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Sleep staging with deep structured neural net using Gabor layer and data augmentation

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Abstract: Slow wave sleep (SWS) and rapid eye movement (REM) are two of the most important sleep stages that are considered in many studies. Detection of these two sleep stages will help researchers in many applications to detect sleep-related diseases and disorders and also in many fields of neuroscience studies such as cognitive impairment and memory consolidation. Since manual sleep staging is time-consuming, subjective, and expensive; designing an efficient automatic sleep scoring system will overcome some of these difficulties. Many studies have proposed automatic sleep staging systems with different methods. In recent years, deep learning methods show their potential in different applications. In this study, we propose SWS and REM detection system by using a deep neural network. In the proposed system we use a kernel-based layer to get the system closer to the manual scoring approach. Also, we use a new method for augmenting EEG signals to prevent overfitting the network. The results show the efficiency of the designed system in SWS and REM detection.

Key words: Sleep staging, deep learning, data augmentation, rapid eye movement, slow wave sleep

1. Introduction

Sleep plays an important role in the health and functionality of the brain [1, 2]. Lack of enough sleep and any disorder of sleep may cause problems in lifestyle behavior or physical illness [3]. Sleep staging is an essential technique for evaluating sleep and its disorders [4]. There are two main standards for sleep staging as American Academy of Sleep Medicine (AASM) and sleep staging Rechtschaffen and Kales (R&K) in which state sleep as four and five stages [5, 6]. AASM, the most recent standard, divides sleep into wake (W), rapid eye movement (REM), and non-REM (NREM), which is divided into N1, N2, and slow wave sleep (SWS). Insomnia, snoring, and obstructive sleep apnea (OSA) [7] are the most common among sleep disorders. OSA involves complete or partial breathing cessation during sleep which is estimated that 10%–36% of OSA patients suffer from REM-related OSA, a condition that increases the number of apnea events during the REM sleep stage [8]. Identification of the REM sleep stage may also help the prediction of other sleep disorders and even mental illnesses. It has been shown that the presence of REM behavior disorder could predict cognitive impairment in Parkinson disease, depression, schizophrenia, mental retardation, and dementia [9–11]. SWS has been considered to be the most restorative sleep stage in some researches [12]. It has been shown that the total amount of SWS decreases drastically as sleep quality declines with aging [13]. In addition, abnormal SWS has also been

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found to be correlated with a variety of clinical problems including acute-phase immune system response [14], memory consolidation [16], psychiatric disorders [17], diabetes risk [15], and hypertension [18]. Many researchers believe that learning can improve some functions of sleep such as long-term memory consolidation [27], synaptic potentials triggered by learning [29], and homeostatic regulation of synaptic connectivity [28]. Recent studies try to improve these functionalities by stimulating the brain including sleep slow waves induction [30–33], sleep spindles enhancement [37, 38] and memory consolidation [34–36]. In many of these studies, it is necessary to detect SWS or REM sleep stage which is the basis of the presented study. Usually and as a reference, sleep experts try to score polysomnography (PSG) signal segments as sleep stages. Visual scoring PSG signals would naturally require an intensive amount of work and is time and cost consuming. Therefore, in response to these challenges, many automatic sleep staging techniques using different techniques have been developed.

There are many studies that try to introduce an automatic sleep staging system by using machine learning approach [19–26]. In the classic approach, an automatic brain state classifier contains some steps including preprocessing, feature extraction, feature selection, and classification, respectively. Usually, the preprocessing step includes preparing data and filtering to reduce the effects of noise and artifacts. In the feature extraction step some features are extracted from EEG, EOG and other existence signals such as time-domain features [39–42], frequency-domain features [43, 44] and nonlinear features[45–49]. The next step tries to select the best feature set that makes a better distinction between classes such as search methods [50], Relief-based algorithms [51] and least absolute shrinkage and selection operator (LASSO) method [52]. Finally, a classifier tries to classify features into correct classes such as SVM, LDA, and so on. The classic approach of machine learning is fast in training but the evaluation is much slower than new modern approaches such as deep neural network (DNN). DNN is much slower in training than the classic approach but it is much faster in evaluation. Usually, DNN is used as an end-to-end system that merges all steps of the classic approach into one structure. Also, practically it is shown that DNN can achieve better performance in real-world applications such as convolutional neural networks (CNNs) in image processing [53].

