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Automated Epilepsy Prediction by Means of Visual Perception Testing and Digital EEG Processing Data

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Abstract. This paper describes a preliminary algorithm performing epilepsy prediction by means of visual perception tests and digital electroencephalograph data analysis. Special machine learning algorithm and signal processing method are used. The algorithm is tested on real data of epileptic and healthy persons that are treated in Kaunas Medical University Clinics, Lithuania. The detailed examination of results shows that computerized visual perception testing and automated data analysis could be used for brain damages diagnosing.

Key words: machine learning, classification, epilepsy, samples, signal processing.

Introduction

According to the data of the 4th International Congress of Epileptology, Florence, 2000, $\approx$ 1 percent of all the persons suffer from epilepsy. The 30 percent of them have the refractory epilepsy, when medicine is to treat such persons. People, suffering from it are totally discomforted. It is very important to diagnose this disease in time. Physicians use manual testing and diagnosing tools, but the results are not always correct. Sometimes it is impossible to diagnose and treat it precisely. Many computer specialists try to help doctors using various techniques for data processing. New methods are going to be investigated for the epilepsy prediction.

My goal was to create special methodic that could help to solve the problem, mentioned above. Sometimes happens, that people, having epilepsy, tend to have visual perception disorders as well. I was used to create a computerized system, which could be able to test epileptic persons' visual perception and predict epilepsy according the testing (Christianson, 1992). The created system also integrates the digital EEG (electroencephalography) analysis, used for preliminary epilepsy diagnosis.

The visual perception tests were used for apriori patients' diagnosis information. People, having epilepsy, also had some visual perception abnormalities (color perception disorders, size-figures discrimination problems, and others) (Godefroid, 1988).

Epileptic persons were tested by means of Size – Form Discrimination and Munsell color test. Special machine learning (ML) techniques were used for testing data processing and creation of regularities. In parallel, special auto-regressive (ARMA_MULTI) methods were used as well.

Digital EEG processing was also used for the problem solving task.

Visual Perception Tests

Size-Form (SFD) Test

The test procedure consists of sequential presentation of 100 pairs of vertically centered geometrical figures of variable size. The investigated person is given short amount of time to perceive and to compare each pair. Afterwards, he is asked to tell whether the left and the right figures were equal or not.

All figure pairs are clustered into 20 groups containing 5 pairs each. The left figure size is the same for all pictures of one group (Bulatov, Bertulis,, 1994). The right figure size is adjusted to be significantly less, less, equal, greater and significantly greater than the left figure. It is calculated as presented in the (1) expression. The (2) expression is used for the relative size of the left figure, which changes from 20 to 248 display units for different groups.

$$T = 20 + 12^{*}i, \quad i = 0., \ldots, 19, \tag{1}$$

$$K = T + j^{*}5, \quad j = -2, \ldots, 2. \tag{2}$$

Before launching the test supervisor chooses preferred test options. The shapes of both figures are not necessarily the same and are selected form the following set: square, circle, triangle, vertical line, and horizontal line. Each figure and the background are assigned one of 16 possible colors (black and white included). In addition, the figures can be chosen to be solid or hollow.

Farnsworth-Munsel (FM) 100-hue test

The Farnsworth-Munsel 100-hue (FM) test (Lukauskienė *et al.*, 2000) has been used for such purposes:

- for examination the relationships between deficits in color and contrast discrimination;
- to show that impaired color discrimination is related to patho-physiology of various brain diseases and can be a sensitive method for early detection and monitoring of epilepsy.

For testing of colors discrimination, measuring the zones of colors confusion and learning programs of rehabilitation, the computerized Farnsworth-Munsell 100-hue test

was created and applied to test patients with various types of brain damage which was verified by means of EEG, CT or MRI.

The investigated person has to sort the colors according their shadows. Four basic colors are presented: red, green, blue and yellow.

Both of testing results are stored to the special database for their further processing.

