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# Automatic sleep scoring from a single electrode using delay differential equations

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*Abstract:* Sleep scoring is commonly performed from electrooculogram (EOG), and electromyogram (EMG) to produce a so-called hypnogram. A neurologist thus visually encodes each epoch of 30 s into one of the sleep stages (Awake, REM sleep, $S_1$, $S_2$, $S_3$, $S_4$). To avoid such a long process (about 3-4 hours) a technique for automatic sleep scoring from the signal of a single electrode located in the $C_3/A_2$ area using nonlinear delay differential equations (DDEs) is presented here. Our approach considers brain activity as resulting from a dynamical system whose parameters should vary according to the sleep stages. It is thus shown that there is at least one coefficient that depends on sleep stages and which can be used to construct an hypnogram. The correlation between manual hypnograms and the coefficient evolution is around 80%, that is, about the inter-rater variability. In order to rank sleep quality from the best to the worst, we introduced a global sleep quality index which is used to compare manual and automatic sleep scorings, thus using our ability to state about sleep quality that is the final goal for physicians.

## 1. Introduction

Up to 2007, polysomnographic recordings were scored into sleep stages according to the rules introduced by Rechtschaffen and Kales (1968) which are mainly based on a spectral analysis. The scoring, accomplished by well-trained neurologist, consists in scoring all 30 s epochs into one of the six stages of vigilance, namely Awakeness, Rapid Eyes Movement sleep (REM), and sleep stages S1, S2, S3, S4. RK rules were recently modified to overcome the inter-rater variability (Iber, 2007). The most important change was that stages 3 and 4 merged into a single stage, named Slow Wave Sleep or N3. In spite of that, recent studies only showed slight improvements with the new rules (Danker-Hopfe, 2009) with an inter-rater agreement slightly greater than 72% (Basner, 2008).

Automatic sleep scoring techniques are thus welcome. Most of the computer-assisted scoring techniques stages were based on RK rules (Harper, 1987 — Jansen, 1989 — Principe, 1989). In fact, most of them try to reproduce what is done by neurologists and which can lead to an overall epoch-by-epoch agreement of 80%, they require a quite complex decisional tree (see Fig. 2 in Anderer, 2005). With the emergence of "chaos theory", Recurrence Plots Quantifiers, Lyapunov exponents or correlation dimension were used to obtain hypnograms with an overall agreement which was rarely greater than 60 or 70% (Susmakova, 2008).

Neural networks were also used to distinguished different features exhibited in the spectral domain but were not able to distinguish more than the REM sleep from non-REM sleep (Groezinger, 1997). Another technique was correctly scoring sleep stages but required two EEG channels, one horizontal electro-oculogram channel and one chin electromyogram channel (Schaltenbrand, 1996). An automatic sleep classification, was able to distinguish awake, slow-wave sleep and rapid eye movements sleep stages (Sunderam, 2007), but a specific sensor, a head accelerometer, was required and must be added to conventional sensors.

Our aim is to develop a reliable automatic technique using a single signal for scoring hypnograms. The subsequent part of this paper is organized as follows. In Section 2 the pool of patients which were recorded is described. Section 3 is devoted to our automatic sleep scoring technique and to a new global sleep quality index used to rank a set of hypnograms. In Section 4 the results are presented and Section 5 gives a conclusion.

## 2. Patients

This retrospective observational study was conducted at the sleep laboratory at the medical university hospital Intensive Care Unit in Rouen. We selected 38 recordings but only 35 were associated with a reliable sleep scoring. These patients were long-term ventilated for chronic respiratory failure and grouped into two types. The first type corresponds to an Obesity Hypoventilation Syndrome (OHS) commonly seen in severely overweight people who fail to breathe normally resulting in low blood oxygen levels and high blood carbon dioxide ($CO_2$) levels. Many of these patients have increased upper airway resistances during sleep (obstructive sleep apnea). This induces a significant amount of wake after sleep onset (WASO) leading to abnormal daytime sleepiness. This disease puts strain on the heart, possibly resulting in heart failure, leg swelling, and various other related symptoms. The second group of respiratory failure, considered here, is associated with Chronic Obstructive Pulmonary Disease (COPD). This refers to small airway obstructions and emphysema, two commonly co-existing pulmonary diseases in which the airways progressively narrow inducing shortness of breath. In these patients, the airflow limitation is usually non-reversible when treated with bronchodilators and progressively becomes more and more severe. One efficient

