Slow and fast EEG sleep spindle component extraction using Independent Component Analysis

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***Abstract*— Sleep spindles are groups of rhythmic activity, with a waxing-waning morphology, and are considered a hallmark of stage 2 of the sleep electroencephalogram (EEG). They are present predominantly in stages 2, 3 and 4 of the sleep EEG. Spatial analysis of sleep spindle scalp EEG and EEG inverse problem solutions have provided evidence for the existence of two distinct sleep spindle types, "slow" and "fast" spindles at approximately 12 and 14 Hz, respectively. The present study aimed at processing sleep spindles with Independent Component Analysis (ICA) in order to investigate the possibility of extracting spindle "components" corresponding to separate EEG activity patterns. The EEG activity underlying the components was also investigated, using the Low-Resolution Brain Electromagnetic Tomography (LORETA) technique, inverting the 21-channel EEG recordings to cortical current sources. Results indicate separability and stability of current sources related to sleep spindle "components" reconstructed from separate groups of Independent Components (ICs).**

I. Introduction

A sleep spindle may be defined as a group of rhythmic electroencephalographic (EEG) waves characterized by progressively increasing, then gradually decreasing amplitude, which is mostly below 50 μV peak-to-peak in an adult. The waves have an individual frequency at approximately 12 to 14 Hz, although it may extend from 11 to 16 Hz. They are grouped in sequences lasting up to 2-3 seconds and the sequences may recur every 3 to 10 s [1, 2]. Sleep spindles are used in the classification of sleep stages, because they constitute one of the hallmarks of stage 2 of non-rapid eye movement (non-REM) sleep [3]. The functional significance of sleep spindles has not yet been fully elucidated [4].

Sleep spindles seem to exhibit a bimodal distribution as far as their EEG frequency and spatial distribution is concerned: slow spindles, with about 12 Hz frequency, which are more pronounced in the frontal region of the head, and fast spindles, with about 14 Hz frequency, which are more prominent in the central and parietal region [2,5-7]. There exists an on-going debate concerning whether the topographic and spectral bimodality is due to the existence of at least two functionally separated spindle generators [8-10].

Blind Source or Signal Separation (BSS) is a commonly encountered problem in science and engineering. The problem relates to revealing unknown signals, called sources, from their linear mixtures, which are usually known quantities, with very limited, if any, prior knowledge about the mixing mechanism. It is assumed that at time instant k the observed n-dimensional data vector, $\mathbf{x}(k) = [x_1(k), \ldots, x_n(k)]^T$ is given by the model:

$x_i(k) = a_{i1}s_1(k) + a_{i2}s_2(k) + \ldots, a_{im}s_m(k)$

or, in an equivalent matrix notation,

$$\mathbf{x}(k) = \sum_{j=1}^{m} \mathbf{a}_j s_j(k) = \mathbf{A}\mathbf{s}(k). \quad (1)$$

The source signals, $s_1(k), \ldots, s_m(k)$, are supposed to be stationary independent but unknown, as are the coefficients of the mixing matrix $\mathbf{A} = [a_1, \ldots, a_m]$. Furthermore, only one source may be Gaussian. Both unknowns have to be estimated from a sample of $\mathbf{x}(k)$. The solution is in the form

$$\hat{\mathbf{s}}(k) = \mathbf{W}\mathbf{x}(k), \quad (2)$$

where $\mathbf{W}$ is called the "separating" matrix. Independent Component Analysis (ICA) is a statistical technique used for solving the BSS problem by finding linear projections of the data that maximize their mutual independence [11]. ICA has been used widely in biomedical signal processing, more prominently for noise extraction, as well as for ERP component extraction in electroencephalography [12-14]. ICA has also been used for detecting sleep spindles [15].

ICA by itself does not provide the intracranial electric sources which are responsible for generating the scalp-recorded EEG. At most, it can be used to recompose the scalp-recorded EEG, by selecting some of the independent components (ICs) to be used in the recomposition process. For computing the unknown electrical sources, a variety of techniques have been developed during the last decades [16]. Low-resolution brain electromagnetic tomography (LORETA) is one of the most widely used techniques. The main assumption imposed for solving the inverse problem is that the solution sought is the smoothest of all possible inverse solutions [17].

