Validation of an EEG-Based Algorithm for Automatic Detection of Sleep Onset in the Multiple Sleep Latency Test

Luis Estrada, Joan Santamaría, Valentina Isetta, Alex Iranzo, Daniel Navajas and Ramon Farré*

***Abstract*—The Multiple Sleep Latency Test (MSLT) is a standard test to objectively evaluate patients with excessive daytime sleepiness. Sleep onset latencies are determined by visual analysis, which is costly and time-consuming. The aim of this study was to implement and test a single automatic algorithm to detect the sleep onset in the MSLT on the basis of electroencephalographic (EEG) signals. The designed algorithm computed the relative EEG spectral powers in the occipital area and detected the sleep onset corresponding to the intersection point between the lower and alpha frequencies. The algorithm performance was evaluated by comparing the sleep latencies computed automatically by the algorithm and by a sleep specialist using MSLT recordings from a total of 19 patients (95 naps).**

The mean difference in sleep latency between the two methods was 0.025 min and the limits of agreement were ± 2.46 min (Bland-Altman analysis). Moreover, the intra-class correlation coefficient showed a considerable inter-rater reliability (0.90).

The algorithm accurately detected the sleep onset in the MSLT. The devised algorithm can be a useful tool to support and speed up the sleep specialist's work in routine clinical MSLT assessment.

***Index Terms*—Automatic Algorithm, Drowsiness, Electroencephalography, Multiple Sleep Latency Test, Polysomnography, Sleep onset.**

I. Introduction

The Multiple Sleep Latency Test (MSLT) is considered the gold standard test for the objective measurement of sleepiness [1], [2]. Clinical routine detection of sleep onset and, therefore, of sleep latency in MSLT is currently carried out by a sleep specialist, who visually inspects the electroencephalographic (EEG), electro-oculographic (EOG), and electromyographic (EMG) patterns following standard criteria [3]. This process is time-consuming and consequently expensive. Accordingly, an automatic method to detect the sleep onset in the MSLT would be useful to facilitate and speed up the clinician's work.

Several studies have reported the development of automatic sleep scoring tools based on the analysis of polysomnographic signals [4]–[12], but very few of them were addressed to the application of these methods to the MSLT. Moreover, these few studies were not systematically tested under routine conditions, with the result that no conclusions could be drawn on the algorithm's suitability for obtaining an accurate value of sleep latency in clinical practice. Accordingly, the aim of the present study was to design, implement and test an automatic EEG-based algorithm for sleep onset detection during routine MSLT carried out on patients with suspected sleepiness.

Manuscript received December 14, 2009; revised December 31, 2009; submitted December 15, 2009. This work was supported in part by the Ministerio de Ciencia e Innovación under Grant SAF2008-02991. *Asterisk indicates corresponding author*.

L. Estrada and V. Isetta are with the Unitat de Biofisica i Bioenginyeria, Facultat de Medicina, Universitat de Barcelona, Barcelona, Spain (e-mail: lestrada@ieee.org; valentina.isetta@ub.edu).

J. Santamaría and A. Iranzo are with the Servei de Neurologia, Unitat Multidisciplinar de Transtorns del Son, Hospital Clinic, Barcelona, Spain; CIBERNED, Spain; and Institut d'Investigacions Biomèdiques August Pi Sunyer (IDIBAPS), Barcelona, Spain (e-mail: jsantama@clinic.ub.es; airanzo@clinic.ub.es),

D. Navajas is with the Unitat de Biofisica i Bioenginyeria, Facultat de Medicina, Universitat de Barcelona, Barcelona, Spain; CIBER de Enfermedades Respiratorias (CIBERES), Bunyola, Spain and Institut de Bioenginyeria de Catalunya, Barcelona, Spain (dnavajas@ub.edu).

*R. Farré is with the Unitat de Biofisica i Bioenginyeria, Facultat de Medicina, Universitat de Barcelona, Barcelona, Spain; CIBER de Enfermedades Respiratorias (CIBERES), Bunyola, Spain and Institut d'Investigacions Biomèdiques August Pi Sunyer (IDIBAPS), Barcelona, Spain (phone: +34 934024515; e-mail: rfarre@ub.edu).

II. Methods

A. Patients and Signal Recording

The MSLT data from 19 patients (9 men, 10 women; mean age: 44.4 (SD=17.1) years) with a complaint of hypersomnia examined by the Multidisciplinary Sleep Disorders Unit of the Hospital Clínic of Barcelona (Barcelona) were analyzed retrospectively. Subjects were randomly selected, the only requirement being that they had to have fallen asleep during the test. The patients were taking no medication at the time of the study. Ten patients had idiopathic hypersomnia, 4 narcolepsy and 5 had normal sleep latency, despite a complaint of hypersomnia.