treatment is to put these patients under noninvasive mechanical ventilatory assistance. In the present case, all patients were ventilated with the bilevel ventilator ResMed VPAP iii. All patients included in this study were in stable condition, as assessed by clinical examination and arterial blood gases.

Main characteristics of the thirty-five patients for which the sleep was scored during one night under mechanical ventilation are reported in Table 1. 20 patients (57%) had OHS and 15 patients (43%) had COPD. Thirteen patients (38%) were diagnosed with obstructive sleep apnea syndrome (defined as more than 10 apneas per hour). Upon study inclusion, the patients were ventilated for a few months. Nineteen patients (56%) were hypercapnic ($PaCo_2 > 5.6$ $cmH_2O$).

**Table 1.** Main clinical characteristics of the patients ($n = 34$).

| Demographics and respiratory parameters | Mean | (SD) |
|---|---|---|
| Age (year) | 64.5 | (11.7) |
| Male:Female | 24:11 | |
| Body Mass Index ($kg.m^{-2}$) | 42.0 | (10.5) |
| $PaO_2$ ($cmH_2O$) | 9.5 | 1.1 |
| $PaCO_2$ ($cmH_2O$) | 5.8 | (0.9) |

Normal values: $(10.7 < PaO_2 < 12.0)$ $cmH_2O$, $PaCO_2 \approx 5.3$ $cmH_2O$, $(18.5 < BMI < 25)$ $kg.m^{-2}$ and obesity is defined by BMI$> 30$ $kg.m^{-2}$.

## 3. Method

### 3.1. Automatic sleep scoring

A nonlinear delay differential equation has the general form

$$\begin{aligned}\dot{x} = \quad & a_1\, x_{\tau_1} + a_2\, x_{\tau_2} + a_3\, x_{\tau_3} + \cdots + a_{i-1}\, x_{\tau_n} + a_i\, x_{\tau_1}^2 + a_{i+1}\, x_{\tau_1} x_{\tau_2} \\ & + a_{i+2}\, x_{\tau_1} x_{\tau_3} + \cdots + a_{j-1}\, x_{\tau_n}^2 + a_j\, x_{\tau_1}^3 + a_{j+1}\, x_{\tau_1}^2 x_{\tau_2} + \ldots \cdots + a_l\, x_{\tau_n}^m \end{aligned} \tag{1}$$

where $x = x(t)$ and $x_{\tau_j} = x(t - \tau_j)$. In this general form, the DDE has $n$ delays, $l$ monomials with their corresponding coefficients $a_i$, and a degree of nonlinearity equal to $m$. In the subsequent part of this paper, we will define a $k$-term DDE as an equation with only $k < l$ monomials selected from the right-hand side of the general form (1). As for any global modeling technique, there is a significant improvement of capturing main characteristics of the underlying dynamics from observed data by carefully selecting the structure of the DDE

model (Aguirre, 1995 — Lainscsek, 2003 — Lainscsek 2012). The minimal mean squared error is used for this process. By structure selection, we mean retaining only monomials in the DDE that have the most significant contribution to classify the data. An equally important task is to select the right time-delays, since linear terms are directly related to the fundamental time-scales and non-linear terms to the nonlinear couplings between them (Lainscsek, 2013). This can be performed by using a genetic algorithm (Lainscsek, 2012) or by an exhaustive search for the best model among the general form with $n = 2$ and $m = 3$ resulting in $l = 9$ monomials as performed in (Lainscsek, 2013).

