On the feasibility of movement detection from portable, cost effective, dry EEG headset

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Abstract

With the democratization of EEG devices, the possibility of on-the-fly EEG analysis has grown, although some of the major locks are the prices of this equipment and the reliability of signal classification. In this study, we propose to use cost-effective materials to develop reliable hardware and to train machine learning algorithm to prove that it is possible to classify EEG signals on open environments. It was decided early in the process to classify EEG signals corresponding to actions as it can be used to help people with medical difficulties better interact with their environment. In addition, long-term monitoring of the subject's actions through their EEG signals could be useful to keep an accurate record of their movements.

Keywords— biosensors, signal processing, EEG, wearable headset, dry EEG, BCI, movements, machine learning

1 Introduction

This work aims to discuss the feasibility of on-the-fly human motion prediction, to improve users' autonomy and environment control, using dry electroencephalography on a wearable headset. Electroencephalography (EEG) is a method to record bioelectrical activity in the brain[1] that can be linked to different actions or behaviors depending on the characteristics of the signal as well as the area of the brain generating the signal[2, 3] and the frequencies within the signal or its waveform[4].
These signals are generated by the simultaneous activation of neurons and can be captured by an indirect measurement of the corresponding electric field. By placing electrodes on a subject's scalp, these signals can be recorded. Usually wet electrodes are used but to reduce stress on the subject we have decided to use dry electrodes, although these dry electrodes provide poorer signal quality from many subjects[5].
EEG has long been reserved for medical fields as a diagnostic tool[6], but the development of electronics and science in general has made EEG more accessible, and the development of devices acquisition to be more versatile. Several EEG helmets are available for purchase, but since prices are a drawback for some research projects, we have de-

cided to work with cost-effective equipment[7]. In the context of actual and active Human movement prediction research[8, 9], the aim of this study is to prove that non-invasive methods can be used to detect precise articulation activation. By being able to classify on the fly EEG signals responsible for specific movements, we could improve brain computer interfaces[10] performances and enable direct control of specific actuators through EEG[11].

2 Hardware

EEG studies are usually primarily performed in clinical or at least highly controlled environments. In order to be able to record data on a less constrained environment, it has been decided to developp a custom wearable EEG headset based on the openBCI[12] project while using dry electrodes in order to simplify experimental protocol and therefore be able to obtain a sufficient amount of data relatively quickly. The headset is composed of 16 dry electrodes placed as shown in Figure 1.

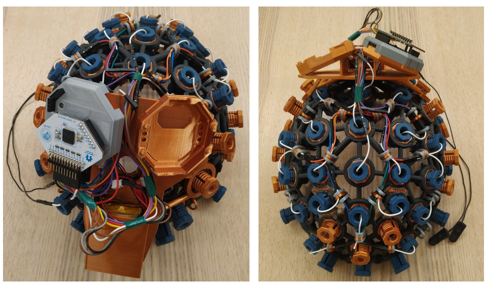

Figure 1: Homemade portable EEG headset with dry electrodes seen from back and front.

The acquisition frequency is 125 Hz, just above the Nyquist condition for useful EEG signals wich is from 1Hz to 60Hz in our case. The helmet is adjustable to fit all head shapes and is completely wireless so the subject can move freely while wearing it while following standard 10-20 electrode placement [13] as presented in Figure 2. A1 and A2 are in contact with earlobes and serves as groundings because of their good vascularization and poor innervation.

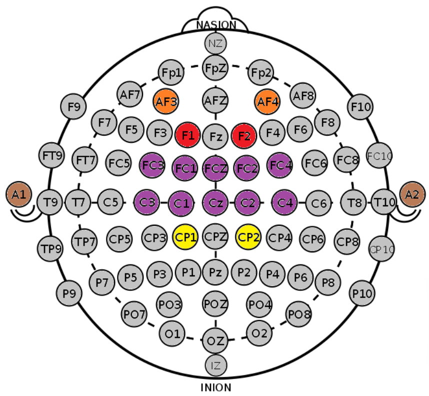

Figure 2: 10-20 electrodes placement, colored points are actual electrodes, gray points are placeholders used to distribute headset weight.

