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Automated detection of sleep EEG slow waves based on matching pursuit using a restricted dictionary

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Abstract— **In this paper, an original method to detect sleep slow waves (SSW) in electroencephalogram (EEG) recordings is proposed. This method takes advantage of a Matching Pursuit algorithm using a dictionary reduced to Gabor functions reproducing the main targeted waveform characteristics. By describing the EEG signals in terms of SSW properties, the corresponding algorithm is able to identify waveforms based on the largest matching coefficients. The implemented algorithm was tested on a database of whole night sleep EEG recordings collected in 9 young healthy subjects where SSW have been visually scored by an expert. Besides being fully automated and much faster than visual scoring analysis, the results obtained to the proposed method were in excellent agreement with the expert with 98% of correct detections and a 77% concordance in event time position and duration. These results were superior from those of the classical method both in terms of sensibility and precision.**

I. Introduction

Human sleep is described through several stages mostly differentiated by their respective brain electrical activity ([10]) as measured by the electroencephalogram (EEG). Two main stages are distinguished: rapid eye movement (REM) and non-rapid eye movement (NREM or non-REM) sleep. According to [10], sleep EEG slow waves (SSW) are key components of NREM sleep, especially stage 3 and 4 also called deep sleep. SSW are defined as an oscillating electrical activity with a frequency between 0.5 and $2Hz$ and a peak-to-peak amplitude higher than $75\mu V$.

Recent medical research studies have shown a strong link between sleep ([4]) and, on one hand, cognitive functions such as memory processing ([8]) and, on another hand, metabolism and hormonal regulations ([11]), both advertently impacted in situations of sleep restriction. These new evidences explain the increasing interest of physiologists in the study and precise characterization of sleep and its components. Meanwhile, visual scoring of raw EEG data is still considered a major clinical tool in sleep analysis, despite its inherent limitations: low repeatability, high cost and disagreement between experts.

Efforts have been made in the recent years to develop techniques that allow the automatic detection of SSW. Massimini et al. have proposed a simple technique based on duration and amplitude criteria ([6]), following the original definition of [10]. The EEG signal is filtered in the band $[0.2\text{-}4]Hz$ (also called the δ band) and slow waves are selected using the following criteria: a negative deflection less than $-40\mu V$, longer than $250ms$ but shorter than $1250ms$, a peak-to-peak amplitude more than $75\mu V$ and a overall length less than $2000ms$. The onset and offset of each phase are defined by zero-crossing. This technique, resumed in fig. 1, has been used repeatedly in several sleep studies ([8], [1], [7]). Nevertheless, it has never been validated and has several limitations: the results depend on the filtering step and it needs to be used on already scored EEG data in order to process deep sleep stages only.

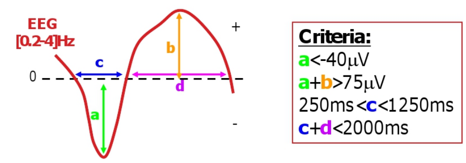

Fig. 1. Classic criteria of slow waves detection

Other techniques have been proposed more recently such as a likeness-based detection using Hilbert transform ([9]) to improve the classic detection algorithm using the SSW phases. Durka et al. have shown in [3] that matching pursuit using Gabor functions provides a good description of the sleep EEG, more particularly slow wave sleep. The matching pursuit (MP) technique is very interesting as it proposes to decompose the EEG signal using a dictionary of elementary waveforms and seems to provide a good description of the different patterns present in the EEG. Nevertheless, the description depends on the choice of the dictionary which needs to be rich enough to provide an accurate description of the signal. Moreover, this technique is time consuming and quite costly since all the components of the signal are described.

The method described here proposes to describe the EEG signal using a MP technique while restricting the dictionary to "slow wave look alike" waveforms only. In this way, the signal is described using only slow components and slow waves are detected where these components are the highest. Moreover, reducing the dictionary makes the processing faster as we have less choices to describe the signal.

The outline of the paper is the following. The restricted

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matching pursuit (RMP) technique is presented in section II. The proposed technique is then evaluated on several EEG recordings manually marked in section III and the results are compared to those obtained by the classic method presented in [6] and discussed.

