Sleep Sensing

Distributed Systems Seminar FS 2015 (D-INFK)

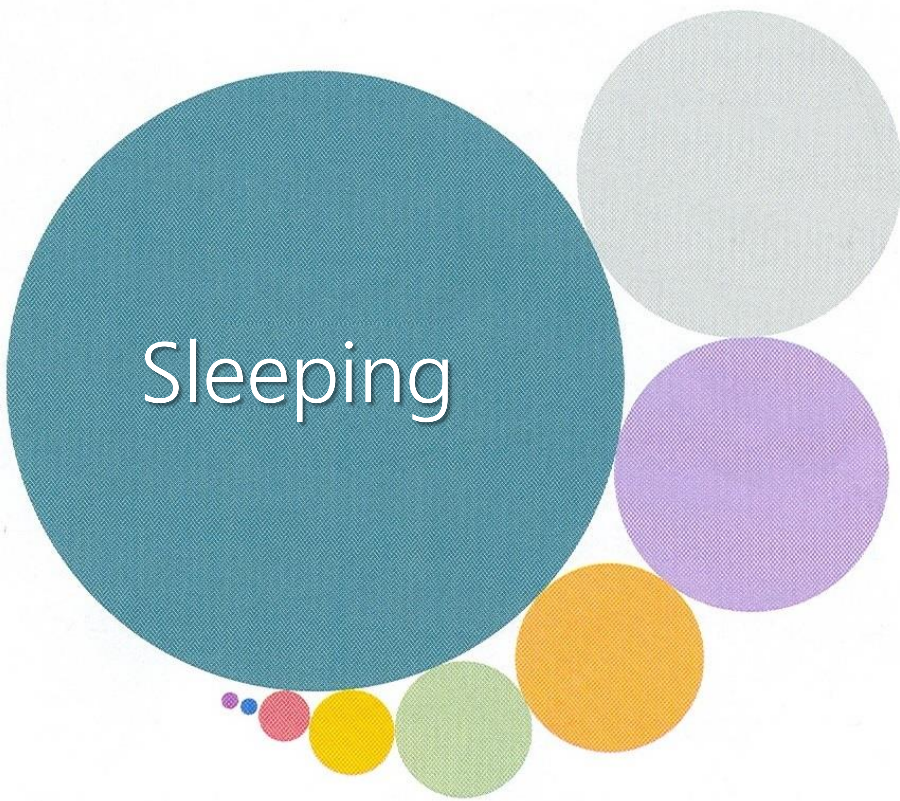
Speaker Dominik Kovacs

Supervisor Jara Uitto

Motivation

The Hours of Our Lives

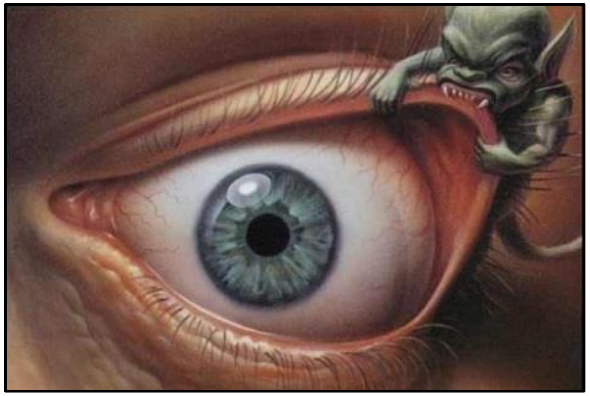
How much time do we sleep during a lifetime, compared with other activities?



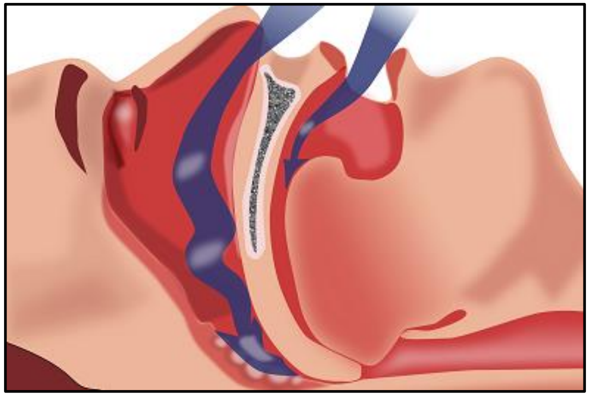
Activity	% of lifetime
Sleeping	36
Other activities	19
Working and work-related activities	16
Watching television	11
Household activities (housework, lawn care)	8
Eating and drinking	5
Socializing and communicating	3
Sports, exercise, recreation	1
Telephone calls, mail, and e-mail	1

Source: American Time Use Survey, Bureau of Labor Statistics, 2007 annual averages. Calculations based on U.S. life expectancy of 77.8 years, per National Center for Health Statistics, which includes an average 243,362 hours of sleeping.

Why Sleep Sensing?

