A BCI Driving System to Understand Brain Signals Related to Steering

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Abstract: In the last years, the manufactured vehicles were designed to focus on prevention of some risky situations caused by a human driver. The aim of this paper is to illustrate the design and implementation of a BCI system which can detect the arm movements by the EEG signal during a simulated driving session. The proposed approach to realize a classifier able to recognize the arm movement by EEG feature analysis is based on the consecutive application of a Time Delay Neural Network (TDNN) and a Pattern Recognition Neural Network (PRNN). Preliminary tests are shown on three different participants between 24 and 45 years old.

1 INTRODUCTION

In the recent automotive market, the main challenging activities are related to the realization of autonomous vehicles (AV) (SAE, 2014). The SAE, On-Road Automated Vehicle Standards Committee (SAE, 2014) classified the levels of automation according to the different roles of the driver. Level 0 means the vehicle is devoid of automation while the last level 5 refers to vehicle completely autonomous (Graffione et al., 2020). In this latter case, any human intervention or interaction is required during driving task and the automated system monitors autonomously the driving environment (Wang et al, 2021). The main important factor which contributed to increase the attention of academic and industrial scientists in the adoption of AV concerns mainly the safety. Many studies demonstrated that the human errors represent the first cause of road accidents (Khattak et al., 2021, Bersani et al., 2012) and the possibility to replace the driver with a partial or complete advanced driver assistance system (ADAS) may represent an opportunity for a safer road transport system.

Above all for AV at the level 3 and 4 of automation, the ADAS needs to be integrated by intelligent systems which support the interaction between the car driver and the AV (Graffione et al., 2020, June). Special attention has to be dedicated to the driver's behaviour when he/she tackles critical situation during the travel and his/her related reaction to manage in real time the Human Machine Interface (HMI). The importance of the human- machine interaction in the context of AV inspired a field of literature which aims to describe the driver's mental model in order to support the development of the AV features.

The behavioural data coming from the user, in fact, are essential to define a safer driving system which has properly to intervene in real time during critical traffic situations. Consequently, the ADAS has to have the capability to evaluate and identify the driver performance in order to recognize anomalous behaviour.

In this context, the integration of Brain Computer Interface (BCI) with HMI in the driving environment have been introduced to determine the reaction of drivers by brain activities when he/she makes driving task. This approach supports the development of systems able to identify motor intention of the driver and, consequently, to produce commands in order to support the user to prevent car accident (Gougeh et

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al., 2021). The main promising technologies to integrate the monitoring of the cognitive user's state with the external environment refers to the electroencephalographic (EEG)-based BCI applications (Gu et al., 2021). The driver, the vehicle, the sensors on board, the HMI and the BCI represent a complex system (Benza et al., 2012).

Different techniques may be used to analyse the EEG features in terms of frequency, power or bandwidth. The main objective is to define a proper classifier able to correlate the EEG signals with the related user's cognitive state and, Artificial Neural Network (ANN) appear one of the promising methodologies to be applied. In (Chakole et al., 2019), a review on EEG signals classification is proposed while (Yger et al., 2017) presents a review on BCI.

EEG consists of a special helmet equipped with electrodes able to record the brain neural signals which reproduce the user's brain activities in the different lobes (Zero et al, 2019). Large literature is dedicated to the identification of human movement by EEG signals related to human machine collaboration with special reference to rehabilitation and robot applications (Buerkle et al., 2021). Planelles et al. (2014) compared different classifiers to identify the user's arm movements by his/her intention. They concluded that support vector machine (SVM) obtained a prediction accuracy of around 72% with better performances in respect to k-nearest neighbour (k-NN) and naive Bayes (NB) classifiers. Other approaches confirmed the successful use of SVM to recognize, by EGG signals, the human movements. Classification accuracy in a range of 94%–97% is verified to identify the motion intention to stand up, sit and walk (Wang et al., 2018) while in Narayan Y. (2021), the accuracy reached the 98% by SVM in respect to linear discriminant analysis (LDA) and multi-layer perceptron (MLP) classifiers to discriminate left-hand and right-hand movements. Other research groups proposed classifiers based on the random forest technique (Kim et al., 2016), on recurrent neural networks (RNN) (Idowu et al., 2021) and on convolutional neural network (CNN) for hand motor imagery tasks (Bressan et al., 2021) or linear neural network, multilayer perceptron (MP), radial basis function (RBF) network for the recognition of imaginary movements of legs (Kurkin et al., 2018)

