Journal of Physics: Conference Series

PAPER • **OPEN ACCESS**

Feature extraction and classification of epileptic seizures from combined EEG and ECG signals

To cite this article: Lahcen Zougagh *et al* 2023 *J. Phys.: Conf. Ser.* **2550** 012028

Feature extraction and classification of epileptic seizures from combined EEG and ECG signals

ZOUGAGH Lahcen*, BOUYGHF Hamid, NAHID Mohammed and OUACHA Brahim

SIB Laboratory Faculty of Sciences and Techniques Mohammedia, University Hassan II of Casablanca, Morocco.

Email: *lahcen.zougagh-etu@etu.univh2c.ma

Abstract. Research has been conducted to support an automatic diagnosis system that will relieve clinicians of their weary work by detecting epileptic seizures. In this paper, we suggest a novel method to automatically identify epilepsy crises based on electroencephalogram (EEG) and electrocardiogram (ECG) signals. The work to detect epileptic seizures from EEG and ECG signals is carried out in three stages. In the first stage, simultaneous EEG and ECG recordings captured from 24 channels are segmented into 10-second periods (where 23 are the EEG signals and one is the ECG signal). In the second stage, the extraction of the parameters of each channel from the time domain and, finally, the classification of the EEG and ECG signals into epileptic seizure and normal have been done using ANN. Experiment analysis shows that using the ECG signal as extra information has a high capacity for classification.

Keywords: Epilepsy, seizure detection algorithm, EEG, ECG, artificial neural network

1. Introduction

The brain is one of the most complex organs in the human body. It controls all the functions of the body. It also manages consciousness, intelligence, emotion, and memory [1]. The human brain contains billions of nerve cells called neurons that communicate with each other by sending and receiving messages. Many neurological diseases affect the brain. The most well-known of these diseases is epilepsy [2]. Epileptic seizures have been studied by many researchers. All of them aim to stop the progression of epileptic seizures.

The electroencephalogram (EEG) is a unique and valuable measure of the electrical function of the brain, obtained through electrodes placed on the skull [3]. The EEG signal represents the difference in electrical potential between two different sites on the head, covering the cerebral cortex [4]. In this paper, we present a technique for detecting epileptic seizures based on artificial intelligence. The aim of this technique, on the one hand, is to validate the idea of information provided by the two systems, cardiac and cerebral, for a more efficient detection, and at this level, we will be able to confirm the presence of the influence of the seizures on the cardiac activity. On the other hand, this technique allows the design of an automatic detection module based on different binary classification models existing in the literature.

The task of classification occurs in a wide range of human activities. The study of the models developed in this context allows for a better understanding of the general functioning of classification algorithms. We will present in detail conventional two-class classification models, showing their efficiency for our

purpose.
The classifier chosen in this study is the artificial neural network (ANN). This classifier enables the creation of binary classification algorithms with the goal of assigning class labels. according to two predefined categories (the epileptic or non-epileptic class). It should be noted that the use of the classification approach requires a characterization of the medical data, which is performed by extracting parameters from the electrophysiological signals (EEG and ECG). In this context and because of the influence of the seizure on the morphology of the electrophysiological signals, several temporal and frequency components forming the signal will be significantly changed during the seizure. We based this study's objective on the exploitation of relevant parameters deduced from the temporal domain only, which are a set of characteristics and statistical factors.

2. Related work

Recently, many automated methods of seizure detection and classification have been found, such as multi-fractal relaxed fluctuation analysis (MFDFA), which is used to observe different changes in the different lobes of the brain [5]. Another algorithm is based on the mean absolute deviation (MAD) using the lower vector dimension with a linear classifier for automatic detection of seizures using EEG signals [6]. Another different algorithm uses an adaptive combination of parameters, including autoregressive parameters, for the classification of epileptic EEG signals [7]. also uses odd-pair autoregressive coefficients (Yule-Walker and Burg) for feature extraction from electroencephalogram (EEG) signals [8]. Another proposed detection algorithm based on EEG signals using PCA with ANN model [9]. There have been other different approaches to EEG signal analysis for seizure detection. The brain controls all body functions, which means that any dysfunction in the brain can affect other organs. Among these organs, we can mention the heart. Indeed, during epileptic seizures, the changes in cardiac functions involve the activation of the central autonomic network. The study of electrocardiographic (ECG) signals can also provide valuable information about electrical discharges during seizures. Several studies have indicated that seizures are often associated with alterations in the cardiovascular and respiratory systems [10]. Specifically, heart rate-related measures (mean heart rate, heart rate variability, and acceleration). In addition to heart rate-based features, significant changes in the characteristics and morphology of the ECG signal can be directly related to a possible seizure. There are studies that allow the detection of these seizures and that rely essentially on the combination of EEG and ECG signals to make the diagnosis of epileptic seizures more efficient. As an example, the detection of epileptic seizures using EEG and ECG signals for computerized monitoring, analysis, and management of epilepsy patients with an impressive rate [11].

