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A Deep Learning-Based Approach for the Recognition of Sleep Disorders in Patients with Cognitive Diseases: A Case Study

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***Abstract*—Alzheimer's disease is the most common type of dementia. Patients suffer from of this kind of disease could show symptoms such as sleep disturbances, muscle rigidity or other typical Alzheimer's movement irregularities. In our work, we have focused on those types of disturbances related to sleep disorders. Due to their not well-known nature, it is difficult to develop software able to identify sleep disorders. In this work, we have addressed the problem of the automatic recognition of sleep disorders in patients with Alzheimer's disease by using deep learning algorithms.**

***Index Terms*—Deep Learning, Convolutional Neural Network, Deep Neural Network, Human Behaviors Recognition**

I. Introduction

THE aging of the world population during the last few decades has been highlighting problems related to the increase in the incidence of cognitive diseases such as dementia and consequent issues about how to assist those patients who suffer from them.

Alzheimer's disease (AD) is the most common type of dementia. Patients with AD could show symptoms such as sleep disturbance, well-formed visual hallucinations, muscle rigidity or other typical Alzheimer's movement irregularities.

In this work, we have focused on those types of disturbances related to sleep disorders (SD).

The strong correlation between sleep disorders and Alzheimer disease has been highlighted in a lot of works in which showing that changes in sleep patterns may predict Alzheimer disease [1], [2].

The study of sleeping disorders, in particular, the ones related to movements such as agitation and restless sleep, take on an important role for an early prediction and prevention of AD and more in general of cognitive diseases.

The etiology of these kinds of disorders is unknown[3], for this reason, ICT technologies should provide solutions able to accurately recognize these kinds of disorders.

In order to recognize anomalous behaviors it is basic to monitor patients during their lifetime, we have been already facing the challenge of monitoring patients with cognitive diseases by proposing methodologies and approaches for the design of systems aimed to achieve this task [4], [5].

In this work, we have addressed the problem of the recognition of a sleep agitation disorders in patients with Alzheimer's disease.

The purpose of our study is to identify two sleep states: { *Normal Sleep* (N), *Anomalous Sleep* (A) }.

A normal sleep is a state in which a patient sleeps calm, an anomalous sleep is a state in which there are anomalous movements characterized by a strong agitation.

The main issues related to the recognition of such kinds of disorders is their unknown and unpredictable nature; in other words, there are not well-known patterns which describe how these disorders arise, for this reason, the development of system able to automatically recognize them it is quite hard.

We have faced the problem of identification of sleep disorders in [6] by means of threshold-based approach. The main limitation was the identification of the best values of the threshold to avoid a high false positive rate (FP) and guarantee a good level of accuracy of the identification of the disorders. This issue was due to the strong dependency between the threshold and the patient's movements that made the approach complex to tune and patient-dependent.

In order to overcome the problem of high FP and develop a patient-independent solution, we have defined a deep learning based approach for both the classification of sleep disorders and identification of sleep states.

In order to provide an initial level of validation of our solution, we have monitored one pilot patient with Alzheimer's disease and recorded both its movements and stress level.

We have created a preliminary dataset by monitoring an amount of seven nights.

The aim of our work is to classify the anomalous sleep states of the patient during the night by analyzing both the movements and EDA signals.

We have extracted two biometric signals: the movements and the stress level of the patient. Both signals have been acquired by means of a sensor placed on his right leg, the *E4 wristband* sensor [7].

The movements are described by means of the 3-axes acceleration values and the stress level is described by the electrodermal activity (EDA).

We have used these signals as input for two kinds of deep learning (DL) algorithms: deep neural network (DNN) [8] and conventional neural network (CNN) [8].

In this paper, we present the results of the application of those algorithms for the classification of the sleep states of the patient in order to automatically recognize the anomalous ones.

In our first experiment, the results have demonstrated that our

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Fig. 1. Polysomnography [1]

solution is able to recognize and classify the patients' status both with DNN and CNN.
The results show a better performance of the CCN with an overall accuracy ranges from 80 % to 89% against the accuracy of DNN ranges from 50% to 80%.

II. Related Work

Today the gold standard, for the treating of sleep disorders is the polysomnography, a type of sleep study, which involves the acquisition of data from a multi-parametric test used in the study of sleep and as a diagnostic tool in sleep medicine.