Based on the success of DNN techniques in different applications, they are used widely for biosignal and bioimage processing in recent years. Also, DNNs are used widely for EEG signal processing in different applications with different approaches such as feature extraction and classification [54–58]. DNNs are highly complex models with a huge number of parameters and they are trained based on extracting knowledge from the observed samples. Therefore, in most cases, it is very hard to represent the learned knowledge from the trained DNN. There are some methods to visualize and interpret the learned knowledge from the trained DNN such as highlighting the portions of a particular image that are responsible for the firing of each neural unit [59], investigating a network directly without any data from a dataset [60] and some others [61–63]. This study used Gabor function as a kernel in the first layer of the DNN to improve the ability to visualize the learned knowledge of the network after training. Gabor is a flexible function with four parameters. It is shown that Gabor function is an efficient basis for modeling EEG patterns and it is used in different EEG-related applications [64–67].

This study tries to design and develop a DNN for SWS and REM detection using a new layer by considering the main EEG patterns. Also, a new data augmentation method is employed based on nonlinear characteristics of the EEG signals to improve the training process and prevent overfitting. The remainder of this paper is organized as follows: Section 2 introduces the proposed method and database which is used. Section 3 provides the results of the evaluation and discussion. Finally, Section 4 concludes the paper.

2. Materials and method

In the real world, an expert tries to score sleep signals by considering some typical characteristics of signals as follows:

a) Some specific microstructure patterns in EEG such as spindles, K-complex, and cyclic alternating pattern (CAP).
b) Some specific waves in EEG such as slow wave activity (SWA), delta waves, and alpha waves.
c) Time ratio of EEG frequency subbands.
d) Other signals activities such as electrooculography (EOG) and electromyography (EMG).

So, based on the mentioned factors this study tries to introduce a deep CNN network for detecting SWS and REM sleep stages.

2.1. Database

This study uses Physionet expanded sleep dataset, which is available online. It contains the number of 153 whole-night polysmnographic sleep recordings containing EEG (from Fpz-Cz and Pz-Oz electrode locations), horizontal EOG and submental chin EMG. The EOG and EEG signals were each sampled at 100 Hz. The submental-EMG signal was electronically highpass filtered, rectified and low-pass filtered after which the resulting EMG envelope expressed in µV rms (root-mean-square) was sampled at 1 Hz. The signals are scored by experts according to R&K but in this study, we consider stages 3 and 4 as SWS stage. The whole dataset contains 285536 segments of the length of 30 s after removing movement and wake, the details of stages are presented in Table 1.

Table 1. The number of samples in each class.

	Wake	NREM		REM
		non-SWS	SWS	
Number of segments	156676	90102	12991	25767
Total	285536			

2.2. The method

Based on the mentioned items in Section 2 this study tries to employ a CNN which includes a new kernel based convolutional layer. The new layer can use some filters to detect sleep microstructure patterns. The Gabor function (Eq.1) is used as the kernel of this layer.

$$g(t) = e^{-\pi(\frac{t-u}{s})^2} cos(\omega(t-u)+\varphi), \tag{1}$$

where u, s, ω and φ are parameters of the function which can be tuned during the training process. In this study we consider t as 1 s with 100 samples. The Gabor function has the ability to produce waveforms likes sleep microstructures and alpha and delta waves. Figure 1 presents samples of Gabor function waveforms in the five different parameter sets.

By using Gabor function as the kernel of a layer, after proper training the network can detect these microstructures and basic waves in that layer. Two approaches are considered to score sleep stages as non-REM vs. REM and non-SWS vs. SWS. As Table 1 shows there are huge differences in the number of samples between

