Recognition of Epileptiform Patterns in the Human Electroencephalogram using Multi-layer Perceptron

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Abstract

Automatic detection of epileptiform patterns is highly desirable during continuous monitoring of patients with epilepsy. This paper describes an unconvential system for automatic off-line recognition of epileptic sharp transients in the human electroencephalogram (EEG), based on a standard neural network architecture - multi-layer perceptron (MLP), and implemented on a Silicon Graphics Indigo workstation. The system makes comprehensive use of wide spatial contextual information available on 12 channels of EEG and takes advantage of discrete dyadic wavelet transfrom (DDWT) for efficient parameterisation of EEG data. The EEG database consists of 12 patients, 7 of which are used in the process of training of MLP. The resulting MLP is presented with the testing data set consisting of all data vectors from all 12 patients, and is shown to be capable to recognise a wide variety of epileptic signals.

Keywords:

Epilepsy, Multi-channel EEG, Wavelet Transform, Multi-layer perceptron

1. Electroencephalogram

If a pair of electrodes attached to the scalp of a human subject are connected to a high input impedance differential amplifier, a time varying electrical signal is observed. This signal, called the *electroencephalogram* (EEG), is of typical peak-to-peak amplitude 10 - 100 μV and varies depending upon the *brain state* of the subject, i.e. a person is awake, asleep, under anaesthesia etc. It is characterised by potentials fluctuating over the brain in a frequency range of approximately 0.1 - 100 Hz. According to the predominant frequency of the signal, EEG has been historically categorised into the following broad groups of activity (Fig. 1):

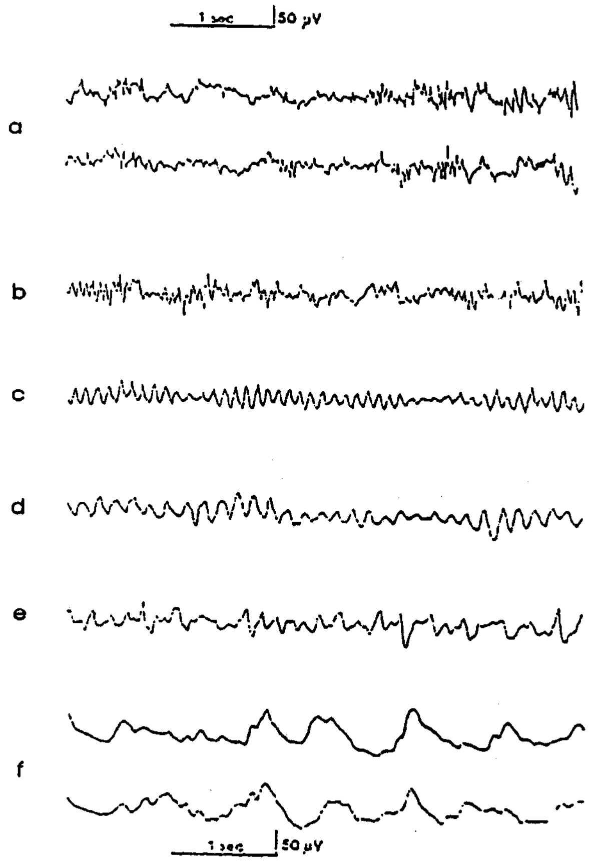

Fig.1 EEG activities
a) gamma activity, b) beta activity, c) alpha activity
d) theta activity, e) mixed delta-theta activity
f) delta activity

- δ-activity: 0.5 - 4 Hz
- θ-activity: 4 - 8 Hz
- α-activity: 8 - 12 Hz
- σ-activity: 12 - 14 Hz
- β-activity: 14 - 22 Hz
- γ-activity: 22 - 30 Hz

2. The EEG of Patients with Epilepsy

The characteristic activity observed in the scalp EEG of patients with epilepsy are *sharp transients* (ST's) (Fig. 2):

