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Deep CNN for EEG in Sleep Staging

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Abstract. There is recently a large amount of deep learning algorithms developed for sleep staging using the signals, especially EEG, recorded by sleep monitoring devices for sleep related patients. Among them, those based on CNN architecture have some advantages over the others. This paper mainly discusses the CNN-based sleep staging algorithms for EEG, and meanwhile considers their upstream monitoring devices and the downstream clinical tasks. The relationship between these three parts of the sleep staging in the clinical context is discussed in this study. According to the overall picture built for the three parts, suggestions are proposed for the scientists and physicians working in these fields. Considering the clinical demands, the CNN-based sleep stage classifiers are expected to perform better on real-time analysis and generalization, while keep improving the precision on two different modality of signals both including EEG. The monitoring devices, correspondingly, should deal with the trade-off between lightweightness and the amount of information recorded. These suggestions should offer an overall view for the scientists to have a clear knowledge about how to work together to contribute to the effective treatment for patients.

Keywords: CNN-based algorithms; EEG-based sleep staging; Sleep monitoring; Deep learning.

1. Introduction

Sleeping quality is closely related to human's both mental and physical health, and a significant measure for it is the patterns of sleep stage. Therefore, monitoring sleeping and getting a precise classification of the sleep stages is really important for the physicians to offer more reasonable treatments to the patients. Based on many different indicators recorded during sleeping including electrophysiologic signals like EEG, the commonly used standard to divide the sleeping stages is proposed by American Academic of Sleep Medicine [1]. Many sleep recording datasets are successfully labeled by the experts with the proposed standard, facilitating the sleeping study. However, the usual way of manual classification work done by physicians is neither efficient nor convenient. So in recent years, scientists are developing many sleep stage classification algorithms to solve this problem.

The initial trying includes algorithms using traditional machine learning methods. For instance, some support vector machine-based classifiers have been invented to realize the automatic sleep staging [2]. Yet the information extraction step of the traditional machine learning method-based algorithms like the work mentioned above is dependent on the prior knowledge from the human experts. Therefore, this classification method is not sufficiently unbiased, as the choices of features to extract influences the consequence.

Trying to develop unbiased automatic sleep stage classification peplines, the scientists turn to deep learning in recent years. Deep learning simply uses the principled mathematical methods and the powerful computing power of the computers to learn the optimal classification functions. With fewer biological assumptions and prior knowledge, deep learning is regarded as a fairer approach. Some remarkable work have been done using recurrent neural network (RNN). SeqSleepNet is one of them that perform a satisfying precision [3]. However, the model complexity nature of the RNN architecture prevents the RNN-based methods from completing the training and classifying in a short time. As an alternative, convolutional neural network (CNN) architecture manage to do the classification in a more efficient way. And the combination of it with other modules like attention mechanism-based modules shows its potential to reach a higher precision while reduce the time cost compared with RNN.

Besides the recent advance in algorithm field, the monitoring devices are also improved. To be further discussed in detail in the next part though, the monitoring devices are evolving towards a more lightweight direction, in a nutshell. Since the signal collecting by the devices is the upstream step of the classification, the changes took place on them need to be considered when the scientists develop new algorithms. On the other hand, authentic clinical content is a part that cannot be ignored throughout the discussion. As the sleeping study deepens, the newly discovered relationships between sleeping stage patterns and many different kinds of sleeping disorders allow physicians to utilize sleep monitoring and sleep stage analysis to treat patients better. To truly bring well-fare to the patients, the sleep stage classifying algorithms have to consider the complicated clinical factors, like the monitoring environment and the risk of the monitored diseases. In this way, they could have a better chance to be adopted by the physicians and making contributions to the medical field in the coming future.

As the upstream and the downstream of the sleep stage classification algorithms, the monitoring devices designation and the medical application, together with the algorithms themselves, should be viewed as a whole. Centered on EEG-based algorithms using CNN, this paper discussed the complete picture of the sleep staging. The aim of this work is to sort out how the nature of each of the three parts influences the future developing direction of the other two, and offer constructive suggestions for the scientists or physicians.

2. Analysis of the problems

2.1. Algorithms analysis

In this section, some different state-of-the-art algorithms based on CNN are analyzed. One of the aims is to identify the characteristics of the input data with which the algorithms perform best. In addition, the aiming clinical tasks indicated by the multi-dimensional performance of these algorithms are also significant for physicians to choose the best classifying method in clinical practice.

