Classification of Electroencephalogram Signals Using Artificial Neural Networks

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***Abstract* - The study of Artificial Neural Networks (ANN) has been fascinating over the years and its development has strongly grown in recent years. The neural networks methods have become to be increasingly convincing for solving complex problems, through artificial intelligence. In particular, this work, focused on the development of an artificial neural network for identifying diseases: Parkinson's, Huntington's and Amyotrophic Lateral Sclerosis, based on signals from the Electroencephalogram (EEG). The project was developed through a number of operations implemented in Matlab. The Fourier transform was seen as the main technique of signal processing, in order to analyze and diagnose diseases in the study. The work consisted first in the EEG signals to serve as an entry into the ANN in order to reveal a distinctive feature in the different diseases, and then, create an ANN architecture capable to distinguish the diseases. For this purpose 4 methodologies were used with different processing of the EEG signal. The 4 methodologies are compared in this paper.**

Keywords-component; Artificial Neural Networks, EEG, Classification, FFT.

I. INTRODUTION

The era of Electroencephalogram (EEG) began with the pioneering work of Hans Berger (1929). Hans Berger was a German psychiatrist. He spent some years thinking about electrical activity generated by the human brain and how this activity could be recorded.

EEG is a valuable tool in the detection of neurological diseases. To accomplish this examination technique, the procedure is the placement of electrodes on the skin of the patient's head which in turn are connected to a power amplifier voltage. This amplifier increases the amplitude of the electrical signal generated by the brain thousands of times, through a device called a galvanometer. The oscillations of electric current are drawn on a piece of paper in the form of waves.

Electroencephalographers current allow simultaneous recording of 40 channels (electrodes).

When we made an EEG there are some important aspects that should be considered for a well executed examination: a judiciously distribution of the electrodes (confront Fig.1). A carefully selection of reference electrodes to prevent contamination of the signal; in the hardware it is very important the placement of conductive gel, the calibration of

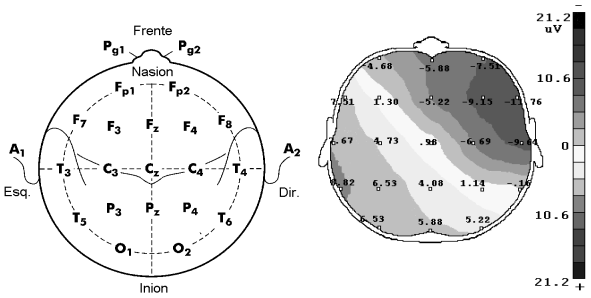

Figure 1 - Distribution of the electrodes and electrode potentials in the human brain ("F"-Frontal lobe, "T"-Temporal lobe, "C"-Central lobe, "P"-Parietal lobe, "O" - Occipital lobe. (Note: There is no central lobe in the cerebral cortex. "C" is just used for identification purposes only.) Even numbers (2, 4, 6, 8) refer to the right hemisphere and odd numbers (1, 3, 5, 7) refer to the left hemisphere. "Z" refers to an electrode placed on the mid line. "Fp" stands for Front polar. "Nasion" is the point between the forehead and nose. "Inion" is the bump at the back of the skull.)

the electrodes, the amplification, the filters, and if the signal will be digitalized: the anti-aliasing filters, the resolution of the signal, the acquisition rate of registration and the digital filters. In software, there are several numbers of signal processing applied to the EEG: viewing maps, average signal, the Fourier transform, several statistics, different setups, finding sources and evaluation of the signal dynamics.

The main objective of this research project is to develop an artificial neural network for the identification of three diseases: Parkinson's, Huntington's and Amyotrophic Lateral Sclerosis, or control group.

A. Studied pathologies

Parkinson's disease is evidenced by a disturbance and slowly progressive degenerative nervous system. Parkinson's disease begins, usually so insidious and gradually progresses. The first symptom in most people manifests as a tremor when the hand is at rest. The tremor is not the first symptom in one third of people with this disease, and some people never manifested this symptom. This disease affects about 1% of the population over 65 years and 0.4% of the population over 40 years worldwide [1].

