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Processing and recognition of EMG signals through CNN networks for the control of electric vehicles

Procesamiento y reconocimientos de señales EMG mediante redes CNN para el control de vehículos eléctricos

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Abstract

The increase in autonomous driving technologies, as well as biometrics using biosignals from vehicle drivers, provide information that can be used for the development of personalized biosecurity and driving systems for each user. Currently, studies are being carried out on the extraction and classification of driver characteristics with great precision, to generate intelligent systems that are auxiliary and that help to safeguard the integrity of people while driving vehicles. This work presents the recognition of 5 hand gestures to control the driving actions of an electric vehicle using the EMG signals from the MYO™ bracelet, these signals have also been used to detect users and thus allow the use only of the people registered in the application. To perform gesture recognition, a convolutional neural network was trained and implemented for the classification of actions. Finally, a cross-validation was carried out to validate the reliability of the proposed system, obtaining 99.2% accuracy during the classification.

Convolutional Neural Networks, Biosecurity, Autonomous

Resumen

El incremento de las tecnologías de conducción autónoma, así como las biométricas mediante el uso de bioseñales provenientes de los conductores de vehículos, proporcionan información que puede ser utilizada para el desarrollo de sistemas de bioseguridad y de conducción personalizado para cada usuario. Actualmente se realizan estudios sobre la extracción y clasificación de características de conductores con gran precisión, con la finalidad de generar sistemas inteligentes que sean auxiliares y que ayuden a salvaguardar la integridad de las personas durante la conducción de vehículos. Este trabajo presenta el reconocimiento de 5 gestos realizados con la mano para el control de las acciones de conducción de un vehículo eléctrico utilizando las señales EMG procedentes del brazalete MYO™, estas señales también han sido utilizadas para detectar a los usuarios y así permitir el uso únicamente de las personas registradas en la aplicación. Para realizar el reconocimiento de los gestos, se entrenó e implemento una red neuronal convolucional para la clasificación de las acciones. Finalmente, se realizó una validación cruzada para validar la confiabilidad del sistema propuesto obteniendo un 99.2% de exactitud durante la clasificación.

Red Neuronal Convolucional, Bioseguridad, Autónomos

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1. Introduction

Gesture recognition refers to the process of interpreting and classifying the meaningful movements of a person's limbs, hands, face and head. Gesture recognition is of great importance in the field of research and technological development for the development of human-machine interfaces.

With the technological development that has taken place in recent years and the great progress in the field of artificial intelligence, there is now a wide variety of smart devices (tablets, mobile phones, bracelets, watches, gadgets, etc.) which are equipped with a large number of sensors (accelerometer, gyroscope, GPS, heart rate sensor, bioimpedance sensor, EMG sensors, etc.) thus allowing the development of human-machine interfaces [1, 2, 3, 4, 34]. The use of sensor data from these types of devices has been of great interest to researchers and developers of intelligent applications (Apps) for making inferences in different aspects of life [5]. Previously, application development had been for health monitoring, fitness tracking and security [6, 7, 8].

To perform the task of human activity recognition through the use of sensors, two main actions have to be taken into account. The first action to be taken into account is to perform the segmentation of the signal containing the activity (or gesture) to be recognised during monitoring. In the case of electrical signals as it is for our case study of the present work, is to perform a segmentation in time steps of the signal, this action can be carried out by means of a sliding window of fixed length, dividing the signal into equal segments. However, when performing a segmentation by sliding window, there is a question about the size of the window to be used and to have as a consequence a good accuracy in the task of classification or recognition of the signal in question.

The solution to this task has been proposed and carried out in different ways [9, 10, 11]. The second action that has to be performed is an extraction of the features of the segmented signal in order to perform a good signal classification or recognition task.

