Adaptive Segmentation Optimization for Sleep Spindle Detector

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Abstract. Segmentation is a crucial part of the signal processing as it has a significant influence on further analysis quality. Adaptive segmentation based on sliding windows is relatively simple, works quite good and can work online. It has however many tunable parameters whose proper values depend on the task and signal type. The paper proposes a method of defining optimal parameters for detection of sleep spindles in electroencephalogram. Segmentation algorithm based on Varri method was utilized. Fitness function was proposed for estimation of agreement between the segmentation result and borders of the target classification. Particle swarm optimization was used to find optimal parameters. On the data of 11 insomniac subjects the method reached 28 % improvement in comparison to the baseline method using default parameters.

Keywords: Sleep EEG · Adaptive segmentation · Optimization · Sleep spindles · Particle swarm optimization

1 Introduction

Signal segmentation is an important step of many signal processing applications. The task of signal segmentation consists of splitting a non-stationary signal into quasi-stationary epochs. This is particularly important and frequently used for long-term electroencephalogram (EEG) analysis. One of the typical problems in EEG analysis is detection of important EEG patterns like epileptic seizures or sleep spindles. Typically, pattern classification is applied on features extracted from short segments [1,13,18,21]. Therefore, the segmentation directly affects the quality of further signal analysis. Segment borders should correspond to the borders of the EEG patterns detected by expert as much as possible, otherwise it would be difficult for the classifier to detect that pattern.

There are two types of segmentation: constant and adaptive. Constant segmentation divides the signal into pieces with the same length, whereas adaptive

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one adjusts the segment size to the signal change points. The paper focuses on methods of adaptive segmentation. Adaptive segmentation approaches divide the signal into segments within which the statistics do not change too much. There is a huge family of algorithms based on calculating metrics using sliding window technique. The most popular algorithm is named after its author Alpo Värri [19] and it is based on computing frequency and amplitude measures in two successive sliding windows. A more complex algorithm uses a fractal dimension of the signal in a sliding window as a feature for segmentation [3,5]. Other methods utilize non-linear energy operator [2,10]. These methods have linear complexity, can work online and are very suitable for long-term signal analysis. Other approaches are based on the signal prediction. If a mismatch between the prediction and the original signal is higher than a defined threshold then it suggests a potential segment boundary. Adaptive approaches have many advantages to the constant ones, however the constant segmentation is usually used in patterns detection because of its easy implementation [9].

The sleep spindle can be characterized as sinusoidal wave with 9–16 Hz frequency and 0.5–3 s duration [7]. Sleep spindles play a significant role in modern neuroscience. Along with K-complex they hallmark the second non-rapid eye movement (NREM) sleep stage [7], but can occur in 3rd or 4th NREM sleep stage (according to Rechtschaffen-Kales staging methodology [17]). Moreover, they are connected with cognitive capabilities such a memory consolidation [7,20]. Also the density of sleep spindles (number of events per minute) is an important index in studies of brain and psychological disorders like schizophrenia [6,20], epilepsy [16], and autism [15].

In the most real bio-medical signals it is not an easy task to define clearly the borders between patterns, sometimes they are just unknown. Therefore the majority of studies uses the simulated signals such as [4,14] for segmentation results evaluation. There are two possibilities to measure goodness of segmentation: evaluation based on segments [2] and evaluation based on segment boundaries positions [8]. The sleep spindles are defined by their boundaries and the latter type of evaluation is more natural. It has an intuitively clear way of calculation of goodness of fit using statistical measures of the performance of a binary classification test such as F1 score and Matthews correlation coefficient.

This paper is devoted to developing a method of optimization of adaptive segmentation in sleep spindle detection task. For that purpose a suitable fitness function was proposed, it takes into consideration requirements on the segmentation results. The method is tested on the real EEG data of insomniac subjects. An analysis of parameters optimized on subsets of those data is provided.

2 Materials and Methods

2.1 Dataset

To evaluate the method sufficiently, whole night polysomnography data of 11 patients with main diagnosis of non-organic insomnia (5 women and 6 men) were measured. The age of subjects is between 29 and 53, average age is 41.5.

Data was recorded in National Institute of Mental Health, Prague. Sleep stages were evaluated by trained clinician. EEG was recorded with C3 and C4 against Cz electrodes, the sampling rate is 250 Hz. For future analysis the mean value of channel C3-Cz and C4-Cz was utilized.