Here only models with up to three terms were considered (see Tab. 2 in Lainscsek, 2013). The variable $x$ corresponds to the signal provided by the electrode located in the $C_3/A_2$ area of the scalp. We ran a genetic algorithm to minimize the least square error of 30 s data windows to select the best models and delays for each 30 s window (Goldberg, 1989 — Lainscsek, 2012). For 95% of the data windows (corresponding to the 35 patients), the four models

$$\dot{x} = a_1\, x_{\tau_1} + a_2\, x_{\tau_2} + a_3\, x_{\tau_1}^2\,; \tag{2}$$

$$\dot{x} = a_1\, x_{\tau_1} + a_2\, x_{\tau_2} + a_4\, x_{\tau_1}\, x_{\tau_2}\,; \tag{3}$$

$$\dot{x} = a_1\, x_{\tau_1} + a_2\, x_{\tau_2} + a_6\, x_{\tau_1}^3\,; \tag{4}$$

$$\dot{x} = a_1\, x_{\tau_1} + a_2\, x_{\tau_2} + a_7\, x_{\tau_1}^2\, x_{\tau_2}\,; \tag{5}$$

were selected as well as delays between $1\,\delta t$ and $4\,\delta t$ with $\delta t = \frac{1}{64}$ s. Among these four models, model (5) is the best to distinguish wake, REM and S1 from the sleep stages S2, S3 and S4 (see left panel from Fig. 1). Delay $\tau_1 = 1$ is useful to distinguish wake, S2, S3 and S4 from REM and S1 (right panel from Fig. 1). Delay $\tau_2 = 3$ allows to distinguish wake from sleep stages. Thus, combining model (5) with delays $\tau_1 = 1$ and $\tau_2 = 3$ provides the model with the most discriminative ability. Among the three coefficients of model (5), parameter $a_2$ was found to be the most correlated ($r = 0.95$) to the manually scored hypnogram, as exemplified in Figs 2 in the case of patient 15. We then used this model and this coefficient to score the sleep for our 35 patients.

It was then necessary to convert the $a_2$-time series which corresponds to the time evolution of a real number sampled at 0.1 Hz (one point per 10 s) into a sequence of integers from 1 (stage S1) to 6 (awake). This is the tricky part of our technique. In the case of patient 15, we got an automatically scored hypnogram which was quite close to the manually scored one (Fig. 2b).

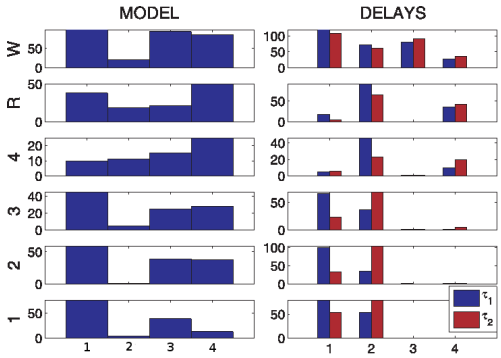
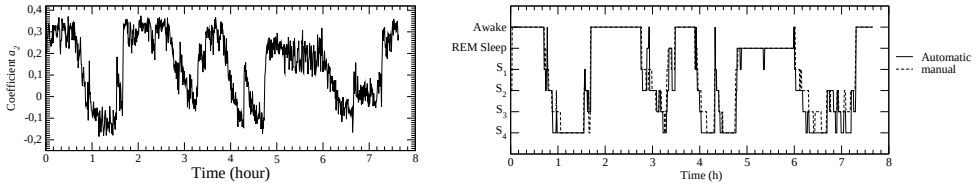



**Figure 1.** Histograms of the number of time each of the four selective DDEs (left) and each delays (right) were selected with minimum error for each sleep stage.




