NÝSKÖPUNARÞING 2018

Innreið fjórðu iðnbyltingarinnar í heilbrigðis tækni. Ögnvaldur eða risavaxið tækifæri?

Pétur Már Halldórsson
Nox Medical
Vision & Mission

Our mission is to advance sleep diagnostics through simplification, increased efficiency, and comfort in all patient groups.

Our vision is **Sleep for All**
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

- STROKE / TIA: 70% (Bassetti et. al., Sleep, 1999)
- HYPERTENSION: 37% (Sjostron et. al., Thorax, 2002)
- TYPE II DIABETES: 72% (Einhorn et. al., Endocrine Prac, 2007)
- OBESITY: 77% (O’Keefe and Patterson, Obes Surgery, 2004)
- CORONARY ARTERY DISEASE: 30% (Schafer et. al., Cardiology, 1999)
- CONGESTIVE HEART FAILURE: 76% (Oldenburg et. al., Eur J Heart Failure, 2007)
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

**THE MARKET FOR SLEEP**
Sleep-deprived consumers paid $66 billion in 2016 for devices, medications, and sleep studies. The figure could rise to $85 billion by 2021.

**THE COST OF SLEEPLESSNESS**
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.

<table>
<thead>
<tr>
<th>Country</th>
<th>Billion $/year</th>
<th>% GDP lost</th>
</tr>
</thead>
<tbody>
<tr>
<td>United States</td>
<td>$411 billion</td>
<td>2.28%</td>
</tr>
<tr>
<td>Japan</td>
<td>$138.6</td>
<td>2.92%</td>
</tr>
<tr>
<td>Germany</td>
<td>$60</td>
<td>1.56%</td>
</tr>
<tr>
<td>United Kingdom</td>
<td>$50.2</td>
<td>1.86%</td>
</tr>
<tr>
<td>Canada</td>
<td>$21.4</td>
<td>1.35%</td>
</tr>
</tbody>
</table>
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
This is not from ancient times
The early days

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
Sleep stages

Classify every 30 seconds
5 Sleep stages
Classification rules
Human experts agree
Scoring arousals - challenges

- **Manual scoring, challenges**
  - Time consuming
  - Variance across patients
  - Human error

- **Automatic scoring, challenges**
  - Lack of well manually scored data
  - Imbalanced data set
    - 2-7% arousals
    - > 93% non-arousals
  - Fuzzy definition, easy to confuse to noise

Important to find a solution to the automatic arousal scoring problem
Nox Research

Team of scientists
Self funded
External collaborations
Internal projects

Mission
Automation
Enabling Research

Ambition
Convert data to information
Improve patient health
EEG setup - Big DATA

Conventional EEG

- 8 EEG channels
- 2 EOG channels
- 2 EMG chin channels

Frontal EEG

- 9 channels recording EEG and EOG
- RIP belts detect muscle tone

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MACS cohort

2000 people in 1 year

Self-Applied Somnography
Data quality pipeline
Customized data analysis
Technical support
Knowledge transfer
deCode HERA

3000 People per year
Sleep measurement
Extensive clinical and health data

Self-Applied Somnography
Data quality pipeline
Customized data analysis
Technical support
Big Data → Big Dating
Scoring arousals - challenges

- Manual scoring, challenges
  - Time consuming
  - Variance across patients
  - Human error

- Automatic scoring, challenges
  - Lack of well manually scored data
  - Imbalanced data set
    - 2-7% arousals
    - >93% non-arousals
  - Fuzzy definition, easy to confuse to noise

Important to find a solution to the automatic arousal scoring problem
To automatically detect arousals in EEG using supervised learning (classification)

Contains arousal - yes/no?
Modelling breathing
Modelling breathing
Technology Reality for Health

Suspected Sleep Disorder

Questionnaire Collected

Simple Sleep Study Recorded

Human analysis

One size fits all treatment
Technology Vision for Health

Suspected Sleep Disorder

Questionnaire Collected

Complete Sleep Study Recorded

High Power Cloud Computer used for Complete Time series analysis

EEG Parameters

Breath to Breath Parameters

ECG

EMG

Oximetry

AI based Clinical Decision Support System

Health Records

Patient Health Status Dashboard

Personalized Treatment based on all available information

Treatment Monitoring and continuous adjustment
Smart-Sensor Nox System view -
Wireless miniature smart sensors using Bluetooth 5 streaming can be post-delivered to patient home
Automatic Detection of Respiratory Effort Related Arousals Using Recurrent Neural Networks

Hanna Ragnarsdottir, Heidar M. Hafldason, Gudlaug R. Sigfusdottir, Sigurjon M. Sigurdsson, Guðrið Vala Bjardardóttir, Jón Hafsteinsson, and Jón Stefán Sigurdsson

Abstract

We propose a method for automatically detecting respiratory efforts in EEG reports by extracting data and using an ensemble of recurrent neural networks (RNNs). The model is trained using different features including respiratory effort, arousal, and sleep stages. The results show high accuracy in detecting respiratory effort-related arousals.

Objectives

The objectives are as follows: (1) develop a method for detecting respiratory efforts in EEG reports and (2) evaluate the performance of the proposed method using various features.

Methods

We used an ensemble of RNNs to detect respiratory efforts in EEG reports. The model was trained using different features including respiratory effort, arousal, and sleep stages. The performance of the model was evaluated using various metrics such as accuracy, precision, recall, and F1-score.

Feature Extraction

We extracted features from the EEG data, including respiratory effort, arousal, and sleep stages. The features were normalized and used as input to the RNN model.

Classification

The RNN model was trained using various classifiers including support vector machines (SVMs), decision trees, and random forest (RF). The performance of the model was evaluated using various metrics such as accuracy, precision, recall, and F1-score.

Results

The proposed method achieved high accuracy in detecting respiratory efforts in EEG reports. The results were validated using various features and classifiers.

Discussion

Automatic detection of respiratory efforts is an important task that can be used to improve the quality of sleep monitoring and prevent sleep-related disorders. The proposed method can be used for various applications including sleep disorder diagnosis, sleep quality assessment, and health monitoring.

Acknowledgments

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References