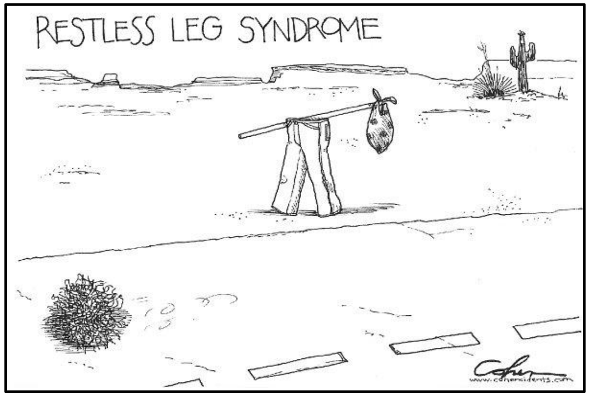


Dyssomnia



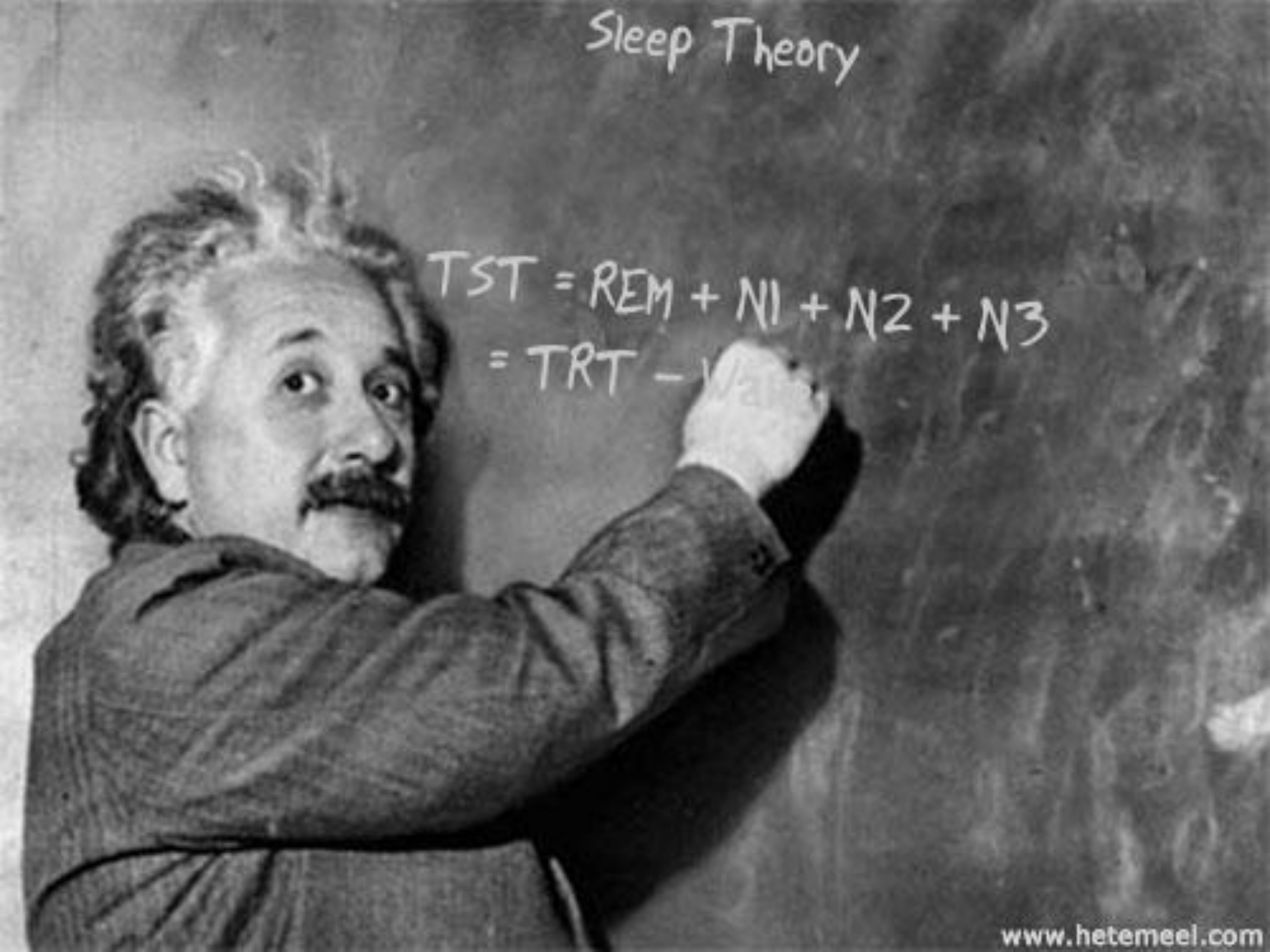
Apnea

Improve Sleep Quality

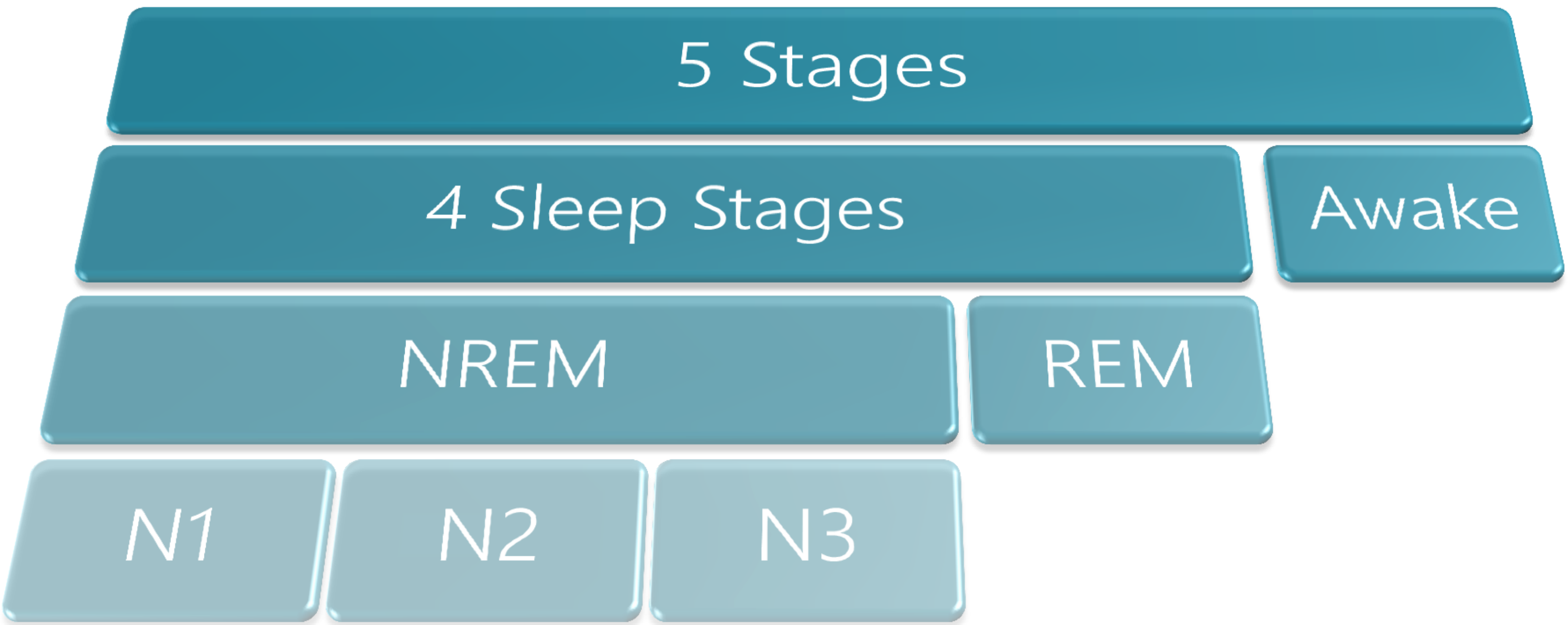


Restless Leg Syndrome

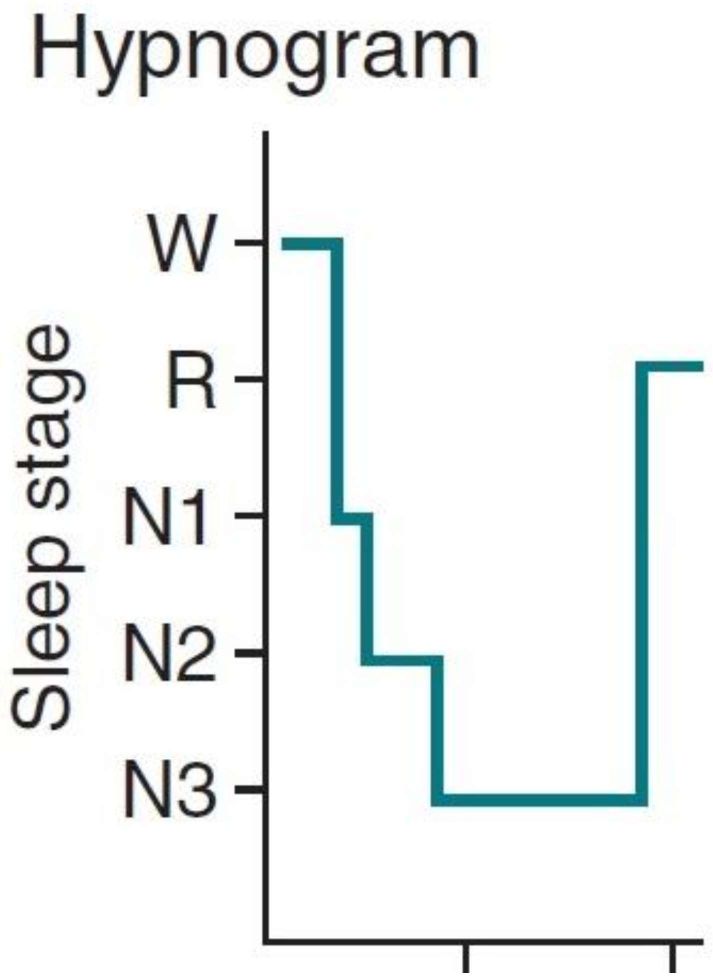
Narcolepsy


Sleep Theory
TST = REM + N1 + N2 + N3
= TRT –
www.hetemeel.com

American Academy of Sleep Medicine (AASM) 2007

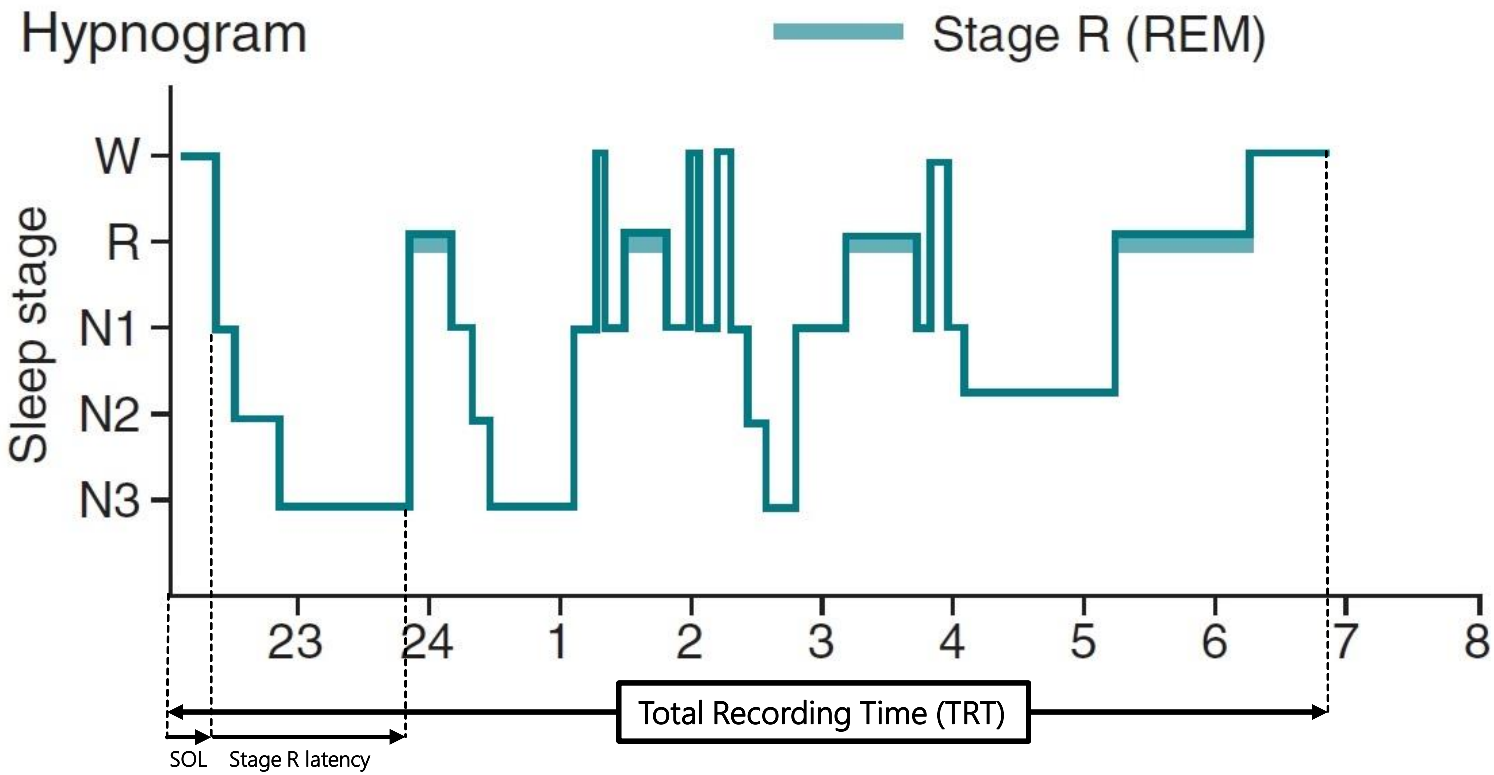


Sleep Cycle and its Sleep Stages



- N1 (Light Sleep)
  - Can be awakened easily
  - Slow eye movements and muscle activity
  - Sudden muscle contractions followed by a sensation of falling
- N2 (Light Sleep)
  - Eye movement stops
  - Brain waves become slower
- N3 (Deep Sleep)
  - Extremely slow brain waves (delta waves)
  - Difficult to be awakened
  - No eye movement or muscle activity
- REM (Rapid Eye Movements)
  - Rapid and irregular breathing, increasing heart rate
  - Skeletal muscles paralyzed
  - Dreaming

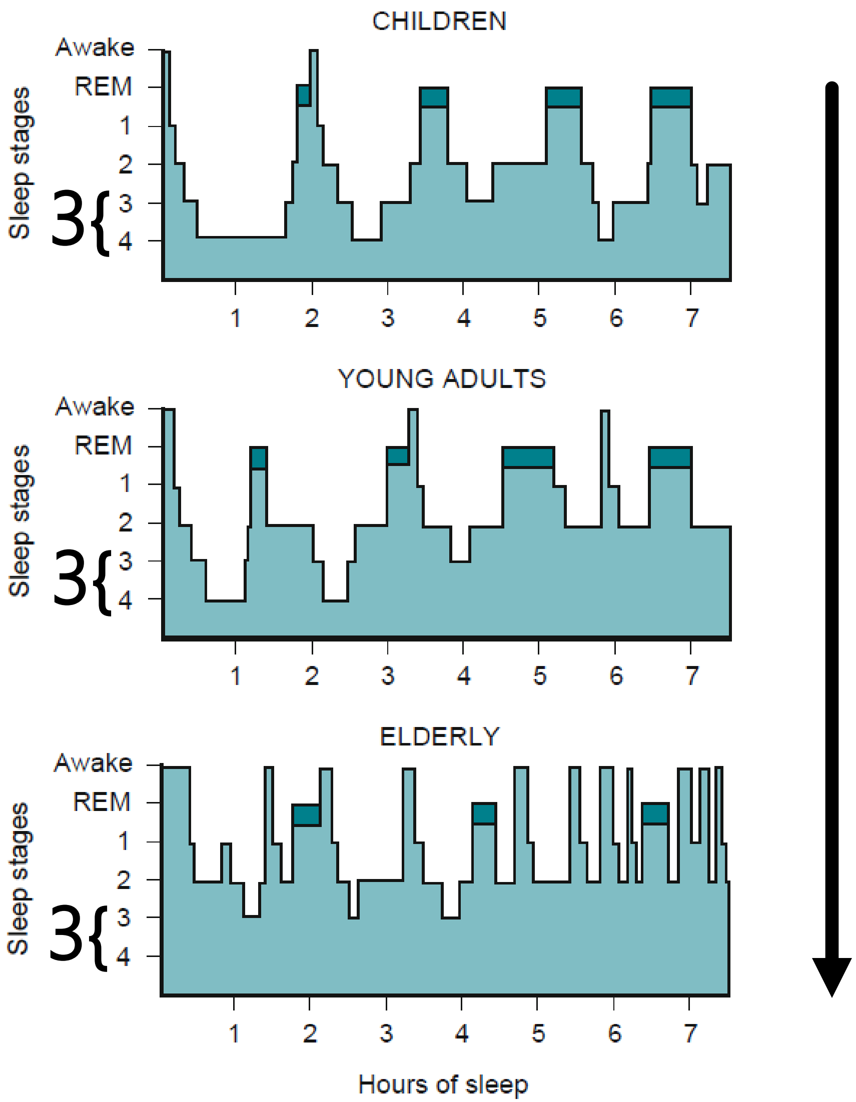
American Academy of Sleep Medicine (AASM) 2007



- Total sleep time $\mathrm{TST} = T_R + T_{N1} + T_{N2} + T_{N3} = \mathrm{TRT} - \mathrm{T_W}$
- Sleep efficiency: $\frac{\mathrm{TST}}{\mathrm{TRT}} \cdot 100$
- Wakefulness after sleep onset $\mathrm{WASO} = T_W - \mathrm{SOL}$

Source: Richard B. Berry MD. Fundamentals of Sleep Medicine. Published by Saunders, 2011.

Change of Hypnogram over the age

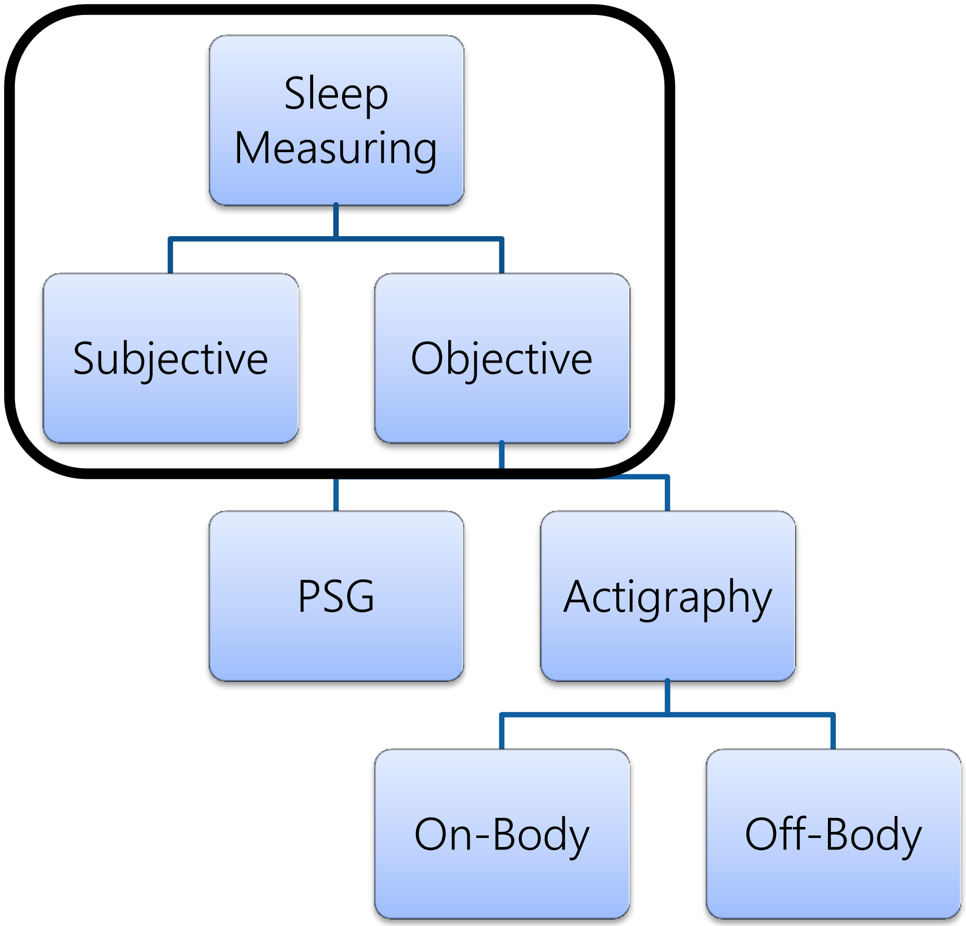


- Increase in #awakenings
- Decrease in REM sleep
- Decrease in N3 (deep) sleep

Source: Sudhansu Chokroverty MD FRCP FACP. Sleep Disorders Medicine, 3rd Edition. Published by Saunders, 2009.