3. MATERIALS AND METHODS

3.1. Database description

There is a large body of work in the literature on seizure detection based on EEG signals alone. Recently, we can find databases enriched by new physiological signals recorded simultaneously, and this is the case for our study. We used a database containing recordings of EEG and ECG signals to exploit in a more quantitative way the information concerning the seizures. This study was performed on the CHB-MIT scalp EEG database, freely available on Physionet. This database was collected at the Children's Hospital in the city of Boston. It consists of recordings of EEG and ECG signals from pediatric subjects with epileptic seizures. Subjects were followed for several days after discontinuation of antiepileptic therapy to characterize their seizures and to assess their candidacy for surgery. Simultaneous EEG and ECG recording was performed for a single subject. Four recordings are used in the test. Each recording contains about 3 hours of digitized EEG signals recorded simultaneously with the ECG signal (1 channel for the ECG signal and 23 channels for the EEG signal). These recordings contain three epileptic seizures. All signals were sampled at a sampling rate of 256 Hz (256 samples per second) with a resolution of 16 bits. The international 10-20 system for electrode nomenclature was used for these recordings [12].

Journal of Physics: Conference Series **2550** (2023) 012028 doi:10.1088/1742-6596/2550/1/012028

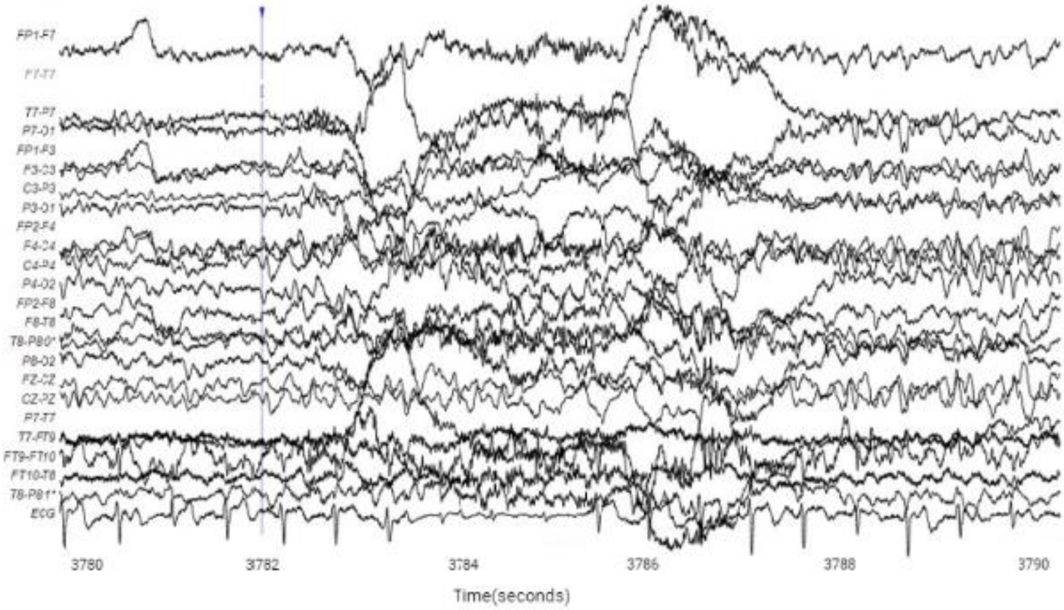

Figure 1. Example of a multi-channel electrographic seizure. Seizure begins at 3782 seconds.

3.2. *Proposed method*

Based on the standard 10-20 international system, the 23-channel electrodes were placed on the scalp of the epileptic patients, and the recordings were measured for 24 h.