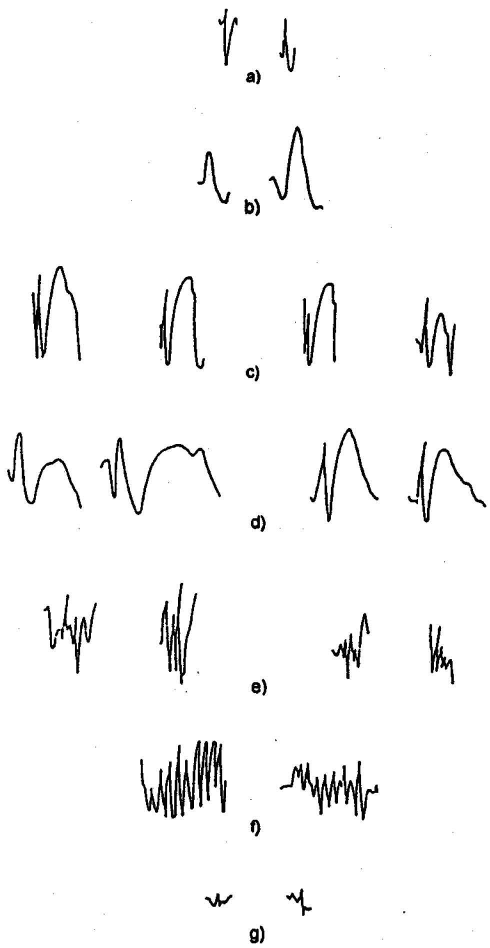

Fig.2

a: Spike
b: Sharp wave
c: Spike-wave complex
d: Slow spike-wave complex
e: Polyspikes
f: Runs of rapid spikes
g: Small sharp spikes

- spike (duration 10 - 70 ms)
- sharp-wave (duration 80 - 150 ms)
- classical spike-wave complex (3 - 5 /s)
- slow spike-wave complex (1 - 2.5 /s)
- polyspikes (20 - 60 /s)
- runs of small spikes (10 - 20 /s)
- small sharp spikes (low voltage spikes)

3. Detection of Epileptic Discharges in EEG

The detection and classification of STs by visually scoring the EEG record is a rather complex operation. Besides being a laborious process, visual screening of the EEG record is highly dependent on the electroencephalographer's (EEGer's) training and experience. As a result, there exists disagreement among EEGers, as well as inconsistencies in the same EEGer, in the detection of individual STs [1].

Long-term monitoring of patients with known or suspected epilepsy can lead to lengthy EEG records. In recent years, ambulatory monitoring has become widely used, and it may involve 24 hours or more continuous EEG recording. Hence, automated methods for EEG analysis in such cases provide an attractive alternative to visual analysis procedures and can offer several advantages over visual scoring:

- They can ease the work-load of the EEGer by providing off-line, faster than real-time analysis of lengthy records.
- They can provide reliability and repeatibily in the analysis of EEG data.
- They can offer a tool for detailed quantification of the ST activity, which could be used to study the effect of drug treatment.
- They could eventually lead to a comprehensive definition of an ST, and thus contribute to the standardisation of ST detection.

4. Methods of Automatic Detection of Epileptic Sharp Transients

Several techniques have been applied to the detection of epileptic sharp transients in the EEG signal. These include template matching, parametric methods, mimetic methods, syntactic methods, expert systems, artificial neural networks.

Artificial neural networks (ANN) represent a powerful method for recognition of epileptic patterns in EEG [2]-[8]. An ANN is a teachable non-algorithmic information processing system, that consists of densely interconnected simple neuron-like elements (neurons or nodes). Information is represented in the strengths of connections between elements. Among various types of ANN designed so far, *multi-layer perceptrons* (Fig. 3) trained with the *backpropagation method* have been the most popular due to their flexibility and high efficiency.