EEG based BCI is used in healthcare applications but, recently, it has a significant research perspective also in the context of safety transport. Interesting works are published on the monitoring of driver's fatigue (Abbas et al., 2021, Borghini et al., 2014) awareness (Kästle et al., 2021), distraction (Taherisadr et al., 2019) or workload (Diaz-Piedra et al., 2021). Limited literature is dedicated to the identification of driver's intent to compute movements, as an example, to apply pressure on the accelerator or on the braking pedals (Aydarkhanov et al., 2021) or to detect braking intention in emergency situations (Xing et al., 2019). Other approaches focused on the recognition of driver's actual actions computed during the driving tasks. Zero et al. (2021a) developed a time delay neural network (TDNN) classification model to predict driver's right and left turns in a virtual driving environment. Zero et al., (2021b) adopted an ANN to recognize head yaw rotations when the participant is subjected to visual stimulus. The head positions directed toward a light target were classified by three classes for the left and the right positions and for the forward one. Bi at al. (2016) integrated an extended queuing network classifier in an EEG based BCI in order to convert the desired steering wheel angle change into a desired steering command for the vehicle.

This work has been developed in this latter framework in order to realize a classifier able to identify the driver's arms motion on the right or on the left while rotating the steering wheel of a car in a simulated environment. The main objective is to recognize, by the brain activities acquired by a EEG helmet, the driver's arm movements while he/she carried out the turning task when the car have to change the cruising line.

In this paper, a Time Delay Neural Network (TDNN) classifier to recognize the direction of the human arm movements is implemented and tested by the adoption of EEG signals coming of six different electrodes located in the central part of the brain. Due to the complexity of this purpose, the output of the TDNN is further elaborated by a pattern recognition neural network (PRNN). The final results highlight a strong correlation among the input spectral EEG features and the targets associated to the subject's movements.

2 MODELS AND METHODS

2.1 Enobio Cap

A Enobio Cap (Enobio® EEG systems) with 8 channels is used in the EEG based BCI development. In the proposed approach, the brain signals are recorded by the following 6 electrodes according to the International Standard System 10/20: C3, C1, CZ, C5, C4, FZ. Figure. 1 shows the location of the used electrodes (in orange are highlighted the selected electrodes). The electrodes are located in the central area of the brain between the frontal and parietal lobes. This part of the brain contains the primary and secondary motor cortex areas which generate the neural impulse for the execution of voluntary movements (Bhattacharyya et al., 2011).

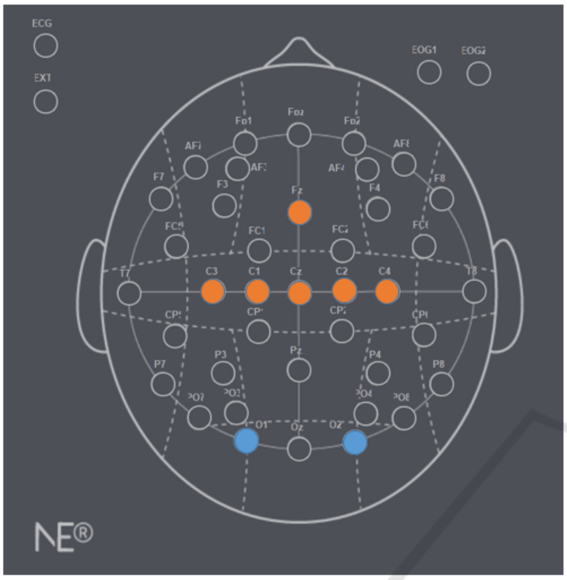

Figure 1: Electrode placement based on the simulation.