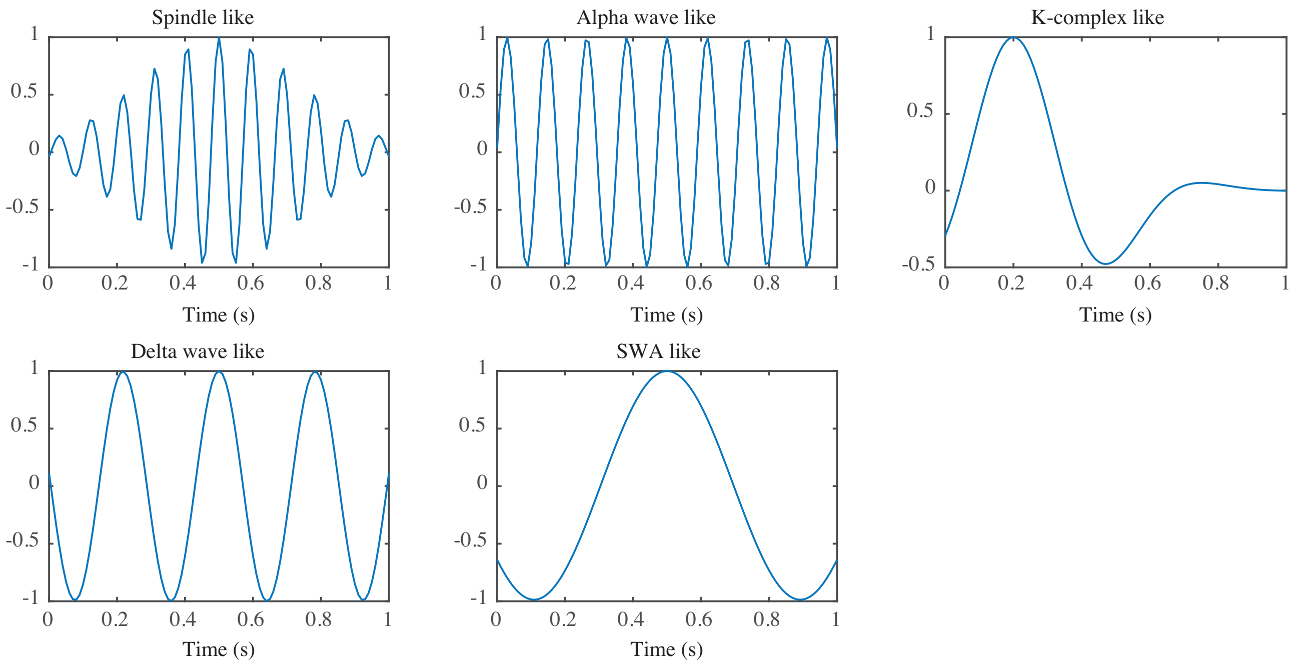

Figure 1. Some waveforms of Gabor function in the different parameter sets.

classes and it is necessary to balance the number of samples in each class to prevent biasing to one of the classes during the training phase. For balancing the number of samples, we use a new data augmentation to increase samples as it is described in subsection 2.2.1.

The structure of the used CNN to detect SWS and REM is illustrated in Figure 2.

