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A new Measure to quantify Sleepiness using Higher Order Statistical Analysis of EEG.

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Abstract— **Chronic sleepiness is a common symptom in the sleep disorders, such as, Obstructive Sleep Apnea, Periodic leg movement syndrome, narcolepsy etc. It affects 5% of the adult population and is associated with significant morbidity and increased risk to individual and society. MSLT and MWT are the existing tests for measuring sleepiness. Sleep Latency (SL) is the main measures of sleepiness computed in these tests. Existing method of SL computation relies on the visual extraction of specific features in multi-channel electrophysiological data (EEG, EOG, and EMG) using the R&K criteria (1968). This process is cumbersome, time consuming, and prone to inter and intra-scorer variability. In this paper we propose a fully automated, objective sleepiness analysis technique based on the single channel of EEG. The method uses a one-dimensional slice of the EEG Bisprectrum representing a nonlinear transformation of the underlying EEG generator to compute a novel index called Sleepiness Index. The SL is then computed from the SI. A strong correlation (r=0.93, ρ=0.0001) was found between technician scored SL and that computed via SI. The proposed Sleepiness Index can provide an elegant solution to the problems surrounding manual scoring and objective sleepiness.**

I. INTRODUCTION

Sleepiness is defined as the probability of a person to fall sleep at a given time[1]. Excessive sleepiness is one of the common symptom in several sleep disorders, such as, Obstructive Sleep Apnea (OSA), Upper Airways Resistance Syndrome, Periodic Leg Movement Syndrome (PLMS) etc[2]. It is estimated to affect approximately 5% of the adult population [3]. It is associated with the increased risk of road and work related accident and is harmful to both individual and the society[4, 5]. According to a report[6] the total cost of sleepiness related accidents in USA is estimated to be between $43.15 billion and 56.02 billion per year. AASM [7] definition of micro-sleep is: "…an episode lasting up-to 30s during which external stimuli are not perceived. The neuro-physiological signals suddenly shift from waking characteristics to sleep". It is generally believed that micro-sleep is closely associated with excessive sleepiness. Even though diurnal micro-sleep is an important phenomenon related to sleep disturbances, there is no objective system of measurements to detect micro-sleep or express its severity. The standard clinical tests to measure sleepiness are Multiple Sleep Latency Test (MSLT)[8] and Maintenance of Wakefulness Test (MWT)[9]. The MSLT and MWT are the objective tests, which measure the individual ability to fall asleep and ability to remain awake respectively. In MSLT/MWT, a series of nap opportunities (4-6) are presented to the subject undergoing test at 2 hour intervals beginning approximately 2 hour after morning awakening. Each recording goes for at least 20 minutes in MSLT and 40 minutes in MWT. In these tests, several neuro-physiological signals (at-least 7, 4-EEG, 2-EOG and 1-EMG) are continuously monitored and recorded. Sleep technicians have to simultaneously look at multiple signals and apply several rules [10] to identify sleep onset. Sleepiness is then expressed by the measure *Sleep Latency* (SL), which is the length of time required to fall sleep.

Manual scoring of SL is a tedious and subjective process resulting in inter and intra-rater variability[11]. The scorers from different laboratories tend to agree less than scorers from the same laboratories, due to differences in interpretation and subjective implementations. Moreover MSLT and MWT are clinical tests and need proper sleep laboratory and trained sleep technicians to perform them. There are no tests available to detect inadvertent sleep onset in real time and which can be performed in any professional work environment to measure sleepiness level. To address these issues, in this paper we present a novel index called *Sleepiness Index* (SI) to quantify sleepiness via computing the time-density of 'micro-sleep events'. The method is fully automated and uses EEG data from just single channel. The SI computation is completely independent from other physiological signals such as EOG or EMG which are needed by traditional R&K[10] based methods. Our method is based on the Higher-Order-Statistics (HOS), which makes the technique robust against Gaussian noise present in EEG measurements[12, 13]. In the next section we present our method to compute SI.

