MATCHED FILTERING APPLIED TO THE DETECTION OF SPINDLES AND K-COMPLEXES IN SLEEP EEG

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RÉSUMÉ

Résumé: L'analyse visuelle des signaux EEGs du sommeil est astreignante. Les spindels ainsi que les complexes-K jouent un rôle majeur dans l'analyse de l'activité cérébrale pendant le sommeil. Ce papier présente une méthode de détection basée sur les techniques de filtrage adapté.

ABSTRACT

Abstract: Visual analysis of sleep EEG signals is cumbersome. Sleep spindles and K-complexes play a major role in the analysis of cerebral activity in sleep. This paper presents a computerised detection method based on matched filtering.

1. INTRODUCTION

Sleep spindles and K-complexes are specific EEG patterns which play a major role in the analysis of cerebral activity in sleep. Sleep stage 2, which comprises of up to 50% of the total sleep time, is solely defined on the basis of the presence of one or both of these patterns. This rule established by Rechtshaffen and Kales in 1968 [6], is considered as a standard convention in the area of sleep EEG.

The amount and the distribution of a pattern can indicate a change within the fine structure of sleep. For the neurologist, it is extremely time consuming to visually analyse the EEG recordings. Moreover, since visual assessors only achieve 80 % agreement, it is a problem to compare their analyses. This variability between visual assessors can be overcome using a computer-assisted detection.

The technique employed for this task is based on matched filtering [5] [8]. The objective was to develop an algorithm which could simultaneously detect sleep spindles and K-complexes.

After a description of the technique employed, the results of the evaluation will be discussed and an application to a pharmacological EEG study will be presented.

2. MATCHED FILTERING

Matched filters are used to detect the presence of known signals buried in noise. Suppose we want to detect a transitory signal **p(t)** (of length T) surrounded by a noise **n(t)**. If **s(t)** is the composite signal,

$$s(t) = p(t) + n(t) \quad (1)$$

then the matched filter is designed to maximize the signal to noise ratio at the particular time **t=T**. It has been shown [3][5] that, if the noise is white, the impulse response of the matched filter takes on the form of the signal:

$$h(t) = p(T-t)u(t) \quad (2)$$

where **h(t)** is the impulse response, **p(t)** the signal to be detected and **u(t)** is the unit step function. The desired impulse response is simply the signal waveform reversed in time and delayed by **T** seconds.

The time delay **T** means that, in order to detect a signal of length **T**, a period of length **T** is required for the apparition of the signal. If the signal appears at a time t_0, the output of the matched filter will then be maximum at $t=t_0 + T$. Therefore, in order to detect a pattern **p(t)**, using matched filtering, a filter which impulse response (of length T) is **p(-t)** must be created.

The theory of matched filtering is based on the hypothesis of a surrounding white noise. For sleep spindles and K-complexes detection, the surrounding "noise" **n(t)** consists of the background EEG sleep stage 2 activity which is neither white noise nor stationary over a long period of time.

The white noise hypothesis being unsatisfied, an optimal filter should be created. However, in this situation, the matched filter can be considered as a good approximation of an optimal filter. The matched filter will be derived assuming that the background EEG sleep stage 2 activity is white noise even though this is known to be sub-optimal: the signal to noise ratio is adversely affected.

The output of the matched filter (or detection function) is then analysed in order to decide whether a sleep spindle or a K-complex is present in the input signal. If one of the pattern is encountered, the detection function shows a maximum. The difficulty consists in differentiating the maxima which indicate true detection from the others (false detection). This problem is solved during the learning phase.

3. DEFINITION OF THE TEMPLATES

The templates are defined in conjunction with the neurophysiologists. According to the Rechtschaffen and Kales rules, a sleep spindle is defined by a sine wave which length is longer than 500 msec and whose frequency is within the band 12 to 14 Hz. The sleep spindle template was therefore defined by a 13 Hz sinewave modulated with a cosine (in which the 1/2 period is the length of the template). The length of the template was set to 1 second. This defines a band-pass filter centred on 13 Hz (see Fig. 1).

