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Generative Adversarial Networks Applied to Brain Signals to Control Cyber-Physical Systems

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Abstract: Brain-computer interfaces (BCI) use brain intent to convert it primarily into control commands, usually using EEG devices to acquire brain signals. Its applications have been extended to all areas, including industrial, that is why it has been proposed to use a BCI system for control of cyber-physical systems (CPS), however, the acquisition of EEG data does not allow to acquire a large volume of them. due to the mental fatigue that is generated when making the recordings. To solve this, in this article we present the results of the EEG data generation through the adaptation of the Generative Adversarial Networks (GAN). For this, the signals were obtained using a low-cost EEG device, in which signals were obtained for four classes two of motor imagination (MI), relaxation state, and mathematical activity, later a GANs network was used to increase the data and finally, were classified using a convolutional (CNN) network. The results show the difference in the classification between real data and the genera(Altaheri et al., 2021)ted data, which will be used for its future application in the control of CPS.

Keywords: BCI, EEG, GANs, CPS

1. Background

Industrial 4.0 has generated various changes of paradigms that promote the interconnection of sensors and electronic devices. That is why its main objective is to migrate to self-aware and self-learning machines to make their processes more efficient. For this it is based on 9 pillars, some of them are the internet of things, cloud computing, and cyber-physical systems (CSP) (Vaidya et al., n.d.). CPS is used in manufacturing systems, as well as in different cybernetic physical systems, such as control systems.

Another important advance in the study of Brain-Computer Interface (BCI), these have become popular in recent years, for this reason, various systems have been developed improving both software and hardware (Amiri et al., 2013). BCIs are complete systems that allow the user to communicate with devices by capturing the signals emitted by the brain through the generation of mental tasks, the signals are recorded, processed, and classified to give them an application.

It should be noted that BCI within Industry 4.0 has the potential to become an interface that could improve communication between a human being and a machine. According to Schmidt et al., (2020), BCIs have an opportunity for socio-technical integration through the interconnection of technology and workers. However, these new opportunities have been little explored within the industry (Peruzzini et al., 2017). Despite this, it is intended that BCIs in the industry make industrial processes more efficient through direct collaboration between humans and machines (Ji et al., n.d.).

One of the problems found by the BCI is the lack of massive data. Since the signals obtained by the devices are not stationary and are limited by noise, variability in thoughts, and user fatigue when generating the signals. signs [quote]. A large amount of data is required to create an efficient and robust classifier. However, the calibration times for the BCIs are long, so it is necessary to generate synthetic data to improve the classifier (Altaheri et al., 2021).

For this study, signals acquired through the imagination of the movement of the left foot, the imagination of the movement of the right foot, mathematical activity, and state of relaxation were used, the signals were converted into images, later the database was increased using generative neural networks (GANs), and finally, they were classified using a convolutional network. This is to effectively integrate the BCIs into the CSPs in the future.

1.1 Brain-computer interfaces (BCI)

Brain-computer interfaces (BCI) are a way of communicating with the outside world through the generation and interpretation of signals emitted by the brain. Complexity BCIs is an interdisciplinary field involving neuroscience, engineering, psychology, informatics, mathematics, and clinical rehabilitation (Agarwal et al., 2015).

Some studies have focused on developing systems that allow controlling, for example, wheelchairs, spellers, robotic arms, drones, Gifts, Prosthesis, home automation, classification of emotions, and rehabilitation (Altaheri et al., 2021).

The signal acquisition methods are mainly divided into two, invasive and non-invasive. The most widely used method is the non-invasive electroencephalogram (EEG) method when it was shown that brain activity is related to mental state (Alotaiby et al., 2015). The EEG signals are recorded as temporal and spatial waves, their reading in the cerebral cortex, the bioelectric potentials observed in the skin are caused by the flow of ion-based electrical currents within the volume of the body (Carmeli et al., n.d.). EEG signals are classified primarily based on their morphology, amplitude, and frequency. The latter is studied through frequency bands, the most used are delta (0.5Hz-4Hz), theta (4Hz-7Hz), alpha (8Hz-12Hz), and beta (13Hz-30Hz) (Nayak & Anilkumar, 2019).