II. Restricted Matching Pursuit

The purpose of the method proposed is to detect SSW in the EEG signal by describing this signal only with waveforms reproducing the SSW characteristics using matching pursuit.

A. Matching Pursuit

Matching pursuit (MP) has been introduced by Mallat and Zhang in [5]. This algorithm gives an approximation of a signal y as a linear combination of waveforms chosen in a redundant dictionary $\mathcal{D}$. In the first step of the MP, the waveform w_0 that best fits the signal x is selected from $\mathcal{D}$. In each consecutive step, the waveform w_n that best fits the residual signal left after subtracting all previous iterations $R^n(y)$ is selected. At each step, the waveform selected is the one with the largest scalar product $|\langle w_n, R^n(y)\rangle|$. This algorithm is described in (1).

$$\begin{cases} R^0(y) = y \\ R^n(y) = \langle R^n(y), w_n\rangle w_n + R^{n+1}(y) \\ w_n = arg\,max_{w_i \in \mathcal{D}}|\langle w_i, R^i(y)\rangle| \end{cases} \quad (1)$$

The process is iterated until some stopping criterion, such as minimal residual energy threshold, is reached. After M iterations, the approximation of y is given by (2).

$$y \approx \sum_{n=1}^{M} \langle R^n(y), w_n\rangle w_n \quad where \quad w_n \in \mathcal{D} \quad (2)$$

B. Restricting the dictionary

It has been demonstrated in [5] that Gabor functions dictionary provides optimal joint time-frequency localization that allows to describe y with a finite number of waveforms. This dictionary has besides been used in [3] to accurately describe EEG signals. So, we decided to use real valued Gabor functions. These functions can be expressed as

$$g_\gamma(t) = K(\gamma)e^{-\pi((t-u)/s)^2} cos(\omega((t-u)+\phi) \quad (3)$$

where $K(\gamma)$ is such as $||g_\gamma|| = 1$ and $\gamma = \{u, \omega, s, \phi\}$.

As we want to restrict the dictionary to SSW pattern only, several criteria are applied on parameters γ depending on the SSW characteristics.

First, the frequency of SSW is between 0.5 and $2Hz$. So, the frequency parameter ω is defined according to (4) where F_s is the sampling frequency of y and $f \in [0.5; 2]Hz$ the frequency of the Gabor function.

$$\omega(f) = 2\pi\frac{f}{F_s} \quad (4)$$

Then, a SSW should be only one oscillation (as we want to detect each SSW separately) so the scale parameter s is defined according to (5).

$$s(f) = \frac{Fs}{2f} \quad (5)$$

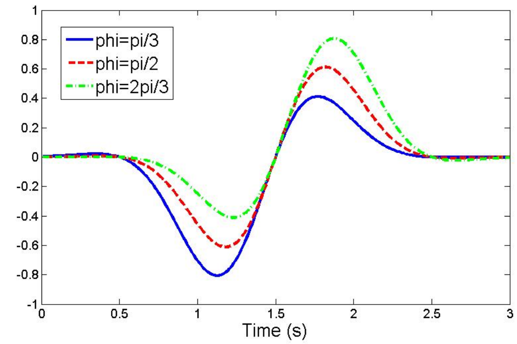

Fig. 2. Example of Gabor functions for $f = 1Hz$, $Fs = 100Hz$ and $z = 1s$

Thereby, for each value $f \in [0.5; 2]Hz$ corresponds a single value of $\omega(f)$ and $s(f)$.

Moreover, SSW should have both a negative and then a positive deflection. So, we restrict the phase ϕ between $\frac{\pi}{3}$ and $\frac{2\pi}{3}$, as described in (6).

$$\phi \in [\frac{\pi}{3}; \frac{2\pi}{3}] \quad (6)$$

At last, SSW are centered around a zero crossing corresponding to the passage from negative to positive deflection. So, we want the Gabor functions to have the same negative to positive zero-crossing. If z is a negative to positive zero-crossing in the signal, the Gabor functions will be centered around $u(z, f, \phi)$, according to (7).

