Attention-based LSTM: A Machine Leanring Approach for Automatic Sleep Stages Classification

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***Abstract*—The abstract goes here.**

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I. Introduction

SLEEP st age classification is a very important problem in the field of Medical diagnosis. Classifying sleep stages of patients becomes one of the bases for clinical researches. Due to the pressure of work and burden of life, incidences of sleep disorder increases in morden society. What is more, some serious disturbance or diseases have relation with certain patterns of sleep disorder [1]. Since the detections of sleep quality and sleep cycles are the crucial parts of the diagnosis and treatment, the recording and classification of sleep stages becomes the first and significant step of sleep analysis [2]. Thus, more attention has been paid on the research of sleep quality scoring and sleep stage classficiation.

Traditional methods of sleep stage classification depends on multi-channel biological signals named polysomnography (PSG) [3]. The PSG recording experiments are usually conducted in a hospital or sleep center with signals like electroencephalogram (EEG), electrooculogram (EOG), electrocardiogram (ECG) and electromyogram (EMG). This biological information being recorded simulatenously during a whole night experiment [4].

After the data collection procedures, these recorded data will be split into epochs with 30 seconds. In clinical practice, the classfication for sleep stages mainly depends on manual visual observations on epochs referring to standards and terminologies established by Rechtschaffen and Kales (R&K) sleep scoring manual [5], or the manual of American Academy of Sleep Medicine (AASM) [6]. The sleep stages are classified as: wake, rapid eye movement and non-rapid eye movement (3 stages included).

One of the main challenges of this manual method is that the observation and scoring are onerous and time-consuming due to the need of finding characterisstic waveform like K complex and sleep spindle by staring on the screen. Since the number of doctors with rich experience and their time and energy are limited, it is difficult to cope with the surging number of patients. Worse than the time they cost is the accuracy of manual operation: because of the influence of subjective factors, the accuracy of manual classification performed by experts is often less than 90% [7]. Thus, for an more efficient diagnosis, we need to develop automatic methods for objective and accurate sleep classifications.

To solve this problem, a lot of automatic sleep stage classification algorithms have been investigated and employed in recent years. Most of the proposed scoring models belong to a family of feature selection, with a certain feature set extracted from the PSG data and a general model like Support Vector Machine, Random Forest or Artificial Neural Network. Such a method has been applied by several groups of researchers. The algorithm used in feature extraction can be defined as two categories: the first category contains algorithms rely on hand-crafted features extracted using expert knowledge learned from previous clinical experience [1, 4, 8–10]. Features like Power Spectral Density (PSD), Shannon Entropy, Wavelet Coefficients and the statistical features are frequently used in these models. On the contrary, algorithms in the second category acquire feature representations by feeding the raw signal data into specific neural network such as Deep Belief Network (DBN), convolutional neural network (CNN) and the like [11–13].

The potential issue with this feature selection approach is that the features selected need to compress all the necessary information of the specific bio-information signals into a fixed length of output vector. The compression is difficult to interpret since it is done by the auto-encoder networks. Thus leaving a question of which parts and how much a model can benefit from these selected features.

In this paper, we employed attention mechanism in the long short term memory (LSTM) network to mine deeper relationships between sleep stages and features. Our proposed approach solve both the time-consuming and feature encoding problems. The attention-based LSTM model outperforms the baseline models and achieves the perform of currently state-of-the-arts methods in our own dataset. What is more, it visualizes the connection with attention on each features when scoring the stages of sleep. For the classification of the NREM-1 stage, our proposed method also shows a great performance.

Following is the organization of this paper. We firstly introduce the attention mechanism and the architecture of our model of temporal sleep stage classification. Then, we detail our own dataset and the feature selection for this experiment. Finally, we discuss about the result of the experiment. We furthermore show the performence in different kind of classification tasks in sleep stage scoring to demonstrate the capacity of our network.

II. METHODS

A. Attention Mechanism

Nueral processing mechanisms involving attention have been deeply investigated in Neuroscience and Computational Neuroscience [14, 15].As the mental activity perfromed by human, attention is definded as an ability of focusing on specific subsets of the received information despite of their position. By applying this mechanism, neural network can learn as what human being can do[16, 17].

