

Can ICA improve sleep-spindles detection ?

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Abstract

We investigated the possibility to use the Independent Component Analysis as a method for preprocessing the sleep EEG data with the aim to improve detection of sleep spindles - specific phenomena of sleep EEG recordings prevailing during the stage 2 of the sleep.

1 Introduction

Sleep spindles are specific phenomena of electroencephalograms (EEG), (i.e. recordings of the electrical activity of the brain) during sleep. They may be defined as a group of rather broad frequency (11.5 - 15 Hz) oscillations with evidence for variability and heterogeneity [10]. Occurrence of sleep spindles is one criterion of standard criteria of sleep stages classification defined 30 years ago by Rechtschaffen and Kales [7]. Thus the correct automated detection of spindles can increase the accuracy of sleep stage classification.

The visual analysis of sleep spindles is highly time-consuming and difficult in the case of multi-channels recordings. In [8] automatic sleep spindle detection algorithm was proposed. Criteria based on definition of frequency, amplitude and duration properties of human sleep spindles were used on raw EEG recordings. The another heuristic criteria were used to distinguish among muscle artifacts, fast alpha activity and sleep spindles. Although the results using one EEG channel are promising the problem of multi-channel sleep spindle detection caused by time-delays between occurrence of spindles in different channels is still open.

In this paper we used a Independent Component Analysis (ICA) to separate a sleep spindle activity from multi-channels EEG recordings. The method is based on the assumption that the

EEG measured on the human scalp is a linear mixture of anatomically and physiologically separate processes of the brain. The results of using ICA for auditory event-related potentials detection [6], extraction of ocular artifacts from EEG [9] and removing artifacts from EEG [4] encourage us to use ICA in our case. The separated 'sleep spindle' signal we used for successive sleep spindle classification.

2 Independent component analysis (ICA)

The problem of ICA can be simply formulated as finding a set of statistically independent signal sources from their linear mixture. Usually in ICA we observe m scalar random variables x_1, x_2, \dots, x_m which are assumed to be linear combinations of n unknown independent components (ICs) s_1, s_2, \dots, s_n . In matrix notation we can write

$$\mathbf{x} = \mathbf{A}\mathbf{s},$$

where \mathbf{A} is an unknown $m \times n$ mixing matrix (here we will assume that $n \leq m$). The goal of the ICA is then to estimate the matrix \mathbf{A} and the ICs using only observations \mathbf{x} . Several algorithms based on information theory were proposed (see review [5]). Generally they assume neural-like structure with a input vector \mathbf{x} , a weight matrix \mathbf{W} and a monotonically transformed output vector $\mathbf{y} = G(\mathbf{W}\mathbf{x})$. Minimising mutual information, as a measure of the independence between random variables, of outputs \mathbf{y} leads to determination of matrix \mathbf{W} which is an estimate of the matrix \mathbf{A} .

In our simulations we used the method introduced in [2, 1]¹. The main idea of the algorithm is based on using a new contrast function

$$J_G(\mathbf{w}) = [E\{G(\mathbf{w}^T \mathbf{x})\} - E\{G(\nu)\}]^2,$$

as an approximation of the negentropy (i.e. negative normalized entropy) measure of a zero-mean random variable \mathbf{x} . Maximising of the negentropy corresponds to minimising the mutual information. ν is a standardized Gaussian variable and it is assumed that $E(\mathbf{w}^T \mathbf{x})^2 = 1$. Such a contrast function can reflect a different statistical property of the individual sources. For example, using $G(z) = z^4$, J_G becomes simply the kurtosis of \mathbf{z} . Maximising $J_G(\mathbf{w})$ leads to finding a vector \mathbf{w} in one step and thus to determine one IC. Decorrelation of $\mathbf{w}_k^T \mathbf{x}$ after k th iteration from previously determined outputs $\mathbf{w}_1^T \mathbf{x}, \mathbf{w}_2^T \mathbf{x}, \dots, \mathbf{w}_{(k-1)}^T \mathbf{x}$ allows to estimate ICs one by one [2]. The vectors $\mathbf{w}_1, \dots, \mathbf{w}_m$ form the unmixing matrix \mathbf{W} and components of the vector $\mathbf{u} = (u_1, u_2, \dots, u_n)^T = \mathbf{W}\mathbf{x}$ are estimated ICs. As \mathbf{W} is not the exact inverse of \mathbf{A} , $\mathbf{W}\mathbf{A} = \mathbf{P}\mathbf{D}$ (where \mathbf{P} is a permutation matrix and \mathbf{D} is a diagonal matrix), separation is unambiguous only up to permutation and scaling of the source signals.

