Prediction of Driver's Turning Intention using Low-Cost Brain-Computer Interface

Patrícia Figueiredo, Francisco Serralheiro, Jorge Palha, José Silva, António Ramalho

***Abstract*—In this work it is used EEG data to predict the drivers' intention to turn. To do so, a low-cost setup was built, using open-source software and a commercial EEG acquisition device, to study EEG activity during simulated driving. To validate the prediction offline, only EEG data prior to the drivers' action was used in the classification. The classification was conducted independently for two distinct features (RPs and ERDs) and the results were compared. The results obtained proved the existence of a correlation between EEG data prior to the drivers' action and the action taken. The results also suggest that using low-dimension features improves the classification accuracy for limited training data.**

***Index Terms*—Brain Computer Interface, EEG, movement prediction, low-cost, driving**

I. Introduction

BRAIN-Computer Interfaces (BCI) had a big evolution over the years. A BCI is a communications system, including software and hardware, which allows controlling computers or external devices using brain activity ([1]). In general, there's a conversion from an analog signal to a digital signal. A wearable, like a BCI, also has the same objective - conversion from an analog signal to a digital signal. Wearable's market is projected to grow and reach a value of 25 billion dollars [2], in particular, the global market of health wearables has an annual growth rate of 18.3% [3].

An autonomous vehicle is defined as any ground vehicle with the capacity to carry both a person and a property without any driver. A conventional vehicle is defined as any ground vehicle whose autonomous level is between 0 (without any Driver Assistance Systems) and 3 - a semi-autonomous vehicle. [4].

According to Boston Consulting Group (BCG), in 2035, just 40% of the global car market will be autonomous cars [5]. Thus, it's concluded that the coexistence of autonomous and conventional cars is inevitable wherefore related problems will emerge.

A. Sensors and detection systems

Despite the sensory completeness of modern semi-autonomous vehicles, it is not yet uncommon reports of bugs and errors of hardware that vehicles use to sense surrounding areas. For example, a crash [6] between a Tesla car and a truck. The autonomous car could not distinguish between the particular white color of that day's sky and a white trailer, and did not brake. Although the hardware errors will decline over time, there will be always blind spots, for instance, one that caused an accident [7] between an Uber autonomous car that was being tested and a conventional car. This driver could not see the road that would cross and the autonomous car could not detect, as well, the conventional car, following a crash.

B. Intervention Window

It is possible to identify an opportunity for BCI technology in the future urban roads. Even with the continuous improvement of autonomous cars sensors, there will be always blind spots to fill in. To help with these spots, vehicles will communicate in the future, through Vehicle to Vehicle (V2V) Communication [8]. This kind of communication will help broadcast information, like velocity and the current GPS position of the specific vehicle, in the present time.

It is known that BCI technology can predict human movement [9], [10]. In order to tackle and fill in unpredictability, the "next movement" information of the conventional cars can be predicted and transmitted through V2V Communication, complementing the package of information that will be used to prevent accidents. For instance, in a close situation of an accident-prone maneuver caused by a driver, using BCI systems it would be possible to predict this maneuver and possibly prevent the accident. Therefore, this solution would result in an increase of available reaction time for autonomous vehicles to deal with human behavior.

II. Literature Review

A brief literature review on prior scientific work related to the present one is now presented. All the reviewed works in this section use non-invasive EEG devices.

Ou Bai et al. [11] predicted human voluntary movement before it occurs. Although this work is not directly related to driving scenarios it shows the capability of BCI technology to predict humen movement. In this experiment results were taken online, in real-time. It was able to predict movement until 1.5 seconds before it occurs. In this work the authors decided to, not only analyze slow DC potentials (MRPs), but also shifts in the frequency bands alpha and beta.

There are also works on the application of BCI to driving situations. Many of these works aim to predict the dirver's intention.