Sleep Sensing

Ways of Measuring Sleep

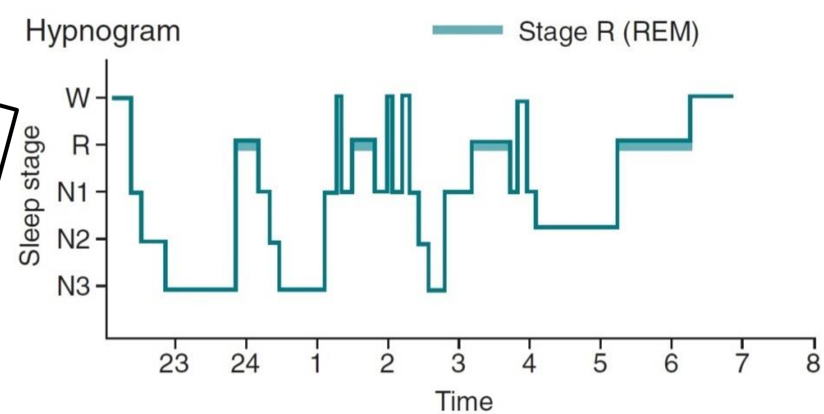


Ways of Measuring Sleep Subjective vs Objective

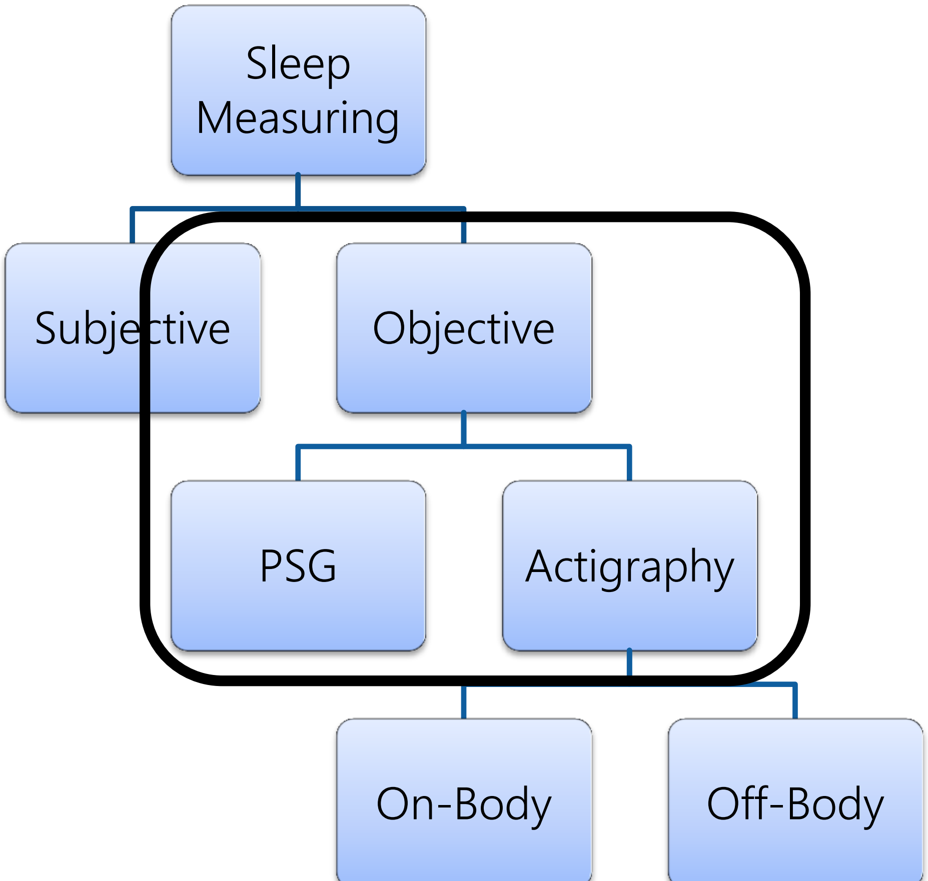
- Subjective (Questionnaire)
  - Falling asleep
  - Overall sleep quality
  - Number of awakenings
  - Feeling after wakeup

- Objective
  - Sleep onset latency (SOL)
  - Number of movements
  - Number of awakenings
  - Total time in REM sleep

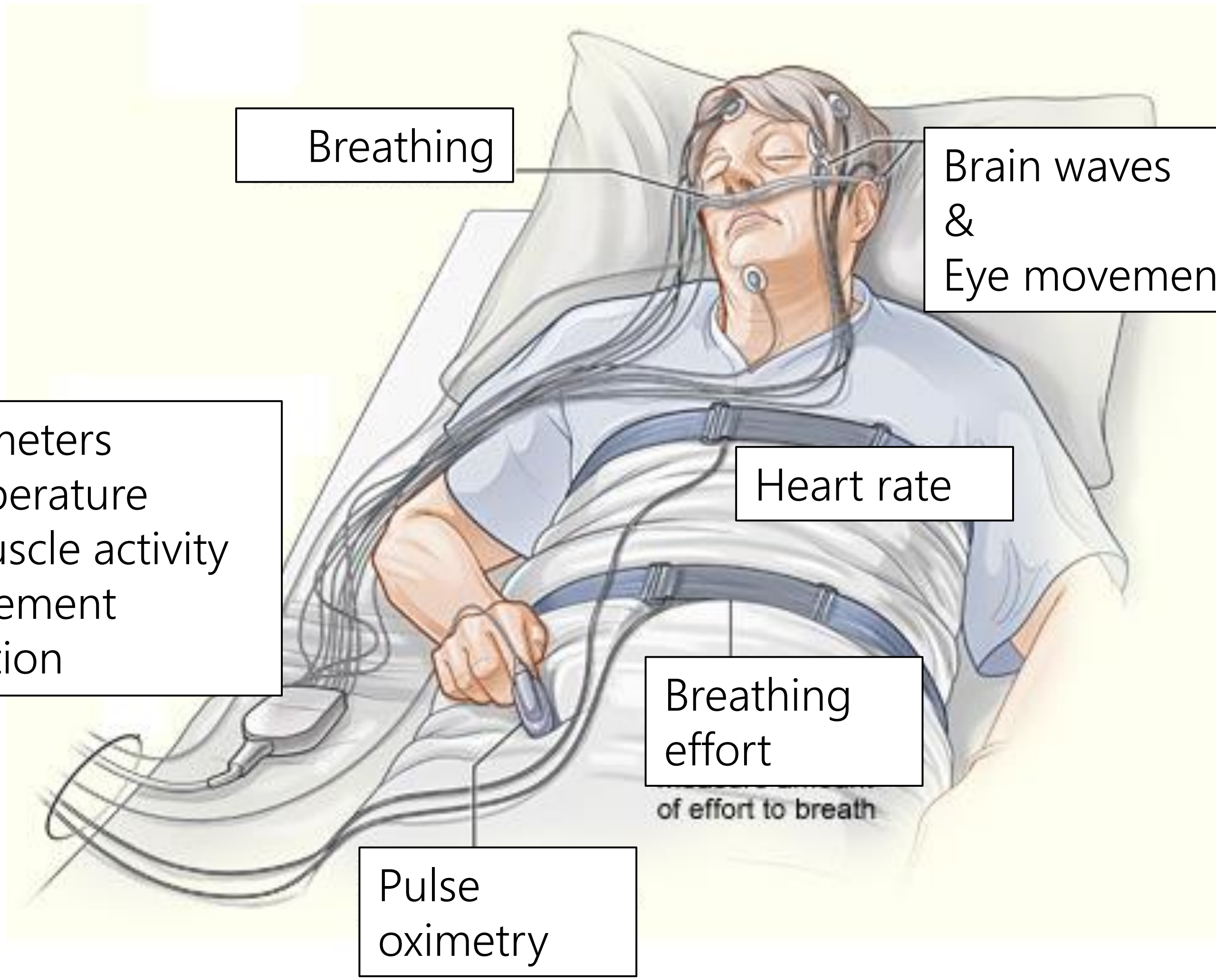
≠



Ways of Measuring Sleep



Polysomnography (PSG)

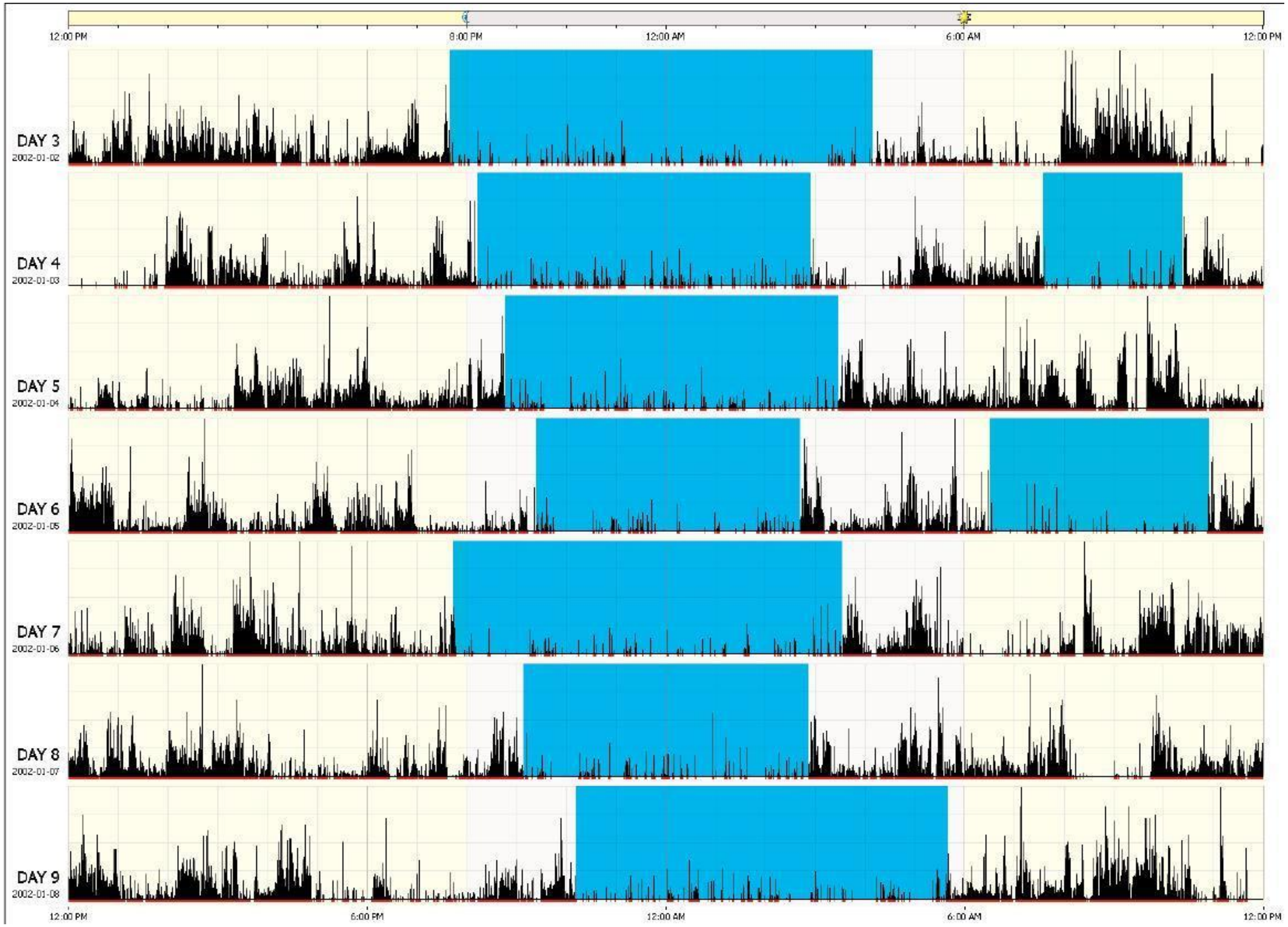


Further parameters

- Body temperature
- Overall muscle activity
- Body movement
- Body position

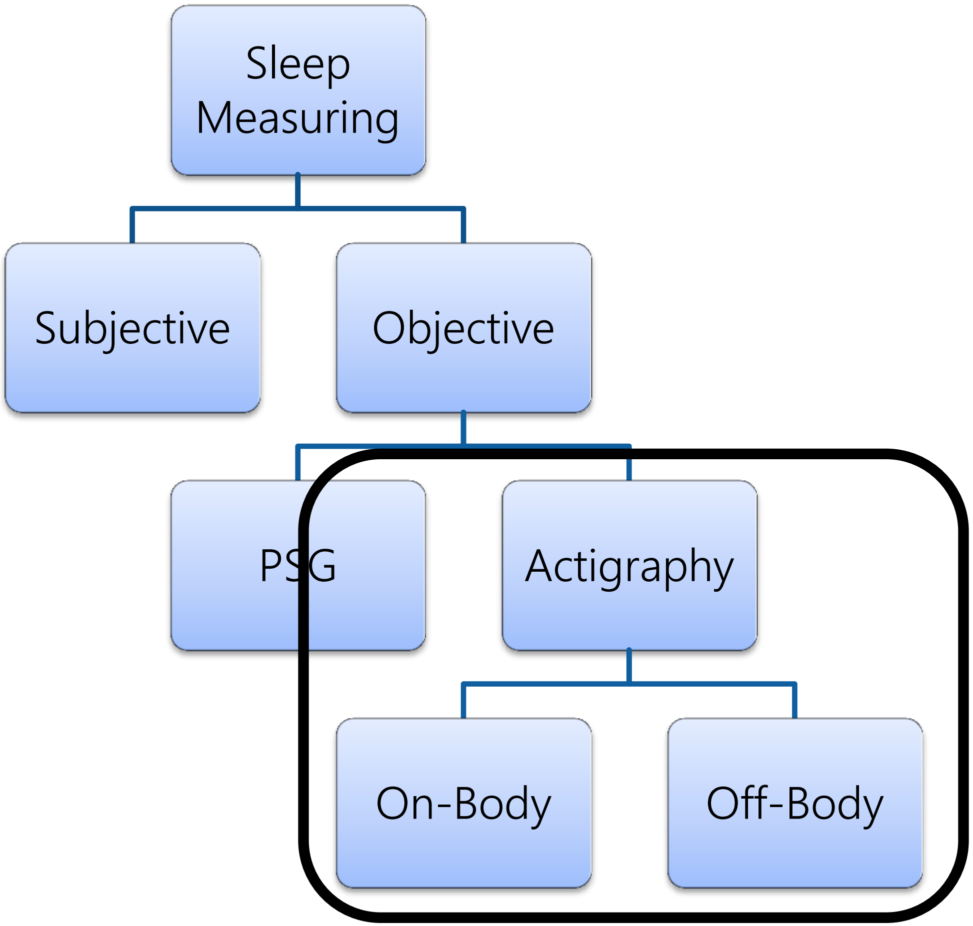
Source: http://www.nhlbi.nih.gov/health/health-topics/topics/slpst/during