In [2, 3] computationally a very efficient *fixed-point algorithm* to search maximum of $J_G(\mathbf{w})$ was derived. First the data are sphered or whitened. This means that \mathbf{x} is linearly transformed by matrix \mathbf{S} to a new variable with correlations matrix equaling unity. This can be achieved by classical Principal Components Analysis. This will change the total estimated unmixing matrix to $\mathbf{W}\mathbf{S}$ instead of \mathbf{W} . Next, one vector \mathbf{w} is estimated by an iterative *fixed-point algorithm*:

$$\begin{aligned} \mathbf{w}^+ &= E\{\mathbf{x}g(\mathbf{w}^T \mathbf{x})\} - E\{g'(\mathbf{w}^T \mathbf{x})\}\mathbf{w} \\ \mathbf{w}^* &= \mathbf{w}^+ / \|\mathbf{w}^+\| \end{aligned}$$

where g and g' are first and second derivatives of the function G and \mathbf{w}^* is a new estimated value of \mathbf{w} . As a concrete choice of non-linearity we chose the following function: $G = \text{logcosh}(x)$. The benefits of several non-linear function G were discussed in [2].

¹Matlab code is available from <http://www.cis.hut.fi/projects/ica/fastica/>

3 Simulated data

We reconstructed the artificial problem to demonstrate the possibility of ICA to separate the signal (s_1), consisted from several consequent sleep spindles, from its random mixture with periodic (s_2) and white noise with Gaussian distribution (s_3) signals.

The source signals (s_1, s_2, s_3), mixed signals (x_1, x_2, x_3) and estimated source signals (u_1, u_2, u_3) are presented in Fig.1, Fig.2 and Fig.3, respectively.

In spite of the fact that sleep spindles are transient events in range of 0.5sec to several seconds, it is clear that ICA separates spindle signal with high accuracy. The permutation and scaling of the original sources is easy to notice.

4 Real data

A 7min recording of 18 channels EEG (Fp1, F8, F4, Fz, F3, F7, T4, C4, Cz, C3, T3, T6, P4, Pz, P3, T5, O2, O1) was used. Electrodes were placed according to the international 10-20 system. The data were digitized with a sampling rate of 102.4 Hz.

The fast *fixed-point* ICA algorithm was applied on all 43008 data points (7min). To evaluate efficacy of ICA preprocessing we compared the accuracy of spindles detection using the raw EEG data and the IC data. The raw EEG and IC were band pass filtered using the spindle-frequency band 11.5 - 16 Hz [8]. The filtered data were transformed to the ± 1 range and mean-square amplitude (MSA) was calculated at each data point by sliding window with length 0.5sec (the 0.5sec was defined as minimum of sleep spindle duration [8]). A random 30sec data interval was selected to determine the threshold constant (TC) for MSA. The TC was empirically set up to correctly classify the spindles detected by an experienced electroencephalographer during this 30sec time interval. This was done for every EEG channel and filtered 'spindle' IC, separately. The optimal TC for unambiguous classification for selected 30sec interval was unable to determine for several EEG channels due to a impossibility to distinguish between the correct classification and false positive classification as is illustrated in Fig.4. Using the TC criterion the spindle was detected if at least 0.25sec was value of MSA greater as TC.

The time delays between the spindles in different channels make the detection problem more complicated. We simply detected a spindle at time point i if the spindle was detected at least in one of the channels. This 'advantage' in the detection procedure can lead to unwanted effect, i.e. by classifying several consequent spindles as one event (this was confirm in our experiments).

5 Results

Fig.5 depicts 8 channels of EEG (Fp1, F8, F4, Fz, C4, C3, P4, Pz) during a random 12sec interval. The sleep spindles detected by electroencephalographer are expressed by marks. The first 10 time aligned ICs are shown in Fig.6. The correct locations of spindles as determined by the electroencephalographer are depicted at the bottom of the graph (the detection of the spindle in one channel was sufficient). IC5 was visually settled as the 'spindle' IC.

The results of classification for all 7min recording are presented in Table 1. The number of spindles detected by electroencephalographer was 95. The total number of detected spindles is shown in the first column. The number of cases in which spindle was detected more than once is in the last column of the table. Classifications using two different values of TC (number in brackets) for 'spindle' IC (IC5) case are presented. The results using two ICs are in the last row.

