Deep Convolutional and Recurrent Neural Networks for Interpretable Analysis of EEG Sleep Stage Scoring

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Github: anderslaunerbaek/Deep_Learning_Project

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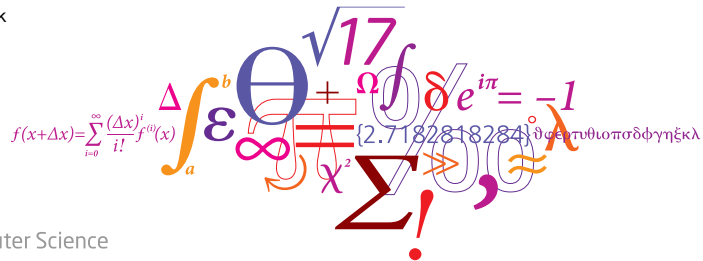

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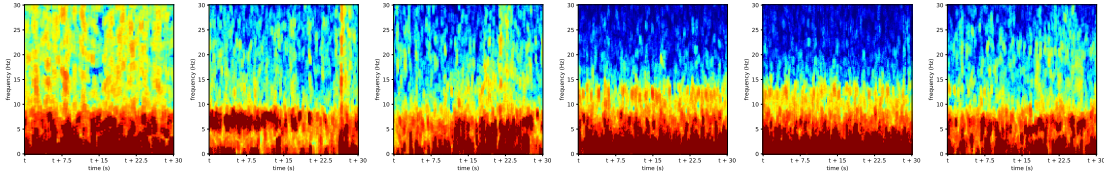
Sleeping Stages



(a) W (b) N1 (c) N2 (d) N3 (e) N4 (f) R

Figure: This figure illustrates a random epoch of the multi-taper spectrum for each sleeping stage. There is high similarity between sleeping stage N3 and N4.

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

Table: 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.

Networks

- CNN: VGGNet 16
- RNN: VGGNet 16 + LSTM cell

Confusion Matrices

		Predicted						Normalized pred. (in %)					
		W	N1	N2	N3	N4	R	W	N1	N2	N3	N4	R
CNN	W	495	145	29	11	1	20	71	21	4	2	0	3
	N1	25	211	43	0	0	62	7	62	13	0	0	18
	N2	4	51	1313	104	17	68	0	3	84	7	1	4
	N3	0	2	11	164	64	0	0	1	5	68	27	0
	N4	0	0	0	54	91	0	0	0	0	37	63	0
	R	17	80	46	0	0	591	2	11	6	0	0	81
RNN	W	578	39	26	7	1	43	83	6	4	1	0	6
	N1	38	107	64	0	0	132	11	31	19	0	0	39
	N2	8	13	1314	102	28	92	1	1	84	7	2	6
	N3	3	0	18	125	95	0	1	0	7	52	39	0
	N4	0	0	1	60	84	0	0	0	1	41	58	0
	R	19	36	43	0	0	636	3	5	6	0	0	87

Table: Confusion matrices and normalized confusion matrices for the CNN and RNN network.

Bootstrapped Performance Metrics

Study	Precision	Sensitivity	F_1-score	Accuracy
CNN	65-**68**-70	71-**71**-72	67-**69**-70	92-**92**-92
RNN	62-**65**-67	63-**66**-69	62-**64**-67	92-**92**-92

Table: **Mean** and corresponding 95% confident values computed by 100.000 bootstrap iterations with replacement.

Sensitivity Maps

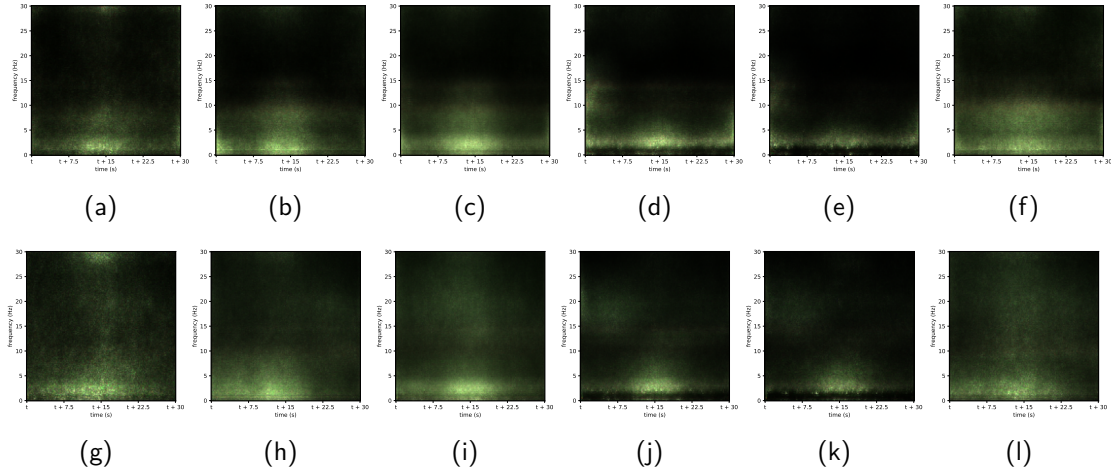


Figure: Illustration of the average sensitivity maps from the CNN (top) and the RNN (bottom) for the two validation subjects.

Conclusions

- Successfully re-produced [1] in TF which was one of the objectives, despite using few different approaches.
- Added a LSTM cell to the of the VGGNet 16 network. The of the RNN does out-perform the baseline on average (table 3), despite the RNN does archive better classification sensitivity in the following sleeping stages W and R.
- Improvements in this projects can be archived by merging sleeping stage N3 and N4, then follow the newest regulations.
- Study the effect of stacking multiple LSTM cells and applied the LSTM cells from layers with a lower-level feature representation higher and spectral variance.

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References


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.

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