(a) Raw $a_2$ time series (b) Sequence of integers

**Figure 2.** Time series of coefficient $a_2$ of the delay differential equation (5) and the corresponding hypnogram. Case of patient 15 (male, 76 years, BMI=50 kg.m$^{-2}$). The manually scored hypnogram (green) is also reported for comparison.

### 3.2. Assessing the sleep quality

Since patients with chronic respiratory failures are ventilated during their sleep, it is important to assess whether the ventilation improves the sleep quality or, at least, that it does not degrade it. In order to do that, it is necessary to be able to rank hypnograms according to sleep quality. From a subjective point of view, sleep quality refers to patient feelings about the refreshing effect of sleep which can be assessed using some sleep diary or the Pittsburgh Quality Index (Buysse 1989). The characteristics commonly taken into account in such an evaluation are sleep latency, sleep duration, regular sleep efficiency, sleep disturbances (including sleep disruptive events such as snoring, apnea or pains), use of sleeping medication, and daytime dysfunction (Buysse 1989).

Up-to-now, the objective evaluation of sleep quality was based on the same characteristics but directly measured from hypnograms (Iber, 2007). Also considered are the arousal index (number of arousals per hour) and the number of various respiratory events. To assess the evolution of sleep quality, all these quantities are then subjectively combined and

compared since none of them can alone allow to rank hypnograms according to sleep quality (see Messager, 2013 for details). In order to avoid this last subjective step, we introduced a new index which combines the most important sleep characteristics. Thus, our global sleep quality index takes into account the number of sleep cycles (each cycle, between 90 and 120 min, contents some slow-wave sleep restoring physical functions and some rapid eye movements restoring cognitive functions), the fraction of WASO, the number of micro-arousals, and the number of stage transitions. The global sleep quality index $\eta_{\mathrm{GQ}}$ is defined as

$$\eta_{\mathrm{GSQ}} = \eta_{\mathrm{cycle}} \cdot \eta_{\mathrm{restoring}} \cdot \eta_{\mathrm{stability}} \cdot (1 - \eta_{\text{M-frag}}) \cdot (1 - \eta_{\mu\text{-frag}}) \tag{6}$$

where $\eta_{\mathrm{cy}} = \mathrm{Max}\left(\frac{N_{cy}}{6}, 1\right)$ and $N_{\mathrm{cy}}$ is the number of sleep cycles that saturates to one when it exceeds 6 cycles; the restoring capacity of sleep is evaluated according to

$$\eta_{\mathrm{restoring}} = \mathrm{Min}\left(\frac{5}{2}\,\frac{\tau_{S3} + \tau_{S4} + \tau_R}{\tau_{S1} + \tau_{S2} + \tau_{S3} + \tau_{S4} + \tau_R}, 1\right) \tag{7}$$

with $\tau_i$ being the time duration spent in the $i$th sleep stage ($i$ = S1, S2, S3, S4 and R) and saturates to 1 when the restorative sleep (S3, S4 and R) exceeds $\frac{2}{5}$ of the effective sleep; the sleep stability is evaluated according to

$$\eta_{\mathrm{stability}} = \frac{\tau'_{S1} + \tau'_{S2} + \tau'_{S3} + \tau'_{S4} + \tau'_R}{\tau_{\text{effective sleep}}} \tag{8}$$

with $\tau'_i$ being the time spent in the $i$th sleep stage without any micro-arousal and not corresponding to an epoch connexe to a stage transition, and $\tau_{\text{effective sleep}}$ being the time duration of sleep stages ($\tau_{S1}+\tau_{S2}+\tau_{S3}+\tau_{S4}+\tau_R$); the sleep macro-fragmentation is evaluated according to

$$\eta_{\text{M-frag}} = \frac{\tau_{\mathrm{WASO}}}{\tau_{\text{effective sleep}}}\,; \tag{9}$$

the sleep micro-fragmentation is evaluated according to

$$\eta_{\mu\text{-frag}} = \frac{(\tau_{S1} - \tau'_{S1}) + (\tau_{S2} - \tau'_{S2}) + (\tau_{S3} - \tau'_{S3}) + (\tau_{S4} - \tau'_{S4}) + (\tau_R - \tau'_R)}{\tau_{\text{effective sleep}}}\,. \tag{10}$$

with $\tau_i - \tau'_i$ being the time spent in an epoch of the $i$th sleep stage with a micro-arousal or connection to a stage transition.

