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# Marking stages of REM and non-REM sleep using recurrent analysis

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***Abstract.*** The *purpose* of this study is to develop a simple technique for labeling sleep stages according to EEG data obtained from half-somnography recordings. To test the work of the method, it will be applied to three groups of subjects: conditionally healthy, patients with Parkinson's disease, patients with sleep apnea. *Methods.* In this work, to recognize sleep stages, we use the calculation of a recurrent indicator and its subsequent assessment. It is shown that the stages of REM (Rapid Eye Movement) and non-REM sleep demonstrate different values of the recurrent index. *Results.* Depending on the range in which the recurrent indicator falls, the stages of REM and non-REM sleep were determined for the subjects, according to their nightly polysomnographic records. For three groups of subjects, the average knowledge of the accuracy of the method was calculated, which for all groups exceeded 72.5%. *Conclusion.* It is shown that on the basis of recurrent analysis it is possible to create a simple and effective method for recognizing sleep stages. For patients with apnea, the average accuracy of the method is higher than for apparently healthy subjects, for whom, in turn, this value was higher than for patients with Parkinson's disease. This can be explained by the fact that the variability in the group of statistical characteristics of sleep stages in patients with apnea is lower, and in patients with Parkinson's disease is higher, compared with apparently healthy subjects.

***Keywords***: recurrent analysis, polysomnography, electroencephalography, sleep stages, automatic markup.

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## Introduction

This paper presents a method for automatically marking sleep stages by calculating recurrent indicators and their subsequent analysis. The problem of automating sleep marking is currently acute for sleep specialists [1]. Due to the large amount of data, this task is not trivial, especially considering that polysomnographic records are usually made two nights in a row and it is necessary to analyze both records [2]. In this regard, recurrent analysis seems to be a good

method for marking up data, since the method itself is easy to implement and does not require a large number of complex calculations [3]. If the method shows good accuracy and low machine time consumption, you can use it to quickly process nighttime sleep data and highlight sleep stages in real time.

The method is based on the calculation of recurrent indicators in small time windows. According to the dynamics of the recurrent indicator, it is possible to determine the stages of non-REM and REM sleep, allowing you to record a hypnogram (a graphical representation of the stages of sleep). The method was tested on three groups of subjects: conditionally healthy, patients with Parkinson's disease and patients with nocturnal apnea.

The purpose of this study is to develop a method for marking sleep stages based on recurrent analysis.

## 1. Methods

**1.1. Description of a neurophysiological experiment.** The subjects voluntarily participated in the experiment on a free basis. All subjects signed an informed consent to participate in the clinical trial, received all necessary clarifications about the study and agreed to the subsequent publication of the results of the study. The collected experimental data were processed taking into account the confidentiality and anonymity of the study participants. All procedures performed in human studies were consistent with the Helsinki Declaration of 1964 and its later amendments. All clinical data and design of the clinical trial have been approved by the local research ethics committee.

Our study included data from 32 subjects over the age of 18, divided into three groups. The group of conditionally healthy subjects (group number 1) included practically healthy study participants ($N = 14$, average age $46.7 \pm 19.5$ years, median age 40 years, male-female ratio 9/5). The group of patients with Parkinson's disease (group number 2) included patients with this disease ($N = 8$, average age $57.0 \pm 12.3$ years, median age 56 years, male-female ratio 5/3). The group of patients with apnea (group number 3) included persons with nocturnal respiratory failure in the form of obstructive sleep apnea syndrome (OAS) ($N = 10$, average age $54.0 \pm 17.1$ years, median age 46 years, male-female ratio 6/4). Each subject participated in a polysomnographic (PSG) study twice with an interval of 1-3 nights in a specially equipped sleep laboratory. The sleep duration was 6 to 9 hours, from 21:30 to 23:30 to the usual wake-up time.

The polysomnography recording included an electrocardiogram (ECG), respiratory function signals, oculography (OCG), electromyogram (EMG) and six electroencephalogram (EEG) signals recorded during a night's sleep. The ECG signal was recorded in standard lead I according to Einthoven. Respiratory signals were recorded using an oronasal flow temperature sensor and a snoring sensor. EMG signals were recorded on the patient's chin, right forearm and left shin. The OCG signals included recordings of horizontal and vertical eye movements.

