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Recurrent Neural Network Based classification of ECG signal Features for Obstruction of Sleep Apnea Detection

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***Abstract*—This paper introduces an OSA detection method based on Recurrent Neural network. At the first step, RR interval (time interval from one R wave to the next R wave) is employed to extract the signals from Apnea- Electrocardiogram (ECG) where all extracted features are then used as an input for the designed deep model. Then an architecture having four recurrent layers and batch normalization layers are designed and trained with the extracted features for OSA detection. Apnea-ECG datasets from physionet.org are used for training and testing our model. Experimental results reveal that our automatic OSA detection model provides better classification accuracy.**

***Index Terms*—Feature extraction; Sleep Apnea; ECG; Apnea Detection; RNN;**

I. Introduction

Obstructive sleep apnea (OSA) is a prolonged respiratory ailment that happens in 10% of population [1]. The reason of OSA is the repetitive collapse of the upper airway at the time of sleeping. Also, former studies have shown that OSA is linked with the higher risk of stroke, heart failure [2] and vehicle accident [3]. OSA can be treated by undertaking a full night polysomnography (PSG) at a laboratory of sleep. It records the breath air flow, movement of respiratory, oxygen saturation, position of the body, electromyography (EMG), electroencephalography (EEG) and electrocardiogram (ECG) [4] where the recorded signals are used for multipurpose such as OSA detection [5]. However, as a result of high cost of in-lab sleep investigation and the time it cost to study, more than 90% of patients at risk of obstructive sleep apneas are not treated.

Two common difficulties in a number of the OSA detection studies lie in the high-dimension feature domain and the black box conclusion making process. Nowadays, most of the OSA detection system focus on extracting frequency domain, the time domain, and other nonlinear features from several ECG-based signals and then building classifiers with these features to decide OSA existence.

In the literature, numerous feature selection means, including statistical estimation [6], wrapper approaches [7] and principal component analysis [8] have been exploited to minimize the dimension of the feature space. For the decision making process, [9] proposed a guideline used to extract features and detect OSA by associating the value of extracted features with preset parameters, thus, causing in strong description of the detection outcome. Using Neural networks as classifiers, [10], [11] proposed an OSA detection based on snoring sound directly taken from people. As snoring sound is generated because of narrowing in the upper airway and the resulting vibration of the upper airway tissue, this method employed snoring for OSA detection. After extracting the snoring signal features using RR-interval, they employed the traditional neural network called artificial neural network for classification. [12] proposed Neural network (NN) based features selection and identification of OSA and gains up to 70% classification accuracy. Here the NN used for two purposes; one is to choose the optimal frequency bands that can be used for identification at the time of features extraction and the other is used for detection during the features matching stage. Also, [13], adopted a support vector machine (SVM) for OSA patient classification, and feature extraction using RR intervals and wavelet decomposition. In their work, about 90% of the subjects in the testing set are properly detected

Most of the aforementioned methods used the simple NN to classify OSA and non optimal features extraction methods which lead to poor classification results. In this paper, we propose a recurrent neural networks [14], [15] model that automatically detects an OSA signal from apnea- ECG signals. Our method first extracts features from apnea-ECG recording and then the extracted features are used as an input for the recurrent neural networks (RNN) composed of recurrent layers and batch normalization where Sigmoid function is used as an activation function. The recurrent neural network we consider as our base is the long short term memory as illustrated in figure 2 and discussed in detail in section II. Once the training process is accomplished, this recurrent model can be used for OSA detection. The detail of our model's framework is illustrated in figure 3.

The rest of this paper is organized as follows. Section II provides some highlighted description about RNN as primary concepts. The detail of proposed model is explained in section III. Section IV presents the experimental results. Finally, Section V concludes the paper.