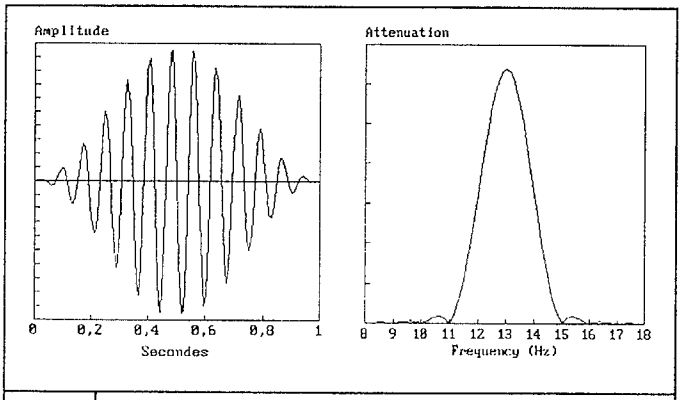

Fig. 1 Template for spindle analysis

There is no real morphological definition of the K-complex. The pattern consists mainly of a biphasic depolarisation-repolarisation sequence. The shape varies from one subject to another and depends on the electrode position. Therefore, the shape of the K-complex template was designed to detect a plain biphasic depolarisation-repolarisation sequence. Fig. 2 shows the shape and the Fast Fourier Transform (FFT) of the chosen template.

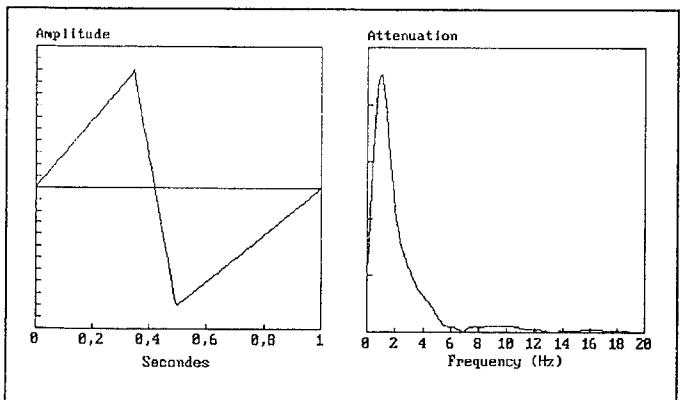

Fig. 2 Template for K-complexe analysis

4. DEFINITION OF THE REJECTION CRITERIA

The output of the matched filter must be analysed in order to decide whether a pattern has been identified. The larger the amplitude of the detection function, the higher the probability of recognition. Experience proved that a simple threshold is not adequate has a rejection criteria. In addition, many maxima within the detection function may not indicate a pattern recognition. Therefore, it was necessary to define a threshold at which all low amplitude maxima are rejected. This threshold was set during the learning phase.

Other rejection criteria are based on the specialist analysis. In the case of K-complexes, it is necessary to have a minimum time of 2 seconds between two K-complexes for them to be recognized as such [1]. If this time interval between two K-complexes is too short then sleep stage 3 and 4 delta activity may be implied. For spindles, the problem is different. The length of the spindle must be longer than 500 ms.

5. IMPLEMENTATION ON A PC

The algorithm was implemented on a PC-386 with co-processor. The filters were implemented in the frequency domain using a circular convolution algorithm as described by Oppenheim [4]. The detection functions for both patterns were then simultaneously computed as shown in Fig. 3.

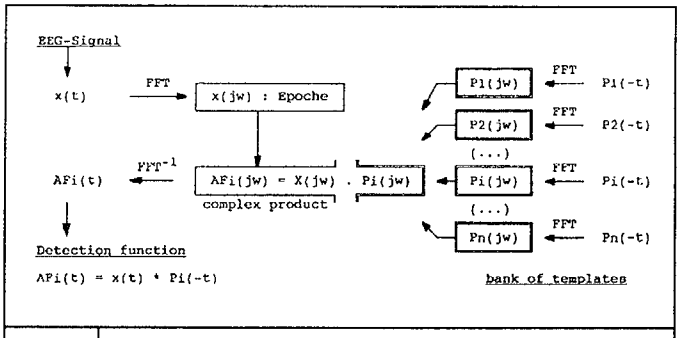

Fig. 3 Algorithm for a multi-template detection.

The templates and their FFT are computed and stored within a bank of templates. The EEG signal is read epoch per epoch, Fourier transformed and then convoluted with the FFTs of the templates (spectra multiplication). After that, the inverse FFT of the convolution product is computed, providing the detection function.

If the EEG signals are considered as real, it is possible to combine the signal from two channels into a complex signal:

$$c(t) = a(t) + i.b(t) \qquad (3)$$

The output of the matched filter is then a complex detection function, in which real and imaginary parts are the detection function from **a(t)** and **b(t)** respectively. This enhancement permits a large reduction (almost 50%) in computational time. Two signals can be simultaneously processed.

6. ALGORITHM VALIDATION

The method was tested on night sleep recordings from 5 healthy volunteers aged 26-37 (mean = 32.2). Normal EEG sleep activity and regularly distributed sleep stages were indicated for this volunteers. These EEG recordings were visually analysed.

The validation consisted of two steps. First the learning phase: the thresholds were adjusted in order to maximize the number of true detections and minimize the number of false detections. Then, using EEG recordings different from those used during the learning phase, the automatically detected patterns were compare to those found by the visual rater. This one to one matching was performed on five (20 minutes long) periods of sleep stage 2. The results were then validated based on the comparison of the total number of pattern detected.

