Sleep State Prediction Using Accelerometry Data

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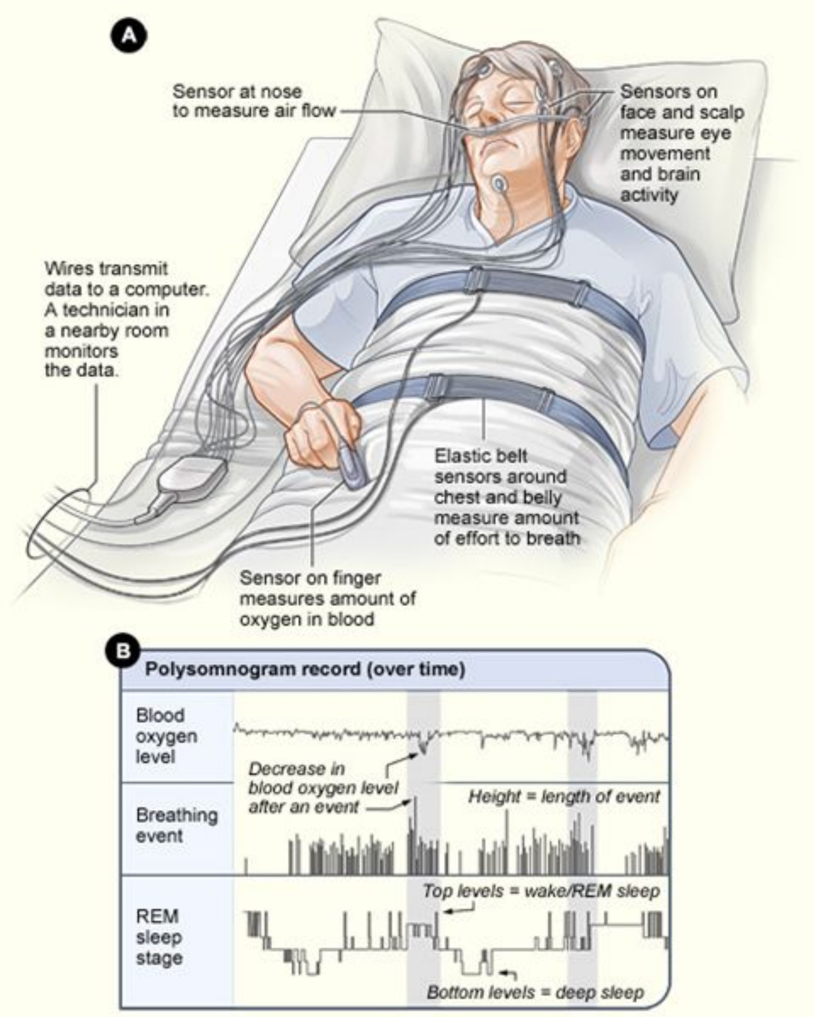
Introduction

Sleep is a fundamental complex biological process composed of several distinct states which interruptions or unbalanced on this process may come with important physical and mental health issues, affecting millions worldwide and are linked to chronic diseases.

How does it study sleep?

- Traditionally sleep had been studied and monitored using **Polysomnography** (PSG) a technology that captures the following detailed physiological signals:
- EOG (Eye movements)
- EMG (Muscle tone)
- ECG (Heart rate)
- EEG (Brain activity)