II. Recurrent Neural Network

There are several variations of RNN, such as Long short term memory(LSTM), Gate recurrent unit(GRU) and associative long short term memory(ALSTM). Since we focus on

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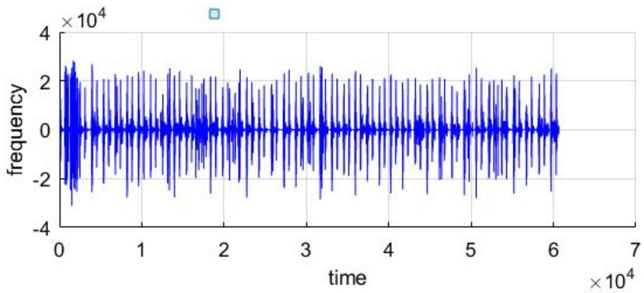

Fig. 1. The Apnea ECG signal.

LSTM to detect OSA, so we give the detail descriptions of LSTM only.

A. *Long Short Term Memory*

Hochreiter and Schmidhuber initially proposed the term Long Short Term Memory (LSTM) unit in 1997. However, currently there are different versions of LST proposed by researchers. We give the detail of LSTM proposed by Zaremba [14], [16]. Assume that y_t, c_t and h_t denote the input, cell and hidden states, respectively, at iteration t. For current input y_t, the previous cell state c_{t-1}, and its corresponding previous hidden state h_{t-1}, the cell state c_t and hidden state y_t are obtained as

$$f, i, o = \sigma((Hy_t + Uh_{t-1}) + b) \tag{1}$$

$$j = tanh((Hy_t + Uh_{t-1}) + b) \tag{2}$$

$$c_t = f * c_{t-1} + i * j \tag{3}$$

$$h_t = o * tanh(c_t) \tag{4}$$

Where * denotes an element wise multiplication, b is a vector of bias, and an activation function σ is a sigmoid function,

$$\sigma(x) = 1/(1 + exp(-x)) \tag{5}$$

H and U are two convolution linear transformation applied to y_t and h_{t-1} respectively and finally, the output of an LSTM layer at iteration t is h_t. Figure 2 represents a graphical illustration of LSTM.

B. *ECG Data's in Sleep Apnea*

Heart rate, and other features of the ECG, vary in characteristic techniques in similar with sleep related breathing ailments [17]. Earlier work made use of cyclical variations of heart rate but did not found effective algorithms to quantify sleep allied breathing disorders based on heart rate only [18]–[20]. It is clear that an estimation of heart rate cannot produce an apnea index or an, hypopnea index. Both values are obtained by the evaluation of airflow, respiratory effort and oxygen saturation. Considering this limitation, it is proved that evaluation of ECG can provide an approximate of disturbed breathing during the night which should correspond to the results obtained by standardized apnea scoring [21]. The ECG of sleep apnea database is collected to detect sleep associated

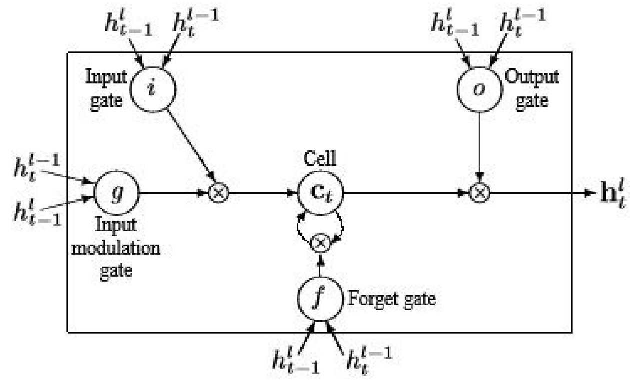

Fig. 2. An illustration of LSTM

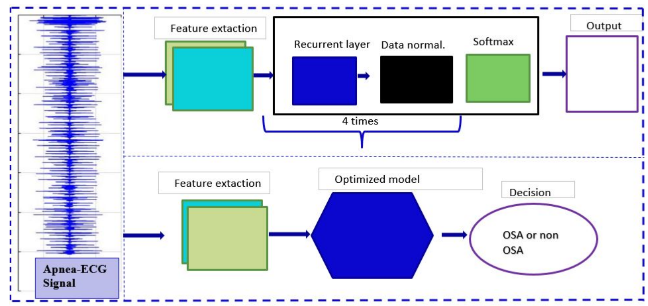

Fig. 3. The over all farme work of our RNN based OSA detection model

breathing disorders based on a single channel ECG recording. According to this database, all polysomnographic recordings were scored by one expert in a diverse way.