Hernández et al. [12] is developed an application to detect breaking intention before it occurs. To achieve this, two different types of classifiers are trained, Support Vector Machine (SVM) and Convolutional Neural Network (CNN), to

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discriminate between normal driving situations and situations immediately before breaking occurs. A stimulus on the driving simulator was given to make the subjects break. Comparing an equal number of epochs for each class (normal driving and before breaking) an average accuracy of 71.1% and 71.8% was achieved (for SVM and CNN respectively).

In the work by Zahra et al. [13] it was aimed to distinguish between EEG activity more than one second before and less than one second before acceleration or breaking. For acquiring the data, a countdown was displayed on a screen, showing the remaining time until the subject was prompted to accelerate or to brake.

An application to detect steering intention is created in [14]. The authors of [14] claim that it was a pioneer application of EEG measurements. It was achieved a true positive rate of 74.6% and the steering intention was detected on average 811ms before the steering occurred. The timing of the steering (a lane change) has self-paced, unlike in [12], [13], [15], [16], [17] where the action was triggered by a stimulus. The feature used to discriminate between EEG epochs was the Movement Related Potentials (MRPs), which is an electric potential drop that occurs before a movement is performed. This feature is also used in [13].

In another work on predicting breaking intention by Haufe et al. [15], the results of the prediction using EEG are compared to the prediction using electromyography (EMG) and the signal from the simulator's braking pedal. It is proved that it is possible to predict an emergency breaking using EEG sooner than when using EMG or the deflection of the braking pedal. In this work a pseudo-online situation, where the algorithms would continuously classify the EEG signal along the time, validated the capability of predicting the breaking in a driving scenario.

Going beyond simply predicting breaking intention, Il-Hwa Kim et al. [16] were able to discriminate between different types of breaking situation , besides predicting emergency breaking and detect dangerous situations that do not require breaking. To achieve such, the authors of [16] used several different features of the EEG signal.

Prediction of steering direction was addressed in a previous work by Zhang et al. [17]. In this work, however, the subjects were instructed with the turning direction shortly before the turning. The work aimed to distinguish, using EEG signal, when the instructed turning direction was different from the one turning signs displayed in the simulated environment.

III. Proof of concept

Humans are, by nature, unpredictable. Facing distinct situations, distinct people react in distinct ways. Google's Alphabet accounts for a number of accidents caused by erratic driver's human behavior [18]. In this work it will be explored the possibility of using Brain Computer Interfaces to prevent possible accidents. For such the most dangerous maneuvers were studied and a critical driving scenario was identified. This scenario is described in this section and the following sections of this work will address the implementation of a Brain Computer Interface for predicting the drivers maneuver in that same scenario.

A. *Most dangerous maneuver*

The most dangerous car maneuvers are the overtaking in two-way roads and the change of direction in intersections. This last one caused 31% of serious accidents, in 2013, of insurance company Arbella Insurance [19]. According to the US Transportation Department [20], 22.2% of accidents, between 2005 and 2007 were caused by these left turns in intersections. Left turns are not just dangerous for conventional drivers, but they also represent a big challenge for autonomous cars as well [20]. Even though autonomous vehicles can measure with precision distances and velocities, they cannot predict pedestrian behavior or a conventional car next maneuver.

B. *Target scenario*

To prove this concept, and possibly adding value to BCI technology in the prevention of car accidents, a scenario of interaction of an autonomous car in an intersection will be designed. Using low-cost BCI equipment and software, it is going to be anticipated the direction taken by a driver in an intersection.

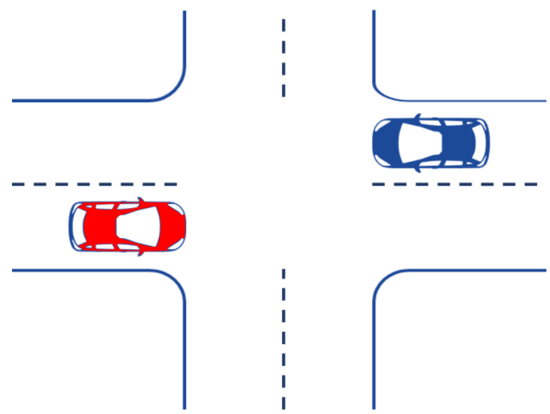

Fig. 1. Representative scheme of the proof of concept scenario

This scenario is now described. Figure 1 represents the road situation to be studied. An autonomous car (red) and a conventional car (blue) approach an intersection. To deal with a possible unpredictability of the human driver, the present work presents a Brain-Computer Interface which determines what is the human driver's intention before the conventional car reaches the crossing road, predicting if the driver will go forward or turn (any direction) on the intersection.