Data Interpretation Methods

CHARADE

Our system incorporates a simplified and slightly modified version of symbolic machine learning algorithm *CHARADE* (Ganascia, 1987). This algorithm generalizes over pre-classified training examples inducing set of classification rules. In our case, the rule set corresponds to detected regularities and relates SFD test results to medical diagnosis.

Parameter Space Transformation

In order to improve the interpretability of constructed rules, the mapping of all original 100-dimensional person's response vectors into the new parameter space precedes the induction process. Given the test data, the value of each new parameter corresponds to the percentage of correct answers within a specified set of test answers. We have defined and used 72 overlapping answer sets $A_{i,j}$ $(i = 1, \ldots, 6, j = 1, \ldots, 12)$.

Table 1

Partition of SFD test answers into subsets

	Small	Medium	Large	(Left Fig.)
Sgnf. Less	$A_{1,1}$	$A_{2,1}$	$A_{3,1}$	(size)
Less	$A_{1,2}$	$A_{2,2}$	$A_{3,2}$	
Equal	$A_{1,3}$	$A_{2,3}$	$A_{3,3}$	
Greater	$A_{1,4}$	$A_{2,4}$	$A_{3,4}$	
Sgnf. Greater (right fig. size)	$A_{1,5}$	$A_{2,5}$	$A_{3,5}$	

$$A_{i,6} = A_{i,1} \cup A_{i,2} \quad A_{i,7} = A_{i,4} \cup A_{i,5}$$
$$A_{i,8} = A_{i,1} \cup A_{i,5} \quad A_{i,9} = A_{i,2} \cup A_{i,4}$$
$$A_{i,10} = A_{i,2} \cup A_{i,3} \cup A_{i,4}$$
$$A_{i,11} = A_{i,1} \cup A_{i,2} \cup A_{i,4} \cup A_{i,5}$$
$$A_{i,12} = A_{i,1} \cup A_{i,2} \cup A_{i,3} \cup A_{i,4} \cup A_{i,5}$$
$$A_{4,j} = A_{1,j} \cup A_{2,j} \quad A_{5,j} = A_{2,j} \cup A_{3,j}$$
$$A_{6,j} = A_{1,j} \cup A_{2,j} \cup A_{3,j}.$$

Induction Results

We obtained two different rule sets. The first set covered all epilepsy forms, discriminating them from the rest of diagnoses (including healthy). The second rule set discriminated between possible epilepsy variations (temporal, frontal, occipital, parietal). Each collection contained tens or even hundreds of rules depending on learning algorithm settings. Thus, we present only a few examples taken from both rule sets:

- if $(C_{5,5} \leqslant 39\%)$ then diagnosis = epilepsy;
- if $(24\% \leqslant C_{3,12} \leqslant 43\%)$ then diagnosis = epilepsy;
- if $(C_{4,11} > 68\%) \cup (C_{3,1} > 67\%) \cup (33\% \leqslant C_{3,3} \leqslant 67\%)$ then diagnosis = other;
- if $(C_{6,5} > 68\%) \cup (C_{2,9} > 67\%) \cup (42\% \leqslant C_{4,12} \leqslant 62\%)$ then diagnosis = other;
- if $(C_{1,4} > 71\%) \cup (33\% \leqslant C_{5,3} \leqslant 67\%)$ then diagnosis = temporal epilepsy;
- if $(C_{6,3} \leqslant 32\%) \cup (63\% \leqslant C_{2,12} \leqslant 86\%) \cup (38\% \leqslant C_{3,7} \leqslant 69\%)$ then diagnosis = frontal epilepsy;
- if $(C_{6,3} \leqslant 32\%) \cup (C_{2,1} \leqslant 33\%) \cup (42\% \leqslant C_{3,12} \leqslant 60\%)$ then diagnosis = occipital epilepsy;
- if $(C_{3,8} \leqslant 35\%) \cup (33\% \leqslant C_{5,3} \leqslant 67\%) \cup (30\% \leqslant C_{1,10} \leqslant 43\%)$ then diagnosis = parietal epilepsy.