6 Discussion

The experiments on simulated data confirmed the theoretical possibility of ICA method to separate a signal containing sleep spindles. The results obtained on real EEG data showed that ICA can partly separate the spindle activity into one IC. Using longer data intervals (in our case 7min

	# of detections	# of correct	# of false negat.	# of false posit.	# of overlaps
EEG	121	91	4	30	3
IC5 (0.02)	80	70	25	9	1
IC5 (0.01)	102	76	19	26	2
IC5 (0.02) + IC3 (0.04)	87	76	19	11	1

Table 1: Numbers of total detected, correct, false negative, false positive and overlapped cases of sleep spindle classification: comparison of using raw EEG data and 'spindle' ICs data. Values in brackets correspond to selected threshold constant (TC).

EEG) two 'spindle' ICs were detected. In this case one 'spindle' IC was dominant in the sense that stronger evidence of sleep spindles was visually observed.

The delays between occurrence of the spindles in different EEG channels complicate the classification algorithm proposed in [8]. The simple classification technique used for raw EEG data in our research led to a high number of spindle detections and thus to a high number of false positive classifications and to unsuitable overlap detections. Using 'spindle' IC for detection showed a high percentage of false negative classification. Smaller TCs decrease number of false negative classification at the expense of false positive classification. Using two ICs with different TC improved overall classification. We think that the big advantage of ICA to separate sleep spindle activity into 1 or 2 ICs should be expressed by proposing better classification algorithm in future.

In [10] two different type of sleep spindles were detected and thus the hypothesis about two different spindle sources arose. Regarding to this, the question to separate spindle activity into one channel remains open.

For more accurate classification the problem of time delays has to be solved. In future work, we will investigate the possibility of using an extension of ICA for problems with time-delayed sources. We hypothesize that this could lead to more exact evidence and location of the spindles in 'spindle' IC.

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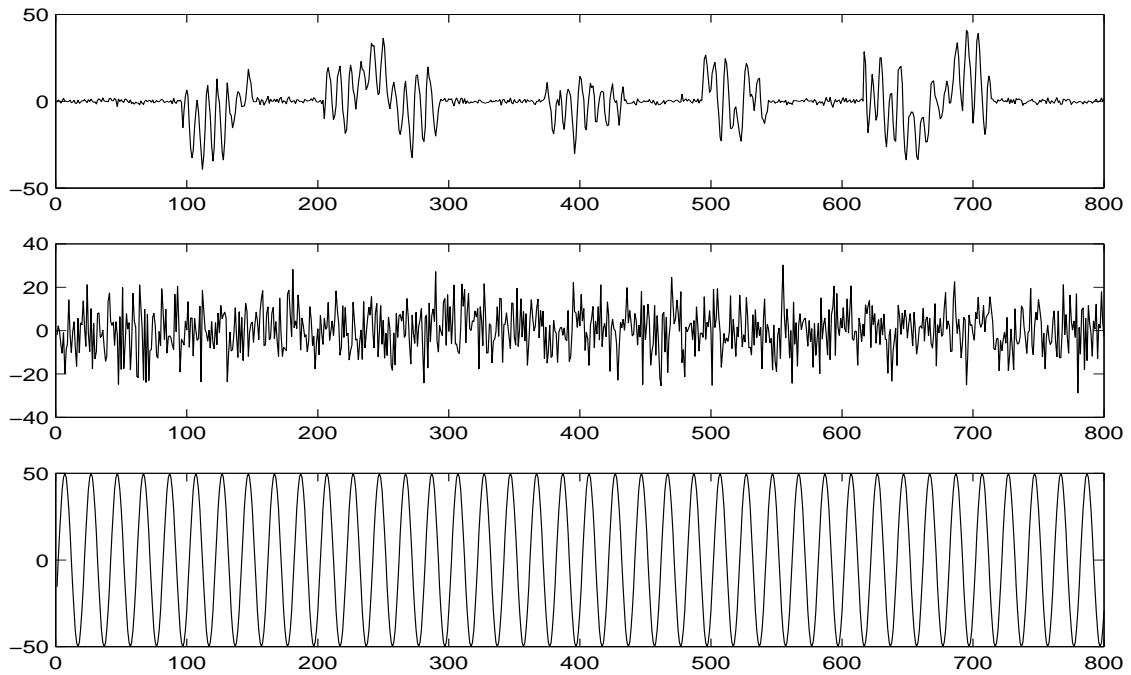


Figure 1: The source signals. Sleep spindles signal (s_1), white noise with Gaussian distribution (s_2) and periodic signal (s_3). Estimated kurtosis: $k(s_1) = 6.661$, $k(s_2) = 0.031$, $k(s_3) = -1.5$.