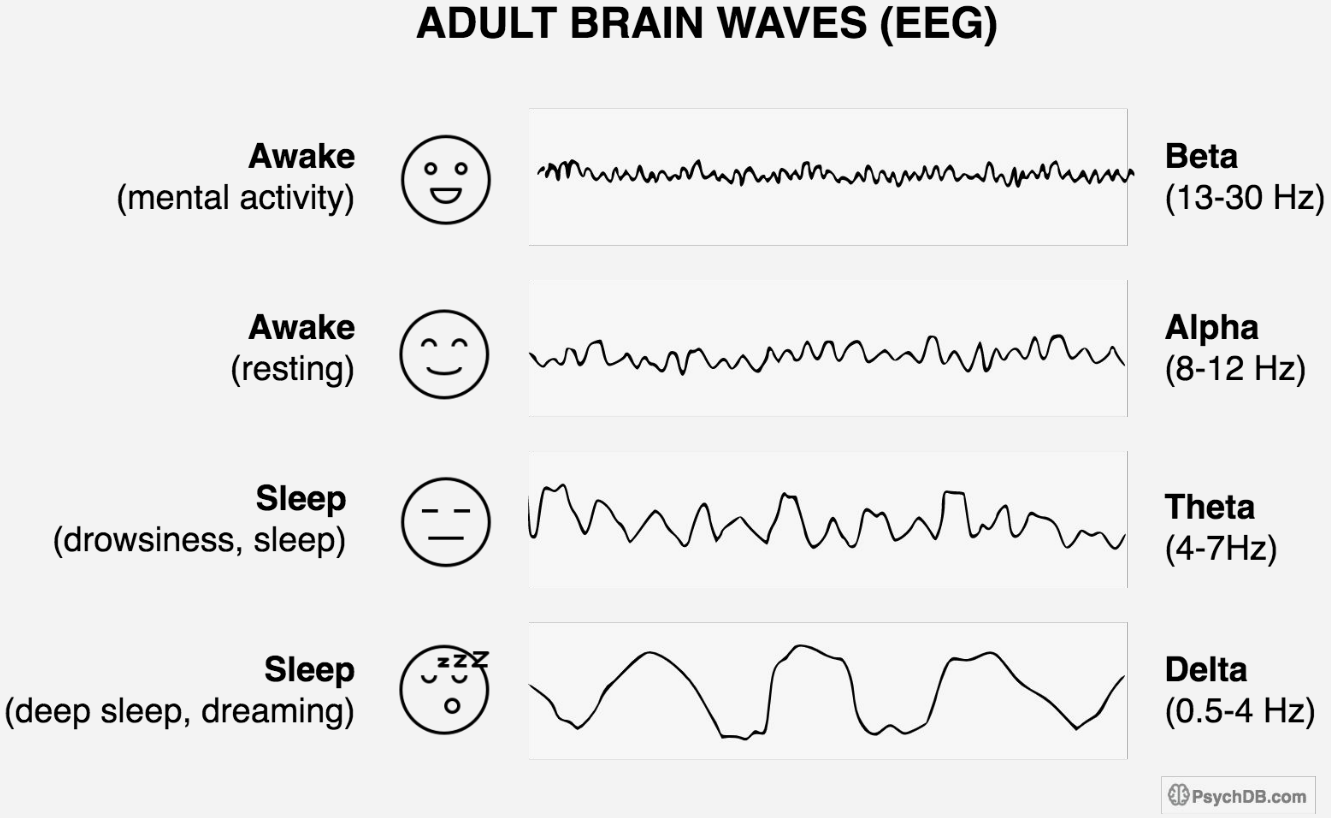


Sleep States

Stage	EEG Characteristics	EOG	EMG
Wake (W)	Alpha rhythm (8-13 Hz) when eyes closed; Low-voltage, mixed-frequency activity when eyes open	Rapid eye movements	High tone
N1	Low-voltage, mixed-frequency (4-7 Hz); Vertex sharp waves; Alpha replaced by theta	Slow rolling eye movements	Moderate tone
N2	Sleep spindles (12-14 Hz bursts); K-complexes; Background theta activitv	Minimal eye movements	Moderate tone
N3	Slow wave activity; High-amplitude (>75 µV) delta waves (0.5-2 Hz) in >20% of epoch	Minimal eye movements	Moderate to low tone
REM	Low-voltage, mixed frequency; Saw tooth waves; EEG desynchronization similar to wakefulness	Rapid eye movements	Lowest tone; Atonia

