Automatic classification of Multi-Sleep Stages Using Two Stage Recurrent Neural Network

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Abstract

AutomaticSleep Stage classification is an vital task for identification of Sleep quality that are prone to Insomnia and Sleep apnea events which further lead to changes in the immune system especially on the various memory and metabolism properties. However, its significant single channel ECG signals is divided into 30 second segments containing complex time characteristicsand frequency characteristics which makes it difficult for manual techniques to discriminate between the different sleep stages patterns. In order to address those challenges, automated sleep stage classification model using deep learning mechanism has to be proposed. In this paper, two stage Recurrent Neural Network has been framed as prediction function to detect and classifies the type of Sleep Patterns with domain knowledge. It is capable for predicting without priori definition of specific signal features or thresholding value. Recurrent neural network that will automatically extract from the Signal information on both Time and Frequency constraints as raw spectra that is optimal for the identification of the different sleep stages on employment of LTSM model. We used approximately 100 patches of signals from different patients extracted from a SC4001E0-PSGdataset and 80% of data has used to train corresponding expert signal characterizations and 20% is used to validate the proposed time and frequency constrained two stages Recurrent Neural Network. The results of K fold cross-validation experiments show that the proposed model achieves correlation of about 0.90 with the estimation of multiple sleep stages asas highly automated model for characterization of sleeppatterns.

Keywords: **Sleep Stage Classification, Recurrent Neural Network, Feature Extraction, Long Term Short Memory,**

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1. Introduction

Automatic Sleep Stage classification has been employed to classify the Sleep Patterns of the patients with sleep disorder difficulties within the specified time period which cause Insomnia and Sleep Apnea to the muscle fromcrucial degrees of contracting of the immune system. Sleep Disorder presents important risk to the affected patient. To determine the risk of the patient, a non invasive scanning technique named Polysomnography (PSG) has been employed to determine the sleep patterns of the patients [1]. However, interpreting PSG examinations for the sleep disorder on basis of various classes is a cumbersome labor-intensive procedure and necessities interpretive expertise[2].

In an intend to automatically extract the Sleep patterns from the PSG signals, numerous existing literature has employed machine learning model using supervised and unsupervised learning. But the task remains challenging due to the small amount of the patterns and the complication of the signal appearance. However Random forest classifier based classification method uses the tissues optical attenuation coefficient to distinguishsleep pattern constituents and to extract the combination of traditional time and frequency-based features of the sleep signal [3][4]. Although Random Forest classifier is capable to obtain the Discriminant characteristics of signals but it fails to measure the intrinsic spectra inmbalance properties of sleep patterns due to the amount of the signal data sets is comparatively small, and classifier outcome and generalizability can decline with sample[5].

In this article, a novel deep learning technique for sleep stage classification has been named as Time and frequency constrained Two Stage Recurrent Neural Network. It has been framed as prediction function to detect and classifies the type of Sleep Stage. Recurrent Neural Network automatically characterizes sleep patterns on basis of intrinsic spectra properties of Sleep signals [6][7]. RNN implements AlexNetmodel [8] as a feature generator by eliminating the output layer and fine-tuning each layer by adjusting the learning rate. Further it is capable to segmentingthe signals on basis of 30 seconds segments. It is capable for predicting without priori definition of specific spectrasignals or thresholding value. In this framework, fully automated Recurrent neural network will automatically extract from the sleep signal information on both time and frequency constraints that is optimal for the determination of the varioussleep stages[9].

The remaining section of the article is segmented as follows, section 2 details the review of the literature work followed by section 3 to define the proposed methodology and section 4 discusses the experimental result and at last section 5 concludes the article.

2. Related Works

In this part, numerous existing model applied to sleep stage classification and prediction by utilizing machine learning model has been detailed as follows.

2.1. Random Forest Classifier

Random forest classifier is tree structured classifier capable of extracting and classifying the time- and frequency-based features of the PGS signal dataset. The class information contains sleep type and its characteristics. It is capable of discriminating the signal characteristic of the brainfunctioning of the patient along result of changes in human immune system. In addition, it classifiers the sleep based on the effects of extrinsic forces on abrainwall [10].

3. Proposed Model

In this part, we define a Time and Frequency constrained Two stage Recurrent Neural Network framework on PSG Edf dataset to detect and classify the type of sleep characteristics in detail on terms of sleep patterns volumes and body structures during sleep using various processing steps of the dataset.