In this way, a dataset was obtained, which is large enough for the our particular task of evaluation of segmentation results. Concretely, total analyzed time was 26 h and 4 min, which included 3167 sleep spindles corresponding to 6334 segment borders. Spindles were found manually for these segments by expert. It should be noted, that only parts of the signal with NREM 2 sleep stage were used in the paper.

2.2 Method Overview

The method scheme is introduced on Fig. 1. In the first step the raw signal was filtered using band-pass filter in range 9–16 Hz. Further, the entire dataset was divided into training and validation subsets. Optimization was performed on the training set using particle swarm optimization (PSO). In order to compute the fitness value, the candidate parameters are used in the segmentation described in the Sect. 2.3 and the results are evaluated based on agreement with manually labeled spindles boundaries. The fitness function measures how close the obtained segmentation and the expert signal labels are (see Sect. 2.5).

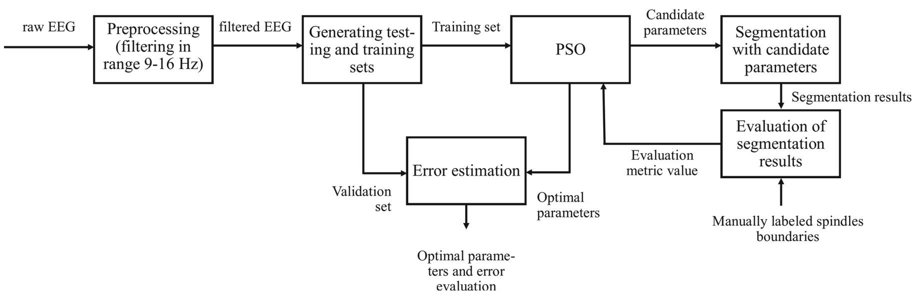

Fig. 1. Method overview.

2.3 Segmentation

Prior to the segmentation itself, appropriate preprocessing was applied to the signal. It was filtered in frequency range associated with sleep spindles (9–16 Hz). Further, segment boundaries are detected by detecting changes in the signal using a sliding window method [14]. In this step two successive windows are sliding along the signal and for each window a metric is computed. The Varri's method [14,19] is used to compute such metric.

Let $[x_1, x_2, x_3, \ldots, x_{N-1}, x_N]$ be the signal of length N and let $W_i = [x_i, x_i + 1, x_i + 2, \ldots, x_{i+L-1}]$ be a window of length L starting at each sample of the signal. The frequency measure for window W_i is defined as

$$F(W_i) = \sum_{j=1}^{L-1} |x_{i+j} - x_{i+j-1}| \tag{1}$$

and the amplitude measure is

$$A(W_i) = \sum_{j=1}^{L} |x_{i+j-1}|. \tag{2}$$

A function M evaluates a window W_i using a combination of the frequency and amplitude measures:

$$M(W_i) = k_1 F(W_i) + k_2 A(W_i), \tag{3}$$

where k_1 and k_2 are coefficients weighting the amplitude and frequency components. Those coefficient are parameters of the segmentation that are optimized in our experiments. Further, one window is evaluated by M every K steps so that one obtains $J + 1$ values

$$[M(W_1), M(W_{1+K}), M(W_{1+2K}), \ldots, M(W_{1+JK})]. \tag{4}$$

The step K between two windows is another parameter of the adaptive segmentation to be optimized. The segment border detection is based on evaluation of the absolute difference between two successive windows j and $j + 1$:

$$G_j = |M(W_{1+jK}) - M(W_{1+(j-1)K})|, \tag{5}$$

where $j \in \{1, \ldots, J\}$. Thus, a sequence of J values for all $J + 1$ windows is obtained:

$$G = [G_1, G_2, ..G_J], \tag{6}$$

which reflects the change of statistical properties of the signal. G is further normalized by division of each G_j by $\max_j G_j$. The border detection is performed by thresholding the G, detecting local maxima, and simultaneously satisfying two other constraints. The distance between the peaks must be higher th the window size L and the amplitude of the peak must be higher than standard deviation of the thresholded signal. Adaptive threshold is used, which is obtained as a moving average value of the G sequence multiplied by threshold coefficient c. The size of the moving average window and the threshold coefficient are also parameters to be optimized. In Fig. 2 one can see an example of the raw and the filtered signals, G sequence and corresponding segmentation.

