

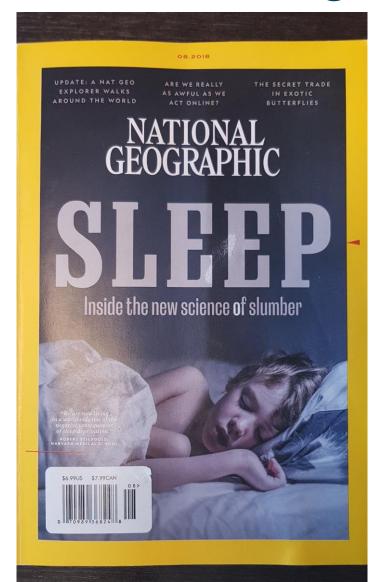
MÓTUM FRAMTÍÐINA SAMAN

Framtíðaráskoranir

Harpa 7. nóv 2018

Pétur Már Halldórsson Nox Medical

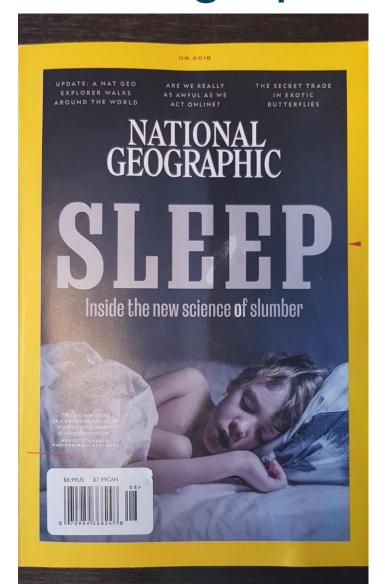
National Geographic (August issue 2018)



"We are now living in a worldwide test of the negative consequences of sleep deprivation"

Robert Stickgold, Harvard Medical School

National Geographic (August issue 2018) USA CDC



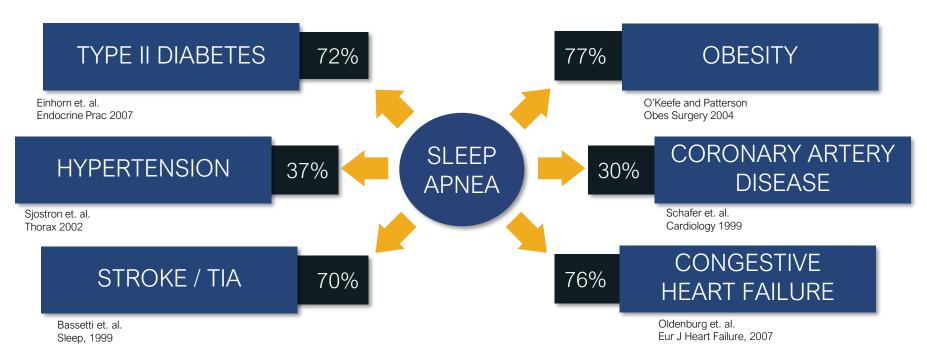


A 2017 Rand study found that lack of sleep can result in reduced productivity as well as more work absences, industrial and road accidents, health care expenses, and medical errors.

	Billion \$/year	% GDP lost
United States		:
	\$411 billion	2.28%
Japan \$138.6		2.92%
Germany \$60		1.56%
United Kingdom \$50.2		1.86%
Canada \$21.4		1.35%

Sleep Apnea – The Silent Killer

Obstructive Sleep Apnea (OSA)
Public Health Problem of Epidemic Proportions



OSA and Sleep Related Chronic Diseases (SRCD)
Cost \$1 Trillion Annually - OSA Alone Accounts for \$165B





The Nox entrepreneur's



Our People



- More than 50 employees
- Expertise and experience in medical engineering and software development
- High level of domain knowledge
- Tight knit group with a diverse set of qualifications and skills

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This is not from ancient times





The early days



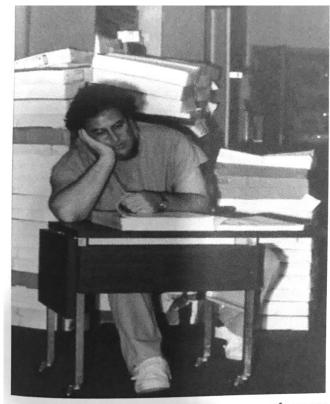


Fig. 4. Author surrounded by a sea of paper polysomnograms.