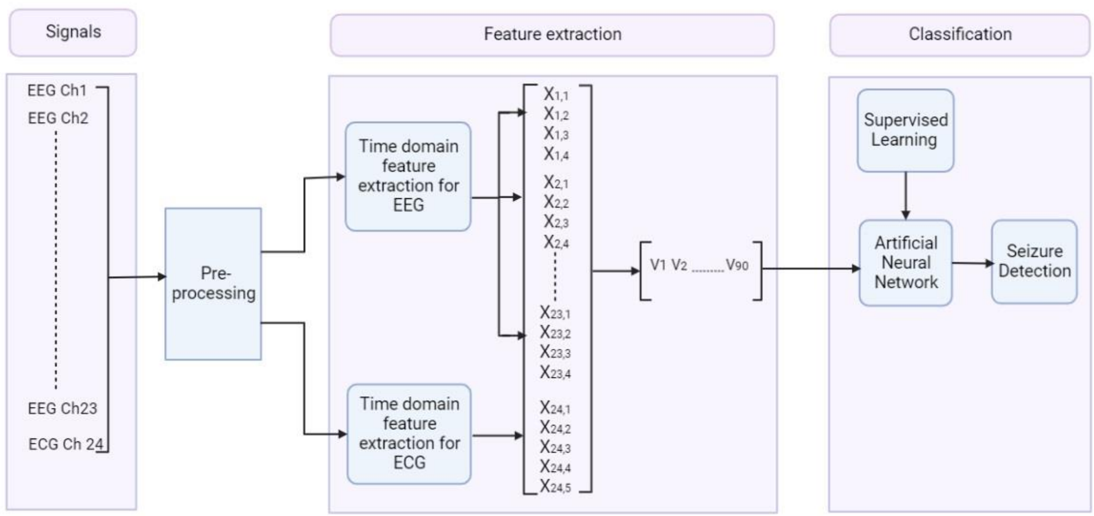

Figure 2. block diagram of our crisis detector using a supervised classification algorithm.

The algorithm consists of selecting 10-second periods randomly chosen in each of the 23 bipolar channels of the EEG signal. Four parameters belonging to the time domain were extracted from each segment and concatenated into a single large vector. Finally, the vector of parameters is then assigned as a normal segment (absence of seizure) or pathological segment (presence of seizure) using a type of classifier, artificial neural networks (ANN). Moreover, for a better classification, we plan to change each time the parameters forming the architecture of the classifier: on the one hand, the activation functions, the optimization functions, and the number of hidden layers in the neural network.

To further improve the performance of seizure detection, we proposed to include the ECG signal as additional information in the detection process.

In addition to the four parameters extracted from the ECG signal, such as the EEG signal, the rhythmic activity (heart rate) is calculated for each segment and is considered another parameter added to our vector. So we have for each segment ((4 * 23) +5), which equals 97 parameters.
As we mentioned before, we used a database tagged by experts, so all records contain annotations by experts; two records contain records of epileptic seizures. Our test was evaluated on 90 selected segments, each containing 10 seconds. The seizure event is represented by 30 segments between them, while the remaining 60 segments are considered normal activity without a seizure.

3.3. Parameter Extraction

In this study, the parameter array is used for the classification process. These parameters concern a single channel for the EEG signal and a single channel for the ECG signal. It remains to derive the same parameters for the 22 remaining channels of the EEG signal.
The measured energies for each segment (respectively noted $EECG10$ and $EEEG10$) are given by:

$$E_{ECG10}(n) = \sum_{K=1}^{L} |ECG(K)|^2 \tag{1}$$

$$E_{EEG10}(i,n) = \sum_{K=1}^{L} |EEG(i,K)|^2 \tag{2}$$

L is the length of the record (10*256 = 2560 samples).
$i = 1 \ldots M$ where M=23 is the number of channels of the EEG signal.
$\sigma ECG10$ and $\sigma EEG10$ are the standard deviation of the ECG signal and EEG signal, respectively, which are calculated as follows:

$$\sigma_{\text{ECG10}}(n) = \left(\frac{1}{L} \sum_{K=1}^{L} (ECG(K) - \overline{ECG(n)})^2 \right)^{\frac{1}{2}} \tag{3}$$

$$\sigma_{\text{EEG10}}(i,n) = \left(\frac{1}{L} \sum_{K=1}^{L} (EEG(i,K) - \overline{ECG(i)})^2 \right)^{\frac{1}{2}} \tag{4}$$

