Automatic characterization of sleep need dissipation using a single hidden layer neural network

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***Abstract*— In the two process sleep model, the rate of sleep need dissipation is proportional to slow wave activity (SWA; EEG power in the 0.5 to 4 Hz band). The dynamics of sleep need dissipation are characterized by two parameters (the initial sleep need S_0 and the decay rate γ) that can be calculated from SWA values in NREM sleep. The goal in this paper is to use a neural network classifier to automatically detect NREM sleep and estimate $\hat{S}_0$ and $\hat{\gamma}$ using a single EEG signal that is captured during sleep at home. The data from twenty subjects (4 sleep nights per subject) was used in this research.**

The neural network architecture was optimized using as training and validation sets the EEG sleep data from a previous study. Given the nature of the model, only three stages were considered (NREM, REM, and WAKE). The classification accuracy characterized by the Kappa value achieved in this study dataset was 0.63 (substantial agreement with manual staging) and the specificity/sensitivity for NREM detection were 0.87 and 0.8 respectively. The higher specificity in NREM detection led to systematic S_0 underestimation (i.e. $S_0 > \hat{S}_0$) and γ overestimation (i.e. $\gamma < \hat{\gamma}$). However the variability of the $\hat{S}_0$ and $\hat{\gamma}$ across nights of the same subject is lower compared to the variability of S_0 and γ. This shows that using automatic staging to characterize sleep need dissipation leads to capturing the most specific and less variable EEG segments that contribute to SWA. This is suitable to characterize sleep need outside sleep lab settings (e.g. at home) that cannot be controlled to the same extent as sleep lab studies.

I. INTRODUCTION

In humans, rapid eye movement (REM) and non-rapid eye movement (NREM) sleep alternate with a 90-minute long periodicity. Compared to the low voltage, high frequency patterns appearing in the awake electroencephalogram (EEG), NREM sleep is associated with a synchronized large amplitude EEG pattern. NREM is subdivided into three stages N1, N2, and N3. During REM sleep, the EEG exhibits a pattern similar to that observed during wakefulness [1].

Sleep need is homeostatically regulated and depends on prior wakefulness duration. In the sleep regulation model in [2], slow-wave activity (SWA) which is the EEG power in the 0.5-4 Hz band, is considered a direct indicator of sleep need. SWA builds up during non-rapid eye movement sleep (NREM), declines before the onset of rapid-eye-movement (REM) sleep, remains low during REM and the level reached in successive NREM episodes gets progressively lower (see Fig. 1).

The characterization of the sleep need dissimilation dynamics requires both SWA and sleep stage information. The latter can be obtained from manual staging by a sleep expert of polysomnography signals (PSG) which includes electroencephalogram, electromyogram, and electrooculogram signals.

In this research the goal is to evaluate the characterization of sleep need dissipation dynamics throughout sleep using a single EEG signal obtained at a frontal location (FPz according to the 10-20 EEG standard [3]), and an automatic sleep staging algorithm based on a single hidden layer neural network which can classify three sleep stages: NREM, REM, and Wake. In a previous work [4], we have explored the estimation of sleep-need dissipation using a Kernel based single-class classifier using a smaller dataset.

II. METHODS

A. Experiment design

Sleep EEG and EOG data were collected at 250 samples/second from 20 subjects (12F and 8M; 35.6 $\pm$ 7.4 years old; age range: 22 to 47) sleeping 4 nights at home using an investigational wearable device to monitor sleep EEG/EOG. The device consisted of a headband with 4 electrodes positioned on the forehead area and a reference electrode on the right mastoid. The EEG electrode was located on the standard FPz [3], the right EOG above the right eyebrow, and the left EOG near the left outer canthus.

Subjects were instructed to keep regular sleep/wake times throughout their involvement with the study. The data was manually scored by a sleep expert into sleep stages according to AASM rules and on the basis of 30-second long non-overlapping EEG/EOG segments. To characterize sleep need dissipation, 6-second long EEG segments (*epochs*) are considered as in [4]. Sleep stages are consequently assigned to each epoch. The recordings took place on weekdays (Monday to Thursday). The average total sleep duration and standard deviation across all subjects and nights was: 312.5 $\pm$ 37.7 minutes.