The present work aimed at studying the possibility of extracting spindle "components", by applying ICA to sleep

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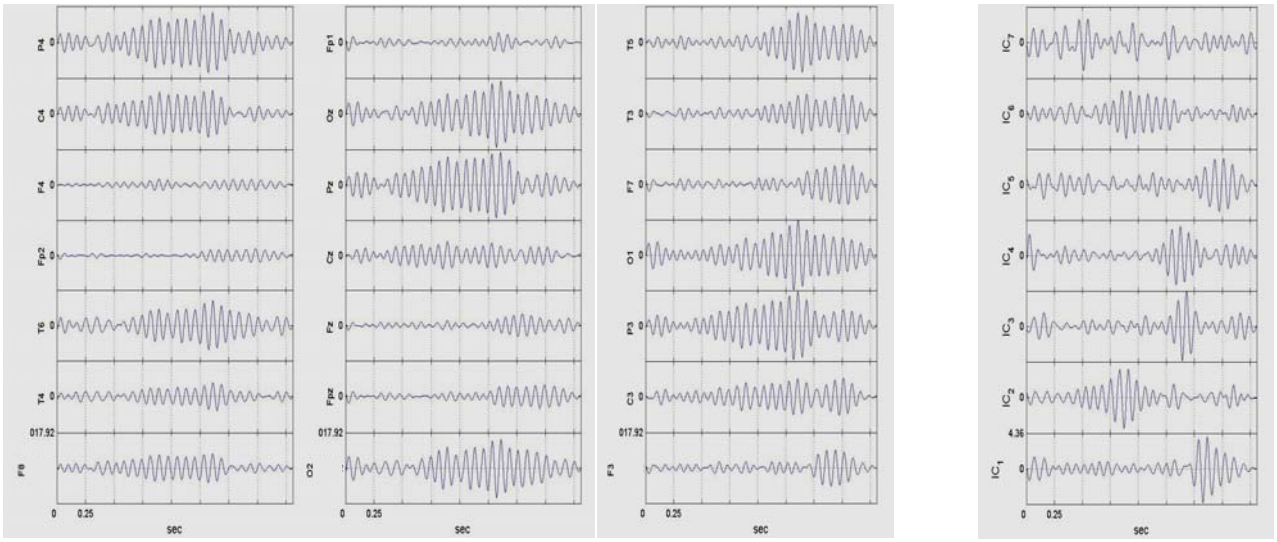

Fig. 1. Original filtered sleep spindle EEG (left) and ICs (right). Potentials of EEG recordings are in microvolts. The exact IC values do not possess an interest, due to the sign and multiplicative constant indeterminacy of the results of ICA. The absolute maximum value of all ICs dictated a common magnitude range for the representation of the ICs. The order of the numbering of the ICs is not related to the ordering of the EEG channels.

