Recognition of Epileptic Activity on the Basis of EEG Using Support Vector Machines

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***Abstract* - The electroencephalogram (EEG) of the person who suffers from epilepsy is characterized by the occasional spikes between seizures. They are not easy to detect even for clinicians. Therefore the automatic computerized methods are needed. The paper presents the solution to this problem by applying Support Vector Machine (SVM) network. The important stage of this approach includes the generation of the features on the basis of which SVM will recognize all spikes appearing in the registered EEG. The results of numerical experiments will be presented and discussed in the paper**

I. INTRODUCTION

The epilepsy is defined as a chronic brain disorder of various aetiologies characterized by recurrent seizures (ictal disturbances) due to the excessive discharge of cerebral neurons [2,3]. Between seizures, the EEG of subjects who suffers from epilepsy is characterized by the occasional inter-ictal activity in the form of so called spikes and wave complexes. A spike is a sudden burst of electrical activity lasting up to 70 ms. The sharp wave is sort of spike of longer duration, usually between 70ms and 200ms.

At the EEG recording of the suspected epileptic patient we almost always record the inter-ictal spikes. Only occasionally a seizure may occur directly at the hospital investigation and be recorded by EEG. Hence epilepsy is confirmed mainly on the basis of inter-ictal recordings found in EEG. Unfortunately the inter-ictal activity is usually relatively rare and may be missed by the clinicians, who check the recording of the suspected patient at the routine inspection. Therefore the need for an automated analysis systems, which can reliably identify spikes in the recorded EEG waveform and recognize between spiky and non-spiky types, are highly required.

This paper will present the solution of an automatic system for detecting inter-spike activity by applying the time and frequency analysis of the recorded EEG waveforms and using the Support Vector Machine (SVM) as the final recognizing system. The recognition of epileptic activity by SVM will use the features generated on the basis of EEG waveform analysis. The SVM network itself performs the separation of the data corresponding to spiky and non-spiky waveforms in this feature space for different types of registered EEG signals.

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II. GENERATION OF FEATURES

Fig. 1 presents the typical EEG recordings of different channels containing spikes and sharp waves. The spikes are visible in the first four channels as very quick sudden bursts of electrical activity of the brain. It should be noted that their magnitude as well as lasting time are patient dependent.

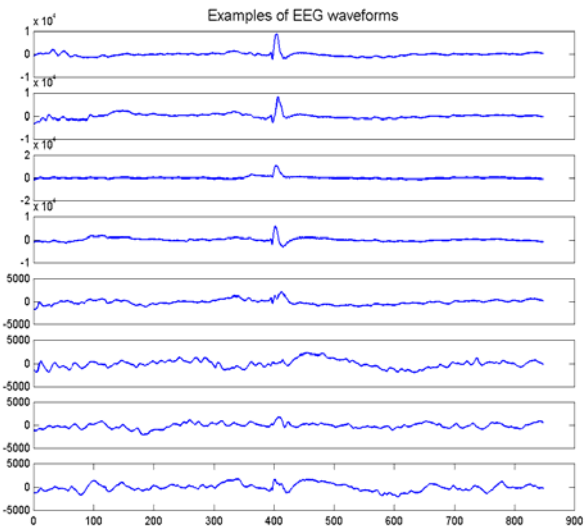

Fig. 1 The inter-ictal spikes visible in the excerpt of the EEG recording of the epileptic patient

To develop an automatic system for discovering the ictal spikes, we need an efficient feature extraction technique. The features should suppress the differences between the recorded EEG signals belonging to spiky class (or non-spiky – normal class) and enhance these differences for signals belonging to two different classes (spiky and non-spiky). In our work we will rely on the time and frequency dependent parameters [1,2,3], developed on the basis of the analysis of the recorded EEG waveforms.