To acquire EEG signals, the generation of mental tasks is required. Mental tasks are neurological activities, which generate various patterns in the signal, these patterns are acquired, processed, and classified. The response to mental tasks (RMT) indicates the state of activity of the brain, for example, imagine writing a letter, counting, calculating, or lifting a hand, a leg, among others (Chew et al., n.d.), from here the motor imagination (MI) arises, which is to imagine the movement of some limb, without executing it.

1.2 Cyber-physis Systems (CSP) for BCI.

The inclusion of BCIs in the design of production systems from the sociotechnical perspective in still little explored in the industry. Some studies have tried to incorporate BCI into the industry using mainly eye movement in combination with augment reality glasses (Knoll et al., 2020), motor movement (Elektrotechniczny & 2017, n.d.), through hybrid interfaces where they use different sensors (Peruzzini et al., 2017). Other studies of BCIs have been used to investigate emotions of workers when interacting with collaborative robots, mainly to prevent accidents, also to explore cognitive abilities in decision making, and for biometric recognition within the industry (Ajrawi et al., 2021).

1.2 Generative Adversarial Networks (GANs) for EEG

The GAN implementation is based on two neural networks which are the generator and discriminator, where the generator is in charge of creation images or artificial data and the discriminator of evaluating whether the created image is real or synthetic (Debie et al., n.d.). Figure 1 shows the operation of GANs.

Several studies have focused on generating synthetic images; however, few have focused on the use of GAN for EEG. In the study by Fahimi et al., n.d. (2019), the performance of a GAN in the generation of artificial electroencephalogram (EEG) signals is evaluated, where the temporal and spectral characteristics of the synthetic signals resemble real data. On the other hand, in Hartmann et al., (2018) signals are generated using a GAN and are evaluated based on their distance with various classifiers. In the study of Corley et al.,(2021), they propose a GAN model in which they generate EEG signals that is focused on improving the spatial resolution of low-density EEG signals. Also Wang et al., (2021), generated images from the EEG and fMRI signals where a classification accuracy of 0.5 was obtained with the synthetic images. GANs is given by the equation 1:

$$\min minV(D,G) = E_{x\sim Pdata(x)}\left[logD(x)\right] + E_{z\sim Pz(z)}\left[\log\left(1 - D\big(G(z)\big)\right)\right] \tag{1}$$

Where z is the vector of the Gaussian distribution, D is the distributor, G the generator (Cho & Moon, 2020).

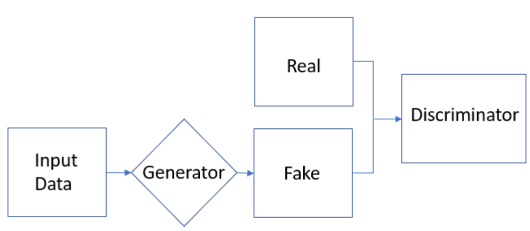

Figure 1. GANs operating system

1.4 Convolutional Neural Network (CNN)

Convolutional neural networks are applied to a great extent for image processing. This type of network receives an input image through which a kernel passes the extracts characteristics of the image, this is done repeatedly and relies on the max-pooling which looks for the maximum value through a kernel and thereby generates another image, ReLU functions (Taheri et al., 2020) whose expression is given by:

$$f(x) = maximum\ (0, x) \qquad (2)$$

2. Materials and Methods

2.1 Data collecting

For data acquisition, an electroencephalogram device called Muse was used, which has four sensors in positions AF7, AF8, TP9 and TP10 according to the 10-20 system. For the recording of the signals, 200 recordings were generated for 30 seconds for four different thoughts, which are the imagination of the movement of the left foot, the imagination of the movement of the left hand, in a relaxed state, and 50 mathematical activity. where a total of 800 signals were obtained. with an input shape of (1000,2800,4).

2.2 Data Processing

The signals were converted into images and reshaped to (100,100,3), Subsequently, four free licensed google images representing each thought were chosen and finally mixed where the signal image represents 0.7 and image2 a 0.5 in the mix for a total of 800 images created. Figure 2 shows the diagram of this process.