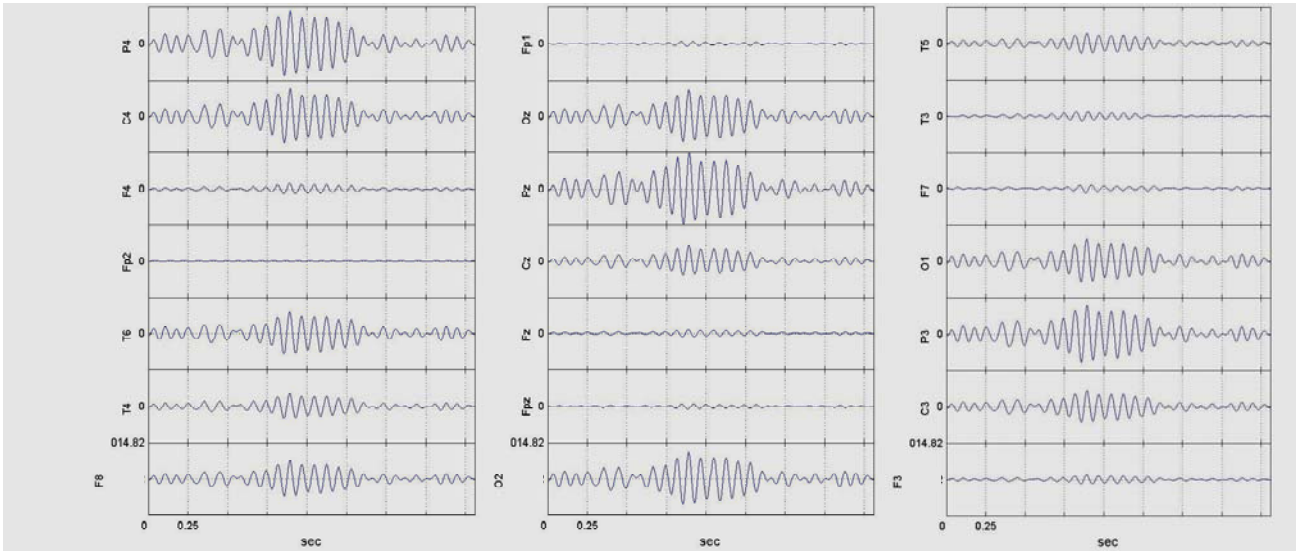

Fig. 2. ICA-reconstructed EEG corresponding to the spindle component which is dominant in the first part of the spindle. Potentials of EEG recordings are in microvolts.

spindle EEG. These components, present in the ICA-reconstructed EEG, corresponded to distinct EEG activity patterns. Furthermore, the presumed electrical sources of the spindle components were computed through the LORETA technique, in order to provide indications about the existence of distinct sources for the two spindle types. This study employs 21-electrode-recorded EEG, in contradistinction to a previous study which was based on 8-channel EEG [18].

II. Materials and Methods

A single subject's all-night polysmonographic recording, obtained at the Sleep Research Unit of the University of Athens Department of Psychiatry, was examined. The EEG was recorded at 21 electrodes (referential montage, reference at G2), at positions F8, T4, T6, Fp2, F4, C4, P4, O2, Fpz, Fz, Cz, Pz, Oz, Fp1, F3, C3, P3, O1, F7, T3, T5, with a sampling frequency of 256 Hz. Sleep spindles were visually detected and filtered using a 128^{th}-order finite impulse response (FIR) band-pass filter, with cut-off frequencies at 10,5 and 16 Hz.

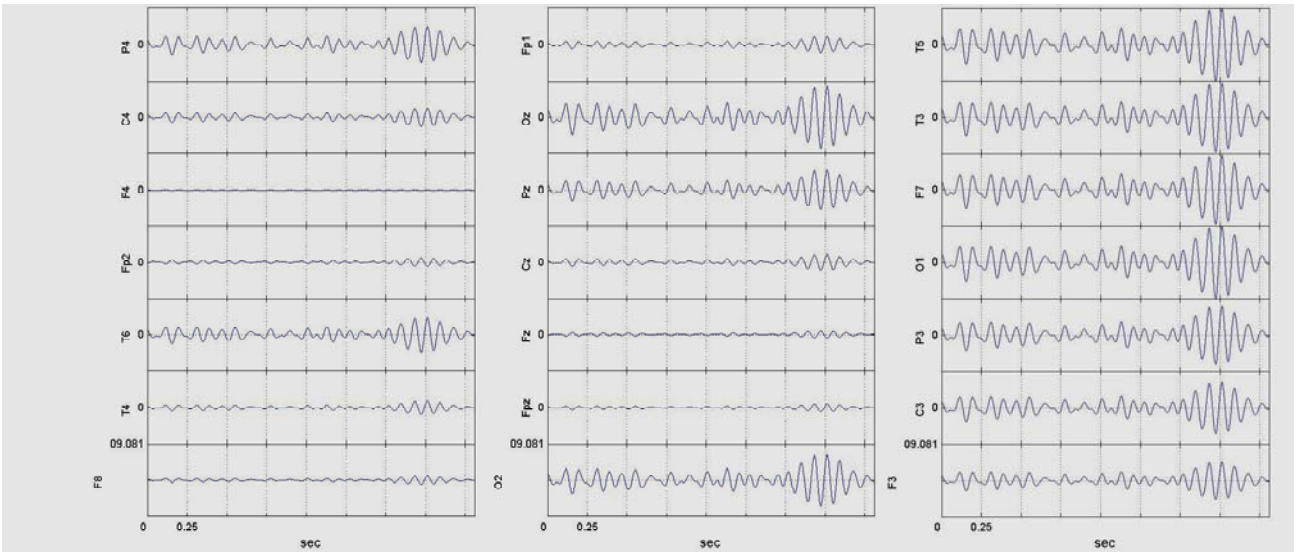

Fig. 3. ICA-reconstructed EEG corresponding to the spindle component which is dominant in the second part of the spindle. Potentials of EEG recordings are in microvolts.