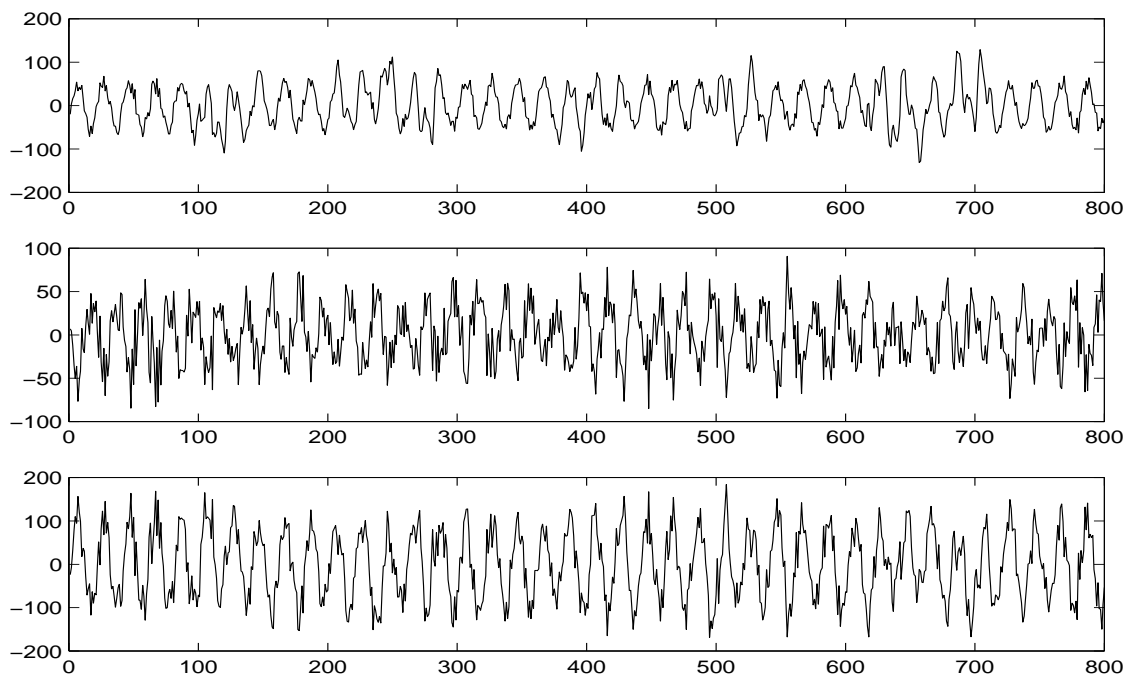


Figure 2: Mixed signals x_1, x_2, x_3 . Estimated kurtosis: $k(x_1) = 0.622$, $k(x_2) = -0.553$, $k(x_3) = -0.735$.