$$u(z, f, \phi) = z - \frac{\frac{\pi}{2} - \phi}{\omega(f)} \quad (7)$$

A dictionary $\mathcal{D}$ containing only waveforms corresponding to SSW is then constructed using these different restrictions as defined in (8) where $\gamma(f, \phi) = \{u(z, f, \phi), \omega(f), s(f), \phi\}$. Fig. 2 shows an example of Gabor functions at $f = 1Hz$, $Fs = 100Hz$ and $z = 1,5s$ for three different phases. The plain blue line corresponds to $\phi = \frac{\pi}{3}$, the dotted red line to $\phi = \frac{\pi}{2}$ and the point-dotted green line to $\phi = \frac{2\pi}{3}$.

$$\mathcal{D} = \{g_{\gamma(f,\phi)}|f \in [0, 5; 2]Hz, \phi \in [\frac{\pi}{3}; \frac{2\pi}{3}]\} \quad (8)$$

C. Sleep EEG slow wave detection

The MP algorithm is processed with the dictionary $\mathcal{D}$ defined in (8) on EEG signal, filtered in the band $[0.3; 45]Hz$ in order to remove the continuous component and the artefacts caused by electrical power lines. The MP is processed on 30s data segment with $2s$ of overlap in order to be sure to detect SSW that could be at the end of the segment.

In order to decrease the computation time and because SSW is always centered on a negative to positive zero-crossing, only the negative to positive zero-crossing of the signal are considered for the MP. The MP is processed until the largest scalar product obtained is less than 40. This criteria has been empirically chosen as it seems a satisfying threshold to only detect SSW.

For each waveform thus detected, the EEG signal is filtered in the δ band in order to compute the features described in [6]: length, amplitude and slopes of the EEG waveform. The onset of the waveform is considered as the first positive to negative zero-crossing before the centre of the waveform and the offset as the first positive to negative zero-crossing after. If the peak-to-peak amplitude is less than $75\mu V$ or the duration is less than $0.5s$, the waveform is rejected. Else, it is considered as a SSW.

III. Results and discussion

A. Material

The database used to evaluate the proposed method is composed of polysomnographic recordings collected in 9 different young healthy adults during a night of undisturbed sleep (around 8 hours) in usual laboratory conditions. The database thus contains around 72 hours of EEG signals. SSW have been visually scored by a registered sleep polysomnography technologist. According to the guidelines, the analysis was based on a frontal EEG channel (standard derivation F3-A2) and, for the purpose of the present study, it was performed regardless of the sleep stage. SSW have been scored as trains of slow waves, which generally includes several consecutive elementary waveforms. A total of 4780 SSW trains, the equivalent of 618 minutes, have been scored from the whole database.

The PRANA software package (PhiTools, Strasbourg, FRANCE) has been used for the visual scoring of sleep stages and EEG slow waves, as well as for the automated detection of EEG slow waves using a software plug-in based on a classical algorithm ([5,7]). The PRANA software developer kit, available as a MATLAB toolbox, has been used to implement and test the proposed method.

SSW detected by the proposed method were compared one by one to the slow waves trains scored by the specialist. If a detected SSW is part of a scored SSW train, the detected wave was considered as a correct detection or *true positive (TP)*, else it was considered as false detection or *false positive (FP)*. Scored SSW trains during which no SSW has been detected by the algorithm were considered as missed SSW or *false negatives (FN)*. Several measures were then computed to evaluate the accuracy of the detection. The true positive rate (TPR) or *sensibility*, which is the rate between the number of SSW correctly detected and the total number of SSW to detect, was computed according to (9). The positive predictive value (PPV) or *precision*, which is the rate between the number of SSW correctly detected and the total number of SSW detected, was computed according to (10). The closer to 1 these two measures, the more accurate the detection.

$$TPR = \frac{TP}{TP + FN} \tag{9}$$

$$PPV = \frac{TP}{TP + FP} \tag{10}$$

Nevertheless, as SSW are scored by the expert as trains of slow waves that generally includes several SSW, the TPR score might not be completely relevant as detecting one SSW or several ones in a scored train would give the same result. So, the common SSW duration (CD) was also computed according to (11). This feature is the rate between the total duration of SSW correctly detected and the total duration of SSW scored by the specialist. In (11), $\mathcal{T}$ is the set of SSW correctly detected by the proposed method and $\mathcal{E}$ the set of SSW scored by the sleep technologist, $D(sw)$ is the duration of the SSW sw. The closer to 1 this measure, the more accurate the detection.