IV. Data Acquisition

A. *Experimental Setup*

The experimental setup is based on the proof of concept idea represented in section III-B. To mimic this scenario in a laboratory setup it was used the Microsoft AirSim simulator [21], which allows simulating driving scenarios, among other capabilities. The scenario represented in Figure 1 was simulated in the software, the subjects would drive the simulated vehicle (representing the conventional car) towards an intersection, without any cars in the road. To keep the situation as realistic as possible, it was displayed, during the

Fig. 2. Simulator virtual driver's view, as shown to the subjects during the data acquisition.

simulation, the virtual driver's view (as in Fig. 2) in a 51" screen, around 1.5 meters away from the subject, and it was provided a low-end and low-cost gaming steering wheel to allow the subjects to control the virtual vehicle.

The subjects brain activity was monitored using *EMOTIV Epoch+*, a commercial low-cost electroencephalogram (EEG) device, with 14 electrodes on the positions AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8 and AF4 according to the 10-20 system [22]. A single commercial laptop (Intel Core i5-7300HQ 2.50Ghz, 8Gb, NVIDIA GeForce GTX 1050) was used to conduct the experiment. The computer was connected to the steering wheel (Arduino), the display screen and the EEG device. The setup of the hardware is shown in Figure 3.

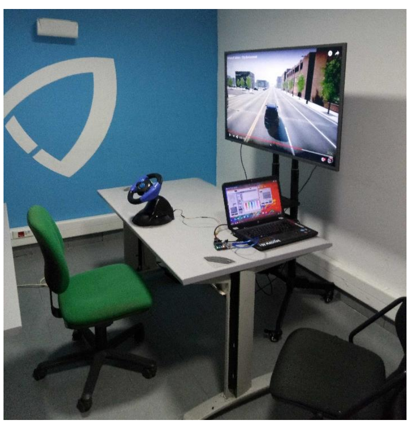

Fig. 3. Picture of the hardware setup used for the data acquisition

B. Hardware/software interfaces

The steering wheel was disassembled and connected, electrically, to an Arduino. The Arduino was then connected to the laptop via a USB port.

A single Python script would then perform several different tasks:

- Read the steering wheel state
- Control the virtual vehicle as an API
- Label the EEG signal on the run
- Monitor the virtual vehicle position

The steering wheel (connected to an Arduino) would be monitored using the PyGame module ([23]). This module allows an asynchronous reading of the steering wheel state (the information would be updated every time a change was detected in the steering wheel position). Each update on the steering wheel position would be communicated to the AirSim simulator, for controlling the vehicle. Finally, every time one of the defined triggers would be activated, the python script process would communicate with the headset recording software to insert markers in the EEG signal. The defined triggers are described further on, in section IV-D. The interfaces between hardware and software components are shown in a simplified scheme in Figure 4. The hardware and software were also prepared to include gas and brake pedals, for both control and marking, however, they were not used and the vehicle speed was controlled automatically using a PID controller.