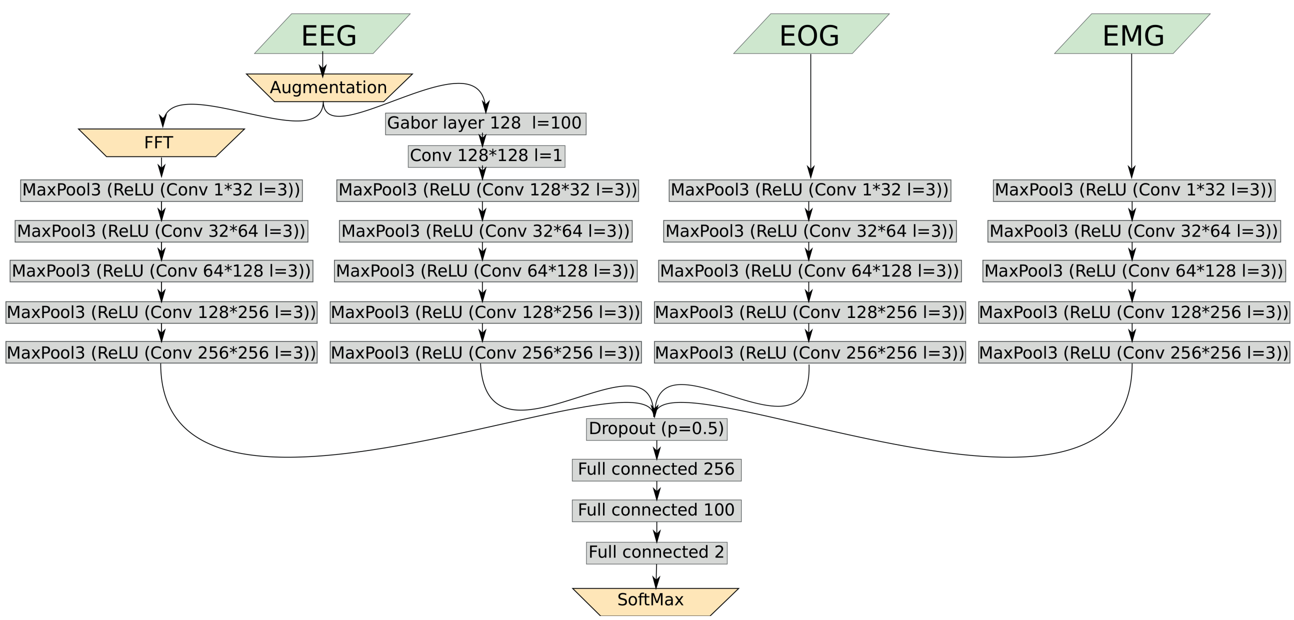

Figure 2. Architecture of the designed network.

In this structure EEG, EOG, and EMG signals are fed into the network. The EOG and EMG signals are fed into sequential convolutional layers and EEG signal is fed into two sequential layers path after the augmentation. In the first path, the magnitude of the Fourier transform of EEG signal enters into convolutional layers. As it is described, frequency domain characteristic of EEG signal plays an important role in sleep scoring by experts. Therefore, this layer provides frequency domain information of EEG signal for classification. The second path, by using Gabor function, provides microstructure patterns of sleep information for classification. In this path the first layer contains 128 instances of Gabor function with length of 100 in which EEG signal is convolved with each instance as Eq. 2.

$$out[i]_j^{gabor} = \sum_{n=0}^{l} EEG[n]g[n-i]_j, \tag{2}$$

where l is the size of filter, and in this case, the number of Gabor function samples $l = 100$ and j is index of Gabor instance.

After the first layer (Gabor layer) 128 signals are obtained, The second layer mixes these signals and produces 128 new signals which feed next convolutional layers. Next layers are similar to other paths and are conventional sequence of convolutional layers whereby each layer contains some filters (32, 64, 128, 256 and 256 filters, respectively) with length of l and nonlinear ReLU function and a MaxPool function (Eq. 3).

$$output[i]_p = max_{n=0,\ldots,l-1}\{ReLU(b_p + \sum_{k=0}^{m} filter_{(p,k)} \star input[i+n]_k)\}, \tag{3}$$

where $output_p$ is p-th output signal of layer, b_p is bias value of p-th channel of layer and $\star$ is cross-correlation function.

After the sequential layers paths, outputs are considered as features for classification. The Dropout [68] method is considered as a regularization technique. During training, Dropout method randomly zeroes some elements of the input features with probability of p using samples from a Bernoulli distribution and in evaluation all features are multiplied by p. Next layers are fully connected layers and the Softmax function is used to produce the output of the net. For training, the output of the network must be optimized by calculating the loss function (cross entropy) and the gradient of the loss backpropagated to update the weights and parameters using Adam optimizer [69].

So, by feeding the network with EMG, EOG and augmented EEG and its Fourier transform and calculating the gradient of loss parameters of Gabor function, the filters of convolutional layers and the weight of fully connected layers are updated (and optimized) in each iteration during the training process.

2.2.1. Data augmentation

Because of the unbalanced number of samples in each class, an augmentation method is used to produce new EEG samples. According to some studies of the community of neurophysiology researchers, EEG is a highly nonlinear, multidimensional and chaotic signal when the brain activity is normal [70]. The dynamics of a nonlinear and chaotic system in its phase space play an important role in detecting the state of system. In most cases and real-world applications, the phase space of the system is not accessible directly and one or multiple signals of the system are observable. In this case, there are some methods to estimate the phase space by having an observed signal of the system. Takens' method [71] is frequently used for reconstructing phase space from signal x(t) using two parameters embedding dimension D and delay τ (Eq. 4).

$$\mathbf{x}_i^{Embedded} = [x_i, x_{i+\tau}, ..., x_{i+(D-1)\tau}], \tag{4}$$

where D and τ are the embedding parameters, dimension and delay, that can be inferred from the box counting method [72] and minimizing average mutual information method [73]. The embedded phase space represents dynamics of the origin system independent of axes.

