Automatic Sleep Spindle Detection in Patients with Sleep Disorders

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***Abstract* - In this paper, we present a new automatic method for sleep spindle detection. It consist of a generalisation of the Schimicek's method [12] that takes more types of artefacts into account and uses variable thresholds regarding the statistical properties of the signal. Validity of our process is examined on the basis of visual spindle scoring performed by an expert. Results obtained are compared to those obtained by Schimicek's method. For a specificity of 90%, we obtain a sensitivity of 76.9% while Schimicek's method has a sensitivity of 70.4%. Moreover an increase of the area under the ROC curve is observed and confirms that the detection process is improved.**

I. INTRODUCTION

Sleep spindles are transient EEG events occurring in sleep stages 2, 3 and 4, where highest density is observed in stage 2. They consist in sinus-like bursts that increase and decrease progressively in amplitude, with minimum duration of 0.5 s (Figure 1). Their frequencies have been defined between 12 and 14 Hz in [11]. However, this interval has been proved to be too narrow [8] and it was extended up in several recent studies (11.5-15 in [12], 12-15 in [3], 11-16 in [1]).

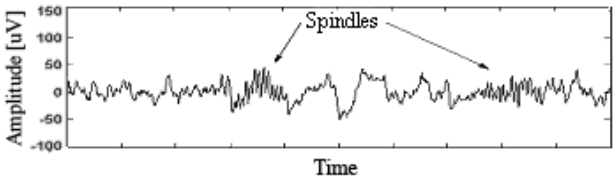

Figure 1: *CZ-A1 EEG recording with two spindles*

Current research about sleep spindles includes topics such as localisation in the brain, sleep stages classification, microstructure analysis, effect of drugs on sleep spindles, relationship between sleep spindles and memory consolidation, etc. [1]-[3],[9].

Visual analysis is however time-consuming and tedious since there are typically 1000 spindles in a full night recording. Moreover, some sleep spindles are difficult to identify because they are borderline in frequency or duration, or superimposed on other waveforms. Therefore hardware [13] and software [5]-[7],[12] methods have been developed for automatic analysis.

Fixed thresholds are used in some of these software methods [5],[12],[13] but the strong inter-patients variability of the spindle amplitudes remains an important problem. Moreover, most of these algorithms are badly adapted to recordings of pathological patients. Indeed, they often do not take care of all artefacts which are more present in pathological patients' recordings than in healthy subjects' recordings (i.e. in those from persons without any pathology). Schimicek and co-workers [12] have limited the number of false detections by rejecting segments with alpha interferences and muscle artefacts, but they did not consider other artefacts like EOG artefact, sweat, arousal, etc.

In this study, we report on an extension of the Schimicek's method to better fit with patients' recordings. Firstly, variable thresholds are used regarding the statistical properties of the considered signal, and secondly more types of artefacts are taken into account.

The validity of our process is examined based on visual spindle scoring performed by an expert, and the results obtained are compared to those obtained by Schimicek's method.

II. METHODS

A. Recording

Data used in this study were recorded at the Sleep Laboratory of the André Vésale hospital (Montigny-le-Tilleul, Belgium). They consist of six whole-night recordings coming from patients (3 males and 3 females aged between 31 and 54) with different pathologies (dysomnia, restless legs syndrome, insomnia, apnoea/hypopnoea syndrome). Two EOG channels (P8-A1, P18-A1), three EEG channels (CZ-A1, FP1-A1 and O1-A1) and one submental EMG channel were used to perform the whole-night polysomnography, according to the criteria of the Rechtschaffen and Kales [11]. The sampling rate was 200Hz. A segment of 30 minutes was extracted from each night from the CZ-A1 channel for spindle scoring. A total of

3 hours of EEG recordings were then available for automatic sleep spindle detection.

To check the validity of our process, visual spindle scoring was also performed on these signals by an expert. The total number of identified spindles was 575.

B. Automatic analysis

Our process is a generalisation of the Schimicek's algorithm [12]. In a first step, the EEG is filtered in the 11.5-15Hz frequency band. Spindles larger than a given threshold are then detected. While *Schimicek et al.* have used a fixed threshold (e.g. 25µV peak-to-peak), we have preferred a variable threshold completely adapted to the statistical properties of the signal. It is defined as:

$$threshold = \mu + K \cdot \sigma$$

where µ is the average of the signal amplitude and σ is its standard deviation. K will be varied in the following in order to illustrate its influence on the results.