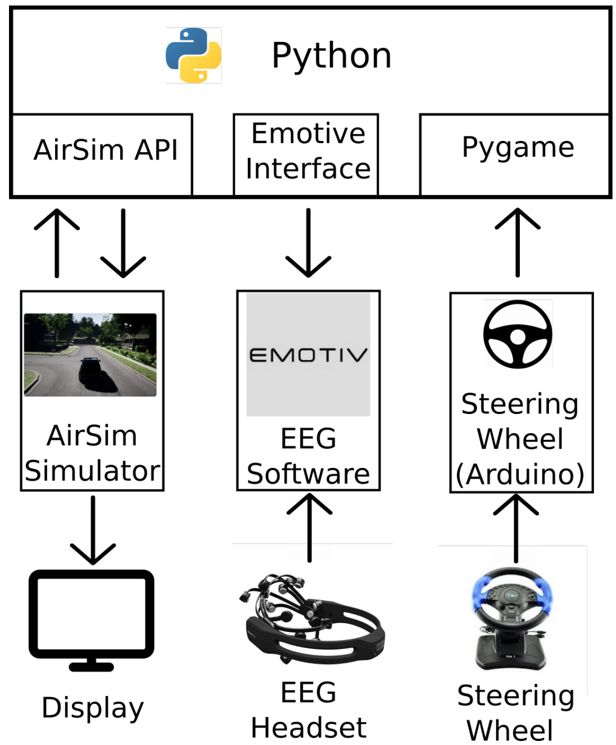

Fig. 4. Hardware (bottom) and software (top) components and their interfaces.

C. Acquisition protocol and subjects

1) Subjects: For the acquisition, 7 subjects were selected, all male, aged 21-24 years old. None of the subjects had a history of neurological problems neither wore glasses and all of then had a driving license for 3 years or more. None of them had participated previously in a BCI experiment. Some of the subjects were more frequent drivers than others, this, however, didn't seem to affect their performance on the simulator, likely because of the simplicity of the task. All the subjects were right-handed accordingly to the Portuguese adaptation of the Edinburgh Handedness Inventory [24].

All the subjects were volunteers and signed a document allowing the anonymous usage of the data acquired in the experiments. All the information about each subject was provided on a form, by the subject.

2) Task and instructions: The subjects were sat in front of the steering wheel and screen described in section IV-A and shown in Figure 3. All the electronic equipment was removed from the room except for the acquisition laptop, the EEG device and the display screen.

The subjects controlled the steering wheel of the virtual vehicle that would start around 100 meters before an intersection. The subjects had the choice of turning left, right or going forward in the intersection, nevertheless, they were instructed to try to make the same number of executions for each direction (left, right and front). Every time the simulated vehicle would exit the intersection (either by going forward, left or right) there would be a reset, and the simulated vehicle would again be placed in the initial position, around 100 meters away from the intersection.

The subjects were also instructed to avoid blinking, swallowing and clenching the teeth while the vehicle was on the intersection. This was made to avoid EEG artifacts in critical data segments.

3) Sessions: The acquisitions were split into 4 sessions of 12 minutes, separated by 4-minute breaks, for each subject. Before the EEG data start to be recorded a period of 4 minutes was given for the subjects to get used to the simulated driving. Between sessions the headset was kept on the subjects, to avoid the electrodes to move in the subjects' scalp.

During the data acquisition for subject 1 two of the sessions were not concluded. For subject 5 the last sessions only lasted 7 minutes. These interruptions on the acquisition were due to technical problems.

D. Synchronized marking of the data

The EEG was marked and labeled automatically during the acquisition sessions. The signal would be marked each time the steering-wheel would twist over a 30° threshold and when the simulated vehicle would exit the intersection by going forward.

These markers were later used to segment the signal.

V. Data segmentation

THE segmentation of the data is now described. To analyze the data it is necessary to define the epochs that should be extracted for analysis. These epochs should correspond to critical periods of time for determining the drivers' intention. In other words, the epochs must contain data before the drivers' action was taken, to allow a prediction of the action.

For the situations in which the subjects went forward in the intersection, the epochs correspond to the EEG signal between 1 and 2.5 seconds before the vehicle exits the intersection (matching the time the vehicle is approaching the intersection). The epochs acquired in these situations are referred to as *no-turn* epochs. The time representation is shown in figure 5.

