DEEP CONVOLUTIONAL AND RECURRENT NEURAL NETWORKS FOR INTERPRETABLE ANALYSIS OF EEG SLEEP STAGE SCORING

Anders Launer Baek

Technical University of Denmark
s160159@student.dtu.dk

ABSTRACT

The purpose of this paper is to investigate the time domain in automatic scoring of sleep stages by combining a recurrent neural network with a convolutional neural network. The raw polisomnography signals have been transformed into visuel interpretable images by using multitaper spectral analysis. The six different sleeping stages are represented in the transformed images with different visuel patterns. By learning those visuel sleeping pattern, it is possible to automatically classify the current stage of the sleep. The basis of this project are based upon the article by [1] and their produces has been re-created in order to create the base line. The base line are here compared to an extended model, which combines a convolutional neural network and a recurrent neural network. Due to the experimentally setup and the implementations of the networks in this project, the results are not comparable with the archived results in [1].

The performances of the two models are close to similar. The extended model does not out perform the base line model.

***Index Terms*—** Convulutional Neural Networks, Recurrent Neural Networks, Sleep Stage Scoring, Computer Vision and Pattern Recognition.

1 Introduction

Sleep is most important part of the human health. it is possible to diagonitise serevel dieasie by analysis the sleeping pattern of a human. The current approach of annotating sleep stages is done manually by highly trained professionals and based upon complex transition with high probability of a subjective interpretion.

It is possible to find the abnormalities within the sleep and hereby recognize some dieasies, by analysis the annotated transitions between the sleeping pattern. The annotated sleep patterns can be visualized by using a hypnogram (see figure 2).

The measurements which is used to classify the sleep stages, are collected during the whole night of sleep. Several of biological signals can be measured during the sleep and the interesting signals for this project is the brain activity. The brain activity can be aquried by using electroencephalography (EEG) method. The main frequencies of the EEG signales are: $delta = 3\,[Hz]$ and below, $theta = 3.5 - 7.5\,[Hz]$, $alpha = 7.5 - 13\,[Hz]$, $beta = 13\,[Hz]$ and above.

The above mentioned burst of rhythmic components are represented in different degrees within each stage of sleep. The newest definition of sleep stages are defined by the American Academy of Sleep Medicine. They defines the sleep stages into five (six) as followed [1, 2]:

- W: wakefulness to drowsiness. The alpha and delta waves are present. The low frequency delta waves is affected by small eye movements, when the eyes switching from open to closed. See the multi-taper frequency spectrum in figure 1a.
- N1: Non-REM 1. This is the first sleep stage after the transition from W. There are slow eye movements, See the multi-taper frequency spectrum in figure 1b.
- N2: Non-REM 2. One or more K-complexes present. See the multi-taper frequency spectrum in figure 1c.
- N3-N4: Non-REM 3-4. Slow delta wave activity. The dreaming starts here. This is the stage between been fully awake and fully asleep. The newest definition combines the sleep stage N3 and N4. See the multi-taper frequency spectrum in figure 1d-1e.
- R: REM is short for rapidly eye movements. Mixed rhythmic components are present in the EEG and the brain activity is similar to W. See the multi-taper frequency spectrum in figure 1f.

The scope of this project is to create a re-implementation of the chosen CNN ([1]) in TensorFlow (TF), in order to get the base line. When the base line has been archived, the task is to implement a recurrent neural network and hereby learn the transitions rule between each of the sleeping stages. This research will hopefully give improve the sleep stage classifier, and be more profitable for patients and doctors around the world.

2 Materials and Methods

As a requirements for this project, the professor and assistant teahters needs to have acces to the running code which produces the results within this paper. The two bullets below links to what you need in order to reproduce the presented results.

- Github: Deep_Learning_Project.git
- DTU SharePoint: Data_dicts_and_Code_models.zip

2.1 Image Creation

There have been applied multi-taper spectrum analysis in order to turn the EEG signals into images. A given image represents an epoch in seconds of the complete recorded EEG signal along the first axis. The second axis represents the spectrum for the rhythmic components of interest, mentioned above. The third axis (the color) represents the amplitudes of the rhythmic components to a given time.

The WFDB Toolbox ([3]) for Matlab have been used to download, preprocess and transform the EEG signals into images. The applied script[1] for this process has been provided by the supervisor. The multi-taper spectrum analysis which estimates the images, is not within the scope of the project. The hyperparameters, such as the duration (in $[s]$) of an epoch, number of multi-tapers, frequency resolution (in $[Hz]$), etc., within the image estimation process have been decided to remove from possible hyperparameter in this project. This ensures that the results of the baseline model, in this project, can be comparable with the main article [1] and keep the correct focus.