The window length parameter L is important. It should be large enough to detect difference in the two windows at all, but it should not be too large, which could avoid to detect some borders by capturing lot of real segments

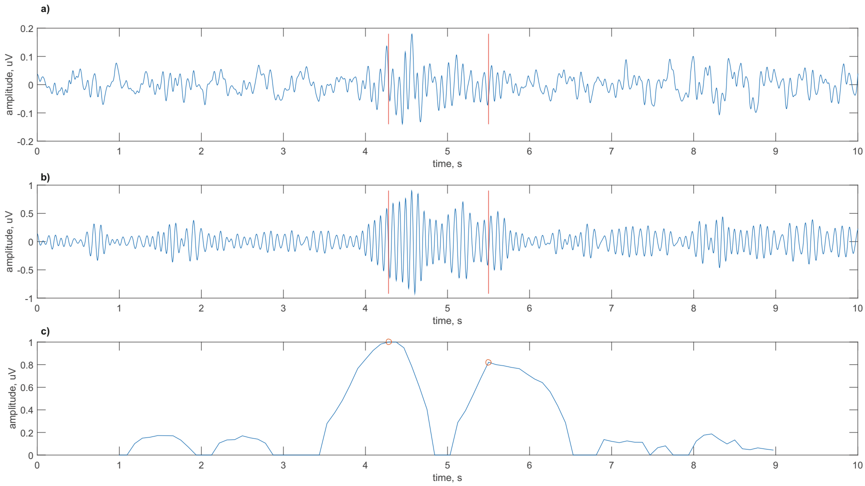

Fig. 2. Segmentation process. From top to bottom: (a) original raw EEG data; (b) signal filtered in range 9–16 Hz; (c) G function based on Varri metric of filtered signal with labeled as red circles maximum of the function. Red lines show the segmentation obtained using G function. (Color figure online)

in one window. The proper window length can be chosen using energy of the G sequence. Ideally, G function with the proper window size should be highly above zero close to segment boundaries and almost zero elsewhere. This property can be evaluated using energy value. For an improper window length, G function has more energy compared to a proper window length. Thus, for an analyzing window with length L, the energy of the G sequence can be calculated as its mean squared value:

$$E = \frac{\sum_{j=1}^{J} {G_j}^2}{J}, \tag{7}$$

where J is the length of the G sequence. A proper window length should correspond to the minimum of the energy curve. In the paper energy of the corresponding G function was calculated for optimal segmentation and segmentation with default parameters.

2.4 Optimization Using Particle Swarms

The six parameters of the adaptive segmentation defined above were optimized by the particle swarm optimization (PSO) method. It is one of optimization methods developed for finding a global optimum of some nonlinear function [11]. It has been inspired by social behavior of birds and fish. The method applies the approach of problem solving in groups. Each solution consists of a set of parameters and represents a position in multidimensional space. In continuous PSO, the solutions move in the search space in a swarm-like group. In the binary

PSO, the solutions are binary vectors and the optimization process has rather a socio-psychological metaphor [12].

The main entity of the algorithm is a particle. Each particle consists of $\mathbf{s}_i, \mathbf{v}_i, \mathbf{s}_i^P, \mathbf{s}_i^G$, where $\mathbf{s}_i$ is a candidate solution consisting of the six parameters of the adaptive segmentation, $\mathbf{s}_i^P$ is the best so far solution found by ith particle and represents individual experience. $\mathbf{s}_i^G$ is the best solution so far found by a predefined neighborhood of ith particle (subset of the whole swarm) and represents the social knowledge.

Although the ring lattice sociometry is often used, we use another common setting called gBest topology, in which the neighborhood is the whole swarm for all particles. The solution vectors are usually called position, because of analogy between position in the search space and position of social animals. The velocity vector $\mathbf{v}_i$ represents the difference between new and actual position of a particle i and is used for the position update.