Here, $C_{i,j}$ means correct answer percentage in $A_{i,j}$ answer set.

The Effectiveness of CHARADE

In order to try the *CHARADE* effectiveness:

- The algorithm was learned by SFD testing results of five basic classes.
  1. ET (patients, having temporal lobe epilepsy).
  2. EO (patients, having occipital lobe epilepsy).
  3. EF (patients, having frontal lobe epilepsy).
  4. EP (patients, having parietal lobe epilepsy).
  5. HEALTHY (healthy persons)

After that the algorithm was tested with other data of the same classes. We tried to find out how many diagnoses *CHARADE* recognizes correctly. The results are presented in the Fig. 1.

- The algorithm was learned using 13 classes, when the basic five ones were diveded into subclasses. For example, ET was divided into ETS (temporal lobe epilepsy of right brain part), ETD (temporal lobe epilepsy of left brain part), EU (temporal lobe epilepsy of the both brain parts). The learning and recognition procedure was the same as for five classes. The results are presented in the Fig. 2.

According to the received data, we can state that *CHARADE* is more effective, when it is learned within five basic classes data. Without dividing them to sub-classes, it is possible to receive about 70 percent effectiveness.

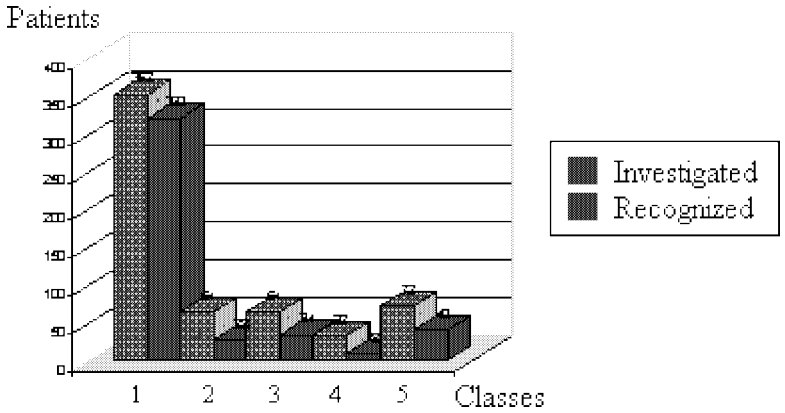

Fig. 1. *CHARADE* efectiveness for basic five classes.

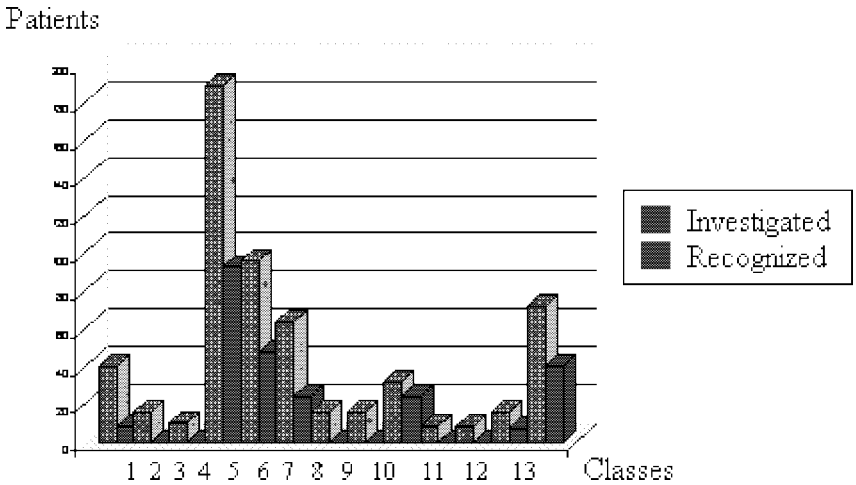

Fig. 2. Charade efectiveness for 13 classes.