Fig. 5. Analog sleep system. Two-bed sleep laboratory at the University of Wisconsin, 1988. (Courtesy of S. Weber, Madison, WI.)









up until 2018

5 Million lives

Affected with Nox Medical technology world wide

Al and 4th industrial revolutin in HealthCare



Sleep stages

Cycle 2

1am

Cycle 1

12pm

11pm

Awake

- REM sleep

Non-REM stage 1

Non-REM stage 2

Non-REM stage 3 (formerly stage 3 & 4)

Classify every 30 seconds 5 Sleep stages Classification rules Human experts agree

Cycle 3

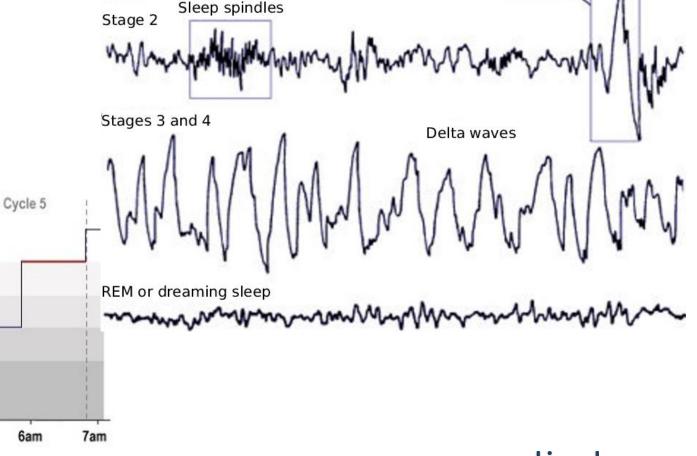
3am

2am

Cycle 4

5am

4am



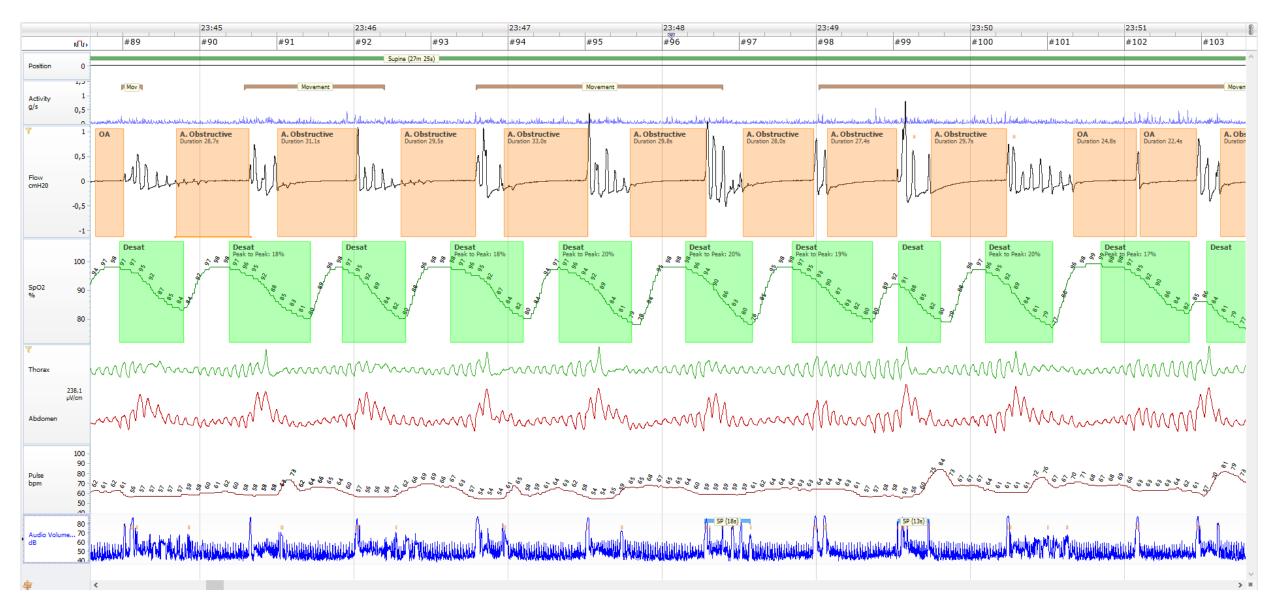
Alpha waves

K-complex.