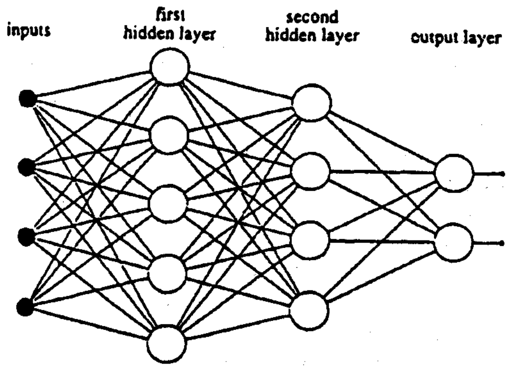

Fig.3 A typical multi-layer perceptron architecture

5. Recognition of Epilepsy by Multi-layer Perceptron

5.1 Data Preprocessing

5.1.1 EEG Database

- Number of patients: 12 (*denoted anonymously as* A,B,C,D,E,F,H,I,J,K,L,M)
- position of electrodes:

  $F_8 - T_4, T_4 - T_6, Fp_2 - F_4, F_4 - C_4$

  $C_4 - P_4, P_4 - O_2, Fp_1 - F_3, F_3 - C_3$

  $C_3 - P_3, P_3 - O_1, F_7 - T_3, T_3 - T_5$

  (The International "10-20" Electrode System)
- type of recording: bipolar
- Number of channels: 12
- Bandwidth of recorders: 0.2 - 32 Hz
- Sampling frequency: 64 Hz
- Digitisation: 8-bit precision
- Storage media: Hard disk, floppy disks
- Storage format: Binary unsigned char

The 12-channel EEG recordings of each individual patient were visually scored by expert neurologist (Dr. Mokráň). These recordings were classified into two classes:

- epileptic data class
- normal data class

by assigning each 1-second segment a label of 1 (epileptic segment) or 0 (normal segment) on the time scale of 1 second. The time scale of 1 second is generally accepted time scale for both automatic and visual detection of epileptic events (Fig. 2). Thus for each individual patient we obtained **gold standard** epileptic and normal 1-second segments of EEG data. The characteristics of patients's data files are covered in Table 1.

Each channel's 1-second segment of EEG was parameterised by 6-dimensional vector of instantaneous maximum powers in 6 different frequency bands. This type of parameterisation was performed by means of the *discrete dyadic wavelet transform*. As a *mother wavelet function* we used the first derivative of a Gaussian function[2],[10]:

$$\psi(t) = \frac{-t}{\sqrt{2\pi\sigma}} \exp\left(\frac{-t^2}{2\sigma^2}\right)$$

5.2 Training of MLP

The dataset consisting of patients A,B,C,D,E,F,H contained 382 epileptic and 8384 normal 1-second segments of 12-channel EEG (patients I,J, K,L,M were not included in the MLP training database). Epileptic events in this dataset covered mainly spike-wave complexes (2-4 /s), polyspikes and epileptic K-complexes, and were representative examples of these types.

Our aim was to design a powerful patient-independent MLP architecture for off-line instantaneous processing of all 12 channels of EEG. The process of design consisted of the *training phase* and *testing phase*. The training phase was broken into two stages:

- Creating a training database
- Finding an optimal MLP architecture

5.2.1 Creating a Training Database for MLP

The training database of neural network should contain equal numbers of epileptic and normal vectors. Otherwise after training, the network would prefer

Table 1

Patient	A	B	C	D	E	F	H	I	J	K	L	M
Recording lenght	1808	938	1146	624	1524	1451	1274	1844	1862	1819	1840	1624
Number of epileptic 1-s segments	23	7	10	72	153	63	54	74	244	602	412	412
Number of normal 1-s segments	1785	931	1136	552	1371	1388	1221	1770	1618	1217	1428	1212

