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Brain Computer Interface for Control of Cyber Physical Systems in Industry 4.0

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Abstract. Brain computer interface design has diverse applications from motor rehabilitation to recreational applications. In this article we propose a machine learning algorithm for the analysis of electroencephalographic signals (EEG). This can be applied to the brain computer interface (BCI) for control of cyber physical systems in industry 4.0 to employ people with motor disabilities. This research classifies EEG signals for four classes, mathematical thinking, relaxation state, left foot movement imagination, left hand movement imagination, and then implement it in a BCI system for cybersecurity monitoring. physical systems in industry 4.0. For this, signals generated with motor imagination were obtained, which were classified with a GRU neural network. The proposed algorithm has a classification efficiency greater than 90%.

Keywords: Brain computer interface, cyber physical, industry 4.0, electroencephalography.

1 Introduction

The fourth industrial revolution has unleashed various changes, which promote the connection of sensors, electronic devices and business assets, with each other and with the Internet.

The main goal of Industry 4.0 is to turn normal machines into self-aware and self-learning machines. The monitoring of data in real time, the monitoring of the status and positions of the product, as well as the maintenance of the instructions to control the production processes, are the main needs to be covered.

Along with Industry 4.0, supply networks have evolved, considered cyber-physical systems (CPS), which mainly depend on the adoption and reconfiguration of product structures. CPS are used in manufacturing systems, as well as in different cybernetic physical systems such as urban traffic control and control systems [43].

In recent decades, studies in the field of Brain Computer Interface (BCI) have had an exponential growth, which is why it is required that BCI's be increasingly implemented within industry 4.0, since it has the potential to become in an interface that could improve communication between a human and a machine [44].

Within the BCI there are different acquisition methods, for the purposes of this study electroencephalogram (EEG) signals were used, since it is a non-invasive and portable

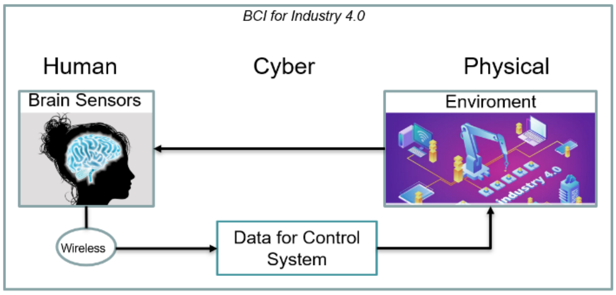

Fig. 1. Shows the loop between a BCI system within Industry 4.0 and the use of cyber-physical.

technique. The signals were acquired using motor imagery and classified using a neural network called the Gated Recurrent Unit (GRU).

The results obtained by this research will be implemented in the industry 4.0 environment and satisfy the loop of figure 1[45].

2 Background

Brain-computer interfaces (BCIs) are a way of connecting with the external world through the generation and interpretation of signals emitted by our brain. The study of BCI became an inherently interdisciplinary field involving neuroscience, psychology, engineering, mathematics, informatics, and clinical rehabilitation [1]. This type of systems according to [2] has allowed people to control devices such as spellers, robotic arms, drones and wheelchairs. However, most of these BCI applications are restricted to research laboratories.

The main BCI studies are based on: systems that use slow cortical potentials (SCP for its acronym in English) such as the TTD system [2-4] which regulates SPCs using letters, words or pictograms; this same principle is used by some web browser designs, for example in the work of [6], an attempt is made to move a cursor up or down generating positive and negative UCS. Other BCI studies use sensorimotor rhythm (SMR) such as the Graz BCI system, which consists of controlling the movement of a cursor [5-9] or the study [12], which shows that it is possible to place a ball in a basket generating signals with different rhythms and wave amplitude, thereby producing variations that go from alpha waves to beta waves, additionally [13-14] use motor imaging. This same principle is used in some game applications such as in the studio [15], virtual environments [10], control of external devices [11-13], among others.

In addition, there are BCI studies that use a method called P300, which evokes potentials using images and audios as stimuli. Among these studies are spelling systems in works such as [20-21], web browsers developed by [22], painting applications made by [14] and [23]. This type of system has the limitation of requiring additional hardware, so it will not be used in this research.

Another important and recurring application is that of rehabilitation and training [14]. These applications use motor imagination (IM for its acronym in English) which consists of imagining the movement of a limb. IMs in combination with physical therapy or robotic assistive orthotics assist motor recovery.

For [25] the EEG signal processing (electroencephalogram) for BCI involves the extraction and classification of features. For this, various processing methods have been used in the literature, [26-27] conducted their studies with the wavelet transform, while [28] used the Fourier transform. Other works have used the autoregressive model, such as [29]. Regarding the common spatial pattern (CSP) technique, this was used in various studies such as those of [30-33], to extract the characteristics of these EEG signals.

Different machine learning algorithms have been used to carry out the classification of EEG signals [15]. [35-36] developed an algorithm based on support vector machines (SVM). Others such as [30-32] carried out their work by applying linear discriminant analysis (LDA for its acronym in English). In recent years, neural networks have been positioned in the treatment of EEG signals, such is the case of the investigations of [26-28, 34, 37-39], among others.