Next, the detected spindles are rejected each time their duration is shorter than 0.5 s. Pseudo-spindles superimposed with artefact detection are also discarded. However, in contrast with Schimicek's method where only alpha activity interference and muscle artefacts are considered, we take more artefacts into account before any spindle detection, such as saturations, unusual increase of EEG (e.g. EOG interferences), abrupt transitions and movement artefacts. Moreover, errors due to cardiac interference and unusual low-frequency waveforms (caused by sweat for example) superimposed with EEG are also corrected (see [4] for more details about our artefacts detection/correction process).

Finally, the number of false detections is limited by using a second specific algorithm that confirms or infirms the presence of a spindle. This process, called "*analysis by blocks*" hereafter, examines the signal by blocks of 0.5s. For each block, it computes the Fourier transform of the signal and checks its maximum in the 7-20Hz frequency band. If this maximum stands between 11.5Hz and 15 Hz, the corresponding spindle is accepted, otherwise it is rejected.

III. RESULTS AND DISCUSSION

To assess our process performance, we have implemented the Schimicek's method [12] and we have observed its results on our database. A true positive result was counted when a sample was detected as a spindle by the automatic method and the expert simultaneously. A true negative result was set when a correct decision of absence of spindle was made. If the automatic result indicated a presence of spindle and there was no spindle visual scoring, a false positive result was counted. On the opposite, if the output indicated no spindle while the expert scored some, a false negative result was counted.

Figure 2 displays the influence of a variable threshold on the results. The extraction of alpha interference or other artefacts is not used at this stage. The X-axis of Figure 2(a) corresponds to different fixed threshold value as in the Schimicek's method, while different variable thresholds (corresponding to different value of parameter K) were reported in abscissa of Figure 2(b). The dotted line corresponds to the recognition rate in percent, namely

$$sensitivity\ (\%) = \frac{true\ \ positive}{true\ \ positive + \ false\ \ positive} \cdot 100 \cdot$$

The other lines represent the percentage of true positive, false positive, false negative, and true negative decisions with regard to the total number of samples. We can see that the recognition rate obtained by setting the false negative equal to the false positive is already better if a variable threshold is used.

Now, let us compare (in Figure 3) the complete Schimicek's method which extracts alpha interferences and muscle artefacts, to our own method which takes more artefacts into account (at this stage, the analysis by blocks is still not used).

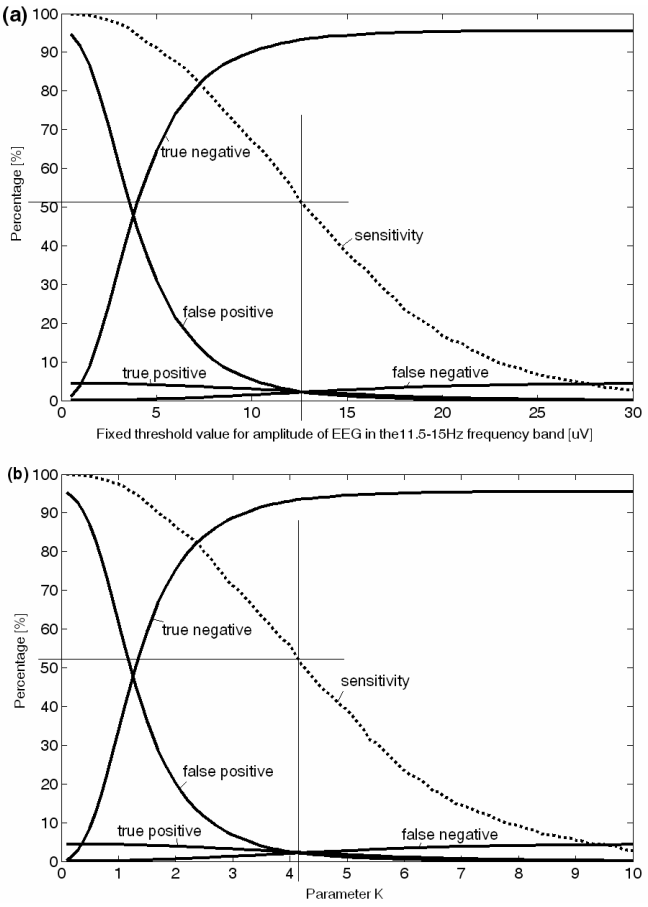

Figure 2: *(a) The Schimicek's method without artefact detection and with fixed threshold; (b) generalisation of the Schimicek's method without artefact detection and with variable threshold*

