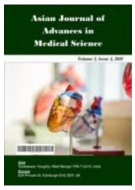
Asian Journal of Advances in Medical Science

2(1): 83-87, 2020



TRANSFER LEARNING METHOD FOR SLEEP STAGES CLASSIFICATION USING DIFFERENT DOMAIN

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AUTHORS' CONTRIBUTIONS

This work was carried out in collaboration among all authors. Author MMM designed the study, performed the statistical analysis, wrote the protocol and wrote the first draft of the manuscript. Authors MHF and HM managed the analyses of the study. Authors MHF and MT managed the literature searches. All authors read and approved the final manuscript.

Received: 28 September 2020
Accepted: 05 December 2020
Published: 16 December 2020

Original Research Article

ABSTRACT

Sleep stages classification using the signal analysis includes electroencephalogram (EEG), Electrooculography (EOG), Electromyography (EMG), Photoplethysmogram (PPG), and electrocardiogram (ECG). In this study, the proposed method using transfer learning to sleep stages classification. First, we have used the PPG and ECG signals, because they are less complex. This signal has the least complexity, and in this article we used this signal for transitional learning. n this study, we extracted 52 features from two signals and prepared for the classification stage. This method includes two steps, (a) Train data PPG and Test data ECG, (b) Train data ECG and Test data PPG. Results proved that our method has acceptable reliability for classification. The accuracy of 95.25% and 94.63% has been reached.

Keywords: PPG signal; ECG signal; sleep stages classification; transfer learning.

1. INTRODUCTION

According to the American Academy of Sleep Medicine (AASM) and (R&K) and [1,2], Sleep has 6 stages, Rapid-Eye Movement stage (REM), No Rapid-Eye Movement stage (NREM), NREM stage 1, NREM stage 2, and NREM stage 3. In the process of sleep stages each 30 sec of signals, called an epoch [3, 4]. Sleep stage classification have been used the signals EEG, EOG, EMG, ECG, PPG and etc. In last years, have been used machine learning and deep learning method for sleep stage classification.

In these years, deep learning and transfer learning have been widely used in image processing, number recognition and disease diagnosis. These methods are always increasing and have even been widely used in medicine. Not using manual methods with duplicate data, an effective method in diagnosing diseases is a very useful method due to the lack of data and data variability. This study has two steps: (1) PPG Train data and ECG test data and (2) ECG Train data and PPG test data.

The first time for sleep stage classifications based on deep learning was proposed in [5]. Extract features from bio-signals for sleep stage classification. The deep learning method proposed to classification of sleep stage using bio-signals (EEG, EOG, PPG and EMG). In [6] model is using CNNs network for

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features extract in EEG signal. The transfer learning for classification of sleep stages using the data in PhysioNet database [7,8,9]. The Transfer Learning based on time-frequency image (TFI) for classification of Sleep Stage [10,11].

2. PROPOSED METHODS

In This article, used the dataset online in [12] have been used PPG signals.

In this study, using the time-frequency image (TFI) of ECG and PPG signals, the sleep steps are classification with high accuracy by deep learning method.

In this study, for the first time, using the time-frequency image (TFI) from ECG and PPG signals, the sleep steps are classified with high accuracy by learning and extracting deep features.

TFI obtain using the Smoothed Pseudo Wigner-Ville Distribution method in [13,14,15]. And the ALEXNET network is used, with the difference that in [3,16,17] 1000 fully connected layer (fc8) with 1000 features.

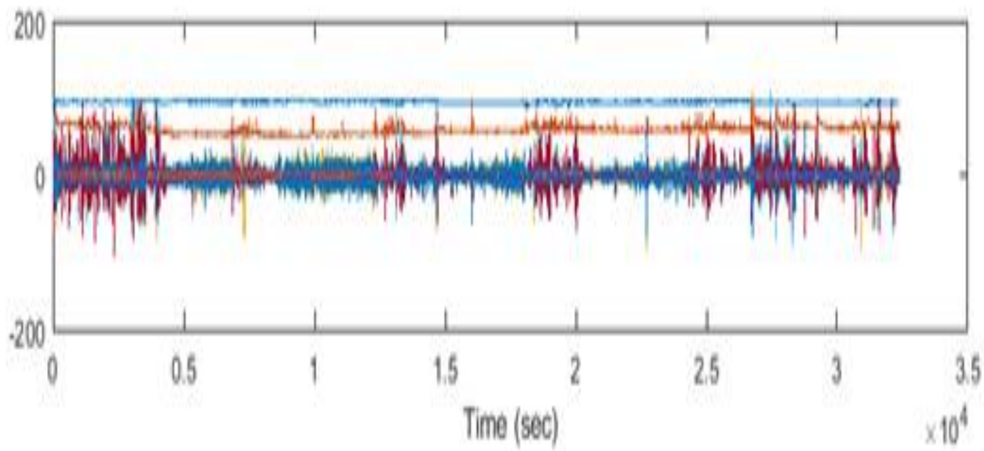

Fig 1. All signals in the database

Table 1. Sleep stages labels

Number sleep	Sleep stage
-1	Wake stage
0	REM stage
1	S1 stage
2	S2 Stage
3	S3 Stage
4	S4 Stage

