# SINGLE CHANNEL ANALYSIS OF SLEEP EEG : AN ADAPTIVE DATABASE METHOD

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**ABSTRACT**

An automatic procedure for the spectral analysis of an all-night sleep electroencephalogram (EEG) is presented. This method relies on a fixed database initializing a procedure which adapts parameters so that they match to the signal to be analyzed. Parameters coming from database are normalized power spectra in predefined frequency bands. The novelty of our approach is to use flexible sleep stage patterns rather than fixed ones, these patterns being iteratively updated (thanks to a short/long term analysis) in order to cope with the EEG variability. The main part of the procedure, performed on-line, is followed by a very short off-line processing yielding a real time implementation. The procedure adaptation ability is shown on detection of Rapid Eyes Movement (REM) events, the latter being well known for their inter as well as for their intra individual extreme variability.

## 1 INTRODUCTION

The visual analysis of polygraphic sleep recordings by an expert, based on criteria established by Rechtschaffen and Kales [6], is time consuming (requiring some 2-5h of expert time per 8h recording) and tedious. Moreover, the hypnogram obtained is much depending on the scorer. An automatic method should be time saving, and should also lead to a much more objective analysis as well as providing a standardization.

In the last 20 years, different methods for computer analysis of sleep EEG have been introduced [5]. Some of these methods use a priori fixed patterns, that make difficult fitting to the subjects individual sleep patterns which are highly variable from one to another. Some other methods are semi-automatic, e.g. human-assisted, which sets the problem of the analysis subjectivity again. Other approaches use polychannel data (electrooculogram (EOG), electromyogram (EMG), temperature...) or involve heavy off-line processing.

The aim of this study is to introduce a new method for an analysis using a single channel EEG data, without getting information from neither EOG nor EMG. This method is fully automatic thanks to an adaptive procedure, so that it does not require supervised learning before each analysis. It can be mainly operated on-line, with a very short off-line processing beside.

## 2 METHOD

### 2.1 Automatic analysis

The described procedure is the automatic version of a semi-automatic sleep analysis method : Telco [7].

#### *2.1.1 Semi-automatic analysis*

Telco is a human-assisted procedure, analyzing a single EEG channel by 30s intervals (epochs). A blind classification based on autocorrelation is first computed, the association class→sleep vigilance state (SVS, which are closed to the classical sleep stages) being next performed by the expert.

#### *2.1.2 Automatic analysis*

Making Telco becoming automatic means to automate the association class→SVS. The problem is that the 30s epoch analysis introduces a smoothing, this making it difficult to discriminate REM events from some other sleep stages by using a single EEG channel. This leads us to compute a double scale data analysis, by 30s epoch (long term analysis) and by 2s epoch (short term analysis), in order to detect short EEG events that are discriminating. We choose to detect two of them, the *sleep spindles* (12-16 Hz, 0.5-2 s duration), and the $\alpha$ *bursts* (8-12 Hz, 1-2 s duration). Spindles are considered as hallmarks of the stage 2, stages 3 & 4 contain a few of them, they are nearly absent of the stage 1 and REM sleep and totally absent of the wake vigilance state. $\alpha$ bursts can only be found during awakening episodes.

### 2.2 EEG data preprocessing

#### *2.2.1 Recording technique*

The study involved 30 healthy males volunteers. The EEG signal, recorded using conventional procedures from the $C_zP_z$ electrodes sites, is passed through a 40 Hz analog low-pass anti-aliasing filter and sampled at 400 Hz by a 16 bits A/D converter. A low-pass linear phase FIR filter is then used in order to reach a sampling frequency of 100 Hz. This improves the signal to noise ratio of the EEG sleep signal.