Although the polysomnography is the main treatment for sleep studies, it has a few drawbacks: *(i)* the procedure is quite disturbing due to the huge amount of wearing sensors (e.g. Fig 1) *(ii)* it must be performed in hospital environment only *(iii)* it has been performed when the subject is already aware that he/she may be suffer from the disease.
Our solution has been designed to overcome the first two points.
Our approach uses only one multi-parameters sensor which can be used at home without clinical support.
Other out-of-hospital solutions focus their effort on the study of Electroencephalography (EEG) in order to detect anomalies during the sleep with results obtained through the use of uncomfortable devices.
Poree et al [9] proposed a sleep recording system to perform the monitoring of sleeping disorders; the solution adopts five electrodes: two temporal, two frontal and one reference.
In [10] authors proposed a video-polysomnography method to determine sleep disorders. At first, they used an infrared night-vision video webcam for recording a polysomnographic video during sleep period at night and using a motion detection algorithm over the captured images.
Although the approaches widely used are based on EEG/EMG signals, other kinds of parameters have been adopted. An example is provided by Flores et al [11]. In their work, the authors used a motion sensor to catch significant body movements. During waking time, respiratory movements are masked by other motor activities. An automatic pattern recognition system has been developed to identify periods of sleep and waking using a piezoelectric generated signal.
Prashanth et al [12] adopted an olfactory loss and REM features to develop support vector machine-based prediction models using data from the Parkinson's Progression Marker's Initiative (PPMI) database.
Alves de Mesquita et al [13] present a monitoring system to recognize sleep breathing disorders by means of nasal pressure recording technique.
Occhiuzzi et al [14] investigate the feasibility of using a passive RF identification technology for the wireless monitoring of human body movements in some common sleep disorders by means of passive tags equipped with inertial switches.
Park et al [15] proposed an accelerometer-based solution for the classification of the state of healthy users to "sleep" or "wakefulness". The authors face the problem of miss-classification rate by employing a dynamic classifier which analyzes similarity between the neighboring data scores obtained from support vector machine classifier.

III. Approach

In this section we describe the approach that we have adopted for the classification of the sleep stages. We have set two kinds of experiments: one by using CNN and another one by using DNN.
The aim of this work is to evaluate how well deep learning algorithms, such as CNN and DNN, work for the classification of sleep states by taking in input biomedical signals like movements and EDA.
In Figure 2 we have highlighted (green line) an example of anomaly period that we have identified in our previous work [6].
We define *anomaly* that period because by comparing how the patient has moved in with the other periods, it is clear that its movements were strangely stronger.
In [6] we detected such as periods by a thresholds-based approach that evaluated the *intensity* of the patient's movement. The anomalous behaviors of the movements signal are clear and well-characterized, unlike the EDA.
The input of our process is a couple of biomedical signals: the movements of the patients and the stress level.
The first one is described by means of XYZ acceleration measure, the second one by means of electrodermal activity (EDA). Both signals have acquired by the same sensor, *E4 wristband*.
The E4 Wristband is a Bluetooth sensor for the acquisition of biomedical data of patients such as body temperature and stress level and movements.
For the purpose of this paper, we focus only on acceleration signals (x,y,z) and the stress level (EDA). The data have been acquired with a sample rate of 32 Hz(f0). The dynamic of the amplitude of the acceleration was [-2G,2G].
The first step was to collect the data, in order to do that we have placed the E4 sensor on the patient's leg who has been monitored for one week each night for an amount of 7 nights. The data has been acquired as log files for each night then we have merged all logs to create our dataset.
The size of the dataset is around 320 MG. It counts of about 6 Millions of points in the format of $\{$*timestamp, x, z, y, EDA*$\}$.