An additional dataset from a previous study [4] was used to optimize the architecture of the neural network that performs the automatic sleep staging. This dataset consisted of sleep EEG from 8 subjects also collected at home (3 sleep nights per subject) with a device similar to the one used in this study.

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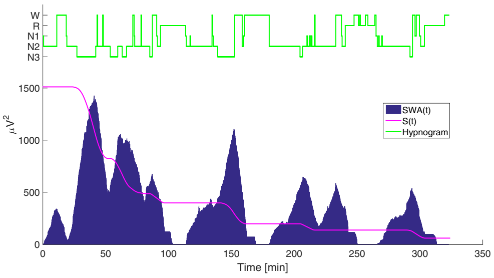


Fig. 1. (Top) Hypnogram in green. (Bottom) SWA in blue and sleep need in pink.

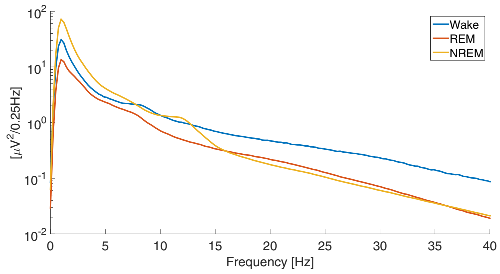


Fig. 2. Power spectrum density per sleep stage.

B. *Sleep need dissipation*

Sleep need dissipates during sleep and builds up during wakefulness. In [2], [5], [6], a model for sleep need dissipation is proposed (see Eqs. 1 and 2), which states that the rate of decrease of sleep need is proportional to SWA during NREM sleep. The proportionality constant $\gamma > 0$ is the sleep need decay rate.

In Eqs. 1 and 2, $S(t)$ and $\mathrm{SWA}(t)$ are respectively the sleep need and slow wave activity at time t. In Eq. 2, $r_c > 0$ is the SWA rising constant.

$$\frac{dS(t)}{dt} = -\gamma \mathrm{SWA}(t), \tag{1}$$

$$\frac{d\mathrm{SWA}}{dt} = r_c \mathrm{SWA}(t)(1 - \frac{\mathrm{SWA}(t)}{S(t)}). \tag{2}$$

Taking the integral in Eq. 1 from sleep onset (referred to as t_0) to an arbitrary time t results in:

$$\int_{t_0}^{t} \frac{dS(t)}{dt} dt = \int_{t_0}^{t} -\gamma \cdot \mathrm{SWA}(t) dt,$$
$$\Rightarrow S_0 - S(t) = \gamma \mathrm{CSWA}(t). \tag{3}$$

where S_0 is the *initial* sleep need at the beginning of the sleep session. The integral of the SWA from sleep onset t_0 until time t is referred to as cumulative SWA and noted as $\mathrm{CSWA}(t)$. Equation 3 shows that the decrease in sleep need $S_0 - S(t)$ is proportional to $\mathrm{CSWA}(t)$ which can be visualized as the area under the SWA curve (see Fig. 1). In Fig. 1, it can be seen that $S(t)$ decreases faster when SWA is high and this is particularly the case (as expected) during N3 sleep.

The parameters γ and S_0 together with SWA values completely characterize sleep need dissipation. γ and S_0 can be experimentally estimated using the discrete form of Eq. 3. The discretization step is 6-seconds as used in [4].

$$S_0 - S(n) = \gamma \sum_{i=1}^{n} \mathrm{SWA}(i); \; n = 1, \ldots, N. \tag{4}$$
$$S_0 - S(n) = \gamma \mathrm{CSWA}(n),$$

where N is the total number of epochs.

During REM sleep and in wake, the EEG power in the 0.5 to 4 Hz band is substantially lower than that in NREM sleep (see Fig. 2). However the presence of artifacts, movement, or ocular activity in these stages can cause high SWA values. For this reason, the SWA for sleep stages other than NREM sleep is set to 0. In this research, NREM sleep only includes N2 and N3 because N1 is a transition state.