A. *Time-domain features*

In the time domain analysis we determine the parameters associated with the speed of change of EEG waveform values v, i.e., slope $s=dv/dt$ and sharpness, defined as the second derivative $d=d^2v/dt^2$. Let us consider three consecutive points of EEG denoted by v_o, v_1 and v_2 . The slopes between them are equal s_0 and s_1 and defined on the difference basis. For these points we define the average slope between the points v_0 and v_2 as

$$s = \frac{|s_0| + |s_1|}{2} \quad (1)$$

Similarly the average sharpness d is expressed by

$$d = |s_1 - s_0| \quad (2)$$

Two next important time-domain parameters determined in this work are the mobility M and complexity C. They have been defined as [1,2]

$$M = \frac{1}{(\Delta t)^2} \frac{s_{av}^2}{v_{av}^2} \quad (3)$$

$$C = \frac{1}{(\Delta t)^2} \frac{(s_1 - s_o)^2}{s_{av}^2} - M \quad (4)$$

where $s_{av}^2 = \frac{s_0^2 + s_1^2}{2}$ and $v_{av}^2 = \frac{v_0^2 + v_1^2 + v_2^2}{2}$.

The features are associated with the maximal values of these four parameters defined above. In one second of EEG segment at N Hz of sampling frequency we get N-2 values of slope, sharpness, mobility and complexity, for which we find the maximum values s_{max}, d_{max}, M_{max} and C_{max}. We scale them with the appropriate normalization factor NF, and define the following features

- normalized maximum slope

$$sn_{max} = \frac{s_{max}}{NF_s} \quad (5)$$

- normalized maximum sharpness

$$dn_{max} = \frac{d_{max}}{NF_d} \quad (6)$$

- normalized maximum mobility

$$Mn_{max} = \frac{M_{max}}{NF_M} \quad (7)$$

- normalized maximum complexity

$$Cn_{max} = \frac{C_{max}}{NF_C} \quad (8)$$

The normalizing coefficients NF_s, NF_d, NF_M and NF_C have been determined in our work for each parameter as the average values in the actual one-second time segment.

B. *Frequency-domain features*

The next set of features has been obtained by using Fourier transform of the one-second segment. At applied N Hz sampling rate we get N/2 points of amplitude spectrum of each segment. To reduce this number we have represented them by an all pole AR model. The concept behind the AR model is the assumption that the sequence V=V(f) obtained from Fourier transformation of v(t) is the output of a linear system driven by a white noise. If the successive samples of V are denoted by V_k, we can estimate a sample V_k by the linearly weighted summation of the previous p sample values

$$\hat{V}_k = -\sum_{i=1}^{p} a_i V_{k-i} \quad (9)$$

where p is the model order and a_i are the AR coefficients used as the next features of the frequency representation. On the basis of previous works in this field [1] we have applied p=6 as the optimal AR model order. In this way the following features have been taken into account in our experiments: sn_{max}, dn_{max}, Mn_{max}, Cn_{max}, a_1, a_2, a_3, a_4, a_5, and a_6. All these coefficients have been normalized. The a_i parameters have been normalized by subtracting the mean value and dividing by standard deviation of the appropriate coefficient.

As a result in our numerical experiments we have applied 10 features forming the input vector to the neural classifier. Four of them result from time-domain representation and six are the AR parameters a_i following from frequency-domain representation of the EEG waveform. All of them have been generated for one-second segments of the registered curve. These features have been applied as the inputs to the Support Vector Machine, working in the classification mode.

III. SVM CLASSIFIER

Basically, the SVM [4,6,7] is a linear machine working in the high dimensional feature space formed by the nonlinear mapping of the *N*-dimensional input vector **x** into a *K*-dimensional feature space (K>N) through the use of a function $\varphi(\mathbf{x})$. The equation of the hyperplane separating two different classes is given by $\mathbf{w}^T \boldsymbol{\varphi}(\mathbf{x}) = \sum_{j=1}^{K} w_j \varphi_j(\mathbf{x}) + w_0 = 0$, where $\boldsymbol{\varphi}(\mathbf{x})$ is a K-dimensional vector and **w** – the weight vector of the network $\mathbf{w} = [w_1, ..., w_K]^T$. The learning problem of SVM is formulated as the task of separating learning vectors $\mathbf{x}_i$ into two classes ($d_i=1$ or $d_i=-1$) with maximal separation margin. The most distinctive fact about SVM is that the learning task is simplified to the quadratic programming by introducing the so called Lagrange multipliers α_i. All operations in learning and testing modes are done in SVM using so called kernel functions, satisfying the Mercer conditions [12]. The kernel is defined as $K(\mathbf{x}, \mathbf{x}_i) = \boldsymbol{\varphi}^T(\mathbf{x}_i)\boldsymbol{\varphi}(\mathbf{x})$. The most known kernels are radial Gaussian, polynomial, spline or sigmoidal functions [5,6].