## 4. Results

The time series of coefficient $a_2$ were found quite well correlated to the corresponding hypnograms ($\overline{r} = 0.86 \pm 0.1$). To assess the quality of our sleep scorings using the coefficient $a_2$

we computed the confusion matrix (Kohavi, 1998) which is a specific table layout used to assess performance of classifier. Each column of the matrix represents the instances in a predicted class, while each row represents the instances in an actual class. The confusion matrix for all epochs of all patients is reported in Fig. 3. To get a graphical representation the numbers were also converted to a percentage. A dark diagonal from the upper left corner to the lower right corner with all other squares in white would indicate perfect scoring of each data window into the correct sleep stage.

| | | predicted | | | | | |
|---|---|---|---|---|---|---|---|
| | | W | R | 1 | 2 | 3 | 4 |
| actual | W | 3026 | 1642 | 147 | 29 | 1 | 4 |
| | R | 225 | 1288 | 762 | 62 | 5 | 11 |
| | 1 | 61 | 733 | 3841 | 2388 | 607 | 164 |
| | 2 | 7 | 13 | 191 | 703 | 524 | 528 |
| | 3 | 1 | 34 | 394 | 790 | 1669 | 97 |
| | 4 | 27 | 54 | 166 | 557 | 1050 | 8615 |

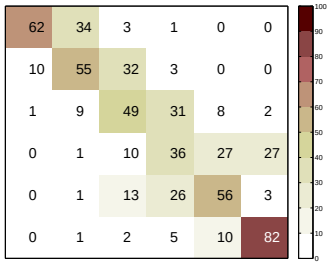



**Figure 3.** Confusion matrix for all subjects: The table on the left side shows the numbers of predicted and actual sleep stage windows. The plot on the right side visualizes the percentage of predicted and actual sleep stage windows.

As additional measure of performance we used Cohen's kappa $\kappa$ which can be computed directly from the confusion matrix as $\kappa = \frac{p_a - p_e}{1 - p_e}$, where $p_a = \sum_{k=1}^{q} p_{kk}$, and $p_e = \sum_{k=1}^{q} p_{k+} p_{+k}$ where $q = 6$ for the 6 classes, $p_a$ is the observed percentage of agreement, $p_e$ is the expected percentage of agreement, $p_{k+}$ is the percentage of actual classification, and $p_{+k}$ is the percentage of predicted classification. We got $\overline{\kappa} = 0.51 \pm 0.1$ when comparing automatically scored hypnograms with the manually scored ones. Detailed results are reported in Table 2.

The global sleep quality index $\eta_{\mathrm{GSQ}}$ was first computed from the hypnograms scored by the neurologist. Patients were then ranked according to a decreasing $\eta_{\mathrm{GSQ}}$ (Fig. 4). The hypnogram of the patient with the largest $\eta_{\mathrm{GSQ}}$ (35.4) is shown in Fig. 5a: it presents 3 sleep cycles quite well structured. Contrary to this, the hypnogram of patient 22 with the smallest $\eta_{\mathrm{GSQ}}$ (0.1) is shown in Fig. 5b: it does not present a single well-structured sleep cycle and the effective sleep time duration is small ($\tau_{\text{effective sleep}} = 146$ min).