Actigraphy



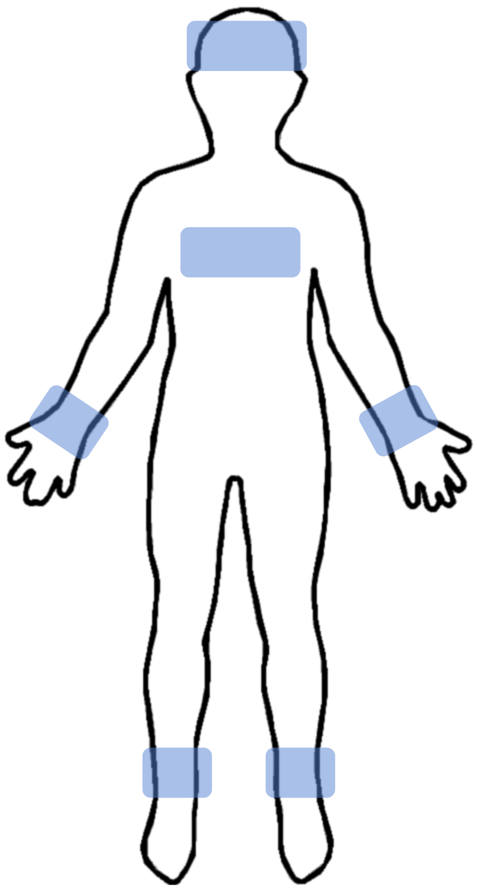
Source: http://www.bio-lynx.com/Sleep_Monitoring.htm

Ways of Measuring Sleep



Actigraphy Placements

On-Body



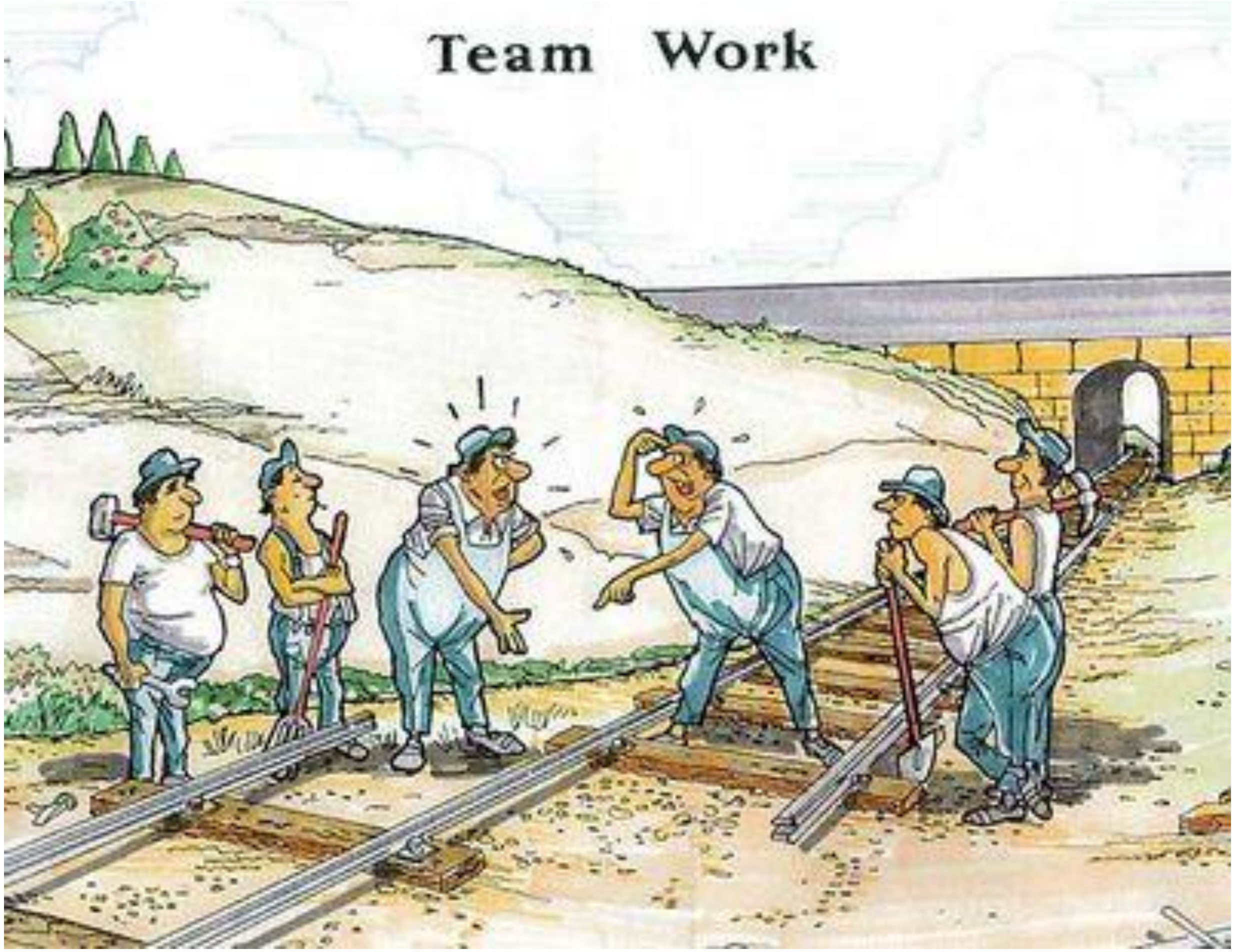
Off-Body

Objective Sleep Measurements
PSG vs Actigraphy

[wikimedia.org]

[http://www.healthcare.philips.com/main/homehealth/sleep/actiwatch/default.wpd]

Building a sleep sensing App



How to measure sleep with your smartphone

Accelerometer

Microphone

Light Sensor

Gyroscope

Magnetic Field

Pressure

Ambient Temperature

Relative Humidity

Common sleep-related smartphone tasks

Task	How?	Difficulty?
Detect snoring	On-board microphone	Easy
Detect sleep talking	On-board microphone	Easy
Detect sleep walking	Accelerometer/Gyroscope	Easy
Offer Smart Alarm	Accelerometer, Timer	Medium
Measure Sleep Quality	Accelerometer, Timer	Medium
Detect Sleep Stages	*[Intentionally left blank]*	Hard

DEER HUNTING

You're doing it wrong...

Sleep Hunter

[Weixi Gu et al. 2014 Intelligent Sleep Stage Mining Service with Smartphones]

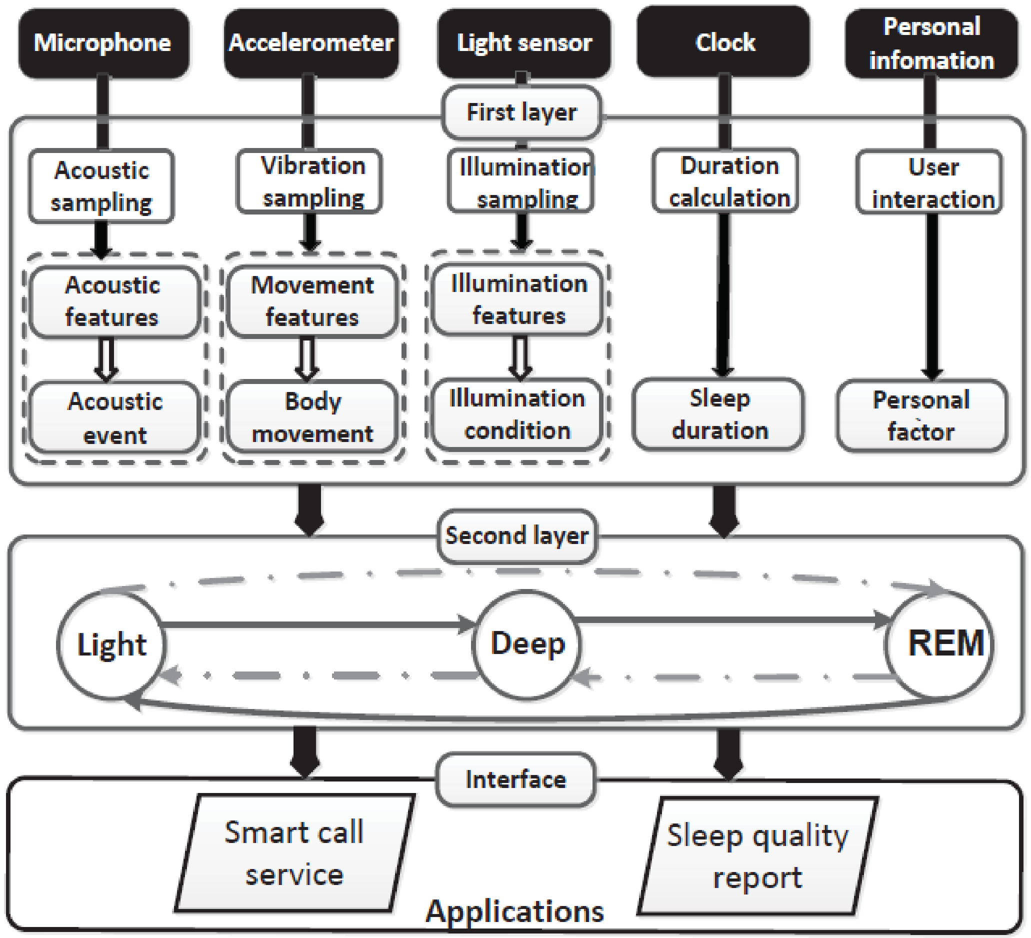


Figure 2. The architecture of Sleep Hunter

Smart Alarm / Smart Call Service

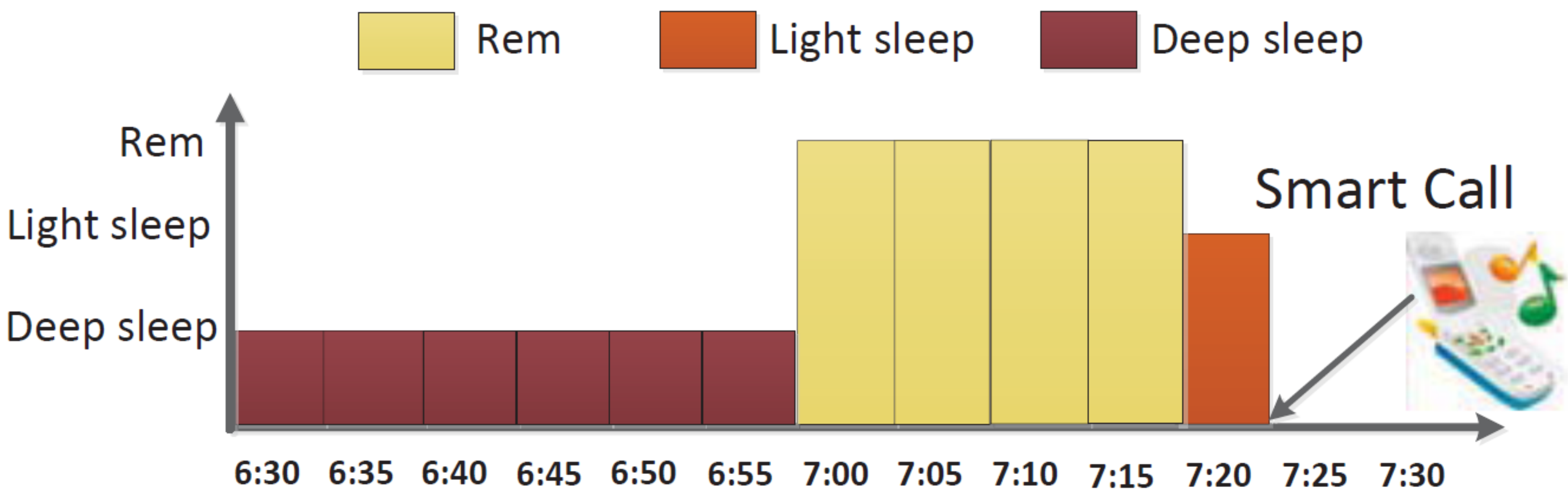


Figure 15. Smart call service

Source: Weixi Gu et al. 2014 Intelligent Sleep Stage Mining Service with Smartphones

Sleep Hunter

[Weixi Gu et al. 2014 Intelligent Sleep Stage Mining Service with Smartphones]