First, values of $\mathbf{s}_i$ and $\mathbf{v}_i$ are initialized randomly. At each iteration, the memories $\mathbf{s}_i^P$ and $\mathbf{s}_i^G$ are updated according to the cost values and new velocities are computed. Finally, the position update is performed. In the original version of the PSO, the velocity update is accomplished by the following equation:

$$\mathbf{v}_{i(t+1)} = \omega \mathbf{v}_{i(t)} + \varphi_1 \mathbf{R}_1 \big(\mathbf{s}_i^P{}_{(t)} - \mathbf{s}_{i(t)}\big) + \varphi_2 \mathbf{R}_2 \big(\mathbf{s}_i^G{}_{(t)} - \mathbf{s}_{i(t)}\big), \tag{8}$$

where the symbols $\mathbf{R}_1$ and $\mathbf{R}_2$ represent the diagonal matrices with random diagonal elements drawn from a uniform distribution between 0 and 1. The parameters φ_1 and φ_2 are scalar constants that weight influence of particles' own experience and the social knowledge. The parameter ω is called inertia weight and its behavior determines the character of the search. Further, new candidate solutions (new positions) are updated. For continuous optimization, the position update is simple:

$$\mathbf{s}_{i(t+1)} = \mathbf{s}_{i(t)} + \mathbf{v}_{i(t+1)}. \tag{9}$$

At each step, the PSO algorithm modifies the distance that each particle moves on each dimension. Changes in the velocity are stochastic, and it can cause an undesirable expansion of particles trajectory into wider and wider cycles [12]. One solution is to implement boundaries for the velocity. If any component of $\mathbf{v}_i$, v_i^a is lower than $-v_{max}^a$ or greater than $+v_{max}^a$, its value is replaced by $-v_{max}^a$ or $+v_{max}^a$, respectively. Note that there is different maximum velocities for different components of the velocity vectors. The maximum velocity was set as the range of the search space in the particular component.

Finally, a constraint handling technique was used to keep the parameter values within their feasible range. If any component of the position vector gets out of the range, it is re-initiated on the border of the range and the corresponding component of the velocity is inverted. Thus, the particles are repelled from the constraint barrier.

Within the experiments, we used the following setting for PSO parameters. The weight parameters $\varphi_1 = \varphi_2 = 2.1$, the inertia was linearly decreasing from

0.6 to 0.3, swarm size was 25 and the number of iterations was 100. Those parameters were not tuned as they correspond to typical and most common setting in literature.

2.5 Fitness Function

In the paper the real EEG data with manually labeled sleep spindles were used. It could be taken as the target segmentation, but the segment boundaries are not always so unambiguous. For this reason instead of real borders as a gold standard segmentation we used set of ranges where spindle border could occur like it was in [8]. Each range is neighborhood of the real spindle border of size 0.125 s, the size of the neighborhood was chosen empirically. The minimal length of spindle is 0.5 s, so the ranges do not overlap.

Since the target segmentation is determined, the true positives (TP) could be defined as number of ranges where there is at least one of found segmentation borders and false negatives (FN) as number of ranges where there is no segmentation borders. Sum of TP and FN equals the number of ranges in the target segmentation.

Moreover, spindles are not distributed equally in the whole signal. So, it can happen that segmentation algorithm finds additional borders, but it could be connected with signal change because of other processes. Those false positive however do not matter if non-spindle segments are long enough. Assuming that segment is a signal part between two successive borders and minimal length of the segment equals the minimal spindle length (0.5 s), penalty value (PV) has been introduced and it equals the number of segments shorter than the minimal length. TP, FN and PV examples are presented on Fig. 3.

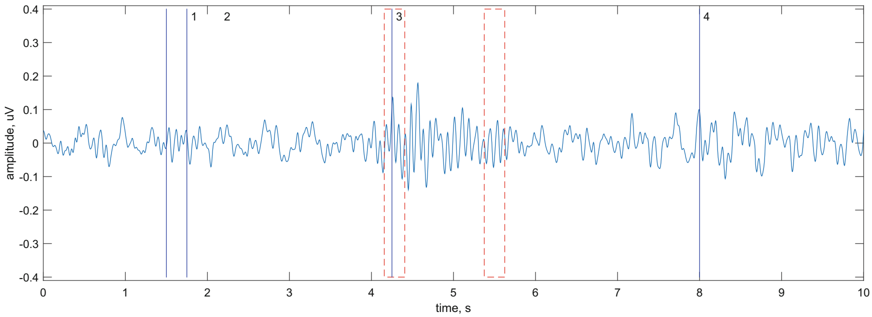

Fig. 3. Examples of TP, FN and PV. The red rectangles represent the ranges where the real spindle borders occur, the blue lines are the result of segmentation. Line number 3 represents TP and absence of any found borders in the second range points on FN. Distance between lines 1 and 2 is less than 0.5 s which increases PV by 1 point. And line number 4 stands further than 0.5 s from other borders, it does not change PV value. (Color figure online)