All subjects were studied using a 32-channel digital polygraph (Deltamed, Coherence 3 NT, software version 4.0, Paris, France). The MSLT protocol consisted of 5 naps in each patient, recorded at 9:30, 11:30, 13:30; 15:30 and 17:30, subsequent to a full polysomnogram the previous night. The collected data (a total of 95 naps) included EEG, two EOG and submental EMG. The EEG electrodes were mounted on the scalp (F3, F4, C3, C4, O1, O2, A1, and A2) according to the International 10-20 System. The EEG signals were sampled at 256 Hz, digitized with a 16-bit A/D converter within a bandwidth of 0-48 Hz.

B. Assessment of Sleep Latency by a Sleep Specialist

Conventional visual scoring of each nap recording was conducted by a sleep specialist using 30-s epochs. The first epoch, with at least 16 s of any sleep stage, was considered

ISBN: 978-988-17012-9-9
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

the sleep onset in that nap. For each patient, the mean visually determined sleep latency (SLv) was computed as the mean of the values corresponding to the 5 naps.

C. Algorithm for Automatic Assessment of Sleep Latency

The algorithm designed for the automatic detection of the sleep onset was applied on the O1 occipital EEG channel. First the EEG power spectral density was calculated by applying Welch's periodogram to epochs lasting 2 s each (Hamming window, 50% overlapping). The relative EEG powers corresponding to each of the four classic frequency bands ($0.2<\delta\leq3.5$ Hz, $3.5<\theta\leq7.5$ Hz, $7.5<\alpha\leq13.0$ Hz, $13.0<\beta\leq28.0$ Hz) were computed by dividing the power within each band by the total power across all bands. Signals were smoothed by robust loess (locally weighted scatterplot smoothing; 10% of data span), which is a non-parametric fitting smooth curve technique [13].

Second, the algorithm searched the first time from the "lights out" that α power decreased and δ power increased reaching an intersection. This point was identified as the sleep onset for that nap. If such an intersection was not found during the nap, the algorithm restarted the search of an intersection between α and θ powers and this point was considered the sleep onset. For each patient, the sleep latency automatically determined by the algorithm (SLa) was the mean of the values corresponding to the 5 patient's naps.

D. Comparison between Visually and Automatically Computed Sleep Latencies

SLv and SLa were compared by a Bland-Altman analysis [14] to provide an estimate of the mean difference and limits of agreement of automatic and visual assessment of the sleep latency. Moreover, the Pearson correlation coefficient and the intra-class correlation coefficient were calculated to provide more indices of comparison between both methods. The statistical analysis was performed using SPSS 15.0.

III. RESULTS

An example of the performance of the algorithm to automatically detect the sleep onset in a nap is presented in Fig. 1 (a). After the test started, when the patient closed his/her eyes, α power increased while δ power decreased. When he/she was falling asleep, α power decreased and δ power increased. The algorithm located the sleep onset at the α-δ intersection. The solid vertical line indicates the time of the sleep onset independently detected by the clinician through conventional visual inspection of the polysomnographic signals. The algorithm was able to automatically detect the sleep onset by means of a α-δ intersection in 78 of the 95 naps. In 17 naps the sleep onset was detected by a α-θ intersection. The comparison between SLv and SLa is shown in Fig. 1 (b).

The mean difference was 0.025 min and the limits of agreement were ±2.46 min. The good agreement between SLa and SLv was also reflected by the high values of their Pearson and intra-class correlation coefficients (0.90 in both cases).

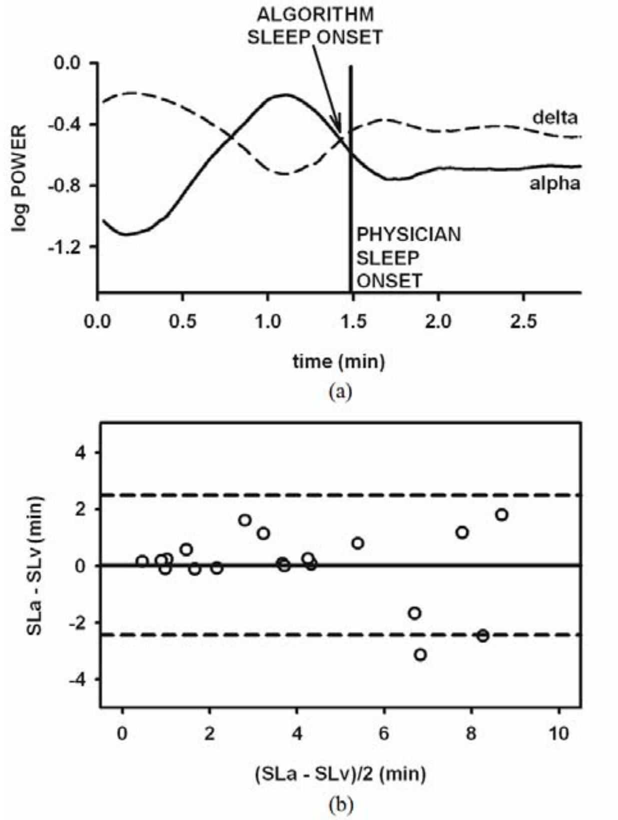

Fig. 1. (a) Example of the evolution of α and δ EEG powers from the start of one nap (see text for explanation). (b) Bland-Altman plot comparing the sleep latencies computed visually by a sleep expert (SLv) and those computed automatically by the algorithm developed in this study (SLa). The solid line represents the mean difference and the dashed lines are the limits of agreement.