Carrying out the task of extracting signal features can be done by using classical techniques such as the wavelet transform [12], fast Fourier transform (FFT) [12], common spatial pattern (CSP) [13], autoregressive models [14], etc. However, the accelerated progress in the development of artificial intelligence (AI) algorithms has generated a new approach in the extraction of features from a signal based on deep learning, whose main idea focuses on the automatic learning of the features extracted from the raw data coming directly from the sensors without having performed a preprocessing to the signals [9, 15]. However, sometimes some filtering technique can be used for signal smoothing, in order to obtain the cleanest possible signal for an AI or Machine Learning system [16].

For this work, a convolutional neural network (CNN) architecture was implemented for hand gesture recognition using the MYOTM bracelet as the EMG signal acquisition system. The reason for using CNN networks is because these types of architectures perform excellent feature extraction from the data, which makes it unnecessary to perform signal pre-processing or feature extraction from the signals.

2. State of the art

Previously it has been mentioned that there are already previous works on gesture recognition through EMG signal processing using devices such as the MYO, or by means of sensors placed directly in the area where the signal is required to perform a specific task [4]. In order to perform the recognition of movements, the first step is to perform the segmentation (beginning and end) of each gesture or stroke properly, this action can be performed automatically as in [20] or by visual inspection of the signal and perform it manually [21].

EMG signals have been used for the development of vehicles for disabled people, where some series of adaptations have to be made to be operated by hands. Carrying out this task is not easy, because the person has to control all the functionalities of the vehicle with the same limb. This can increase the risk of a car accident [17].

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Driving a car provides significant forms of independence, especially for people with disabilities. Since driving can provide an easy and comfortable form of mobility, it can help prevent social isolation, making activities such as participation in work and social interactions easier [18].

There are several types of injuries, which lead to many disabilities related to disabled drivers, so there must be the generation and development of new devices that contribute to the adaptability or inclusion of people in working life, as well as to lead as independent a life as possible [19].

3. Convolutional Neural Networks

Convolutional Neural Networks (CNNs) are hierarchical architectures whose structure and development are inspired by the biological visual system [22]. The difference between a classical or standard neural network architecture (ANN) and CNNs is that in addition to using fully connected layers, they perform a series of convolution operations, where learning filters are used to slide along the input data. In general terms, a CNN architecture can be described as follows:

Convolutional Layer

For a one-dimensional system, the convolution between two vectors $x \in \mathbb{R}^n$ and $f \in \mathbb{R}^m$is a vector $c \in \mathbb{R}^{n-m+1}$, where the vector f also known as the convolution filter, which slides along the vector *x*, obtaining the scalar product at each step and whose obtained values form the output of the convolutional layer. Such that $c_i = f^T x_{i:i+m-1}$, where each element of c is calculated as the scalar product between the vector *f* and a sub-segment of *x*.

Non-linearity

To learn the non-linearity of systems, the convolutional layer is usually accompanied by a non-linear activation function applied pointwise to the output. Three activation functions are commonly used: sigmoidal, hyperbolic tangent and ReLU (Rectified Linear Unit).

Pooling layer

This layer commonly follows a convolutional layer, whose objective is to reduce the dimension of the representation obtained after convolution. There are two ways to perform this task, to obtain a maximum or an average of small rectangular blocks of the data.

Fully connected layer

After performing the process in the convolutional layers, it is necessary that the output of these layers is converted into a vector which will be used in the classification. In order for a CNN architecture to learn non-linear dependencies, one or more fully connected layers can be used to perform the classification.

Soft-Max layer

Finally, the output obtained in the last layer is passed through a Soft-Max layer that obtains the probability estimation of the classes. In general, these are the layers present in a CNN architecture, which are coupled to form a CNN network, which can be trained as a whole.

3.1 Implemented Architecture.

For the present work, the CNN architecture shown in Figure 1 has been proposed, where it can be seen that the signals come from the Myo™ bracelet, which has an Inertial Measurement Unit (IMU) equipped with an accelerometer, a gyroscope, a magnetometer and sensors for EMG signals. Once the signals are captured, they are sent to the convolutional neural network for further processing and classification. The architecture of the CNN proposed in Figure 1 is described as follows.