3.1. Extracting the Region of Interest on Time and Frequency Properties

Initial stage of the framework is to extract the Time and frequency of the spectra of the signal which is termed as sleep volume and their branches within the PSG Edf datasets using region growing algorithm. Extracted sleep features branches are constitute by Sleep volumes, which are adjusted using centerline based approaches along the centerline of the pattern [11]. The extracted features are processed using the local isotropic feature extraction model to determine the spatial characteristics of the target sleep signal. Robust intensity maxima function on spatial feature to select the appropriate points of the vessel.

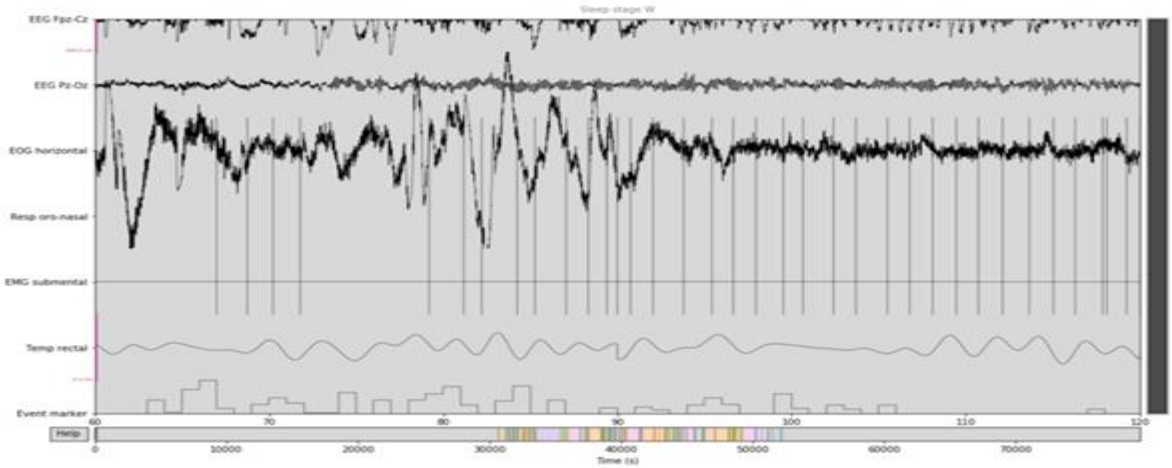

Figure 1: Sleep Volume Extracted using Region Growing Algorithm

Second order derivatives have been used to detect and characterize the sleep patterns on the temporal properties of the features of Sleep cycle which is represented in the figure 1. Further hessian matrix can be employed to distinguish the sleep features. The extracted sleep features have differentlengths of the sleep volumes. It is needed to be reshaped for sequential processing in LTSM modelthrough RNN. Resizing of the sleep volume in LTSM is carried out by inducing the empty frames to the end of the each stage of the sleep cycle areone of the significant signal clues for stage of the sleep.

3.2. RNN Architecture

The network architecture consists of RNN with various deep layers to form the connection between the sleep feature is represented in form of undirected graph with kernels composed of 3 × 3 × 3 elements to process the variable length sequence of input. The number of Hidden layers is determinedon basis of the impulse response which finally dependson the performance of the proposed model on the validation set. The number of training iteration is identified automatically elicited from the model performance on the validation andtraining set. The figure 2 represents the proposed framework of the work

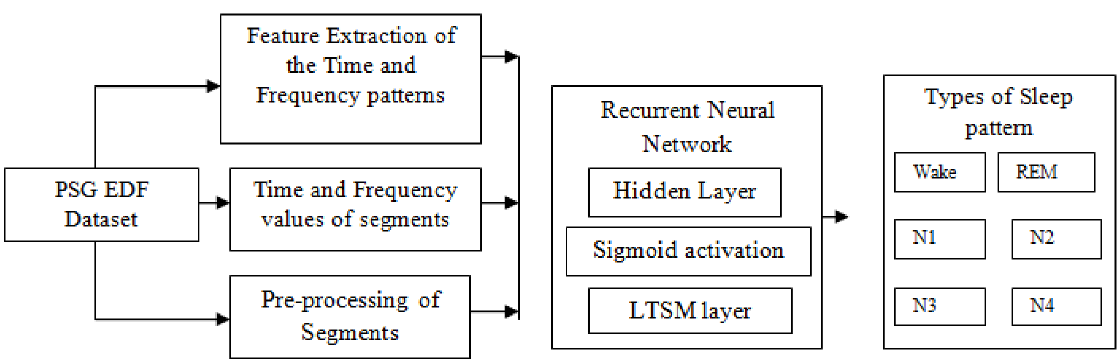

Figure 2: Architecture of proposed framework

- **LTSM Layer**

LTSM layer is employed to process the data sequence consist of feature set as storage model to regulate the flow of information in RNN. The LTSM process the feature through Input gate, eliminate the unwanted features in the forget and output the parameter reduction form of the data in the output gate. It further increases the model generalization capacity [13].