IV. DISCUSSION

In this study we designed and implemented a computer algorithm for automatically assessing the sleep latency in the MSLT. When tested under routine clinical conditions, the algorithm was able to automatically provide sleep latency values very close to the ones conventionally determined by an expert visual inspection.

Several authors have reported algorithms that detect sleepiness based on EEG recordings. Due to the recent interest in reducing driver risks, many of these sought to detect fatigue and drowsiness and to assess the alertness level during driving [15], [16]. Nevertheless, only few studies were focused on the application of automatic methods to detect sleep in the MSLT.

Hasan et al. presented a computer classification system based on EEG, EOG and EMG signals as a clinical support tool for sleep onset detection during a MSLT [4]. The comparison between the computer and the visual scores showed a relatively good agreement, but the validation of the algorithm was rather poor since it was assessed for only 9 naps randomly selected from the MSLT studies of 9 patients. In a subsequent work, the same algorithm was tested on ambulatory recordings of seven healthy subjects, but the analysis was limited to identifying the different wakefulness and sleep stages, with no computation and validation of the sleep latency [5].

ISBN: 978-988-17012-9-9
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

Another study compared sleep latencies obtained from the standard analysis of MSLT and an automatic method for the detection of slow eye movements (SEMs) [10]. Despite the authors found SEMs useful as a marker of sleepiness, they reported the potential inadequacy of the method in conditions where sleep onset can occur with REM sleep, as in narcolepsy.

The algorithm used in this study is simple and straightforward since it is based on the well accepted concept that sleep onset is characterized by a decrease in α waves of the EEG [17]. The algorithm computes the relative EEG power of the different conventional frequency bands from the left occipital area and identifies the sleep onset as the point where α power decreases over the lower EEG frequency bands, in keeping with the standard sleep stage detection procedure [3].

As this algorithm is based on the presence of an occipital α rhythm, it would probably not work in those subjects that do not have α waves when awake – approximately 10% of the healthy adult population [17]. In contrast with the more complex methods previously proposed [6]–[12], [18], the algorithm devised for this study has the advantage of detecting sleep onset by means of a general criterion (α vs. δ or α vs. θ). Accordingly, it does not require the optimization of several mathematical parameters nor the application of a threshold to be tuned for a specific group of patients to improve detections.

When comparing the values of sleep latency determined by the specialist (SLv) and by the automatic algorithm (SLa) in 19 patients subjected to standardized MSLT in the sleep lab, the results obtained in this study provided evidence of the suitability of the devised algorithm. The difference between SLa and SLv was small (1.52 s) and similar to that expected when comparing results obtained by different sleep specialists. Furthermore, the Pearson and intra-class correlation coefficients found in this study (0.90) were within the range of the inter-rater reliabilities reported when comparing the performance of clinical scorers in conventional MSLT analysis (0.79 [19] and 0.96 [20]).

In conclusion, the proposed algorithm proved to be a robust and precise tool for locating the sleep onset and deriving the sleep latency in MSLT. This algorithm, used alone or in combination with information obtained automatically from other PSG signals such as EOG [7], [10], [12], could be a reliable tool for supporting and speeding up the sleep specialist's task in MSLT analysis. Moreover, the simplicity of the method proposed in this study, which requires only one occipital EEG channel, suggests its potential application for the automatic sleep onset detection in 24-h screening tests.

REFERENCES

[1] J. Santamaria, "How to evaluate excessive daytime sleepiness in Parkinson's disease," *Neurology*, vol. 63, no. 8 Suppl 3, pp. S21-S23, Oct. 2004.

[2] M. R. Littner, C. Kushida, M. Wise, D. G. Davila, T. Morgenthaler, T. Lee-Chiong, M. Hirshkowitz, L. L. Daniel, D. Bailey, and R. B. Berry, "Standards of Practice Committee of the American Academy of Sleep Medicine. Practice parameters for clinical use of the multiple sleep latency test and the maintenance of wakefulness test," *Sleep*, vol. 28, no. 1, pp. 113-121, Jan. 2005.

[3] A. Rechtschaffen and A. Kales, *A manual of standardized terminology, techniques and scoring system for sleep stages of human subjects*. University of California, Los Angeles. Brain Information Service. US Dept. of Health, Education, and Welfare, 1968.