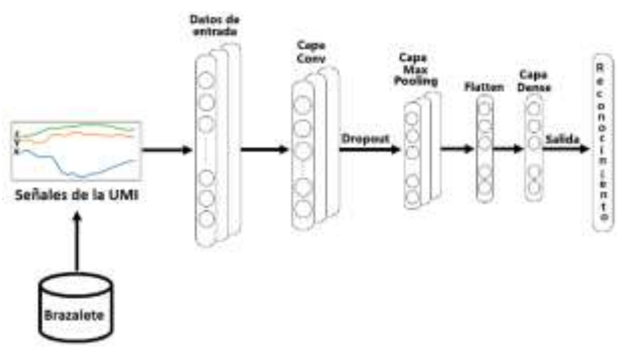

Figure 1 Proposed Convolutional Neural Network (CNN) architecture

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The architecture shown in Figure 1 consists of a convolutional layer with 16 convolutional filters of size 1×8 using a ReLU activation function for feature extraction. After the convolutional layer a *dropout* with a rate of 0.9 has been used to avoid over-learning. Finally, a fully connected layer (Dense) with *Soft-Max* activation function has been implemented to perform the classification into 12 classes. This architecture was trained for 50 epochs using the Adam optimiser and a *batch size* of 36 and a learning rate of 10^{-5}.

The architecture presented in this paper was implemented based on the works [10, 23, 24], however, the final architecture is different from the aforementioned works. The selection of the number of layers, the activation function, dropout rate, pooling type, etc., as well as other hyper-parameters were based on the studies [25, 26, 27, 35]. However, the final design of the architecture was basically obtained empirically, i.e. by trial and error until the CNN network design that obtained the best results was found.

4. Experimentation and Results

In order to test the performance of the system proposed in this work, a database large enough to have data in the training phase and in the test phase was generated. The data acquisition was performed using a commercial interface called MYO™, a portable device developed by Thalmatic Labs Inc., which is a bracelet made of an expandable material that allows it to stretch and contract, thus allowing it to adapt to the physiognomy of each user's arm. This armband is equipped with an Inertial Measurement Unit (IMU) and 8 sensors for measuring electromyogram (EMG) signals.

The IMU of the Myo™ bracelet consists of an accelerometer, a gyroscope and a magnetometer, all delivering three-dimensional signals. This device can be connected to a device (computer, tablet, mobile phone, etc.) and the sampling rate for each IMU sensor is 50Hz and 200Hz for the EMG sensors. This bracelet has been used in several research works [28, 29, 30] obtaining good results, which is why we chose to use the Myo™.

Figure 2 Gestures to recognise with the CNN network

In this work, the recognition of 5 gestures $(t_1 - t_5)$, which are shown in figure 2, was carried out to control the forward, backward, left turn, right turn and stop functions. For the experimental analysis of the signals, it is common to carry out a preprocessing of these, which allows the extraction of properties and characteristics of a group of data. Some of the most common ways is to work in frequency space, since in this way the frequency response of a system can be found, although it is also possible to work in time space [31]. Another technique widely used in the task of signal preprocessing is the filtering of these in order to obtain the characteristic frequencies of the signals [32], another common technique in signal preprocessing is to obtain the mean square error [33], the fast Fourier transform, among others.

Thanks to advances in the field of Artificial Intelligence, the signal preprocessing stage can be omitted for some systems, because Artificial Intelligence algorithms can take the raw data or without preprocessing to extract features that can help the system during the training and testing phase. For the present work we took the data delivered by the bracelet and sent it directly to a CNN architecture described above. The database is built by 50 samples for each class (gesture), however, an analysis has been performed by taking different numbers of samples to test the proposed CNN architecture and thus observe how susceptible the proposed neural network is to the number of samples.

