1D Convolutional Neural Network approach to classify voluntary eye blinks in EEG signals for BCI applications

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***Abstract*—The goal of this paper is to develop a Brain Computer Interface (BCI) based on voluntary eye blinks decoding. In particular, the study was focused on the signals generated in the cortex by eye blinking, which can be collected by frontopolar scalp Electroencephalographic (EEG) sensors. Normally, EEG recording systems meant for clinical applications are expensive and cannot be used in large-scale user-friendly applications. Thanks to a prototype made by the STMicroelectronics company, based on an Open Source EEG project, a low-cost EEG recording system was created in this work. The goal is to develop an algorithm that can detect and discriminate between voluntary (forced) and involuntary (natural) blinking so that, in the future, an EEG-based BCI system that is able to control a device through eye movements could be developed, which would be of great use for all people with motor disabilities who can control eye movements. The proposed algorithm is based on a one-dimensional (1D) Convolutional Neural Network (CNN) architecture. Frontopolar EEG signals were collected during the execution of voluntary and spontaneous blinks by four healthy subjects. A dataset of EEG epochs of including blinks was constructed and used to train and validate the proposed CNN. The proposed system allowed to discriminate the blinks performed by the subjects (voluntary vs. involuntary) with an average accuracy of 97.92%.**

***Index Terms*—Brain Computer Interface, Electroencephalography, Eye blink, Convolutional Neural Networks**

I. Introduction

The term “interface” is used to identify a logical link between two entities of different types that allows them to communicate with each other. A Brain Computer Interface (BCI) is a direct communication system between the brain and an electronic or other device [1]. However, it does not depend on the normal output pathways of the brain, consisting of peripheral nerves or muscles. BCI technology can have a great impact on the quality of life of people with motor disabilities, allowing them to interact with virtual avatars in the computer, with devices or with real objects through neural prosthetics [2]. In recent years, BCI has gained a great deal of interest. The increase in computational power and data storage allowed scientists to apply deep learning techniques on large amounts of biological data, previously intractable due to their size and complexity [3]. Most of research works in the field of BCI are based on Electroencephalography (EEG) or Electromyography (EMG) with the aim of decoding the intended movement and controlling a device accordingly [4]. EEG is a measure of the electrical activity generated by the human brain, recorded on the scalp of the head, whereas EMG records the electrical activity of the skeletal muscles. Finding neural correlates of the intended movement in the motor cortex can be of great interest towards the goal of explaining how movements are “planned” by the brain, however, if the ultimate goal is to give a contribution to the development of a user-friendly BCI meant for people with motor disabilities, decoding eye movements could be of great help as many motor-impaired subjects can effectively control eyes and may use such movements to drive a device [5]. Eye movements can be detected by eye trackers equipped with Charge-Coupled Device (CCD) sensors in Infrared radiation (IR) camera [6] (which are unfortunately expensive, not wearable and require practice to get familiar with it) or by EEG. Eyeball indeed behaves as a dipole with a positive anterior pole (cornea) and a negative posterior pole oriented (retina) and generates visible changes in the EEG traces while moving. In particular, blinks are a semi-autonomic rapid closing of the eyelid, typical blinking spikes in the EEGs are generated when cornea is short-circuited to the eyelid [7]. Spontaneous (involuntary) blinking occurs without external stimuli and conscious effort whereas voluntary blinking is forced by the subject and involves the use of all the 3 divisions of the orbicularis oculi muscles [8]. Low-cost EEG are widespread (even used to monitor neural deficit [9]) and, although the quality of the recorded signals is not as good as that provided by equipment meant for clinical purpose, eye movements can be clearly recorded, due to the relatively high amplitude of the related signals, as compared to the background EEG due to the electrical activity generated by the brain [7]. The aim of the present work is to develop a system, based on the analysis of EEG signals collected by a low-cost EEG recording equipment, that can effectively discriminate between voluntary end spontaneous (involuntary) blinks. The ultimate goal is to associate voluntary blinking to the control command of a device in future applications.

In the context of the literature on BCI dealing with eye blinks in EEG signals, most of papers consider blinks as "artifacts" and aim at rejecting them [10], conversely, the present paper considers them a possible source of control that is worth to be analysed to decode the subject's intention to issue a command associated to voluntary (forced) blinking.