### 2.2.2 Double scale data analysis

The digital EEG signal $s[n]$ is split into epochs of 30s (resp. 2s) duration. The normalized power spectrum of each epoch is estimated using $30^{th}$ order A.R. model [3][2]. This spectral activity is computed for the following ten frequency bands : (0-0.7 Hz), $D_1$ (0.7-1.5 Hz), $D_2$ (1.5-3 Hz), $T_1$ (3-4 Hz), $T_2$ (4-6 Hz) $T_3$ (6-8 Hz), $\alpha$ (8-12 Hz), $\sigma$ (12-16 Hz), $B_1$ (16-25 Hz) and $B_2$ (25-50 Hz). $D_1$ $D_2$ belonging to the $\delta$ band, $T_1$ $T_2$ $T_3$ to the $\theta$ one, and $B_1$ $B_2$ corresponding to the $\beta$ band. Each epoch can then be characterized by a vector $L_{bd}^{epoch}$ (resp. $S_{bd}^{epoch}$) which components are the normalized power in each band $bd$, so we have

$$\sum_{bd=1}^{10} L_{bd}^{epoch} = 1 \ , \quad and \quad \sum_{bd=1}^{10} S_{bd}^{epoch} = 1$$

EEG signal absolute amplitude is not taken into consideration. However it is not really a sleep-related variable as it is dependent on factors such as age, electrode placement and skull morphology.

## 2.3 Classification into sleep vigilance states

In order to classify EEG 30s epochs into SVS, each spectral repartition of normalized power $L^{epoch}$ has to be compared to a set of repartitions corresponding to the different SVS patterns. Because of the EEG variability (possibly inter or intra individual), some epochs are difficult to classify by using a priori fixed patterns. Actually we gave up the idea of using those sorts of reference, we deal instead with adaptive patterns updated by using an iterative procedure (fig.1).

This one involves several steps of computation, each of them requiring the all-night EEG processing. The first step is an initialization one, using a priori fixed patterns, in order to perform a first classification. During next iterations, adaptive patterns are updated according to the spectral characteristics of the current signal to be analyzed. With regard to computation time, the

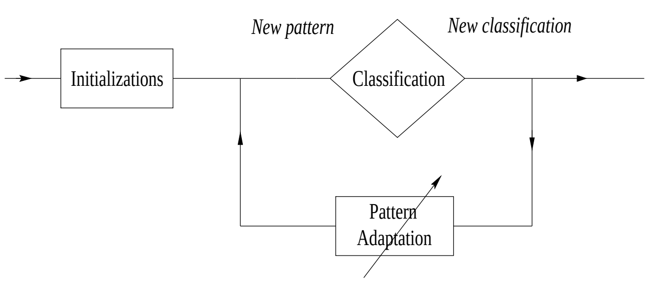


Figure 1: Iterative procedure.

30s-2s EEG epochs analysis is performed on-line : indeed this heavy processing part can easily be performed between each epoch recording. At the end of the night, the classification part is computed off-line, but its computation time is so short (a few minutes) with respect to the night duration (about 8 hours), that this step can be as well considered as an on-line one.

### 2.3.1 Distance definition

During the classification step (after an artefact rejection), each $L^{epoch}$ is compared [1][4] to each pattern repartition of a database in order to classify this epoch into a specific SVS. The database is constituted by the patterns of the different SVS, $P_{st}(\mu_{bd,st}, \sigma_{bd,st})$. $\mu_{bd,st}$ expresses the value of the normalized power in the frequency band $bd$ of the SVS pattern $st$, and $\sigma_{bd,st}$ is the corresponding standard deviation.