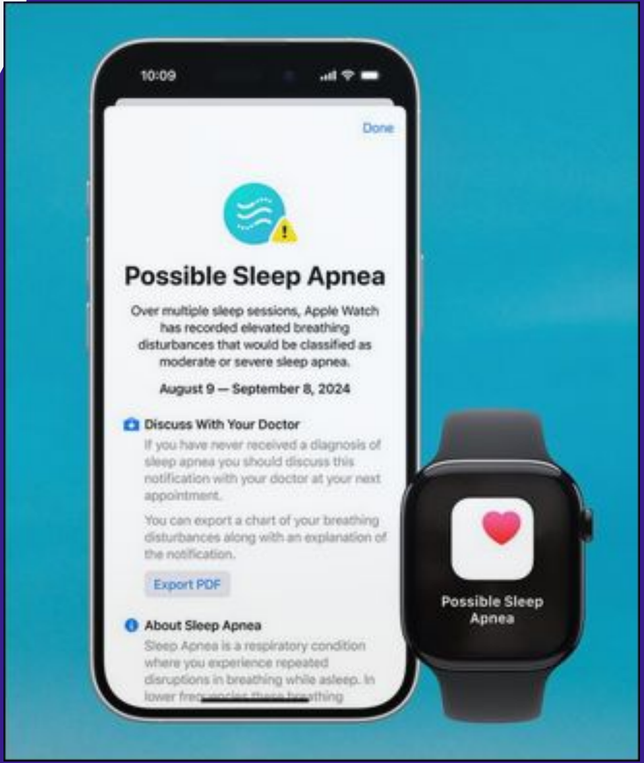
SLEEP STAGE CLASSIFICATION ACCORDING TO AASM GUIDELINES

Example of Sleep state patterns

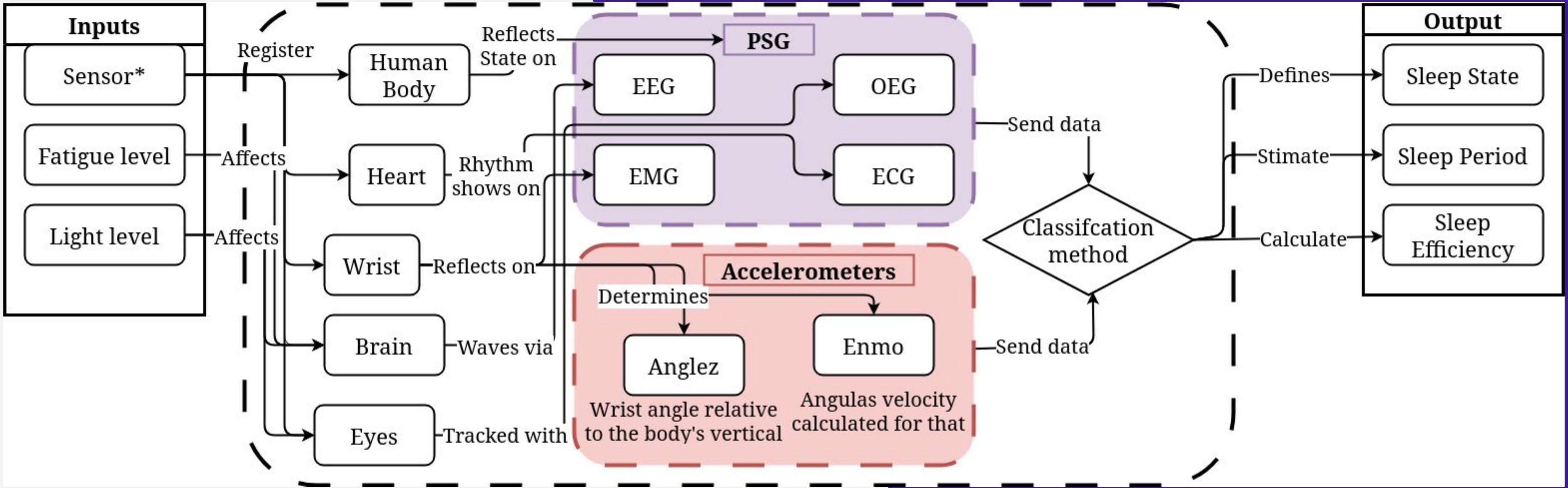


How does it study sleep?

- Recent advances in wearable technology have enabled the use of accelerometers as a **non-invasive, low-cost alternative** for sleep state prediction. These sensors, embedded in consumer devices like smartwatches and fitness trackers, measure body movement to infer sleep and wake state, following the next variables:
- Anglez : Wrist angle relative to body’s vertical
- ENMO : Angular velocity



Systematic approach



Which models can be applied?

- **Threshold-based algorithms**: These use simple rules based on movement intensity to distinguish sleep from wake. For example, the Sadeh and Cole-Kripke algorithms are widely used in actigraphy-based sleep scoring.
- **Machine learning models**: Supervised classifiers such as random forests, support vector machines, and logistic regression are trained on labeled data to improve classification accuracy.
- **Deep learning:** Recurrent neural networks (RNNs), convolutional neural networks (CNNs), and hybrid models are increasingly used to capture temporal dependencies and complex patterns in accelerometry data

Processing data pipeline

Data Acquisition

Raw signals Detected

Data Processing

Produce a clean and organized dataset

Feature Extraction

Events are tagged and sorted to prepare for classification.