Huntington is a hereditary and degenerative disease, caused by a genetic disorder and is characterized by motor and mental problems. The main characteristic of this disease is chorea, translated by involuntary movements that are

characterized by irregular muscle contractions, spontaneous and transient. Over 90% of patients with the disease exhibit this symptom [2].

The Amyotrophic Lateral Sclerosis (ALS) is a chronic progressive neuro-degenerative disease and unfortunately fatal, deeply marked by degeneration of motor neurons. This disease is the most common form of motor neuron disease. The term lateral sclerosis is due to "hardening" side of the spinal cord, where there are located nerve fibers originating from upper motor neurons that form the cortico-spinal system side. The first and the main symptom of the disease manifestation is chorea which may persist until the later stages, half of patients develop muscle rigidity (hypertonia), although the force of muscle contraction is normal. Voluntary movements of the patient becomes more slowly as the disease progresses, the involuntary movements are intensified, thus affecting the head, trunk and limbs [3].

The normal situation consists in EEG of patients without any disease. It is used a control group.

B. The EEG signal

Brain waves are forms of electromagnetic waves produced by electrical activity of brain cells.

These waves can be measured with electronic devices such as the electroencephalogram.

The frequencies of these electrical waves are measured in cycles per second or Hz (Hertz).

Brain waves change frequencies based on the electrical activity of neurons and are related to changes of states of conscience (concentration, relaxation, meditation, etc.). Every human being has its own characteristics in their brain activity. This activity has a pattern and a rhythm - and incorporates the frequencies ranges, delta theta, alpha, beta and gamma, as in Table I, on several levels due to various daily activities undertaken by each individual.

Delta is the lowest of all the frequencies of brain waves. It is associated with deep sleep, expanded awareness, healing and recovery. The Delta frequency range is between 0.5 to 3.5 Hz.

Theta state is the situation where the low brain activity almost drops to the point of sleep. Here many mental abilities occur. Theta state allows creativity, flashes of images of the unconscious and access to long memories forgotten. Theta carries us deep states of meditation. The frequency range of Theta waves lies between 4-8 Hz.

Alpha is associated with states of relaxation, visualization and meditation. The frequency range of Alfa waves lies between 9-13 Hz.

The beta state happens when we are awake and alert. The mind is concentrated, and stands ready to work projects that require full attention. The frequency range of Beta waves lies between 14-30 Hz.

The gamma range is defined as a pattern of brain waves associated with perception and consciousness. Gamma waves

TABLE I - MAIN FREQUENCY RANGES OF EEG

Type of Waves	Frequency (Hz)
Delta	0.5-3.5
Theta	4-8
Alfa	9-13
Beta	14-30
Gamma	30-45

are produced when masses of neurons emit electrical signals at a rate of approximately forty times per second, but can also occur between 30 and 45Hz;This frequency range here not used because these waves are not normally associated with the studied diseases [4].

II. METHODOLOGIES

This work was conducted mainly in three phases: get the EEG signals, processing of EEG signals (using FFT as main processing [5]) in order to adequately accomplish the input of the ANN and development of the neural network considering its architecture and training.

The EEG signals here obtained from PhysioNet organization of three diseases (Parkinson's, Amyotrophic Lateral Sclerosis and Huntington) and the group of control. They provided 15 EEG's from patients with Parkinson's disease, 20 EEG's from patients with Huntington's disease, 13 EEG from patients with the disease Amyotrophic Lateral Sclerosis and 16 EEG's from a control group of patients. EEG signals had previously recorded at the sampling frequency of 1000Hz. Each EEG consist of 12 signals recorded by the 12 electrodes. Each EEG signal corresponds to approximately 250 ms.