II. METHOD

The data was recorded using clinical Polysomnography (PSG) equipment (*Siesta*, *Compumedics*®). The patient preparation, and instrumental set-up were done by an experienced sleep technician according to AASM guidelines[2]. Table 1 describes the demographic details of the subjects studied. **Database A**: From each subject in this database, routine PSG [2] data was collected. EEG data was

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recorded from both hemispheres using electrode positions C4, C3, A2, and A1, based on the standard international 10-20 system of electrode placement. The subject population includes, individual with symptoms of sleep apnea. **Database B:** This database contains data from the subjects referred for the MSLT or MWT tests. Typical physiologicalsignals which are recorded in MSLT and MWT are (i) 4 channels of EEG (C3, C4, O1, O2 reference to A1 and A2). (ii) left and right EOGs, and (iii) sub-mentalis EMG. EEG signal was sampled at f_s = 256Hz, with a gain of 125μV. For the work of this paper we have used EEG data recorded from position C4 over the skull. We segmented the collected data into sub-records of length *M* samples for further analysis. Note in the field of sleep medicine these segments are called as 'epochs'. We use the terms segments and epochs

A. HOS based analysis of EEG

Let $x^i(k)$, $i = 1,2,3.....,N$, denote the *k*-th sample of the *i*-th segment of digitized EEG data where *N* is the total number of segments in a recording. In this paper we model $x^i(k)$ as*:*

$$x^i(k) = h^i(k) * e^i(k) + w^i(k) \quad (1)$$

where $e^i(k)$ is a white non-Gaussian process, and $h^i(k)$ is a stable, possibly non-minimum phase kernel representing the underlying system generating the EEG segment $x^i(k)$. The term $w^i(k)$ represents measurement noise within the frequency band of interest, which is traditionally modeled as a white Gaussian process. In this work, we relax this constraint and allow the measurement noise to be either a white or colored Gaussian noise, or, any noise process with a symmetrical probability density function.

1) Filtering of EEG segments: EEG is a low-frequency signal and the frequency band of interest to us is contained within 1-45Hz. Thus we filtered $x^i(k)$ using a 5th order, zero-phase digital Butterworth bandpass filter $f(k)$ with lower and higher cut-off frequency f_l=1Hz and f_h=45 Hz to remove out-of-band noise, including the ubiquitous power line interference at 50Hz. Let the filtered segments $x^i(k)$ be denoted by $y^i(k)$. **2) The Bispectrum estimation:** The bispectrum can be estimated via estimating the 3rd order cumulant[13], $C^{yi}(\tau1,\tau2)$ of the $y^i(k)$, and then taking a 2D-Fourier transform (2). This method, known as the indirect method of estimating the bispectrum, was followed in this paper.

$$B^{yi}(\omega_1,\omega_2) = \sum_{\tau_1=-\infty}^{\tau_1=+\infty}\sum_{\tau_2=-\infty}^{\tau_2=+\infty} C^{yi}(\tau_1,\tau_2)\, e^{-j(\tau_1\omega_1+\tau_2\omega_2)} \quad (2)$$

The bispectrum obtained using (2) will be a complex number. Unlike the power spectrum (2nd order statistics) based on the autocorrelation, bispectrum preserves Fourier phase information. In contrast, power spectrum (or autocorrelation based) techniques lose phase information, and the EEG System Response estimated from it will be the minimum-phase equivalent of the original response.

TABLE 1: PATIENTS DEMOGRAPHIC DETAILS AND SLEEP LATENCY REULTS

Pat.ID	Age	Sex	RDI	SL-TS	SL-SI
Database A - PSG Data					
1	45	F	0.6	38	36.5
2	34	F	1.5	20	22.25
3	62	F	3.5	48	51.25
4	63	F	4.1	13	14.75
5	36	F	4.7	21	6
6	52	M	4.9	19.5	22.75
7	62	F	5.1	13	14.25
8	44	F	6.8	15.5	17
9	50	M	20.8	48	51.25
10	62	M	37.5	14	11
11	56	F	40.1	31.5	25.5
12	53	M	40.3	15.5	22.25
13	63	F	45.8	23	30.75
14	30	F	49.9	35.5	34.5
15	50	F	0	8	8.75
16	44	M	2.4	30.5	27.75
17	73	F	3.2	48	63.5
18	58	F	3.3	48	45.5
19	72	M	4.8	32.5	33
20	42	M	4.8	36.5	35
Database B - MSLT Data					
21	34	M		5.5	4.34
22	57	F		6.5	4.53