For time-sequence data, learning a soft alignment between the input and the output improves performance [17]. Attention-based model are mainly consiss of the encoder-decoder sequence with fixed length of inner representation. The encoder is used to represent important features of the input sequence with fixed outputs, and the decoder is built to generate the output according to the results of the encoder. Both of the encoder and the decoder are comprised of one or more RNN layers [3]. An attention layer between the encoder and the decoder helps the system to mining and select profounder relationship between the representation of encoder and the prediction of decoder. By keeping each output of the encoder, training to focus on subsets of them selectively and then re-link them to the output of decoder, the attention layer frees the model from the loss of compressing features into a fixed length vector and the training of the network will concentrate more on the most important parts [17] .

In previously proposed feature-selection-based model, the goal of the sleep stage classifier is to learn and represent the possibility distribution over output prediction y conditioned on the input feature set X, i.e. $P(y|X)$ [3].. By combining with the attention model, the RNN model will be able to learn the distribution of each output y_n in condition with the previous epochs of the sleep stage, i.e. $y_{i<n}$, and the input feature stream, $X = x_1, x_2, X_3, ..., x_m$:

$$P(y|X) = \prod_n P(y_n|X, y_{i<n}) \tag{1}$$

With the attention mechanism, the conditional probability in Eq.(1) can be rewrited as:

$$\begin{aligned} P(y|X) &= \prod_n P(\ y_n|\ \{y_1, ..., y_{n-1}\}, C_n) \\ &= g(y_{n-1}, s_n, C_n), \end{aligned} \tag{2}$$

where g is a nonliear function used to represent the posibility of y_n, and s_n is the hidden state of th multi-layered RNN. The goal of the attention module is then to derive the features of encoder in s_n which need to be attended to for the next output of decoder [3]. The goal of the encoder is to represent the input with each state s_n contains information about the whole input sequence and the previous output of decoder y_{n-1} to produce a fixed-demensional context vector, C_n.

The context vector is an extraction with the most relevant information in the hidden states seqeuence and the previous output which are used to generate the next output label. It can be calculated as an weighted sum:

$$\begin{aligned} C_i &= f(y_{i-1}, s_i) \\ &= \sum_j \alpha_{ij} s_j \\ &= \sum_j e(y_{i-1}, s_j) s_j \end{aligned} , \tag{3}$$

where the weight coefficient e is a non-linear function with respect to the previous output y_{i-1} and the hidden states s_j [17]. It can be seen as an alignment model which scores the relationship between the j_{th} input and the i_{th} output.

Though this mechanism increase the computing burden, the model can be more purposeful and perform better. Furthermore, the attention layer can tell us what the network actually focus on and to what extent it concentrate on specific input-output pairs.

B. Attention-based LSTM Architecture

As Fig. 1 shows, to implement the attention model, we parameterize it as a simple concatenation layer of perceptron to combine the information from hidden state s and the source-side cortex vector C to generate a hidden state as follows [18]:

$$\tilde{h}_n = tanh(\mathbf{W}_c C_n, \mathbf{W}_s s_n), \tag{4}$$

and then feed the output vector $\tilde{h}$ into an single softmax layer. The output of this layer is the weighted sum of the information contained in part of the hidden state stream that the model focus on. The output z represents the relevance for each variable encoded by a layer of Bi-RNN in each time step according to the context C.

Then z is fed through the decoder consist by single layer of LSTM and a multi-layer dense connected perceptron as shown in Fig. 2. The key equation of the proposed network are described below:

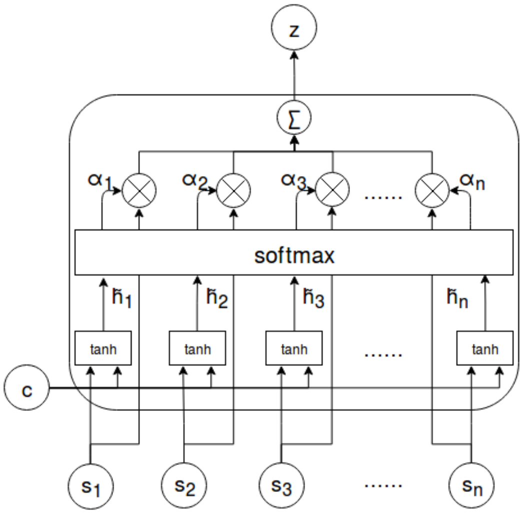
$$\begin{aligned} s_t &= f_{Bi-LSTM}(X_{input})) \\ z_t &= f_{Attention}(Sum(\alpha \cdot S_i)) \\ &= f_{Attention}(Sum(softmax(C, s), s)) \\ h_t &= f_{LSTM}(z_t, C_t, y_{i<t}) \\ O &= y_t = softmax(h_t) \end{aligned}$$