Some methods have been reported in the literature in this context. Agarwal et al. [11] proposed an automated open eye detection algorithm capable of estimating the timestamps of the start and end of the blinks. Kartsch et al. [12] have developed a drowsiness detection system based on the estimation of blinking rate from EEG recordings. Sharma et al. [13] presented a method to detect eye closing/opening from the EOG signals. They proposed the "Virtual Windows Method" in order to carefully observe the blinks online and asynchronously with a detection accuracy of 96.9%, 95.6% and 91.9% for multiple blinks, eye closing and eye opening respectively. EOG and EMG signals are applied simultaneously with the EEG signals by Minati et al. [14] to control of a 5+1 degrees-of-freedom robot arm based on a wireless headband in the form of four control methods meant on different signal combinations. Ahmed [15] controlled a wheelchair through eye blinks with a sensitivity of 80%. Left and right winks are associated to "move left" and "move right", double blinking is associated to "move backward". In their work no distinction is made between spontaneous and forced blinking, single blink is associated to the command "move forward" but the possibility of false detection due to spontaneous blinking is not investigated.

The present paper introduces a one-dimensional (1D) Convolutional Neural Network (CNN) to discriminate between spontaneous and voluntary blinks recorded from four healthy subjects (Sb_j, with j=1,2,3,4), reporting high accuracy values (97.92%). CNNs are indeed very useful for extracting features from the input representation achieving encouraging and impressive results in several applications [4], [16], [17].

The paper is organized as follows: Section II-A illustrates our experimental paradigm for EEG recording, Section II-B describes how the training and test dataset were constructed from the recorded EEG signals, Section II-C introduces the proposed 1D CNN, Section III reports the achieved results and Section IV draws some conclusions and addresses future extensions of the study.

II. Methodology

The flowchart of the procedure is described in Figure 1. The main steps can be summarized as follows: (A) acquisition of the EEG recording (channels FP1 and FP2); (B) detection of blinks and subsequent selection of the related EEG epochs; (C) the extracted epochs are used as input to a customized 1D Convolutional Neural Network that will classify the epoch as "voluntary blink" or "involuntary blink". The proposed CNN is featured by 1 convolution layer, 1 max pooling layer, 1 fully connected layer followed by a softmax layer which fulfils the 2-ways (voluntary vs. involuntary blinks) classification and will be described in detail in Section II.

A. EEG recording and preprocessing

Data acquisition setup and EEG data recording process were carried out in the controlled lab environment at STMicroelectronics Catania R&D (Italy). EEGs was acquired by means of consumer-grade OpenBCI platform [19] [20] and the 4 channels Ultracortex Mark IV helmet. The brain activity of 4 healthy male and female volunteers (3 male and 1 female subjects) was recorded and analyzed for each customized setup. Their mean age was 23 years old and none of them suffered from any disease or pain during the recordings. All the experiments were conducted in a quiet and dimly lit room with the subject seated in a comfortable chair. The subject received information and instruction about the experimental setup. The reference and ground electrodes were on the ear clip (A1 and A2 position) and the EEG electrodes were placed on the forehead above the eye (Fp1 and Fp2 position) and were used as input channel (Figure 2). A sampling frequency of 250 Hz with 24 bit/s resolution was used to collect EEG signals. The brain-computer interface device was used to record 15-minute sessions. The registration protocol was structured as follows. For each subject, two recordings were acquired: in the first recording, the subject was asked to blink involuntarily, in a natural way; in the second recording, the subject was asked to blink voluntarily at regular intervals of 5 seconds, with the support of a sound stopwatch that marked the time interval.

The acquired EEG time series were processed off-line using MATLAB® R2018b. Each EEG signal was first band-pass filtered between 1 and 49Hz by using a 2nd order Butterworth filter. A DC correction was performed. No further pre-processing was applied.

In this study, an open-source biosignal data acquisition (DAQ) and a 3D printed Mark IV EEG helmet with STM32L475 Chip on Board (CoB), as illustrated in Figure

