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

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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 recongize some dieasies, by analysis the annotatin transistions 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. Severel of biological signles can be measured during the sleep and the interesting signals for this project is the brain activity. The brain activity can be aqquried 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 rythmic components are represeneted in different degrees within each stage of sleep. The American Academy of Sleep Medicine defines the different stages of sleep as follows [**?**]:

- W: wakefulness to drowsiness.
- N1: Non-REM 1.
- N2: Non-REM 2.
- N3: Non-REM 3.
- *N4: Non-REM 4.*
- R: REM.

Write some meaning full stuff here.

The data

0: 11.959906833110884, 1: 7.2282850488079351, 2: 45.999842977153179, 3: 8.6624270498024121, 4: 5.9694852267671612, 5: 20.18005286435843

Developing an automated sleep stage classifier, which is able to learn the transition rules between the five (six) stages of sleep, is profitable for patients and doctors around the world. The scope of this project is to re-create the implementation of their ([1]) chosen CCN in TensorFlow (TF) and extend the model with a RNN on top.

2 Materials and Methods

The code for preproducing those resultes are stored in [**?**].

2.1 Image Creation

2.2 Neural Network Architectures

2.2.1 Convolutional Neural Network

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.

2.4 Hyperparameter

3 Experimental Evaluation

3.1 Setup

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

3.2 Results

ada

4 Discussion

5 Conclusion

6 Acknowledgment

7 REFERENCES

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[2]

8 References

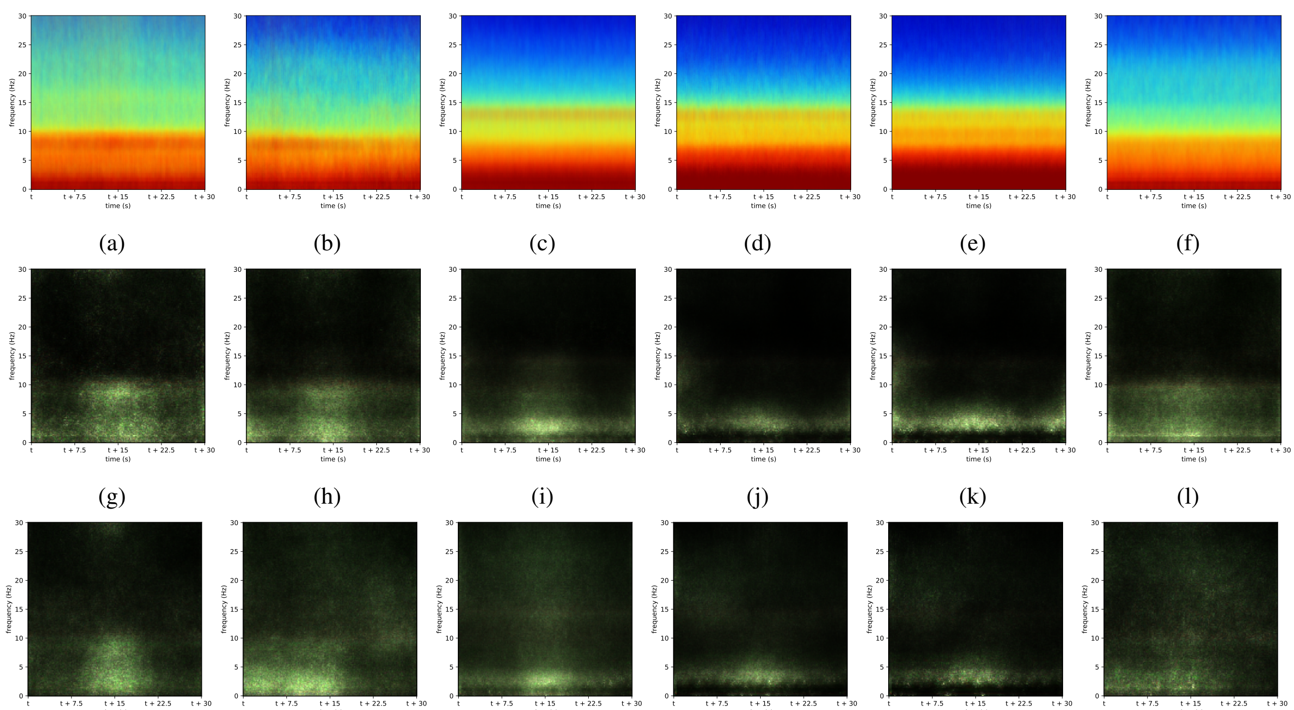
[1] A. Vilamala, K. H. Madsen, and L. K. Hansen, "Deep Convolutional Neural Networks for Interpretable Analysis of EEG Sleep Stage Scoring," *ArXiv e-prints*, Oct. 2017.

[2] C.D. Jones, A.B. Smith, and E.F. Roberts, "Article title," in *Proceedings Title*. IEEE, 2003, vol. II, pp. 803–806.

9 Appendix

		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 1: My caption

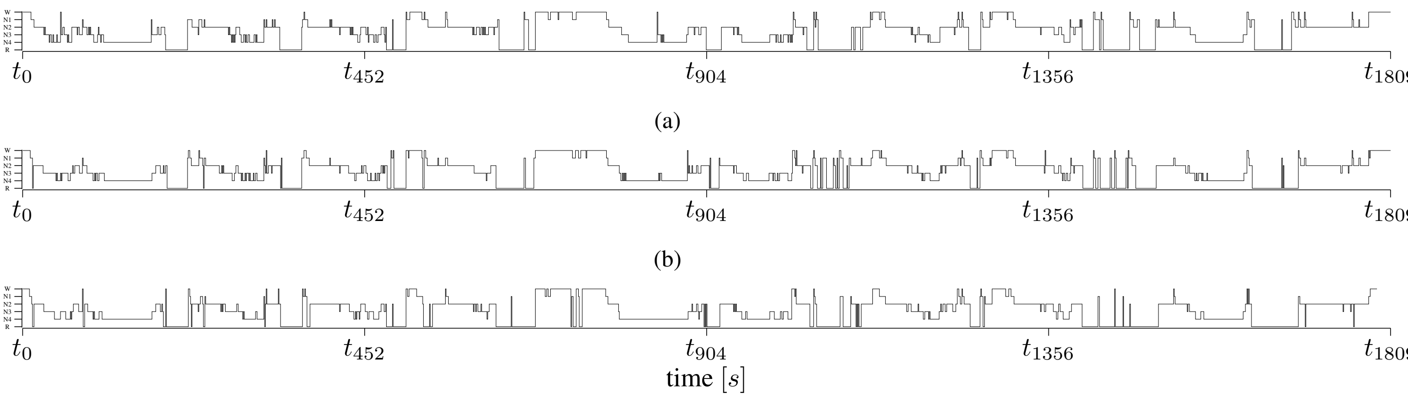


(a) (b) (c) (d) (e) (f)

(g) (h) (i) (j) (k) (l)

(m) (n) (o) (p) (q) (r)

Fig. 1: A figure with two subfigures



(a)

(b)

(c)

Fig. 2: A figure with two subfigures