classification of EEG patterns into the class of normal vectors, because in majority of EEG recordings this class is dominant. This is unacceptable, since our primary idea was to design an automatic machine for recognition of epileptic events. Another possibility was to create a training database from all epileptic vectors and equal number of normal vectors obtained by random picking of all normal vectors. However, if we had used only 382 epileptic and 382 normal vectors, there would not have been enough training data for a single 12-channel-input MLP [9]. Moreover, if we had used only 382 normal vectors, we would have voluntarily got rid off important normal vectors and thus deformed the training process. Therefore we decided to create a training database for a single 12-channel-input MLP containing 8000 normal and 8000 epileptic vectors. This training database consisted of *training set* and *cross-validation* set, each having equal numbers of normal and epileptic vectors (4000). 8000 normal vectors were obtained by random picking of 8384 initial normal vectors. Initial 382 epileptic vectors were split randomly into two halves (191 vectors). Each of such halves was duplicated 21 times. As a result we obtained 4011 epileptic vectors for each half, from which we picked randomly 4000 vectors for both the training and cross-validation sets. Putting together, we obtained the training and cross-validation set, containing 8000 non-overlapping 72-dimensional EEG vectors each.

5.2.2 Finding an Optimal MLP Architecture

To find an optimal MLP architecture for solving a given problem means to find an optimal number of layers and nodes with respect to average and final error rates. According to [2] we decided to design an MLP with the following specifications:

- Number of hidden layers: 1
- Number of input units: 72
- Number of hidden-layer neurons: 2 - 10
- Number of output neurons: 2 (one for epipleptic data class, one for normal data class)
- Parameter β of neurons: 1.00
- Coefficient α of momentum term: 0.01

The only unclear matter was the number of hidden-layer units. The values of average and final error rates corresponding to different MLP architectures are present in Table 2 (The number of data passes through the network was 1500. The average error rate was computed during the last 20 % of data passes through the network.).

According to the results in Table 2 we made a decision to use the MLP structure 72-6-2.

5.3 Testing of MLP

In this phase the MLP 72-6-2 (computer program written in C code) was presented with data from the training set (patients A,B,C,D,E,F,H) and also with *never-before-seen* data (patients I,J,K,L,M). The classification results are shown in Table 3, where as a measure of the quality of MLP classification capabilities we used the following criteria:

- **Number of true positives**
- **Number of false positives**
- **Number of true negatives**
- **Number of false negatives**
- **Sensitivity of MLP**
- **Selectivity of MLP**
- **Specificity of MLP**
- **Accuracy of MLP**

True positives (t_p) are events detected by MLP which are indeed gold standard epileptic events.

False positives (f_p) are events detected by MLP which are, in fact, not gold standard epileptic events.

True negatives (t_n) are events rejected by MLP which indeed were not gold standard epileptic events.

False negatives (f_n) are events rejected by MLP, but which were, in fact gold standard epileptic events.

Sensitivity of MLP (or recall) is defined as: "What percentage of all gold standard epileptic events were detected by MLP?"

$$Sensitivity = \frac{t_p}{t_p + f_n}$$

Selectivity of MLP (or precision) is defined as: "What percentage of all events detected by MLP were actually gold standard epileptic events?"

$$Selectivity = \frac{t_p}{t_p + f_p}$$

Specificity of MLP is defined as: "What percentage of all gold standard normal segments of EEG were recognised by MLP?"

Table 2

MLP structure	72-2-2	72-3-2	72-4-2	72-5-2	72-6-2	72-7-2	72-8-2	72-9-2	72-10-2
Average error rate [%]	5,6	3,1	3,3	3,1	3,0	3,0	3,0	3,1	3,0
Final error rate [%]	5,7	3,1	3,3	3,1	2,9	3,0	3,0	3,1	3,0

$$Specificity = \frac{t_n}{t_n + f_p}$$

Accuracy of MLP is defined as: "What percentage of all epileptic and normal segments detected by MLP were actually gold standard epileptic and normal segments?"

$$Accuracy = \frac{t_p + t_n}{t_p + f_n + t_n + f_p}$$

The total number of gold standard epileptic events in each recording is the sum of true positives and false negatives ($t_p + f_n$). The total number of gold standard normal segments in each recording is the sum of true negatives and false positives ($t_n + f_p$). Finally the length of recording corresponds to the sum of true positives, false negatives, true negatives and false positives ($t_p + f_n + t_n + f_p$).