The Matlab toolbox are able to download the data set of interest and the data which have been used in this projects consists of PSG recordings for 20 Subjects. The Subjects have been monitored for two nights except Subject 20. There is 38211 images after the preprocessing of the EEG signals. All images have labeled-values which employs a supervised learning approach. Table 1 illustrates how the labels of 38211 images are distributed for the sleeping stages.

Sleep Stage	W	N1	N2	N3	N4	R
Dist. (in %)	12	7	46	9	6	20

Table 1: This table summerises the aggregates the distribution of the labels for all 20 Subjects. The distribution of the labels illustrates the sleep stages of subjects during the recordings.

In order to create a state of the art sleep stage classifier, WE need to consider methods to balance the six classes prior to training of the models.

[1] Git repo: "Code/2. from_edf_to_pic.m"

2.2 Neural Network Architectures

The selected baseline CNN from the article is.......

2.2.1 Convolutional Neural Network

Implementations found in...

Describe the network

2.2.2 Recurrent Neural Network

Describe the network

RNN LSTM

2.3 Network Visualization

The problem of understanding the aspects of visuel appreaches

artificial images which represent the class of interest by calculating the gradient w.r.t. its loss function.

In [1] they have create a function, which calculates the gradients at the loss w.r.t. an input images and its labels. The mathematically expression are given in equation 1, [1].

$$s^{(j)} = \tag{1}$$

By applying the function (1) for all images within each sleeping stage, it is possible to see how the network has been activated during for the given stage. Figure 1g-1r illustatres the

other examples could be to

2.4 Hyperparameter

3 Experimental Evaluation

3.1 Setup

I only use one picture epouch at the time.....

3.2 Results

ada

4 Discussion

data targets have not been cross checked by the skill professionals..

how to encounter imblanced data classe:

- random down sample in each epoch.. It can remove useful imformation - use weigthingPenalized Models the the loss function - learn the distribution of the miniorty classes and up sample those his change is called sampling your dataset and there are two main methods that you can use to even-up the classes:

		Predicted						Normalized pred. (in %)						Per-class metric (in %)			
		W	N1	N2	N3	N4	R	W	N1	N2	N3	N4	R	Pre.	Sen.	F_1	Acc.
CNN	W	495	145	29	11	1	20	71	21	4	2	0	3	91	71	80	93
	N1	25	211	43	0	0	62	7	62	13	0	0	18	43	62	51	89
	N2	4	51	1313	104	17	68	0	3	84	7	1	4	91	84	88	90
	N3	0	2	11	164	64	0	0	1	5	68	27	0	49	68	57	93
	N4	0	0	0	54	91	0	0	0	0	37	63	0	53	63	57	96
	R	17	80	46	0	0	591	2	11	6	0	0	81	80	81	80	92
RNN	W	578	39	26	7	1	43	83	6	4	1	0	6	89	83	86	95
	N1	38	107	64	0	0	132	11	31	19	0	0	39	55	31	40	91
	N2	8	13	1314	102	28	92	1	1	84	7	2	6	90	84	87	89
	N3	3	0	18	125	95	0	1	0	7	52	39	0	43	52	47	92
	N4	0	0	1	60	84	0	0	0	1	41	58	0	40	58	48	95
	R	19	36	43	0	0	636	3	5	6	0	0	87	70	87	78	90