EEG signals were recorded in 6 standard leads according to the scheme 10-20. The following channels were used: O1, O2, T3, T4, Fp1, Fp2. The EEG signals were filtered with a bandwidth of 0.1...40 Hz and sampled at a frequency of 500 Hz and $\Delta t = 0.002$ s. The recording of each EEG channel can be considered as a separate one-dimensional signal $x(t_i)$.

All PSG were tested by a certified sleep medicine specialist in order to stage a night's sleep. Sleep staging was carried out according to standard epochs (30-second recording segments). Any dream begins with the waking stage, characterized by alpha waves. If the activity of the alpha rhythm occupies more than 50% of the epoch, then this epoch is called the waking state. The greatest power of the alpha rhythm is observed in the occipital leads (O1, O2). The first stage

(N1 of non-REM sleep) is characterized by a decrease in the amplitude of the waves and the appearance of a visually pronounced theta rhythm, observed in all leads in approximately the same way. The second stage (N2) begins with the appearance of K-complexes and characteristic sleep spindles. The third stage (N3) of sleep is characterized by powerful slow-wave activity and the development of pronounced delta waves. Sometimes the fourth stage of sleep is distinguished, characterized by a further increase in the amplitude of delta activity, which is best visualized in the frontal leads (Fp1, Fp2). The third and fourth stages of sleep are usually considered as a single block. REM sleep is characterized by a low amplitude mixed frequency without K-complexes and carotid spindles, low muscle tone of the chin (EMG of the chin forms an isoline) with simultaneous rapid movements of the eyeballs and so-called mirror waves on electrooculography (EOG).

**1.2. Recurrent analysis.** One of the methods of nonlinear dynamics used to analyze various data is recurrent analysis, which allows you to establish relationships and correlations between signals in complex distributed systems [4]. This method has found application in a wide range of tasks for processing complex signals of various nature [5]. The calculation algorithm itself is characterized by the simplicity of [6]. This makes it promising for working with big data and real-time signal processing. Consider the signal $x(t)$, the values of which are known at time points $t_i$, where $i = 1, ..., n$. You can build a recurrent matrix for it according to the following rule:

$$R_{i,j} = \theta(\varepsilon - \|x(t_i) - x(t_j)\|), \tag{1}$$

where $R_{i,j}$ is an element of the recurrent matrix for the signal $x$; $t_i$ and $t_j$ are the time points $t$; $\varepsilon$ is an empirically determined threshold value that ensures the necessary accuracy of the method; $\theta$ is Heaviside function, which takes a zero value for negative arguments and a single value for non-negative ones. Thus, if at time $t_j$ the signal returned to $\varepsilon$ neighborhood of the signal value at time $t_i$, then there will be 1 in the recurrent matrix.

To estimate the number of repetitions in the signal, a recurrent indicator is used, which is the sum of all non-zero values of the recurrent matrix normalized by its size [7]. Such an

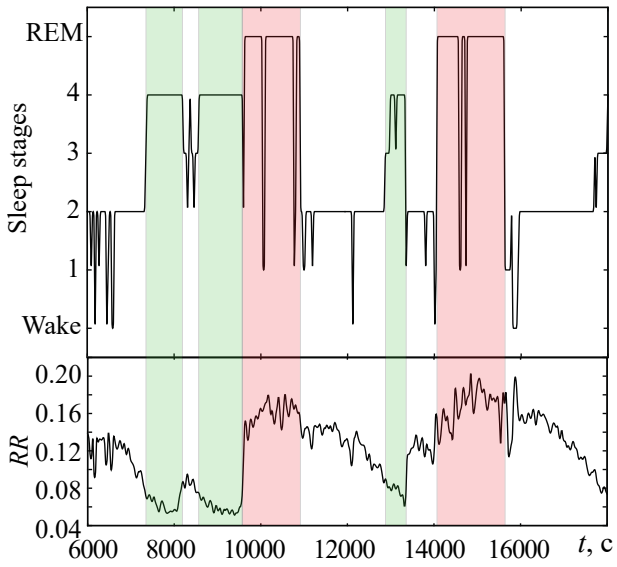


Fig. 1. Hypnogram for one of the subjects, which shows the cases of awakening, stages of REM sleep and four stages of non-REM sleep. Below there are the values of the recurrent indicator calculated in the corresponding time windows. Stages 3 and 4 of sleep are marked in green, stages of REM sleep are marked in red (color online)

indicator can be calculated for each analyzed signal $x$ over the entire length of the time series or over a small time fragment. Due to the very large amount of data in polysomnography signals, the recurrent indicator should be calculated for relatively small time fragments in a sliding time window.

