Original Article

Estimating daytime sleepiness with previous night electroencephalography, electrooculography, and electromyography spectrograms in patients with suspected sleep apnea using a convolutional neural network

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Abstract

A common symptom of obstructive sleep apnea (OSA) is excessive daytime sleepiness (EDS). The gold standard test for EDS is the multiple sleep latency test (MSLT). However, due to its high cost, MSLT is not routinely conducted for OSA patients and EDS is instead evaluated using sleep questionnaires. This is problematic however, since sleep questionnaires are subjective and correlate poorly with the MSLT. Therefore, new objective tools are needed for reliable evaluation of EDS. The aim of this study was to test our hypothesis that EDS can be estimated with neural network analysis of previous night polysomnographic signals. We trained a convolutional neural network (CNN) classifier using electroencephalography, electrooculography, and chin electromyography signals from 2,014 patients with suspected OSA. The CNN was trained to classify the patients into four sleepiness categories based on their mean sleep latency (MSL); severe (MSL < 5min), moderate (5 ≤ MSL < 10), mild (10 ≤ MSL < 15), and normal (MSL ≥ 15). The CNN classified patients to the four sleepiness categories with an overall accuracy of 60.6% and Cohen's kappa value of 0.464. In two-group classification scheme with sleepy (MSL < 10 min) and non-sleepy (MSL ≥ 10) patients, the CNN achieved an accuracy of 77.2%, with sensitivity of 76.5%, and specificity of 77.9%. Our results show that previous night's polysomnographic signals can be used for objective estimation of EDS with at least moderate accuracy. Since the diagnosis of OSA is currently confirmed by polysomnography, the classifier could be used simultaneously to get an objective estimate of the daytime sleepiness with minimal extra workload.

Key words: daytime sleepiness; obstructive sleep apnea; MSLT; EEG

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Introduction

Obstructive sleep apnea (OSA) is a common sleep disorder affecting approximately half of the adult population [1, 2]. A major symptom of OSA is excessive daytime sleepiness (EDS). Although EDS is not directly lethal, it has a significant deteriorating impact on the quality of life causing depression and cognitive impairment [3–5]. In addition, EDS is a major cause of motor vehicle accidents and sick leaves making it a substantial economic burden [6].

The gold-standard test for EDS is the multiple sleep latency test (MSLT) [7]. The MSLT is an objective, full-day trial performed in a sleep laboratory where sleep latency is measured multiple times and the average of these latencies, that is, mean sleep latency (MSL) is used to assess EDS [7]. The subjects are clinically classified into four sleepiness categories based on their MSL: severe (MSL < 5 min), moderate (5 ≤ MSL < 10), mild (10 ≤ MSL < 15), and normal (MSL ≥ 15) [8, 9]. Alternatively, a single MSL threshold of 8 or 10 min is often used to differentiate between normal patients and patients suffering from EDS [10, 11]. However, as MSLT is time-consuming and expensive, it is not routinely performed for OSA patients and EDS is instead evaluated using simpler tests, such as sleep questionnaires [12, 13]. Sleep questionnaires are problematic however, since they are dependent on the patients’ interpretation of the rating system and therefore only offer an estimation on subjective sleepiness. For example, the results of the most common subjective test, the Epworth Sleepiness Scale (ESS), do not correlate well with MSLT and have been proven to be insufficient in estimating daytime sleepiness [12, 14–16]. Due to these shortcomings, simpler and easier objective tools are needed for evaluation of EDS especially for OSA patients.

Machine learning has been proven to be a powerful tool in medical signal analysis and has also shown promise in automatic diagnostics of OSA [17–19]. For example, artificial neural networks have been used for automated sleep staging using electroencephalography (EEG) [20, 21]. Based on the promising previous research, we hypothesized that previous night EEG could be used to estimate the daytime sleepiness of an OSA patient. Therefore, the aim of this study was to develop an objective, neural network method for estimation of EDS in patients with suspected OSA. We test our hypothesis by training a convolutional neural network (CNN) that estimates the results of the MSLT based on the previous night’s EEG, electrooculography (EOG), and electromyography (EMG) signals.