[1]Robert Lawton - Own work

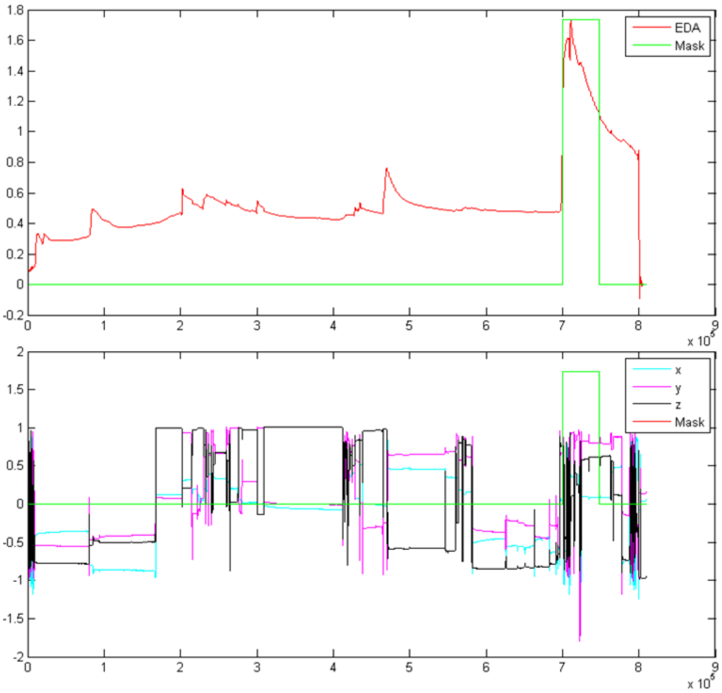

Fig. 2. (a) EDA Signals - (b) Acceleration Signals

Row ID	D Diff	D SD	D Mean	S Class
Row297	0.001	-0.003	0	norm
Row298	0.002	-0	0.001	norm
Row299	0	-0.001	0.001	norm
Row300	0	-0.001	0.001	norm
Row301	0.002	0.001	0.001	norm
Row302	0	0.001	0	norm
Row303	0	0.001	0	norm
Row304	0	0.002	0.001	norm
Row305	0.001	0.001	0.001	norm
Row306	0	0.001	0.001	norm
Row307	0.001	0.001	0.002	norm
Row308	0.005	-0.004	0.005	norm
Row309	0.001	-0.002	0.004	anorm
Row310	0.002	0	0.007	anorm
Row311	0.031	0.031	0.059	anorm
Row312	0.031	0.031	0.002	anorm

Fig. 3. Training Data-Set of the Deep Neural Network

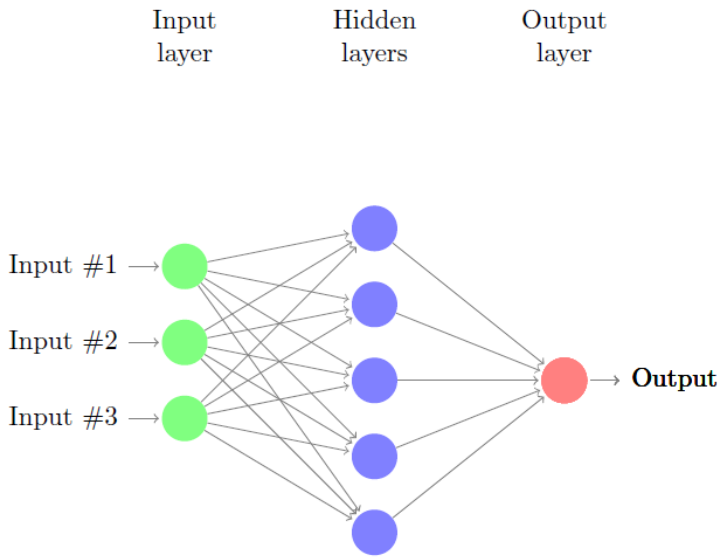

Fig. 4. Generic Structure of a Neural Network

From the whole dataset, we have extracted 80% for the definition of the training set and the 20% for the testing set. The TD has been used to train both the deep neural network (DNN) [8] and conventional neural network (CNN) [8].

A. Deep Neural Network

The first step is to define a suitable training dataset (TD) from the training set for the DNN.
In our scenario the TD is composed of a set of vector of features f_i extracted from a temporal windows w_i, with $i = 1...N$.
We define a *temporal windows* (w_i) as a piece of the raw signals with a duration time of 10 seconds.
The selected features are: the *mean*, *standard deviation* and the difference $|mean(w_i) - mean(w_{i-1})|$.
For each features we have assigned the correct class: { *Normal Sleep* (N), *Anomalous Sleep* (A) }.
In order to do that, we have reused the results obtained from our previous works [6] in which we have recognized the sleep states of the temporal windows by means of threshold-based approach.
Figure 3 shows a piece of the training dataset that we have created. Each line is a vector of futures f_i.
The second step is the building of the DNN. Figure 4 shows a generic structure of a neural network.
Basically, a generic neural network is formed in three layers, called the input layer, hidden layer, and output layer. Each layer consists of one or more nodes, represented in this diagram by the small circle.
The nodes of the input layer receive a single value on their input and duplicate the value to their output.
The hidden layers are in charge to get the data and analyzed them and provide results to the next layer.
The output layers show the results of the learning process(e.g. a prediction/classification).
In our paper, the numbers of the nodes of the output layers are two ({ *Normal Sleep* (N), *Anomalous Sleep* (A) }).
The size of the input layer is equal to the size of the features vectors.
The number of the units of each hidden layer and the number of the hidden layers are two hyperparameters that we have considered for the tuning of the DNN.
In order to find the best hyper-parameters setting, we have performed a set of experiments changing the values of the hyper-parameters.
We have tested the number of hidden layer in a range from 2 to 4 layers.
In the same way, we have evaluated the number of the units