The bias terms are omitted for notational simplicity. The 's' is a sequence of vector with the length as the input X. 'f' denotes some non-linear functions learned by the network, Sum denotes the accumulation, and 'O' denotes the final output of the whole network. Note that for attention mechanism, each time span should have different importance, thus, the proposed non-linear function $f_{Attention}$ is not a static function but should be updated in each time step instead.

III. EXPERIMENT

A. Material

In this investigation, we introduced a dataset contains PSGs of overnight record with 512 Hz of sampling rate recorded from 28 Asian female and male adults. According to recently



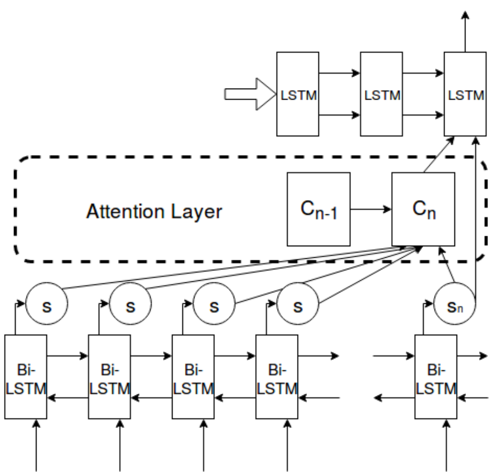


Fig. 1. (Upper) The **attention layer architecture** employed in the network. At each time step n, this layer computes the attentional hidden state on each previous state and then produces and screened weighted summery of the relevance for each input state according to the context vector

Fig. 2. (Lower) The **whole Attention-based network** propsoed in this paper.

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TABLE I
SLEEP STAGES AFTER REMOVING NOISY EPOCHS (NUMBER OF EPOCHS AND RATIO[%]

	W	N1	N2	N3	R	Total
Number	5833	4248	8611	3538	3206	25436
Ratio(%)	22.9	16.7	33.9	13.9	12.6	

proposed research [13], there is a trade-off for classification performance among the number of channels, the number of records and spatial extension. The PSG data we investigated includes 6 EEGs, 2 EOG, 4 EMGs 1 ECG and the snore signal. The labels were tagged by several experienced experts according to the AASM guidebook with 5 labels, Wake (W), NREM-1 (N1), NREM-2 (N2), NREM-3 (N3) and REM (R). We firstly separated the records into 30-second long epochs combined with label, excluded the epochs labeled by ”?” and then concatenated them into two type of set: one was mixed with respect to epochs, the other was mixed with respect to subjects. Thus we have two kind of dataset, one has 25436 epochs as example shown in Table I; the other has 28 examples with 900 to 1000 epochs. Details about the dataset is attached on the appendix. In this paper, we test The model was tained to minimize the categorical crossentropy with a balanced loss function in order to obtain a relatively impartiality model prediction for all of the sleep stage. What is more, for the purpose of enchancing the discrimination of the normaly under-represented stage, like N1, we increased its weight in the loss function. To test our model, we trained the model with 5-fold cross-validation (CV) with the two datasets respectively for its abilities of learning representations for each sleep stage and the generalization among different people. The model was implemented in *Keras* with a *Tensorflow* backend. As an extension, we also evaluate the classifier's performance with multiple values of class, i.e. $C = 2\ to\ 6$, as our model on both of these two dataset and it all achieve performs of the state-of-the-art methods.

B. Preprocessing

In preprocessing procedure, we filter the EEG signals into five frequency band, alpha, delta, theta, beta and gamma according to previous studies and the AASM manual [4, 6, 8]. Then the signals are combined together again to produce a new single signal with the shape of $(-1, 512 \times 30)$. The '-1' denotes the number of the epochs in each sample.

C. Feature extraction

In this experiment, we trained our models on the features extracted from original PSG data records: time domain and frequency domain features through previous proposed methods [4, 8, 9].