III. Proposed model

In this section, we provide the detail description of proposed Obstructive sleep apnea detection model, taking the current success of deep learning as an advantage.

A. *Proposed Architecture*

In various application of pattern recognition and detection tasks, deep learning has been widely used. Based on the size and the structure of an input data, the number of layers and nodes in the network always differs. Our proposed model is based on RNN specifically LSTM proposed by zaremba, which learns a predefined set of input-output example pairs. As demonstrated in figure 3, our end-to-end model has four basic sections; features extraction, recurrent layers, batch normalization and an output layer explained one by one below.

1) Features extraction: It is common to extract a set of features from speech signals where detection is carried out on a set of these features instead of the original signal itself. In our features extraction part, apnea ECG recordings used for training the model passed through feature extraction process using RR intervals. Formally, RR- interval is a time interval between two successive R peaks [17], which can be written in a simple mathematical form as,

$$RR(i) = R(i+1) - R(i), i = 1, 2, , n-1 \quad (6)$$

The extracted feature is then used as an input for the next layer called recurrent layer.

2) Recurrent Layer: This part takes the extracted features as an input and produces a final output used for detection. It has four recurrent layers where the first two sweeps horizontally and vertically and the other two recurrent layers sweeps right and left over all extracted features.

More formally, Let $Y = \{y_{i,j}\}$ be an extracted feature from ECG signal using RR interval where $Y \in R^{w \times h \times c}$ with w, h and c the width, height and feature dimension respectively. Given a patch with size $w_p \times h_p$, we divide Y into a set $I \times J$ patches, $P = \{p_{i,j}\}$ where $I = \frac{w}{w_p}$, $J = \frac{h}{h_p}$ and $p_{i,j} \in R^{w_p \times h_p \times c}$ is the (i,j)th patches of an input features. The first index i represents the horizontal indices and j represents the vertical indices. Primarily, we sweep the features with two RNN where one is in the bottom up and the other is in the reverse direction. Next, we sweep the features with other two RNN where one is in the right direction and the other is in the left direction. For each recurrent layer, the hidden state is updated as,

$$u^F_{i,j} = f_{v\uparrow}(Z^F_{i,j-1}, p_{i,j}) for j = 1, 2, ..., J \quad (7)$$

$$u^R_{i,j} = f_{v\downarrow}(Z^R_{i,j+1}, p_{i,j}) for j = J, ..., 2, 1 \quad (8)$$

These two equations are for the first two RNN, where the second two RNNs also formulated accordingly. After the first two RNN and the second two RNN, we concatenate the intermediate hidden states $u^F_{i,j}$ and $u^R_{i,j}$ of the first two RNN and $h^F_{i,j}$ and $h^R_{i,j}$ of the second two RNN at each location (i,j) to get a composite features map $U, H \in R^{2d}$ respectively. Now each of these vectors represent the feature of the original batch $\{p_{i,j}\}$ in the context of the whole extracted features.

3) Data Normalization: After recurrent layer is followed by sigmoid activation function, each feature map is normalized for better performance. Assume that $x = \{x_1, ..., x_d\}$ is an input to a layer with dimension d. Each dimension of x is normalized by,

$$\hat{x}_k = \frac{(x_k - E(x_k))}{\sqrt{(var[x_k])}} \quad (9)$$

where $E(x_k)$ is an expectation of x_k and $var[x_k]$ is the variance of x_k and they are computed over the training data. This type of normalization speeds up convergence [22] even when the features are not decorrelated. Normalizing each input in the layer may sometimes change what really the layer should represent. To address this problem, the transformation inserted in the network is chosen to be an identity transform. For this matter, a pair of parameters γ_k and β_k for each x_k scales and shifts the normalized value as:

$$y_k = \gamma_k \hat{x}_k + \beta_k \quad (10)$$

γ_k and β_k are learned along with other model parameters. In such manner or formulation, recurrent neural network is benefited from data normalization [19]. Data normalization help the network train faster and provide higher accuracy.