The rates of each sleep stage was computed for each hypnograms which were ranked according to decreasing $\eta_{\mathrm{GSQ}}$ (Fig. 6). The best hypnogram (patient 34, $\eta_{\mathrm{GSQ}} = 35.4$) presents a good proportion of restorative sleep. Contrary to this, the worst hypnogram (patient 22, $\eta_{\mathrm{GSQ}} = 0.1$) associated with a very small fraction of restorative sleep and a

**Table 2.** Correlation coefficient $r$ and Cohen's $\kappa$ between the manually scored hypnograms and the time series of coefficient $a_2$ of model (5) for each subject.

| # | $r$ | $\kappa$ | # | $r$ | $\kappa$ | # | $r$ | $\kappa$ | # | $r$ | $\kappa$ | # | $r$ | $\kappa$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0.82 | 0.36 | 9 | 0.91 | 0.53 | 17 | 0.70 | 0.28 | 24 | 0.95 | 0.65 | 32 | 0.91 | 0.55 |
| 2 | 0.95 | 0.61 | 11 | 0.80 | 0.36 | 18 | 0.81 | 0.44 | 25 | 0.78 | 0.41 | 33 | 0.84 | 0.41 |
| 3 | 0.89 | 0.59 | 12 | 0.90 | 0.64 | 19 | 0.87 | 0.53 | 26 | 0.82 | 0.50 | 34 | 0.93 | 0.66 |
| 5 | 0.91 | 0.63 | 13 | 0.91 | 0.57 | 20 | 0.78 | 0.59 | 27 | 0.92 | 0.64 | 35 | 0.82 | 0.37 |
| 6 | 0.92 | 0.51 | 14 | 0.76 | 0.36 | 21 | 0.79 | 0.39 | 29 | 0.94 | 0.61 | 36 | 0.89 | 0.55 |
| 7 | 0.92 | 0.68 | 15 | 0.95 | 0.67 | 22 | 0.80 | 0.40 | 30 | 0.87 | 0.51 | 37 | 0.91 | 0.59 |
| 8 | 0.79 | 0.43 | 16 | 0.90 | 0.54 | 23 | 0.80 | 0.41 | 31 | 0.79 | 0.43 | 38 | 0.91 | 0.51 |

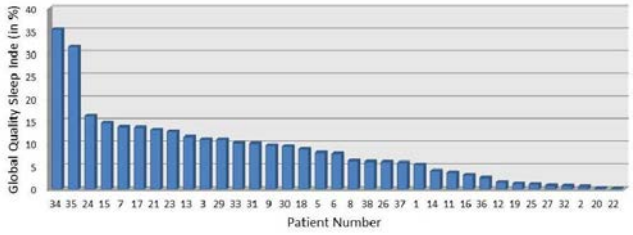
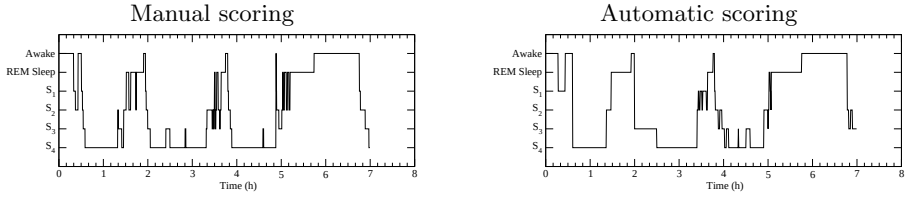
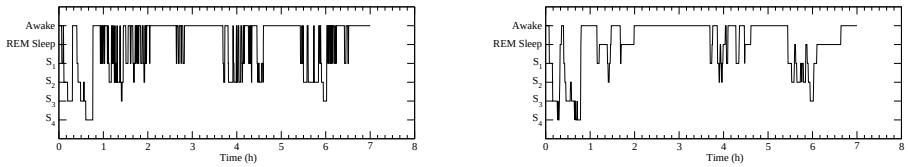



**Figure 4.** Global sleep quality index computed from the manually scored hypnograms for the 35 patients of our protocol.