2.2 Simulation Environment

The simulation environment is based on two different subsystems. Firstly, the BCI consists in a driving interface available by a video screen. The second system consists of a real car seat, a steering wheel and the pedals which work as in a tradition car. This second subsystem appears in the Figure 2.

The simulation environment was built using the Add-On "Simulink 3D Simulation" of MATLAB® software and it consists of a vehicle which travels on one road with three lanes of 4 meters wide identified by the following code: -1 (line on the left), 0 (central line), 1 (line on the right). (See Figure 3).

The objective of the proposed test consists in monitoring brain activities of a participant who have to simulate a driving task. The proposed BCI provides the user with a simulated environmental scenario, displayed on a video, where a car rides on a straight multilane road and it moves from one line to the adjacent one. During the experiment, the BCI system drives autonomously the vehicle across the different carriage lanes. The participant, according to the car path, has to move his arms in order to turn the real steering wheel simulating the required changing line. In detail, when the BCI system generates the command and the car moves toward the new cruising lane, this latter is highlighted in the environment scenario, and the participant has to turn the steering wheel according to the new requested vehicle position.

Figure 2: Driving position.

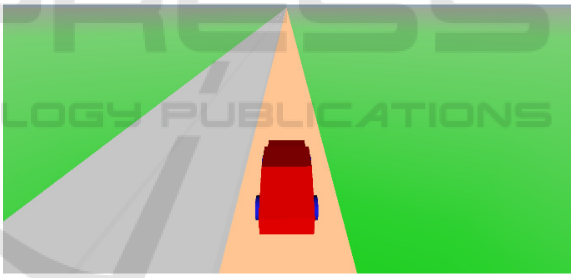

Figure 3: Simulation environment (in the image, the line on the right is highlighted to provide the user with the information about the line to be covered and to simulate the changing lane by turning the steering wheel).

During the simulation, the lane that the car has to reach and keep is highlighted until a new turning is requested. The vehicle may be moved with a lateral speed of 0.8 m/s and a longitudinal speed of 10 m/s.

During the training phase, a random sequence of car movements for changing line is generated by the system in order to induce the participant to turn the steering wheel by his arms in order to follow the car path. The simulation system works in real-time to synchronize the car movement and the related EEG signals recorded during the turning action.

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2.3 Test Driver

The simulations have been performed by three different men between 24 and 45 years old with driving license. The simulation was 5 minutes long. During the test the participants was sitting in a driver seat in front of a LCD screen where the simulation environment was projected.

When the simulation started, the participant followed the car on the screen. When a new line to be covered was indicated and the car started the movement, the user had to turn the steering wheel, held by his hands, by rotating his arms to make the turning motion according to the car behaviour on the screen, as shown in Figure 4.

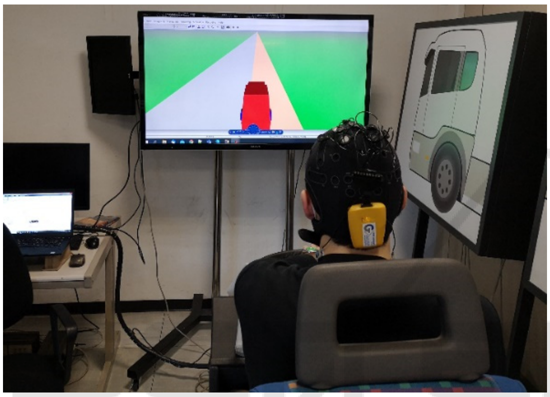

Figure 4: Driving simulation.