Specifically, we firstly caculated the power spectral density as the energy of the 5 frequency band for each channel: delta (δ, 1 - 4 Hz), theta (θ, 4 - 8 Hz), alpha (α, 8 - 14 Hz), beta (β 14 - 31 Hz), gamma (γ, 31 - 50 Hz). The ratio (PSD of each band to PSD of the whole) and the relative value (PSD of each band to another band) are also extracted from the PSD result. What is more, the statistic values such as maximum, minimum, mean, standard deviation, skewness and kurtosis are calculated from both the time and frequency domain. Furthermore, the Hjorth features, 95% and 50% of spectral edge frequency and the statistics of them are included as suppplementary features. Finally the feature set contains 770 features with 30 time-step (one second for each without overlap).

Since some of the sleep stages' definition and classification contains the stages of the previous epochs, such as the N1 stage [6], we included features from 1 - 2 epochs before and after the current epoch respectively ($30\ or\ 30 \times 2$ seconds for both side) according to the previously proposed experiment in article[13].

D. Training

In the experiments, we used one single machine with Intel E5-2683v2 CPU$\times$2, and 128GB memory, equiped with a Nvidia GeForce GTX 1080 graphics card. We used the recorded data and the devision of dataset as mentioned in $Subsection\ A$.

The model was tained to minimize the categorical crossentropy with a balanced loss function in order to obtain a relatively impartiality model prediction for all of the sleep stage. What is more, for the purpose of enchancing the discrimination of the normaly under-represented stage, like N1, we increased its weight in the loss function. To test our model, we trained the model with 5-fold cross-validation (CV) with the two datasets respectively for its abilities of learning representations for each sleep stage and the generalization among different people. The model was implemented in *Keras* with a *Tensorflow* backend. As an extension, we also evaluate the classifier's performance with multiple values of class, i.e. $C = 2\ to\ 6$, as other previous research [1]. As a comparison, we employed an Gradient Boosting Classifier implemented with *XGBoost* [19] and a 2-layer LSTM network training on the same data.

IV. Results

The features we used was extracted from the original data with Python 2.7. In this section, we will firstly conduct the results and comparison among diffrerent models. Then we will discuss the classification performance with respect to varied number of class and time span (with +/- 30 or 60s). Finally we will show the visualizaion of the attention paid to the relevant parts of the input features for each classification action.

A. Comparison of different methods

In this experiment, we trained our proposed model as well as the Gradient Boosting method and the LSTM network on both the subject-as-sample dataset and the epoch-as-sample dataset. For evaluation, we calculated the accuracy, sensitivity, precision, F1 score and the confusion matrix shown as below.

V. Conclusion

The conclusion goes here.

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APPENDIX A
DETAILS ABOUT THE DATASET

Subject	W	N1	N2	N3	R	'?'	Subject	W	N1	N2	N3	R	'?'
Subject 1	199	103	214	397	132	0	Subject 2	148	27	215	374	174	0
Subject 3	227	186	353	91	205	0	Subject 4	317	224	292	125	60	21
Subject 5	738	96	107	70	0	0	Subject 6	172	47	375	240	129	0
Subject 7	43	6	41	58	0	861	Subject 8	62	197	517	90	112	0
Subject 9	149	183	373	90	158	0	Subject 10	177	340	286	4	179	0
Subject 11	190	339	444	18	42	74	Subject 12	69	120	414	156	140	0
Subject 13	107	45	308	228	208	0	Subject 14	390	427	126	0	82	0
Subject 15	131	167	386	134	144	1	Subject 16	109	19	4	0	0	856
Subject 17	312	135	356	119	99	0	Subject 18	318	144	362	32	116	0
Subject 19	100	46	326	355	189	0	Subject 20	0	0	7	0	0	964
Subject 21	366	189	282	87	93	2	Subject 22	121	128	320	321	166	0
Subject 23	193	130	480	159	200	0	Subject 24	46	104	197	76	33	483
Subject 25	265	259	303	87	147	0	Subject 26	271	91	374	118	66	0
Subject 27	219	205	390	9	71	0	Subject 28	143	175	424	31	145	12
Subject 29	251	116	335	69	116	0							

Note that we have excluded the Subject 20 due to its lack of effective records and labels