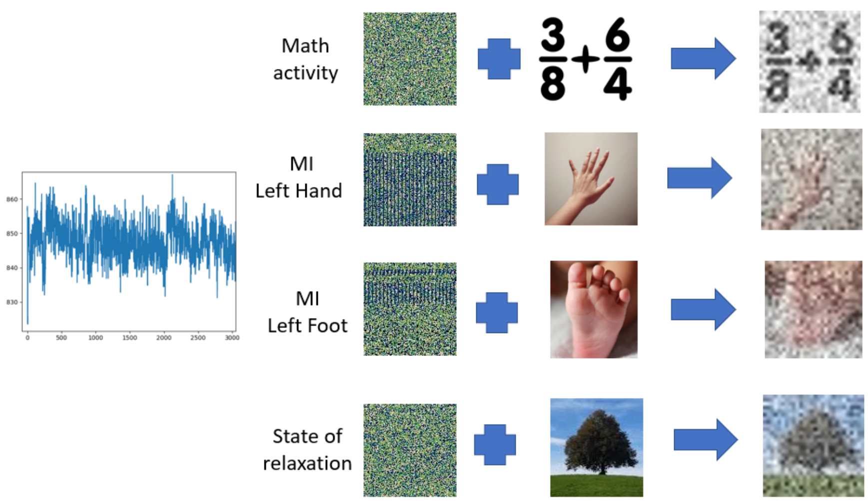

Figure 2. Generation of images from EEG signals.

2.3 GANs implementation

The images entered a deep convolutional generative adversarial network (DCGAN), which uses convolutional networks for the generation of synthetic images. Of these, 440 images were obtained for each class, for a total of 1760. In the figure 3 you can see the images generated.

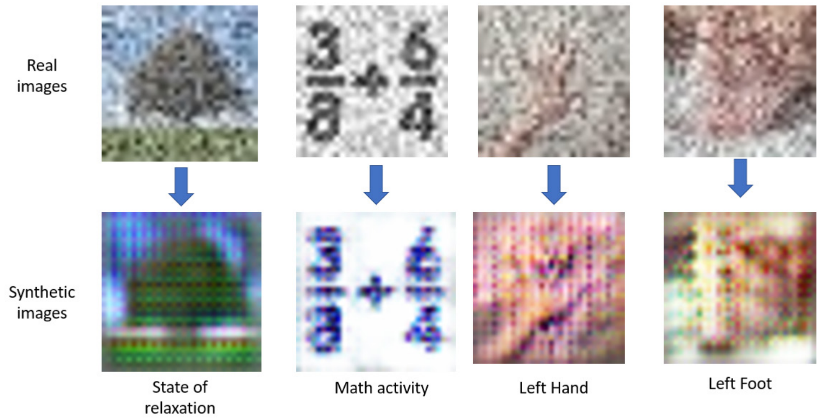

Figure 3. GANs images.

2.4 Classification

Finally, the synthetic data obtained were classified, a convolutional CNN network was used, the training was with 80% of the data. The architecture of the proposed network is shown in figure 4.

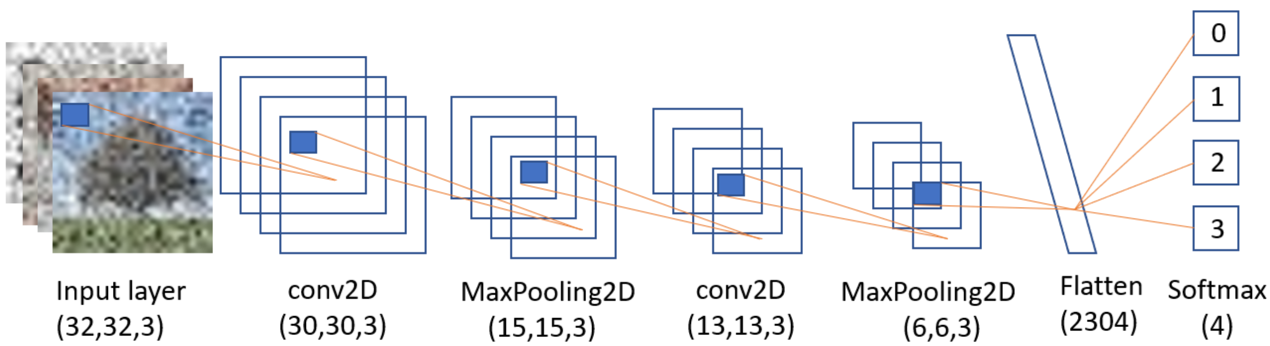

Figure 4. CNN model.

3. Results

The visual evaluation of the images created by DCGAN shows that the images are very similar to the input images since it is possible to distinguish between them which class they belong to. The GAN was trained with 50 epochs, each class was trained separately, of which 1000 images were created per class, however, the images created by the first 30 epochs were judged, since the GAN showed losses greater than 2, both in the generator as well as the discriminator.