[4] J. Hasan, K. Hirvonen, A. Värri, V. Häkkinen, and P. Loula, "Validation of computer analysed polygraphic patterns during drowsiness and sleep onset," *Electroencephalogr. Clin. Neurophysiol.*, vol. 87, no. 3, pp. 117-127, Sept. 1993.

[5] K. Hirvonen, J. Hasan, V. Häkkinen, A. Värri, and P. Loula, "The detection of drowsiness and sleep onset periods from ambulatory recorded polygraphic data," *Electroencephalogr. Clin. Neurophysiol.*, vol. 102, no. 2, pp. 132-137, Feb. 1997.

[6] M. Modarres-Zadeh, "A Neuro-behavioral test and algorithms for quantification of sleepiness and characterization of wake-sleep transitions," in *Proc. 27th Annu. Int. Conf. IEEE Engineering in Medicine and Biology Society*, Shanghai, China, Sept. 2005, vol. 6, pp. 5746-5749.

[7] E. Magosso, M. Ursino, F. Provini, and P. Montagna, "Wavelet analysis of electroencephalographic and electro-oculographic changes during the sleep onset period," in *Proc. 29th Annu. Int. Conf. IEEE Engineering in Medicine and Biology Society*, Lyon, France, Aug. 2007, pp. 4006-4010.

[8] C. Berthomier, X. Drouot, M. Herman-Stoica, P. Berthomier, J. Prado, D. Bokar-Thire, O. Benoit, J. Mattout, and M.P. d'Ortho, "Automatic analysis of single-channel sleep EEG: validation in healthy individuals," *Sleep*, vol. 30, no. 11, pp. 1587-1595, Nov. 2007.

[9] D. Cvetkovic and I. Cosic, "Sleep onset estimator: evaluation of parameters," in *Proc. 30th Annu. Int. Conf. IEEE Engineering in Medicine and Biology Society*, Vancouver, Canada, Aug. 2008, pp. 3860-3863.

[10] M. Fabbri, F. Provini, E. Magosso, A. Zaniboni, A. Bisulli, G. Plazzi, M. Ursino, and P. Montagna," Detection of sleep onset by analysis of slow eye movements: a preliminary study of MSLT recordings," *Sleep Med.*, vol. 10, no. 6, pp. 637-640, June 2009.

[11] M. K. Kiymik, M. Akin, and A. Subasi, "Automatic recognition of alertness level by using wavelet transform and artificial neural network," *J. Neurosci. Methods*, vol. 139, no. 2, pp. 231-240, Oct. 2004.

[12] J. Virkkala, J. Hasan, A. Värri, S. L. Himanen, and K. Müller, "Automatic sleep stage classification using two-channel electro-oculography," *J. Neurosci. Methods*, vol. 166, no. 1, pp. 109-115, Oct. 2007.

[13] W. S. Cleveland, "Robust locally weighted regression and smoothing scatterplots," *J. Amer. Statist. Assoc.*, vol. 74, no. 368, pp. 829-836, Dec. 1979.

[14] J. M. Bland and D. G. Altman," Statistical methods for assessing agreement between two methods of clinical measurement," *Lancet*, vol. 1, no. 8, pp. 307-310, 1986.

[15] S. K. Lal, A. Craig, P. Boord, L. Kirkup, and H. Nguyen, "Development of an algorithm for an EEG-based driver fatigue countermeasure," *J. Safety Res.*, vol. 34, no. 3, pp. 321-328, Aug. 2003.

[16] B. T. Jap, S. Lal, P. Fischer, and E. Bekiaris, "Using EEG spectral components to assess algorithms for detecting fatigue," *Expert Syst. Applicat.*, vol. 36, no. 2, Part 1, pp. 2352-2359, March 2009.

[17] J. Santamaria and K. H. Chiappa, *The EEG of Drowsiness*. New York: Demos Publications, 1987.

[18] Q. Ni, Z. Hajenga, D. R. Daum, J. E. Stahmann, J. D. Hatlestad, and K. Lee, "Sleep detection using an adjustable threshold," U.S. Patent 7 189 204, March 13, 2007.

[19] S. R. Benbadis, Y. Qu, M. C. Perry, D. S. Dinner, and H. Warnes, "Interrater reliability of the multiple sleep latency test," *Electroencephalogr. Clin. Neurophysiol.*, vol. 95, no. 4, pp. 302-304, Oct. 1995.

[20] L. Chen, C. K. Ho, V. K. Lam, S. Y. Fong, A. M. Li, S. P. Lam, and Y. K. Wing, "Interrater and intrarater reliability in multiple sleep latency test," *J. Clin. Neurophysiol.*, vol. 25, no. 4, pp. 218-221, Aug. 2008.