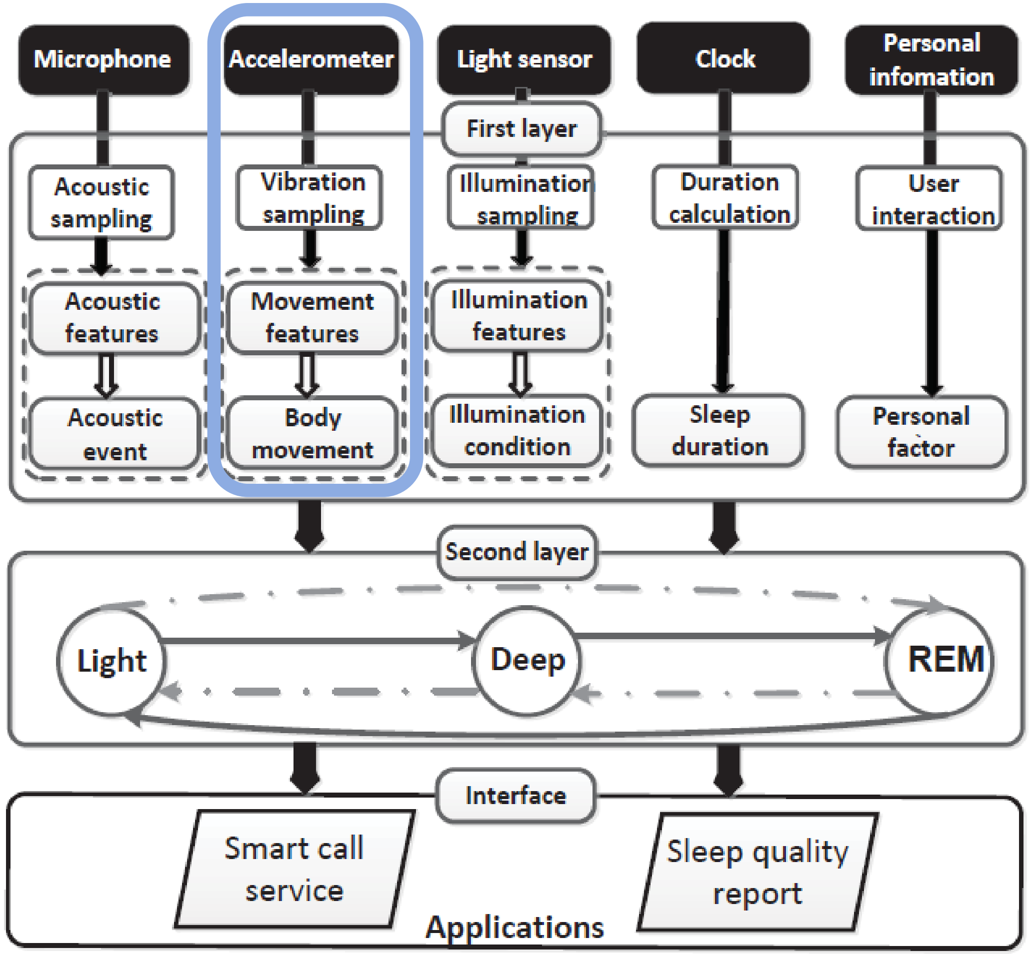


Figure 2. The architecture of Sleep Hunter

Body Movement Detection
Vibration Sampling

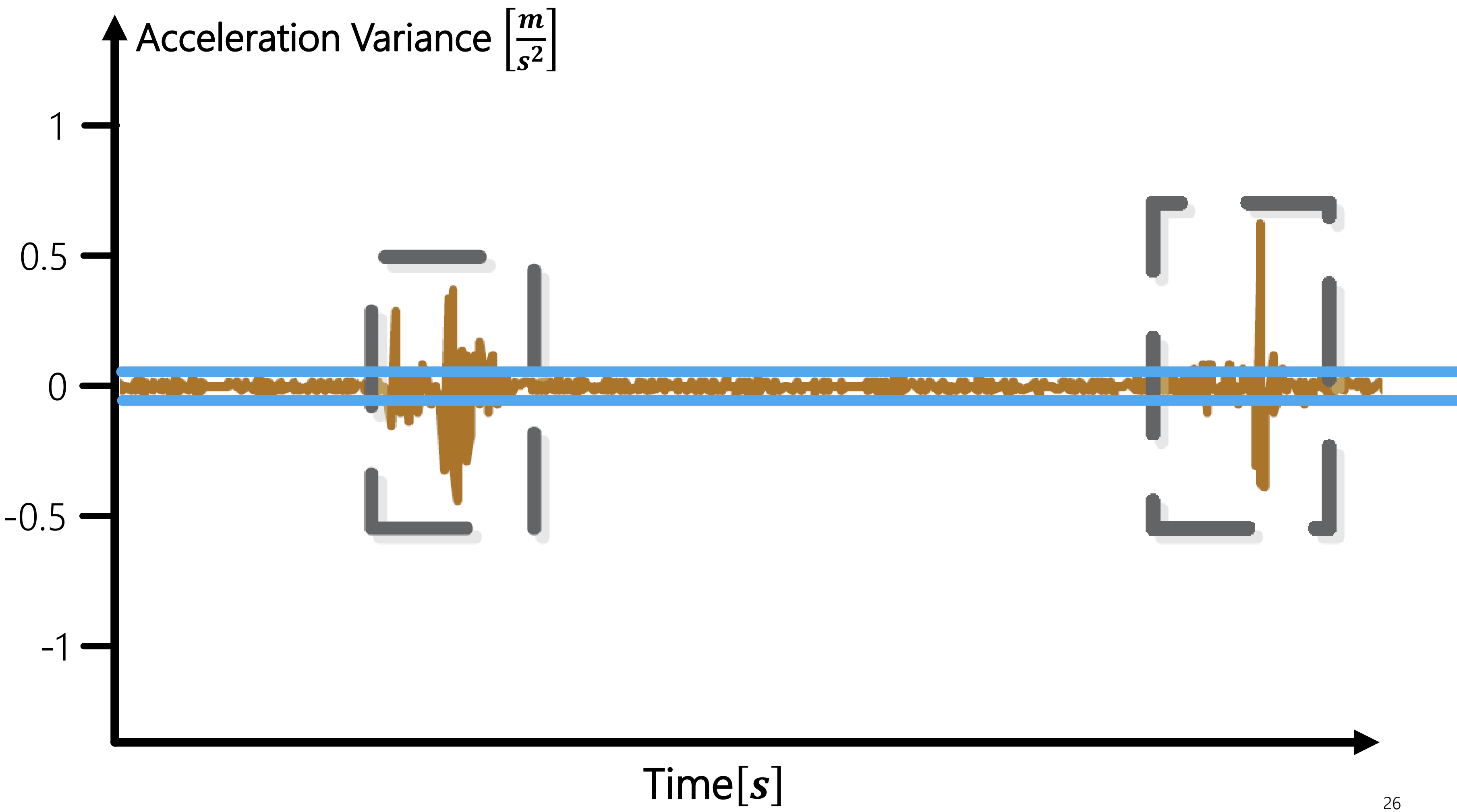
- Raw Acceleration Data

$$\left.\begin{matrix} a_x(i) \\ a_y(i) \\ a_z(i) \end{matrix}\right\} a(i) = \sqrt{a_x(i)^2 + a_y(i)^2 + a_z(i)^2}$$

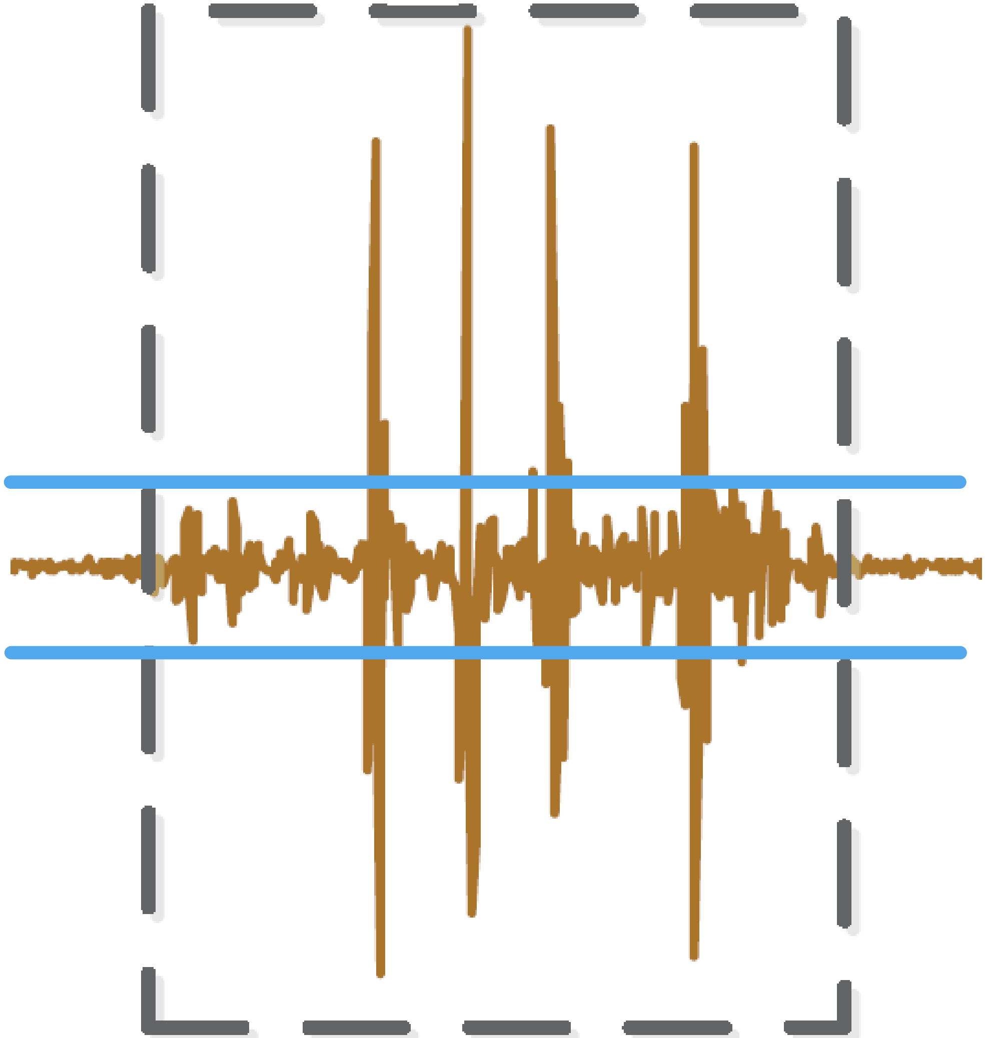
- Acceleration Variance

$$V(i) \coloneqq a(i) - a(i-1)$$

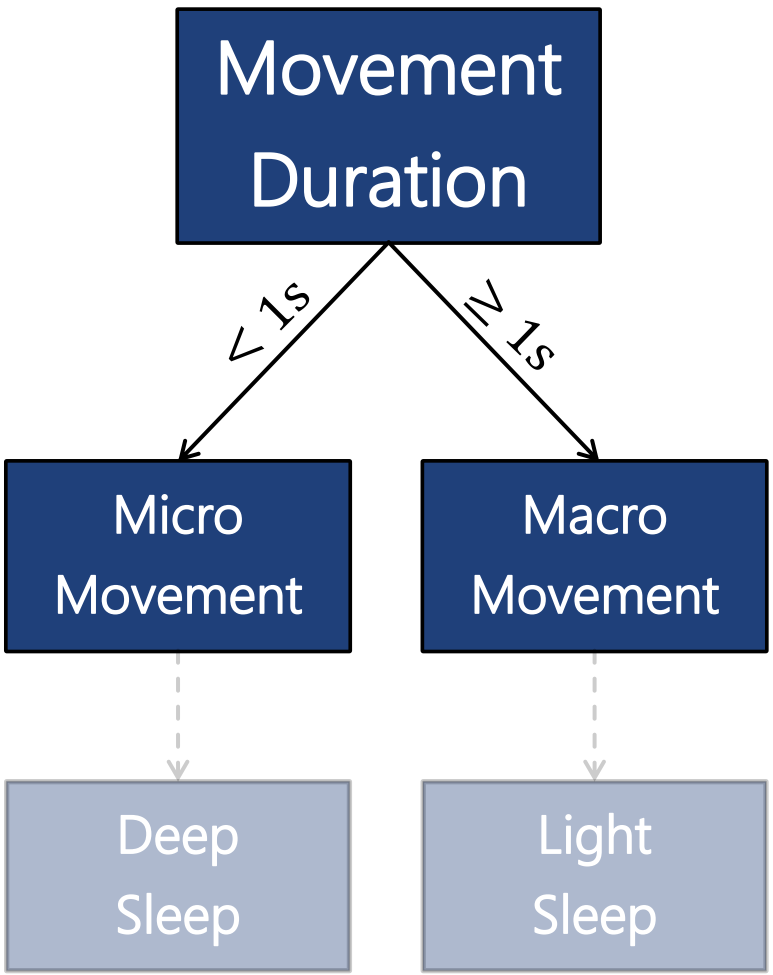
Body Movement Detection
Noise Elimination



Body Movement Detection
Noise Elimination



Body Movement Detection Classification



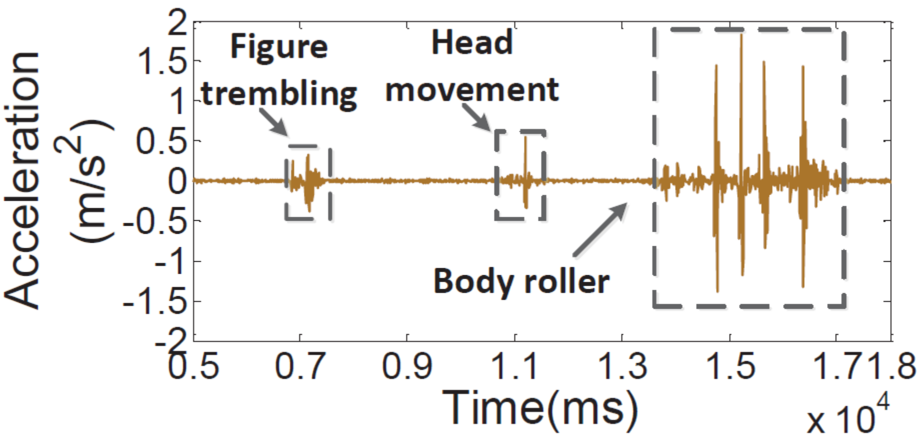


Figure 3. Acceleration trace of body movement

Naive Bayes classifier
Example

- Given Macro movements, which sleep stage to classify?
  - $P(Light|Macro),\ \ P(REM|Macro),\ P(Deep|Macro)$
- Bayes Rule
  - $P(Light|Macro) = \frac{P(Macro|Light) \cdot P(Light)}{P(Macro)}$
  - $P(Light|Macro) = \frac{\frac{8}{10} \cdot \frac{1}{3}}{\frac{1}{2}} = \frac{\frac{8}{30}}{\frac{1}{2}} = \frac{16}{30} = \frac{8}{15}$
  - $P(REM|Macro) = \frac{\frac{1}{10} \cdot \frac{1}{3}}{\frac{1}{2}} = \frac{\frac{1}{30}}{\frac{1}{2}} = \frac{2}{30} = \frac{1}{15}$
  - $P(Deep|Macro) = \frac{\frac{1}{10} \cdot \frac{1}{3}}{\frac{1}{2}} = \frac{\frac{1}{30}}{\frac{1}{2}} = \frac{2}{30} = \frac{1}{15}$

