Providing Facilities in Health Care via Brain-Computer Interface and Internet of Things

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***Abstract*—Internet of Things (IoT) technologies are steadily growing. Millions of devices are now connected to each other and the internet; they communicate and share data. Another technology that has been taking traction is Brain-Computer Interface (BCI), which get brain signals and convert them into commands that are employed for control of different applications. There is then a clear link between IoT and BCI: the IoT device can receive the commands generated by the BCI and perform the desired action. This combination is useful in health care for supporting disabled patients and old people to have more autonomy. This research aims to assess the combination of the BCI and IoT, specially focusing on health care to facilitate everyday life activities by developing simple home appliances such as door opening and turning on the lights. In the present study, three voluntary candidates participated the experiment of controlling a light based on BCI and IoT systems. The average accuracy results obtained 87.33% and 73.33% with ANOVA $P < 0.05$ for offline and real-time processing modes. Our results indicates that the speed of IoT is fast enough for a BCI real-time system for the case under study.**

***Index Terms*—Brain-Computer Interface, EEG Signal Processing, IoT**

I. Introduction

The Internet of Things (IoT) is a network, in which Things are connected to each other and the internet and communicate with each other and share data. The IoT is not the network of computer only but it is also the network of devices of different types and sizes such as home appliances, toys, cameras, vehicles, medical instruments, and industrial system [1]. The key characteristics of the IoT are interconnectivity, things related services, heterogeneity, dynamic change and safety [2]. It is expected that the pervasiveness of the IoT devices will lead to several positive impacts in healthcare. People will be able to interact and control a large number of objects through different interactions including, for example, software running on their smartphones, wearable devices and voice recognition devices [3].

To efficiently utilize the IoT in the field of healthcare, Brain-Computer Interface (BCI) has emerged and is working very effectively for communication between IoT and individuals. The BCI in the IoT is the communication link between the brain and IoT devices, it converts the brain signals to commands and sends it to the IoT devices. Then, the concerned IoT devices recognize the command sent by the BCI and performed the required action [1], [4]. The BCI is a technology that can help disabled patients by a wide variety of devastating neuromuscular disorders and improve functions in healthy individuals [5]. Recently, there has been a great research interest in how BCI and IoT can effectively communicates. BCI allows to create maps between brain activities and actions. This can be the basis for a translation of human thinking capabilities into physical actions by the help of IoT-enabled machines such as wheelchairs, bionic hand and etc. The cyber-physical system built upon BCI-IoT has great benefits. For example, the BCI communication is in most cases secure as the brain activities are invisible and cannot be copied or hacked [6]. Besides, the BCI can convert the thinking idea about a deliberate action related to a IoT-controlled device into a command in a real-time interaction [7].

In our previous BCI experiences, a bionic hand and a remote vehicle are controlled through thinking. In order to have better accuracy results, different algorithms have been implemented such as wavelet, Common Spatial Pattern (CSP), optimization algorithms and chaotic approaches [8]–[13]. In the present research, we extend the previous studies by combining the benefits of the BCI and IoT to switch on and off a light bulb as an example of an home appliance.

The rest of the paper is presented as follows: Section II contains related studies; Section III explains the components of the BCI; Section IV contains the components of the IoT; Section V explains the proposed research process and discussion; Section VI contains results; Section VII contains discussion, and section VIII contains conclusions and future work.

II. Related Studies

According to the literature, BCI is a system that analyses brain neuron's activities in the central nervous system (CNS) that can also change them into an artificial output. The CNS is responsible of responding to the events in the environment or inside the body and then produces an output [5]. According to the research, the first BCI presentation occurred in 1960 to control a slide projector using electroencephalogram (EEG) signals. Later in 1970, another experiment has been conducted by scientists to control the movement of the computer cursor using the human eyes [14]. In 1988, the BCI paradigm known as “P300-speller” was developed, which was used for the spelling letters based on Event-Related Potentials (ERPs), which are the EEG deflections in the response of an activity or event [15].

The BCI field is growing at fast speed over the past few years and especially the European Commission is providing outstanding funds for the improvements in the field of the BCI and EEG sensors. In USA, Nicolelis’ group performs research where rats and monkeys can control robotic arms using the neural signals recorded from their motor cortex neurons while the electrodes are implanted in their brains [16]. In 1999, the BCI research groups were trying to organize themselves and the first international BCI meeting was conducted in the USA. About 50 participants from 22 groups participated in that meeting [17]. The number of participants and the ground numbers increased very rapidly and in the 6th international BCI meeting, there were about 400 participants and 188 research groups that were participating in the conference [18]. The EEG signal processing algorithms are improved and the scope of the BCI also expands [19] and many new BCI applications with free software [20] are explored for stroke rehabilitation, gaming, mobile BCI [21], [22] applications.