The Nearest Neighbor Classifier

The Nearest Neighbor (NN) Classifier (Ruseckaitė, 2000) is the classical method, which is used for data classification. The main principle of it is to find the minimum distance between classified data and the given class centers. All the distances are calculated, and the minimum of them describes the possible class, to which the person belongs.

At first the NN should be learned with the given apriori data in order to find the class

centers. The class center can be expressed in the following way:

$$\overline{X_l} = \begin{pmatrix} \overline{x}_{1,l} \\ \overline{x}_{2,l} \\ \ldots \\ \overline{x}_{N,L} \end{pmatrix}, \quad (i = 1, \ldots, N; \;\; l = 1, \ldots, L), \tag{3}$$

where $N = 100$ is the number of features, (SFD tests answers); $l = 1, \ldots, L$, $L = 6$ is the number of classes.

The $\overline{x}_{i,L}$ is one of the class center coordinates.

$$\overline{x}_{i,L} = \frac{1}{N} \sum_{k=1}^{N} x_{ikL}, \quad (i = 1, \ldots, L; k = 1, \ldots, K), \tag{4}$$

where K is the ammount of patients' data. x_{ikL} is one of the SFD (or FM) test set answer.

Consider, that $x \in \Omega_r$, where x is the patient' data, to be classified, belongs to class Ω_r, where Ω_r is the class ($r = 1, \ldots, R = 6$). We calculate the distances $d_1, \ldots, d_6$ between sample and class centers. The minimum values among $d_{\min} = \underset{l=1,2,\ldots,L}{\arg\min}\, d_l$ of them shows that x belongs to class r.

Experiment

The algorithm effectiveness was tested twice:

- With the FM test results. Six different classes were used for training ET, EO, EP, EF, HEALTHY and MTR (traumatic persons class). Unfortunately, the classification results were bad. The 25 patients' data were used for NN training and 25 – for recognition. Only 10 persons' diagnoses were recognized correctly. According to this, we decided to refuse using of FM testing results for diagnosis prediction.
- With the SFD test data. The classification results were significantly better. NN classified about 60 percent of data correctly. The classification results are presented in the Fig. 3.

Regressive Methods

The *CHARADE* and NN system results were positive and showed 70 percent corectiviness. Anyway, it was not sufficient for good diagnose detection and creation of regularities. Some of the rules overloaded, the finite interpretation was not informative in some cases (it was stated that person can have temporal as well as parietal epilepsy, while those diagnoses are totally separate).

In comparison with the mentioned above methods, the AR method (J. Mockus and L. Mockus, 1991) had been chosen. This method is able to process many factors (features) in a tim1e as well. This algorithm was very good in currency rate prognosing.

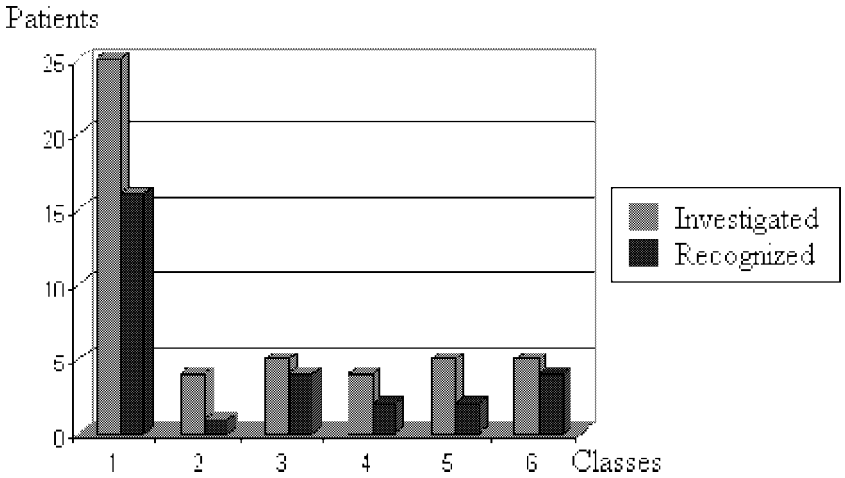

Fig. 3. NN efectiveness for SFD testing results.