Sleep Hunter

[Weixi Gu et al. 2014 Intelligent Sleep Stage Mining Service with Smartphones]

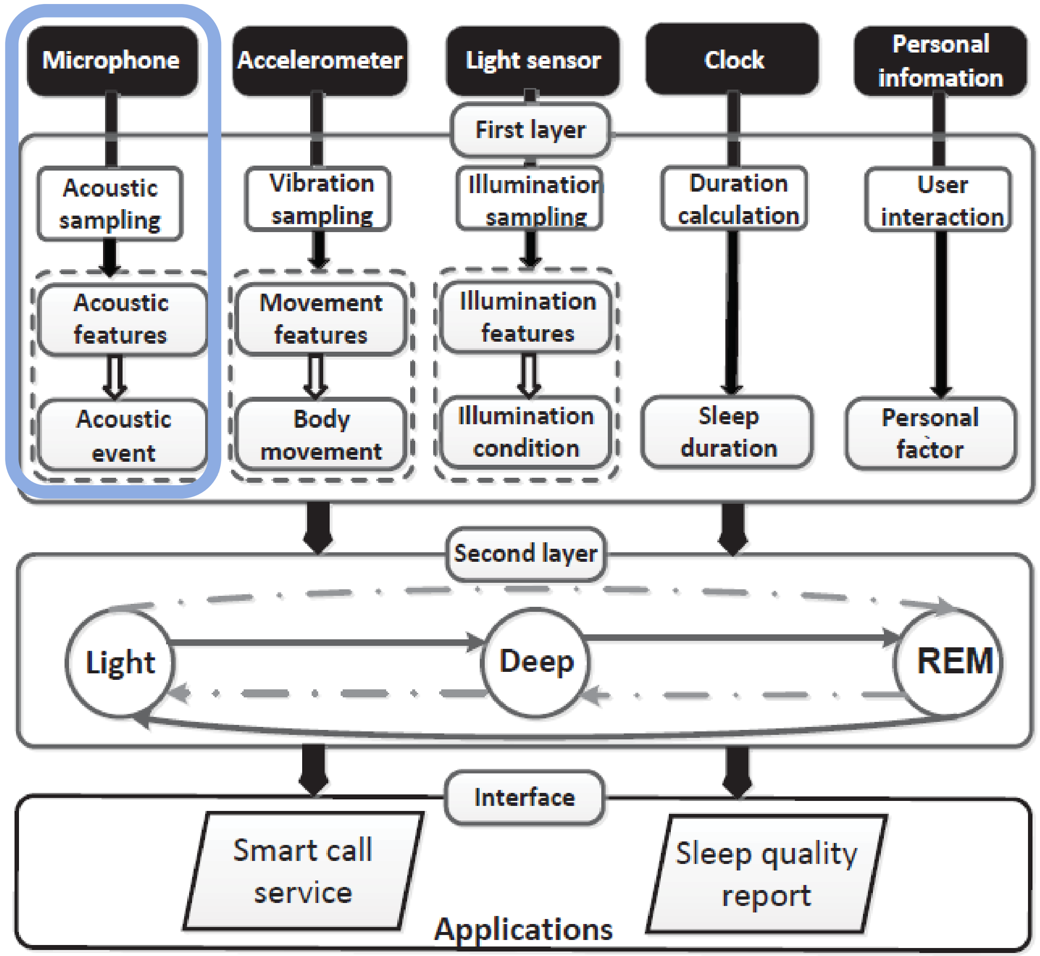
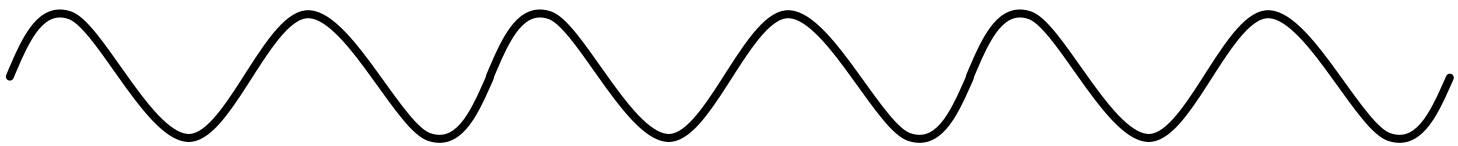


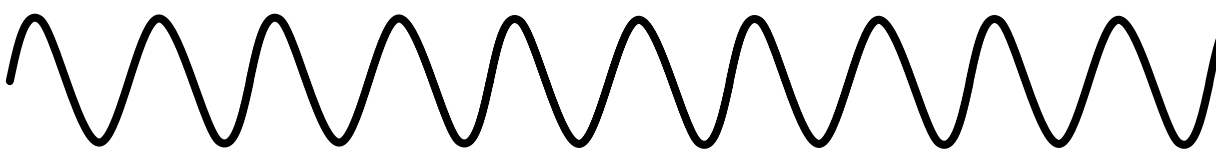
Figure 2. The architecture of Sleep Hunter

Acoustic Event Detection
Common acoustic events

- Normal breathing: 12-20 breaths per minute

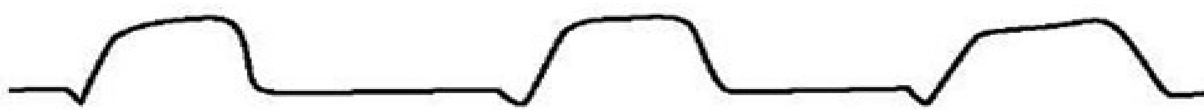


- Rapid (tachypneic) breathing: >20 breaths per minute



Light Sleep

- Abnormal (apneustic) breathing



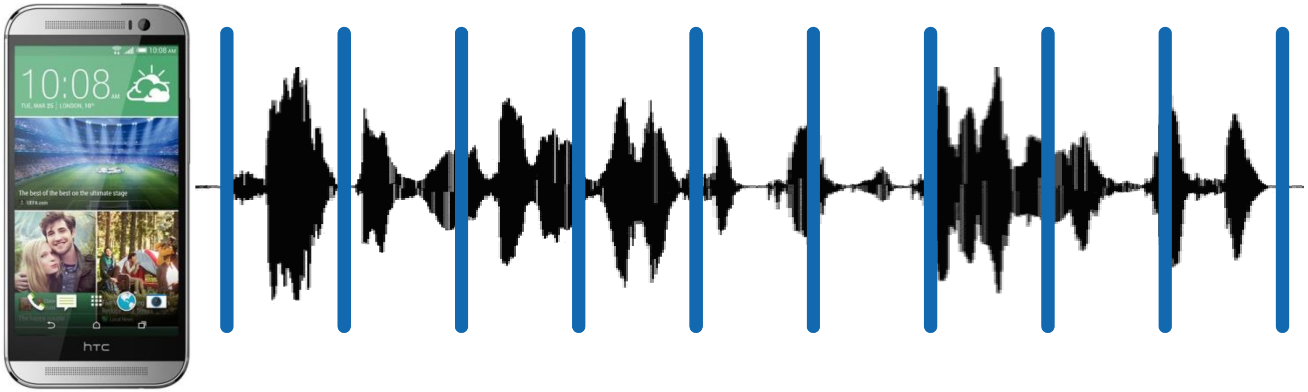
Deep Sleep

- Sleep talking (Somniloquy)

REM Sleep

Acoustic Event Detection
Acoustic Sampling

- Microphone



- Divide audio stream into equally long frames
  - Assign frames to acoustic events
  - Analyze frequency domain of each frame

Acoustic Event Detection
Noise Elimination

Typical acoustic noise	How to detect it
Ambient noise	Root-mean-square (RMS) error $< Th_{rms}$ (see Slide 34) Spectral entropy $> Th_{entropy}$ (see Slide 37)
Body movement	Body movement
Traffic noise	Specific acoustic features (see Slide 41)

Acoustic Event Detection
Root-Mean-Square (RMS)

- RMS over a set of discrete values x_i where $1 \leq i \leq n$

$$x_{rms} = \sqrt{\frac{1}{n}(x_1^2 + x_2^2 + \cdots + x_n^2)}$$

- RMS over a continuous function f(t) over the interval $T_1 \leq t \leq T_2$

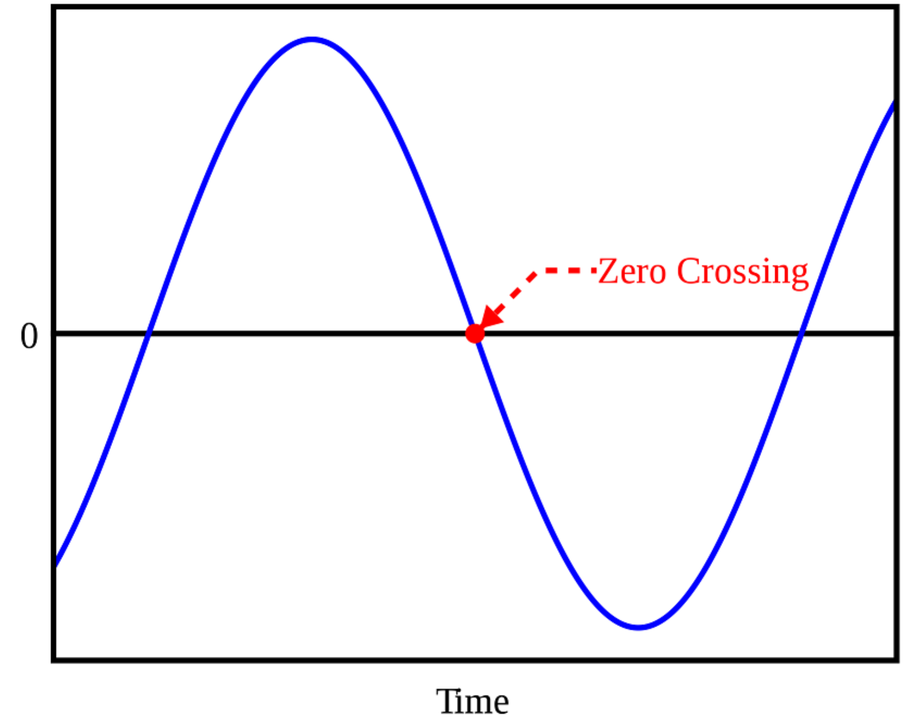
$$f_{rms} = \sqrt{\frac{1}{T_2 - T_1} \int_{T_1}^{T_2} [f(t)]^2 dt}$$

Acoustic Event Detection
Time-domain Feature Selection

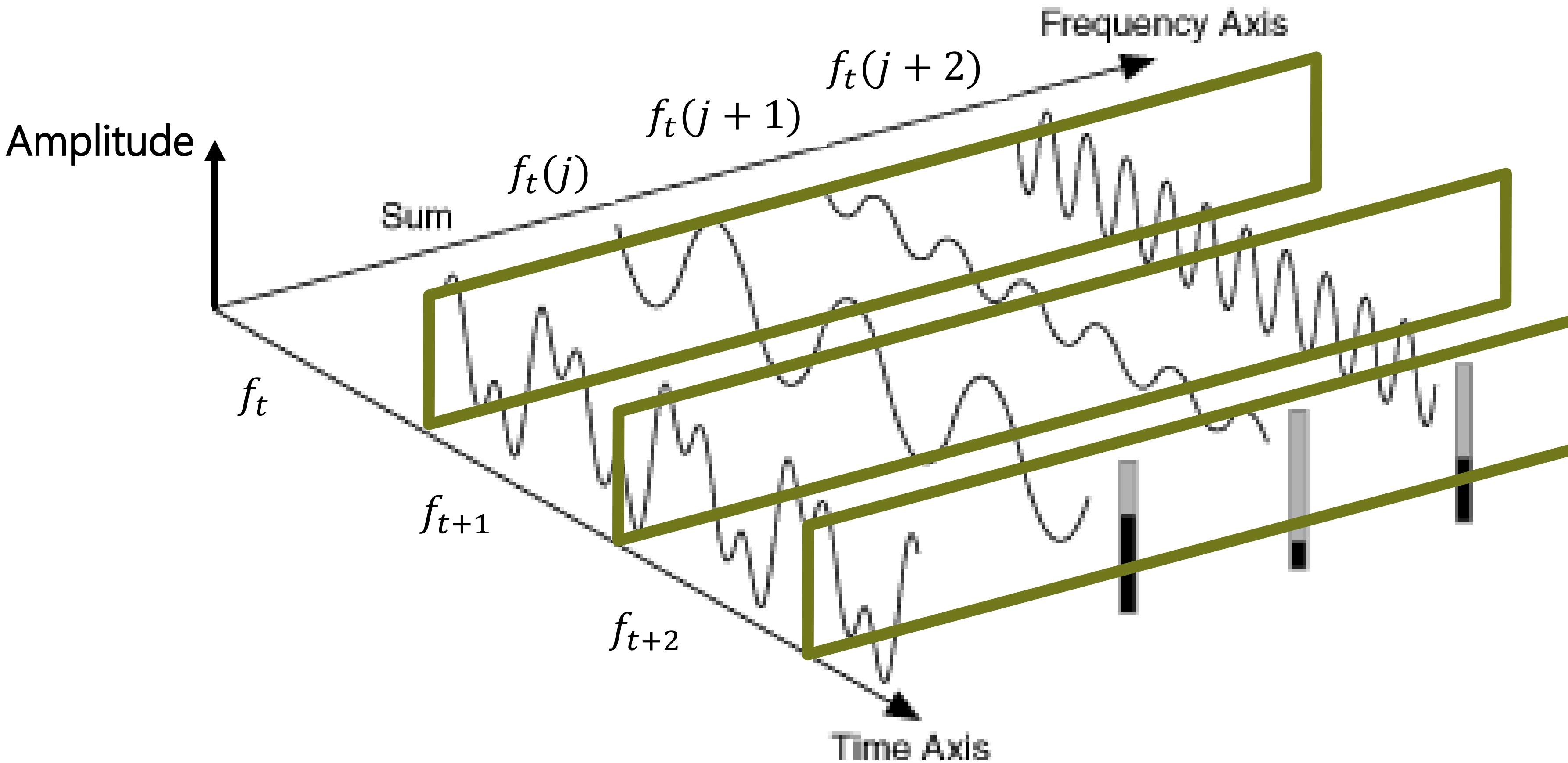
- Zero Crossing Rate (ZCR) (Indicator)