One primitive achieved successful developed algorithms were the CSP spatial filtering algorithm [23] and machine learning methods such as Support Vector Machine (SVM) and neural classifiers [24], [25]. In the previous years, the developed algorithms and discovered patterns in the EEG lead researches into a deeper understanding of brain functionality such as visual and auditory evoked potentials patterns based on the BCI was discovered [26], Steady-State Visually Evoked Potential (SSVEP) [27], Event Related Desynchronization (ERD) and Event Related Synchronization (ERS) [9]. The ERD patterns appears in the EEG, when human has an intention of movement and the ERS appears, when the intention of movement turns to action. In order to improve the detection results, hybrid BCI technique is also developed, which is a combination of different biometrics techniques and different type of biosignals such as using functional magnetic resonance imaging, near-infrared spectroscopy, SSVEP and ERD in one algorithm [28].

Our aim in the BCI research area is rehabilitation for patients with movement disabilities. The BCI can be used with the combination of other systems, in particular IoT-enabled applications. Recently, the BCI is used with the IoT so that the brain signals are converted into commands using the BCI techniques and then received by the IoT application (through mobile device etc.). Finally, the IoT application send the commands to the aim smart objects for the required actions [29]–[32].

III. Components of BCI

The main purpose of the BCI based on the EEG is to collect the brain signals that contain human intentions and converts signals to the hardware commands that can fulfill the human intent. To convert the input signals into the output, the BCI algorithms consist of following steps [5], [17]:

1) **Signal Acquisition and Preprocessing:** In the signal acquisition, the EEG signals are amplified, transferred and recorded using the Enobio32 amplifier that the topography of the channel locations are presented in Figure 1. Then, in the preprocessing step following steps are applied: normalizing data between zero and one, segmentation and filtering are applied to remove the noise and reach to the frequency range of 8-16 Hz. The ERD/ERS patterns are observable in the frequency range of 8-16 Hz. Computing power of the ERD, gives information about the location of neuron’s activation during the task as shown in Figure 2. The preprocessed signals are then ready for post processing.
2) **Feature Extraction and Selection:** In the feature extraction process, the segmented and filtered signals are analyzed to separate pertinent signal characteristics from extraneous content and represent them in a suitable way for translation into output commands. These features should have a strong correlation with the user intent because most of the brain activities are either transient or oscillatory. Sometimes the features are computed based on a signal, which is highly affected by noise. Feature selection helps to remove the useless features from the feature space. In this study, a Filter Bank CSP using a DSLVQ (FBCSP-DSLVQ) weighting algorithm is employed to compute features. In this research the Kernel Linear Discriminant Analysis (KLDA) is utilized as the feature selection approach [11].
3) **Feature Translation:** The computed features from the feature extraction process are passed through the feature translation algorithm, which converts those features into suitable commands for the output devices. The feature translation algorithm changes the independent variables (features) to dependent variables (output device commands). If the feature translation algorithm is dynamic, it accommodates spontaneous changes in the signal features and provides better results. In this study, a combination of soft-margin SVM classifier [33] with the generalized radial basis function (SSVM-GRBF) [34], [35] in is employed for categorizing the features [9].

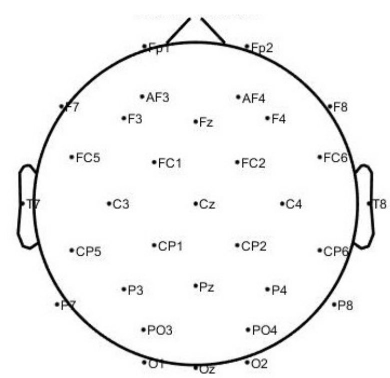

Fig. 1. The location of the EEG sensors on the scalp map for the Enobio32 device.

4) **Device Output:** The device output is the commands from the feature translation to the concerned external device (in this research the external device is the IoT application). The external device provides feedback to the user and is the end of the control loop.
5) **Operating Protocol:** To guide the operations, each BCI has some sort of algorithm that defines how the system is turned on and off, how the system communicates (continuous or discontinuous). The algorithm manages the transmission of the message is executed by the user or by the system. The algorithm also defines the feedback provided to the user from the system.