2.4 Elaboration Data

The EEG signals recorded by the NIC software, property of Enobio, have been saved and elaborated by Matlab R2020b. After the synchronization between the signals regarding the brain activity and the car movements, a bandstop/notch filter between 49 Hz and 51 Hz is applied to EEG signals in order to delete the noises produced by the electric components of the devices. Besides, a high pass filtering to 1 Hz is performed to remove the common components.

In the proposed work, two different classifiers have been applied to categorize the EEG signals. Firstly, the signals have been processed by a TDNN according to the input-output function (1)

$$y(t) = f(x(t+1), x(t+2), \dots x(t+10)) \quad (1)$$

where $y(t)$ is the codified arm movements prediction (-1, 0, 1) and $x(t)$ represent the input EEG signal coming from the six selected electrodes.

According to the non-linear function f in (1), the TDNN produces a classification which is the input of the PRNN. The proposed architecture of the system appears in the figure 5.

The TDNN is specific class of feedforward neural network which works on sequential data and it is able to realize the recognition of the EEG patterns or features. The output of the TDNN is a real number and the PRNN related to the pattern recognition classifies the values into one of the three classes.

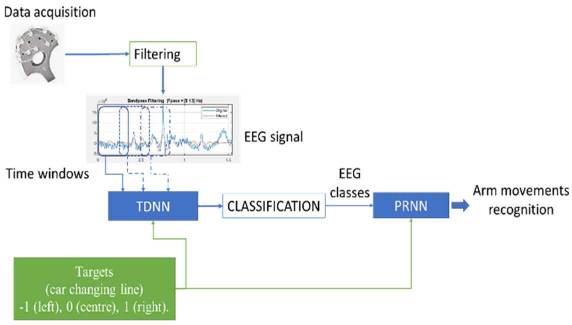

Figure 5: Architecture.

The used TDNN consists of 10 time delays and 10 hidden fields. The proposed PRNN, which consists of three neurons, solves a data classification problem using a two-layer feed-forward network. It provides a statistical analysis of the TDNN output in order to assign the different patterns to the different categories represented by the targets.

In this way, the EEG signals may be assigned to the correct pattern and they are classified according to the three classes of arm movements such as -1 (left), 0 (centre), 1 (right).

The performance indexes used to evaluate the accuracy of the prediction generated by the TDNN are the correlation and the MSE values. Regarding the PRNN, cross-entropy will be analysed. The cross-entropy (*CE*) aims to minimize the loss function used in the NN. Besides, it measures the distance between the output probabilities and the related true values with the objective to make the model output closest to the expected values. In the training phase, the model weights are continuously adjusted in order to minimize the cross-entropy loss. Thus, a reliable model should have a *CE* loss near to 0.

3 RESULTS

Table 1 shows the prediction performance indexes related to the TDNN for each participant. In this case, the 50% of the EEG signals are used the training phase and the remaining 50% for the test.

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The correlation indexes, evaluated according to Cohen classification (Cohen, 1988), demonstrate a strong linear correlation in two of a three participants.

Table 1: Prediction performance for the TDNN.

PARTECIPANT ID	*R*	*MSE*
1	0.75	0.237
2	0.65	0.310
3	0.30	0.312

Also MSE values demonstrate good performances in the prediction considering as target the actual car changing lines and the predicted value of the related arm movements to turn the steering wheel realized in the last 2,5 minutes of the simulations.

In the Fig. 6, a comparison between the target values and the predicted ones appears. In the proposed image, the line associated to the prediction presents positive and negative peaks in accordance to the targets associated to the car changing line. Value 1, for the real pattern, represented a request to change line on the right while value -1 a turning on the left. This means that for each line shift of the car along the route, the TDNN identifies, by the human brain activities, a participant's cognitive reaction to realize the correct driving task to turn the steering wheel by his arms.

