Classification

Based on the general guidelines for design of experiments for EEG data acquisition [3] and the experimental protocols of the above mentioned datasets, EEG experiments for recording of motor imagery mental tasks is designed and conducted.

A. Environment

All experiments are conducted in a laboratory environment at the Technical University of Sofia. The experiment environment is a silent laboratory with fresh air, comfortable chair and a desk. The experiments are carried out in October 2021 during several time slots: T1 (9:30–12:00), T2 (12:30–15:00), T3 (15:30–18:00). The background noise level in the room is 37–39 decibels.

B. Recording device and software

The recording device for the acquisition of EEG data is Emotiv Epoc+ EEG Headset by Company Emotiv (Fig. 1). Emotiv Epoc+ is 14 channel EEG whole-brain sensing device with 9 axis motion sensors to detect head movements. The device allows fast set up time, uses saline-based electrodes, wet sensors with no sticky gels and wirelessly connects to PC and mobile devices.

The recording software is a custom Python script using several libraries for data acquisition, recording, transfer and storage: websocket, datetime, json, ssl, time, sys, and cortex.

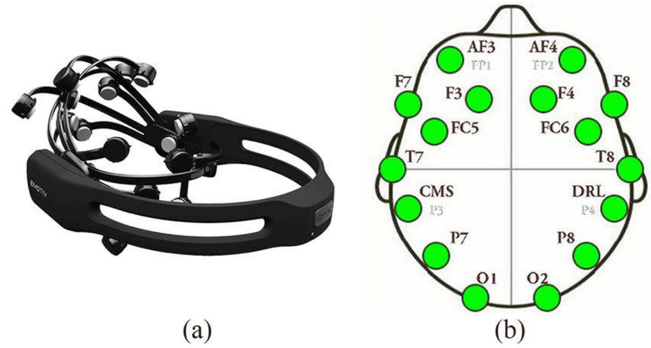

Fig. 1. (a) Emotiv EPOC+ headset (b) Spatial mapping of the electrodes on the scalp, Reprinted from [43].

The software utilizes Emotiv Epoc+ data for given user, record name, record description, record length. It records the EEG data as band pass data and exports them as csv file to a destination folder. The data are recorded using laptop with 4x Intel Pentium CPU N4200 @ 1.10GHz, 4 GiB RAM, Windows 10 Pro Operating System.

C. Questionnaire and Ethics Approval

According to the general requirements and guidelines for design of EEG experiments all participants should be protected from mental, psychological, physical, social, and legal risks throughout the experimentation. Each participant in the EEG dataset acquisition has the right not to participate in the experiment and to withdraw from the experiment. The participants are provided with full information about the research experiments to be conducted. Their privacy and identity is protected.

The participants are asked to fill out a printed questionnaire before the mental motor imagery experiment and data recording is conducted. The questionnaire comprises questions that are required in order to find out if the participant is eligible to take part in the EEG experiment and if the data recorded are relevant for inclusion in the EEG dataset. The answers to the questionnaire can also be used to analyze the results of the motor imagery mental task classification using the recorded data. The questions to be answered concern the state and the habits of the participant: taking any daily medications, existing health problems, experienced head injury or brain disorder, experienced cardiac disorder, existing skin allergy, smoking habits, usual sleep hours, usual time spend in front of a computer, times per week watching a movie, times 3D movie is watched, playing video games at all, playing Nintendo DS and Nintendo 3DS games, playing Sony Playstation games and 3D games.

D. Motor imagery instructions and experimental procedure

All data are recorded in a synchronous (cue-paced) BCI paradigm. A visual action signal is used to instruct the participant to invoke given mental image corresponding to certain mental task. Motor imagery instructions are presented to the participants as a video file with total length of 3 minutes and 30 seconds and a content presented in Table 1.

The video file comprises sequence of resting periods and mental task instructions for movement of an object (basketball). The mental tasks are right, left, up, down, push and pull movement of the object. After 40 seconds of resting period a basketball appears on the screen for 5 second

TABLE I
EXPERIMENTAL PROCEDURE

Number	Task	Duration
1	Resting period	30 sec.
2	Resting period	10 sec.
3	Left movement for mental task left	16 sec.
4	Resting period	10 sec.
5	Right movement for mental task right	16 sec.
6	Resting period	10 sec.
7	Up movement for mental task up	16 sec.
8	Resting period	10 sec.
9	Down movement for mental task down	16 sec.
10	Resting period	10 sec.
11	Push movement for mental task push	16 sec.
12	Resting period	10 sec.
13	Pull movement for mental task pull	16 sec.
14	Resting period	10 sec.
15	Resting period	~30 sec.

followed by 8 seconds period for left movement of the ball for the mental task left and 3 seconds resting period.