For each EEG epoch to be classified, a degree of membership of each frequency band $bd$ to each SVS $st$, $F_{bd,st}$, is computed :

$$F_{bd,st}(L_{bd}^{epoch}) = exp\left(\frac{-\left(L_{bd}^{epoch} - \mu_{bd,st}\right)^2}{\mu_{bd,st}\sigma_{bd,st}}\right)$$

So, the degree of membership of the current 30s epoch to the stage $st$, $D_{st}(L^{epoch})$, is then written :

$$D_{st}(L^{epoch}) = \sum_{bd=1}^{10} F_{bd,st}(L_{bd}^{epoch})$$

The SVS chosen is the one relating to the higher degree of membership :

$$Decision(L^{epoch}) = \max_{st} \quad D_{st}(L^{epoch})$$

### 2.3.2 A priori fixed patterns construction

The a priori fixed patterns are set up from several EEG recordings (six healthy male subjects) with Telco. All the epochs that have been classified in the same SVS by Telco are analyzed as described in (§2.2.2). This analysis provides the $P_{st}^{fixed}$ for each SVS. These fixed patterns constitute the database. This one, which is the same for all the recordings to be analyzed, will be automatically adapted at each new recording.

### 2.3.3 Adaptive patterns update

After each new classification, only *almost likely* detections are considered. Almost likely means that during the classification there was nearly no doubt about the SVS according to the degree of membership computed, and means also that the decision was coherent with the short term analysis results, e.g. with spindles and $\alpha$ bursts detection. We also reject detections that are by the side of artefact detection for not disturbing adaptive pattern. Indeed, the artefact might have overlapped two successive epochs.

Once this strict selection of classified epochs is performed, adaptive pattern can be updated. $L_{st}^i$ being the normalized power repartition of the $i^{th}$ almost likely detection of the SVS $st$, the adaptive pattern of this SVS stands for the mean spectral repartition :

$$P_{st}^{adaptive} = mean(L_{st}^i)$$

Each new almost likely detection set provides a new mean repartition, standing for the new adaptive pattern. This allows a new iteration to be performed.
The procedure converges typically within 3 iterations.

## 3 RESULTS

In order to validate the proposed method, we detail detection of REM events. Indeed, the latter are well known as for both their inter as well as intra individual variability, and for the difficulty to differentiate from other sleep stages (2, 1 or Wake stage) based only on one EEG derivation without using EOG and EMG criteria. We present results for different subjects, the latter do not belong to the corpus used for the fixed pattern setup.

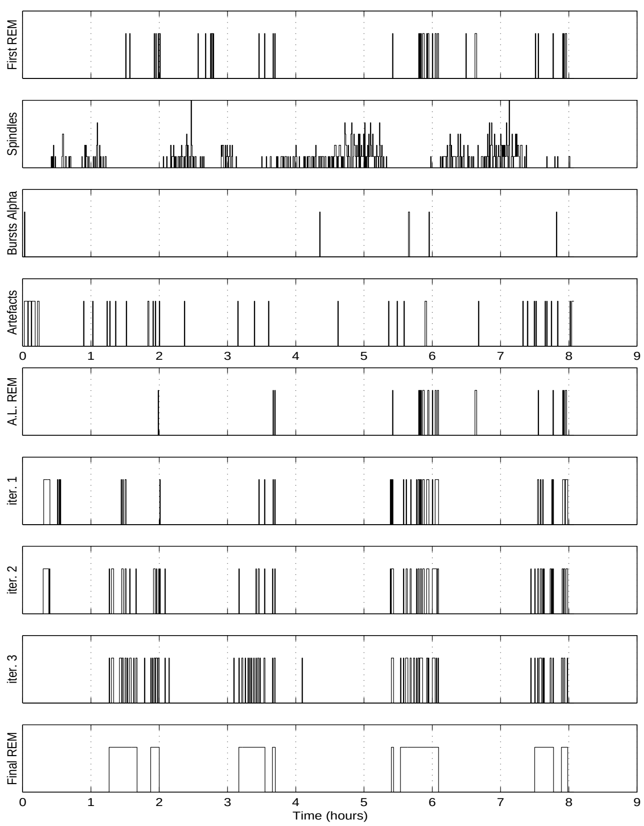


Figure 2: REM epochs iterative selections.