We chose to use a convolutional neural network, which is a type of deep neural network inspired by the human visual cortex and developed specifically for visual machine learning tasks [22]. CNNs also have less parameters and are faster to train than equally sized multilayer perceptron networks which is important with large inputs such as high resolution images. Like in regular multilayer perceptron networks, layers of a CNN have neurons, which receive inputs, calculate a weighed sum from them according to thelearnable weights, pass them through an activation function and generate an output. However, in CNNs, the layers are not fully connected and instead only a small part of the input layer is being operated on by the convolution kernel at a time. This kernel is then moved over the whole input layer generating the full output.

Methods

We developed a convolutional neural network (CNN) classifier to automatically estimate the MSLT result using EEG, EOG, and chin EMG signals recorded during in-lab polysomnography (PSG) the previous night. The CNN classifier was trained to classify the patients with suspected OSA into four sleepiness categories based on their MSL: severe (MSL < 5 min), moderate (5 ≤ MSL < 10), mild (10 ≤ MSL < 15), and normal (MSL ≥ 15). Additionally, we classified patients to EDS and normal groups using an MSL < 10 min as the threshold for EDS.

Dataset

The patient population consisted of 2,014 patients with suspected OSA who had undergone in-lab PSG and a next day MSLT (Table 1). The recordings were conducted during 2001–2011 in the Sleep Disorders Unit, Loewenstein Hospital—Rehabilitation Center, Raanana, Israel and analyzed using the prevailing American Academy of Sleep Medicine (AASM) guidelines [23, 24]. According to the clinical protocol at the Loewenstein Hospital, patients were referred to the MSLT because they had complained of daytime sleepiness during the clinical interview. No preliminary sleep questionnaires were performed. Ethical permission was obtained from the Ethical Committee of Loewenstein Hospital (Permission number: 0006-17-LOE). The MSLTs were conducted using four-nap protocol in uninterrupted conditions with 2 h intervals between each nap attempt [25]. The sleep onset was determined from the first stage of sleep. If no sleep occurred, the nap attempt was terminated at 20 min and the sleep latency was determined to be 20 min for that nap attempt. A total of four nap attempts were conducted and the MSL was calculated as the mean of these four readings.

The EEG electrodes were placed according to the international 10–20 system [26]. Two EEG channels, C4-A1 and PZ-A1, EOG channel (ROC-A1), and chin EMG were used as an input to the CNN. AASM recommends C4-A1, F4-A1, and O2-A1 EEG channels together with EOG and EMG channels for sleep staging [24]. However, as our dataset included frontal and occipital EEG channels only for a very limited number of patients, we chose to use C4 and PZ channels because they were most frequently recorded among the patients and thus the highest possible number of patients could be included in the study. We also chose to include the EOG and chin EMG channels since according to our preliminary testing, slightly better results were obtained with all four channels compared to using EEG only.

Signal processing

The raw signals sampled at 256 Hz frequency were exported from REMbrandt Manager System (MedCare Co, Amsterdam, the Netherlands) and imported to MATLAB 2018b (MathWorks Inc., Natick, Massachusetts, USA), which was used to conduct all preprocessing tasks. The signals were truncated so that only the time between the lights off mark and lights on mark was included and normalized using z-score normalization, that is, subtracting the signal mean and dividing by standard deviation resulting in a signal with zero mean and a standard deviation of one. The normalization was done to unify the greatly varying signal amplitudes between different patients.
Table 1. Subject characteristics