In the employed augmentation method, signals follow the state and dynamics of original signal. First, the original signal is embedded into phase space using Takens' theorem by using Eq. 4. The reconstructed phase space has dynamic properties of the main system which produced the first signal and the first signal is a projection of the main phase space of the system. Therefore, to reconstruct a signal which follows the main dynamics of the system, embedded trajectory in phase space can be reprojected into an another direction $\vec{p}$. So, the embedded signal can be obtained using Eq. 5.

$$x_i^{Augmented} = \|\mathbf{x}_i^{Embedded}\|.cos(\angle(\mathbf{x}_i^{Embedded}, \vec{p})), \tag{5}$$

where $\vec{p}$ can be considered a random D-dimensional vector to have access to an infinite number of possibilities for generating new signals based on the main signal. Figure 3 shows an example of the used signal augmentation method and how a signal is transferred to the phase space and came back to the one-dimensional signal by projecting to a direction (the red vector).

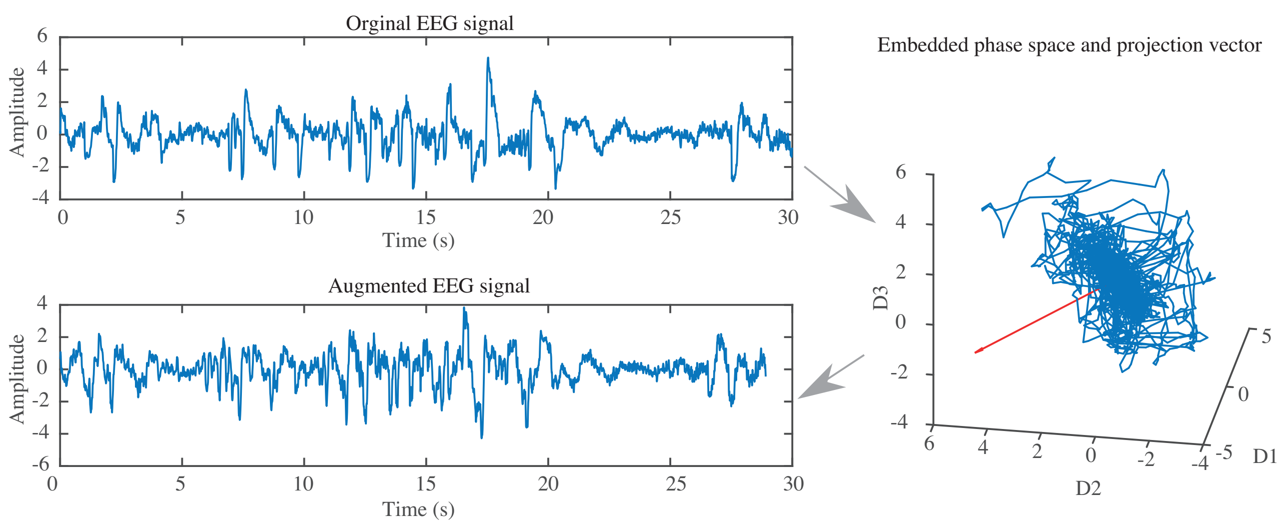

Figure 3. An example of using the data augmentation method on EEG signal.

2.2.2. Evaluation measures

Three measures are used to evaluate the performance of the presented deep network for sleep staging including the sensitivity measure that is the rate of true prediction (TP) against population of the class (P) for each class as Eq. 6.

$$Sensitivity = \frac{TP}{P} \tag{6}$$

Sensitivity can show efficiency of the classifier for each class. The second measure is accuracy that quantifies the rate of true prediction for all classes (T) against the population of all classes (N) as Eq. 7.

$$Accuracy = \frac{T}{N} \tag{7}$$

The accuracy measure suffers from the unbalanced classes problem. So, the accuracy is not a comprehensive measure for presenting the efficiency of a classifier for sleep staging. There are some other measures that try to introduce a comprehensive quantifier of efficiency of a classifier without suffering the unbalancing problem such as Cohen's kappa (k) which is one of the most used measures in sleep staging (Eq. 8).

$$k = \frac{Acc - p_e}{1 - p_e} \quad , \quad p_e = \frac{1}{N^2}\sum_i n_{i,1}n_{i,2} \tag{8}$$

where p_e is the hypothetical probability of chance agreement.