In [12] we considered the problem of signal reconstruction from the bispectrum, and proved that any 1-dimensional slice of the bispectrum carries sufficient information to estimate a system response within a time-shift, as long as the chosen slice is not parallel to any one of the frequency axes or to the diagonal at 135 degrees. In this paper, we rely on that result to reduce the computational complexity of the HOS techniques. The flexibility offered by the choosing arbitrarily oriented and shifted oblique slices also give us the advantage of avoiding unfavorable regions in the bispectrum [12]. **3) The Bispectogram Time Series (BTS) :** In the frequency domain, a quantity $P_i(\omega;\phi,\rho)$ can be defined for each data segment $x_i(k)$ such that $P_i(\omega;\phi,\rho) = B^{yi}(\omega, \phi\omega+\rho)$ describes a one-dimensional slice inclined to the ω_1-axis at an angle $tan^{-1}\phi$ and shifted from the origin along the ω_2-axis by the amount ρ, $(-\pi < \rho < \pi)$ [12]. The slice $P_i(\omega;\phi,\rho)$ carries complete information on the EEG system response (i.e. the underlying EEG generating system) according to the model we have adopted. We can describe the data in a graphical way by defining a matrix $S_B(\omega;\phi,\rho)$ such that:

$S_B(\omega;\phi,\rho) = [P_0(\omega;\phi,\rho) \mid P_1(\omega;\phi,\rho) \mid \ldots, P_i(\omega;\phi,\rho), \ldots \mid P_{N-1}(\omega;\phi,\rho)]$ (3)

where the i[th] column of S_B represents a vector $[P_i(\omega;\phi,\rho), -\pi < \omega < \pi]^T$. We call this matrix the Slice-Bispectrogram. We form a times series, called Bispectogram-Time-Series (BTS, ξ_f), by considering a fixed ω, i.e. $\omega = \omega_0$, $\omega = \omega_1$, ω_2 …, ω_{N-1} as follows:

Time series N-1(ξ_{N-1}):

$S_B(\omega_{N-1};\phi,\rho) = \{P_0(\omega_{N-1};\phi,\rho), \quad P_1(\omega_{N-1};\phi,\rho), \quad \ldots. \quad ,P_i(\omega_{N-1};\phi,\rho), \ldots , P_{N-1}(\omega_1;\phi,\rho)\}.$ (4)

Symbol ξ_f represents the Bispectogram-Time-Series at frequency *f*. In this paper, we illustrate that it is possible to choose particular values for '*f*' such that the Bispectogram-Time-Series, ξ_f carries sufficient information to characterize micro-sleep events. In the next section we give some of the implementation details to compute SI and present our results.

III. RESULTS

The length of data segments (M) were set to the standard 'epoch length' of M=30s as used in routine sleep scoring and the segment overlap was set to 15s. Thus, the sleep data was assessed every 15s, based on the last 30s data. The method described in this paper needs EEG data only from one channel. Without a loss of generality (see [12]), we set ϕ=1 and ρ=0 in (3). The slice of the bispectrum considered to form bispectogram, is inclined to the ω_1-axis by 45 degrees and passes through the origin (i.e. the line described by $\omega_1=\omega_2$ in the (ω_1, ω_2)-plane) as symbolized by $S_B(2\pi f;1,0)$.

A. Bispectogram Time Series (BTS, $\xi_{f=20}$)

From the Slice-Bispectogram (S_B) the Bispectogram-Time-Series (BTS, ξ_f) was estimated. For the results reported in this paper, we set *f*=20Hz for its ability to discriminate Sleep/Wake states. Note that the entries of BTS are complex valued. For the rest of the paper, let us define ξ_{20}=Abs($S_B(2\pi f;1,0)$). Figure 1(a) and Fig.1(b) show the ξ_{20} and technician scored Sleep/Wake states for whole night PSG data. The EEG data for this figure is taken from subject ID 6. The magnitude of the 20Hz component

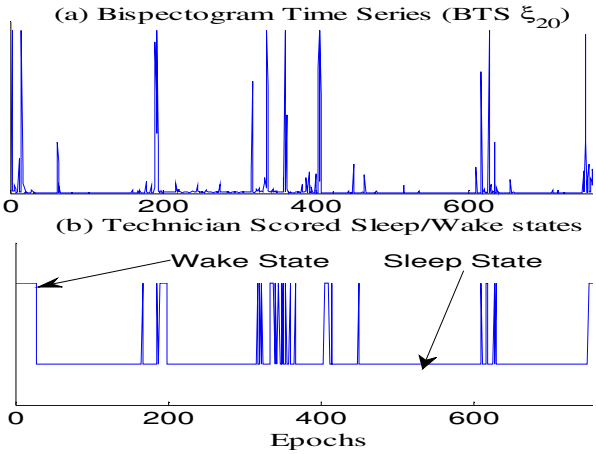

Fig. 1. (a) Bispectogram Time Series (ξ_{20}), (b) Technician Scored Sleep/Wake states.

consistently remained low during the sleep; however it increased considerably with the episodes of Wake states during the night. This characteristic feature of the BTS was consistently seen in all the patients in our database.