- **Activation Function**

The architectureuses the sigmoid activation function, whichestablishes a non-linearity to the model to acquire the impulse response. Eachactivation function is preceded by normalization to eliminate the overfitting issue and error in the network. It improves the generalizationof the classifier by normalizing the activation function output.

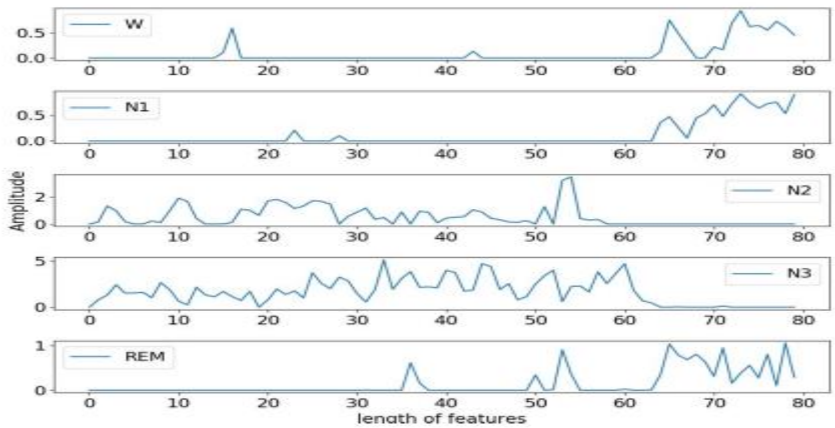

Figure 3: Stage Classification on Sleep volume of PGS Edf dataset

- **Output Layer**

The deepest layer output isflattened and passed to the fully connected layer, which acts as a classifier in the proposed architecture and processes extracted features on the parts ofconvolutional layers. The model learns the large discriminative features among various sleep stages during the training and validation of the system.

Algorithm 1: Sleep Stage classification

Input : Sleep Signal feature set F={S1,x2,…SN**}**

Output: Sleep Stage LabelL={w, Rem, N1,N2, N3,N4}

Process

Generate Segments of the Signal N

Define M(p) Model Parameter

While LTSM: Input gate(N) → output N(f) do

Compute Epoch E_p

Compute the activation function using Sigmoid on N(f)

Compute Loss L

Hd= Hidden(N(f))

Calculate class C = {V1, V2, V3...}

Where v1, v2 are input vectors

Class label c = Stages of N(f)

Finalize the class formation

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3.3. Sleep Stage Classification

Sleep Stage is determined using sigmoid activation functions and model parameter map with segments. The spectra of frequency represent the most discriminative signal type for the input data to indicate sleep stage [15]. Signal spectra showimpartially discreteimportant abnormal regions (e.g., abnormal sleep patterns of the patient).The model predicts the sleep disorder and apnea asdiseased, which is tomention (localize) the immunity changes (abnormalities, such as brain function disorder). Thementioned clues to the existence of an abnormality concludes thatthe model is capable of finalizing its decision elicited on the discriminative features (sleep abnormalities), not by outside arbitrary parameter.

4. Simulation Results

Results of the proposed framework are analyzed using PSG Edf dataset which is collected from physionet.org. The dataset contain 100 patches of signals in the edf format. The approach is simulated in python. In that processing of the inputsignalto train and validate the modelis highly demanding. In this 80% of data has employed to train particular expert sleep characterizations and 20% is used to validate the proposed time and frequency constrained Recurrent Neural Network. On 80% training data, it has been categorized as 60% to train the model and 20% to validate the trained model. Validation is performed in 5 fold cross validation in order to enhance the accuracy of the training model. The training parameter of the two stages RNN has been mentioned in the table 1

Table 1: Two stage RNN training parameters

RNN Parameter	Value
Signal	Edf
Positive Learning rate of the RNN	0.7
Loss Function	Mean Square Error
Batch Segment	30
Max epoch for batch	100

Classification Performance Evaluation

The performance of the RNN-LTSM model is validated at the Sleep Signal at each fold of validation to measure the accuracy. Precision, Recall and F measure is computed to determine the classification performance. Sleep stage for various segments in form events has been computed on various time segment is depicted in the figure 4