ICA was applied on the original filtered EEG data, using the FastICA algorithm [19, 20] (Fig.1). In contradistinction to ICA applied to 8-channel EEG data [18], the ICs which were produced when a 21x21 mixing matrix was computed were composed of short-duration (less than 4 cycles) wavelets, with no apparent spindle-like activity and/or correspondence to the EEG spindle activity. In order to overcome this problem, Principal Component Analysis (PCA) was applied to the filtered EEG data and n_{red} ICs were computed. n_{red} was selected as the number of PCs needed so that the variance explained by the PCs exceeded 99% of the total variance of the EEG signal. Therefore, a $21xn_{red}$ mixing matrix was computed instead of a 21x21 matrix. Extensive trials showed that the ICs which were computed through this dimension-reduction technique retained a much more spindle-like morphology, as was the case for ICA applied to 8-channel EEG data [18]. Then, Short-Time Fourier Transform (STFT) was applied to the EEG and the ICs, so that the temporal evolution of the main frequency of the signals might be inspected. Next, the original single spindle timeframe was divided into parts that reflected different spindle-like activities, within that spindle. The division was based on the existence of distinct waning-waxing cycles and/or on transitions from "low" (≤12 Hz) to "high" (≥13 Hz) frequencies (or vice versa). ICs were inspected, in order to detect those ICs who possessed spindle-like morphology and would best correspond to the previously selected parts of the spindle EEG, both concerning their time duration and their frequency content. Suppose that the EEG was divided into two parts, A and B. Then some ICs would be grouped together and be considered as "representative" ("main" ICs) for part A, and some other ICs for part B. After ICs had been selected as representative of the parts, the EEG was reconstructed, for the whole time duration of the spindle, once based only on the ICs of group A, and once based only on the ICs of group B. The expected aim of the above procedure was the extraction of spindle components corresponding to separate EEG activity patterns in the EEG. Each spindle component was expected to provide predominantly the spindle-like morphology in the part where its generating ICs were considered as "representative".

Next the cortical electrical sources of the spindle components were computed, using the publicly available software version of LORETA [21]. Distributions of current density were computed, for each time sample, for both the original EEGs and the reconstructed ones. In order to reduce the amount of information available for processing, the data from each source point were averaged for the whole duration of the respective spindle part. Therefore, for each spindle part, three mean source activity images were produced, one for the sources of the original EEG in that part, and one for the sources of each EEG reconstruction. The mean value images were compared, concerning the anatomical location of the strongest spatial local maxima of the current density distribution.

III. Results

A representative case is shown in Fig. 1. On the left part of the figure, a multi-channel original sleep spindle EEG is shown. The spindle started as a high-frequency one, with main frequency at 13 Hz, and then, at all electrodes except electrode F3, a transition to low frequency (12Hz) took place, which ranged from approximately 1.1 sec at F4 to 1.7 sec at electrodes T6, P4, O2, Pz, Oz, P3, O1, T5. In electrodes F8, T4, C4, P4, Pz a clear waxing-waning

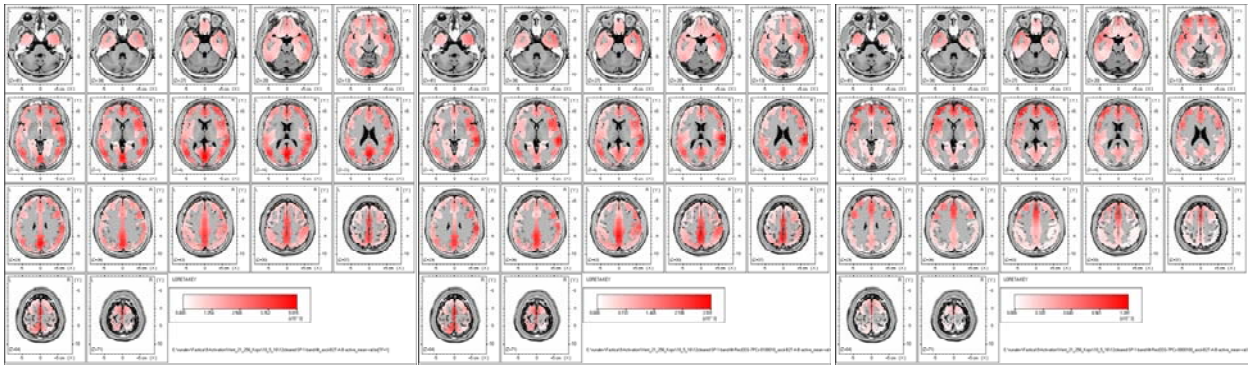

Fig. 4. Distributions of mean source activity for part A. Sources of the original EEG are given at left, of the ICA-reconstructed EEG representing the dominant component in this part at center and of the ICA-reconstructed EEG representing the other (non-dominant) component, at right. Each distribution is displayed relative to its own maximum.