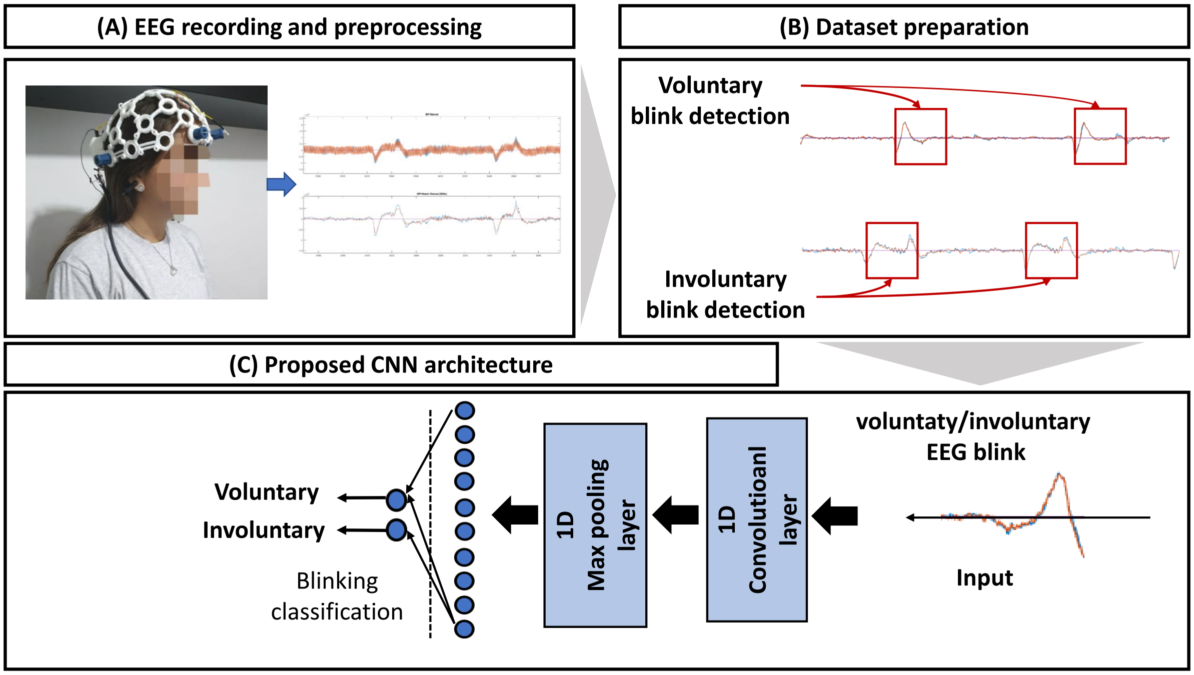

Fig. 1. Procedure of the proposed classification framework. (A) Ultracortex Mark IV helmet is used for recording EEG signals from channels FP1 and FP2, subsequently filtered between 1 and 49Hz by using a 2nd order Butterworth filter. (B) Voluntary and Involuntary blinks are detected through *PeakUtils* package [18] (C) and used as input to the proposed 1D Convolutional Neural Network that performs the binary classification task (voluntary blink vs. involuntary blink).

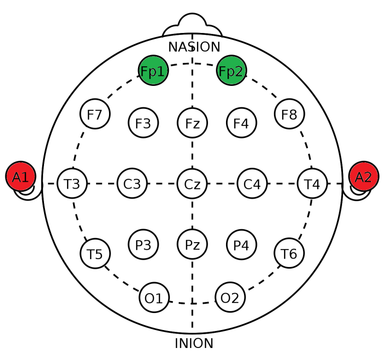

Fig. 2. 10/20 System consisting of the 19 channels montage (Fp1, Fp2, F3, F4, C3, C4, P3, P4, O1, O2, F7, F8, T3, T4, T5, T6, Fz, Cz, Pz). A1 and A2 (highlighted in red) represent the reference and ground electrodes, respectively; whereas, Fp1 and Fp2 (highlighted in green) represent the electrodes used to record the EEG signals.

3, was constructed to record EEGs. Our CoB supports 4-EEG channel screwable dry 5 mm Ag/AgCl electrodes, ear clip electrodes, amplifier and data recording using customized GUI. Dry electrodes do not require any skin preparation or conductive pastes. Ultracortex Mark IV EEG helmet carries 35 node to accommodate electrodes placemat based on International 10-20 system. Our CoB uses as input two differential high-impedance amplifiers [21] (about 40 kΩ) [22]. EEG stream data are transferred from CoB to PC through an USB cable.

B. Dataset preparation

Blink signals' magnitude is twice larger than EEG signals generated by the brain cortex and exhibit a characteristic waveform. A typical eye-blink can be characterized by its waveform pattern (spike), amplitude and duration. An eye-blink waveform pattern is defined as the voltage variation over the time during a natural or forced eye-blink. Eye-blink amplitude is the depth of the waveform pattern and the duration is simply the time taken by the user to perform a complete eye-blink. To this aim, the EEG traces recorded and preprocessed as described in II-A were stored in optical disk for further analysis. Our DB manage EEGs stored as matrices. In each matrices, the rows represent channels (Fp1, Fp2) and columns represent the samples. EEGs are then further processed to detect the blinks and select the epochs related to blinks. Since blinks show up as spikes, an algorithm of peak detection was applied to detect spikes. In particular, peak detection was carried out by the *PeakUtils* package [18] that includes functions that find peaks in the data.