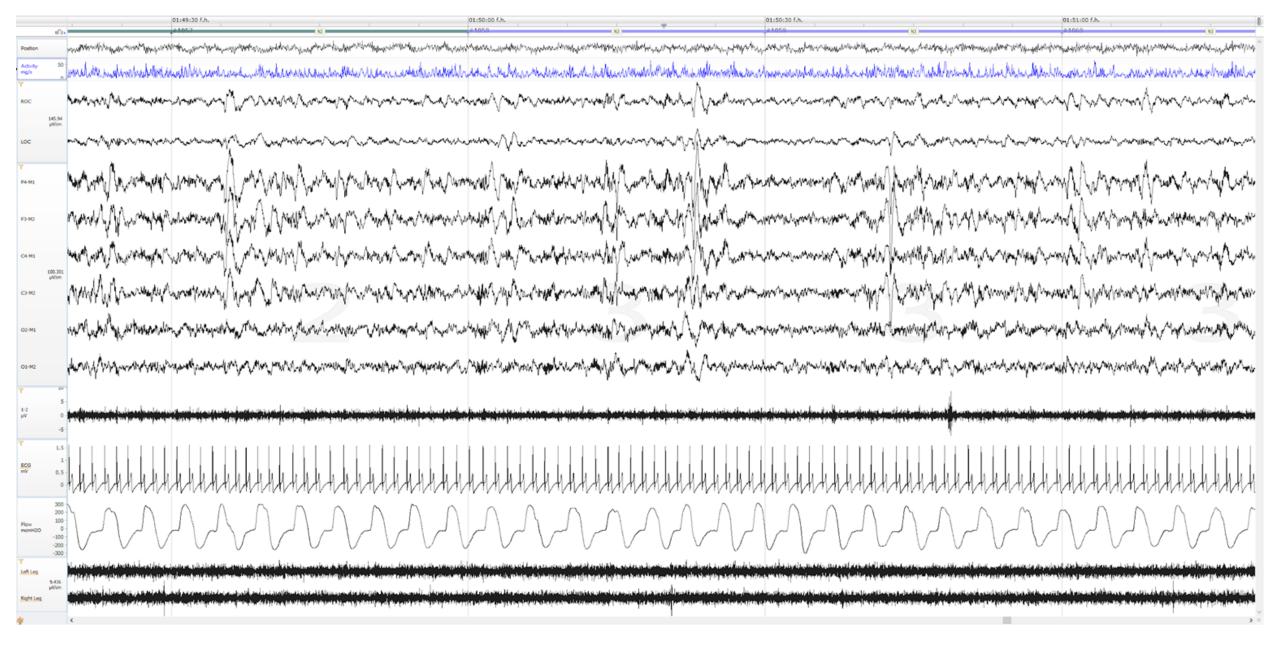
Relaxed wakefulness

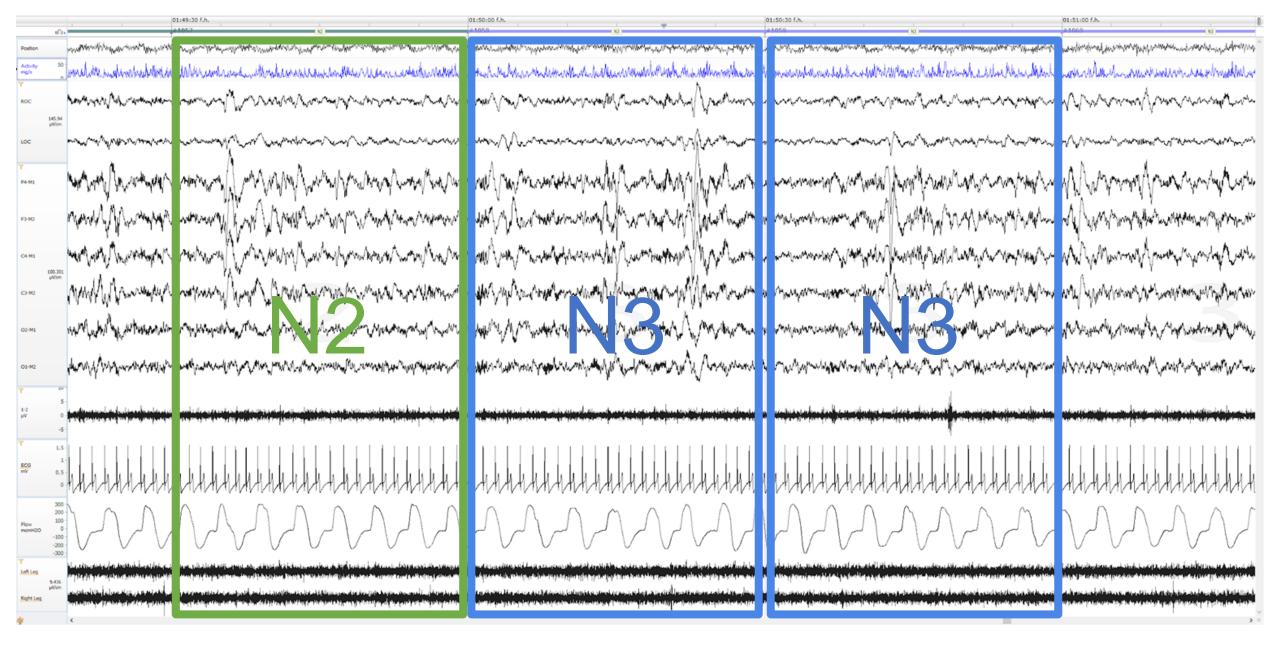
Stage 1

Theta waves



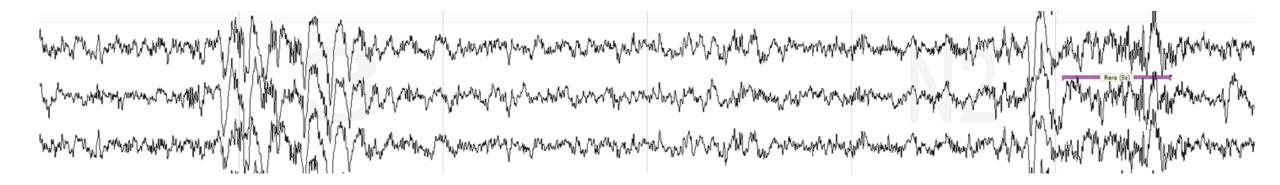
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Arousal detection



Nox Research

Team of scientists
Self funded
External collaborations
Internal projects

Mission

Automation Enabling Research

Ambition

Convert data to information Improve patient health





Horizon 2020 European Union funding for Research & Innovation





Big Data → Big Dating







JOHNS HOPKINS

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BRIGHAM HEALTH















University of Pennsylvania