As mentioned before, we have already developed methods to detect eye blinks using EEG signals [14], the ground truth of which was obtained by the use of a camera [15, 16] , and automatic detection by image processing. For this work, we reused the same method using image computation to detect eye blinks. To record the images, we use a simple webcam which provides 30 images in 720p definition per second. We wanted to include the detection of eye blinks to prove that it is possible to detect different types of human actions through their EEG signals while building on already proven results. The second piece of hardware that has been developed is a homemade glove that covers the hand and elbow which is able to measure the mechanical movements of these joints. This glove consists of 3 main parts, the hand part where we measure fingers flexion, the elbow part from which is measured the elbow flexion, and the supply part that we fixed on the forearm so that it does not hamper subject movements. As can be observed in Figure 3 marker (1) indicates location of the hand part, marker (2) the elbow part and finally marker (3) the power and transmission part.

Figure 3: Mechanical movement measurement device.

For each joint measured, we used flexible resistors that we attached to cotton fabric so that the component was not in direct contact with the skin. We used 100% cotton fabric to avoid allergic reactions. The fabric is adjustable to fit all body types and provide more accurate results, unlike loose fabric that could create wrinkles that can reduce measurement accuracy. When the subject moves, for instance its elbow or its fingers, the value of the flexible resistance will vary, the higher the value, the higher the angle formed by the articulation, as illustrated in Figure 4 where the subject fully closes its fist then open it.

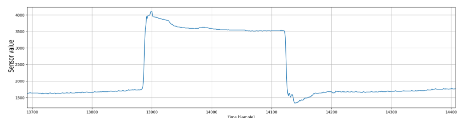

Figure 4: Exemple of resistance variation during a movement, here closing then opening of the hand.

Flexion measurement is based on a simple concept of resistance measure and mapping. The more the articulation is flexed, the more the resistance will go up. Then by measuring the angle formed by the articulation, we can perform a correspondence between the angle and the resistance value.

3 Database

As this paper deals with machine learning, the database part is one of the most important. For this work, we have developed our own database for which an experimental protocol has been defined. We decided to work on our own data because at the time we started this research, we could not find any pre-existing database corresponding to our needs.
The experimental protocol is as follows:
-The subject is placed so that its face is within the camera range.
-The subject is asked to choose form a variety of demanding task including but not limited to, reading and summarazing texts, playing video or board games, watching video and summarizing its content, writing an essay on specific questions, exercising...
-The subject is asked to perform this task as long as he feels comfortable and willing to do so.
-At the end of the session the subject is debriefed.
This experimental protocol is developed and tested to allow the subject to pass through a wide variety of cognitive states and to "forget" about the ongoing experiment[17, 18, 19, 20] and to reduce cognitive bias [21, 22, 23]. This should allow us to retrieve a wide variety of signals and among them those that should approximate "real life signals". Some subjects underwent this protocol for as long as two hours, those extreme cases were treated with caution but showed little to no differences in retrieved signals from shorter experiments. This experimental protocol was applied 56 times on 30 different subjects, mostly between 18 and 25 years old. Around 1/3 of the participants declared themselves as females, the others as males. Later we observed that some subjects were very static during those experiments leading to a non equalized repartition of events observed. We took this disparity into account for the following data processing.

4 Processing

With the database generated we decided to work on six different events, for each event we extract and pre-process the EEG signal[24] corresponding to its time stamp and then flag it with the detected event. The events are presented belows alongside with signal examples that are chosen from specific channels to provide visual cue for the reader to better understand the kind of events classified.

- Event0: "something else" because there is no time when there is no brain activity, so an action is occurring but not one that we are able to record. Those events are randomly picked when no other event are detected. An illustration of such cases is shown in Figure 5.

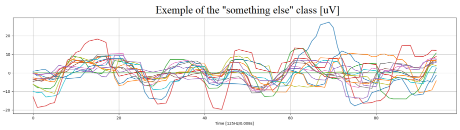

Figure 5: Exemple of signals corresponding to no specific measured action.

- Event1: "blink"; the ground truth of these events is determined when eyelid closure goes under then over an automatically calculated trigger. An exemple of this event in presented in Figure 6. We used eye blinks detection because we already worked on them with other methods[14, 25] and it should provide great comparison points.

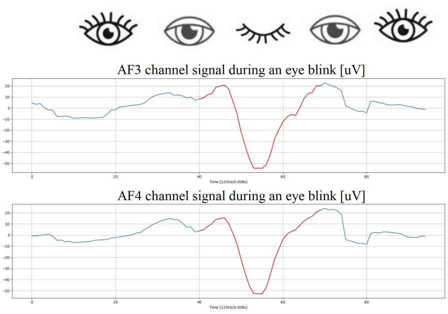

Figure 6: Eyeblink illustration, with illustration signal from AF3 and AF4.