|                          | Mean   | Range    | SD     |
|--------------------------|--------|----------|--------|
| Age (years)              | 50.9   | 18.0–88.0| 13.8   |
| BMI (kg/m²)              | 30.8   | 13.8–63.7| 6.4    |
| AHI 1/h                  | 30.0   | 0.3–148.1| 28.9   |
| MSL (min)                | 10.2   | 0.5–20.0 | 5.1    |
| Recording duration (h)   | 7.2    | 6.0–8.7  | 0.4    |
| Total number of patients | 2,014  |          |        |
| Male patients            | 1,492  | 74.1     |        |
| Female patients          | 522    | 25.9     |        |
| EDS category             |        |          |        |
| Normal                   | 368    | 18.3     |        |
| Mild                     | 649    | 32.2     |        |
| Moderate                 | 580    | 28.8     |        |
| Severe                   | 417    | 20.7     |        |
| OSA category             |        |          |        |
| Normal                   | 401    | 19.9     |        |
| Mild                     | 438    | 21.8     |        |
| Moderate                 | 422    | 21.0     |        |
| Severe                   | 753    | 37.4     |        |

Number and percentage for categorical variables and mean, range and standard deviation for continuous variables.

EDS, excessive daytime sleepiness; OSA, obstructive sleep apnea; BMI, body mass index; AHI, apnea-hypopnea index; MSL, mean sleep latency; SD, standard deviation.

The signals were divided into 512 epochs with 50% overlap. No padding at the start or end was used. As a result, each epoch length was 2/513rd of the time between lights off and lights on marks. Welch's power spectral density (PSD) estimate [27] was then calculated for each epoch using 8 windows with 50% overlap. The PSD estimate was calculated for a frequency range of 0.3–30.3Hz using 512 data points. This frequency range was chosen since it contains the common diagnostic bands (Delta, Theta, Alpha, and Beta) and, for example, AASM recommends filtering out frequencies outside 0.3–35Hz when scoring sleep [28, 29]. The PSD estimates were converted to dB scale ($x_{db} = 10 \log_{10}x$) and arranged into a 512×512 spectrogram image where one column corresponds to one epoch. The same procedure was repeated for all four channels and for each patient. Finally, all spectrograms were arranged into a 2,014×512×512×4 matrix where the first dimension represents patients, the second and third dimensions represent the spectrograms, and the fourth dimension represents the four signal channels. Example figure of the spectrograms are presented in Figure 1.

Neural network

The CNN was trained in Python 3.7.3 with Tensorflow 1.14.0 using Keras 2.2.4. The CNN consisted of four convolutional blocks and one fully connected block (Figure 2). Each convolutional block consisted of two 2D-convolution layers followed by a max pooling layer with a pool size of 2×2 and a stride of 2–2. All convolution layers used 3×3 convolution kernels, stride of 1–1 and a tanh activation function. The number of output filters of the convolutional layers was 12 in the first block, 18 in the second block, 24 in the third block, and 30 in the fourth block. The last block consisted of a dropout layer with a 0.3 dropout followed by a flattening layer and two fully connected layers with layer sizes of 4 and 12 and a ReLU activation. The last layer, that is, the output layer, was a fully connected layer with a size of 4 and a softmax activation. The network was trained with the Adam optimizer using a learning rate of 0.0001. Different neural network structures were also tested but they resulted in worse performance (see Table S2). The network with the lowest mean validation set loss was selected from the tested networks. We used class weighting during training to mitigate the effect of
imbalanced classes. Each class weight was set to be inversely proportional to the number of patients in the class.

We used 10-fold cross-validation to test the performance of the classifier. The patient population was randomly divided into 10 subpopulations, each consisting of 201 or 202 patients. The CNN was trained 10 times such that each subpopulation was used once as a test set, and 9 times in the training set. During each fold, 10% of the training set was further used as the validation set to assess the performance during training and to avoid overfitting. The training accuracy was monitored during training using sparse categorical cross-entropy as the loss function. The training was stopped after the validation set loss did not decrease for 100 continuous epochs after which the model with the lowest validation loss was selected as the model for that fold.

To further interpret the model, we performed an occlusion test to estimate the relative importance of different parts of the spectrogram. A 32 × 32 mask, that sets the spectrogram values under the mask to zero, was used to occlude part of the spectrogram and these occluded spectrograms were given as an input to the trained classifier. The process was repeated by moving the mask over the whole spectrogram with no overlap resulting in a total of 256 occlusions. The accuracy of the classifier was then calculated for each occlusion.