$\overline{ECG}$ and $\overline{ECG}$ Represent the mean values.
Concatenating the vectors X1 through X4, gives us a vector Xi,

$$[Xi] = [X1\ X2\ X3\ X4] \tag{5}$$

so for the 23 channels corresponds to the EEG signal we have a vector Z of size equal to $23 * 4 = 92$, or

$$[Z] = [X1\ X2\ \ldots\ \ldots\ \ldots\ X23] \tag{6}$$

we then need to add the parameters associated with the ECG signal in order to realize the global parameters vector for each segment and finally we can use as input to our classifier:

$$[Y] = [Z\ X5\ X6\ X7\ X8\ X9] \tag{7}$$

3.4. Classification

3.4.1. Learning stage

Many neural network topologies are tested for the ANN architecture, and different activation functions are used to adapt the neural networks to the different numbers of neurons in the hidden layer. In the structures labeled MLP, the parameters are extracted from the EEG signal, while in the MLPE structure, the parameters are deduced from both the EEG and ECG signals. In the first step, we used a single

structure for the activation functions: the hyperbolic tangent function for the hidden layers and the normalized exponential function for the output layer. By varying the number of hidden layers and the network optimization functions, three types of optimization functions were selected with three different values for the number of hidden layers.
The number of hidden layers of the neural network and its optimization function are now fixed in the second step. By modifying the activation functions for the hidden layers and the layers as well as the output layers, we have chosen three types of activation functions: the hyperbolic tangent function, the sigmoid or logistic function, and the normalized exponential function. Eight different structures were applied to our study.

3.4.2. Testing phase

Once the neural network is trained, it is necessary to test it on a different database than the one used during training. As mentioned above, 900 seconds of ECG and EEG data are divided into 10-second segments, giving a total of 90 segments. 24 are used for the learning phase (1/3 of the total recordings), and 56 are used for the testing and classification phase (2/3 of the total recordings). Both algorithms were tested on 24 signals, 23 of which were EEG signals and 1 ECG signal, where nine signals contained seizure symptoms and the other 14 signals corresponded to normal activity.
The goal of our research is to obtain the highest percentage of classifications that will help us distinguish between seizure and non-seizure classes with high accuracy. We will also discuss how the information extracted from the ECG signal is incorporated into the classifiers to make a better distinction between the two classes.
Three statistical indicators are used to evaluate the performance of the different classification systems: accuracy (Acc), sensitivity (Se), and specificity (Sp), are normally calculated by:

$$Se = \frac{TP}{TP+FN} \tag{8}$$

$$Sp = \frac{TN}{TN+FP} \tag{9}$$

and Accuracy is defined as follows:

$$Acc = \frac{TN+TP}{TN+TP+FP+FN} \tag{10}$$

TP: true positive is the number of truly positive seizures recognized on a daily basis.
TN: true negative is the number of recognized truly negative seizures.
FP: false positive is the number of recognized false positive seizures.
FN: is the number of seizures detected as false-negative.
The classification matrix, or confusion matrix, is a very important standard tool for classifier evaluation. It determines whether the predicted value corresponds to the actual value. Then each category is counted, and the totals are displayed.

		Actual	
		Positive	Negative
Predicted	Positive	TP	FP
	Negative	FN	TN

Figure 3. classification matrix

4. Results

4.1. Obtained results

In this study, a supervised learning neural network was used. This type of network is primarily based on calculating the error of the hidden neurons' outputs. The backpropagation algorithm is the most commonly used algorithm to solve the error problem. This algorithm's applications have been spectacularly successful, and its performance has occasionally surprised. The backpropagation method uses the following technique: It provides an input model to the network; its output is compared to the desired output; and a distance or error between them is calculated. The network provides input models, compares output with desired output, and calculates the distance between them and the errors.
The performance of the proposed multilayer structures (MLP) in this study concerns the classification by using EEG signals alone, as shown in the table 1. The table illustrates the performance of classifiers with specific MLPE structures for classification based on the fusion of parameters drawn from the two electrophysiological activities.

Table 1: Performance of classifier using EEG signal with MLP structure.

Results	Accuracy	Sensitivity	Specificity
SC-MLP	85.9(%)	62.1(%)	100(%)
CG-MLP	87.7(%)	66.9(%)	97.3(%)

Table 2: Performance of classifier using EEG and ECG signals with MLP structure.