The solution of the quadratic programming task is done with respect to the Lagrange multipliers. The output signal y(**x**) of the SVM network is determined as the function of kernels

$$y(\mathbf{x}) = \sum_{i=1}^{N_s} \alpha_{oi} d_i K(\mathbf{x}_{si}, \mathbf{x}) + w_o \quad (10)$$

and the explicit form of the nonlinear function $\varphi(\mathbf{x})$ is not needed to be known. In this equation index *s* points to the set of N_s support vectors, i.e. the learning vectors $\mathbf{x}_i$, for which the decision function $d_i\left(\sum_{j=1}^{K} w_j \varphi_j(\mathbf{x}_i) + w_0\right) \geq 1 - \xi_i$ ($\xi_i \geq 0$ - the slack variables) is fulfilled with the equality sign. The value of y(**x**) bigger than 0.5 is associated with 1 (membership of the particular class) and smaller than 0.5 with –1 (lack of membership). In our task the unity output signal of SVM has been associated with the spike, appearing in the analyzed period, and zero signal with no spike (the normal registered EEG waveform).

IV. RESULTS OF NUMERICAL EXPERIMENTS

The numerical experiments of detecting the inter-ictal spikes have been performed for the EEG recordings taken for five different patients. The EEG was sampled at N=256Hz with 8-bit accuracy. The data base was acquired in Banach Hospital in Warsaw, using 20 channel montage. In all cases the recordings have been made using the 10-20 international system of electrode placement. The length of measuring window applied in the work was equal 130 samples. The segments of EEG annotated by expert have been used in all experiments. They have been arranged in such a way that neighboring segments overlap with each others. All waveforms have been transformed into features, generated for one-second segments according to the procedure presented above. The typical values of chosen features corresponding to two types of waveforms: one corresponding to the epileptic patient (spiky - S) and one corresponding to the healthy subject (non-spiky – NS waveform) are presented in table 1.

TABLE 1 THE EXEMPLARY FEATURES CORRESPONDING TO SPIKY (S) AND NON-SPIKY (NS) EEG WAVEFORMS

	S	S	S	NS	NS	NS
sn_{max}	4,69	4,63	4,60	2,03	1,8432	1,80
dn_{max}	2,69	2,71	2,68	2,40	2,20	2,17
Mn_{max}	1,80	2,13	2,30	2,18	2,75	2,59
Cn_{max}	2,73	2,27	2,09	2,13	1,82	1,92
a_1	-0,70	-0,78	-0,70	0,14	-0,01	0,12
a_2	0,55	0,69	0,60	0,09	0,09	0,04
a_3	-0,64	-0,75	-0,66	-0,56	-0,71	-0,70
a_4	0,66	0,76	0,67	-0,08	0,03	-0,01
a_5	0,03	-0,07	0,01	0,34	0,27	0,38
a_6	-0,18	-0,11	-0,15	0,04	0,1020	0,21

There are visible differences between the epileptic and healthy patients for most of the parameters. Especially good separating abilities possess the feature sn_{max}, a_1, a_2, a_4 and a_5. The values depicted in Table 1 stand a very good prospect for efficient recognition between both types of patients by applying the neural network SVM classifier.

The Support Vector Machine has used in experiments the input vectors **x** composed of features generated in a way described in section 2 (ten features). We have applied the Gaussian kernel function of the parameters adjusted in additional runs of the program. As a result of such runs we have chosen the following parameter values: C=100 and $\sigma = 0.7$, found as the most optimal set of network parameters.