For the situations in which the subjects chose to turn (left or right) the epochs of the signal considered critical for prediction were the EEG signal segments defined between 2 and 0.5 seconds before the subjects turned the steering wheel over 30° to any side. These epochs are named *turn* epochs. The time representation is shown in figure 6.

The number of situations in which the subjects chose to drive forward, left or write was roughly similar. This means that there were roughly twice the *turn* epochs, when compared to the *no-turn* epochs

Reinforcing what was presented in this section, two groups of critical EEG signal segments were created: the group of the *no-turn* epochs (subject went forward) and the group of the *turn* epochs (subject turned left or right).

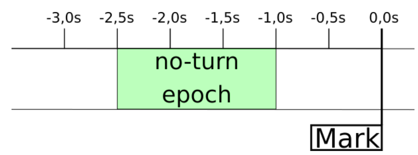

Fig. 5. Time interval corresponding to the *no-turn* epochs.

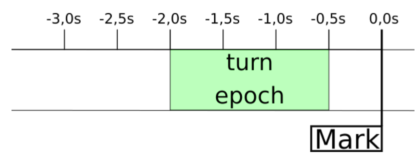

Fig. 6. Time interval corresponding to the *turn* epochs.

VI. Data processing

IN this work, two different types of processing were preformed, using in each one, different features. One of the approaches aimed to predict turning intention using the readiness potentials (RP), also known as Bereitschaftspotential (BP), which is a change that occurs in the DC potentials before movement occurs. In the other approach, the feature that was studied was the shifts in the power spectral density (PSD) of the alpha and beta bands.

A common first-stage filtering of the signal was done for both approaches. The headset Emotiv Epoch+ has a bandwidth defined between 0.16 and 43Hz. The equipment already has integrated notch filters at 50Hz and 60Hz to reduce the effect of the power grid. An additional low-pass filter was applied, with a cut-off frequency of 45Hz to completely erase influences from the power grid. This low-pass filtering, and all the further band-pass filtering, were executed using the default *pop_eegfilt()* from the EEG lab toolbox.

The processing was implemented using MATLAB, using the EEG lab toolbox [25] among others.

The classification was made independently for both features. Both classifications were performed using Linear Discriminant Analysis (LDA), with no kernel. For both processing pipelines (each one using one of the features), the data was separated, for each subject in a training set (70% of epochs) and validation set (30% of epochs). The training and classification were made separately for each subject once the EEG patterns differ from person to person, the experiment showed poor results when the data was mixed.

The processing pipeline is represented in figure 7.

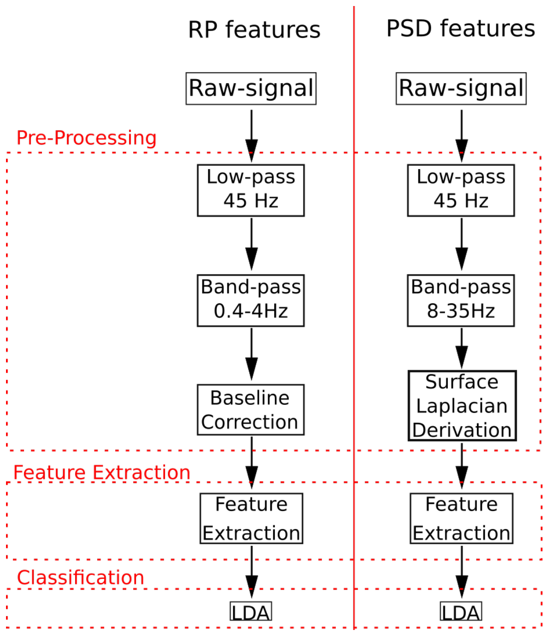

Fig. 7. Both processing pipelines, for each of the extracted features

A. Readiness Potentials (RP) approach

1) Pre-processing: In this approach, it was aimed to detect slow DC potential changes. For that reason, a band-pass filter was applied using as cut-off frequencies 0.4-4Hz. Baseline correction is then performed by averaging the signal on the first 100ms of each epoch and subtracting that value to the entire epoch signal.