This library implements a function for approximating the baseline by using an iterative polynomial regression algorithm. *PeakUtils* finds the peak and puts the corresponding time label into a vector t, where t[i] is the time sample of the

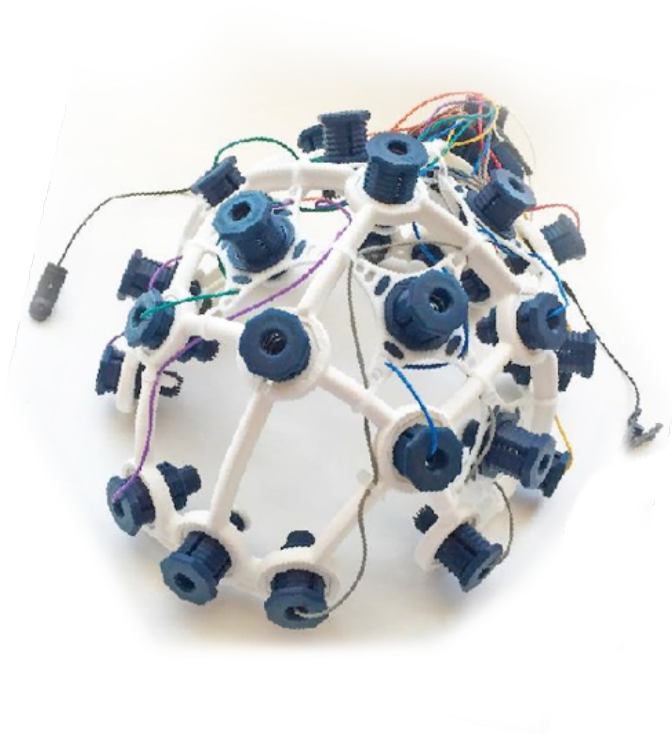

Fig. 3. Ultracortex Mark IV EEG.

i_{th} detected peak. Blink EEG epochs were extracted using a rectangular window with a length of T = 0.8s. The epoch$_i$ is represented by x[n], with n=0,1,...,N-1 where N=T x fs, with fs = 250Hz. Each x[n] contains N= 0.8 x 250 =200 samples. Each x_i EEG segment starts from the t_i index and ends in t_i +200 samples, both for voluntary and involuntary blinks. It is to be noted that, the initial seconds of a blink were discarded since there is a common trend for voluntary and involuntary blinks (up to the peak) not useful for binary classification purpose.

C. Convolutional Neural Networks: Backgroud

Convolutional Neural Networks (CNN) belong to the deep learning architectures commonly employed for the classification of 2-dimensional images or videos [23], [16]. However, CNN have been recently developed to analyze also 1D signals (such as EEG). 1D CNN and 2D CNN have structural differences (one processes mono-dimensional arrays; the other one, 2-dimensional matrices) but are based on the same principle of operation. A standard CNN contains several processing modules consisted of convolution and sub-sampling (or pooling) operations, followed by a multi-layer fully connected neural network. The convolutional layer consists of C filters that perform the dot product (i.e., convolution operation) with the input data. Each filter moves along the input with a specific step size (sharing the same weights), estimating C *feature maps*. The extracted feature maps are usually downsampled through a max or average pooling layer, where a filter scans the input feature map and computes the maximum or the mean of each sub-region under analysis. Note that, in this study, the max pooling operation was used since allows to capture better invariant features [24]. The network ends with one or more fully connected layers (as a standard multi-layer NN configuration) for performing the discrimination task.

1) Proposed CNN: The proposed 1D CNN is mainly composed of 1 convolutional layer (followed by a non-linear activation function), 1 dropout layer and 1 pooling layer. The network ends with a standard multi-layer fully connected neural network with softmax output function for the 2-way classification task: voluntary vs. involuntary blinks (Figure 4). Specifically, the proposed CNN is designed to receive as input EEG epochs sized 1 x 200 x 2 (where 200 is the number of samples in a 0.8s window, as described in Section II-B; 2 is the number of channels taken into account: FP1 and FP2). The convolution layer has 10 1-dimensional filters sized 1 x 10. Every filter convolves with each temporal input representation with stride and padding parameter of 1 and 0, respectively, producing 10 feature vectors (i.e., feature maps) sized 1 x 191. After applying the sigmoid non-linearity, the dropout layer (with dropout hyper-parameter set to 0.5) is used to prevent overfitting [25]. Note that we employed a sigmoidal function since we observed better performance than the Rectified Linear Unit function (ReLU), typically used in a CNN architecture. The (max) pooling layer consists of a filter sized 1 x 8 that slides over each feature vector with a step of 8 reducing the spatial resolution to 1 x 23. Finally, the 10 features maps are flattened into a single 1-dimensional vector of size 1 x 230 and used as input to a 1-fully connected layer NN (of 10 hidden neurons) followed by a softmax layer that performs the binary classification.

