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Deep neural network method for classification of sleep stages using spectrogram of signal based on transfer learning with different domain data

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Abstract. Classification of sleep stages is an efficient way of diagnosing sleep problems based on processing the bio-signals (ECG, EEG, EOG, and PPG). The less complex this signal is, the better the detection and processing will be. Feature extraction methods that are done manually are tedious and time-consuming. On the contrary, those features with no hand intervention are called deep features that are usually extracted from images. Analysis of the time-frequency characteristics of non-static bio-signals is of importance since it can provide useful information. The current study aimed to extract the time-frequency image using ECG signal spectrogram as well as the deep features using the convolutional neural network. After extracting the deep features, sleep stages were classified based on deep transfer learning method. Network training was then performed using one of the ECG signals, and testing was done considering the other ECG signal channel. According to the findings, it is possible to detect sleep stages with acceptable accuracy and different amplitudes of signals. Finally, the accuracy and sensitivity values of the sleep stages were measured as 98.92% and 96.52%, respectively.

1. Introduction

Rechtschaffen and Kales (R&K) suggested six steps for sleep recording: Wake (W), Rapid Eye Movements (REM), NREM 1 (S1), NREM 2 (S2), NREM 3 (S3), and NREM 4 (S4) [1]. Extraction of the features from signals is considered in the classification of the sleep stages. In this regard, PSD features are used for classifying sleep stages using EEG signals [2]. In [3], FFT was used to classify the sleep stages. In deep learning, features were not manually extracted [4,5]; instead, they were extracted automatically with high precision. Convolution Neural Network (CNN)-based learning is usually used in medical image analyses [6,7], tumor detection [8], skin diseases [9], and identification, classification, and quantification of diseases [10]. In all learning methods, deep features were found effective in distinguishing between disorders and diagnosing them. In this respect, CNN-based transfer learning methods are employed to reduce the costs and achieve good accuracy [11]. These features are derived from pre-trained CNN video data [12,13]. Machine learning used for classification includes several stages: (a) preprocessing, (b) feature extraction, (c) feature selection, (d) dimensional reduction, and (e) classification. In the following, several problems raised in the feature extraction based on the traditional machine learning are listed: (a) extraction of low- or high-level features, and (b) extraction of handmade features. In [14,15], the deep

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features were extracted from images using pre-trained networks. Heenam et al. [16] highlighted the ability to learn transfer with smaller datasets used by GoogLeNet and AlexNet. Time-frequency characteristics were then used in [17] to classify the sleep stages. TFI suggested the EEG signals in [18] for sleep stage classification. Deep learning methods were then proposed to detect and classify the sleep phase of the EEG signal. However, no method for classification of the sleep stages based on the TFI of the ECG signal using deep learning has been proposed so far. Of note, deep learning methods are quite practical in medical records [19].

AlexNet and GoogLeNet are two pre-trained methods capable of classifying images into 1000 classes that have been trained and tested on a large number of images [20]. Their desirable accuracy has made them appropriate candidates for image analysis and classification [21].

In this study, the ECG signal spectrogram and transfer learning were used for feature extraction and training, respectively.

Time-frequency domains are very suitable for medical signals that can provide very useful information [22]. For this reason, the current study considered the time-frequency domain based on the spectrograms given in [23].

In [24], a novel feature extraction method based on Local Graph Structure (LGS) was used for EEG signal classification. As a result, a novel ensemble feature extraction network was formed based on Discrete Wavelet Transform (DWT).

LGS is commonly used for feature extraction and 2D-DWT for pooling. At the feature reduction phase, two widely known feature reduction techniques namely ReliefF and Neighborhood Component Analysis (NCA) are used together.

In [25], a proof of principle was given for conceptualization of the sleep stages as the attractor states in a nonlinear dynamical system to develop new empirical criteria for sleep stages. In addition, sleep was regarded as a nonlinear dynamical system that could be used for defining the sleep qualities, i.e., stability and accessibility of an equilibrium state, as well as the disrupted sleep criteria such as constant shifting between instable sleep states.

A hybrid lightweight deep feature extractor was introduced in [26] to obtain high classification performance which was tested with a big EEG dataset of signals taken from autism patients and normal controls.

A new signal-to-image conversion model was proposed in this research. In this regard, the features were extracted from the EEG signal using 1D Local Binary Pattern (1D-LBP) and used as the inputs of Short-Time Fourier Transform (STFT) to generate the spectrogram images.