In the numerical experiments with SVM learning, we have applied so called cross-validation technique. The total set of data (23160 vectors) has been split into 10 equal size subsets, each containing the same proportion of healthy and spiky segments of EEG. Nine of subsets have been used in learning and the tenth one for testing. The process has been repeated so that each of 10 subsets act as the test sets in turn, while the other 9 subsets took common part in learning. The final classification performance is the average of all 10 set results. Thanks to application of cross-validation technique we remove the dependence on the choice of patterns for the test set. By the time of completing the procedure each pattern will have appeared once in the test set.

Table 2 presents the results of cross-validation in the form of absolute testing errors (number of misclassifications of spikes) obtained for all 10 runs of the procedure.

TABLE 2 THE ERRORS OF INTER-SPIKE RECOGNITION FOR 10 RUNS OF CROSS-VALIDATION ALGORITHM

Testing subset	Number of misclassifications
1	2
2	0
3	0
4	2
5	2
6	3
7	1
8	5
9	3
10	1
Total	19

As it is seen from the results, the total number of misclassifications was equal 19 for 23160 testing samples. The average error of recognition is on a very good level. The average rate of misclassifications of the spikes within the whole set of data was below 1%.

However it should be observed that the testing of the system has been done on the same EEG registered for the same patients that has been used previously in learning phase (different segments of data). The next set of experiments has been performed as the real life checking of the learned system in the on-line mode of EEG registration of the patients not taking part in learning. This time the EEG waveform has been split into separate segments and each segment has been checked for the presence of spikes. The results of automatic system have been compared with the expert opinion. For the total of 250 checked segments the percentage of misclassification was equal 8.24%. This rate of error may be further improved by extending the number of patients and EEG waveforms used in the learning phase.

V. CONCLUSIONS

The results presented in the paper have confirmed, that Support Vector Machine combined with time- and frequency-domain representation of the EEG waveform, proposed in the paper is a good solution to the automatic identification of the inter-ictal spikes for the confirmation of the epileptic type of the EEG waveforms. The method may find practical application in developing the automatic system for recognition between healthy and epileptic patients on the basis of registered EEG waveforms. --++In comparison to other automatic methods applying different neural solutions [1,8,9], the recognition error is smaller. For example the identification of spikes based on the radial basis function (RBF) networks presented in [1] produces the results with an error in the range of 5-10%, much higher than the similar figures presented in this paper. However it should be noted, that we have tested only five patients, so the given figures may be not fully representative for large data sets, covering many patients, of different waveforms, recorded at different conditions.

REFERENCES

[1] L. Tarassenko, Y. U. Khan, M. R. Holt, Identification of inter-ictal spikes in the EEG using neural network analysis, IEE Proceedings Sci. Meas. Techn., vol. 145, 1998, pp. 270-278

[2] N. Hjorth, The physical significance of time-domain descriptors in EEG analysis, Electroencephalogr. Clin. Neurophysiol., 1973, vol. 34, pp. 306-310

[3] M. Walmsley, On the normalized slope descriptor method of quantifying EEG, IEEE Trans. Biomed. Eng., vol. 31, 1984, pp. 720-723

[4] V. Vapnik, Statistical Learning Theory, Wiley, N.Y., 1998

[5] J. Platt, Fast training of SVM using sequential optimization, (in "Advances in kernel methods – support vector learning", B. Scholkopf, C. Burges, A. Smola eds), MIT Press, Cambridge, 1998, pp. 185-208

[6] C. Burges, "A tutorial on support vector machines for pattern recognition", (in "Knowledge discovery and data mining ", ed. Usama Fayyad), Kluwer, 2000, pp. 1-43

[7] S. Haykin, Neural Networks, Comprehensive Foundation, Prentice Hall, 2000, New Jersey

[8] C. Pang, A. Upton, G. Shine, M. Kamath, A comparison of algorithms for detection of spikes in the encephalogram, IEEE Trans. On Biomedical Eng., 2003, vol. 50, pp. 521 – 526

[9] W. Webber, R. Lesser, R. Richardson, K. Wilson, An approach to seizure detection using ANN, Electroenceph. Clin. Neurophysiol., 1996, vol. 98, pp. 250-272

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