An approximate calculation scheme is shown in Fig. 1. Time windows of 60 seconds were used to calculate recurrent indicators. This includes 30 000 signal counts, with a window offset step of 30 seconds. This corresponds to the expert marking of sleep stages on the hypnogram and allows you to determine the average value of the recurrent indicator for each stage of sleep.

**1.3. Method for determining sleep stages.** Now it is possible to perform a simple statistical analysis for various stages of sleep (Fig. 2). The figure shows the variation of the recurrent indicator for each stage of sleep, normalized by the average recurrent indicator across the entire polysomnographic record for all three groups of subjects. The recurrent indicators of awakenings, the first and second stages of sleep approximately coincide with the average indicator for the entire signal. But stages 3 and 4, as well as the stage of sleep with rapid eye movements (REM), are very different. For slow sleep, the recurrent indicator decreases, for fast sleep it increases. The data were obtained for thirty-two people, each of whom underwent polysomnographic examination for two consecutive nights.

According to the data in Fig. 2 we can offer a fairly simple method for determining the stages of REM and non-REM sleep. It is clearly noticeable that the stages of non-REM sleep show a decrease in the recurrent indicator, and the stages of REM sleep show an increase in the recurrent indicator.

Thus, the algorithm for marking the fast and slow stages of sleep is the following sequence of actions.

i. Search for the maximum and minimum values of recurrent indicators for a given hypnogram.
ii. Determining the values of $RR^1$ and $RR^2$ according to the following rules: $RR^1 = RR_{\min} + 0.3 \cdot (RR_{\max} - RR_{\min})$, $RR^2 = RR_{\max} - 0.4 \cdot (RR_{\max} - RR_{\min})$.
iii. Determination of sleep stages according to the following rules: if the recurrent indicator is $RR < RR^2$, then sleep stages 3 and 4 are marked; if $RR > RR^1$, then the REM sleep stage is marked; if $RR^1 < RR < RR^2$, then sleep stages 1 are marked and 2.

This method has a number of obvious advantages and serious disadvantages. The advantages include its simplicity and speed of calculations. This is very important for fast post-processing of polysomnography data (due to their large volume). This is also important for the implementation of devices for analyzing sleep stages in real time (where the speed of calculations plays a crucial role). Recurrent analysis is applicable to all types of signals. Therefore, it is possible to use the same method both for EEG processing and for analyzing ECG data obtained during a single recording. If a similar simple way of marking sleep stages is identified for data obtained from ECG data analysis, this will greatly simplify the possible diagnosis of sleep disorders, since recording an ECG signal is much easier and cheaper, which is very important for personalized medicine devices.

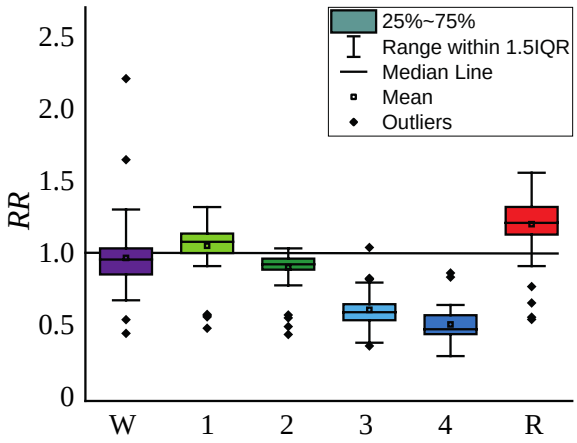

Fig. 2. Statistical patterns of subjects for different stages of sleep (color online)

The disadvantages of the method include the inability to separate stages 1 and 2, as well as 3 and 4. Within the framework of the above algorithm, it is not possible to identify

cases of awakening, which are very important for assessing the quality of sleep. An important point is the choice of rules for determining the values of $RR^1$ and $RR^2$, since for greater accuracy of the method it is necessary to determine them each time not only for a new subject, but also for each of his polysomnographic records. However, this is not possible if the method is used for practical purposes to mark the stages of sleep. The specific values (0.3 and 0.4) of the recurrent parameters were selected from an available selection of polysomnographic recordings with hypnograms marked up by specialists, so that errors in determining sleep stages were minimal. However, there is no certainty that these values of recurrent parameters are universal.