Results	Accuracy	Sensitivity	Specificity
SC-MLPE	91.3(%)	76.5(%)	91.1(%)
CG-MLPE	98.4(%)	95.4(%)	100(%)

The results obtained showed that when we used the EEG parameters as a parametric vector, the classifier named CG-MLP3 (3 hidden layers, conjugate gradient) produced the best performance with a seizure detection rate of 87.7% and with a sensitivity and specificity of 66.9% and 100%, respectively. While when the parametric vector is combined and assembled from both EEG and ECG signals, the classifier named CG-MLPE3 (3 hidden layers, conjugated gradient) produces the best detection performance with a classification rate of 98.4% and a sensitivity and specificity of 95.4% and 100%, respectively. Generally speaking, for both MLP and MLPE structures, we can conclude that the structures with three hidden layers provide better performance. In terms of learning algorithms, the structures with conjugate gradient (CG) always produce the highest classification rate, followed in second place by the structures with gradient backpropagation (SC). This can be translated by saying that the ECG signal has obviously contributed to the detection of the seizure using artificial neural networks (ANN).

5. conclusion

A novel method of epileptic seizure detection based on EEG and ECG signals was suggested, with characterization through temporal parameters extracted from EEG and ECG signals. This characterization allowed us to demonstrate the importance of the incorporation of complementary information deduced from the ECG for the recognition of epileptic seizures through artificial neural network algorithms (ANN). We have also tested several structures of artificial neural networks by changing the parameters constituting the neural networks, and that allowed us to achieve a good performance in crisis detection.

6. References

[1] Wang, Y., Li, Z., Feng, L., Bai, H. and Wang, C., 2018. Hardware design of multiclass SVM classification for epilepsy and epileptic seizure detection. *IET Circuits, Devices & Systems*, *12*(1), pp.108-115.

[2] Mormann, F., Andrzejak, R.G., Elger, C.E. and Lehnertz, K., 2007. Seizure prediction: the long and winding road. *Brain*, *130*(2), pp.314-333.

[3] Oikonomou, V.P., Tzallas, A.T. and Fotiadis, D.I., 2007. A Kalman filter based methodology for EEG spike enhancement. *Computer methods and programs in biomedicine*, *85*(2), pp.101-108.

[4] Mohseni, H.R., Maghsoudi, A. and Shamsollahi, M.B., 2006, August. Seizure detection in EEG signals: A comparison of different approaches. In *2006 International conference of the IEEE engineering in medicine and biology society* (pp. 6724-6727). IEEE.

[5] Rakshit, A., Banerjee, A., Mazumder, A., Ghosh, P., Dey, A. and Tibarewala, D.N., 2017. Fractal analysis of EEG signals for studying the effect of cognitive stress on brain. *International Journal of Biomedical Engineering and Technology*, *25*(2-4), pp.336-369.

[6] Chandel, G., Shanir, P.M., Farooq, O. and Khan, Y.U., 2017. A simplified method for classification of epileptic EEG signals. *International Journal of Biomedical Engineering and Technology*, *25*(1), pp.60-76.

[7] Nassim, B., 2016. Adaptive combination methods of autoregressive parameters for epileptic EEG signals classification. *International Journal of Biomedical Engineering and Technology*, *22*(1), pp.47-57.

[8] Nassim, B., 2016. Combined odd pair autoregressive coefficients for epileptic EEG signals classification by radial basis function neural network. *International Journal of Biomedical Engineering and Technology*, *22*(4), pp.314-324.

[9] Shankar, R.S., Raminaidu, C.H., Raju, V.S. and Rajanikanth, J., 2021, November. Detection of Epilepsy based on EEG Signals using PCA with ANN Model. In *Journal of Physics: Conference Series* (Vol. 2070, No. 1, p. 012145). IOP Publishing.

[10] Nasehi, S. and Pourghassem, H., 2012. Seizure detection algorithms based on analysis of EEG and ECG signals: a survey. *Neurophysiology*, *44*(2), pp.174-186.

[11] Mporas, I., Tsirka, V., Zacharaki, E.I., Koutroumanidis, M., Richardson, M. and Megalooikonomou, V., 2015. Seizure detection using EEG and ECG signals for computer-based monitoring, analysis and management of epileptic patients. *Expert systems with applications*, *42*(6), pp.3227-3233.

[12] Goldberger, A.L., Amaral, L.A., Glass, L., Hausdorff, J.M., Ivanov, P.C., Mark, R.G., Mietus, J.E., Moody, G.B., Peng, C.K. and Stanley, H.E., 2000. PhysioBank, PhysioToolkit, and PhysioNet: components of a new research resource for complex physiologic signals. *circulation*, *101*(23), pp.e215-e220.