The network was implemented in Keras [26] with Tensorflow backend and trained using the default parameter of adaptive moment estimation (ADAM) optimizer [27] for 50 iterations and with mini-batch size of 60 until the cross-entropy function converged.

III. RESULTS

In this work, a dataset of 1080 EEG epochs (540 related to voluntary blinks and 540 related to involuntary blinks) was generated from 8 EEG signals, recorded from 4 subjects (Sb_j, with j=1,2,3,4) and used as input to the proposed 1D CNN (Section II-C). Specifically, in order to estimate the effectiveness of the developed model the leave-one-out validation technique was used [28]. In particular, the proposed CNN was trained iteratively by using the whole dataset and leaving out epochs of 1 subject at time. Hence, four models were trained and the instances (i.e., epochs of Sb_j) left-out represented the test set of the j^{th} network. The classification performance were evaluated using the following standard metrics:

$$PRECISION = \frac{TP}{TP+FP}$$

$$RECALL = \frac{TP}{TP+FN}$$

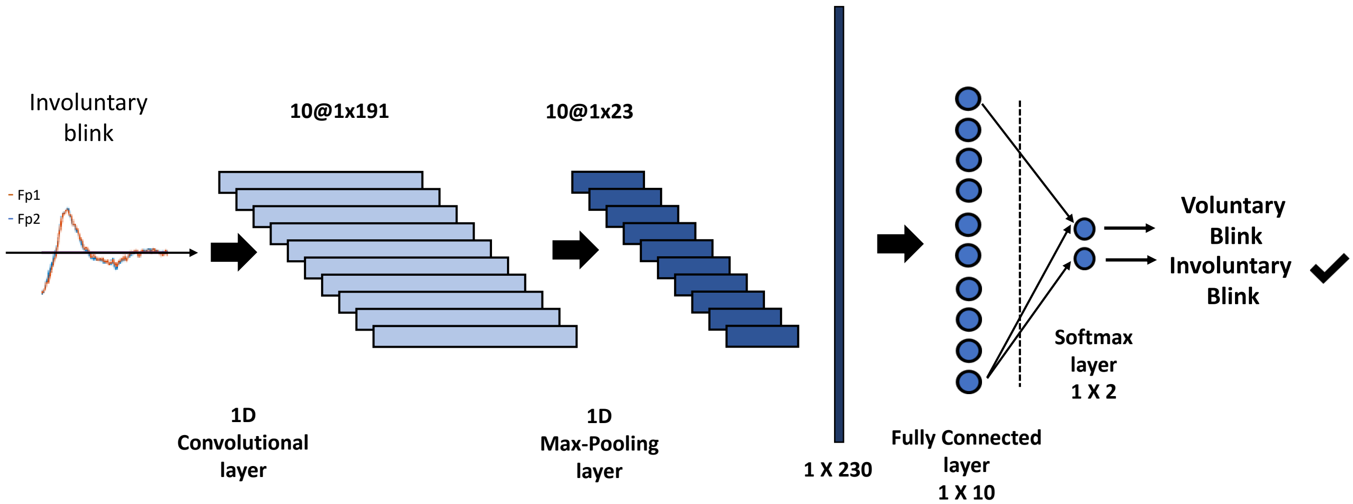

Fig. 4. 1D CNN architecture. It includes 1D convoulutional layer, 1D max pooling layer, 1 fully connected layer and 1 softmax output for classification puporse. It is to be noted that the convolutional layer is followed by a sigmoid activation function and a dropout layer. As an example, in the figure, the proposed 1D CNN receives an involuntary blink correctly classified as involuntary.