2. Methods

2.1. Dataset

The present study used two databases for classification based on transfer learning.

2.1.1. First database

The first database is the Dataset (Sleep Heart Health Study (SHHS) designed for sleep stages) available online at https://archive.physionet.org/physiobank/database/shhpsgdb/.

This database is a study designed to investigate the relationship between the sleep-disordered breathing and cardiovascular disease.

PSG signals were obtained in an unattended setting, usually in the participants' homes, by trained and certified technicians. The recording signal is consisted of:

- C3/A2 and C4/A1 EEGs sampled at 125 Hz;
- Right and left EOGs sampled at 50 Hz;
- EMG sampled at 125 Hz;
- Thoracic and Abdominal excursions (THOR and ABDO) sampled at 10 Hz;
- "Airflow" sampled at 10 Hz;
- Finger-tip pulse oximetry (Nonin, Minneapolis, MN) sampled at 1 Hz;
- ECG from a bipolar lead sampled at 125 Hz;
- Heart rate (PR) sampled at 1 Hz;
- Body position (using a mercury gauge sensor);
- Ambient light (on/off, by a light sensor secured to the recording garment).
- Label of sleep stages in the first database shown in Table 1.

2.1.2. Second database

The second database is available at: https://archive.physionet.org/physiobank/database/ucddb/. This database contains 25 full overnight polysomnograms with simultaneous three-channel Holter ECG derived from adult subjects with suspected sleep-disordered breathing. A revised version of this database was posted on 1 September, 2011.

Table 1. Label of the sleep stages in the first database.

Label	W	R	1	2	3	4
Sleep stage	Wake stage	REM stage	S1 stage	S2 stage	S3 stage	S4 stage

Table 2. Label of the sleep stages in the second database.

Label	0	1	2	3	4	5	6	7
Indeterminate	Artifact	S4 Stage	S3 Stage	S2 Stage	S1 stage	REM stage	Wake stage	Sleep stage

Polysomnograms were obtained using the Jaeger-Toennies system (Erich Jaeger GmbH, Germany). The recorded signals were EEG (C3-A2), EEG (C4-A1), left EOG, right EOG, submental EMG, ECG (modified lead V2), oronasal airflow (thermistor), ribcage movements, abdomen movements (uncalibrated strain gauges), oxygen saturation (finger pulse oximeter), snoring (tracheal microphone), and body position. The files named with .rec suffixes contain these signals in the EDF format.

Three-channel Holter ECGs (V5, CC5, V5R) were recorded using a Reynolds Lifecard CF system (Reynolds Medical, UK) where the files named with lifecard.edf suffixes contain these ECG signals in the EDF format. The recording dates and times are not available. In record ucddb002, only two distinct ECG signals were recorded and the second ECG signal was also used as the third signal.

Table 2 shows the labels of the sleep stages in the second database.

2.2. Time-frequency image method

This study used Time-Frequency Image (TFI) of an ECG signal to classify the high-precision sleep phases based on the deep learning method with acceptable accuracy.

The relationships were taken into account to obtain the time-frequency image. The time-frequency image generates both periodic and spectrogram signals, making it much easier to check the system and improve the detection process, especially the separation.

Here, the signal was first considered in the frequency domain using the Fourier transform of the short time. The calculation formula is given in Eq. (1):

$$STFT(t.\omega) = \int_{-\infty}^{\infty} x(t+\tau)\omega(\tau)e^{-j\omega\tau}d t\tau, \qquad (1)$$

which indicates the fast Foyer conversion according to the mathematical equations. Then, the signal energy, i.e., signal spectrogram, was used to obtain the time-frequency image of the signal. In this paper, in accordance with the instructions given in [26], the signal frequency-time image was extracted based on Winger method. Figure 1 shows the TFI.

2.3. Convolutional Neural Network (CNN)

The AlexNet pre-trained convolutional neural network was employed to extract the deep features of the signal using Fully Connected (FC8) layers. This model is taught in a subset of the Image Net database in

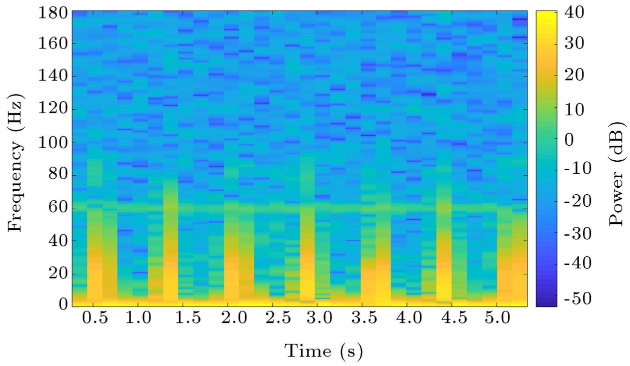

Figure 1. Spectrogram of the ECG Signal.