AttnSleep is a method that is widely used as baseline in the related studies. It uses a typical architecture that combines multi-resolution CNN with the Squeezing-Exciting (SE) module and an attention-based module, as shown in Figure 1. The SE module is to optimize the extracted features by CNN, while the attention-based module is designed to extract the temporal information, replacing the complex RNN in many studies in recent years. In addition, the loss function of AttnSleep is specially designed to solve the data imbalance problem efficiently [4].

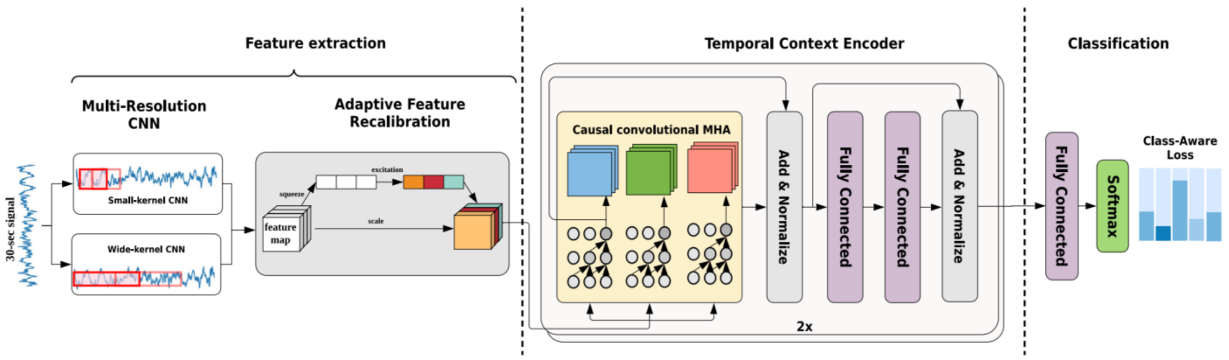

Figure 1. The framework of AttnSleep algorithm [4].

Focusing on the demand for recording convenience in practice, AttnSleep shows remarkable performance in single-channel EEG signal. Regarding the required data amount, a single 30-second epoch of training signal is sufficient for AttnSleep to achieve good accuracy, although adding a few more epochs can improve the model's performance [4]. The low requirement for data amount makes AttnSleep work well with the portable small sleeping monitor devices, which have a large market demand in recent years.

Besides the high accuracy, AttnSleep also has a much shorter training time compared to several RNN-based state-of-the-art methods due to its temporal context encoder module that is easy to be trained in parallel [4]. This characteristic brings AttnSleep the potential to be qualified for automatic sleep stage classifying in clinical practice, since one of the important reasons for the general manual classifying is the high time cost of the models.

MaskSleepNet is another recent work that utilizes the similar architecture as AttnSleep, as shown in Figure 2. However, it targets for a different direction to improve the classification. Before feature extraction, MaskSleepNet adds a masking module to handle the problems brought by multi-sources of the input signals, like EEG, EOG and EMG. A series of corresponding adjustments on the following modules are done to reduce the feature redundancy due to the masking module. Namely, a concatenation layer and a masking operation are added to the CNN feature extracting module and the input of the attention-based temporal information capture module, respectively [5].