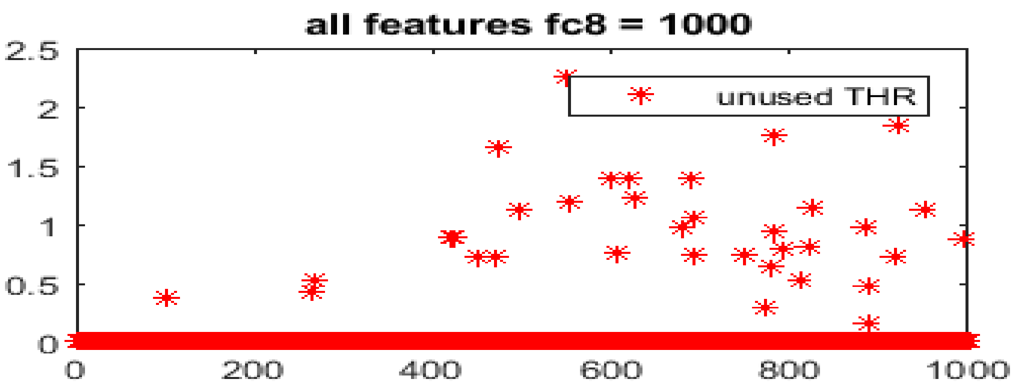

Fig. 2. features extraction using Alex Net

3. RESULTS AND DISCUSSION

In the paper, for the first time, low-complexity signals are used to detect sleep stages. In this method, we extracted the time- frequency images (TFI) from signal using the AlexNet pre-trained method. The extracted features are obtained without manual methods. 1000 features are extracted using the fully connected (fc8) architecture to classify the sleep stages used. In the final part, according to the transitional learning, the sleep stages were separated with high accuracy. Transitional learning is that training data and test data are completely different from the two groups. The results are expressed in these cases, which can be seen in the following tables.

All steps in this study, shown in Fig. 3.

As you can see in Fig. 3, all the steps from the beginning to the end are presented in a flowchart.

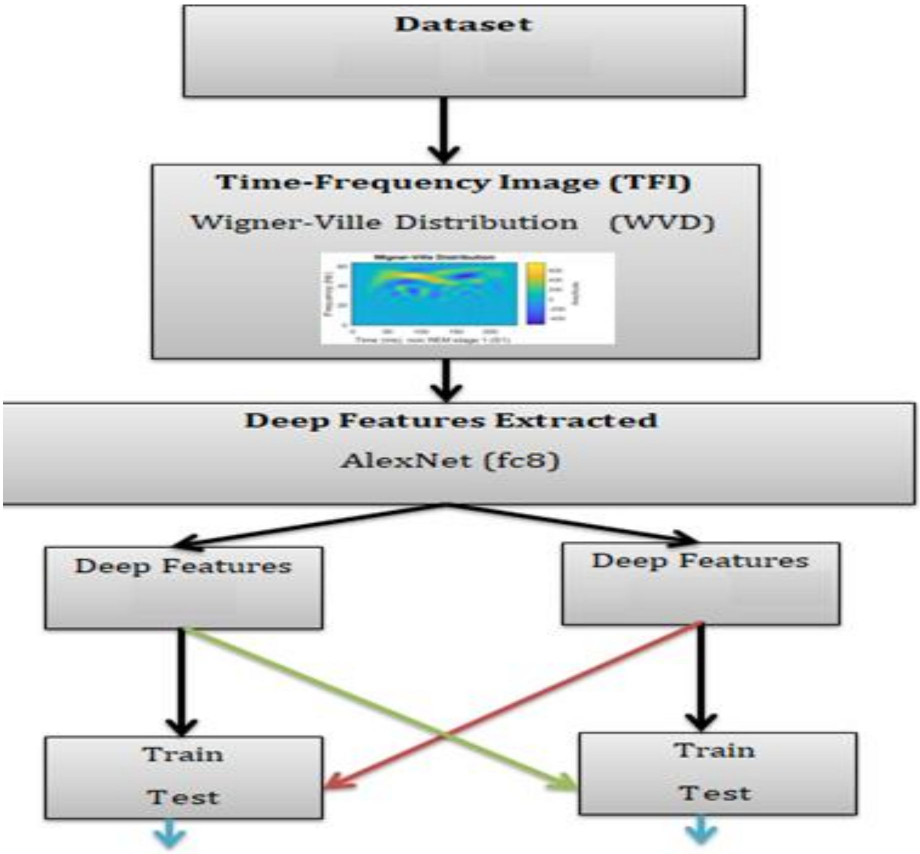

Fig. 3. All steps of sleep stages classification

Table 2. Accuracy and sensitivity of transfer learning

steps	Train data	Test data	accuracy
1	PPG	ECG	95.25%
2	ECG	PPG	94.63%

Table 3. Accuracy of transfer learning

Steps	**Accuracy %**
Our method	95.25
[1]	96.3
[2]	80.8
[3]	68

Table 2 shows the results of the classification of sleep stages using the transfer learning method. It has two steps, the first step is PPG signal training data and ECG signal test data. The second step is ECG signal training data and PPG signal testing data. According to Table 3, the proposed method is compared with other methods in other valid studies.

Table 2 shown Accuracy of sleep stage classification using the deep transfer learning method, that this method are good accuracy for detection sleep stages.

According to the results of Table 3, we conclude that the method presented in this article has an acceptable accuracy.

4. CONCLUSIONS

All processing steps have been using HP laptop with the CORI7 processor and 4 GB RAM and using MATLAB 2020b software.

In this paper, two low-complexity ECG and PPG signals are used to classify sleep stages.

The frequency time image was extracted from the signals, and then handless features were extracted.

1000 features based on fully connected architecture (FC8) were extracted.

This method is different from the traditional methods of feature extraction.

Finally, we used transfer learning method using two signals with different domain to sleep stage classification.

CONSENT

All authors read and approved the final version.

ETHICAL APPROVAL

There are no ethical approval to this research.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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