spindle-like morphology was discernible starting at approximately 0.25 sec and finishing at 1.4-1.6 sec, therefore indicating the possible presence of an initial high-frequency component. The emergence of the 12 Hz as main frequency followed the 13 Hz main frequency, but a distinct waxing-waning spindle-like morphology, following the 13 Hz waxing-waning spindle-like morphology, was apparent as a second, lower energy activity, only at electrodes C4, Pz, P3 and T3, although the amplitude reduction that indicated the passage from the waning of the 13 Hz spindle to the waxing of the 12 Hz frequency was slight. Only at electrode F7, a dominant 12 Hz waxing-waning cycle emerged following lower amplitude 13-14 Hz activity. The above morphological and spectral characteristics of the EEG recordings provide indications that there existed the possibility of division of the original spindle in two parts, the first one (A) containing a high frequency spindle component and the second one (B) a low frequency one.

By applying PCA to the EEG data, 99% of the variance present in the data was explained by the 7 first principal components. In Fig. 1 (right) the 7 ICs are presented which were computed using the 7x21 separating matrix. In order to find ICs representative of part A, ICs were selected which had a spindle-like 13 Hz activity at part A and no spindle-like activity at part B. Inversely, in order to find ICs representative of part B, ICs were selected which had a spindle-like 12 Hz activity at part B and no spindle-like activity at part A. The application of the above criteria led to the selection of ICs 2 and 6 as representative of part A and IC 5 as representative of part B. Taking into consideration the morphologies of both the EEG channels and the selected ICs, an approximation of the time indicating the transition between the two parts was set at 1.5 sec. Fig. 2 shows the reconstructed EEG, based on the ICs representing the first spindle component. Fig. 3 shows the reconstructed EEG, based on the ICs representing the second spindle component

Fig. 4 shows, at left, the mean source activity corresponding to the original data in part A, at center the mean source activity corresponding to the reconstruction of the EEG based on ICs 2 and 6, and at right the mean source activity corresponding to the reconstruction of the EEG based on IC 5. The distribution shown at left had maxima at the cuneus (occipital lobe) and at temporal lobes, bilaterally. As mentioned above, the EEG frequency was high. Therefore, it was expected that this activity should appear as activation mainly at posterior parts. It should be noted that the term “posterior”, in the context of the present work, is used mainly in contradistinction to frontal lobes, including not only sources in the occipital lobes but also in the limbic, parietal and temporal lobes. The source distribution

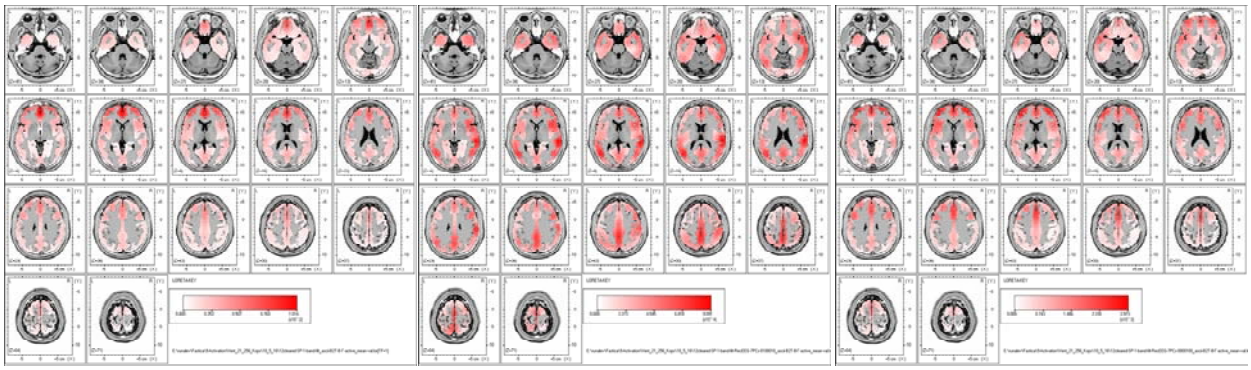

Fig. 5. Distributions of mean source activity for part B. Sources of the original EEG are given at left, of the ICA-reconstructed EEG representing the non-dominant spindle component at center, and of the ICA-reconstructed EEG representing the dominant component, at this part, at right. Each distribution is displayed relative to its own maximum.