3. Results and discussion

The presented deep structured CNN is trained for two cases of classification by 60% of all 30 s relevant segments, 10% and 30% for validation and test respectively which are selected randomly in each of the cases. In training, the learning rate is initialed as 0.00006 and is reduced after each epoch by multiplying by 0.9. The size of minibatch is considered as 16 and total size of epochs is 100.

It is expected that some Gabor functions are tuned to microstructures of sleep EEG after the training procedure. Figure 4 shows the Gabor functions of the trained network in the case of REM vs. non-REM classification.

In Figure 4 some Gabor waves that are similar to some microstructures of sleep EEG are highlighted and it is evident that the CNN has learned to be sensitive to these microstructures. So, by using the Gabor function with length of 100 samples (1 s) and using just four parameters the network can detect microstructures of sleep EEG in the first layer.

The results of testing the trained network for signal classification are presented in Table 2 and 3 as confusion matrices. Table 2 presents the result of classifying segments into REM and non-REM classes. For training and testing the REM classifier only sleep EEG segments are used. As mentioned, sensitivity and accuracy are not proper measures for evaluation when the samples of the classes are not balanced. But, for increasing the comparability of the results to other studies the sensitivity and accuracy are presented.

Table 2. Confusion matrix and result of classifying segments into non-REM and REM stages.

		Expert	
		non-REM	REM
Classifier	non-REM	30186	924
	REM	1224	6322
Sensitivity		96.10%	87.24%
Accuracy		94.44%	
Kappa		0.8204	

Also, the presented deep structured network is trained by 60% of non-REM EEG segments that selected randomly to classify segments into SWS and non-SWS stages. The trained network is tested by the remained