2) Feature extraction: For each epoch and each electrode, the signal was split into 10 non-overlapping 150ms periods. The signal average, at each 150ms period, at each electrode, was taken.

The chosen features to represent each epoch were the maximum and minimum average, among these 10 periods of signal, for each electrode. The feature that represents each epoch is then a vector with $2 \times 14 = 28$ elements (maximum and minimum average on 14 electrodes).

Other features related to the slow DC potentials were tested. One of them was obtained by normalizing the previous feature to obtain 0 mean and unitary standard deviation. The other was using all the 10 averages mentioned before. However, when using these last features, the results obtained were not as good, and, for this reason, are omitted.

B. Event-Related Desynchronization (ERD) approach

In this section shifts in the Power Spectrum Density (PSD) for the alpha and beta frequency bands are studied. This feature extraction was inspired in [11], however in [11] multiple frequency bins were taken into consideration. In the present work, a smaller amount of elements per feature were taken which led to, in the present work, better results. This type of features can also be called Event-Related Desynchronization [26].

1) Pre-processing: Firstly it is aimed to extract the signal corresponding to the alpha and beta bands. For that purpose, a band-pass filter is applied with cut-off frequencies 8-35Hz. A Surface Laplacian Derivation (SLD) is then performed. It is a method that enhances the data by estimating how would the EEG signal be at each electrode if it wasn't as strongly diffused by the skull [27].

2) Feature extraction: Each epoch was split into 30 100ms periods, overlapping 50ms with the neighbor periods. The power spectral density was then taken for all of these periods. Due to the small size of the training data an effort was made to reduce the dimension of the feature space. To accomplish such only the maximum and the minimum PSD is stored for each electrode. This allows keeping information on the PSD shift while significantly reduce the number of elements in each feature. The feature vector that represents each epoch has $2 \times 14 = 28$ elements (maximum and minimum PSD for each of the 14 electrodes).

Two other ERD related features were tested, one of them was the maximum divided by the minimum PSD, the other was directly giving the 10 PSDs normalized by the maximum one. However, when using these last features, the results obtained were not as good, and, for this reason, are omitted.

VII. Results

THE results of the above-mentioned methods for both feature types are showcased in Tables I II in the form of True Positive Rate (TPR), True Negative Rate (TNR), False Positive Rate (FPR), False Negative Rate (FNR) and the Unweighted Average Result (UAR). The positive class is defined as the group of trials in which the subject chose to make a turn (*turn* epochs). The negative class is defined as the group of trials in which the subject chose to drive forward (*no-turn* epochs).

Subject	FPR	TPR	FNR	TNR	UAR
1	25%	13%	86%	75%	55%
2	45%	43%	56%	54%	51%
3	62%	33%	66%	37%	64%
4	45%	24%	75%	54%	60%
5	51%	29%	70%	48%	61%
6	44%	23%	76%	55%	60%
7	52%	42%	57%	48%	54%
average	49.8%	32.3%	66.7%	49.3%	58.3%

TABLE I
RESULTS USING PSD SHIFTS AS FEATURES.

Subject	FPR	TPR	TNR	FNR	UAR
1	80%	39%	60%	20%	70%
2	50%	34%	65%	50%	57%
3	77%	40%	60%	22%	68%
4	50%	53%	46%	50%	48%
5	60%	42%	57%	40%	58%
6	66%	62%	37%	33%	52%
7	62%	62%	37%	37%	49%
average	60.8%	48.8%	50.3%	38.7%	55.3%

TABLE II
RESULTS USING RP RELATED FEATURES.

The results from subject 1 in spite of being present in Tables II and I, were not considered for the average results shown in the bottom row, due to a large unbalance in the number of positive trials in relation with the number of negative trials.