(a) Patient 34 : Male, 82 years, BMI=44.1, 2.1% of asynchronous cycles, $\eta_{\mathrm{GSQ}} = 35.4\%$




(b) Patient 22 : Male, 83 years, BMI=36.3, 8.0% of asynchronous cycles, $\eta_{\mathrm{GSQ}} = 0.1\%$

**Figure 5.** Hypnograms for two of the 35 patients corresponding to the largest, and the smallest global sleep quality index. The gender, age, body-mass index and the rate of synchronous breathing cycles are also reported.

large one of WASO. Hypnograms are rather well ranked since the rate of WASO and sleep micro-fragmentation are anti-correlated to $\eta_{\mathrm{GSQ}}$ ($r = -0.65$, $p < 0.0001$ and $r = -0.75$, $p < 0.0001$, respectively). The rate of slow-wave sleep (S3 and S4) and the rate of REM sleep are correlated to $\eta_{\mathrm{GSQ}}$ ($r = 0.83$, $=< 0.0001$ and $r = 0.59$, $p < 0.0001$, respectively). These features and others that are outside the scope of this paper correspond to an increase of the sleep quality with $\eta_{\mathrm{GSQ}}$.

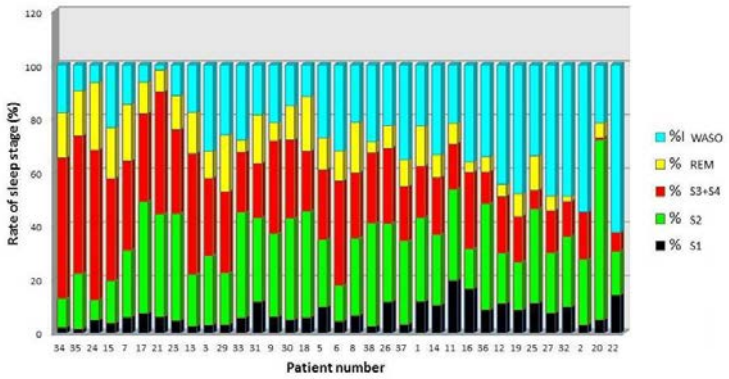



**Figure 6.** Fraction of time for the sleep stages. Patients are ranked according to the global sleep quality index $\eta_{\mathrm{GSQ}}$.

We now computed the global sleep quality index from the automatically scored hypnograms with our technique (Fig. 7). They were ordered in a slighly different order than the manual hypnograms. In order to quantify this disagreement between these two orders, let us designate by $n$ the rank ($n'$) the rank obtained by computing $\eta_{\mathrm{GSQ}}$ from the manual (automatic) hypnograms. Thus $\Delta n = |n - n'|$ corresponds to the rank shift observed between these two orders. We thus have $\overline{\Delta n} = 4.6 \pm 5.4$, meaning that, in average, the good (bad) hypnograms remain the good (bad) ones. There are four notable exceptions with the hypnograms for patients 11, 15, 24 and 35 for which $\Delta n$ equals to -23, +15, +20, and +11, respectively.

The manually scored hypnogram of patient 11 (Fig. 8a) presents many fluctuations between awake and stage S1, very few epochs of stage S3 or S4 and REM sleep, thus associated with a small global quality sleep index ($\eta_{\mathrm{GSQ}} = 3.7$). The evolution of the coefficient of the DDE fluctuates a lot between the values corresponding to awake and S1 stages and, consequently, since REM sleep is between these two stages, our technique returns too often REM sleep (and not WASO), with the effect of significantly increasing the global sleep quality index to 24.9. It is important to note that a neurologist uses a lot the oculogram and the electromyogram to distinguish REM sleep from awake and S1, two signals which are not