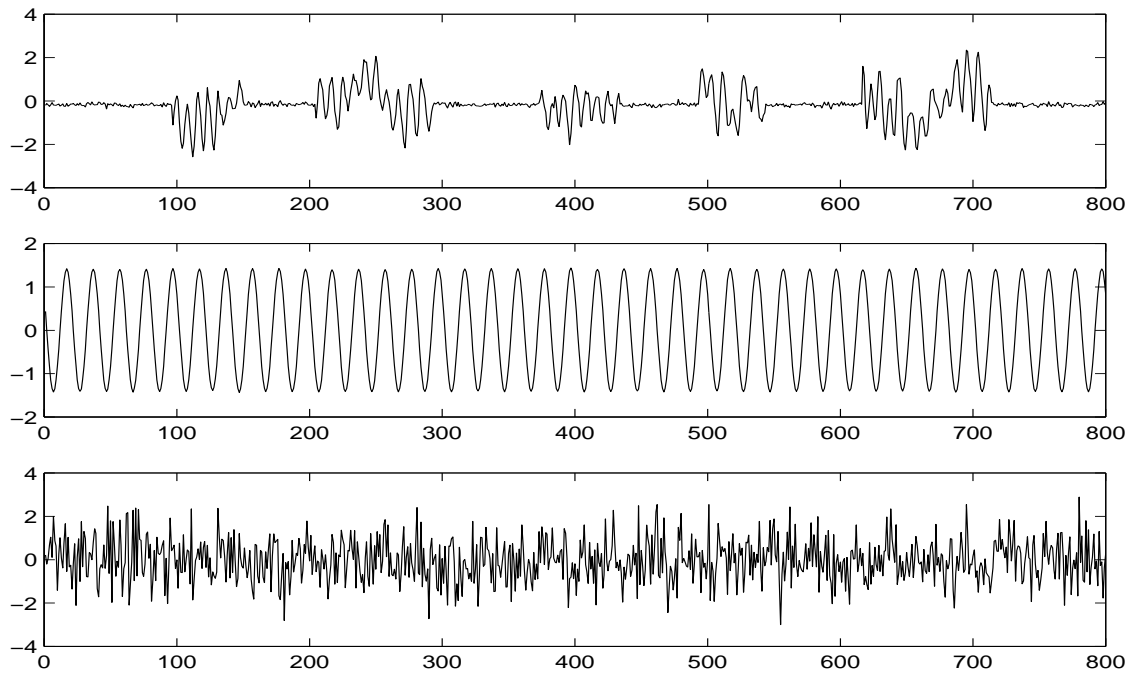


Figure 3: Estimated source signals u_1, u_2, u_3 . Estimated kurtosis: $k(u_1) = 6.667, k(u_2) = -1.5, k(u_3) = 0.032$.

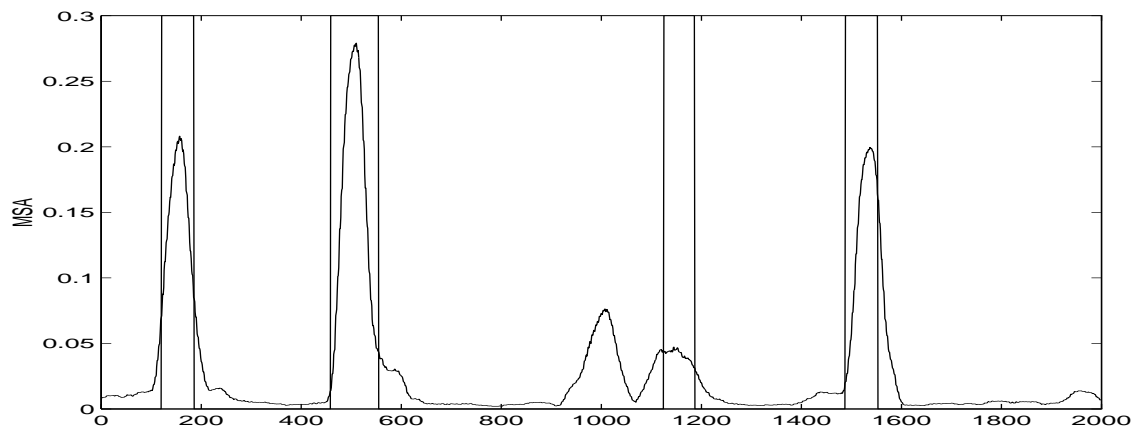


Figure 4: An example of impossibility to determine a unique threshold constant (TC) correct for all sleep-spindles determined by electroencephalographer (intervals between vertical lines). The TC suitable to detect a third 'correct' spindle will lead to one false positive detection ('bump' centered around value 1000).