In the classification, the top accuracy of validation was 0.90, which is defined in equation 3, the graph in figure 5 shows the accuracy of the training vs. the validation.

$$Accuracy = (TP + TN)/(TP + FP + TN + FN) \tag{3}$$

Where according to the classification data, TP is the true positive, TN is the true positive, FP is the false positive, and FN is the false negative.

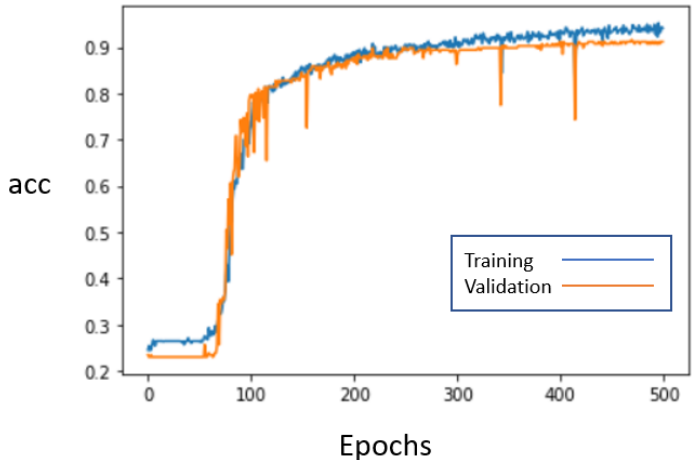

Figure 5. Accuracy graph.

For the validation, 282 images were used, the figure 6 shows the confusion matrix, where it is observed that for the left foot MI, 70 data were used, of which I correctly classified 67, for the left hand MI, 68 images were used Of which 59 data were classified correctly, 81 data were used for mathematical activity and 73 were correctly classified, and finally 63 data were classified for the state of relaxation, of which 61 images were correct.

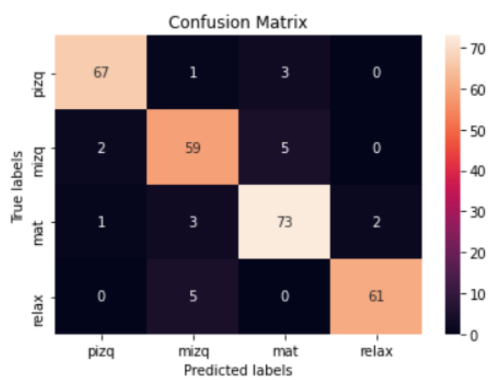

Figure 6. Confusion Matrix.

The ROC curves compare the TP against the FN, this comparison is shown through a curve for each class. For the classification to be good, the area under the curve (AUC) must approach 1. For this model we obtained that for class 0 the AUC is 0.99, for class 1 it is 0.98, for class 2 it is 0.99, and finally for class 3 is 0.99. Figure 7 shown a ROC for this model.

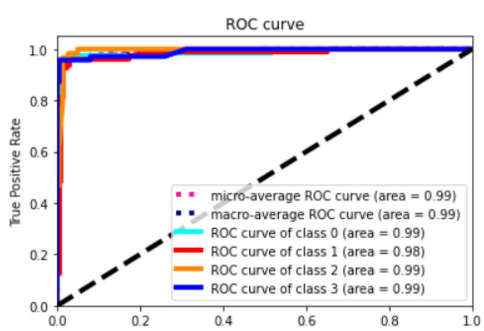

Figure 7. ROC by class

4. Conclusions

This study is part of the research focused on the development of a BCI system with application in the control of CSP, that is why for this study we generated the signals using a low-cost EEG device to generate the signals by motor imagination. The acquired signals were converted to images, subsequently, new data was generated through a GAN and finally classified.

The results obtained show that using DCGAN, synthetic data of a high range of visual similarity can be generated and that they can also be classified successfully since CNN was able to distinguish between classes with an acc of 90%.

For future studies related to the generation of artificial data, it is intended to analyze the resolution and make measurements of the distances between the real image and the image created by the GAN to have exact metrics of the similarity. In addition, we can conclude that the problem of calibration and acquisition of EEG signals for calibration of the BCI system can be solved, this will open the way for in the future to implement BCI to CSPs in industry 4.0.

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