Concerning the EEG processing four methodologies were followed. The objective lied with getting the distinctive information of the EEG in a compact form to serve as input to the neural network, enabling the ANN to learn. In each methodology the following parameters here presented in the ANN inputs:

Method 1

The maximum amplitude and frequency of the FFT in the frequency range, alpha, beta, theta and gamma: This technique attempts to identify the values of the maximum and its frequency for each electrode with patient identification in the frequency ranges, delta, alpha, beta, theta to serve as an entry in the ANN. Fig. 2 presents an example of the four magnitude levels and its frequency values for the EEG of one electrode. Table II show the dimension of each data set of the methodology 1. This methodology had two variants, with and without identification of the electrode. In the case of electrode identification, 12 nodes here used and 1 of 12 here activated. Therefore the ANN input consisted in the 8 nodes for the 4 magnitudes peaks and respective 4 frequencies inside the 4 ranges of delta, theta, alfa and beta, and additionally the 12 nodes for electrode identification, if it is the case. The number of EEGs was 64 EEG (15+20+13+16) x 12 electrodes resulting in a total of 768 cases. These 768 cases here divided

in a training set, validation set and test set according to Table II. The purpose of these sets will be described bellow.

Method 2

Amplitudes of the peaks of the FFT and its frequency value, existing in the frequency range up to 30 Hz, disregarding the delta, theta, alfa and beta ranges: This technique attempts to identify all the values of maximum and its index of frequency of each electrode / patient in the frequency range of 0 to 30 Hz. From experimental observation of several EEG signal usually 8 peaks were present and therefore only the first 8 peaks here considered. Similarly as methodology 1 the two variations here considered (with and without electrode identification). Fig. 3 presents an example of the 8 peaks in the FFT of the EEG signal. Table III presents the dimension of the data set and its division in training, validation and test sets. The input of this ANN has 16 nodes for coding the 8 peaks magnitude and its respective frequency, plus 12 nodes in the case of electrode identification.

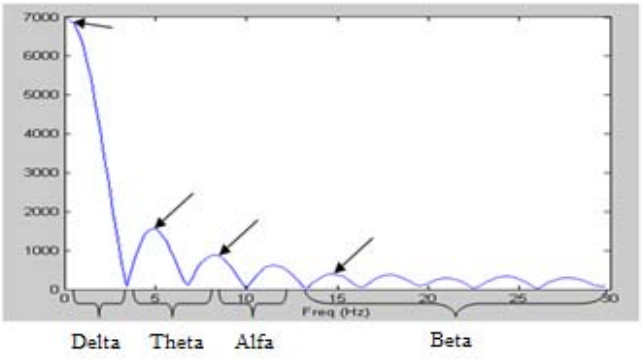

Figure 2 – example of data input for ANN in the methodology 1

TABLE II - JOINT TRAINING, TESTING AND VALIDATION SETS PRESENTED IN THE METHODOLOGY 1 FOR THE ANN

Electrodes	***Dimension***			***Input nodes of ANN***
	Training Set	Validation set	Test set	
Without electrode identification	8x576	8x96	8x96	8
With electrode identification	20x576	20x96	20x96	20

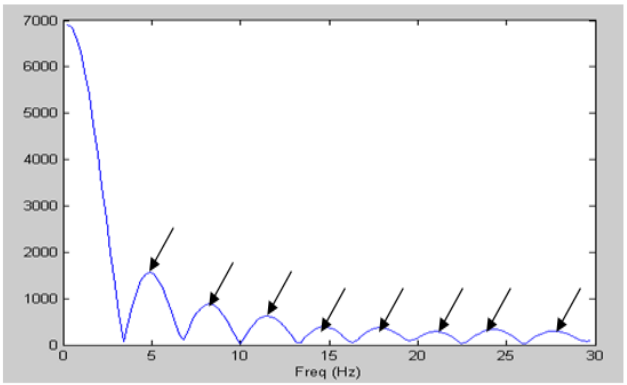

Figure 3 – example of input data for ANN in the methodology 2

TABLE III - JOINT TRAINING, TESTING AND VALIDATION SETS PRESENTED IN THE METHODOLOGY 2 FOR THE ANN

Electrodes	***Dimension***			***Input nodes of ANN***
	Training set	Validation set	Test set	
Without electrode identification	16x576	16x96	16x96	16
With electrode identification	28x576	28x96	28x96	28