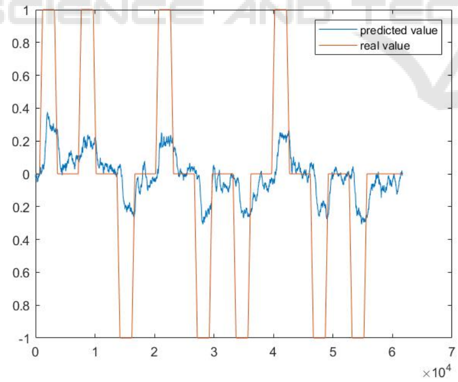

Figure 6: TDNN results.

The results related to the PRNN application are displayed in the Table 2. In second column, the performances of the classifier have been evaluated by the accuracy percentage of the correct classified observations computed as follows:

$$\%Accurancy = \frac{N_c}{N_{test}} * 100$$

where

N_c =Number of samples assigned to the correct class;

N_{test} = Total number of samples used in the testing phase.

The accuracy of the model appears significantly relevant in the three cases with a mean value of about 79% of correct predictions.

Table 2: Prediction performance by PRNN.

PARTECIPANT ID	*Accuracy %*	*CE*
1	81.25	2.24
2	80.40	1.80
3	74.10	1.32

In the third column of the Table II, the performance index associate to the cross-entropy (*CE*) appears. The results are inferior to the value 2 in two of the three cases underlying good performances for the proposed approach.

In addition, the confusion matrix associated to the first participant is provided in Fig. 7. In the diagonal of the matrix, the correct prediction of the class (in bolt) appears with the related percentage of correctness in respect to the overall analysed features that, in the example, are 224. Out of the diagonal, the absolute values and percentage of the wrong predictions related to the different classes are shown.

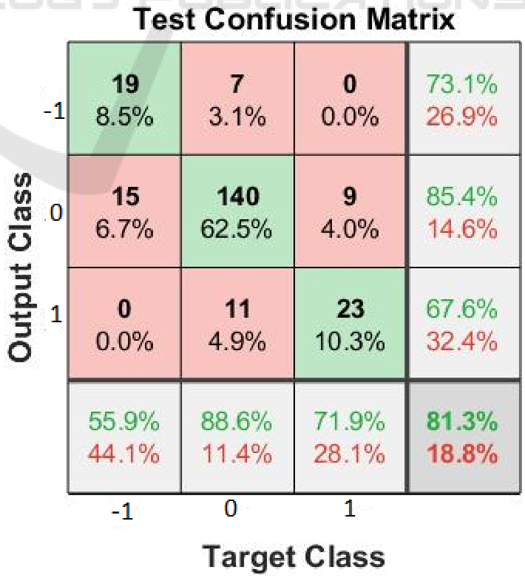

Figure 7: Confusion matrix for the Participant 1.

As an example, in the first row of the matrix, the value 19 (8,5%) means that for 19 times during the test phase (which considers 2,5 minutes of the experiment with a total of 224 requested driving tasks), the classifier associated correctly the driver's arm movement on a left turning (output value= -1) when, in the real scenario, an actual left movement has been realized (target value= -1).

It is possible to note that, never, a completely wrong prediction about the turning left/right has been detected, in fact, in the matrix, for the couples (-1,1) and (1, -1), the values are 0 (0%).

4 CONCLUSIONS

The focus of the work is related to the implementation of BCI based classifier able to identify the human arm movements by the brain activities of a driver who has to turn a real steering wheel following a car which changes line on a straight multilane road visualized in a simulated scenario.

The proposed BCI acquires the brain signals by a EEG cap worn by the participants who have to carry out the requested driving tasks. The signals are pre-processed in order to limit the artefacts and then two different NNs are applied to generate the human arm movements classification.

The analysis of the output coming by the TDNN and the PRNN demonstrated a good correlation among the input brain signals and the output related to the driver's movements codified by three different classes associated to the changing line on the right, on left or to continue the path on the central line.

Further efforts will be dedicated to the pre-processing elaboration data in order to filter the component of the EEG signals not correlated to the human brain activities. Besides, a large set of participants have to be involved to validate the proposed architecture for the classifier model.

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