## 2. Results

To assess the accuracy of the method of marking sleep stages using recurrent analysis, data from conditionally healthy subjects (14 people), patients with Parkinson's disease (8 people) and patients with apnea (10 people) were used. The accuracy of the method was calculated as the ratio of the number of 30-second intervals for which the sleep stage was correctly determined (according to a somnologist) to the total number of 30-second intervals in the recording. The results of using the method on groups of subjects are shown in the Table.

The values of the average accuracy of the method for different groups of subjects took the following form: 72.46% for conditionally healthy subjects, 67.81% for patients with Parkinson's disease and 77.902% for patients with apnea. The accuracy results are not ideal, but they demonstrate good potential for further modification of this method. The best results were obtained for patients with apnea. This means that for them the average characteristics of the repetition of the dynamics of the EEG signals of different subjects are the closest. For patients with Parkinson's disease, the accuracy is the lowest. This indicates a very large instability of repetitions of dynamics during sleep.

Table. Accuracy of applying the method of marking sleep stages for three groups of subjects using recurrent analysis in relation to hypnograms marked by specialists

| № Group 1 | Method accuracy | № Group 2 | Method accuracy | № Group 3 | Method accuracy |
|---|---|---|---|---|---|
| 1 | 80.37578288 | 1 | 53.49753695 | 1 | 63.26742976 |
| 2 | 68.53002070 | 2 | 71.57652474 | 2 | 89.11088911 |
| 3 | 60.24973985 | 3 | 78.33333333 | 3 | 92.86442406 |
| 4 | 81.89386056 | 4 | 69.50053135 | 4 | 79.44214876 |
| 5 | 73.34004024 | 5 | 66.88034188 | 5 | 74.49392713 |
| 6 | 74.90974729 | 6 | 64.94192186 | 6 | 83.95061728 |
| 7 | 86.90344062 | 7 | 72.40356083 | 7 | 80.55842813 |
| 8 | 66.55092593 | 8 | 58.21138211 | 8 | 70.81632653 |
| 9 | 78.76923077 | | | 9 | 70.67209776 |
| 10 | 75.74819401 | | | 10 | 75.39370079 |
| 11 | 61.87500000 | | | | |
| 12 | 60.81081081 | | | | |
| 13 | 80.74921956 | | | | |
| 14 | 58.49843587 | | | | |

## Conclusion

In the framework of this work, a method for marking sleep stages is presented based on the analysis of the values of recurrent indicators calculated in time windows for polysomnographic EEG recordings. The method was tested on three groups of subjects: conditionally healthy, patients with Parkinson's disease and patients with nocturnal apnea. The method allows for fast marking and building a hypnogram, highlighting the non-REM (1-2 and 3-4) and REM stages of sleep. The average accuracy of the method exceeds 72.5%. The accuracy obtained seems to be a fairly good result compared to existing methods of automatic marking of sleep stages. In [2], the accuracy varies depending on the number of stages allocated from 65 to 80 percent. And in the work of [8] using neural networks, the accuracy is slightly higher than 80 percent. The method proposed in this paper is much simpler to implement. The time spent on building a hypnogram is rarely mentioned in articles, but given the simplicity of calculating recurrent indicators, it is most likely higher than for the proposed method. And taking into account the duration of polysomnographic recordings, the simplicity and speed of calculation becomes an important factor for choosing a method for recognizing sleep stages.

The accuracy of the method for conditionally healthy subjects coincides with the average for three groups, for patients with Parkinson's disease, the accuracy of the method is below average, and for patients with cases of sleep apnea is above average. This effect is most likely due to the fact that the average spread of the recurrent index for patients with Parkinson's disease is higher, and for patients with apnea it is lower than for conditionally healthy subjects.

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