The *ARMA_MULTI* model is the AR model, capable with many factors in a time (Mockus, 2000). The *ARMA_MULTI* model could be present in the following expression:

$$w_t = \sum_{i=1}^{p} a_i w_{t-i} + \sum_{j=1}^{q} b_j \varepsilon_{t-j} + \varepsilon_t. \tag{5}$$

The first expression is auto-regressive part of model, and the second – is the multi-average sum. Value w_t describes the real mean of patient's diagnose. ε is the error rate. It can be calculated between real and predicted diagnose value. The a and b expressions are *ARMA_MULTI* parameters.

ARMA_MULTI Algorithm

ARMA_MULTI algorithm can be presented as follows.

The test data set at the $t = t_0$ time moment is being preprocessed. *ARMA_MULTI* is acknowledged, using already existing test data (Munsell color perception testing results and size – form discrimination test results). *ARMA_MULTI* parameters a and b are calculated in the following way:

I used simplified *ARMA_MULTI* version, without MA part, not working with data multi averaging. In my case parameter a is the parameter, presenting the feature dependency on patient's diagnose. The parameter b is set as zero (because of escaping of MA part).

$q = 0$ because of $b = 0, p = 1$ (the prognose does not depend on the patient's number in the data sequence). All parameters are minimized:

$$\min_b \min_a \sum \varepsilon_t^2(a,b) => \min_a \sum \varepsilon_t^2(a), \tag{6}$$

$$a(b) = \arg\min_{a} \sum_{t=t_0}^{T} \varepsilon_T^2(a,b), \quad \text{where} \quad b = 0, \tag{7}$$

$$\min_{b} \sum \varepsilon_t^2(a,b), b) \quad \text{where} \quad b = 0 \tag{8}$$

Risk function is calculated. *ARMA_MULTI* works with $m = 19$ separate factors (Ruseckaitė *et al.*, 1997; Ruseckaitė, 2000) and prognoses four separate classes: $\{a_i^{(j)}, \varepsilon_i^{(j)}\}$, $j = 1, \ldots, N$, where $N = 6$ is the number of classes.

The first four columns are used for patient's brain state: $p_1^{(i)} = \{0, 1\}$, where l-basic factor number, $l = 1, \ldots, 6$, o $i = 1, \ldots, 6$, and i – state number.

Factor can be:

- 0 when a patient is healthy;
- 1 when a patient has epilepsy.

The rest columns serve for features $p_1^{(i)} = \{-1, 0, 1\}$, where l – number, $l = 5, \ldots, 100$, o $i = 1, \ldots, 6$, and i – state number. Each of them can be: $-1, 0$ or 1 valued. *ARMA_MULTI* worked with linear visual perception test data.

They were not transformed in the parameter space. The four classes (brain states) were prognosed: Temporal epilepsy (ET); frontal epilepsy (EF); ocipital epilepsy (EO); parietal epilepsy (EP).

ARMA_MULTI was capable to present so called "likelihood" values, which described the potential diagnose.

Table 2

ARMA_MULTI working results

D	I	ET	EF	EO	EP
EO	ET	1.38e−01	–6.72e−02	–2.18e−02	–2.24e−01
EP	EP	2.39e−01	9.37e−02	2.25e−01	2.76e−01
ET	ET	1.393e−01	–2.38e−03	–2.17e−01	–4.07e−02
ET	EP	–3.66e−01	–1.58e−01	–9.75e−02	–1.234e−01
EF	EF	–2.74636e−02	2.7038e−01	1.10745e−01	1.59746e−01
HL	ET	7.57677e−02	–4.3702e−02	–8.9990e−02	9.32991e−02

The second column is for real diagnose, the third – for *ARMA_MULTI* interpretation. The rest columns shows the "likelihod" diagnose value. The Fig. 4 shows the *ARMA_MULTI* working results.