Figure 2 shows the successive selections of REM epochs during the iterative procedure. The upper graph represents the first REM selection, using the a priori fixed pattern. The next two graphs show the result of spindles automatic detection (number of spindles/epochs) and bursts $\alpha$ automatic detection, which are used for the REM selection. The fourth graph represents the results of artefacts rejection, e.g. recording artefacts or unclassified epochs. The fifth graph shows the *Almost Likely* REM epochs that are used for adaptive REM pattern initialization. The three following graphs show the results of the successive iterations : each new set of REM detection is used for each adaptive pattern update, providing the next REM detections.The last graph shows the final REM selection, after smoothing using contextual rules.

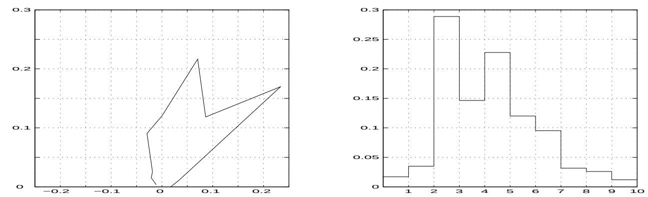

Figure 3: Comparison between histogram and polar representations.

In order to show the successive adaptations of REM adaptive pattern using the iterative procedure, we propose a polar representation (fig.3) instead of representing results as an histogram. Its aim is to show normalized spectral repartition evolution. The module $\rho_n$ stands for the normalized spectral power in the frequency band $n$, and the phase $\theta_n$ is defined by $\theta_n = (n-1)\pi/N$, where $N$ stands for the number of frequency bands. This representation is much dependent on frequency bands number, scale, and even paper size allocated for the figure. Nevertheless, it is particularly useful for evolution visualization, if the above parameters are constant from one figure to another.

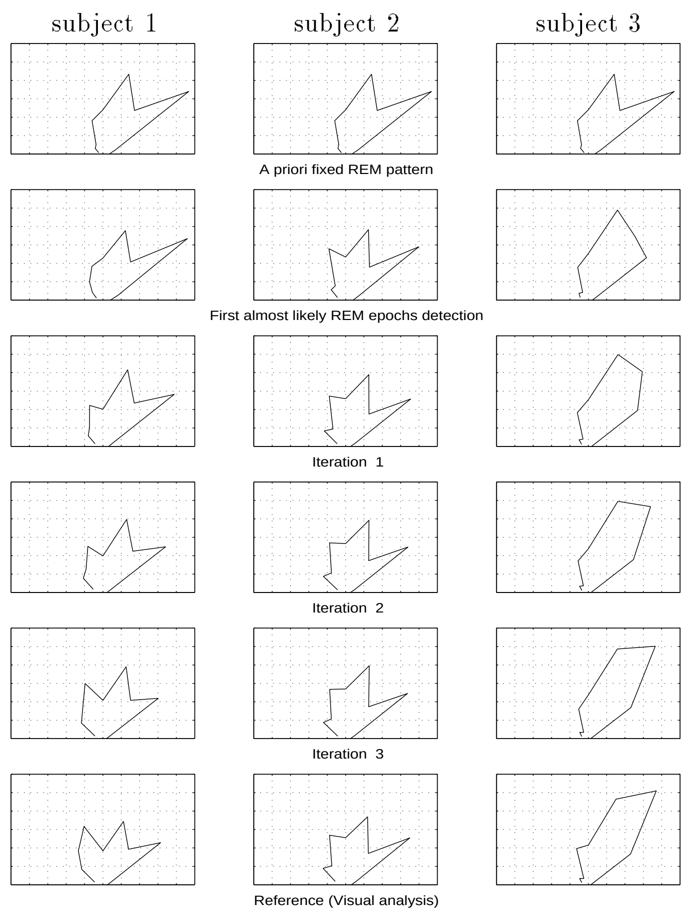


Figure 4: REM pattern adaptation for 3 subjects.