$$F-measure = 2 * \frac{PRECISION * RECALL}{PRECISION + RECALL}$$

$$ACCURACY = \frac{TP+TN}{TP+TN+FP+FN}$$

where TP, TN, FP, FN represent the true positive, true negative, false positive and false negative, respectively. Specifically, TP and TN are the number of voluntary and involuntary blinks classified correctly; FP is the number of involuntary samples incorrectly classified as voluntary and vice versa, FN is the number of voluntary instances misclassified as involuntary. Table I, reports the confusion matrices of each test set (i.e., subject left-out). For example, for Sb_3 only 1 epoch was erroneously classified (FP=1). Table II reports the voluntary vs. involuntary blinks classification performances. As can be seen, the proposed 1D CNN achieved very good values in each test scenario, reporting accuracy rates up to 98.75%, 95.83%, 99.58%, 97.50% when epochs of Sb_1, Sb_2, Sb_3 and Sb_4 were used as test set, respectively. Furthermore, remarkable scores of recall, precision (and consequently F-measure) were also observed. In order to assess the overall efficiency of the proposed model, the average performances were evaluated over the test sets and expressed as *mean value* $\pm$ *standard deviation*. Notably, the average values of recall, precision, F-measure and accuracy were of 97.2 $\pm$ 4.85%, 97.92 $\pm$ 1.91%, $\pm$ 97.46 $\pm$ 2.1% and 97.92 $\pm$ 1.41%, respectively. These results were confirmed also by evaluating the Area Under the Curve (AUC) of the Receiver Operating Characteristic (ROC). As an example, Figure 5 shows the ROC curve evaluated when epochs of Sb_3 were used as test set, reporting an AUC= 99.98%. Similar results were achieved for Sb_1, Sb_2 and Sb_4. Average training and test times were recorded to evaluate the delay introduced by the neural network in real time. Simulations were performed in an Intel Atom E3950 CPU with low consumption, average training and test times were 15.9s and 0.8s, respectively.

IV. Discussion and Conclusions

This work addressed the importance of analyzing eye movements for the development of BCI systems meant for people with disabilities who are able to effectively control their eyes. Eye movements can be detected by infrared eye-trackers, which however are not affordable, or by means of EEG sensors placed on the forehead, to detect the variations in the electrical scalp potentials caused by eyeballs' movements. There are just a few papers in this topic, indeed, signals generated by eye movements are usually considered artifacts in the field of EEG-based BCI with the aim to detect and remove them. Conversely, in this work, eye movements are considered a possible source of control command generation. The attention was focused on blinks, which are clearly visible in EEG recordings, in particular in fronto-polar channels (sensors Fp1

TABLE I
CONFUSION MATRICES EVALUATED ON EACH TEST SET, WHERE: TEST SET 1 INCLUDES EPOCHS OF SUBJECT 1 (Sb_1); TEST SET 2 INCLUDES EPOCHS OF SUBJECT 2 (Sb_2); TEST SET 3 INCLUDES EPOCHS OF SUBJECT 3 (Sb_3); TEST SET 4 INCLUDES EPOCHS OF SUBJECT 4 (Sb_4);

True labels	**Confusion matrix**		*Test set 1* (Sb_1)		*Test set 2* (Sb_2)		*Test set 3* (Sb_3)		*Test set 4* (Sb_4)	
Voluntary	**TP**	**FP**	117	3	120	0	119	1	171	9
Involuntary	**FN**	**TN**	0	120	15	105	0	120	0	180
	Voluntary	Involuntary								

Predicted labels

TABLE II
VOLUNTARY AND INVOLUNTARY BLINKS CLASSIFICATION PERFORMANCES (RECALL, PRECISION, F-MEASURE, ACCURACY) EVALUATED ON EACH TEST SET (I.E., LEFT-OUT SUBJECT (Sb_j WITH j=1,2,3,4))

Test set	Voluntary vs. involuntary blinks			
	Recall	Precision	F-measure	Accuracy
Sb_1	100%	97.5%	98.73%	98.75%
Sb_2	88.8%	100%	94.07%	95.83%
Sb_3	100%	99.17%	99.58%	99.58%
Sb_4	100%	95%	97.44%	97.50%
Average	**97.2 ± 4.85%**	**97.92 ± 1.91%**	**97.46 ± 2.1%**	**97.92 ±1.41%**