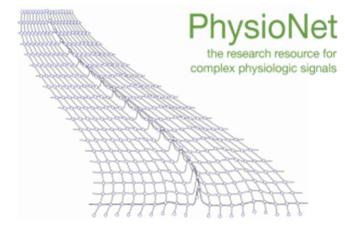


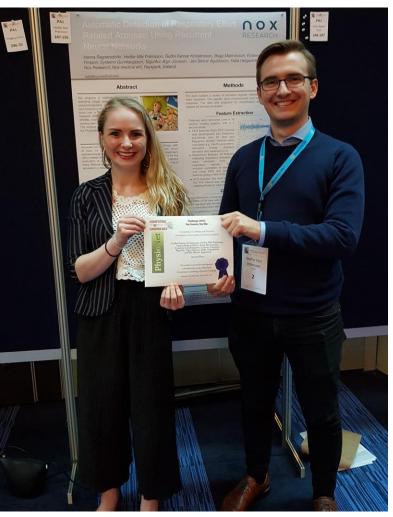












Automatic Detection of Respiratory Effort Related Arousals Using Recurrent Neural Networks

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Abstract

We propose a method for automatically detecting target sleep arousal regions of PNB signals by extracting time- and frequency-domain features and feeding them into a Bidirectional Recurrent Neural Network (BRNN). The predictions of the BRNNs trained using different features and training sets, were averaged for each subject. The method was developed and validated on the PhysioNet 2018 Challenge detabase.

