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Sleep stages classification based on deep transfer learning method using PPG signal

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Abstract
Sleep stages classification using the signal analysis includes EEG, EOG, EMG, PPG, and ECG. In this study, the proposed method using transfer learning to sleep stages classification. First, we have used the two PPG signals for this method It is important to use a less complex signal. The PPG signal has the least complexity, and in this article, we used this signal for transitional learning. In this study, we extracted 52 features from two signals and prepared them for the classification stage. This method includes two steps, (a) Train data PPG1 and Test data PPG2, (b) Train data PPG2 and Test data PPG1. Results proved that our method has acceptable reliability for classification. The accuracy of 94.26% and 96.49% has been reached.

Keywords: PPG signal, sleep stages classification, deep transfer learning.

1. INTRODUCTION

According to the American Academy of Sleep Medicine (AASM) and (R&K) and [5], Sleep has 6 stages, Rapid-Eye Movement stage (REM), 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 [1]. Classification of Sleep stage has been used the signals EEG, EOG, EMG, ECG, PPG and other signals. In past years, have been used too proposed for sleep stage classification using the machine learning and deep learning method.

Deep learning is one of the new methods in signal and image processing. This method does not require manual feature extraction. Also, due to the problems of extracting

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features from images, it has received more attention. Today, in the fields of engineering, medicine, medical engineering and other methods, much attention has been paid It has always had better results than other methods. Due to the lack of multiple medical signals and their differences with each other. The transfer learning method has been widely used and has been satisfactory. In the medical fields, this method is very useful.

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) PPG1 Train data and PPG2 test data and (2) PPG2 Train data and PPG1 test data.

2. RELATED WORKS

The first time for sleep stage classifications based on deep learning was proposed in [6]. That extracts features from bio-signals for sleep stage classification. The deep learning method proposed to the classification of sleep stage using bio-signals. (EEG, EOG, PPG and EMG). In [8] model is using CNNs network for features extract in EEG signals. The transfer learning for classification of sleep stages using the Physionet database [9-10]. The Transfer Learning from TFI for classification of Sleep Stage. The transfer learning for classification of sleep stage using TFI [1].in [17], in which, extracted the deep features from EEG raw and filtered, filtered EOG and filtered EMG data. Different classifiers were applied. The

