IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

ISO 3297:2007 Certified ⁂ Impact Factor 8.102 ⁂ Peer-reviewed / Refereed journal ⁂ Vol. 12, Issue 5, May 2023

DOI: 10.17148/IJARCCE.2023.125149

Advancements in EEG electrode technology

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Abstract—This chapter presents an introductory overview and a tutorial of signal processing techniques that can be used to recognize mental states from electroencephalographic (EEG) signals in Brain-Computer Interfaces. More particularly, this chapter presents how to extract relevant and robust spectral, spatial and temporal information from noisy EEG signals (e.g., Band Power features, spatial filters such as Common Spatial Patterns or xDAWN, etc.), as well as a few classification algorithms (e.g., Linear Discriminant Analysis) used to classifythis information into a class of mental state. It also briefly touches on alternative, but currently less used approaches. The overall objective of this chapter is to provide the reader with practical knowledge about how to analyse EEG signals as well as to stress the key points to understand when performing such an analysis.

Keywords—signal processing; machine learning; deep learning; electroencephalography (EEG); schizophrenia; autobiographical memory

I. INTRODUCTION

The brain is the most complex organ and is composed of billion neurons and trillions of connections called synapses. Its main functions include the interpretation of external information and governing many aspects, such as intelligence, creativity, emotion, and memory. One of the critical steps in the design of Brain- Computer Interface (BCI) applications based on ElectroEncephaloGraphy (EEG) is to process and analyse such EEG signals in real-time, in order to identify the mental state of the user. Musical EEGbased BCI applications are no exception. For instance, in, the application had to recognize the visual target the user was attending to from his/her EEG signals, in order to execute the corresponding musical command. Unfortunately, identifying the user's mental state from EEG signals is no easy task, such signals being noisy, non-stationary, complex and of high dimensionality. Therefore, mental state recognition from EEG signals requires specific signal processing and machine learning tools. This chapter aims at providing the reader with a basic knowledge about how to do EEG signal processing and the kind of algorithms to use to do so. This knowledge is – hopefully- presented in an accessible and intuitive way, by focusing more on the concepts and ideas than on the technical details. This chapter is organized as follows: the general architecture of an EEG signal processing system for BCI. Then, the specific signal processing tools that can be used to design BCI based on oscillatory EEG activity while Section 7.4 describes those that can used for BCI based on Event Related Potentials (ERP), i.e., brain responses to stimulus and events. Some alternative tools, still not as popular as the one mentioned so far but promising, both forBCI based on oscillatory activity and those based on ERP.

As an example, let us consider a Motor Imagery (MI)-based BCI, i.e., a BCI that can recognized imagined movements such left hand or right hand imagined movements. In this case, the two mental states to identify are imagined left hand movement on one side and imagined right hand movement on the other side. To identify them from EEG signals, typical features are band power features, i.e., the power of the EEG signal in a specific frequency band. For MI, band power features are usually extracted in the μ (about 8−12 Hz) and β (about 16−24 Hz) frequency bands, for electrode localized over the motor cortex areas of the brain (around locations C3 and C4 for right and left hand movements respectively) (Pfurtscheller and Neuper, 2001). Such features are then typically classified using a Linear Discriminant Analysis (LDA) classifier. It should be mentioned that EEG signal processing is often built usingmachine learning. This means the classifier and/or the features are automatically tuned, generally for each user, according to examples ofEEG signals from this user. These examples of EEG signals are called a training set, and are labeled with their class of belonging (i.e., the corresponding mental state). Based on these training examples, the classifier will be tuned in order to recognize as appropriately as possible the class of the training EEG signals. Features can also be tuned in such a way, e.g., by automatically selecting the most relevantchannels or frequency bands to recognized the different mental states.

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II. LITERATURE REVIEW

In this paper, the structure of the brain and methods used forsignal acquisition are presented. After the general introduction, the paper focuses on EEG techniques and associated signal processing. EEG analyses can be divided into signal acquisition, preprocessing, feature extraction, and classification (usually using simple inspection methods or more complex procedures such as machine learning). Concerning signal acquisition, it is usually obtained with EEG nets following the internationally recognized 10–20 EEG placement criteria. Next, signal preprocessing permits to remove external artifacts due to power supply interference, electrical noise from the electronic equipment and components, impedance fluctuation of the electrodes, or cable defect [1]. feature extraction methods are typically performed in time, frequency, or space domains and classification is carried out by applying machine learning algorithms classified as supervised, unsupervised, reinforcement systems, or deep learning. In this regard, developments in machine learning have notably increased the possibility of performing reliable diagnoses of neurological impairments and disorders. Mainly, the frontal and temporallobes, and the delta rhythm are affected during memory retrieval. Nevertheless, research associated with autobiographical memory has to yet answer key intrinsic aspects of brain functioning and therefore a great deal of research efforts remains necessary in this area. Thus, ma chine learning insights could show and improve processes involved in the recovery of the specificity of autobiographicalmemory, which is undermined under clinical diagnoses, such as schizophrenia [2].