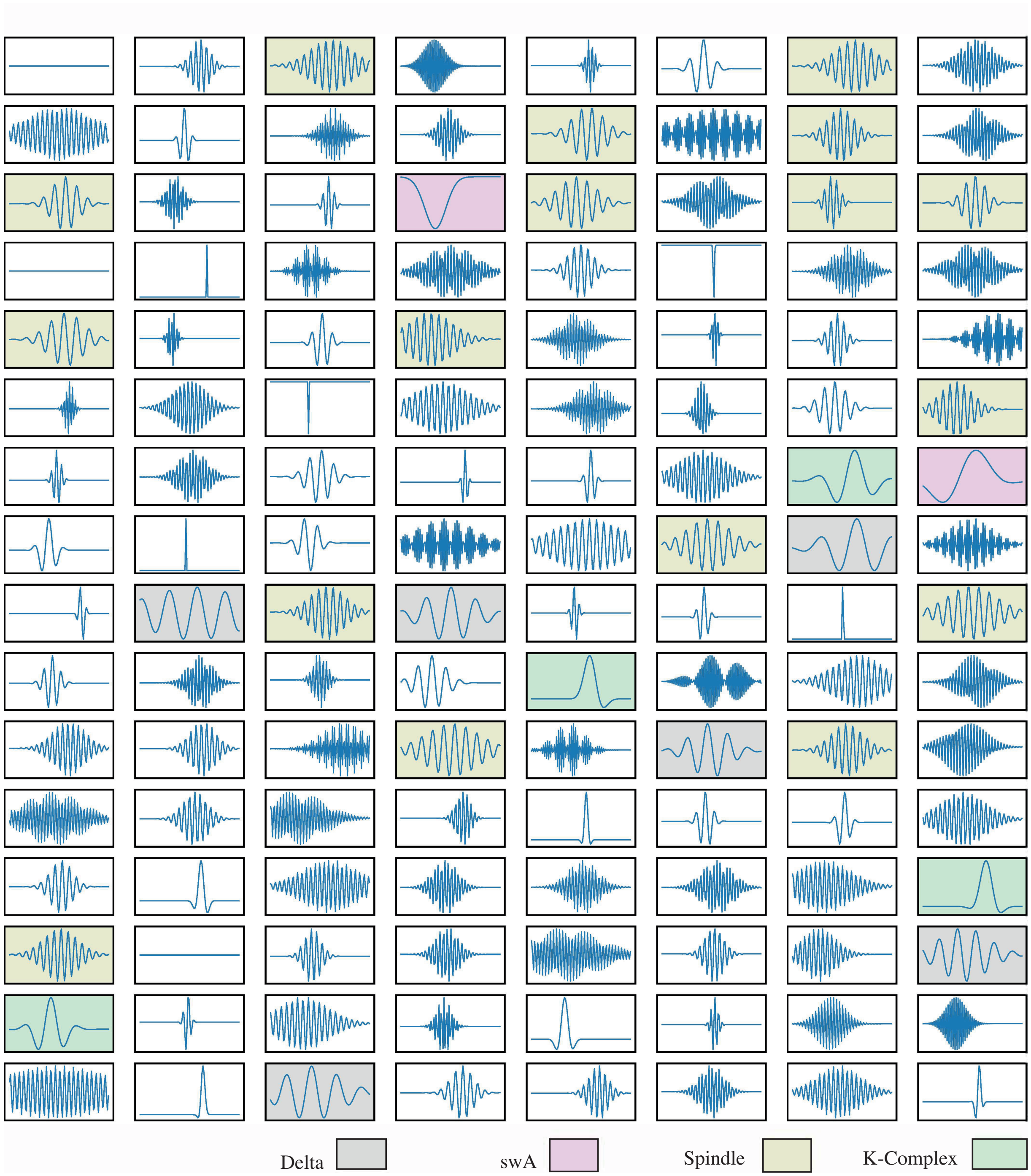

Figure 4. Waveform of the trained Gabor functions.

30% of non-REM EEG segments and the results are presented in Table 3.

To show the efficiency of the proposed method, the result must be compared with other studies. There are many studies that tried to score sleep stages using single-channel EEG signals and for a fair comparison, we also used the proposed approach for sleep scoring without using EOG and EMG signals (Figure 5). Table 4

Table 3. Confusion matrix and result of classifying segments into non-SWS and SWS stages.

		Expert	
		non-SWS	SWS
Classifier	non-SWS	22701	352
	SWS	835	7040
Sensitivity		96.45%	95.23%
Accuracy		96.16%	
Kappa		0.8968	

presents results of some studies that try to score sleep segments to the same classes as this study.