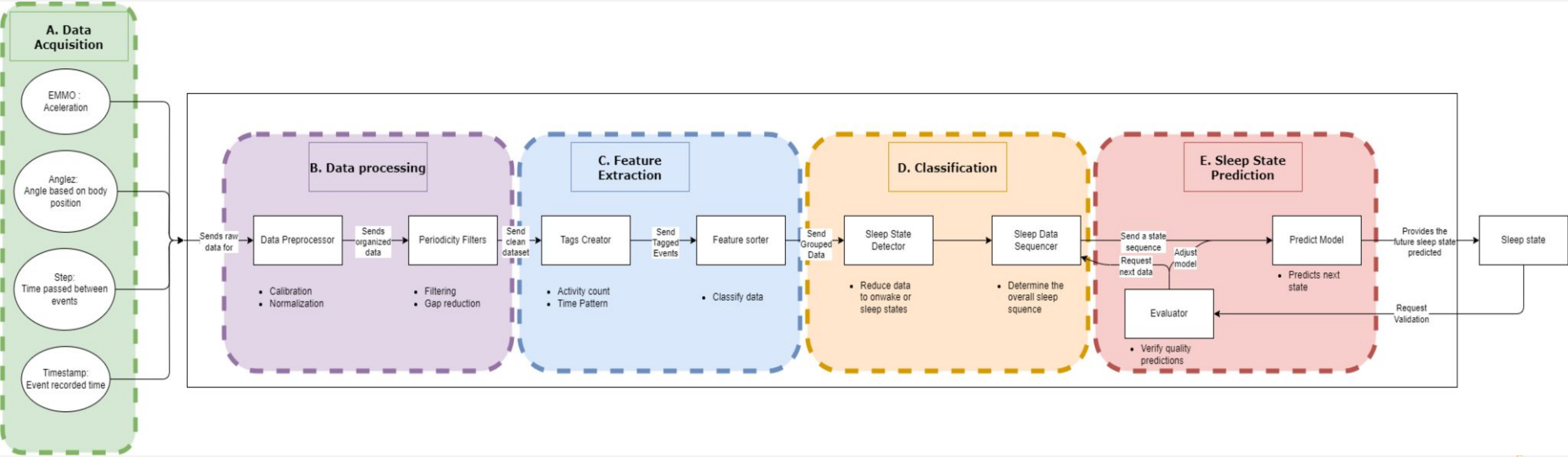
Classification

Reduces data to a binary set and determines the sleep sequence

Prediction

A predictive model estimates the next sleep state based on the sequence

Computational Data flow



Results

Parameter	Polysomnography (PSG)	Accelerometry
Data Acquisition	Multiple physiological signals: EEG, EOG, EMG, ECG, respiratory sensors	Single sensor: 3-axis accelerometer measuring movement intensity
Signal Processing	Channel-specific filtering, artifact removal (blinking, movement), signal synchronization	Low-pass filtering, noise removal, signal normalization, missing data handling
Feature Extraction	Spectral power bands, eye movement patterns, muscle tone measurements, cardiorespiratory features	Activity counts, movement variability, zero-crossing frequency, temporal patterns
Classification Method	AASM scoring manual, 30-second epochs, expert human scoring, rule-based classification	Threshold-based algorithms, machine learning models, deep learning (LSTM, CNN)
Sleep States Detected	Wake (W), N1 (light sleep), N2 (intermediate), N3 (deep sleep), REM sleep	Wake, Sleep (sometimes divided into light and deep sleep)
Performance Metrics	Inter-scorer reliability, gold standard accuracy, comprehensive sleep architecture	Accuracy (82-93%), Sensitivity (87-95%), Specificity (50-83%), Cohen's kappa (0.55-0.80)
Limitations	Expensive equipment, laboratory environment, invasive sensors, limited monitoring duration	Limited sleep stage discrimination, poor detection of wake periods, transition period inaccuracies

Conclusions

Performance

Accelerometers measures present a **low-cost and non-invasive alternative** with consistent accurate reported sensitivity values of **91-93 %**

Limitation

Accelerometry alone **cannot distinguish between all sleep stages** (e.g., REM vs. non-REM) with high accuracy, and it may misclassify periods of quiet wakefulness as sleep.

Scope

Accelerometry is a valuable tool for **population studies and personal health monitoring**, especially when com-bined with advanced computational models and contextual information

Thanks

Do you have any questions?

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