7. RESULTS OF THE EVALUATION

Tables 1 and 2 summarize the results of the evaluation described above. The tables present the number of patterns detected by visual versus automatic analyses. For example 58 of the 346 spindles detected by the algorithm were not detected by the visual rater, whereas 288 of the 346 spindles were detected by both.

Automatic Sleep Spindles Analysis

		false	*true*	
Visual	*false*	0	58	16.7 %
analysis	*true*	14	288	83.3 %
		4.6 %	95.4 %	100 %

Table 1 — Evaluation of sleep spindles detection

Automatic K-Complexes Analysis

		false	*true*	
Visual	*false*	0	16	10.1 %
analysis	*true*	8	142	89.9 %
		5.3 %	94.7 %	100 %

Table 2 — Evaluation of K-complexes detection

Fig. 4 shows the sleep histogram over a one night period with the cumulative percent of sleep spindle detected since the beginning of the night. As expected, the algorithm did not detect any pattern during the REM and awake periods.

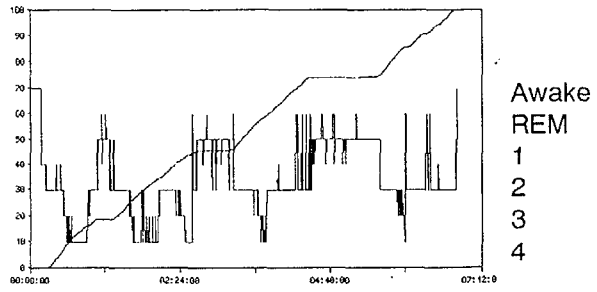

Fig. 4 — Repartition of the sleep spindle detections

8. APPLICATION

This automaton was used in a pharmacological sleep study. The goal was to compare the influence of hypnotics (Lormetazepam and Zopiclone) on the spindle and K-complex density. The study was performed on 16 elderly subjects aged from 61 to 79. The EEG curves were visually rated to determine the sleep stages (hypnogram). Based on this information it was then possible to compute the density of sleep spindles and K-complexes per minute of stage 2.

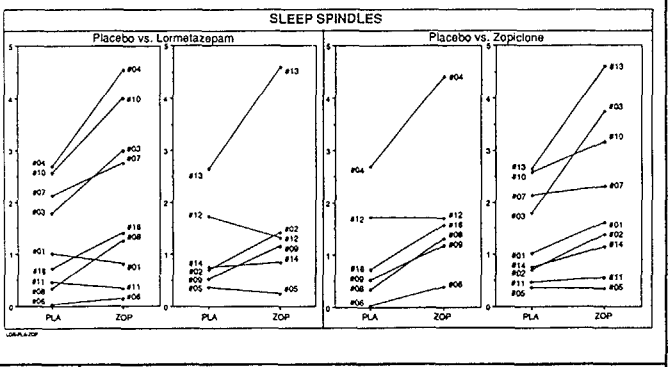

Fig. 5 — Effects of the substances on spindle density

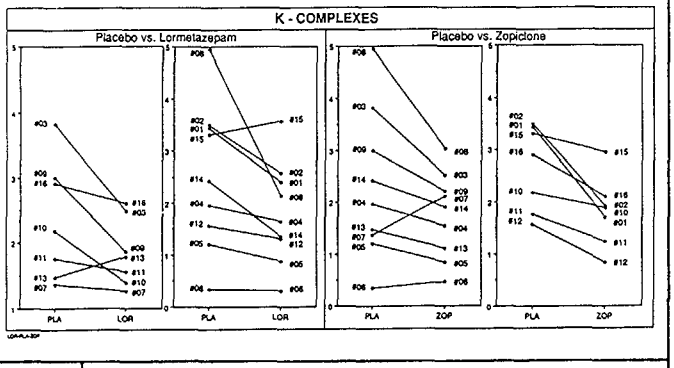

Fig. 6 — Effects of the substances on K-complex density

Fig. 5 and 6 show the effects of both substances on the spindle and K-complex density. The reduction of K-complexes ($p < 0.005$ under both substances) and the increase in sleep spindles ($p < 0.005$ under Zopiclone and Lormetazepam) confirm published results [2].

9. CONCLUSION

The algorithm has shown its ability for accurately detecting sleep spindles and K-complexes. There are many advantages of having the computer performing the analysis: For instance, the quality and the objectivity of the analysis (i.e. the detection criterion) remain constant over the complete night. Moreover, it makes it possible to perform studies on large number of volunteers or patients, all curves being identically scanned and the results easier to compare.

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