A. Online Implementation

The end goal of this study is to aim for a possible implementation of the pipeline proposed above in real-time. However, the results shown in Tables II and I come from an offline implementation. The time taken to make the preprocessing and feature extraction (of the RP features) was computed for the last session of every subject. The algorithm took 131.43 ± 39.77 milliseconds to process each epoch, in a commercial laptop (Intel i5-2450M 2.50GHz, 4Gb, AMD Radeon HD 7400M). This shows that each second, at least 5 epochs of 1.5s can be extracted from the live signal, which means that the proposed pipeline of data processing allows the online processing of the full data-stream originated by the EEG measurement device, validating a possible online implementation, with a delay much shorter than the 0.5 seconds of advance between EEG data and driver action.

VIII. Discussion

There is a noticeable difference between the results of the two sets of features. The first one shows much more consistent results and has a large tendency to classify a trial as negative (high TNR and low FPR). On the other hand, the second set of features shows a little more disparity in results, having a large tendency to classify a trial as positive (high TPR and low FNR).

The results show that for most subjects, it was possible to predict driver's intention to turn, with an accuracy of 55.3% and 58.3% for RP and ERD features, respectively. The standard deviation for the accuracy was $\sigma = 6.77\%$ and $\sigma = 4.42\%$ for RP and ERD features respectively. These results show a correlation between the EEG data before the drivers' decision was taken and the chosen decision, they also present a better accuracy when using the selected ERD features when compared to the RP features. In previous studies using the same headset yielded accuracy results of around 70% on average were found [28], [29], [30]. These studies that used the same headset, however, were performed in motor-imagery related applications, with very simple and distinct movements to be discriminated against. Even though the results in this study are significantly lower than the ones showcased in [28], [29], [30], the actions performed in these studies were far less complex. Another limitation that might have impacted the results is the lack of direct readings in the brain's motor cortex area (usually associated with movement-related activity), which the used low-cost headset is not able to provide, due to the nonexistence of electrodes in the C4 and C5 location on the 10-20 system, this would be very desirable for the present study.

Additionally, most subjects mentioned that the experiment was uncomfortable and hypnotic which led to distractions.

Also, the way in which each subject turns the wheel is different. This leads to some subjects crossing the 30°threshold in different moments of the maneuver, making the data segmentation to be misfitted for some subjects. It would be then desirable for a practical application that the proposed BCI would be able to learn from the drivers behaviour the best way to segment the data used for the training.

IX. Conclusions

Unlike other non-invasive EEG devices, headsets with fixed dry electrodes are of easy usage. This allows quickly setting up the equipment, even without expertise, which makes this sort of headsets fit for common daily life usage.

The low cost associated with the equipment, combined with the ease of use, might allow the generalization of EEG related applications, such as Brain-Computer Interfaces, in the academic environment and practical applications.

In the present work, this sort off headset was combined with a low-cost and flexible set-up that allowed the study of using BCI's to predict the drivers turning intention. The developed set up has also the flexibility to be easily modified to perform a variety of studies on EEG activity during driving situations.

The obtained results show a correlation between the EEG data before the driver takes an action and the action taken. This proves that it is possible to foresee the drivers' intention to make a turning an EEG reading device. The obtained results, however, not as good as the ones obtained in previous works using the headset. These other works often consisted of detecting movement instead of predicting it. The weak results are due to the low signal-noise ration commonly associated with non-invasive EEG data, which prevents non-trivial epoch discrimination from having high accuracy values. The small amount of training data might also have been a key factor in obtaining these results.

The results of this work show a better classification performance using ERD features when compared to RP features.

A key conclusion from this work can be drawn from the finding that, by providing only two features per electrode, the results improved with relation to other experimented features. These results suggest that for small amounts of training data the usage of low dimension features is preferable.

For a practical application in a vehicle equipped with sensors, it would be possible to train the algorithms with the driving data. This would be possible by associating the EEG data prior to each drivers' decision with the decision made, labeled by the GPS and steering wheel data. A big amount of data could then be used to train a more power classifier, for example long short-term networks, and to use features with a higher dimension.

For future work, the authors suggest the elaboration of a solution that allows on-the-run training. The authors also suggest that, for the present application, more data should be acquired in order to obtain better results.

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