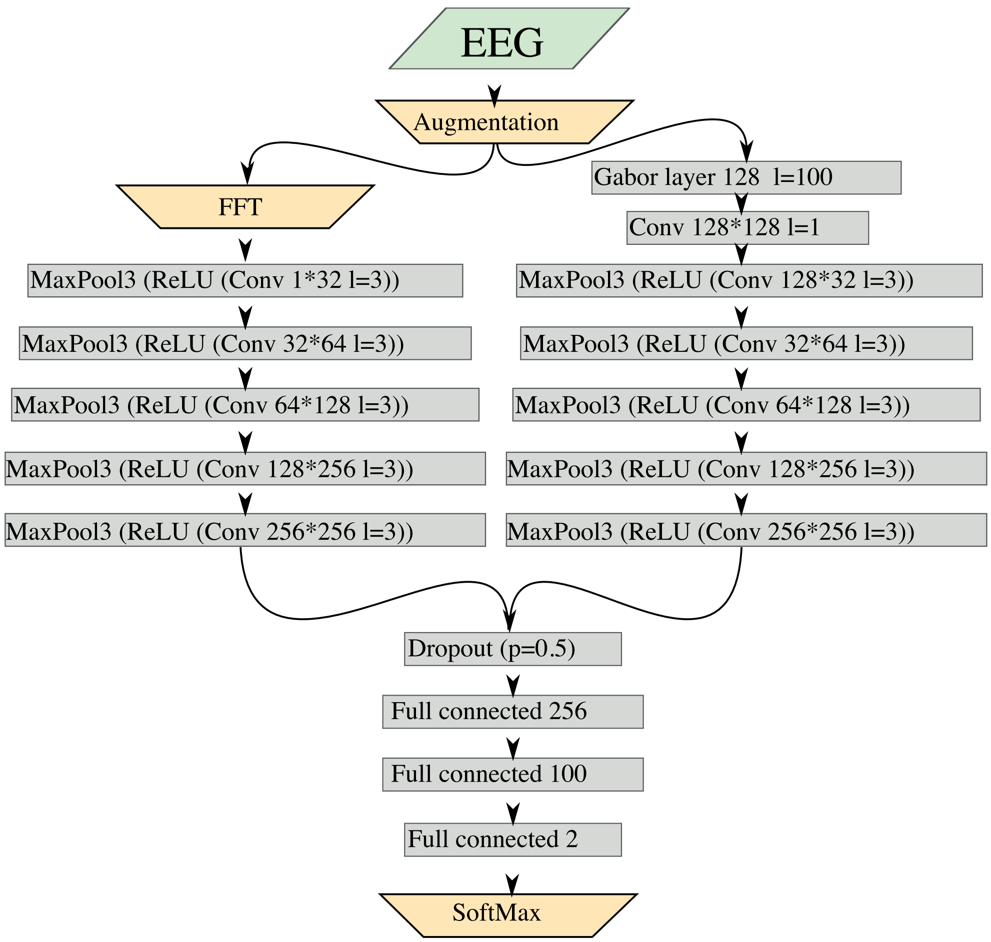

Figure 5. Architecture of the designed network for just EEG signal.

There are some important points in the result comparison of Table 4. There are two important concepts for a system of REM or SWS detection. The first one is sensitivity of the detection. The sensitivity shows the efficiency of the classifier in detecting a specified class (REM or SWS). The result comparison shows that the proposed method is more efficient in REM and SWS detection in comparison to mentioned studies. Although

Table 4. Performance comparison with other studies.

Study		Year	REM sensitivity	REM /non-REM accuracy	REM /non-REM kappa	SWS sensitivity	SWS /non-SWS accuracy	SWS /non-SWS kappa
Durka et al. [74]		2005	_	_	_	81	88	0.72
Virkkala et al. [75]		2007	_	_	_	75	93	0.70
Su et al. [76]		2015	_	_	_	63.6	**97.2**	0.66
Imtiaz et al. [77]		2014	80.6	88.52	0.61	_	_	_
Liang et al. [78]		2012	85.4			_	_	_
Ronzhina et al. [43]		2012	78	90.31		_	_	_
Berthomier et al. [79]		2007	63.0	91.7		_	_	_
Seifpour et al. [80]		2018	_	92.8	0.77	_	94.1	0.83
Golrou et al. [81]		2018	74.21	**94.48**	0.76	87.18	91.96	0.83
This study	EEG		84.6	92.31	0.79	91.14	93.37	0.86
This study	EEG+EOG+EMG		**87.24**	94.44	**0.82**	**95.23**	96.16	**0.90**
This study	EEG without augmentation		80.12	95.31	0.78	86.52	97.13	0.83

the sensitivity is an important measure, it should be used beside a supplemented measure that considers other classes. In Table 4 two efficiency measures are brought as accuracy and Cohen's kappa. The second one is that the accuracy of the proposed method for both cases is higher than most of the other mentioned studies and the Kappas are higher than all of the others. The reason for this disagreement is the unbalanced population of classes. In the case of REM vs. non-REM, the sensitivity of the proposed method is higher than [81] but the accuracy is less, and the Kappa is higher. This is because the number of non-REM segments is greater than the number of REM segments. The classifier of the [81] is more biased to non-REM class in comparison with the proposed study. This also holds for [80] in the case of SWS vs. non-SWS. Also, to investigate the effect of the used data augmentation method, the whole process is repeated excluding the augmentation block and the results are presented in Table 4. As it was expected, lack of balancing between the number of samples in the classes could cause biasing to the class with the greater number of samples (i.e. non-REM and non-SWS). The results showed higher accuracy and lower kappa measure values that represent more biasing than the results with augmented data.

4. Conclusion

This study used a machine learning technique to design a SWS and REM sleep stages detection system. A deep CNN with four types of input was designed and trained to detect SWS and REM stages by using EEG, EMG, and EOG signals as input. To overcome the problem of unbalanced classes and also to make the system sensitive to dynamics of EEG signals, a new data augmentation method considering the nonlinear dynamics property of EEG signal was used. This method produced new samples by transforming signal to the phase space and projecting back to the time domain. Also, we used Gabor kernel at the first layer of the EEG convolutional sequence. Gabor kernel had the ability to create microstructures of sleep EEG. So, after training, it was shown that the network have learned some important patterns of EEG signals that are used in the manual sleep scoring. In this study, different evaluation measures were used to increase comparability of the results. The results showed that in terms of sensitivity and Kappa measures, the proposed system is more efficient than the other studies.

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