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Objectives

Arousais are defined as an abrupt shift of EEG frequency of 3-15 sec. with a least 10 sec. of previous stable sleep [1]. Arousais can occur sportaneously or as a result of various sleep-disorders, such as respiratory effort related arousais [2]. The identification of arousais is important for the avoitation of isolep confinuity, as repeated arousais result in fragmented sleep. Manual scoring of arousais is costy and difficult. Automatic scoring of arousais is a recurring problem, to which we propose a method to solve.

Results

The performance of our method wa evaluated using a five-fold cross-validatio on the training set of the PhysioNet 201 Challenge database.

The final ensemble model performs excellently, with AUPRC-score (area-unde precision recall curve) of 0.45 and AUROC-score (area under receive operating characteristic curve) of 0.9.

Model	AUPRO SCORE	AUROC
Model 1 (BRINN)	0.432	0.893
Model 2 (BRNN)	0.429	0.893
Model 3 (BRINN)	0.426	0.891
Model 4 (BRNN)	0.430	0.893
Model 5 (BRNN)	0.428	0.895
Ensemble model	0.452	0.901

Discussions

Automatic detection of arousals is an important task but not a trivial one. The main challenges include imbalanced and poorly labelled data and variance between patients. Despite the challenges, our method for automatically classifying target arousal regions, shows encouraging results.

Methods

For each subject a variety of biometric signals, relevant to sleep studies, were recorded. The signals were then preprocessed and meaningful features extracted. The data was prepared for classification and finally deep learning applied to predict arousals.

Feature Extraction

Features were extracted over a 10 second moving window, with a 5 second stride.

- EEG features: Each EEG channel was decomposed into frequency sub-bands, and various time and frequency domain features calculated e.g. Hjorth parameters, Sub-band energy, standard deviation and skewness (3.4).
- Respiratory features: Features indicating respiratory disturbance, were extracted from the respiratory signals. These included correlation of abdomen and chest EMG and statistical features
- features

 ECG features: The heart beats were located using an R-peak finder and
 the R-R interval was calculated. Frequency domain features and
 statistical features were calculated from the interpolated R-R interval [5].

Classification

We implemented a three-layer neural network with the following layers:

• BRNN-LSTM layer with 50 LSTM hidden blocks.

- BRNN-LSTM layer with 50 LSTM hidden blocks.
 Dense layer with 50 nodes, using Relu activation function.
- . Dense-output layer with 2 nodes, using Softmax activation function
- The predictions of 5 neural networks were averaged per subje



Before training a classifier, the input data was normalized and reshaped for the recurrent layer. A more balanced training dataset was further created.