**Results**

By using a single, 10-min, threshold for EDS classification, the classifier achieved an accuracy of 77.2% in differentiating sleepy and non-sleepy patients with suspected OSA. Sensitivity and specificity of the classifier were 76.5% and 77.9%, respectively. The receiver operating characteristic (ROC) curves for the classifier in each fold and across all folds are presented in Figure 3. The area under ROC curve (AUC) for the classifier across all folds is 0.464. The training, validation, and test set accuracies varied slightly between the folds. Mean training, validation, and test accuracies were 70.7%, 61.1%, and 60.6% with standard deviations of 4.5%, 7.3%, and 8.3%, respectively (see Table S1 for full cross-validation statistics). Confusion matrix showing the patient classification across all folds is presented in Figure 4. The CNN performed best in the moderate sleepiness category with an accuracy of 66.9% and worst in the normal category with an accuracy of 52.0%.

To assess which group of patients is most likely to be classified correctly, the classification accuracy was compared in age, sex, BMI, and AHI subgroups (Table 1). The classification accuracy varied slightly between the subgroups. Patients with severe OSA were slightly more likely to be classified correctly than patients with lesser severity of OSA. Patients with higher BMI or age were also classified slightly more accurately than patients with low BMI or age.

The results of the occlusion test when classifying the patients to the four sleepiness categories are presented in Figure 5. The accuracy varied greatly between the occlusions. Ocluding the lower frequencies (0–15Hz) had slightly more detrimental effect on the accuracy of the classifier than occluding the higher frequencies.

**Discussion**

We developed a CNN classifier that estimates daytime sleepiness based on polysomnographic (EEG, EOG, and chin EMG) signals recorded the night before MSLT. We found that the classifier was able to estimate sleepiness with moderate accuracy. The classifier classified patients to all sleepiness categories relatively evenly with no apparent bias for any sleepiness category (Figure 3).

In detecting EDS, the sensitivity (76.5%) and specificity (77.9%) were good with reasonably high positive predictive value (78.0%) and negative predictive value (76.5%). In comparison, similar sensitivities (70% and 80%) and negative predictive values (75% and 76%) have been reported with ESS using cohort-optimized cutoff values (16 and 12 points) [31, 32]. However, the
which might be more clearly detectable from the spectrograms.

sleepiness of these patients is mainly caused by the sleep apnea,
gerally increases with age and obesity [34], it could be that the
OSA or patients with low BMI (Table 2). Since OSA severity gen-
erally large, using even larger population would have likely
improved the results. Larger population would also have al-
lowed a larger test set and thus enabled a more robust valid-
ity. Another limiting factor is the
whole night and all frequencies are at least somewhat im-
portant in recovery during the night and greatly affects sleepi-
ness, it could be that the amount of slow wave sleep detected
from the spectrogram is at the lower frequencies. In addition, delta
waves, associated with deep sleep are at this low frequency
range (0.5–4Hz) [28]. As the amount of slow wave sleep is im-
portant in recovery during the night and greatly affects sleepi-
ness, it could be that the amount of slow wave sleep detected
from the spectrogram is a major component of the classifier
function. However, since the accuracy suffered at least slightly
when any part of the image was occluded, it seems that the
whole night and all frequencies are at least somewhat im-
portant for the classifier.

This study has certain limitations. The use of Pz electrode
might limit generalizability of the classifier since it is not a
commonly used electrode placement in PSG montage. However
omitting this electrode would have lowered classifier accuracy
(see supplement). Although the accuracy of the classifier was
moderate, it still leaves room for improvement. One compli-
cating factor in estimating the MSLT result is that the patient’s
sleepiness is not entirely dependent on the previous night.
Some of the patients might have been sleep deprived for a long
time while others might only be sleepy because of poor sleep
during the previous night polysomnography. While they both
might be classified to the severe sleepiness category, their EEG
event when using cohort-optimized cutoff values [31–33].