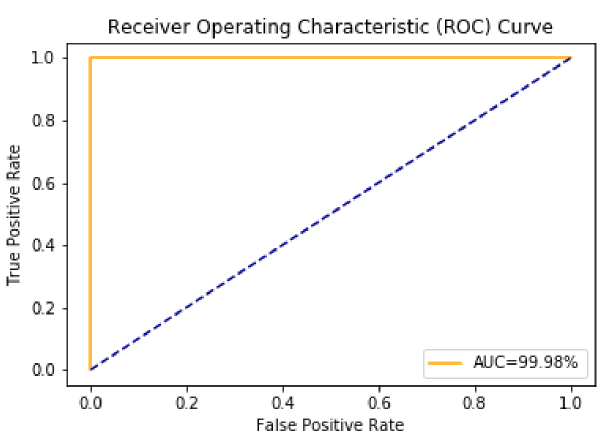

Fig. 5. ROC curve of the proposed 1D CNN for the voluntary vs. involuntary blinks classification, when epochs of Sb_3 are used as test set.

and Fp2). The goal was to discriminate between involuntary (spontaneous) and voluntary (forced) blinks with the ultimate goal of associating voluntary blinks with a control command in a future BCI application. To this end, 4 healthy subjects were recruited and underwent EEG acquisition (through sensors Fp1 and Fp2) during the execution of spontaneous and forced blinks. The recorded EEGs were used to construct two balanced dataset (spontaneous blink dataset and forced blink dataset) of EEG epochs containing blinks. A 1D CNN was designed which receives EEG epochs as input and label them as voluntary/involuntary. The proposed CNN has a shallow architecture with i) one convolutional layer; ii) one dropout layer and one pooling layer. The network ends with a standard multi-layer fully connected neural network with softmax output function for 2-way classification task. The proposed system provided an accuracy of 97.92%. To the best of our knowledge, this is the first work that aims at distinguishing voluntary from forced blinks. Sharma et al. [13] proposed an eye opening and closing detection system, associating such movements with the intention to perform pick and place tasks of a robotic arm. Ahmed et al. [15] controlled a wheelchair by issuing the "move left" and "move right" commands when left and right winks were detected, respectively, and "move backward" 'when a double blink was detected. Single blink was associated to "move forward" but no distinction was provided between spontaneous and forced blinking thus the possibility of false detection due to spontaneous blinking was not investigated. The system here proposed provided promising results.

In the future, the input size will be further reduced in order to avoid useless computation and a larger cohort of patients will be taken into account in order to better validate the performance and with the goal of implementing a real time classification system. Specifically, the neural network will be integrated into the electronic card on the helmet in order to achieve a real-time classification. In addition, the proposed system will be test also to classify other types of eye movements.

REFERENCES

[1] J. R. Wolpaw, N. Birbaumer, W. J. Heetderks, D. J. McFarland, P. H. Peckham, G. Schalk, E. Donchin, L. A. Quatrano, C. J. Robinson, and T. M. Vaughan, "Brain-computer interface technology: a review of the first international meeting," *IEEE transactions on rehabilitation engineering*, vol. 8, no. 2, pp. 164–173, 2000.

[2] L. M. Alonso-Valerdi, R. A. Salido-Ruiz, and R. A. Ramirez-Mendoza, "Motor imagery based brain–computer interfaces: An emerging technology to rehabilitate motor deficits," *Neuropsychologia*, vol. 79, pp. 354–363, 2015.

[3] M. Mahmud, M. S. Kaiser, A. Hussain, and S. Vassanelli, "Applications of deep learning and reinforcement learning to biological data," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 29, no. 6, pp. 2063–2079, 2018.

[4] N. Mammone, C. Ieracitano, and F. C. Morabito, "A deep cnn approach to decode motor preparation of upper limbs from time-frequency maps of eeg signals at source level," *Neural Networks*, vol. in press.

[5] E. C. Lee, J. C. Woo, J. H. Kim, M. Whang, and K. R. Park, "A brain–computer interface method combined with eye tracking for 3d interaction," *Journal of neuroscience methods*, vol. 190, no. 2, pp. 289–298, 2010.

[6] A. Poole and L. J. Ball, "Eye tracking in hci and usability research," in *Encyclopedia of human computer interaction*. IGI Global, 2006, pp. 211–219.

[7] A. Delorme, T. Sejnowski, and S. Makeig, "Enhanced detection of artifacts in EEG data using higher-order statistics and independent component analysis," *Neuroimage*, vol. 34, no. 4, pp. 1443–1449, 2007.

[8] J. Valls-Sole, "Spontaneous, voluntary, and reflex blinking in clinical practice," *Journal of Clinical Neurophysiology*, vol. 36, no. 6, pp. 415–421, 2019.

[9] N. Mammone, S. De Salvo, L. Bonanno, C. Ieracitano, S. Marino, A. Marra, A. Bramanti, and F. C. Morabito, "Brain network analysis of compressive sensed high-density eeg signals in ad and mci subjects," *IEEE Transactions on Industrial Informatics*, vol. 15, no. 1, pp. 527–536, 2018.