Equation 2 provides boundary conditions to estimate S_0 and γ. When $\mathrm{SWA}(t)$ reaches a local maximum (at time t_M) within a sleep cycle, then $d\mathrm{SWA}/dt = 0$ and consequently $S(t_M) = \mathrm{SWA}(t_M)$. In a typical sleep night session several sleep cycles are present. If $m_1, \ldots, m_M$ are the epoch indices corresponding to local SWA maxima, then Eq. 5 holds and can be solved using pseudo-inverse matrices to find S_0 and γ.

$$\begin{bmatrix} 1 & -\mathrm{CSWA}(m_1) \\ \vdots & \vdots \\ 1 & -\mathrm{CSWA}(m_M) \end{bmatrix} \begin{bmatrix} S_0 \\ \gamma \end{bmatrix} = \begin{bmatrix} \mathrm{SWA}(m_1) \\ \vdots \\ \mathrm{SWA}(m_M) \end{bmatrix} \tag{5}$$

C. *Feature extraction and neural network for automatic sleep staging*

The overview of data analysis is shown in Fig. 3. The processing of EEG signals consists of two steps: 1) single pole high pass filtering with transfer function: $(1 - 0.99z^{-1})^{-1}$ to remove the DC-drift, and 2) extraction of EEG power spectrum density (PSD) values per 6-second long epoch. For each epoch, two PSDs of two 4-second long windows (weighted with a Hanning window) with a 2-second long overlap were averaged. Given the 250 Hz sampling frequency, this resulted in 513 power values (with 0.25 Hz resolution) per epoch which were combined in a *feature vector*.

Since the model described in Section II-B considers primarily NREM sleep, the automatic sleep stage classification considers three stages only: REM, NREM which combines N2 and N3, and WAKE. The classifier could have in principle only considered NREM and non-NREM stages but the latter would have included REM and WAKE which are distinct states that need to be treated separately.

Neural network architecture and training
The input layer consists of 513 neurons (same dimension as the feature vector), N_h (parameter to be optimized) neurons in the hidden layer, and 3 neurons in the output layer (to classify NREM, REM, and WAKE). Consistent with latest literature results, the activation functions of input and hidden

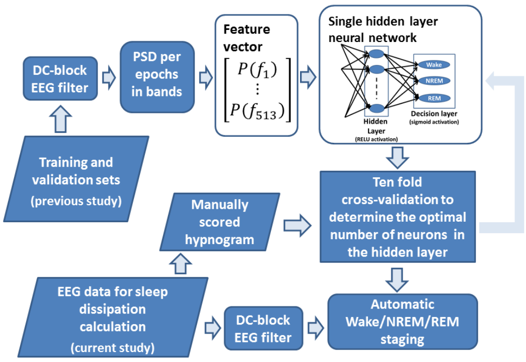


Fig. 3. Data analysis overview and neural network architecture optimization.

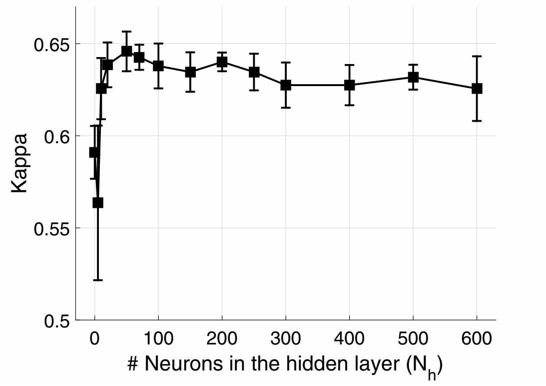


Fig. 4. Kappa in validation set vs. number of neurons in the hidden layer.

layer neurons are rectified linear units [7] and that of the output layer are sigmoid ones.

The data from the study in [4] was used to optimize the number of neurons in the hidden layer. For each of the three considered stages, 15000 feature vectors were used in a 10-fold cross-validation procedure. The optimal number of hidden neurons was the one leading to the highest Cohen's Kappa value [8] which is obtained from the confusion matrix. The Python Keras wrapper library with the Theano library [9] were used to train and test the neural networks used in this study.