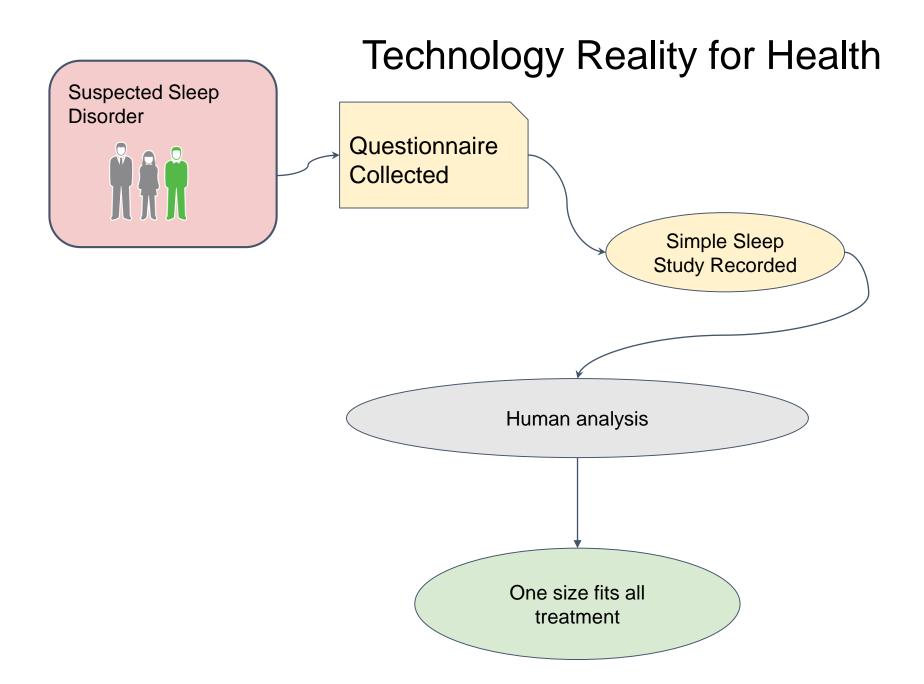
Acknowledgement

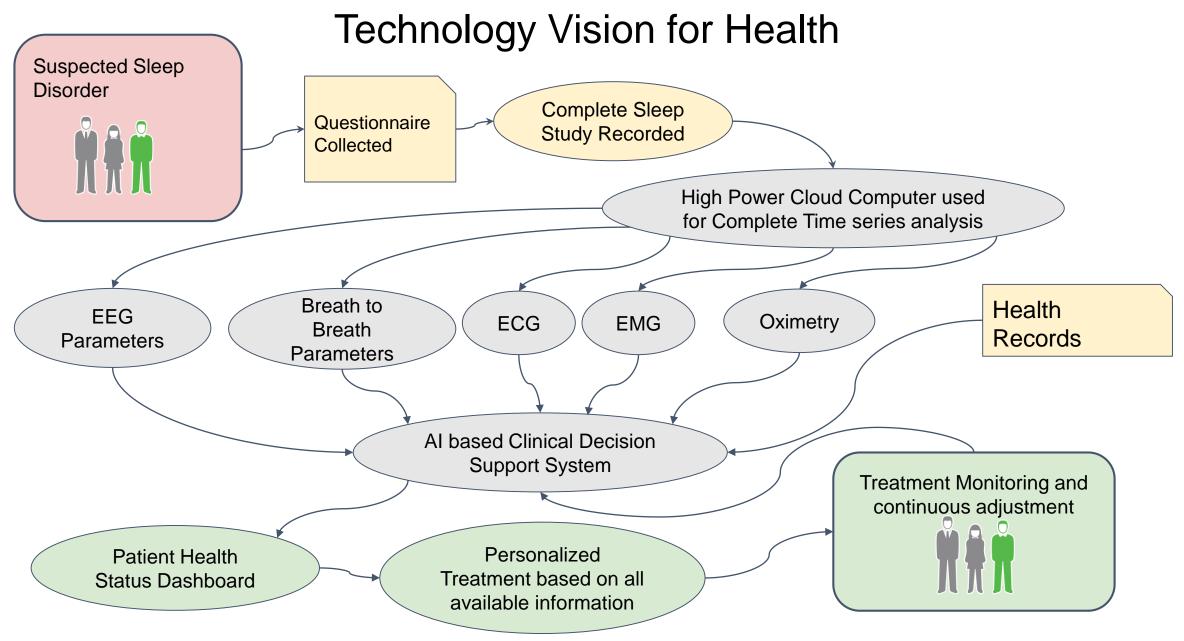
This work was supported by the loalandic Centre for Research under the loalandic Student Innovation Fund and the Holzon 2020 SME Instrument number 7:33401.

References

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- Faust O et al., Wavelet-based EEG processing for computer-sided setture detection and epilepsy diagnosis (90 4. Hjorth B, EEG analysis based on time domain properties (1970)
- 5. Shaffer F & Ginsberg JP, An overview of heart rate variability metrics and norms (2014)









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