Here you can see that the class 1 (ET) – which has the biggest ammount of samples, is not recognized very well. Only 1/3$^{\text{rd}}$ of diagnoses are interpretted correctly.

According to the obtained data, it could be stated that *CHARADE* was the most effective method for VPD classification.

I have already mentioned that *ARMA_MULTI* is not so good as *CHARADE*, which created rules and regularities can better predict patients diagnose. I can state that AI methods are more productive in the concrete situation.

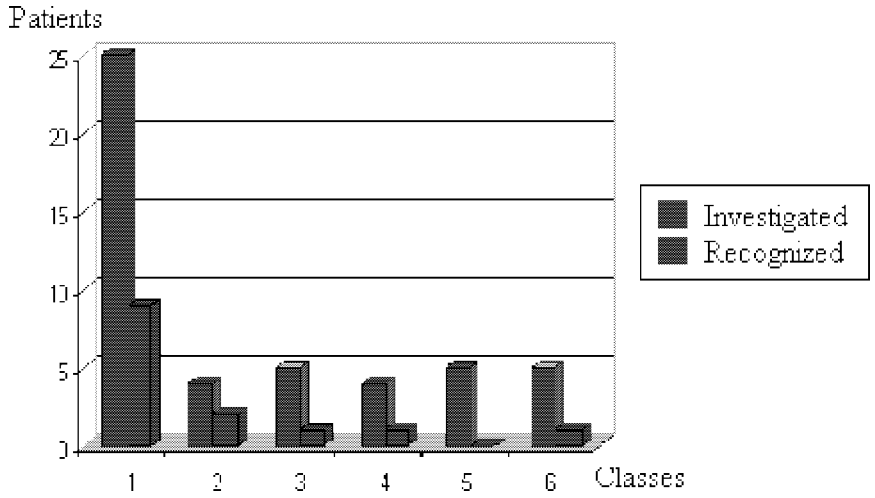

Fig. 4. *ARMA_MULTI* efectiveness.

Three possible reasons, which can tend a bad *ARMA_MULTI* prognosis, are listed below:

- not sufficient amount of patients' data for *ARMA_MULTI* acknowledgement;
- too many factors, used by *ARMA_MULTI*;
- diagnose values: patient is ill, or not. The values have a Boolean expression: $\{1, 0\}$.

CHARADE is being modified at the moment and is going to be used for secondary prognoses and for other data as well. I am planning to include digital EEG data for epilepsy prognosis as well.

The NN classifier was also ineffective and could not be used for epilepsy prediction.

It was decided to combine the *CHARADE* rules and other medical data.

EEG Analysis

The EEG is the most effective and useful method for epilepsy diagnosing. It was decided to combine *CHARADE* rules and digital EEG analysis for epilepsy diagnosis.

I worked with three groups of persons – epileptic persons (EPI), traumatic persons (MTR) and healthy people (HEALTHY). I tried to ascertain whether some EEG data regularity exists for those three groups.

Three EEG realizations of 16-channel digital EEG were used. Realizations were as follows: background, hyperventilation and light influence one.

The whole EEG process can be expressed as matrix, that contains $m = 16$ rows (channels) and N columns (signal lenghts in seconds).

$$Y = \begin{bmatrix} y_1^1 & y_1^2 & \dots & y_1^N \\ y_2^1 & y_2^2 & \dots & y_s^N \\ \vdots & \vdots & \dots & \vdots \\ y_m^1 & y_m^2 & \dots & y_m^N \end{bmatrix}, \quad m = 16, \tag{9}$$

where m – the number of channels; t – the realization lengths (time).