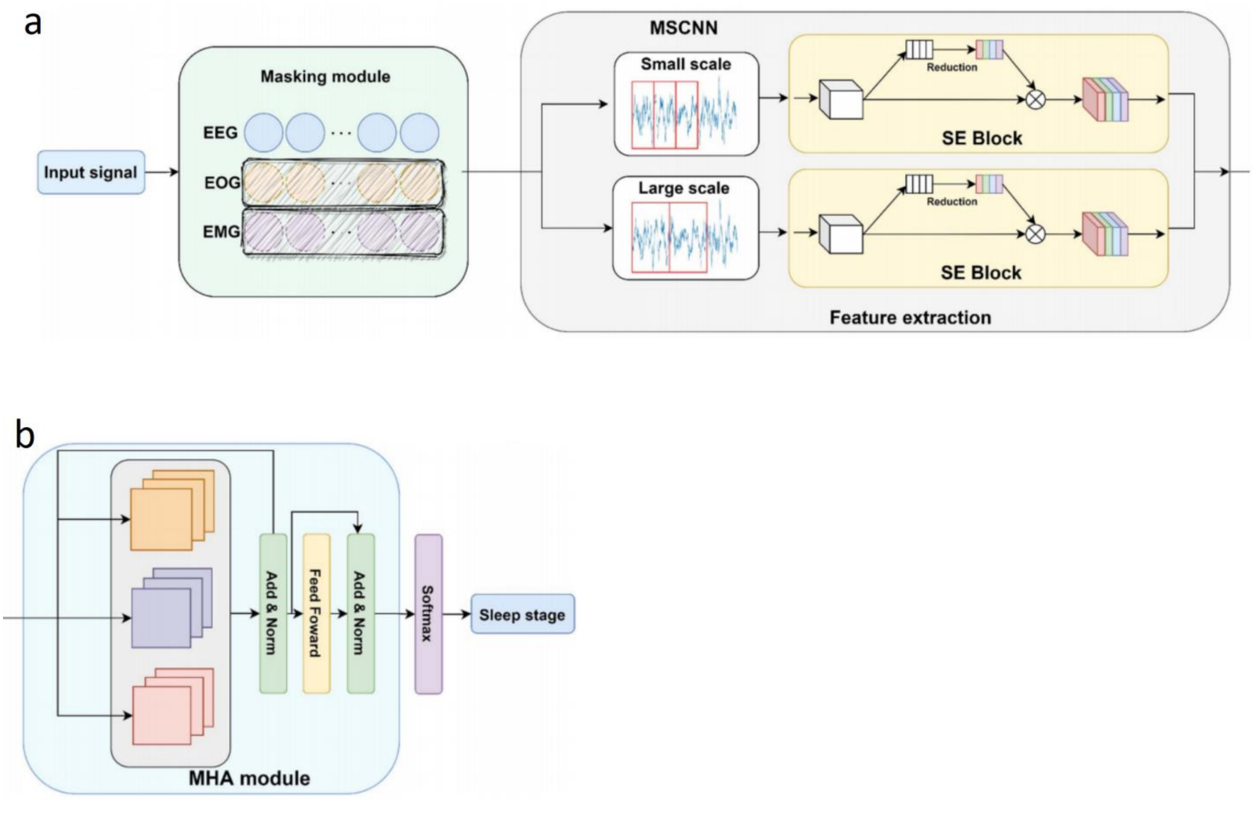

Figure 2. The architecture for MaskSleepNet algorithm [5].

MaskSleepNet is impressing mainly because its cross-modality robustness. With the similar accuracy with other baseline algorithms, this method attains a stable performance at different input conditions, namely the different combinations of EEG, EOG and EMG. This feature allows the algorithm to utilize the multi-modality signal recorded by the whole set of the monitoring devices to the utmost. Not only the information in the EEG, but that in the EOG or EMG can also contribute to the classification, which would raise the accuracy in normal cases [5].

The robust accuracy across different input conditions also brings the masking module architecture a possibility to further improve the cross-datasets transfer ability of the classifying models, since the datasets transfer problem is actually a kind of input heterogeneity [5]. Furthermore, this robustness would be particularly well-suited for the long-term in-home monitoring events, when it’s hard for the input signal to keep the same quality due to the lack of professional adjustment of the device.

2.2. Device limitation

There are certain shortcomings that make polysomnography (PSG), the golden standard of sleep staging, not suitable for some clinical cases. PSG includes multiple types of physiological, chemical, and mechanical recording devices, and the test needs to be conducted in a sleep laboratory. The problems brought by these complex devices and unnatural recording environment have been discussed in recent years [6]. The possibility of failure to capture the tracked sleeping disorder events in few nights of recordings due to the rarity of the disorder events, the untypical sleeping due to the uncomfortability of the devices as well as the environment, and the rapidly increasing demand of sleep monitoring due to the prevailing sleeping problems across the whole modern society, all encourage the development of a more simple sleep monitoring method as an alternative for PSG [7, 8].

Single-lead EEG recorders or those combined with a few other types of signals are such appropriate home-use devices for sleep monitoring. Their advantages are mostly shown in illnesses such as sudden nocturnal diseases or insomnia, when the sleeping problems are either rare to display or easy to be disturbed. On the other hand, the in-home recorded signal by these lightweight devices is proved to be reliable enough for effective monitoring in many cases [9,10]. This indicates that devices simply records a subset of the categories of the PSG-recorded signal can overcome the disadvantages of traditional PSG, and can serve as a substitute when necessary.