B. Micro Sleep Events

In Fig.2(a) we show the time series ξ_{20} where a person is falling sleep. Fig.2(b) shows the technician scored Sleep/Wake states. In this figure we show data for the first

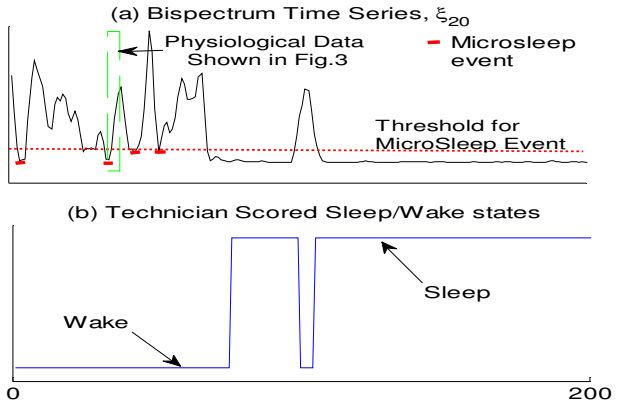

Fig. 2. (a) BTSs at frequency 20Hz, ξ_{20}. (b) Technician scored sleep states. Red mark in (a) indicates the 'micro-sleep' events in the bispectrum slice time series.

200 epochs from the subject ID 1. Fig.2(a) and Fig.2(b) graphically illustrate the close correspondence of the ξ_{20} and the sleep/wake states. Moreover, it is seen that the gradual development of the sleep over time is captured well by the gradual change in ξ_{20}. The red marks under the series ξ_{20} indicate micro-sleep events. Note that the technologist has not attempted to identify states of micro-sleep. It is of great interest to explore how the micro-sleep events defined via ξ_{20} correspond with micro-sleep defined by the AASM. As an illustration, in Fig.3 we show the EEG (C4-A1, C3-A2), EOG and EMG data from the epochs 35, 36, 37, and

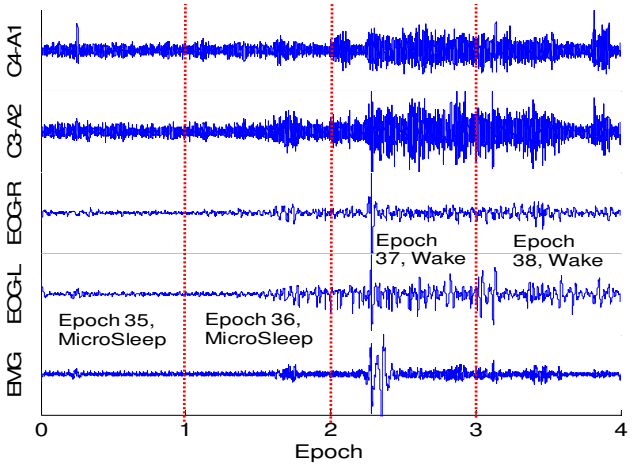

Fig. 3. Physiological data (EEG, EOG and EMG) corresponding to the epoch number 35, 36, 37 and 38 in fig.2.

38 as marked on Fig.2(a). Epochs 35 and 36 of Fig.3 clearly follow micro-sleep characteristics as defined by AASM, whereas epochs 37 and 38 do not. Micro-sleep defined by AASM agrees with the micro-sleep events defined via ξ_{20}.

C. Sleepiness Index

The time series ξ_{20} is highly stable in characterizing sleep and wake states. The wake states correspond to high values of ξ_{20}; sleep states are associated with a consistently low magnitude (s_0) approaching zero for all practical purposes. We have noted that the magnitude of ξ_{20} gradually moves from a high value towards s_0 as a person is falling asleep.