IV. Components of IoT

To understand the functionality and significance of the IoT, it is essential to Six IoT building blocks work together and provide functionality [23] [36]:

1) **Identification Block:** The identification method is used to identify devices in the network. Devices are identified with the Object ID, which is the name of the device, and the object address, which provides the address of the device in the communication network [17]. The main addressing methods of IoT objects are IPv6 and IPv4 [23].
2) **Sensing Block:** Sensors are used for collecting the data of objects in the communication network and sending the collected data to the destination database or the cloud. The data collected is analyzed in the cloud. Actuators, i.e. hardware mechanical devices such as switches, are also used in IoT platforms and operate in the opposite way of a sensor [18], [23], [26].
3) **Communication Block:** This block contains many heterogeneous objects that exchange data and various services with each other and with the IoT platform. The communication block contains IoT communication protocols like MQTT and CoAP to connect to the objects that are connected in the IoT and to send data to the management system. The sensors and other devices are connected to the Internet by communication technologies like ZigBee, NFC, UWB, Wi-Fi, SigFox, and BLE [15], [23].
4) **Computation Block:** The computation block consists of two parts, hardware, and software. Many hardware platforms have been built to run IoT applications, for example, Intel Galileo, Raspberry PI, Gadgeteer, UDOO, and Arduino. Similarly, many software platforms are used to perform the functionalities of IoT. The main software platform is the operating system that runs throughout almost the whole activation time of the device. The cloud platform is also a computational component of the IoT; it enables small objects to send data to the cloud, it facilitates big data processing in real-time and helps the end-user to obtain knowledge extracted from the big data [15], [23].
5) **Services Block:** The IoT services aid IoT application developers by providing a starting point for development. When developers know the services available, they mainly focus on building the application rather than designing the service and architecture for supporting the IoT application. The IoT services are divided into four categories. Identity-related services can be divided into two categories, active and passive. Services that broadcast information and have a constant power or take power from the battery are active identity-related services. Active identity-related services can transmit or send information to another device. Passive identity-related services have no power source and need some external device or mechanism to transmit its identity. Passive identity-related services can only read information from devices. Information aggregation services refer to the actions of collecting data from sensors, processing that data, and transferring it to the IoT application for processing. Collaborative aware services use the data provided by the information aggregation services to make decisions and react accordingly. Ubiquitous services provide collaborative aware services anytime to anyone who needs it anywhere [18], [20], [28].
6) **Semantic Block:** IoT provides different services, for which it needs knowledge, and to get that knowledge smartly, IoT uses different machines. Knowledge extraction can include finding and using resources, modeling information, and recognizing and analyzing data to reach some decision and provide the correct service. So, it can be justifiably claimed that the semantic block is the brain of the IoT [15], [18], [23].

V. Experimental Setup

In the experiment three candidates with the average age of 30 years old participated. The procedure of the experiment was explained to them before the test and promised not to use the private information of participants anywhere. In the experiment, the same task in [33], [37] is designed and employed. In the task, a picture of hand fisting is displayed and asked the subjects to imagine it by open eyes. The identified patterns are then employed for controlling a lamp for turning on and off. The results are presented in the next part.

VI. Results

Candidates attempted to control a lamp light based on real fisting movement. Figure 2 is the spectrum of a subject's scalp before and after hand fisting for one subject based on the ERD computations. The spectrum figures are very useful for finding the source of patterns. Figure 3 is one of the computed ERDs which is generated based on the hand fisting. The obtained ERD pattern is then employed for trained a model and generating the commands for controlling a lamp application. For the training a model, the average of the obtained results was 87.33% with ANOVA $P < 0.05$. By using the trained model for real-time processing, the average results achieved at 73.33% with ANOVA $P < 0.05$. The Utilized software was Matlab 2019a.