presented also a local maximum at frontal sites, albeit with 20% less amplitude than the occipital global maximum. This activity corresponded to sources responsible for the low frequency spindle-like activity that would predominate in part B, but which were also present in part A. The sources corresponding to the EEG reconstruction, based on the main ICs of the spindle for part A (Fig. 4, center), showed also predominant activation at parietal and temporal sites, which is consistent with the high frequency dominant component of part A. The sources corresponding to the EEG reconstruction based on IC 5 (Fig. 4, right) presented a peak of activation at frontal areas, which is consistent with the low frequency of the spindle-like activity that existed in the reconstructed EEG at part A (see Fig. 3). This source activity corresponded to the frontal activity seen in the source distributions of the original EEG for part A (see Fig. 4, left).

Fig. 5 shows the average source activity corresponding to part B. The source activity corresponding to the recorded original EEG (Fig. 5, left) had clearly shifted to anterior areas, as expected, since the dominant frequency at this part was low (12 Hz). It is remarkable that the local maxima of the current sources were nearly the same as the local maxima of current activity that represented the sources of the EEG that was reconstructed by IC 5 (Fig. 5, right), i.e. the main IC for part B. Furthermore, those local maxima were exactly the same as those which were computed for the sources of the EEG reconstruction based on IC 5 for part A (Fig. 4, right). Finally, the sources corresponding to the EEG reconstructed through ICs 2 and 6 were mainly in posterior areas, as expected, since the frequency of the low-amplitude spindle-like activity of the EEG reconstructed by those ICs, in part B, is of high frequency (13 Hz). There was again remarkable stability of the local maxima of source locations, shown in Fig. 5 (center), when compared to the local maxima of the sources corresponding to the EEG that was reconstructed by ICs 2 and 6 for part A, shown in Fig. 4 (center). Therefore, in the example presented, the sources corresponding to the reconstructed EEG for each group of ICs maintained their distribution from part A to part B. This is in accordance with the assumption that ICs reflect separate "local" source activities.

IV. Discussion

The use of ICA in processing sleep spindle EEG was assessed in the present study. Results provide indication that spindle components, which constitute a single-spindle recording, and which may not be easily distinguishable in the recording, may be separated using morphological and frequency spectrum criteria, when these criteria are applied to the original single-spindle recording and its ICs. Spindles were divided into consecutive time parts. At each part, one of the components was found to contribute predominantly to the spindle-like characteristics of the EEG. This was attested by inspecting the morphology and spectral content of the EEG reconstructed by the ICs representing the component.

Concerning source analysis, indication was provided that the positions of the maximal sources corresponding to the spindle component representing the spindle activity in each part were the main loci of sources corresponding to the same part of the original EEG. This was based on the result that the region of maximal activation in the cortex, generating the original EEG in one part, coincided in large extent with the region of maximal activation of sources corresponding to the spindle component representing the spindle activity in that part. Furthermore, concerning the source distribution of fast and slow spindle types, in most spindles analysed in the present study, the sources of fast spindle components were at posterior and central regions, and those of slow spindle components at frontal regions, in accordance with most existing literature [8,10].

The topographic pattern of source distribution corresponding to each component was remarkably stable throughout the duration of the spindle. This indicated that, even when the activity of the component was not clearly apparent, nevertheless the sources, that are responsible for the emergence of that component as predominant in the next part, are already existing as a group from the first part and will retain their topographic stability throughout the spindle EEG recording. Correspondingly, when a component was predominant in the first part, its corresponding sources would remain in large extent the same, albeit with reduced amplitude, in the next part. Since ICs, or groups of ICs, are hypothesised to reflect functionally and topographically separate sources, spatial stability of sources was a characteristic expected from ICA-extracted data [11-13].

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