Method 3

The FFT of the EEG signal below 30 Hz: In this case the complete FFT of the EEG signal until the beta frequency range was used as the input of the ANN, after normalization made along each electrode. The FFT was determined with length of 2048 (with zero padding) corresponding to a resolution ~ 0.5 Hz for each FFT point (the sampling frequency was 1000 Hz). Therefore the first 62 FFT samples were used in the ANN input, plus the 12 nodes in the case of electrode identification. Table IV presents the dimension of the data set and its division in training, validation and test sets.

Method 4

Amplitudes of the FFT peaks and their frequency with 12 electrodes together: This technique attempts to identify the values of the beam and its frequency index set of electrodes in each patient in the frequency range, delta, theta, alpha and beta, so to serve as an solely entry in the ANN. This methodology uses the same information as methodology 1, but combines the information of the 12 electrodes of one EEG in only one entry. The ANN input consist now in 96 nodes corresponding to 12 electrodes x 8 (4 magnitude peaks and 4 respective frequency values). The total number of entries was now reduced to the only 64 EEG signals available. Table V presents the dimension of the data set and its division in training, validation and test sets.

TABLE IV - JOINT TRAINING, TESTING AND VALIDATION SETS PRESENTED IN THE METHODOLOGY 3 FOR THE ANN

Electrodes	***Dimension***			***Input nodes of ANN***
	Training set	Validation set	Test set	
Without electrode identification	62x576	62x96	62x96	62
With electrode identification	74x576	74x96	74x96	74

TABLE V - JOINT TRAINING, TESTING AND VALIDATION SETS PRESENTED IN THE METHODOLOGY 4 FOR THE ANN

Dimension			***Input nodes of ANN***
Train set	Validation set	Test set	
96x48	96x8	96x8	96

III. The Artificial Neural Network

In this work feed-forward architecture artificial neural networks were used with x nodes in the input layer, 16 nodes in hidden layer and 4 nodes in the output layer – one node for each diseases. All of this nodes depend on the concerned methodology as noted earlier on the tables II, III, IV and V. For all ANN presents on this work two activation functions were used, Logsig and Tansig [6], in order to check which one were the best to fits the various methods. The training algorithm used was the Levenberg-Marquardt algorithm [7] for all methodologies, because was verified from the start of the work that would give, on this particular case, better results than Resilient Propagation [8] and [9].

The processed data was divided in training sets to train the ANN, the validation set to do cross validation and test set to evaluate the final performance for each model with data not present during the train. The sets were balanced in terms of pathologies that contained each one. The size of each sets are presented in table II, III, IV and V.

IV. *Discussion of Results*

After the analysis of results obtained (Table VI, Fig. 4 and 5), it was found that the ANN failed to "learn" (correlation coefficient r between target and predicted values are far from 1) remained open the study of new ways of processing EEG's to apply to de entry of ANN. In the methods 1 to 3 was only used as input the signal of one electrode so this may have led to obtaining the poor results given by these three approaches. The results of method 4 showed that the ANN still failure to learn but results are better than the other methodologies. The ANN can fail because the signal were presented to the input of the ANN with 12 electrodes in this methodology, making the number of entries available for training (48) insufficient to train the network with the methodology 4. Therefore one conclusion is already apparent that it is absolutely necessary to use the 12 signals from 12 electrodes on each entry, as confirmed by the results of method 4.

It should be emphasized some reasons because the methods applied in this work have not worked:

- The availability of examples of EEG was very sparse and with little information;
- It is unclear in which situations the EEG's were collected (patient's condition);
- The used EEG's has a short number of samples (1/4 of a second).