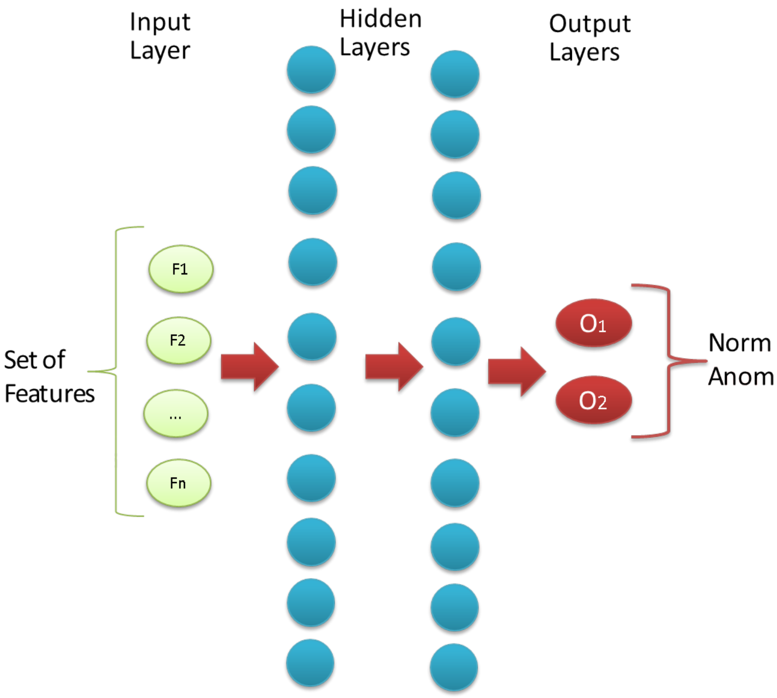

Fig. 5. Structure of the selected Deep Neural Network

for each layer in a range from 5 to 20 units.
The configuration that given the best performance in terms of accuracy was with 2 hidden layers with 10 units for each layer, Figure 5.
Other configurations with a higher numbers of both layers and units have produced the same results of the selected one.

B. Convolution Neural Network

A CNN structure is formed on tree basic type of layers: convolutional layers (CL), polling (P) and fully-connected (FC) layers.
The convolutional layers are in charge to perform the features extraction stage. Each input of the unit in this layer is connected to a local receptive file of the previous one.
The pooling layers perform the features reducing from the results of the previous CL.
The fully-connected layer Finally takes all output/neurons in the previous layer and connects it to every single neuron it has as in a classic neural network, an overall view of the generic structure of a CNN is shown in figure 6.
In our experiment we have adopted as pooling function the max-pool, in other words, for each temporal windows, the network considers only the point with max values from the output of the CL.
The hyper-parameters take in account for our experiments are:

- Learning rate
- Number of Convolutional Layers
- Number of the units of Convolutional Layers
- Number of the Fully-connected Layers
- Dropout

The *Learning rate* is a training parameter that controls the size of the steps of the changes during the learning process of the training algorithm (e.g Stochastic Gradient Descent) [16] .
The *Dropout* is a regularization technique for reducing over-fitting in neural networks by preventing complex co-adaptations on training data [17].