III. RESULTS AND DISCUSSION

A. Neural network optimization

The average Kappa value (and error bars) over the validation sets of the 10-fold cross validation, versus the number of neurons in the hidden layer N_h is shown in Fig. 4. The case $N_h = 0$ corresponds to the single layer neural network for which Kappa=0.59. The maximum Kappa (0.65) occurs for $N_h = 50$ (chosen architecture) and a local maximum (Kappa=0.64) occurs for $N_h = 200$. Given latest trends to use deeper architectures (i.e. higher number of layers), we have also tested 2-hidden layer neural networks with 200/50 (Kappa=0.63), and 50/10 (Kappa=0.56), neurons. The rationale of testing those architectures was guided by the results in Fig. 4 as $N_h = 50$ and $N_h = 200$ are local maxima. However none of those led to higher Kappa than the one obtained with $N_h = 50$. Additional testing of deeper architectures possibly using convolutional networks is needed.

Using the optimized neural network ($N_h = 50$), the EEG data collected in this study (see Section II-A) was automatically staged and the confusion matrix is shown in Table I. The Kappa value corresponding to this confusion matrix is 0.63 which closely matches the average validation Kappa (=0.65). A Kappa value in the 0.61 to 0.8 range indicates substantial agreement between the manual and automatic sleep staging. This confirms the suitability of the neural network architecture with 50 hidden units for this classification task. The sensitivity and specificity of detecting NREM are respectively 0.8 and 0.87.

TABLE I
CONFUSION MATRIX

		Predicted stage		
		NREM	REM	WAKE
Actual stage	NREM	0.80	0.16	0.04
	REM	0.14	0.76	0.10
	WAKE	0.05	0.25	0.70

B. Sleep need dissipation results

With the automatic staging, the initial sleep need S_0 and sleep need decay γ were estimated using Eq. 5. The estimated values are indicated using the hat symbol "$\hat{\cdot}$".

For each subject in the study, within subject (i.e. across nights) averages were calculated. The comparison between the values obtained using manual scoring (S_0, γ) and the estimated ones using automatic staging $(\hat{S}_0, \hat{\gamma})$ is shown in Fig. 5.

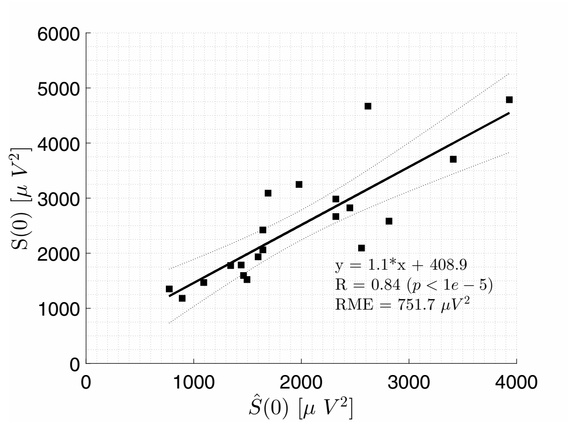
The adjusted correlation "R" between $\hat{S}_0$ and S_0 is 0.84 ($p < 1e-5$). $\hat{S}_0$ systematically underestimates S_0 which can be verified from the regression equation in Fig. 5 (top) and also from the fact that $S_0 - \hat{S}_0 = 512.2 \pm 564.5 \mu V^2$. This can be expected due to high specificity and lower sensitivity of the NREM classification.

γ and $\hat{\gamma}$ are positively correlated $R = 0.54$ (p=0.015). $\hat{\gamma}$ overestimates γ because Eq. 5 implies that: $\gamma \approx (S_0 - \mathrm{SWA}(m_i))/(\mathrm{CSWA}(m_i))$. CSWA is underestimated with the automatic staging method because NREM epochs are not detected as such due to lower NREM detection sensitivity as compared to the higher NREM specificity.