the visual recognition challenge. A large analogy of ImageNet was also utilized in this regard. This model is trained on more than one million images which can classify images into 1000 object classes. As a result, the representation model will learn rich features in a wide range of images. This network consists of 25 layers, in which there are eight layers with learnable weights, five layers of convolution, and three layers fully connected. Figure 2 represents the architecture of the ALEXNET convolution neural network.

Followed by extracting 1000 properties, the classifier stage begins which is based on the transfer learning. In this way, the features of the first signal are classified for training and those of the second signal are used for testing. This stage, which ensures the precision of this research, also includes generalization of the method. In this stage, valid classifiers including LDA, NN, KNN, and SVM are used. The final results were then presented according to which the best classifier was reported.

See the flowchart used in the article in Figure 3.

3. Results

As mentioned earlier, two databases were used for transfer learning method in this study. Two signal ECGs are available online at "https://archive.physio -net.org/physiobank/database/shhpsgdb/" and https://archive.physionet. org/physiobank/ database/ucddb/.

A time-frequency image based on a spectrogram was extracted from two signals, the second of which was different to make it easy to extract the deep features from these images. An example of a frequency-time image is shown in Figure 1. Then, the AlexNet convolutional neural network was employed to extract 1000 deep features from the obtained images.

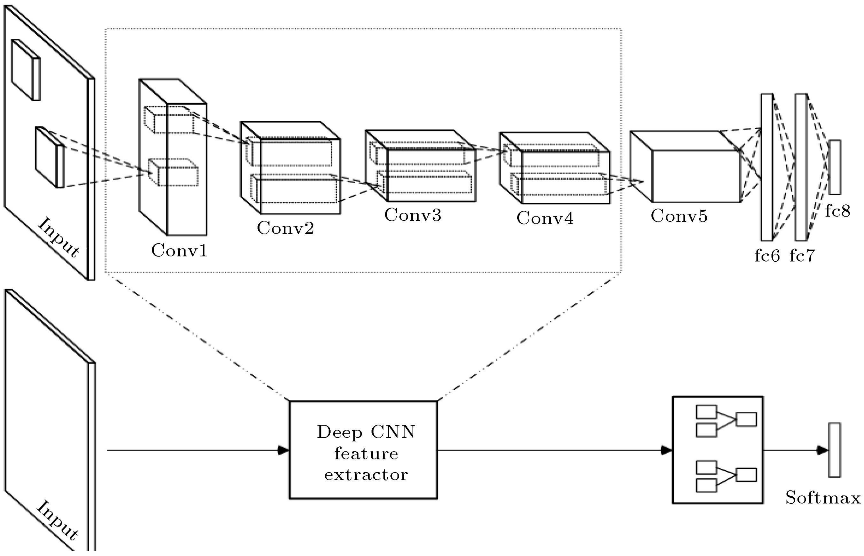

Figure 2. AlexNet convolutional neural network.

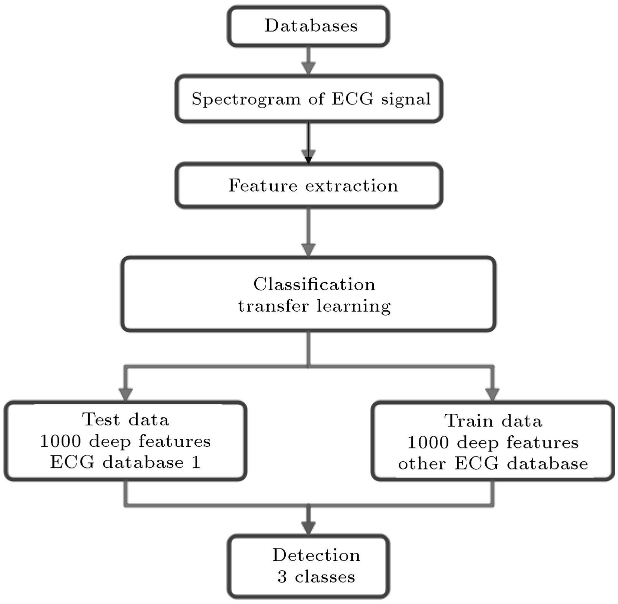

Figure 3. Flowchart of the proposed method.