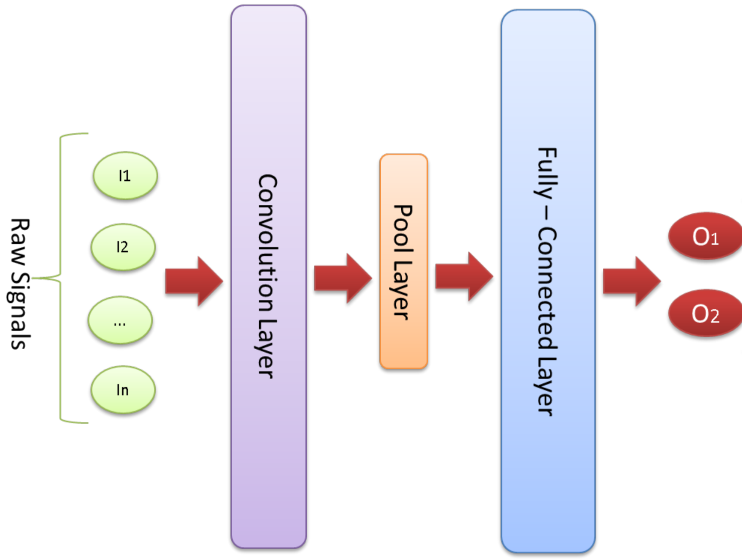

Fig. 6. Generic Structure of a Convolutional Neural Network

In order to find the best configuration for the hyper-parameters of the CNN, we have performed a set of experiments by combining them and changing their values.
The range of the values was:

- Learning rate $\in \{0.01, 0.001, 0.0001\}$
- Number of Convolutional Layers $\in \{1, 2, 3\}$
- Number of the units of Convolutional Layers $\in \{1, 2, 3\}$
- Number of the Fully-connected Layers $\in \{1, 2, 3\}$
- Dropout $\{YES, NO\}$

The *deeper* configuration of out network reach a number of levels composed of 3 level of CL, 3 levels of FC and 1 level of dropout, for an amount of 7 levels.
For that configuration, we have reached a learning time around of 24 hours.
It is important to highlight a different between DNN and CNN about how they have been trained.
In CNN experiments we have not used the TD defined for the DNN, instead, we have used the raw data of the training set for the training of the CNN.
The reason of that is because we want to use one of the most important properties of the CNN, the capability of finding local connections between data [18].
For this reason, the input size of the CNN is equal to the temporal windows *ws* of the training set, the length of the the *ws* is 10 seconds with a sampling rate of 32 Hz(f0) so the number of input of the first convolution level (CL) is to 320 inputs.
The number of output of each CL is set by dividing its number of input by 2.
We have applied the same procedure for the setting the number of output of the FC layers with a number of input of the first

TD	Accuracy DNN	Accuracy CNN
XYZ	89%	84%
EDA	50%	80%
XYZ + EDA	18%	84%

Fig. 7. Accuracy Performance

layer set to 1028 neurons.
After the training of the networks, we have used the test set for the evaluation of the performance of the two algorithms. For the DNN we have created a set of vector features from a temporal window extracted from the test set, for the CNN the have used directly the data of the test set.

IV. Results

We report the results of the experiments in the Figure 7.
We have defined three kinds of training data (TD_i) from the raw data, each one has been created by the biomedical signals acquired.
That motivated in order to evaluate the response of the algorithm to a different type of signals, XYZ, EDA, and XYZ+EDA. In details:

1) TD1: Only signals related to the patient's movements (XYZ)
2) TD2: Only signal related to the patient's Stress level (EDA)
3) TD3: All signals (XYZ + EDA)

We have submitted each type of training data to both CNN and DNN.
As we can see from the results, Figure 7, we have reached a discrete accuracy for XYZ signal with both kinds of the algorithm.
This result shows that both networks are able to recognize an anomalous sleep of stage by analyzing the patient's movements and taking into account only one sensor.
About the EDA signal, the results are very different, the CNN has reached an accuracy at 80% despite the 50% of DNN. A possible motivation of that should be that the EDA signal is not well-characterized unlike the movements so an approach based on features extraction should not be described well this kind of signal for the purpose of our work.
The CNN look like able to find some hidden correlations among the raw data that allow it to both learn better the structure of EDA signal and reach a higher accuracy.
In the last experiments, we have combined both the EDA and the XYZ signals.
The result of the DNN is quite low, 18%, despite the CNN that show a good accuracy, 80%.
The motivation behind this different results is still under investigation.

V. Conclusion

In this paper, we have evaluated a fist trial of experiments for the application of Deep Learning for the classification of sleep disorders in a patient with Alzheimer's Disease. We have evaluated two type of algorithm: Deep Neural Network and Convolution Neural Network.
We have monitored one patient for one week and we have created a data set for both training and testing process.
The preliminary results look like shown that CNN performs a better evaluation for the classification of sleep anomaly stages by using both XYZ signal and EDA. As future, we have several issues to face such as:

- increasing the number of the monitored patient
- evaluating another training dataset by changing type of features
- evaluating the application of the recurrent neural network.
- deploying more sensors both on the patient and into the monitoring environment
- evaluating the reliability and dependability of the sensors by using approach as [19], [20].

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