TABLE II
AVERAGE VARIABILITY ACROSS SUBJECTS

$S_0[\mu V^2]$	$\hat{S}_0[\mu V^2]$	$\gamma[\frac{10^{-3}}{6s}]$	$\hat{\gamma}[\frac{10^{-3}}{6s}]$
922.5	606.15	1.11	1.05

The variability of S_0, $\hat{S}_0$, γ, and $\hat{\gamma}$ across nights of the same subject was estimated using the standard deviation. The



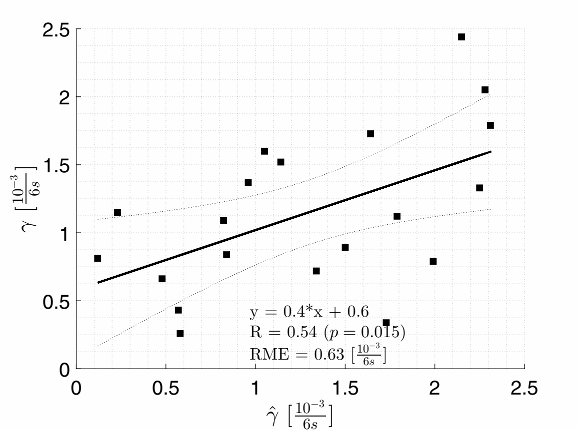


Fig. 5. Top: Initial sleep need (with manual staging S_0 vs automatic staging $\hat{S}_0$). Bottom: Sleep need decay rate (with manual staging γ vs automatic staging $\hat{\gamma}$). The shown values are within subject (across nights) averages. The solid lines are the regression lines and the shaded ones indicate the 95% confidence bounds.

average variability across subjects in the study is reported in Table II. This shows that the variability of estimated values with automatic scoring $\hat{S}_0$ and $\hat{\gamma}$ is lower than that using manual scoring. The regularity of sleep/wake times of subjects in this study is better reflected by $\hat{S}_0$ and $\hat{\gamma}$.

The percentage of N3 epochs that are classified as NREM by the classifier was 96.7%. Thus, N3 epochs primarily contribute to the calculation of $\hat{S}_0$ and $\hat{\gamma}$ and these appear to lead to lower variability of CSWA.

IV. CONCLUSION

In this paper, a method has been proposed to characterize the dynamics of sleep need dissipation using a single EEG signal and leveraging a neural network (single hidden layer) based sleep stage classifier. Given the model of sleep need dissipation used in this paper, the classifier did only consider three classes NREM, REM and WAKE. This method was tested on the sleep EEG data collected on several nights at home from 20 subjects.

The input data to the neural network consisted of 513 spectral power values, the number of neurons in the hidden layer has been optimized using sleep EEG data from a previous study (used as training and validation set), the output layer had 3 neurons consistent with the number of stages that are classified. The value of Kappa characterizing the network classification accuracy on the data collected in this study was 0.63 indicating a substantial agreement between manual and automatic staging. The classifier shows higher NREM sleep detection specificity (0.87) compared to sensitivity (0.8). In addition, 97% of N3 was correctly classified as NREM sleep which shows that the loss of sensitivity results from lower N2 sensitivity.

The dynamics of sleep need dissipation is characterized by the initial sleep need, and the sleep need decay rate. These have been estimated using manual (S_0, γ) and automatic staging $(\hat{S}_0, \hat{\gamma})$. The correlations $(S_0, \hat{S}_0)$ and $(\gamma, \hat{\gamma})$ are statistically significant and equal to 0.84 and 0.54 respectively. The higher specificity of the NREM classification is such that $\hat{S}_0$ underestimates S_0 and $\hat{\gamma}$ overestimates γ. However, the variability of $\hat{S}_0$ and $\hat{\gamma}$ across nights of the same subject is lower than that of S_0 and γ. This shows that the results with automatic scoring reflect well the fact that subjects in the study kept a regular sleep/wake schedule which according to the sleep need dissipation model should lead to low variability of the initial sleep need and decay rate.

V. ACKNOWLEDGEMENTS

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