4) Softmax: After recurrent layers are applied to the extracted features, the activation at the end of recurrent layer may be flattened and fed into a classifier. In our experiments we employed numerous fully-connected layers followed by a softmax classifier. The parameters of the model can be approximated by the stochastic gradient descent algorithm with the gradient computed by backpropagation algorithm to maximize the log-likelihood.

5) Output Layer: When an ECG signal is propagated through the output layer, the final outcome is compared with the desired value and an error value using MSE is computed for all output units. These errors are then back propagated to each node of the in-between layers. After every node in the network established an error value that defines its relative involvement to the overall error, parameters are updated. Once the parameters are optimized, our model is ready to solve the detection problems i.e. with optimized parameters, the features of the dataset prepared for testing are used as an input for the trained model and finally our trained model gives a decision.

IV. Experimental results

In this section, we are mentioning the details about the dataset used for training and testing, the discussion of experimental results and the performance results of the model.

A. Training and testing Data

To train and test our model, we used the data from Apnea-ECG database which is freely available at https://physionet.org/physiobank/database/#ecg/ for download. Figure 1 shows one of the apnea ECG recordings, that are visualized by the toolbox provided by https://physionet.org. The database [23] has been developed for the Physio Net/Computers in Cardiology Challenge 2000. It consists of 70 ECG recordings, each normally 8 hours long, where 35 of them are only annotated.

For our model training, we divide the annotated 35 ECG recorded apnea signals into two categories. The first category is training set consisting of 20 ECG apnea recording signals that are normal and non-normal and the second category is the testing ECG apnea signals. Also, the testing set consists 10 ECG apnea signals which are normal and non-normal and both are not part of training set.

After feature extraction is carried out for each dataset as in equation (1), all ECG recordings are adjusted to 240x240 values for training. As deep learning models are benefitted from large training dataset, we perform data augmentation as in [24], [25] which is then an input for the next model layer for the overall training process and optimized by [26]. The batch size is set to 64. We have trained the model for 50 epochs. The learning rate is decayed exponentially from 0.01 to 0.0001 for the 50 epochs.

B. Performance Evaluation

The effectiveness of our model is evaluated on different records of ECG database. As a detection measure of our model, we compute the three commonly known performance measures i.e. sensitivity (se), specificity (sp) and accuracy (ac) [27] , where they have the following definitions.

$$se = \frac{OSA_s}{(OSA)_t} \times 100\% \tag{11}$$

$$sp = \frac{NOR_s}{(NOR)_t} \times 100\% \tag{12}$$

$$ac = \frac{OSA_s + NOR_s}{(OSA)_t + (NOR)_t} \times 100\% \tag{13}$$

Where 'OSA_s' is the number of properly detected OSA signals, 'NOR_s' is the number of properly detected normal (NOR) signals, $(\text{OSA})_t$ is a total OSA signal and $(\text{NOR})_t$ is a total NOR signal tested [28]. Our experimental results show that, the RNN based model detects OSA effectively and provides up to 97.80% accuracy with the 50th training epoch. Our detection accuracy increases as we increase training epochs from 20 to 50 in 10 increments. However, the model is not providing better accuracy values for more than 50 training epochs.

V. Conclusion and Future work

Effective and efficient obstructive sleep apnea detection model is proposed in this paper. The model used the advantage of current success in deep neural networks on image and audio recognition problems. An efficient RNN learning model based architecture having four layers is designed for OSA detection purpose. The ECG dataset is used for training and testing. Experimental results show that the detection of OSA based on recurrent neural network is more appropriate method than the traditional neural network based. Also, the accuracy of the model based on sensitivity and specificity values show the effectiveness of our model.

In future work, we are considering OSA's case and planning to investigate the target problem with convolutional neural network, with accuracy, sensitivity, and specificity in mind.

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