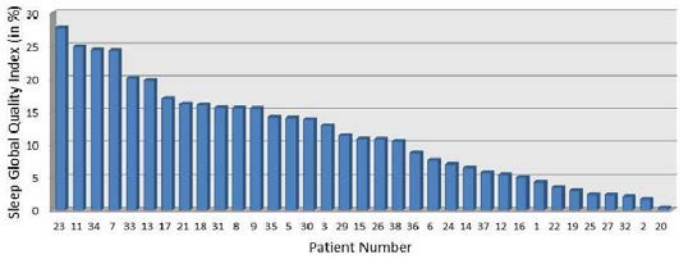
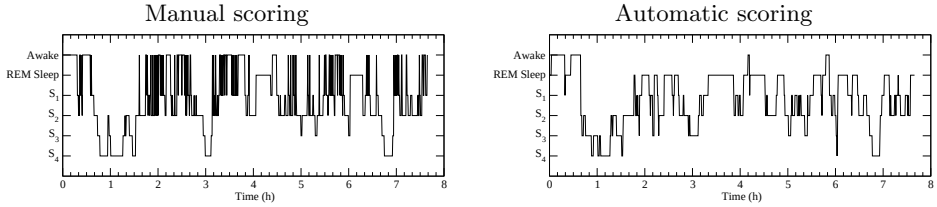
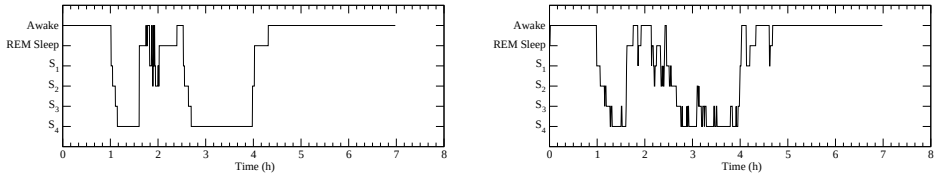



**Figure 7.** Global sleep quality index computed from the automatically scored hypnograms for the 35 patients of our protocol.

considered by our technique.




(a) Patient 11 : Male, 78 years, BMI=32.0, 5.5% of asynchronous cycles, $\eta_{\mathrm{GSQ}} = 35.4\%$




(b) Patient 24 : Male, 62 years, BMI=50.2, 1.7% of asynchronous cycles, $\eta_{\mathrm{GSQ}} = 0.1\%$

**Figure 8.** Hypnograms for two badly scored using our automatic technique.

Contrary to this, the automatically scored hypnograms for patient 24 is characterized by a global sleep quality index $\eta_{\mathrm{GSQ}}$ (7.0) is significantly smaller than the value (16.2) obtained from the manual hypnograms (Fig. 8b). There are few reasons explaining such a large departure between these two $\eta_{\mathrm{GSQ}}$-values. The global sleep duration (between the first and the last sleep epoch) is larger than the one obtained from the automatic scoring (221.5 min and 198 min, respectively) but the number of sleep cycles is 2 in both cases. The rate of WASO in the automatic hypnogram is about three times the rate obtained from the manually scored hypnogram (19.9 and 6.6, respectively). The rate of micro-fragmentation obtained with our technique is about three times the rate returned by the neurologist (31.8 and 11.1,

respectively). The stability is smaller in the hypnograms provided by our technique than in the one scored by the neurologist (38.2 and 58.3, respectively). All these modifications tend to increase the global sleep quality index.

## 5. Conclusions

In 88% of subjects the overall sleep quality index computed from the DDE hypnograms are in agreement with the sleep quality index computed from the visually scored hypnograms. The difference in 12% of all patients results from converting the real number outputs of the DDE to the integers used for indexing the sleep stages (S1, S2, S3, S4, R and awake). This is the weakest part of the present version of our technique. In spite of this, our hypnograms are already sufficiently close to the manual hypnograms that are used to assess the sleep quality. Importantly, this first study has lead to the identification of possible improvements that are currently being developed.

Our automatic scoring technique using DDEs is well correlated to the corresponding visually scored hypnograms ($\overline{r} = 0.86 \pm 0.1$). This excellent agreement becomes even more impressive when considering the use of only one scalp electrode for the DDE method. Indeed, the most promising aspect of our technique is that only one scalp electrode is sufficient to accurately score sleep stages.

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