Based on the present results, the CNN classifier developed
in this study seems to be able to estimate sleepiness slightly
better than ESS [31–33]. However, it is important to note that ESS
is better suited as a measure of chronic, long-time sleepiness
rather than the acute sleepiness. Therefore, ESS is still a valu-
able tool in sleepiness estimation. The classifier could be used
as a simple estimator of the patients’ sleepiness since it is easy
to implement and does not require long and laborious full-day
test (i.e. MSLT) while still providing an objective estimate of the
patient’s acute daytime sleepiness. In addition, ESS could be
used in conjunction with the classifier to provide information
on the chronic situation.

In the subgroup analysis, older patients, patients with severe
OSA or patients with high BMI were classified slightly more ac-
curately than younger patients, patients with lower severity of
OSA or patients with low BMI (Table 2). Since OSA severity gen-
erally increases with age and obesity [34], it could be that the
sleepiness of these patients is mainly caused by the sleep apnea,
which might be more clearly detectable from the spectrograms.

Table 2. Classification accuracy in subgroups across all folds when
classifying patients to the four sleepiness categories

| Subgroup | Number of patients in subgroup | Classification accuracy (%) |
|----------|--------------------------------|-----------------------------|
| Males    | 1,492                          | 61.5                        |
| Females  | 522                            | 57.9                        |
| AHI < 5  | 401                            | 52.1                        |
| 5 ≤ AHI < 15 | 438                         | 59.4                        |
| 15 ≤ AHI < 30 | 422                        | 57.5                        |
| AHI ≥ 30 | 753                            | 67.5                        |
| BMI < 25 | 355                            | 56.7                        |
| 25 ≤ BMI < 30 | 660                        | 60.0                        |
| 30 ≤ BMI < 35 | 598                        | 62.7                        |
| BMI ≥ 35 | 421                            | 61.5                        |
| age < 40 | 430                            | 54.2                        |
| 40 ≤ age < 50 | 406                        | 60.1                        |
| 50 ≤ age < 60 | 668                        | 62.7                        |
| age ≥ 60 | 510                            | 63.5                        |

AHI, apneas–hypopneas index; BMI, body mass index.

The occlusion test showed that there does not seem to be a
well-defined, specific region in the spectrogram image that is
most important for sleepiness classification (Figure 5, A).
However, occluding the frequencies less than 15Hz seemed to
have a more detrimental effect on the accuracy of the classi-
 fier (Figure 5, B). This makes sense since most of the power in
the spectrogram is at the lower frequencies. In addition, delta
waves, associated with deep sleep are at this low frequency
range (0.5–4Hz) [28]. As the amount of slow wave sleep is im-
portant in recovery during the night and greatly affects sleepi-
ness, it could be that the amount of slow wave sleep detected
from the spectrogram is a major component of the classifier
function. However, since the accuracy suffered at least slightly
when any part of the image was occluded, it seems that the
whole night and all frequencies are at least somewhat im-
portant for the classifier.

Figure 5. Occlusion plots for the convolutional neural network classifier when
classifying patients to the four sleepiness categories. All 32 × 32 occlusions
(A) showing the difference in classification accuracy when the corresponding
area of the input spectrograms are occluded. Time average of the occlusions (B)
showing the average drop in accuracy for each frequency. Brighter color corre-
sponds to a larger drop in accuracy, that is, the occluded area is more important,
and darker color corresponds to a smaller drop in accuracy.
same population. In addition, no information on medications or comorbidities was available for this study population. This can be considered a study limitation as both of these could have an effect on the patients’ sleepiness. It is also important to note that all of the patients in this study were suspected OSA patients complaining from daytime sleepiness during clinical interview. This results in a biased population only consisting of patients with subjective sleepiness while including no patients who were objectively sleepy but not subjectively sleepy. Thus, the network might behave differently if applied to a different population such as a healthy population or to a population with different sleep disorders.

In conclusion, objective estimation of daytime sleepiness using polysomnographic signals shows promising results. The developed CNN classifier could be applied for OSA patients that undergo polysomnography to get an objective EDS evaluation with minimal workload.

Supplementary material

Supplementary material is available at SLEEP online.

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