Every of 16^{th} processes could be presented as follows:

$$y_t = \left[y_l^t, y_l^t, \dots, y_L^T\right], \quad t = 1, \dots, N; l = 1, \dots, L = m. \tag{10}$$

The experiment was performed using special MATLAB software, which is very convenient for signal processing and has a lot of possibilities for data processing. Two ways of EEG processing were chosen: spectral and LPC (linear prediction coding) (Dženkis, Vatts, 1989) analysis.

Spectral EEG Analysis

The algorithm is presented below:

1. Three EEG realizations were analyzed for every of EEG 16 channels.
2. Those 16 channels were split to 15 equal parts along the realization length. The lengths of every part is $t = 3$ sec.
3. Fast Furje transformation was calculated for EEG data part, received in Step 2.

$$f(s) = \int f(x) \exp(-i2xs)\, \mathrm{d}x. \tag{11}$$

4. After that 15*16 dimensions signal was received (for every EEG data).
5. 16 spectral characteristics (maximums for frequencies and amplitudes) for three classes (EPI, MTR and HEALTHY) were calculated

$$f_i(s) = \frac{1}{N} \sum_{i=1}^{N=15} f_i(s). \tag{12}$$

6. Spectral maximums were calculated for every given EEG realization

$$s_{\max} = \arg\max f_i(s), \quad 0 \leqslant s \leqslant s_{\max}. \tag{13}$$

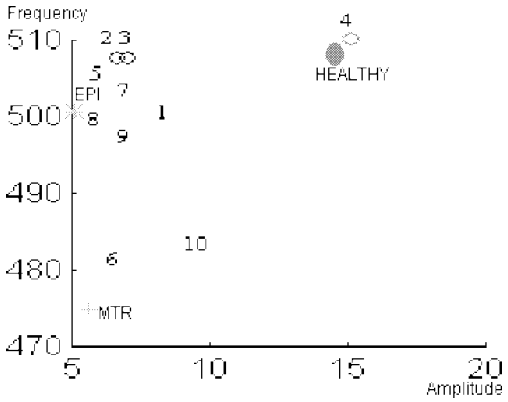

Fig. 5. Classification results for three classes.

30 persons' data were used for algorithm training and 10 patients' data – for algorithm testing. My task was to clarify, whether this algorithm can classify correctly persons' data according their spectral EEG characteristics. The Euclid's (Lukauskienė, Viliūnas, Gurevičius, 2000) classifier was chosen.

The classification results are presented, in the Fig. 5.

Table 3 shows the results for 10 persons according their spectral maximums for EEG background realization. These persons had the temporal lobe epilepsy. Seven of them were classified correctly, two of them – as MTR, and one – as HEALTHY.

EEG LPC Parameters Analysis

In order to solve the problem, the LPC method was chosen. It is also known as Durbin's method (Dzenkins, Vatts, 1998) and can formally be given as the following algorithm.

Table 3

EEG Interpretation after spectral analysis

Pat./Realization	Background	Light	Hipervent
Patient 1	EPI	MTR	–
Patient 2	EPI	EPI	EPI/MTR
Patient 3	EPI	MTR	MTR/EPI
Patient 4	HLT	–	–
Patient 5	EPI	EPI	–
Patient 6	MTR	EPI/MTR	EPI
Patient 7	EPI	EPI	EPI
Patient 8	EPI	EPI	–
Patient 9	EPI	MTR	MTR/EPI
Patient 10	MTR	MTR	EPI

1. The EEG process is a random one and can be described as follows:

$$X_t = -\sum_{i=1}^{p^{(1)}} a_i^{(1)} X_{t-i} + b^{(1)} v_t, \tag{14}$$

where $\theta = (p, b, a_1, \ldots, a_p)$, and $v_t \sim N(0,1)$ are independent random values.