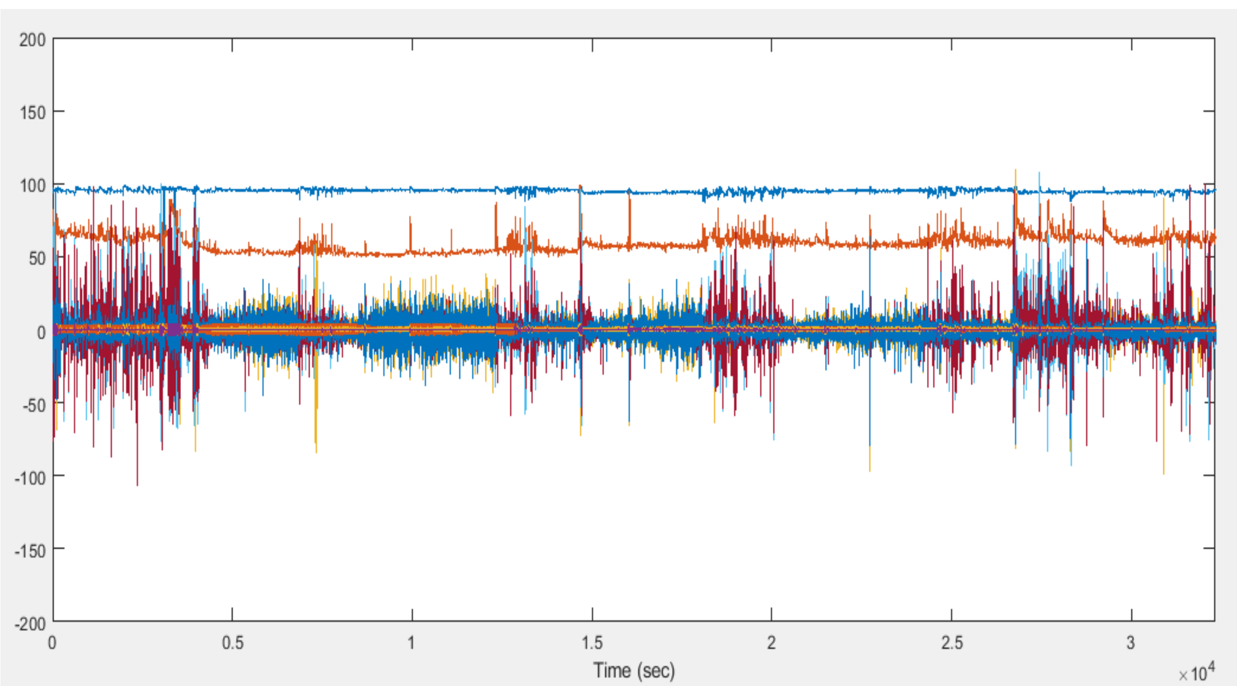

***Fig. 1. All signals in the database*.**

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

total accuracy this method was 91.31%. In [18] proposed Deep Sleep Net based on raw EEG signal and contains two different CNNs to extract features and Long Short-Term Memory (LSTM) for transfer learning. In another method with two different datasets demonstrated that this method was able to learn features from raw EEG signal and classify other EEG signals [19].In another work, the idea of single channel system is combined with transfer learning [20].in this work, Vilamala et al. tested the hypothesis that sleep stage classification based on transfer learning on the data obtained from Physionet database. The Transfer Learning of Spectrogram Image for Sleep Stage Classification from EEG signal is porposed [21]. In [22] used pre-trained Convolutional Neural Network (CNN), VGGNet, to be classified as five sleep stages.

3. PROPOSED METHOD

3.1. Datasets

This study uses the dataset available at https://archive.physionet.org/physiobank/database/shhpsgdb/ in this PSG database, data obtained in an unattended setting. The data includes: C3/A2 and C4/A1 EEGs, right and left (EOGs), electromyogram (EMG), plethysmography, airflow, pulse oximetry, ECG, and (PR).

- C3/A2 and C4/A1 EEGs, sampled at 125 Hz
- right and left electrooculograms (EOGs), sampled at 50 Hz
- a bipolar submental electromyogram (EMG), sampled at 125 Hz
- thoracic and abdominal excursions (THOR and ABDO), recorded by inductive plethysmography bands and sampled at 10 Hz

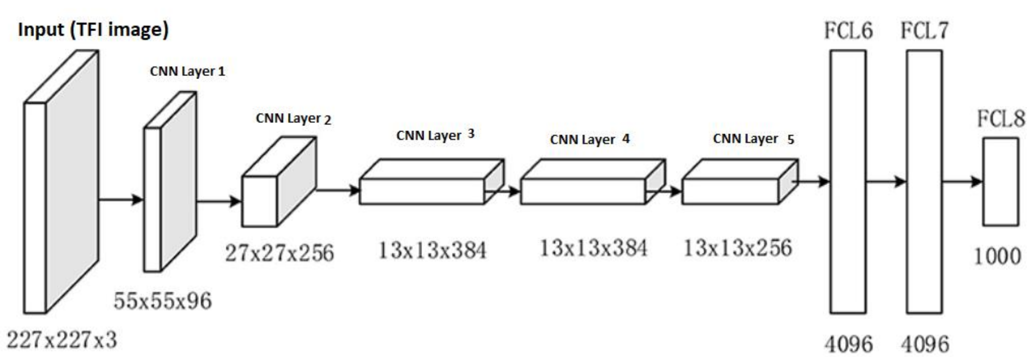

Fig. 2. All layers in AlexNet for features extraction.

Table 2. ***The Alexnet model in matlab.***

No.	Layer Name	Layer Type	Description
1	‘data’	Image Input	227 × 227 × 3 images with 'zerocenter' normalization
2	‘conv1’	Convolution	96 11 × 11 ×3 conv with stride [44], and padding [0000]
3	‘relu1’	ReLU	ReLU
4	‘norm1’	Cross Ch Norm	cross channel normalization with 5 channels per element
5	‘pool1’	Max Pooling	3 × 3 max pooling with stride [2 2] and padding [0000]
6	‘conv2’	Convolution	256 5×5 × 48 conv with stride [11], and padding [2222]
7	‘relu2’	ReLU	ReLU
8	‘norm2’	Cross Ch Norm	cross channel normalization with 5 channels per element
9	‘pool2’	Max Pooling	3 × 3 max pooling with stride [2 2] and padding [0000]
10	‘conv3’	Convolution	384 3×3×256 conv with stride [11], and padding [1111]
11	‘relu3’	ReLU	ReLU
12	‘conv4’	Convolution	384 3 ×3 × 192 conv with stride [11], and padding [111]
13	‘relu4’	ReLU	ReLU
14	‘conv5’	Convolution	256 3 ×3×192 conv with stride [11], and padding [1111]
15	‘relu5’	ReLU	ReLU
16	‘pool5’	Max Pooling	3 × 3 max pooling with stride [2 2] and padding [0000]
17	‘fc6’	Fully Connected	4096 fully connected layer
18	‘relu6’	ReLU	ReLU
19	‘drop6’	Dropout	50% dropout
20	‘fc7’	Fully Connected	4096 fully connected layer
21	‘relu7’	ReLU	ReLU
22	‘drop7’	Dropout	50% dropout
23	‘fc8’	Fully Connected	1000 fully connected layer
24	‘prob’	Softmax	Softmax
25	‘output’	Class Output	crossentropyex with ‘tench’ and 999 other classes

Table 3. ***Two steps of transfer learning.***

steps	Train data	Test data
1	PPG 1	PPG 2
2	PPG 2	PPG 1

- “airflow” detected by a nasal-oral thermocouple (Protec, Woodinville, WA), sampled at 10 Hz
- finger-tip pulse oximetry (Nonin, Minneapolis, MN) sampled at 1 Hz
- ECG from a bipolar lead, sampled at 125 Hz for most SHHS-1 studies and 250 Hz for SHHS-2 studies
- Heart rate (PR) derived from the ECG and sampled at 1 Hz
- body position (using a mercury gauge sensor)
- ambient light (on/off, by a light sensor secured to the recording garment).