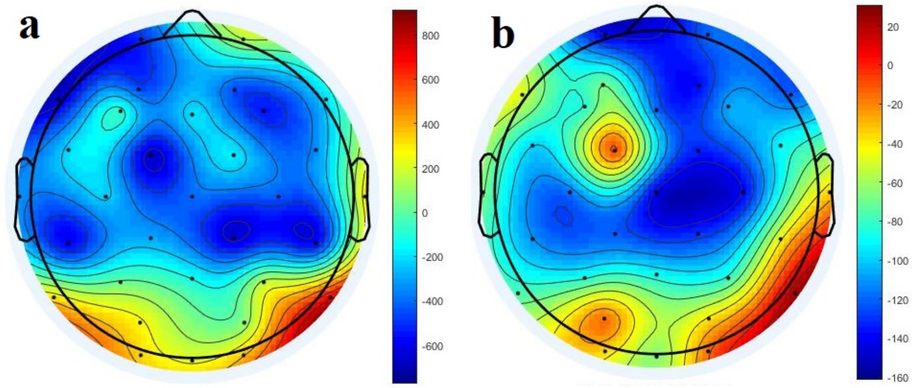

Fig. 2. The power of ERD is computed in the scalp spectrum map. a. The ERD of one participant before applying the task. b. The ERD of the same participant after applying the task.

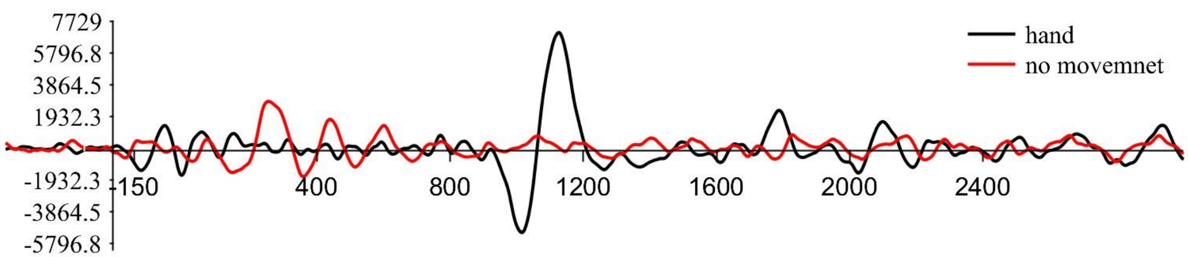

Fig. 3. A sample of identified ERD movement from the C3 channel for one subject. Vertical axes is the amplitude in microvolt and the horizontal axes is time in msec.

VII. Discussion

In this study, the research question rises as follows: is it possible to develop a personalized brain interface that is integrated into the existing IoT infrastructure? To answer the question, Figure 3 is implemented. The architecture of this system is built around a combination of the EEG device, personal computer, motion capture device named as Leap Motion Controller (LMC) [38], which is a small wearable device. The leap motion controller (LMC) is used for the detection of grayscale images of the fingers. The LMC device consist of two cameras and three infrared LEDs for the detection of infrared light. The two cameras are used for creating the grayscale stereo images using the data of infrared light. In the experiment, The device use algorithms to calculate the raw sensors data from hands. Skeletal data of the hand is captured by the LMC device. The motion tracking of this device is about 80 cm. [39].

The BCI algorithm has two steps of offline (training a model) and real-time processing. In order to train a model, the EEG signals were recorded while the same task in [9] was presented. At the same time, the LMC device capture the hand motion to synchronize the hand motion with the EEG. In the experiment 150 trials were recorded for hand fisting state and the moment of hand fisting, the EEG data is marked to find the exact moments of the ERD. To identify which area of the brain is more activated, the power of the obtained ERD before (Figure 2 (a)) and after hand fisting (Figure 2 (b)) is calculated and depicted as scalp spectrum in Figure 2. Figure 2 (b) shows that the area around the location C3 is the source of the generated ERD signals using right hand movements, which is aligned with the theories. One of the obtained ERD based on the C3 location is depicted in Figure 3. The ERD specification is a peak which is started about 850 ms to 1000 ms, and the ERS is then observable immediately from 1000 ms to 1250 ms. The pattern in Figure 3 shows the intention of the subject for movement (ERD) and turning the intention to action of fisting (ERS). Therefore, the aim is designing a model for finding patterns such as Figure 3 automatically. After collecting the EEG signals from three subjects, the FBCSP-DSLVQ features are extracted and the best features are then selected using the KLDA algorithm [11]. The selected features are then classified using the SSVM-GRBF and the results are presented based on the accuracy and validated by the ANOVA statistical analysis. For the real-time experiment, the SSVM-GRBF models are then trained for individual participants and then employed for the real-time mode with 20 trials.

One existing problem in the existing BCI systems is the delay (in some cases, up to 1 second), and wired interface.