Before finally settling down to s_0 corresponding to the state sleep, the magnitude of ξ_{20} briefly touches s_0 several times (see Fig.2 (a)). Such events are associated with EEGs that are characteristic of sleep, and we define them as *micro-sleep* events. We propose to exploit the stability of the ξ_{20} time series to identify micro-sleep events and then use them to form a measure of sleepiness, termed the *Sleepiness Index* (SI). We define the SI as the fraction of the time the magnitude of ξ_{20} maintained its value corresponding to sleep, i.e., s_0, computed over a time frame of 150 seconds. Thus, SI can vary from 0 (no episodes of micro-sleep during the current 150s period) to 1 (micro-sleep/sleep events completely covers the current 150s period). This definition allows the SI index to be computed real time, making it a useful tool to monitor the sleepiness of an individual. *Sleep Onset* can be defined as the instant at which SI reaches 1, and remains at 1 for at-least next 6 points of SI. The *Sleep Latency (SL)* can be defined as the time duration from the 'lights out' to the Sleep Onset.

To test the capability of the SI to estimate the sleep onset and the SL, we computed SI for the subjects in Database A and B. Figure 4 show the ξ_{20}, SI and technician scored sleep/wake states for the subject ID 18. Table 1(b) shows the sleep latency computed from SI (SI-SL) and technician scored SL (TS-SL). Table 2 compares the SI-SL with that from TS-SL for all the 4 naps in the MSLT test patients. According to Fig.4, ξ_{20} and SI closely matches with the technician scored sleep/wake states. There is a significantly high correlation (r=0.93, ρ=0.0001, t=10.38) between SI-SL and TS-SL for the subjects in database A. There was very small insignificant negative bias of -0.72 (ρ=0.59, t=-0.55) min in computing SL from the sleepiness index. The SI based approach, however, has been fully automated and provides consistent results. It does not depend on multiple physiological signals; only one channel of EEG is sufficient for the purpose. On the contrary, sleep technologist requires multiple signals and depends on subjective methods to estimate the SL.

TABLE 2: COMPARISON OF SLEEP LATENCY (SL) COMPUTED FROM SLEEPINESS INDEX (SL-SI) AND TECHNICIAN SCORED (SL-TS). SL COMPUTED IN MINUTES.

		Nap 1	Nap 2	Nap 3	Nap 4
Subject ID 21	SL - TS	7	4	2.5	8.5
	SL - SI	5.6	4.3	1.8	6.7
Subject ID 22	SL - TS	5.5	11.5	6	3
	SL - SI	3.9	8.1	3.3	2.8

IV. Conclusion

In this paper we presented a fully automated method to compute sleep latency (SL) and a novel objective measure of sleepiness level called, Sleepiness Index (SI). The method is based on the higher-order spectral analysis of EEG. Our results from the database of 22 patients show that the SL computed from the SI strongly correlates with that computed by sleep technician. MSLT and MWT are the main measures of sleepiness used in the clinical environment. They are, however, complicated tests requiring access to sleep laboratories and the services of experienced sleep technologists. Even then, the computations of parameters such as the SL and sleep onset are fraught with subjective elements. Our ability to compute the parameters reliably, objectively and using a single channel of EEG should make a dramatic impact on the diagnosis of sleep disorders.

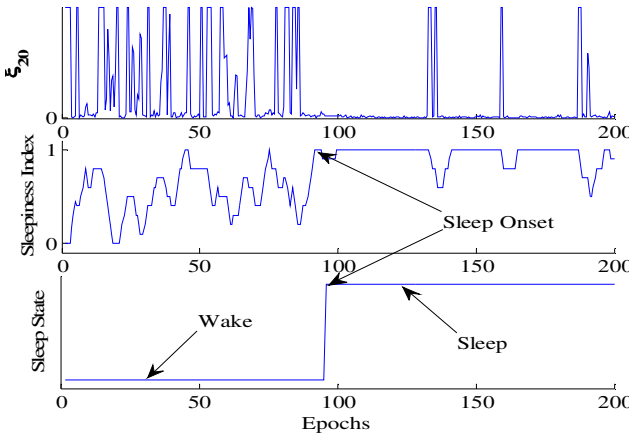

Fig. 4. (a) Bispectogram Time Series (ξ_{20}), (b) SI computed from ξ_{20}. (c) Technician scored sleep state/wake. Data from the patient id 18.

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