[10] R. J. Croft and R. J. Barry, "Removal of ocular artifact from the EEG: a review," *Neurophysiologie Clinique/Clinical Neurophysiology*, vol. 30, no. 1, pp. 5–19, 2000.

[11] M. Agarwal and R. Sivakumar, "Blink: A fully automated unsupervised algorithm for eye-blink detection in EEG signals," in *2019 57th Annual Allerton Conference on Communication, Control, and Computing (Allerton)*. IEEE, 2019, pp. 1113–1121.

[12] V. Kartsch, S. Benatti, D. Rossi, and L. Benini, "A wearable EEG-based drowsiness detection system with blink duration and alpha waves analysis," in *2017 8th International IEEE/EMBS Conference on Neural Engineering (NER)*. IEEE, 2017, pp. 251–254.

[13] K. Sharma, N. Jain, and P. K. Pal, "Detection of eye closing/opening from EOG and its application in robotic arm control," *Biocybernetics and Biomedical Engineering*, vol. 40, no. 1, pp. 173–186, 2020.

[14] L. Minati, N. Yoshimura, and Y. Koike, "Hybrid control of a vision-guided robot arm by EOG, EMG, EEG biosignals and head movement acquired via a consumer-grade wearable device," *Ieee Access*, vol. 4, pp. 9528–9541, 2016.

[15] K. Ahmed, "Wheelchair movement control via human eye blinks," *American Journal of Biomedical Engineering*, vol. 1, no. 1, pp. 55–58, 2011.

[16] C. Ieracitano, N. Mammone, A. Bramanti, A. Hussain, and F. C. Morabito, "A convolutional neural network approach for classification of dementia stages based on 2d-spectral representation of EEG recordings," *Neurocomputing*, vol. 323, pp. 96–107, 2019.

[17] F. C. Morabito, M. Campolo, C. Ieracitano, J. M. Ebadi, L. Bonanno, A. Bramanti, S. Desalvo, N. Mammone, and P. Bramanti, "Deep convolutional neural networks for classification of mild cognitive impaired and alzheimer's disease patients from scalp eeg recordings," in *2016 IEEE 2nd International Forum on Research and Technologies for Society and Industry Leveraging a better tomorrow (RTSI)*. IEEE, 2016, pp. 1–6.

[18] L. Negri and C. Vestri, "lucashn/peakutils: v1. 1.0," 2017.

[19] O. A. online:, 2020. [Online]. Available: http://openbci.com/

[20] P. Berg and M. Scherg, "Dipole models of eye movements and blinks," *Electroencephalography and clinical Neurophysiology*, vol. 79, no. 1, pp. 36–44, 1991.

[21] D. Denney and C. Denney, "The eye blink electro-oculogram." *British journal of ophthalmology*, vol. 68, no. 4, pp. 225–228, 1984.

[22] T. C. Ferree, P. Luu, G. S. Russell, and D. M. Tucker, "Scalp electrode impedance, infection risk, and EEG data quality," *Clinical Neurophysiology*, vol. 112, no. 3, pp. 536–544, 2001.

[23] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "Imagenet classification with deep convolutional neural networks," in *Advances in neural information processing systems*, 2012, pp. 1097–1105.

[24] P. Baldi and P. J. Sadowski, "Understanding dropout," in *Advances in Neural Information Processing Systems 26*, C. J. C. Burges, L. Bottou, M. Welling, Z. Ghahramani, and K. Q. Weinberger, Eds. Curran Associates, Inc., 2013, pp. 2814–2822. [Online]. Available: http://papers.nips.cc/paper/4878-understanding-dropout.pdf

[25] N. Srivastava, G. Hinton, A. Krizhevsky, I. Sutskever, and R. Salakhutdinov, "Dropout: a simple way to prevent neural networks from overfitting," *The journal of machine learning research*, vol. 15, no. 1, pp. 1929–1958, 2014.

[26] F. Chollet *et al.*, "Keras," https://keras.io, 2015.

[27] D. P. Kingma and J. Ba, "Adam: A method for stochastic optimization," *arXiv preprint arXiv:1412.6980*, 2014.

[28] A. Vehtari, A. Gelman, and J. Gabry, "Practical bayesian model evaluation using leave-one-out cross-validation and waic," *Statistics and computing*, vol. 27, no. 5, pp. 1413–1432, 2017.