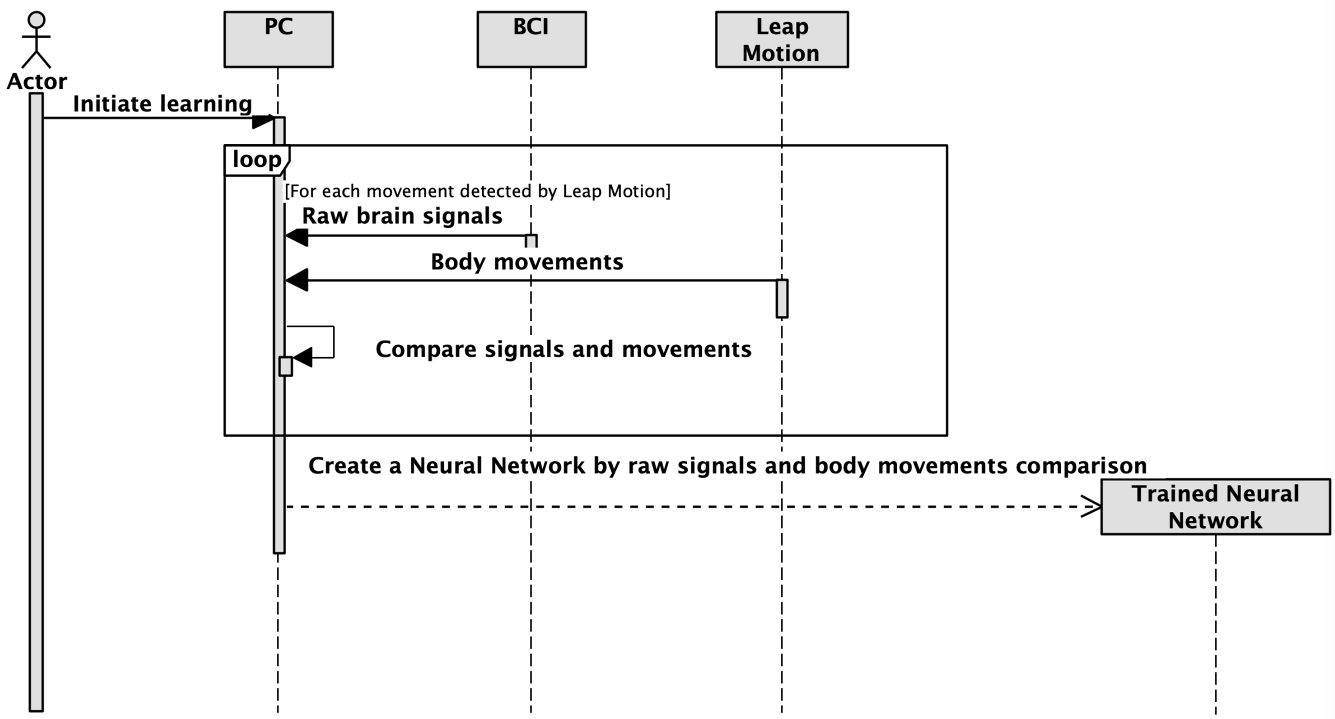

Fig. 4. BCI learning process

Both options are not suitable for wearable IoT-connected devices. To solve above-mentioned problem, a two-step integration process in Figure 4 is proposed. The first step is the learning stage, which are marked with the purple color in Figure 3. The advantages of a house appliances applications such as turn on and off a light in compare to control of a vehicle or bionic hand are only two classes are required to be identified. The SVM-based classifiers are the best choice for two classes identification that achieved high accuracy with low risk of mistakes. Moreover, the mentioned house appliance applications has lower risk of user damages in a case of error in compare with control a bionic hand/leg and vehicle, also they do not expose the users in perilous situation.

VIII. Conclusion and Future Work

Combination of the BCI and IoT has future capability of more convenient life for disabled patients. In the experiment, three subjects participated to control a light as a home appliances based on hand fisting movement. The algorithm for detecting the hand fisting ERD pattern was a combination of the FBCSP with the DSLVQ weighting approach with the SSVM classifier with the GRBF kernel. The average results of the offline and real-time experiments were 87.33% and 73.33% with ANOVA $P < 0.05$, respectively. Based on the obtained significant results and low level of risk in a case of error, it is concluded to develop the work by employing more participants and different home appliances in the experiments.

This research could be extended by applying the combination of the BCI and IoT techniques for providing facilities such as door opening, or even controlling electric appliances.

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