$$\frac{1}{2}\sum_{j=1}^{m}\left|\mathrm{sign}(s_j) - \mathrm{sign}(s_{j-1})\right|$$

$$= \frac{1}{2}(\ldots + 0 + 2 + 0 + \cdots)$$



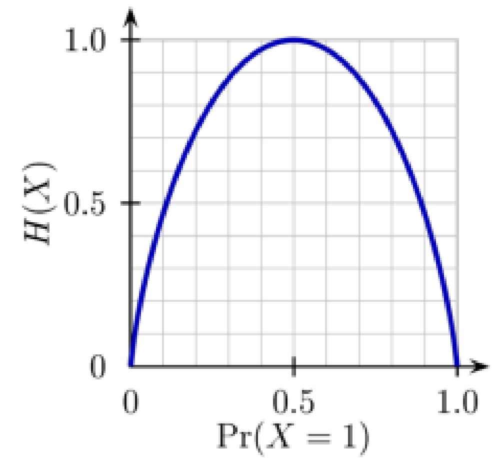
Signal Processing
Time domain and Frequency domain



Acoustic Event Detection
Frequency-domain Feature Selection: Spectral Entropy

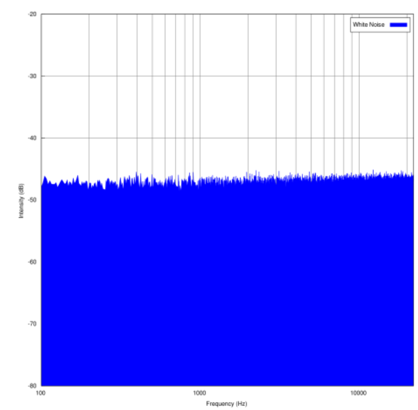
- Entropy of a discrete random variable X with possible values $\{x_1, \dots, x_n\}$ and probability mass function $P(X)$
  - Information of X

$$-\sum_{i} P(x_i) \cdot \log P(x_i)$$



- Spectral entropy of $f_t(j)$ the magnitude of the jth frequency in the spectrum of frame f_t
  - Flatness of the frequency spectrum, noise-likeness

$$-\sum_{j=1}^{N} f_t(j) \cdot \log f_t(j)$$



Acoustic Event Detection
Frequency-domain Feature Selection

- Spectral Centroid
  - Balancing point of the power spectral distribution

$$Cen_t = \frac{\sum_{j=1}^{N} j \cdot |f_t(j)|}{\sum_{j=1}^{N} |f_t(j)|}$$

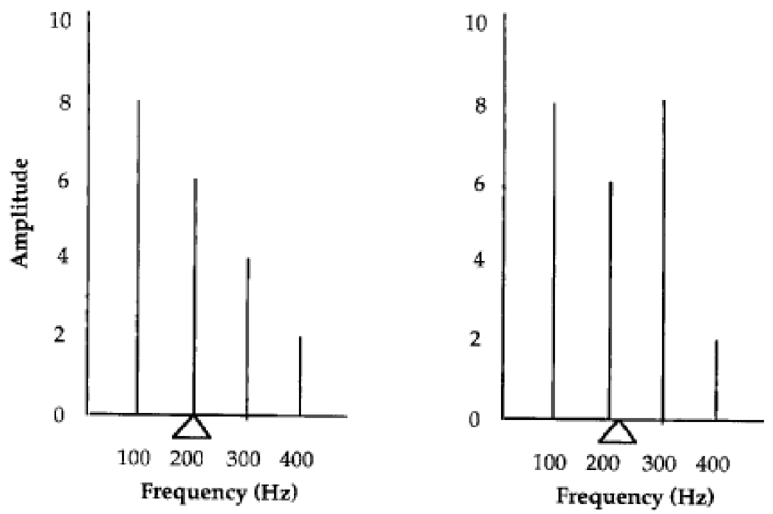


Figure 40. Two spectra with different centroids, the first at 200 Hz., the second at 216.7 Hz.

Example of first centroid:

$$Cen_1 = \frac{100\text{Hz} \cdot 8 + 200\text{Hz} \cdot 6 + 300\text{Hz} \cdot 4 + 400\text{Hz} \cdot 2}{8+6+4+2} = 200\text{Hz}$$

Acoustic Event Detection
Frequency-domain Feature Selection

- Spectral Flux
  - Stability of acoustic events
  - Comparison with previous frame f_{t-1}

$$-\sum_{j=1}^{N}\left(f_t(j) - f_{t-1}(j)\right)^2$$

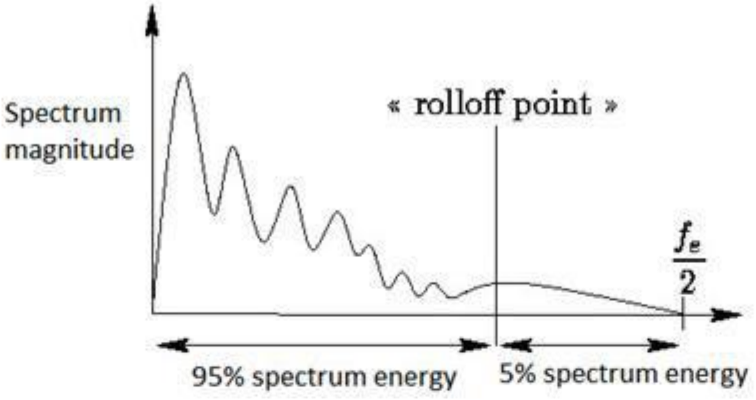
f_t	8	6	4	6	4	6	4	2
f_{t-1}	8	6	4	**4**	4	**8**	4	2

$$= -(\ldots + (6-4)^2 + (4-4)^2 + (6-8)^2 + \cdots)$$
$$= -8$$

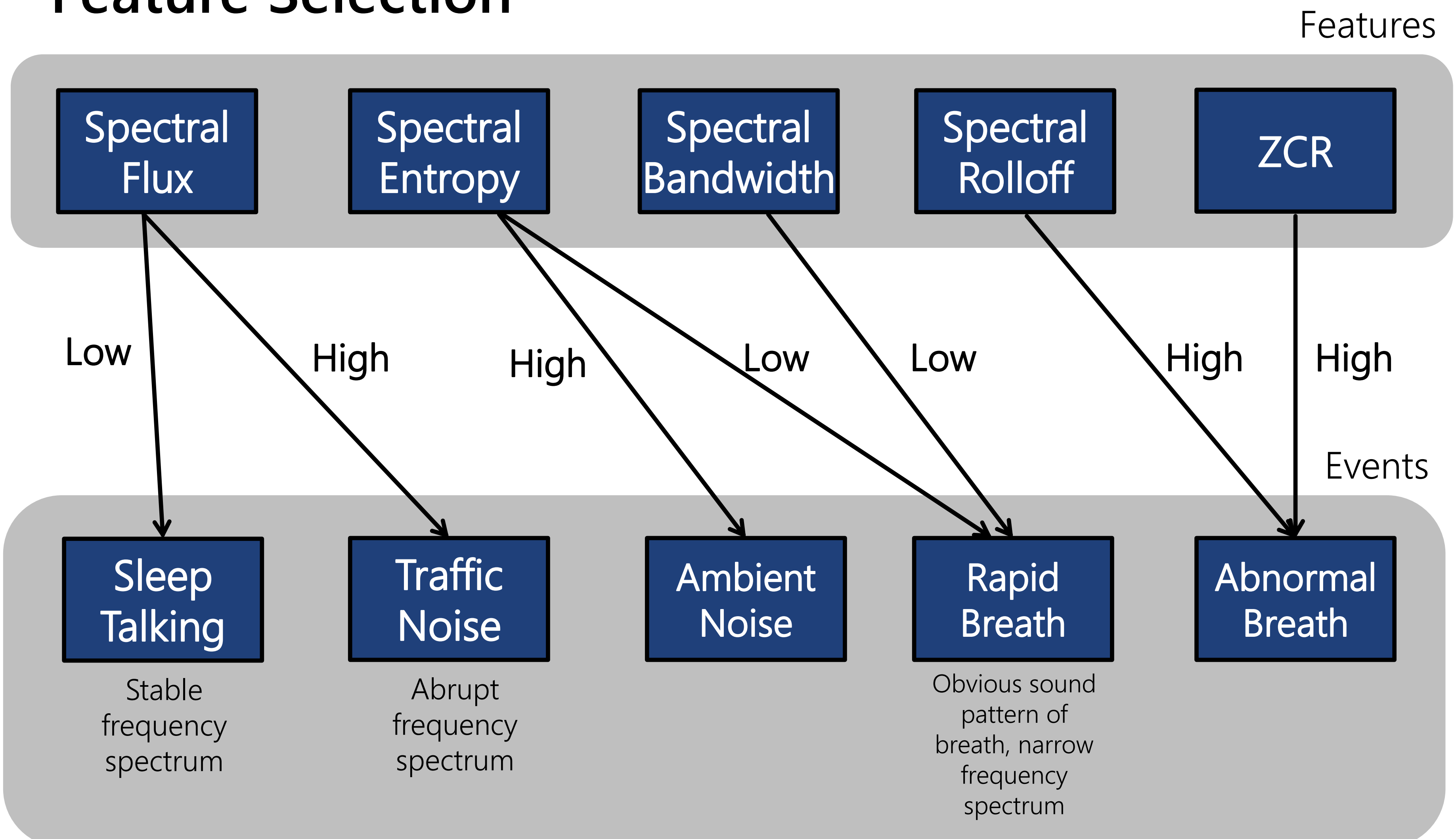
Acoustic Event Detection
Frequency-domain Feature Selection

- Bandwidth
  - Highest frequency minus lowest frequency
- Spectral Rolloff
  - Indicates the percentage frequency bin below a predefined threshold, which is usually set to be 95%
  - Reflects the skewness of the spectral distribution