$$CD = \frac{\sum\limits_{sw \in \mathcal{T}} D(sw)}{\sum\limits_{sw \in \mathcal{E}} D(sw)} \tag{11}$$

TABLE I
Results of the automated SSW detection performed with the RMP method

Subject	1	2	3	4	5
TPR	96,5%	97,7%	99,2%	96,2%	98,5%
PPV	74,5%	76,9%	78,2%	35,3%	66,7%
CD	69,8%	71,7%	82,9%	68,7%	74,5%
Subject	**6**	**7**	**8**	**9**	**Overall**
TPR	98,3%	98,9%	98,9%	99,2%	**98,2%**
PPV	66,8%	73,9%	70,9%	66,6%	**67,8%**
CD	78,8%	87,9%	79,6%	79,4%	**77,0%**

TABLE II
Results of the slow waves detection performed with the method [6]

Subject	1	2	3	4	5
TPR	97,8%	88,9%	99,8%	93,3%	98,9%
PPV	63,0%	70,5%	68,2%	32,5%	60,8%
CD	53,1%	33,1%	75,2%	52,8%	53,3%
Subject	**6**	**7**	**8**	**9**	**Overall**
TPR	99,9%	97,9%	98,7%	91,4%	**96,3%**
PPV	59,7%	62,7%	62,5%	44,6%	**58,3%**
CD	72,2%	52,4%	54,5%	36,4%	**53,7%**

B. Results

The RMP method has been applied on frontal EEG channel (F3-A2) on the whole database. The results obtained are shown in table I. RMP method correctly detected 23658 SSW for 9814 false detections and 382 SSW missed.

In order to compare and discuss these results, the earlier method presented in [6] and considered as a reference has also been applied on F3-A2 channel on the database. This method is labelled as *Massimini method* in the following. It consists in the application of the amplitude and duration criteria presented in fig. 1 on the EEG filtered in $[0,2;4]Hz$. The results are shown in table II. The Massimini method correctly detected 19156 SSW for 11999 false detections and 517 SSW missed.

The results concerning the number of SSW correctly and wrongly detected by both method are summarized in table III.

TABLE III
NUMBER OF SSW DETECTED AND MISSED BY BOTH METHOD

Method	RMP	Massimini
Correct	23658	19156
False	9814	11999
Missed	382	517

C. Discussion

First, it can be seen from table I that the RMP method obtains a very high rate of correct detections (TPR) with an overall percentage of 98,2% correct SSW detections and no less than 96% for each subject. This means that the proposed method is very accurate to detect SSW. The precision (PPV) of the method is high with an overall percentage of 66,7% which significates that 2 SSW detections out of 3 are correct. Exept for subject 4, the precision rate for each subject is even higher and reach a maximum of 78,2% for subject 3. Then, the common duration (CD) is also very good with an overall percentage of 77,0%. The results for each subject varies between 70% and 80%. This point shows that around 3 quarters of the total duration of SSW scored by the sleep expert are correctly detected. It is interesting to mention that the inter-experts variability for sleep scoring is about 20% ([2]) which is close to the difference we obtain with the expert scoring of SSW.

The results in table II show that the Massimini method obtains similar performance in terms of correct SSW detection with an overall TPR=96,3%. Nevertheless, individual results show more variability than the RMP method with TPR varying from 89% to 99%. Moreover, overall precision and common durartion obtained with Massimini method are a bit low with only 58,3% of precision and 53,7% of SSW total duration scored by the sleep technologist correctly detected. This points out that almost 1 out of 2 detections is false and only half of the SSW are detected in each train scored by the expert.

The comparison between results obtained with the two methods shows that the RMP algorithm provides more accurate SSW detections. Although the percentages of SSW correctly detected with both methods are similar, the precision of the RMP-based detection is better (increase of 10 points) and the common duration rate (CD) is significantly better (increase of 20 points) with the proposed method. These results are confirmed by table III. It can be seen in table III that the RMP algorithm detected 4500 more correct SSW than the Massimini method for 3100 less false detections and 120 less SSW missed.