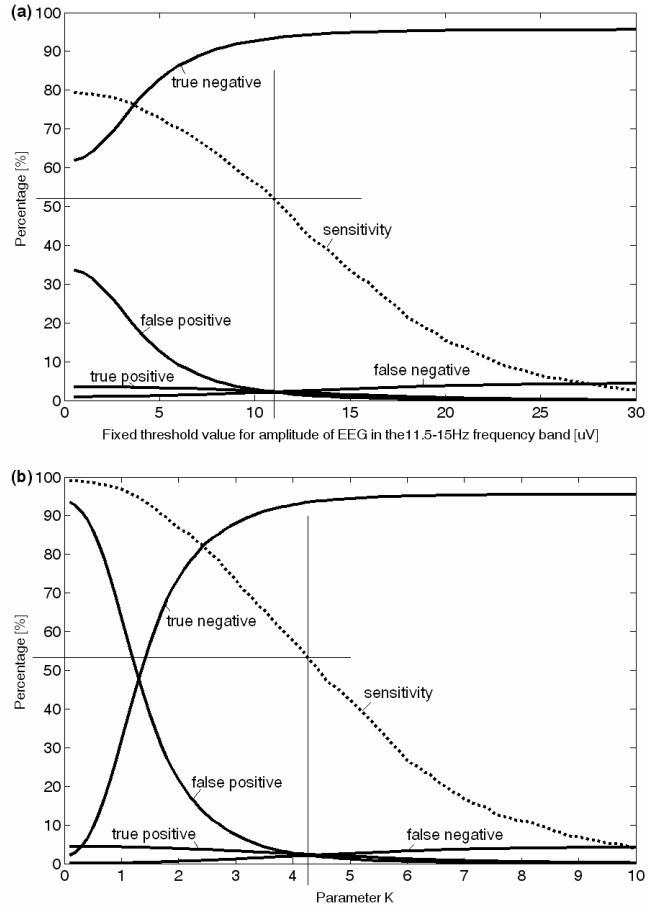

Figure 3: *(a) The Schimicek's method with alpha interference and muscle artefact extraction; (b) our method without the analysis by blocks but with the artefact detection*

We observe that extraction of alpha interference and muscle artefact indeed reduces the amount of false detections but it also increases the amount of false negative detections restricting the maximal sensitivity to 80%. Our process better reduces the number of false detections in the interesting area (where the amount of false negative and false positive detections are equal) but does not significantly reduce the number of correct detections.

If we include our analysis by blocks (Figure 4), we can observe a further decrease in the amount of false detections without much increase in the false negative detections. For the same specificity of 90%, we obtain a sensitivity of 76.9% while Schimicek's method had a sensitivity of 70.4% (Figure 5).

$$\left(specificity\ (\%) = \frac{true\ negative}{true\ negative + false\ positive} \cdot 100 \right.$$

$$\left. sensitivity\ (\%) = \frac{true\ positive}{true\ positive + false\ positive} \cdot 100 \right)$$

This method also allows us to increase the area under the ROC curve (receiver operating characteristic curve which depicts *sensitivity* as a function of *1- specificity*) and thereby improves the detection process (Figure 5).