To analyse the performance of the proposed architecture, we chose to use k-fold cross-validation, which is a widely used statistical technique to evaluate the performance of classification algorithms. To perform the cross-validation (CV), the entire data must be divided into k groups of the same size. Once the database is divided, k-1 groups are used for training the system and the remaining group is used for testing. This process is done k times using a different test group for each iteration, generating in each iteration a $Error_n$ whose average is used as the final estimate.

$$estimadoer\ VC = \frac{1}{K}\sum_{n=1}^{k}(Err_n) \qquad (1)$$

To perform the estimation in this work, a value of *k*=10 was used, which means that, from the database, 90% of the samples were taken for training and the remaining 10% for testing. This value of *k* is the most recommended since larger values may cause the variance of the estimation to increase. Plot 1 shows the averaged ROC curve for all classes. The area under the curve (AUC) is 1.0. So it can be said that the classifier (CNN) is able to separate the classes perfectly. To perform the estimation in this work, a value of *k*=10 was used, which means that, from the database, 90% of the samples were taken for training and the remaining 10% for testing.

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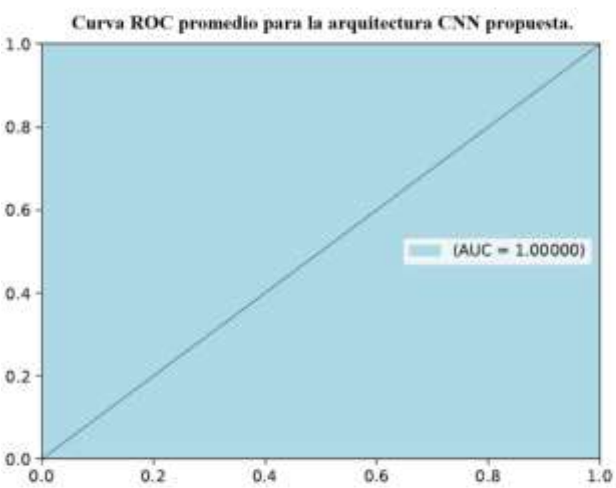
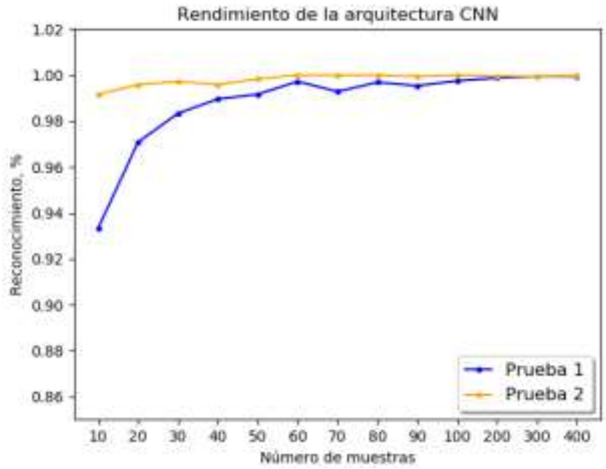


Graph 1 Average ROC curve



Graph 2 Recognition results obtained for different numbers of samples in different tests

The results obtained from the recognition analysis are presented in graph 2, where the performance of the CNN architecture proposed for the classification of the 5 gestures from EMG signals can be observed. From this analysis it can be seen that a good classification of the classes with few samples is achieved by using Convolutional Neural Networks. The results shown refer to the average of the cross-validation for the different numbers of samples used in each test.

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7. Conclusions

This work has proposed a method for performing gesture recognition for the control of actions during the driving of a vehicle based on electromyography (EMG) signals. The results obtained have shown that with the use of artificial intelligence algorithms it is possible to obtain highly accurate gesture recognition. The proposed CNN architecture proved to have sufficient capacity to recognise without problems the 5 gestures of the EMG signals captured from the 8 sensors placed on a person's arm.

Another observation to be taken into account is that it is not necessary to use many samples per class to obtain a good classification rate.

At the moment, the study shows promising results for the recognition of gestures capable of controlling some actions during the driving of electric vehicles, however, there is uncertainty as to whether it is possible to implement more control actions for electric vehicles that show similar results, so research on this topic will continue as future work, as well as the implementation and design of vehicles controlled by EMG signals for people with motor disabilities and for biosafety systems.

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