These better results can be explained by the fact that the RMP method is closer to the way the sleep expert processes the data to score SSW. The sleep expert looks at the EEG data in the whole $[0.3; 45]Hz$ band as the proposed method and not only in the δ band as in [6]. In this way, false detections that might be due to a distortion of the filtered signal are avoided. Moreover, the proposed method is less sensitive to the zero-crossings that defines each phase in the Massimini method as only the central zero-crossing matters in the RMP algorithm. At last, another advantage of the RMP-based detection is that it mainly focuses on the shape of the wave to look like a SSW instead on focusing only on duration and amplitude criteria.

IV. CONCLUSIONS AND FUTURE WORKS

An original method to detect sleep EEG slow waves has been presented in this paper. This method uses a Matching Pursuit algorithm with a reduced dictionary limited to "slow waves look alike" waveforms in order to describe the EEG signal only in terms of slow wave properties. The method has been validated on a database of human sleep EEG recordings form 9 different subjects, visually analyzed by a registered sleep technologist. The results of automated detection using the proposed method show very high performance with an overall correct detection rate of 98% and a precision of 67%. The algorithm was able to detect 77% of the total duration of SSW scored by the expert. The sensibility and precision of our method are superior to those of the method for automated detection proposed earlier and considered as a reference ([6]).

This method can still be improved in terms of precision as 1 out 3 waveforms detected was not a slow wave. Future clinical implications include the diagnosis of patients with sleep disorders as well as the automatic sleep detection and analysis of laboratory and ambulatory sleep recordings.

REFERENCES

[1] T. T. Dang-Vu, M. Schabus, M. Desseilles, G. Albouy, M. Boly, G. Rauchs, V. Sterpenich, G. Vandewalle, J. Carrierand, G. Moonen, E. Balteau, C. Degueldre, A. Luxen, C. Phillips, and P. Maquet. Spontaneous neural activity during human slow wave sleep. *PNAS*, 105(39):15160–15165, 2008.

[2] H. Danker-Hopfe, P. Anderer, J. Zeitlhofer, M. Boeck, H. Dorn, G. Gruber, E. Heller, E. Loretz, D. Moser, S. Parapatics, B. Saletu, A. Schmidt, and G. Dorffner. Interrater reliability for sleep scoring according to the rechtschaffen & kales and the new aasm standard. *Journal of Sleep Research*, 18(1):74–84, 2009.

[3] P. Durka, U. Malinowska, W. Szelenberger, A. Wakarow, and K. Blinowska. High resolution parametric description of slow wave sleep. *Journal of Neuroscience Methods*, 147(1):15–21, 2005.

[4] J. Horne. Human sleep, sleep loss and behaviour. implications for the prefrontal cortex and psychiatric disorder. *Br. J. Psychiatry*, 162:413–419, 1993.

[5] S. Mallat and Z. Zhan. Matching pursuit with time-frequency dictionaries. *IEEE Trans. on Signal Processing*, 41(12):3397–3415, 1993.

[6] M. Massimini, R. Huber, F. Ferrarelli, S. Hill, and G. Tononi. The sleep slow oscillation as a traveling wave. *The Journal of Neuroscience*, 24(31):6862–6870, 2004.

[7] D. Menicucci, A. Piarulli, U. Debarnot, P. d'Ascanio, A. Landi, and A. Gemignani. Fonctional structure of spontaneous sleep slow oscillation activity in humans. *PLoS ONE*, 4(10):e7601, 2009.

[8] M. Mölle, L. Marshall, S. Gais, and J. Born. Grouping of spindle activity during slow oscillations in human non-rapid eye movement sleep. *The Journal of Neuroscience*, 22(24):10941–10947, 2002.

[9] A. Piarulli, D. Menicucci, A. Gemignani, U. Olcese, P. d'Ascanio, A. Pingitore, R. Bedini, and A. Landi. Likeness-based detection of sleep slow oscillations in normal and altered sleep conditions: application on low density eeg recordings. *IEEE Trans. on Biomedical Engineering*, 57(2):363–372, 2010.

[10] A. Rechtschaffen and A. Kales. *A Manual of Standardized Terminology, Techniques and Scoring System for Sleep Stages of Human Subject*. National Institute of Health Publication, Washington DC, us government printing office edition, 1968.

[11] K. Spiegel, R. Leproult, and E. V. Cauter. Impact of sleep debt on metabolic and endocrine function. *Lancet*, 354(9188):1435–1439, 1999.