Aggregating all those requirements on the result of segmentation, fitness function (FF) is defined as:

$$\mathrm{FF} = \frac{2TP}{2TP + FN + PV}. \tag{10}$$

The FF aggregates TP, FN and PV by analogy with f-measure in statistical analysis of binary classification and measures an agreement with expert segmentation on spindles and non-spindles segments. It varies from 0 when there is empty TP set to 1 where there are no FN and PV.

3 Empirical Results

3.1 Experimental Settings

For the experimental results data of 11 subjects was used. The data was divided into 5 folds, each fold corresponds to the data of 2 or 3 subjects. Optimization of parameters described in Table 1 was tested by leave-one-out cross validation scheme. This means that the optimization procedure was repeated for each fold as a validation set and all the remaining folds as a training data. The optimal parameters and their performance values were obtained 5 times, i.e. one for each fold.

3.2 Results

The default and optimized parameter values and their feasible ranges are summarized in Table 1. The FF values averaged over the cross-validation folds are summarized in Table 2. In experiment 1, the segmentation using the default parameters described in the second column of Table 1 was applied to the entire dataset and mean value of FF function was 0.51. On the other hand, the mean FF value of optimized solutions (obtained using cross validation) was 0.79. The FF value is increased by 28 %. The mean optimized values and their standard deviations computed over cross-validation results can be found in the 4th column of the Table 1. Some parameters have quite wide standard deviation of their optimized values caused by multiple optima. For an easy examination of this, one can see the scatter plot of the optimized values of parameters on Fig. 4, where each dot corresponds to one run in one cross-validation fold.

Some other interesting interpretation of the optimization results can be made. At first, the optimized value of the window size is around 0.48 s. This value is very close to a minimal expected length of the spindle.

An obvious question is, if it would be sufficient to optimize only the window size and let all the other parameters default. The comparison is made in Table 2. In experiment 3, adaptive segmentation with the window size $L = 0.48$ s, but all the other parameters default, was used. The average fitness value equals to 0.72, which is outperformed by the fully optimized adaptive segmentation and thus it makes sense to optimize all the parameters.

Table 1. Summary of parameters of the adaptive segmentation, their default values, range and optimized value

Parameter	Default	Range	Optimized
Window length (seconds)	1	$\langle 0.25, 3\rangle$	0.48 ± 0.01
Step K (signal samples)	24	$\langle 5, 56\rangle$	5.1 ± 0.1
Threshold window (G sequence samples)	5	$\langle 2, 20\rangle$	5.16 ± 3.67
Threshold coefficient	1	$\langle 0, 1\rangle$	0.52 ± 0.56
k1	1	$\langle -100, 100\rangle$	-13.52 ± 17.27
k2	7	$\langle -100, 100\rangle$	-21.8 ± 84.96

Table 2. Summary of experiments and average fitness function values

Experiment	Approach	FF value
1	Adaptive, default	0.51
2	Adaptive optimized	0.79
3	Adaptive, L=0.48, other parameters default	0.72
4	Constant, L=1	0.41
5	Constant, L=0.48	0.67

A similar setting, but for constant segmentation, was performed in experiments 4 and 5, where a constant segmentation with $L = 1$ obviously leads to the worst result ($FF = 0.41$) and increases significantly to $FF = 0.67$ if the optimized window size $L = 0.48$ s is used. Nevertheless, the adaptive segmentation with all parameters optimized simultaneously is still much better choice. This conclusion correspond to the difference of energy of G sequence defined in Eq. 7. While in experiment 1, the energy is 0.056, in experiment 2 it is 0.037, which confirms that the window size 0.48 s is better choice for the segmentation.