6. Conclusion

In this paper we described a powerful off-line system for automatic detection of epileptiform patterns in the human EEG using the discrete dyadic wavelet transform and the multi-layer perceptron. The system was realised as a computer program running on a Silicon Graphics Indigo workstation. Its classification capabilities were tested on a statistical group of 12 patients, 7 of which were originally used for training of the MLP. Classification results shown in Table 3 proved that this system is capable of succesful recognition of a wide spectrum of epileptic and normal signals, yet it still has a large number of false positives to be seriously considered for use in a clinical environment. Most of the false positives come from muscle artifacts which are impossible to eliminate unless an architecture which can enable the system to evaluate longer EEG epochs is used. Such an architecture can be developed by adding additional modules which can process long EEG epochs and extract temporal contextual cues needed for the elimination of false positives.

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Table 3

Patient	A	B	C	D	E	F	H	I	J	K	L	M
Recording lenght [s]	1808	938	1146	624	1524	1451	1275	1844	1862	1819	1840	1624
Number of epileptic 1-s segments	23	7	10	72	153	63	54	74	244	602	412	412
Number of normal 1-s segments	1785	931	1136	552	1371	1388	1221	1770	1618	1217	1428	1212
Number of true positives	23	7	10	71	148	62	53	31	179	390	305	296
Number of true negatives	1746	927	1129	541	1234	1344	1195	1763	1503	1053	1177	1120
Number of false positives	39	4	7	11	137	44	26	7	115	164	251	92
Number of false negatives	0	0	0	1	5	1	1	43	65	212	107	116
Sensitivity [%]	100,0	100,0	100,0	98,6	96,7	98,4	98,1	41,9	73,4	64,8	74	71,8
Selectivity [%]	37,1	63,6	58,8	86,6	51,9	58,5	67,1	81,6	60,9	70,4	54,9	76,3
Specificity [%]	97,8	99,6	99,4	98,0	90,0	96,8	97,9	99,6	92,9	86,5	82,4	92,4
Accuracy [%]	97,8	99,6	99,4	98,1	90,7	96,9	97,9	97,3	90,3	79,3	80,5	87,2

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Ján Magdolen was born in Trnava in 1968. He received the MSc in electrical engineering from the Faculty of Electrical Engineering and Information Technology of the Slovak Technical University in Bratislava (FEI STU) in 1992. He received Dean's award for excellently elaborated diploma thesis and Rector's award for excellent academic results during undergraduate studies. After graduation he started to study for PhD in Electronics in the Department of Radioelectronics, FEI STU. He spent 9 months as a visiting research student in the Medical Engineering Unit, Department of Engineering Science, University of Oxford, United Kingdom in 1993-94. His field of expertise covers biomedical signal processing, artificial neural networks, digital transforms and electrical neurostimulation. Ján Magdolen is an associate partner of the EEC group on the use of the neural networks for analysis of EEG signal, and a member of the Biomedical Engineering Section of the Slovak Medical Society.

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Vladimír Mokráň was born in Svinná in 1931. He received M.D. degree from the Medical Faculty of the Comenius University in Bratislava in 1957. He worked 5 years in the Department of Neurology of the Nitra hospital, then was the head of bedless department in the Levice hospital for 4 years. Afterwards he worked for several years as a senior assistant in the Institute of Medical Physics in Bratislava. He received PhD in neurology in 1982. In 1988 he established specialised ambulatory centre for seizure diseases with consiliar function to neurologists and psychiatrists for the region of whole Slovakia. His field of expertise covers epilepsy, migraine, narcolepsy, panic reaction, sleep disorders. His basic diagnostic method is investigation of pathophysiologic disorders in the framework of circadial rhythms by 24-hour EEG monitoring in ambulatory form.