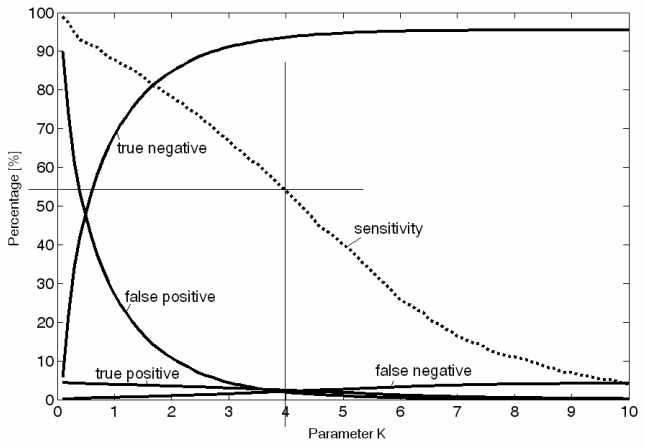

Figure 4: *Our method with the second specific algorithm and with the artefact detection*

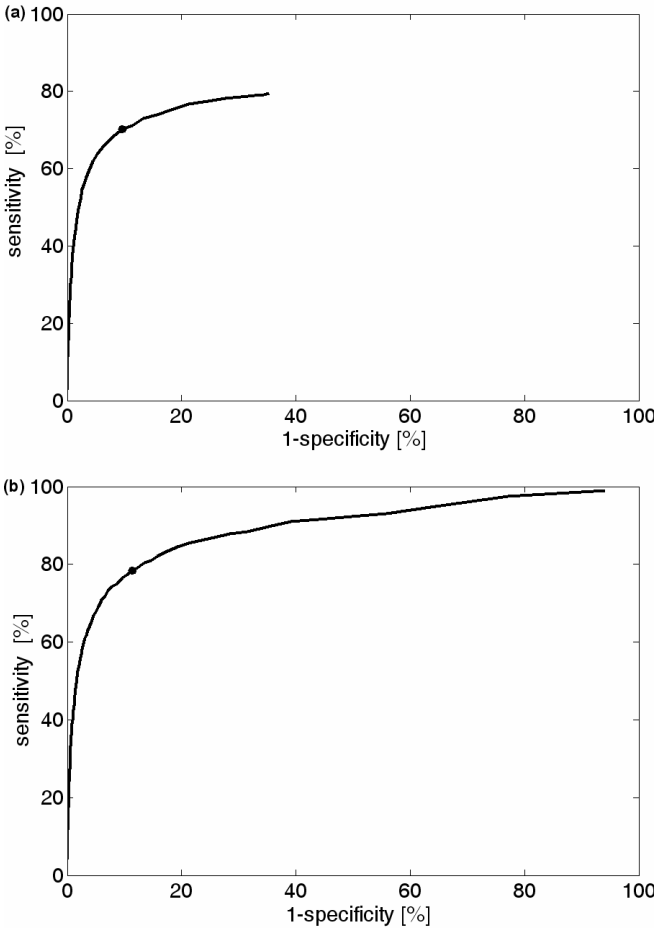

Figure 5: *(a) ROC curve with Schimicek's method; (b) ROC curve with our method. The corresponding optimal point noted by °*

Finally, we have determined the optimal parameter K by analysing the ROC curve. Indeed, as sensitivity improves towards the top and specificity improves towards the left, the most optimal point on the ROC is the point nearest to the top left corner (point noted by ° on the curves of Figure 5). This point is obtained for a parameter K=2 and

correspond to a sensitivity of 78.44% and a specificity of 88.62 %. (cf. Figure 4).

IV. CONCLUSION

In this study, we presented an improved automatic method for sleep spindle detection. This method, which takes more types of artefacts in account (saturations, unusual increase of EEG, abrupt transitions, movement artefacts, interference and unusual low-frequency waveforms) better fits with pathological patients' recordings that usually contain more artefacts. It also uses variable thresholds regarding the statistical properties of the signal so that it can be used for patients with various spindle amplitudes. The optimal threshold value estimated on the basis of ROC curves is:

$$threshold = \mu + 2 \cdot \sigma$$

where μ and σ are the is the mean and the standard deviation of the signal amplitude, respectively. It corresponds to a sensitivity of 78.44% and a specificity of 88.62 %.

The results were also compared with those obtained by Schimicek's method on the same signals [12]. We observed an increase in the area under the ROC curve with our algorithms. This demonstrates the improvement of the detection process.

Finally, our method presents the advantage of a rather simple implementation compared to much more complex processes that have been recently proposed [7]-[10]. Of particular interest, our method is not based on artificial neural networks and does not require any training database: it automatically adapts to the signals it examines.

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