The same is repeated in the video for each mental task as sequences of 10 seconds resting periods, another 5 seconds resting period, 8 seconds mental task for right, up, down, push and pull movement of the ball and 3 seconds resting period. The stimuli video ends with 30 seconds resting period.

Even if participant is suggested not to move and to relax, some unexpected non-task-related and other motor imagery tasks are possible like eye movements, leg and hand movements, mouth chewing and head movements. Therefore, for each participant data for non-task-related and task (motor imagery)-related states are not recorder.

E. Data format and structure

Each recorded EEG trial is stored as csv file with timestamp for the recording time and the EEG data. The EEG channels for which data are recorded are as follows: The EEG channels for which data are recorded are as follows: AF3 (Theta, Alpha, BetaL, BetaH, Gamma), F7 (Theta, Alpha, BetaL, BetaH, Gamma), F3 (Theta, Alpha, BetaL, BetaH, Gamma), FC5 (Theta, Alpha, BetaL, BetaH, Gamma), T7 (Theta, Alpha, BetaL, BetaH, Gamma), P7 (Theta, Alpha, BetaL, BetaH, Gamma), O1 (Theta, Alpha, BetaL, BetaH, Gamma), O2 (Theta, Alpha, BetaL, BetaH, Gamma), P8 (Theta, Alpha, BetaL, BetaH, Gamma), T8 (Theta, Alpha, BetaL, BetaH, Gamma), FC6 (Theta, Alpha, BetaL, BetaH, Gamma), F4 (Theta, Alpha, BetaL, BetaH, Gamma), F8 (Theta, Alpha, BetaL, BetaH, Gamma), AF4 (Theta, Alpha, BetaL, BetaH, Gamma). The EEG data of each trial are stored as csv file of size around 2 MB, ~ 70 row × 2000 column. Each dataset is named with participant's and questionnaire's ID.

V. EXPERIMENTAL RESULTS OF THE EEG DATASET CLASSIFICATION

The EEG data for motor imagery tasks following the above described experimental procedure are acquired for six participants, three male and three female, at an age between 22 and 39 years. The EEG dataset is processed according to the general data processing stages and are used for classification of motor imagery mental tasks using several classification algorithms: logistic regression, k-nearest neighbors, Support Vector Classifier (SVC) with linear regression, SVC with Radial Basis Function (RBF) regression and Gaussian training classifier. In addition, at the feature selection stage wavelet signal de-noising is adopted for noise reduction as described in [44] as well as genetic algorithm and 2-fold cross validation for proper feature selection as described in [45]. The recorded dataset

The experimental results for the accuracy of classification of the EEG dataset using the utilized classification algorithms are given in Table 2. The results in table 2 also present the classification accuracy using wavelet signal de-noising as well as classification accuracy using genetic algorithm and 2-fold cross-validation for feature selection. As can be seen the use of wavelet signal de-noising and genetic algorithm with 2-fold cross validation for feature selection improves the classification accuracy. The overall accuracy is satisfactory (above 50%) for all classification algorithms. The best classification accuracy is achieved using k-nearest neighbor classifier with genetic algorithm based feature selection. Further improvement of the classification accuracy can be expected if the EEG dataset acquisition is extended with more recordings of each participants providing motor imagery training for the mental tasks.

VI. CONCLUSION

The paper presents a procedure for design and conduction of EEG data acquisition for motor imagery mental tasks classification. The experiment is designed in order to collect EEG data for motor imagery tasks and to evaluate several motor imagery task classification algorithms. The experimental results using different classification approaches show satisfactory results that can be improved using wavelet signal de-noising, genetic algorithm and 2-fold cross validation at the feature selection data processing stage.

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TABLE 2
TRAINING ACCURACY OF THE MOTOR IMAGERY TASK CLASSIFICATION

Classifier	Classification accuracy	Classification accuracy with wavelet signal de-noising	Classification accuracy with genetic algorithm and 2-fold cross-validation
Logistic Regression	0.585	0.552	0.602
K-nearest neighbors	0.685	0.696	0.700
SVC Linear Regression	0.594	0.552	0.605
SVC RBF Regression	0.620	0.610	0.538
Gaussian Classification	0.514	0.516	0.539

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