2. While the EEG data are different for different brain lobes, it is possible to find the separate LPC parameters for them.

3. My task – to find the parameters a and b for classes $r = 3$, (EPI, MTR and HLT) which could describe the class of EEG data x_t and could classify it to one of the given classes, as follows:

$$\begin{aligned} &x_t \in \Omega_r, \quad (r = 1, 2, \ldots, M), \\ &x_t (t = 1, \ldots, n). \end{aligned} \tag{15}$$

4. The parameters a are calculated as the (16) and (17) expressions present:

$$\alpha_j^{(i)} = \alpha_j^{(i-1)} - k_i \alpha_{i-j}^{(i-1)}, \tag{16}$$

$$a_m = LPCparameters = \alpha_m^{(p)}, \quad 1 \leqslant m \leqslant p, p = 10. \tag{17}$$

The algorithm was trained within the data of three (EPI, MTR and HEALTHY) classes. LPC parameters were calculated for every process, and for every class. The Euclid's classifier was used for the algorithm efectiveness detection.

It was trained with the 40 persons data, and was tested with the 40 persons data as well.

The Fig. 6 shows the classification results. We see that about 80 percent were classified correctly.

It is possible to state that LPC analysis method is more effective than spectral analysis one.

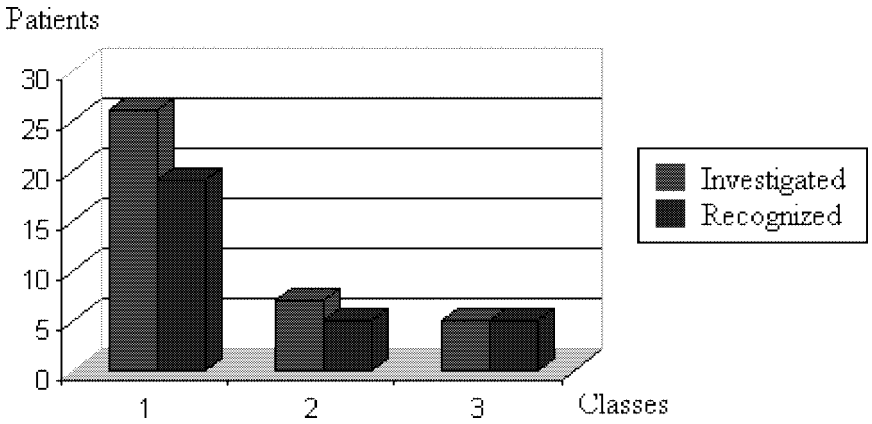

Fig. 6. LPC Classification results for three classes.

Conclusions

We have developed the computer system that encompasses together VP test procedure, symbolic learning algorithm and digital EEG processing methods.

Our machine learning sub-system was capable of extracting interesting dependencies that related VP test results to person's diagnosis. Even if induced rules show near perfect accuracy on the learning set examples additional data and experiences are required for being able to conclude that machine generated rule sets ate appropriate for computer aided diagnosing based on VP test.

The digital EEG analysis showed that, can be LPC methods could be used together with machine generated rule sets (*CHARADE*) for epilepsy prediction. Both combined methods showed the 80 percent efectiviness.

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Automatizuotas epilepsijos atpažinimas, remiantis regėjimo suvokimo testavimu bei skaitmenizuotomis EEG

Rasa RUSECKAITĖ

Daugiau nei vienas procentas viso pasaulio žmonių serga epilepsija. Tai labai sunki ir pavojinga liga, kurią labai svarbu diagnozuoti kuo greičiau. Šis strapsnis aprašo kompiuterizuotus metodus, skirtus automatizuotam epilepsijos atpažinimui. Tai dirbtinio intelekto metodai, skirti regos suvokimo testų analizei. Taip pat aprašomi skaitmenizuotų elektroencefalogramų (EEG) analizės metodai, gebantys pagreitinti epilepsijos atpažinimą.