As for comparison between single-lead EEG devices and that with other supplimentary signals, two evaluation dimensions should be considered. The first one is the user-friendliness of the operation of the devices. Keeping only the most important information source of sleeping stages, single-lead EEG devices could perform an accurate sleep stage classification without the motion sensors bounded tightly around the chest for respiratory effort detection, or the nasal pressure sensors plugged into the nose. The latter components are common in PSG and might cause additional sleeping problems for some patients. Therefore, the single-lead EEG could satisfy the patients who are extremely sensitive to the disturbance during sleeping. The in-home self-applied somnograph products are also acceptable for most of the patients due to the wireless and convenient operation. The second factor is the information that can effectively contribute to the precision of the sleep staging task. In some cases, the combination of EEG and some certain kinds of other signal like EMG are recorded to support a more precise classification for sleep staging than merely EEG, but the improvement brought by EOG and EMG is limited in some patients datasets where muscle movements disorders might introduce misleading information [5, 11].

2.3. Clinical tasks requirements

In this section, several notable requirements considering specific medical goals for doing sleep staging are discussed. These demands would guide the direction of the sleep stage classification algorithms to be improved.

First, the real-time classification has been a valuable goal to pursue. The sleep staging is always the first step for an effective medical care procedure. The in-time intervention is especially needed to be done in nocturnal illnesses that sudden attack or other disorders that might bring danger to patients. Another demand from the increasing number of patients who need sleep monitoring with sleep stage classification is that the algorithms need to have a strong generalization ability. With such a large amount of data to handle, it’s extremely inefficient for the classification models to be trained each time when facing a new set of data. Also, the demand for precision of sleep stage classification does not necessarily lower even though the sleep monitoring is getting increasingly commonplace. Actually, some sleep monitoring tasks are just transferred from sleeping labs to the personal bedrooms for a better recording. The precision of the classification is still the fundamental basis for the further treatments.

3. Suggestions

After the analysis above, a blueprint of the sleep stage classification for future is unfolded, involving algorithm researchers, device designers and physicians, with full awareness of the clinical context.

According to the clinical requirements, the sleep monitoring devices are expected to simplify the types of signals they record. On the other hand, the multi-modality recording devices and the single-lead EEG recording devices are helpful in different cases. Considering the added complexity of the multi-modality recording devices, the application of them should be carefully assessed according to the patients conditions and the features of the illness, in case the limited improvement of precision can't offset the disturbance to sleep monitoring.

Consistent with the direction where sleep monitoring devices are improving towards, the sleep stage classification algorithms should keep raising their classifying precision with both single-channel EEG signal and the combination of some limited combinations of recorded signal, while robustness across data with different qualities are expected to be high. What's more, the ability for real-time classification and the ability to generalize well should be strengthened due to more effective medical treatments and a larger demand for sleep monitoring.

Meanwhile, with the final goal for the classification algorithms to support clinical treatments, the physicians are expected to have the knowledge of how to choose the proper classification methods in the future. Considering the devices limited by the specific clinical conditions and what to do with the sleep stage classification results would help them make the appropriate decisions.

4. Conclusion

In this paper, the structure of sleep staging task using EEG in the clinical context is demonstrated, with the CNN-based classifiers as the core part, the monitoring devices as the connection between the clinical application and the algorithm realization, and the medical demands as the guide for both of the other two parts. On one hand, the CNN-based sleep stage classifiers are expected to satisfy the real-time analysis and generalization need from the fact that an increasing number of patients hope to carry out the sleep monitoring at home, which also puts a limit to the devices designation. On the other hand, the algorithms should focus on the precision with either single-channel EEG or signal combinations with EEG and other limited electrophysiological signals, considering the monitoring devices have these two paths to be improved due to the clinical need.

For the deep learning algorithm field of EEG-based sleep staging, the sleeping monitoring device field and the sleeping-related disease field, this paper should offer an overall view for the scientists. This might be beneficial for them to have a clear knowledge about how to work together to contribute to the effective treatment for patients. Although this paper mainly focuses on CNN-based methods due to their striking performance, there are ascending amount of algorithms using transformer architecture in the sleep staging field, which might be also worth discussing in the future.

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