- Event2: "arm flexion"; an arm flexion event is detected when the subject flexes its elbow by more than 10% of its maximal movement amplitude on a short time range, such as presented in Figure 7.

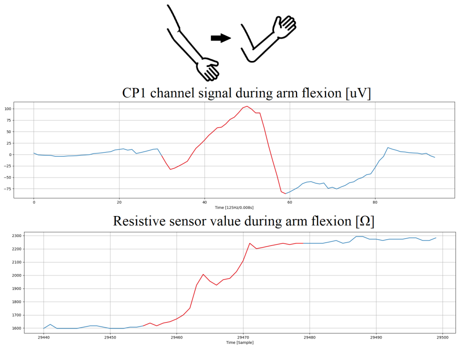

Figure 7: Arm flexion illustration, with signal illustration from CP1, along with sensor variation.

- Event3: "arm extension"; those events are the opposite of arm flexion ones. It is detected when the subject extends its arm by more than 10% of its maximum movement range. An illustration of this event is presented in Figure 8.

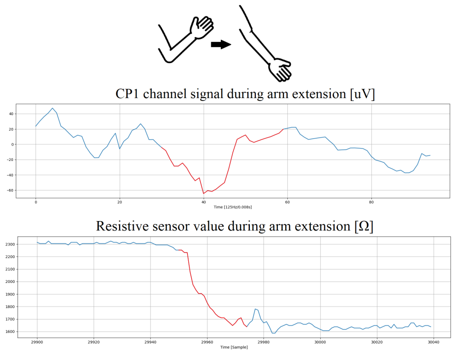

Figure 8: Arm extension illustration, with signal illustration from CP1, along with sensor variation.

- Event4: "fingers flexion"; it corresponds to all fingers closing by more than 10% of their maximal movement range (see Figure 9 for illustration).

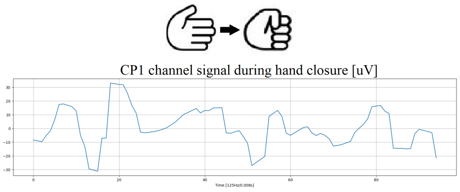

Figure 9: Hand movement illustration.

- Event5: "fingers extension"; it corresponds to all fingers opening, following the same reasoning (see Figure 10 for illustration).

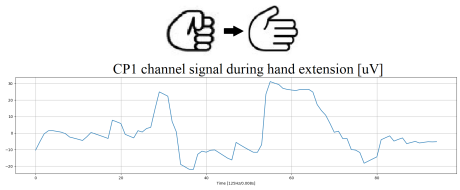

Figure 10: Hand movement illustration.

The groundtruth for flexions and extensions is provided by the glove we introduced earlier. At some point we observed that subjects would frequently perform multiple actions at the same time such as moving their arm and fingers. We decided to reduce the number of data and only keep the four first kinds. Reducing the number of events leads to improve class differentiation and thus classification results, while we continue and try to improve hand movement classification. As a side note, hand movement signals were difficult to interpret even from human expertise.

5 Machine learning

Once all the events are detected, timestamped and that the EEG signals corresponding to those time stamps are extracted we can "feed" them to machine learning algorithms. The database is splitted in three to cross validate the results. We used the deep learning architecture presented in Figure 12 where each step represent a layer. The architecture is an adaptation of the model presented in paper [26] that is specialized in classifying time series[27]. We splitted the database, two third for the train/test process and one for the validation, no training data should be present on the validation set. The set was composed of around 1.5k class 0 events, 1k class 1, 0.3k for class 2 and 0.3k for class 3. After training the model the proposed algorithm reached an average score of 87% accuracy on validation set. The confusion matrix presented in Figure 11 shows very good results.

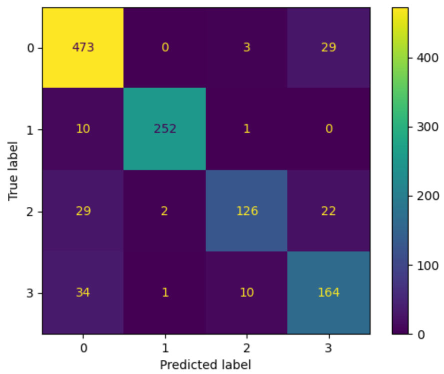

Figure 11: Confusion matrix for EEG signals classification.