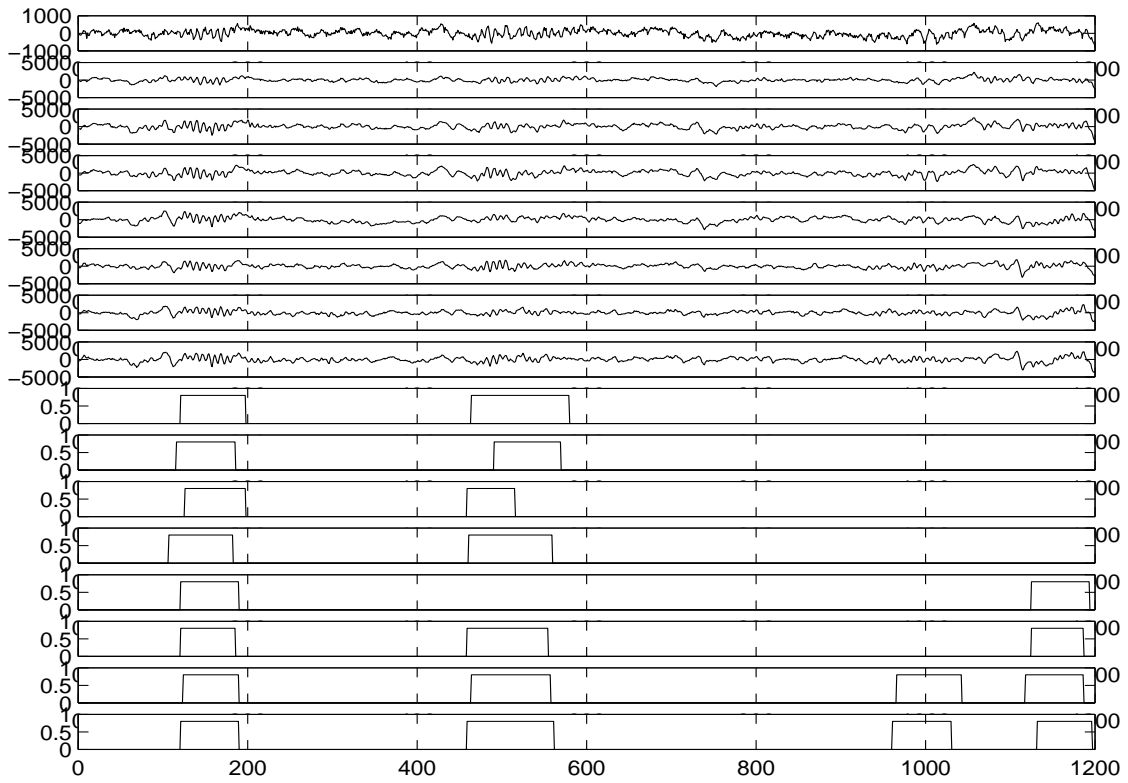


Figure 5: 12sec recording of 8 EEG channels (Fp1, F8, F4, Fz, C4, C3, P4, Pz) with sleep spindles marks determined by electroencephalographer.

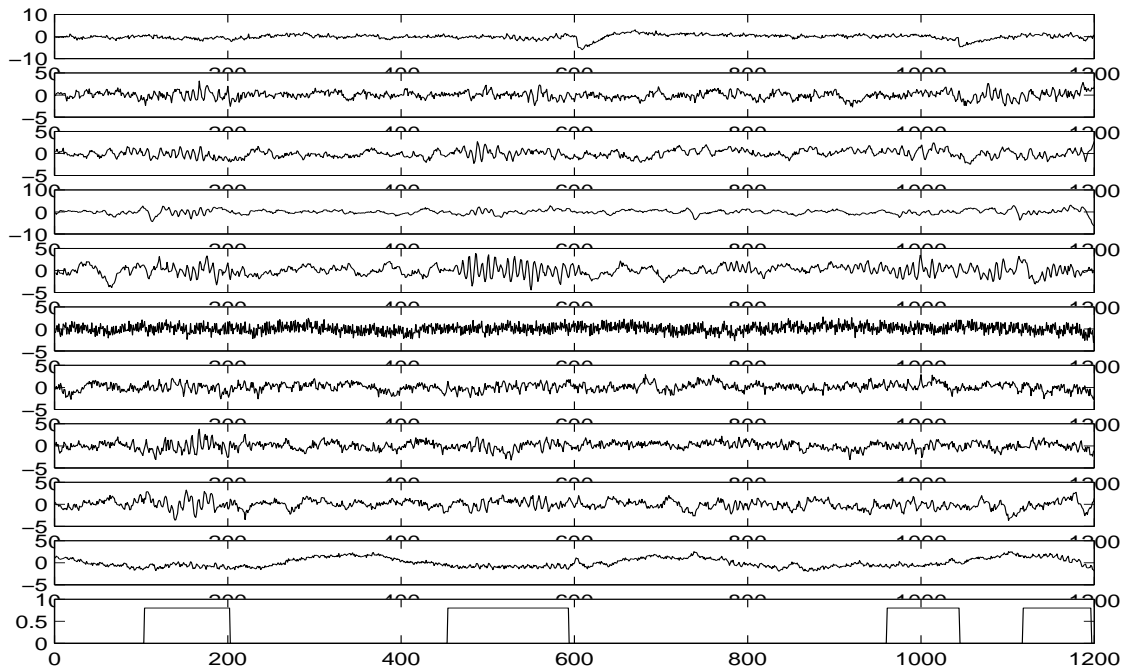


Figure 6: First 10 ICs (time aligned with Fig.5) with sleep spindles marks determined by electroencephalographer.