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A survey on EEG signal processing techniques

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Abstract—In this paper, a general overview regarding neural recording, classical signal processing techniques and machine learning classification algorithms applied to monitor brain activity is presented. Currently, several approaches classified as electrical, magnetic, neuroimaging recordings and brain stimulations are available to obtain neural activity of the human brain. Among them, non-invasive methods like electroencephalography (EEG) are commonly employed, as they can provide a high degree of temporal resolution (on the order of milliseconds) and acceptable space resolution. In addition, it is simple, quick, and does not create any physical harm or stress to patients. Concerning signal processing, once the neural signals are acquired, different procedures can be applied for feature extraction. In particular, brain signals are normally processed in time, frequency, and/or space domains. The features extracted are then used for signal classification depending on its characteristics such us the mean, variance or band power. The role of machine learning in this regard has become of key importance during the last years due to its high capacity to analyze complex amounts of data.

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. As a consequence of all this activity, neurons produce ionic currents and electric signals resulting in small voltage fluctuations. These signals are generally timevarying, non-Gaussian, non-stationary, random, and are often non-linear in nature. Therefore, the measuring and monitoring of electrical activity in the brain is of primary importance as it can provide profound information related to the physiological, functional, and pathological status of the brain. It can be very useful for the identification of brain rhythms, diagnosis of brain disorders, detection of brain impairments, and consequently the possibility to provide, in some cases, precise treatment to correct or improve certain brain-health conditions in patients.

The brain is composed of the cerebrum, cerebellum, and brainstem. More specifically, the cerebrum has two hemispheres, the left and the right hemisphere, which perform higher functions, such as vision, touch, hearing, as well as learning and reasoning, [19–22]. On the other hand, the cerebellum is underneath the cerebrum and its tasks are to control balance and posture.

The measured raw EEG signals can contain interference that is divided into system artifacts and patient-related (physiological). The patient-related or internal artifacts are due to body movements, eye-blinking, breathing, or sweating. The system artifacts are due to 50/60 Hz power-feeding interference, electrical noise from the electronic equipment and components, impedance fluctuations of the electrodes, or cable defects. Consequently, it is of key importance to process and retain effective information of EEG signals, removing artifacts and interference with the aim of obtaining clear information for later classification and diagnosis.

This section provides a concise description of machine learning methods used in EEG analysis for classification. Once feature extraction is successfully carried out, the processed EEG data are finally ready for classification by means of machine learning algorithms.The main difference between deep and machine is how data is processed and how algorithms learn from them. While all machine learning procedures can work and learn from structured and tagged data, deep learning can also process unstructured and unlabeled data. Rather than relying on labels within the data to identify and classify objects and information, deep learning uses a multi-layered neural network to extract characteristics from the data and increasingly improve the identification and classification of the data itself. Recent advances in signal processing and machine learning, as well as improvements in the ability to collect, store, and process massive amounts of data, have provided significant progress and new insights into neurological computerized analysis. EEG signals are intrinsically complex with non-Gaussian, non-stationary, and often non-linear natures.

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II. LITERATURE REVIEW

In this paper, the structure of the brain and methods used for signal 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 temporal lobes, 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, machine learning insights could show and improve processes involved in the recovery of the specificity of autobiographical memory, which is undermined under clinical diagnoses, such as schizophrenia [2]. This paper presents a solution for satellite connectivity 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 upand 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 other necessary 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 the specific 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 from one 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 enough for the classification [7].

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 and applying the result to BUI system, including data preprocessing during data normalization bt the process of Although 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 and applying the result to BUI system, including data preprocessing during data normalization

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

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Fig. 1. EEG signal acquisition

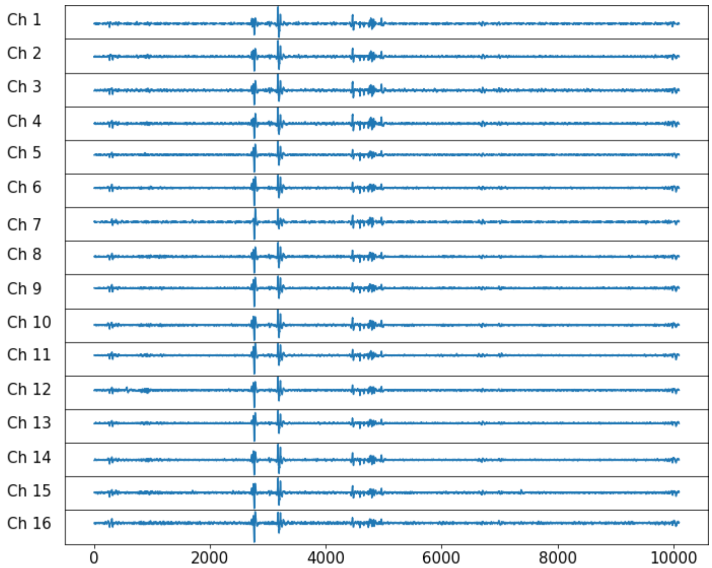

Fig. 2. 16 Channel EEG signal

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, the structure of the brain and methods used for signal 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 defects. On the other hand, 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.

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In this regard, developments in machine learning have notably increased the possibility of performing reliable diagnoses of neurological impairments and disorders. Especially, deep learning algorithms provide the best classification and understanding of brain signals. However, problems related to small datasheets or few relevant data points in datasheets have to be improved.

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