Table 3. Results from the sleep stage classification based on the SVM method.

	Accuracy	**Sensitivity**
Step 1	98.92%	96.52%
Step 2	97.64%	93.49%

Then, two classification steps based on transfer learning method were taken into account. In the first step, the features of the first database were used for data training, and those of the second database were used for network testing. In the second stage, the opposite was done. Table 3 presents the results of accuracy and sensitivity of the two steps in the transfer learning method.

4. Discussion and conclusion

Application of high-complexity signals to detect the sleep stages is one of the major challenges. In this regard, use of low-complexity signals such as cardiac signals is very useful.

Given that consideration of manual features in the image processing is very time-consuming, tedious, and costly, use of automated methods without manual intervention has always been more favorable.

Lack of vital signals for monitoring and diagnosis has been always a problem; however, application of transfer learning methods in the diagnosis process was found to be an effective solution to this problem .

This research used the ECG signal with the least complexity, thus offering better calculations for real-time processing. It is recommended that the signal of one dataset be used to teach the classifier and that of another dataset to test the classifier; of note, it is of high importance in classification. Application of this method, called the transfer learning, is very important for bio-signals. According to the results given in Table 3, this method was proved to be effective, accurate, and reliable regarding the classification of the sleep stages. Finally, as observed in Table 4, the obtained results were more accurate than the other methods, hence the best option.

Use of time-frequency images from the signal could provide useful information with no need for examination of other signal properties. Signal transmission to the frequency domain omitted the performance of the repetitive signal processing.

The features were extracted without manual intervention using convolutional neural network. Convolution neural network creates a fully automated diagnostic system. The extracted deep features reduce

Table 4. Accuracy and sensitivity of other methods.

Reference	[18]	[19]	[20]	Proposed method
Stage classified	W, REM	Long-term sleep monitoring	W, REM, S1, S2, S3, S4	W, REM, S1, S2, S3, S4
Signal use	One EMG and two EEG	R-R intervals and ECG.	EEG	ECG
Sensitivity	82–92%	68.71%	15–98.8%	96.52%
Accuracy	82–93.86%,	89.97%	78.8–98.8%	98.92%

the human need to examine features, thus decreasing the human error.

Consideration of ECG signals in the detection of sleep stages eliminates the need for using high-complexity signals.

Transfer learning compensates for the lack of dependence on multiple signals.

5. Future works

Using signals of completely different nature can be investigated in the future studies. Using other convolutional neural network architectures in diagnosis can improve the diagnosis process. Diagnosis and investigation of other problems using the transfer learning methods can be considered in the future studies.

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Biographies

Mohammad Mahdi Moradi is a PhD scholar at the Department of biomedical, University of Kazeroun, shiraz, Iran. He has published many articles in internationally reputed journals in the field of biosignal and bioimage processing. His research interests include deep learning and transfer learning in biomedical engineering and computer engineering fields. He has published over six papers in different journals and conferences so far.

Mohammad H. Fatehi was born in Shiraz, Iran in 1982 and received his BSc degree from Department of Electrical Engineering, Najafabad branch, Islamic Azad University in 2005 and MSc degree in Control Engineering from Department of Electrical/Control Engineering, MUT University of Tehran, Iran in 2009. He then received the PhD degree from the Department of Electrical/Control Engineering, Science and Research branch, Islamic Azad University, Tehran in 2015. Dr. Fatehi is currently an Assistant Professor in Control Systems at the Department of Electrical and Computer Engineering, Kazerun branch, Islamic Azad University, Iran. His current research is focused on the bio-engineering, power-engineering, and modeling and control of Robotic systems.

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Mehdi Taghizadeh was born in Kazerun, Iran in 1979. He received his BSc degree in Electrical Engineering from Shiraz University, Shiraz (2003), his MSc degree in Electrical Engineering from Tarbiat Modares University, Tehran, Iran (2008), and his PhD in Electrical Engineering from the Science and Research Branch, Islamic Azad University, Tehran, Iran (2015). Since 2008, Dr. Taghizadeh has been working at Islamic Azad University, Kazerun Branch, Iran, where he is currently the head of postgraduate studies. His research work is focused on A/D convertors, i.e., sigma-delta convertors. His research interests include low-voltage low-power analog and mixed-mode integrated circuits, RF communication circuits, and biosignal Processing. He has published over 35 papers in different journals and conferences so far.