Then, using a convolutional neural network based on AlexNet architecture, the features of the images were extracted. 1000 features have been extracted using a 5 layers convolution neural network by the fully connected AlexNet (FC8) architecture. The convolution neural network structure used is shown in Table 2. In this CNN method are 1000 features are extracted, shown in figure 2.

In this paper, 1000 properties were extracted from the first group of data (PPG) according to Figure 2 based on AlexNet network. And the network was trained and Then, features were extracted from the second group of data and the first network was tested and the results were reviewed and reported.

Sleep stages are separated by features extracted using the SVM classifier. This process is done in two steps.

1. PPG signal number one was used for training and PPG signal number two was used for testing.
2. PPG signal number two was used for training and PPG signal number one was used for testing. Which can be seen in Table 3.

4. BRESULTS AND DISCUSSION

All steps in this study, shown in figure 3.

This research. First, according to Table 2, which shows the general structure of Alexnet architecture, the features were extracted. Features were extracted without hand intervention using a convolutional neural network with 5 layers of convolution-based on the fully connected Alexnet (FC 8) architecture. Deep features were extracted from two different signals, PPG 1 and PPG 2, in order to distinguish the sleep stages using the transfer learning method. Sleep stages were separated by features extracted using SVM classifier based on the transitional learning method. This process is done in two steps and the results of these two modes are shown in Table 4.

Table 4. ***accuracy of transfer learning.***

steps	Train data	Test data	accuracy
1	PPG 1	PPG 2	96.49
2	PPG 2	PPG 1	94.26

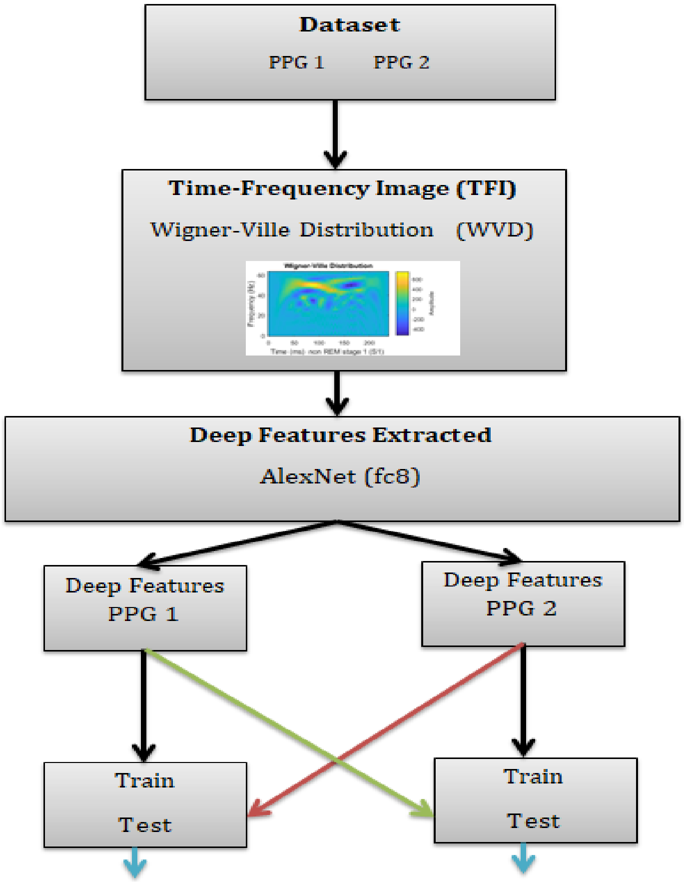

Fig. 3. All steps of sleep stages classification.

Table 5. ***accuracy of transfer learning***.

steps	accuracy
Our method	96.49
[1]	96.3
[2]	80.8
[3]	68

5. CONCLUSIONS

All processing steps have been using HP laptop with the CORI7 processor and 8 GB RAM and using MATLAB 2020b software.

PhysioNet Database is the most reliable database of medical signals and most articles use the same database.

In this paper, we used two signals with different domains to classify sleep stages. Here we use the PPG signal, which has little complexity. Due to the difference in signals between each person, the use of transfer learning method for practical use is very useful and practical. The presented method is very useful due to its high accuracy. According to the obtained accuracy, this method can be used to classify the stages of sleep and according to the results of Table 5, we conclude that the method presented in this article has an acceptable accuracy compared to other methods.

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