$$\max\left(h \,\middle|\, \sum_{j=1}^{h} f_t(j) < threshold \right)$$



Acoustic Event Detection
Feature Selection



Sleep Hunter

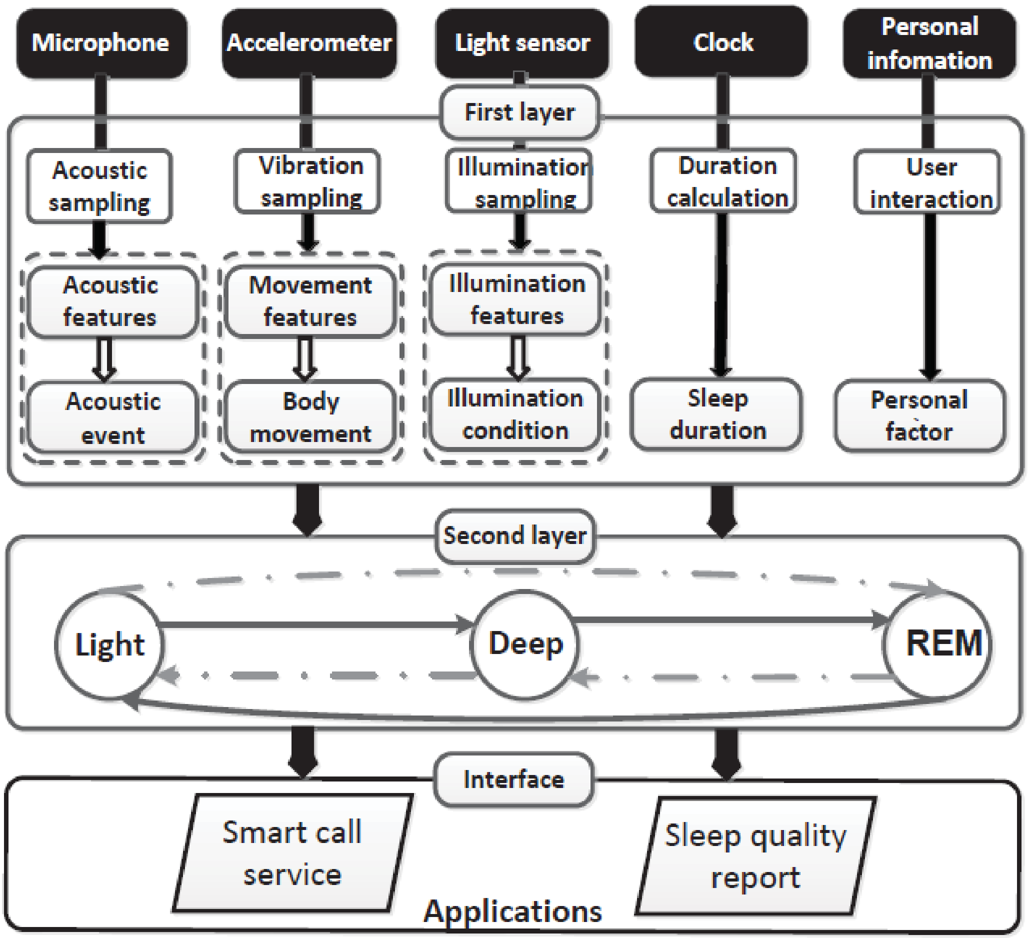
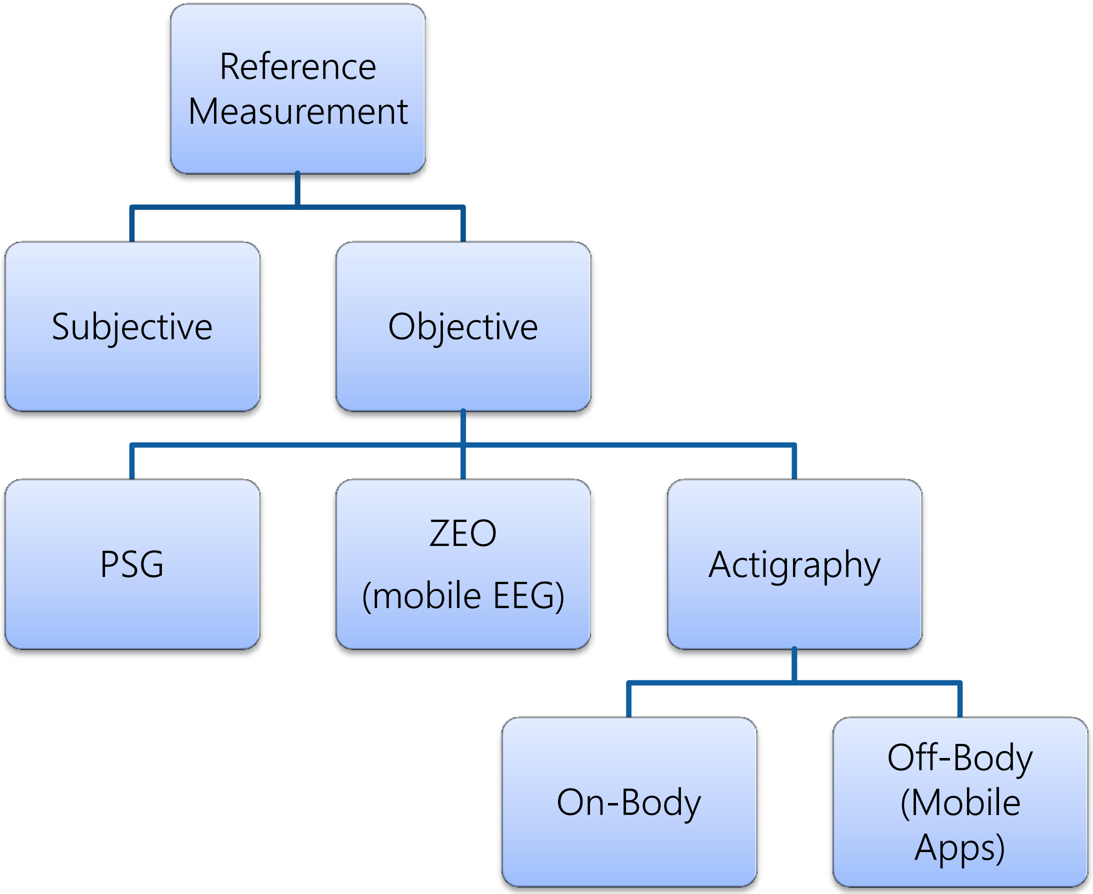


Figure 2. The architecture of Sleep Hunter

Source: Weixi Gu et al. 2014 Intelligent Sleep Stage Mining Service with Smartphones

Reference Model



Performance Analysis
Datasets

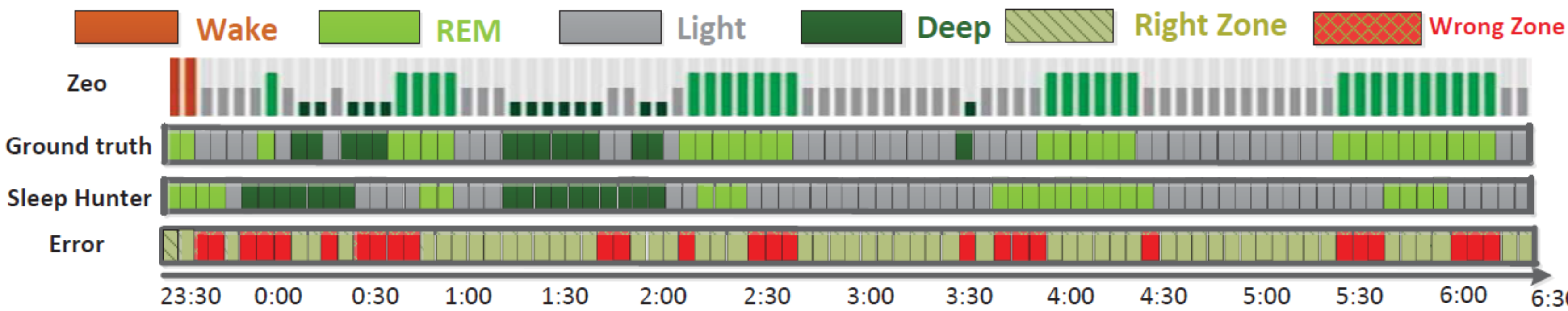


Figure 12. Sleep stage tracking of one user during a night

Source: Weixi Gu et al. 2014 Intelligent Sleep Stage Mining Service with Smartphonesy

Performance Analysis
Confusion Matrix

Ground Truth	Predictions: REM	Predictions: Light Sleep	Predictions: Deep Sleep	Recall
REM	538	206	39	68.71%
Light Sleep	246	630	77	66.11%
Deep Sleep	61	108	174	50.73%
Precision	63.67%	66.74%	60.00%	Accuracy: 64.55%

Recall: $\text{TPR}_\text{i} = \frac{\text{TP}_\text{i}}{\text{P}_\text{i}}$ E.g. $\text{TPR}_{\text{REM}} = \frac{538}{538+206+39} = .687$

Precision: $\text{PPV}_\text{i} = \frac{\text{TP}_\text{i}}{\text{TP}_\text{i}+\text{FP}_\text{i}}$ E.g. $\text{PPV}_{\text{REM}} = \frac{538}{538+246+61} = .6367$

Accuracy: $\text{ACC} = \frac{\text{TP}+\text{TN}}{\text{P}+\text{N}} = \frac{538+630+174}{538+206+39+246+630+77+61+108+174} = .6455$

Source: Weixi Gu et al. 2014 Intelligent Sleep Stage Mining Service with Smartphonesy

Performance Analysis
Comparison to other Actigraphs

Device \ Stage	Light Sleep		Deep Sleep	
	Precision	Recall	Precision	Recall
Sleep Hunter	66.74%	66.11%	60.00%	50.73%
Jawbone UP	37.74%	65.14%	34.62%	29.03%
Sleep As Android	25.71%	32.14%	36.36%	49.61%

Figure 13. Performance comparison

	REM		Light Sleep		Deep Sleep	
Features	Precision	Recall	Precision	Recall	Precision	Recall
BM	39.62%	34.91%	37.84%	47.11%	30.12%	28.27%
BM+AE	45.41%	39.67%	47.83%	49.31%	38.34%	33.27%
BM+AE+IC	46.13%	41.81%	49.10%	52.27%	42.91%	35.84%
BM+AE+IC+SD	60.89%	67.99%	63.36%	59.15%	57.96%	46.53%
BM+AE+IC+SD+PF	63.67%	68.71%	66.74%	66.11%	60.00%	50.73%

Table 3. Evaluation of sleep-related features

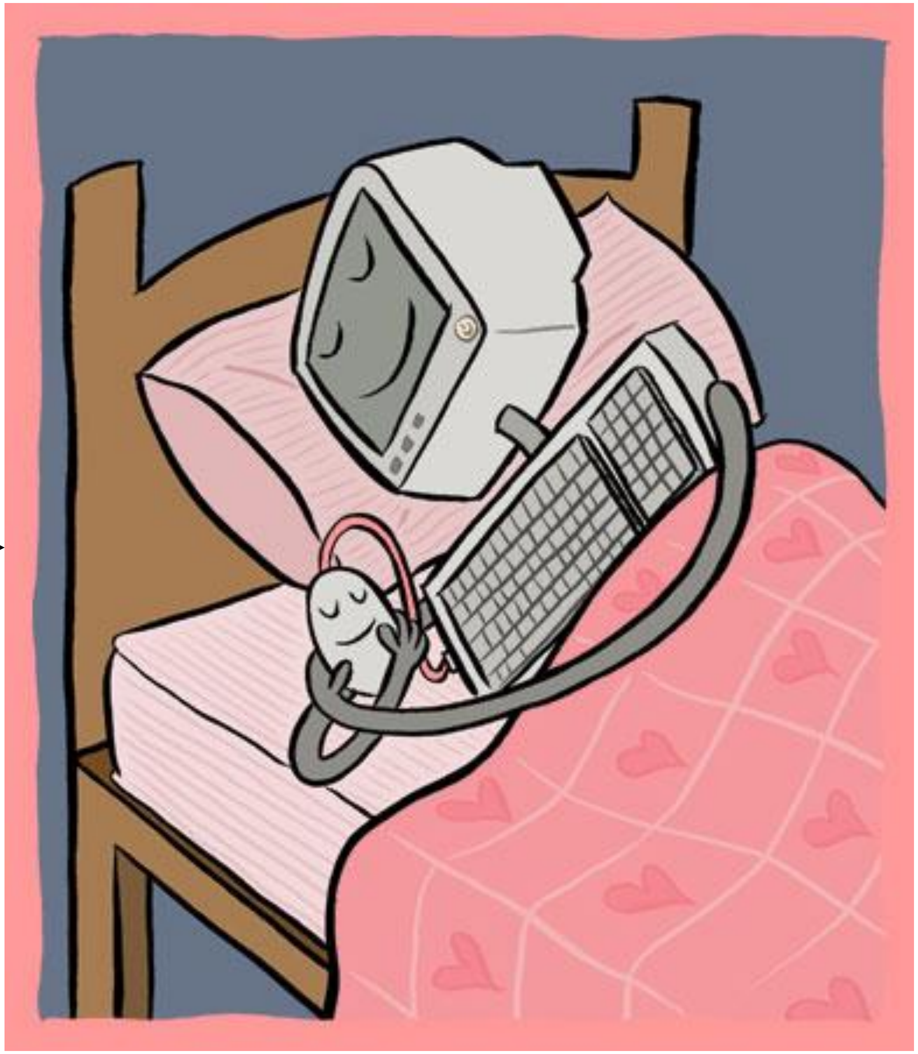
Source: Weixi Gu et al. 2014 Intelligent Sleep Stage Mining Service with Smartphones

Conclusion

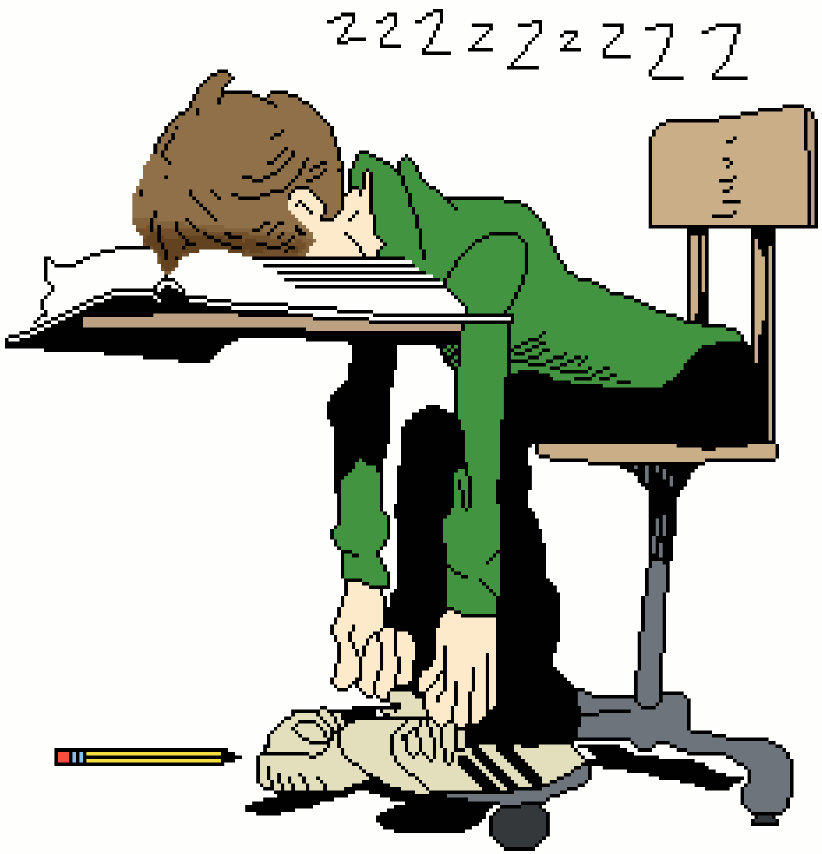
Advances in Sensor Technology

+

Advances in Machine Learning



Q&A



[clipartpal.com]