Class	Precision	Recall	F1-Score
Event0	0.87	0.94	0.90
Event1	0.99	0.96	0.97
Event2	0.90	0.70	0.79
Event3	0.76	0.78	0.77
Average	**0.88**	**0.85**	**0.86**

Table 1: Classification results.

The results can be summarized in Table 1, with which in association with the confusion matrix we can deduce that the classification process is effective to differentiate arm flexion from arm extension and eye blinks, most of the classifications errors are between class 0 and others. Adding hand movements would reduce classification performances to an average of 60%, with virtually random classification between class 0 and hand movements, but little misclassification between classes 1,2,3 and 4,5 meaning that those signals are different but our detection method is not reliable enough between class 0 and 4,5. We can propose some explanations about those classifications errors, the first and most obvious one would be that in some cases the signals were quite similar, another explanation would be that some event were not appropriately detected by our ground truth hardware.

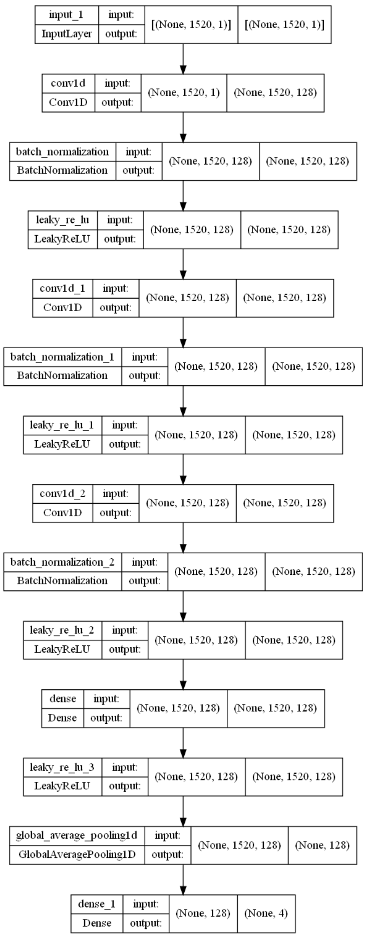

Figure 12: Machine learning model.

6 Results and discussion

In this project, all data are transmitted via Bluetooth Low Energy (BLE) to a computing terminal near the headset, we tested different computing terminals such as laptop or smartphone, the acquired EEG signal is transmitted in real time, given that the classification algorithm works with 90 samples from each channels and that the acquisition rate is 125Hz, it means that the decision process needs at least 0.75s to gather enough information. When we tested the classification process on our hardware (using CPU), it lasted between 0.12s and 0.26s on average, hence we can assume a total decision time under a second from the very begining of the event, or around 0.5s from the peak/middle of the event. This computation time could be optimized.

One of the main issue we faced was the simultaneity of some events, for instance moving the arm and closing the hand. Such overlapping of event triggered errors on the classification process. A possibility we did not have time and resources to try would be to create "double events". We are also quite aware that by using more performant hardware would improve our results but we decided to work with cost effective methods to prove that it is possible to obtain results with cost effective hardware. The proposed method can be improved, especially for hand action detection.

7 Conclusion

This method allows an average of 86% good classification under a second from the start of the event using only EEG signal form portable EEG headset. Machine learning algorithms are efficient to classify time series but when it comes to EEG signals one of the main difficulty is the quality of the signal. Dry electroencephalography provides signals of lesser quality but greatly improves repeatability of experiments. With reliable ground truth the correspondence between EEG signals and actions can be made using machine learning algorithm. Although the classified movement were quite simple this method shows great potential for more complex actions. This method could be used to predict or accompany human movement in BCI applications. The proposed method shows that it is possible to use on the fly EEG analysis to classify certain actions, which could be used to accompany human autonomy through controlling actuators such as mechanical orthosis, or autonomy monitoring by measuring the difference between "command signals" and actions.

Conflict of interest: The authors declare no conflict of interest.

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Data Availability Statement: All data are anonymized and protected to ensure subjects security. The data that support the findings of this study are anonymized and protected to ensure subjects security and are available under reasonable request from the corresponding author.

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