3 Methodology

In this section it is described the proposed architecture, we used for classification of EEG signal of motor imagination. The architecture consisted of a sequential model or linear stack of layers. As input layer, a convolutional layer was used, this type of layers, because they use convolution operations with an adaptive kernel, are capable of extracting relevant characteristics of the signal, these characteristics are extracted during training, so it is expected that the trained kernels are able to obtain particular characteristics of the different types of motor imagination with which they were trained. In this implementation, the convolution layer is prepared to receive a 4-channel input, corresponding to four EEG signals coming from electrodes on the user's skull at different positions. In the proposed architecture, the input convolutional layer, has 10 kernels, with several taps of four, also a stride of five samples was used, and an activation function of type ReLU.

The next layer consisted of a Gated Recurrent Unit (GRU) which is a variation of a recurrent neural network. This type of network can learn a mapping from an input sequence to a target sequence of arbitrary length. The GRU consist of hidden units composed of reset and update gates that adaptively control the amount of information that each hidden unit remembers or forgets while processing a sequence. In the proposed network GRU is used to capture EEG regularities that could be found in each thought analyzed this could help the next stage of the proposed architecture.

The last section of the architecture is composed of four layers of dense networks, these layers will use the characteristics found by the previous layers, and finally give the classification result, the last layer composed of four neurons, one for each class of motor imagination, have activation functions of softmax, while the rest of the layers use ReLU.

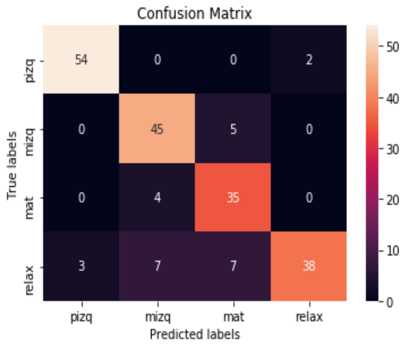

Fig. 3. Confusion matrix.

4 Results

For a cyber-physical system to communicate with a human collaborator using BCI, the interface must be able to collect EEG signal from the collaborator and decode user thoughts into commands that the cyber physical system can decode. In this experiment, for the BCI, we use the MUSE EEG head band, and signal are recorded using the four electrodes in the band, placed at positions AF7, AF8, TP9 and TP10 with reference to the International 10-20 Electrode Placement System.

The EEG data was recorded from one participant during 30 second, 40 of them used the imagery-motor of the left-hand movement, 40 used the imagery motor of the left foot,40 in the state of relapse, and 40 in mathematical activity, for a total of 160 records.

The length of the signals was 3000 samples; however, these were truncated the first 100 samples and the last 100 to give 2800 samples from four channels, data were normalized so that each sample were in the [0,1] interval. The training and test sets were constructed using 80% (800 signals) and 20% (200 signals) of the data, respectively.

The training of the proposed architecture was done using the categorical cross entropy loss function, and the ADAM algorithm to optimize the network parameters and the network was trained with 80 epochs.

The classification of the motor imagery signals for the four states is shown in the confusion matrix in figure 3. From the confusion matrix it can be seen the performance of the proposed algorithm is very acceptable, given that, no previous preprocessing to reduce artifacts or remove noise from the EEG data was done, also demonstrating the robustness of the algorithm.

From the confusion matrix it can be obtained a classification 94% for the imagination of the movement of the left foot and a proper classification 91% for the imagination of the left hand. In the cases of state of relaxation 76% and mathematical activity status 70%. The total accuracy achieved by the proposed network was (correct predictions) / (total predictions) =172/200 =86%.

We analyzed each class in a binary for, that is each class versus the rest. In figure 4, the ROC curves for each of the classes are shown. The results of the area under the curve

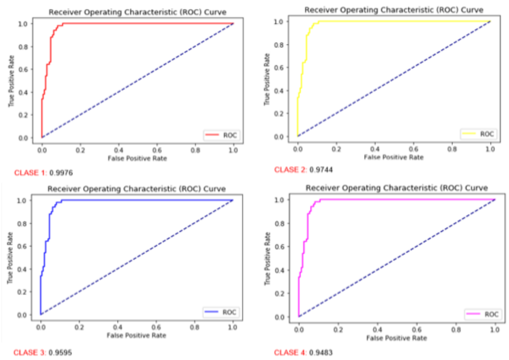

Fig. 4. ROC curves.

for class 1 was 0.997, for class 2 it was 0.974, class 3 was 0.959 and class 4 was 0.948. For this classification the results were very good for all classes according to the ROC scale.

5 Conclusions

In this work we proposed a new deep learning architecture to for classification of EEG signals of motor imagination, this network will be the main element in a Brain Computer Interface for a Cyber-Physical system. The BCI obtained is capable of decode four classes of motor imagination, left-hand movement, left foot, relax, and mathematical activity. This can be used as commands to activate certain functions or communicate with the Cyber-Physical system.

The proposed deep learning architecture uses a combination of a convolutional network with a GRU layer and obtained an accuracy greater than 90% the classification of EEG signals of two of the four motor imagination signals. The network was able to distinguish between imagination thoughts and two different states of brain activity, the most distinguished data were movement of the left foot and movement of the right hand with a percentage greater than 90%, while mathematical thoughts and the state of relaxation where I obtained an advantage greater than 70%.

As future work it is planned to test the system on a factory implementing the paradigm of Industry 4.0 for controlling artifacts, also is planned to make test with people with a motor disability.

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