This paper presents a solution for satelliteconnectivity for IoRT applications, implemented on a single device that acts as a gateway between the terrestrial and the satellite sides. The main goal of the adopted implementation was to significantly lower the hardware and implementation costs, while assuring a high degree of re-configurability by using SDR technologies. Based on an initial requirements analysis, a generic architecture was conceived and subsequently implemented using a standalone SDR platform and COTS modules for covering the main terrestrial IoRT standards. [3]. To lower the implementation cost, the satellite up and downlink was written in the FPGA of the SDR platform, leading to an overall CPU occupation of 82%. This left enough space for the programming of the control interface, local databases, HTTP server, MQTT brokers and all the othernecessary software modules. The memory and CPU constraints of the chosen SDR platform led us to the use of COTS modules connected to the gateway by means of the serial USB interface for the terrestrial side. [4]. we present the results of an explorative study to understand and differentiate human brain activities through EEG signals. During each EEG experiment, all the experimenters performed the same actions in specific time frames. However, the time fragments corresponding to the specific actions were not recorded due to the variations in personal actions; it is left for the future work to collect and analyze the time fragments corresponding to thespecific actions. [5]. We analyze EEG signal based on PCA and SVM. In order to get principal components for pattern differentiation, we consider features similar to those in conventional research. We provide 16 features including statistical and frequency data as well. Total 256 features fromone set of EEG data are projected to low dimensional data by PCA. [6]. For classification, we use SVM with RBK kennel as a discriminant function, which results in 100% classification; the 2- dimensional visualization of principal components in Fig. 3 shows that even a linear discriminant function is enoughfor the classification [7]. Although the results of investigating EEG signal based on PCA and SVM reported in this paper are quite promising, there are stillchallenges to overcome in resolving EEG signal pattern recognition and applying the result to BUI system, including datapreprocessing during data normalization

The Figure.1 indicatesEEG signal acquisition experiment.The Figure.2 indicate 16 Channel EEG signal.

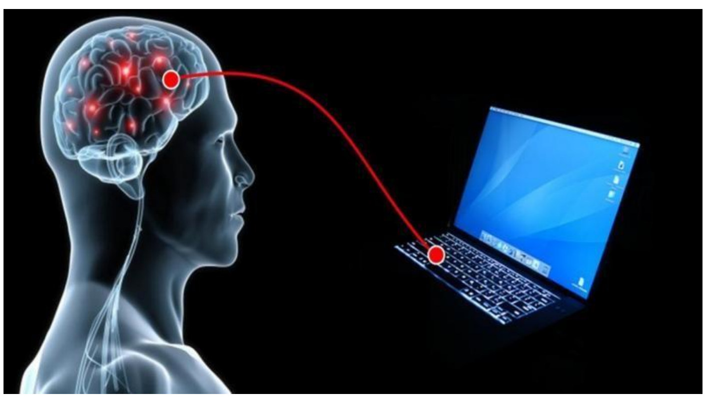

Fig. 1. EEG signal acquisition

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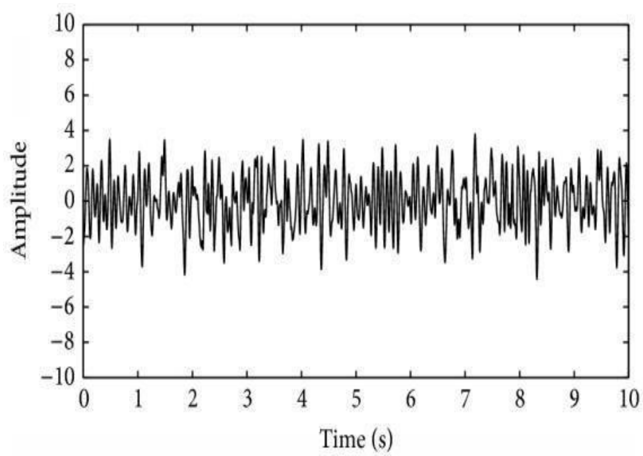

Fig. 2 Channel EEG signal

III. MATERIALS AND METHODOLOGY

The proposed methodology consist of the results of investigating EEG signal based on PCA and SVM reported in this paper are quite promising, there are still challenges to overcome in resolving EEG signal pattern recognition andapplying the result to BUI system, including data preprocessing during data normalization bt the process of

1) EEG signal acquisition*:* EEG signal experiment process, and methodologies to discriminate the EEG signal are illustrated. For themethodology, principal component analysis (PCA) and support vector machine (SVM) are included.

2) 16 Channel EEG signal *:* The DHT11 is used to detect the temperature in the leaves. Based upon the temperature we can predict the leaves is affected or not.

IV. CONCLUSION

In this paper, we have provided a tutorial and overview of EEG signal processing tools for users' mental state recognition. We have presented the importance of the feature extraction and classification components. As we have seen, there are 3 main sources of information that can be used to design EEG-based BCI: 1) the spectral information, which is mostly used with band power features; 2) the temporal information, represented as the amplitude of preprocessed EEG time points and 3) the spatial information, which can be exploited by using channel selection and spatial filtering (e.g., CSP or xDAWN). For BCI based on oscillatory activity, the spectral and spatial information are the most useful, while for ERP-based BCI, the temporal and spatial information are the most relevant. We have also briefly explored some alternative sources of information that can also complement the 3 main sources mentioned above. This chapter aimed at being didacticand easily accessible, in order to help people not already familiar with EEG signal processing to start working in this area or to start designing and using BCI in their own work or activities. Indeed, BCI being such a multidisciplinary topic, it is usually difficult to understand enough of the different scientific domains involved to appropriately use BCI systems.

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