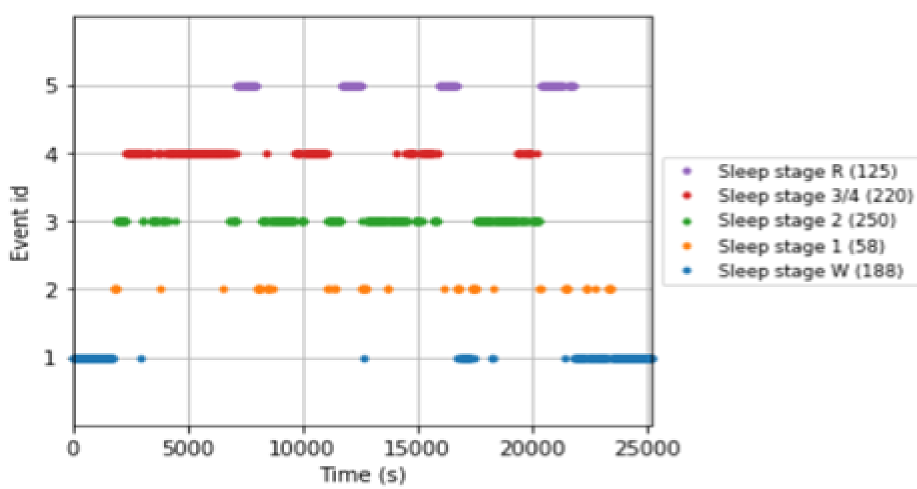

Figure 4: Performance Assessment of Sleep Stages

Precision is determined on basis of the True positive and true negative of the computation of sleep stages. True positive is a measure of similar signal frequencies in the sleeppattern generated and false negative is measure of real dissimilar sleep frequency in the sleep pattern

$$\text{Precision} = \frac{\text{True positive}}{Truepositive+FalsePositive}$$

- **Recall**

Recallis the measure of homogenouspattern of the sleep patternwhich have been extracted over the total number of relevant time frequency signals of the entire dataset obtained.

$$\text{Recall} = \frac{\text{True positive}}{Truepositive+Falsenegative}$$

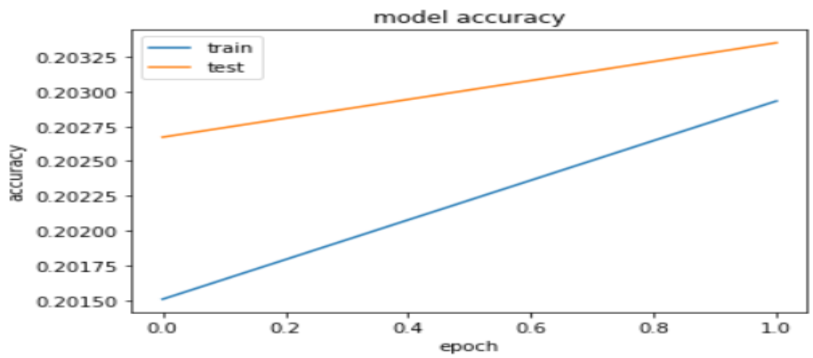

Figure 5: Model Accuracy of the proposed model in sleep stage classification on varying epoch

- **F measure**

It is the measure of exact class predictions to the specified Sleep signal among total number of predictions to entiretype of sleep signal.

Accuracy is given by

$$\frac{\text{True positive} + \text{True Negative}}{Truepositive + TrueNegative + falsepositive + Falsenegative}$$

Table 2: Performance Analysis of Proposed architecture

Technique	**Precision**	**Recall**	**F measure**
LTSM-RNNLearning- Proposed	0.89	0.65	0.75
CNN Learning –Existing	0.58	0.54	0.55

The prediction of the class obtained on the various sleep stage is considered effective on employing LTSM RNN model.

Conclusion

In this research, a novel framework named as Two stage Recurrent Neural Network towards Sleep stage classification has been designed and simulated on 5 fold cross validation. The tine and frequency properties of sleep patterns have been extracted as prominent features using raw spectra of the PSG Edf signal. The Spectra is further reconstructed using hessian matrix and region growing algorithm.. The feature has been processed further using Hidden layer of RNN and LTSM model for normalization of the pattern. Sigmoid based activation function is applied to normalized features to yield better classification results. Output layer provides the classes of the sleep stages of the signal with complex characteristics with increased accurately. The experiments show that the proposed approach achieves high accuracy of about 0.90 with the estimation of sleep classes.

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