Since adaptive threshold was used in the presented method, there are two parameters representing it. The threshold window size is a parameter of moving average filter of the G function and the threshold coefficient which scales the threshold relatively to standard deviation of the G sequence. In Fig. 4, one can see a strong interaction between threshold coefficient and the threshold window causing two different local optima. First one is that the coefficient is very close to 0 and the window size is wider than 5 s. It gives no threshold and local peaks are looking in the function G. The second optimum is very close to 1 but the threshold window is quite narrow (about 2.17 ± 0.15 s). In this case, the adaptive threshold looks like the G function and only the highest peaks are above the threshold.

Concerning the parameters k_1 and k_2, there is a tendency that absolute value of k_2 should be greater than absolute value of k_1 in average on 62.17 ± 24. This can be partly caused by the fact that the band-pass filtering was used for

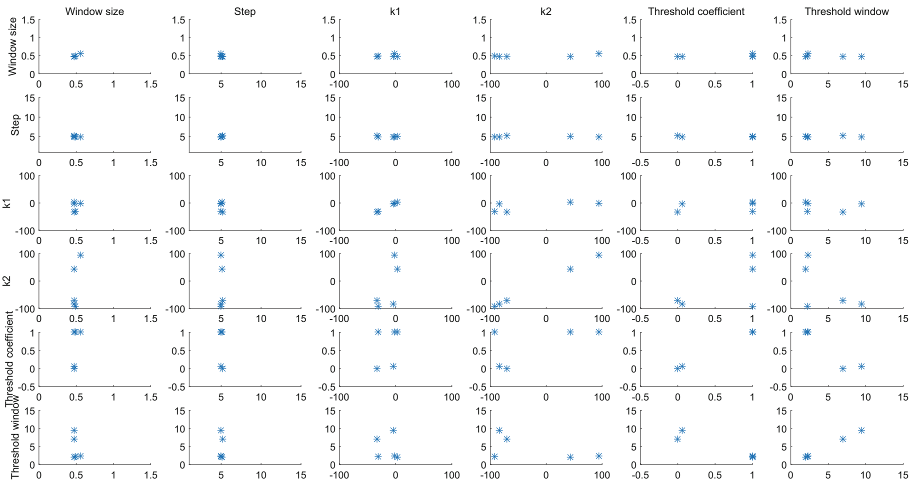

Fig. 4. Optimal parameters obtained in cross validation. Each figure represented distribution of one parameter against the other.

preprocessing, which reduces the relative importance of the frequency measure term.

The optimized value of the window step K was about 5 samples, which is its minimal admissible value. That means that the point of the signal is tested for being a segment border every 5 steps.

It should be noticed that the other important segmentation is an execution time and space complexity, which are directly influenced by the window size and the step. The smaller values of these parameters lead to the higher execution duration and the biggest memory allocation. This aspect is however not considered in our experiments and the optimization does not take the temporal and space complexity into account. Since the swarm size was set to 20 and the number of iterations was 150, FF evaluation (segmentation and evaluation of the results) is performed 20*150 times in one run of PSO, which can make the method time consuming and it could be worth to use some additional penalization of candidate solutions with high complexity of FF evaluation.

4 Conclusion and Discussion

The method to optimize adaptive segmentation for the sleep spindle detection task was presented in the paper. The method is based on the PSO optimization algorithm and maximizes agreement measure between the results of segmentation and manually labeled spindles in the real EEG data. By the cross-validation technique it was shown that using optimized parameters give 28 % higher agreement value than default ones. Obtained optimal parameters were analyzed and the optimal size of a sliding window was found and equals to 0.48. An energy of G sequence was compared for the segmentation with different window size and a reduction of the energy for optimized value against the default one was observed. This points out the proper window size for the spindle segmentation task. It turns out that using that window might not require the threshold and that it leads to increase of the execution time. In the Varri metric it was proved that impact of amplitude measure should be greater than impact of frequency measure.

Future work will be dedicated to the research of the parameters: stability investigation, looking for other minimums of the function and connected parameter clusters, patterns in data. The question about optimal parameters which do not lead to the time and space consuming segmentation process is still open and extended parameters analysis could help with that issue.

In future, the impact of the method for classification of the sleep spindles and its impact on the classification performance will be focused. In fact, it is possible to optimize segmentation using the misclassification rate. Besides the sleep spindles there are another interesting EEG patterns such as K-complexes and proposed method could be applied for the automatic identification of others EEG patterns.

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