For 3 subjects (one for each column), the normalized power repartition of the adaptive REM pattern $P_{REM}^{adaptive}$ is drawn (fig.4) for each iteration, e.g. for each adaptive REM pattern update. The upper row represents the a priori fixed REM patterns, which are the same for all the sleep EEG to be analyzed. The $2^{nd}$ row shows the mean repartitions of the first almost likely REM decisions (corresponding to the $5^{th}$ graph on fig.2). The lower row represents the mean REM repartitions of the current subjects to be analyzed obtained from visual analysis, which is our reference. The extreme inter-individual variability of REM sleep is plain. Therefore the aim of the procedure is to converge to these repartitions. The intermediate rows present the results (in terms of REM adaptive pattern repartition) of each iteration. It can be seen that the adaptive REM patterns converge to the requested repartitions within 3 iterations. In figure 5, comparison between hypnograms is

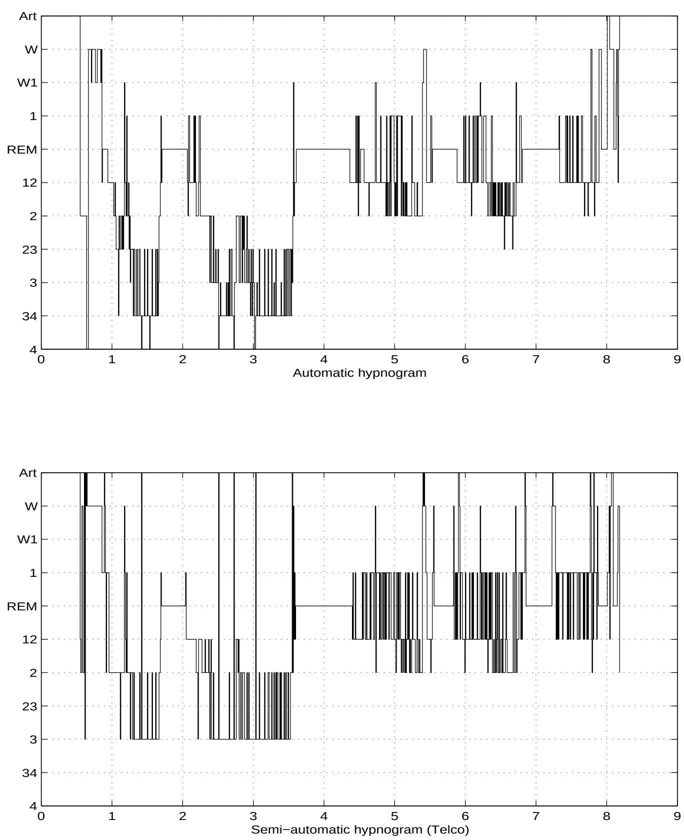


Figure 5: Comparison between automatic and semi-automatic hypnograms.

drawn for one subject. The lower graph is obtained by the semi-automatic method Telco, and stands for our reference. The upper hypnogram is obtained using the described automatic procedure.

## 4 CONCLUSION

An automatic procedure for the classification of an all-night sleep EEG using single channel data has been presented. This double scale method implies several iterations involving the adaptation of various scoring criteria. The first step uses an a priori fixed database in order to perform the initialization of the adaptive patterns. During the next iterations, the adaptive patterns are updated according to the spectral characteristics of the current signal to be analyzed. This computer analysis is nearly on-line, its easy implementation (single channel data) allows applications such as tele-diagnostic.

In order to illustrate this procedure, examples of REM epochs detection, and REM adaptive pattern adaptations have been presented. An example of fully automatic hypnogram is also compared with the corresponding semi-automatic one.

The authors are preparing an epoch-by-epoch statistical comparison between this procedure and visual analysis. The a priori fixed pattern used is the same for all the sleep EEG analysis. However, as spectral characteristics depend on the subject (sex, age) and on the kind of the night (baseline sleep, recovery night after sleep deprivation), it would be deeply interesting to set up different fixed patterns (initialization step) for each case, thus allowing to use these a priori informations available at no cost.

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