V. Conclusion *and Future Work*

In this paper was presented a work with ANN using EEG signal with the objective of automatically give a prognostic of one of 3 diseases.

Four methods were tried to make the processing of EEG signals presented to the entry of ANN.

TABLE VI - Comparison of used Methodologies for identification of disease through an ANN.

Methodologies	Correlation Coefficient (r)					
	Activation function Tansig			*Activation function Logsig*		
	Train	Validation	Test	Train	Validation	Test
1-With electrode identification	0,488	0,211	0,082	0,412	0,412	0,054
1- Without electrode identification	0,567	0,326	0,165	0,446	0,321	0,099
2- With electrode identification	0,568	0,303	0,087	0,598	0,315	0,057
2- Without electrode identification	0,566	0,208	0,322	0,496	0,390	0,093
3- With electrode identification	0,533	0,503	0,085	0,490	0,465	0,142
3- Without electrode identification	0,523	0,468	0,040	0,433	0,463	0,200
4	0,833	0,544	0,255	0,833	0,478	0,352

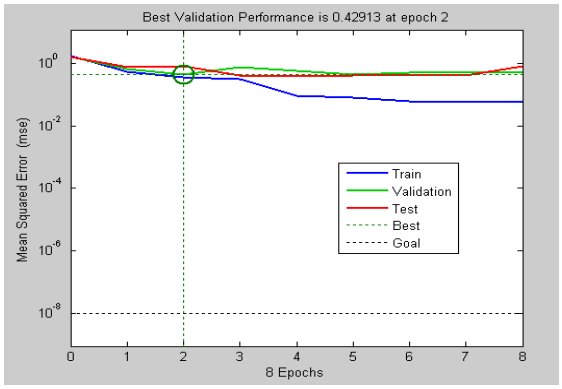

Figure 4 - Changes in the value of the error in training sets, validation and testing methodology 4

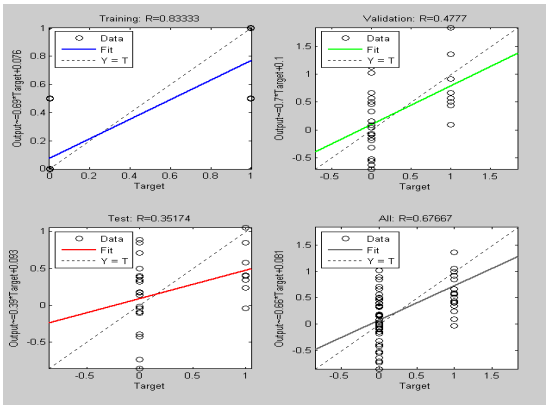

Figure 5 - Lines of correlation obtained during the learning process of ANN in the methodology 4.

On the first three methods (methodologies 1, 2 and 3) the input of ANN contained information of only one electrode. On the other hand, on the fourth method the input uses the 12 electrodes. The ANN had bad results in the first three methodologies and improved in the fourth methodology. But were not achieved the expected results because the EEG signals available were not sufficient to train the ANN with the size of method fourth. They were, however, good clues to continue the work using more EEG signals.

Indeed the neural networks can be a valuable tool in Biomedical Engineering; if this ANN had "learned", it would serve an improvement in decision-making on the medical diagnosis of the diseases studied, because, when the data of the new patient were present to the input of the ANN, with the same symptoms, the ANN would provide a diagnosis for this case. The ANN would allow an initial diagnosis in real time for the doctor that was examining the case.

With the development of new types of processing the EEG signal, the ANN may be a promising tool for the detection of the diseases studied.

The challenge in this work and the results leave open a further search of a better ways to encode the EEG for the ANN to identify the diseases under study or others. This must go through a close contact of an expert in EEG and obtain must more EEG signals and better identified.

The following suggestions for future work go in order to keep on working:

1. Processing with Wavelets because they allow a spectral analysis in varied frequency ranges;
2. Processing by modeling with a linear prediction coefficients model, using the coefficients a_k, as input of ANN;
3. Get more and better EEG signals.

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