Table 2: My caption

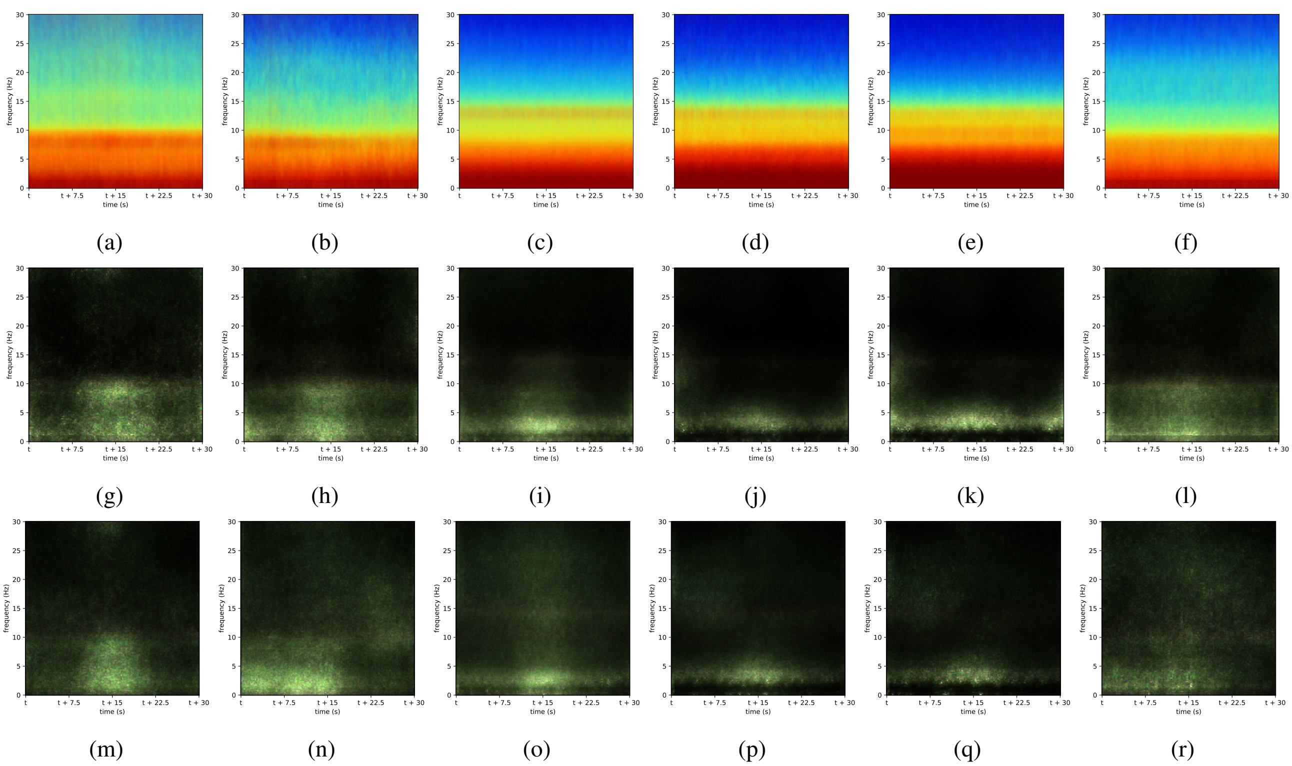
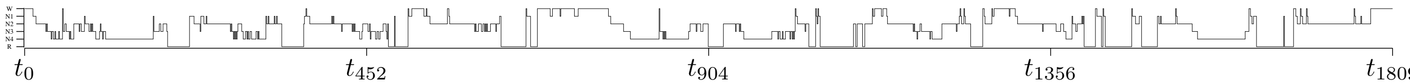


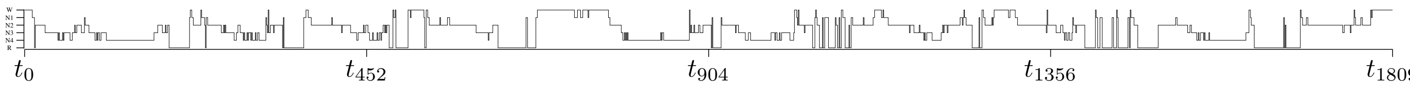
Fig. 1: This figure contains plots of each annotated sleeping stage for Subject 1. The plots are given columnwise from left to right according to the previous mentioned sequence of the sleeping stages. Fig. 1a to 1f illustrates the average multi-taper spectrum for each sleeping stage. It is clear to see a high similarity of sleeping stage N3 and N4 in fig. 1d to 1e. Second and third row, fig 1g to 1r shows the sensitivity map from the CNN and the RNN respectively.

under sampling .. smide information vk... mske kan det give en bedre predectering???

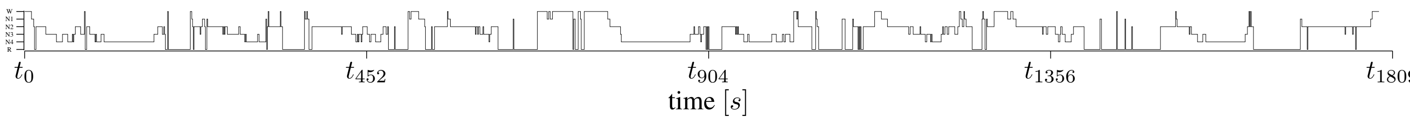
You can add copies of instances from the under-represented class called over-sampling (or more formally sampling with replacement), or You can delete instances from the over-represented class, called under-sampling.



(a)



(b)



(c)

Fig. 2: A figure with two subfigures

5 Conclusion

6 Acknowledgment

7 References

[1] A. Vilamala, K. H. Madsen, and L. K. Hansen, "Deep Convolutional Neural Networks for Interpretable Analysis of EEG Sleep Stage Scoring," *ArXiv e-prints*, Oct. 2017.

[2] Kevin McAffee, "The AASM Manual for the Scoring of Sleep and Associated Events: Version 2.0," 2017.

[3] Physionet.org, "wfdb-app-matlab," 2017.

8 Appendix