Sleep State Prediction Using Accelerometry Data

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Introduction

How does it study sleep?

- 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.
- Traditionally sleep had been studied using Polysomnography (PSG) a technology that captures detailed physiological signals. However, **PSG requires specialized facilities, trained technicians, and sophisticated instrumentation**.
- 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:

Sleep System Approach

Sleep system approach

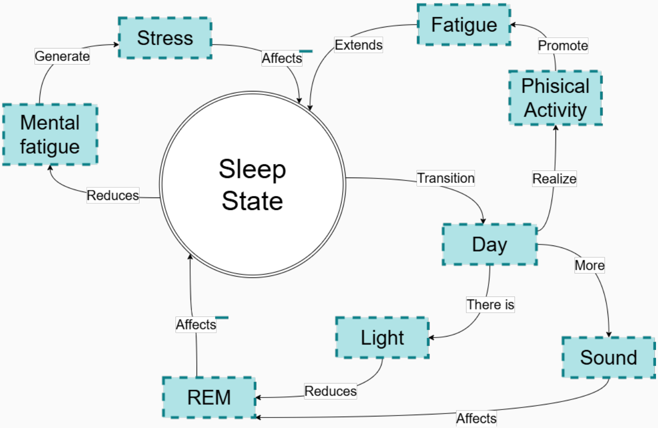


Figure 1: Sleep system diagram

Sleep system approach

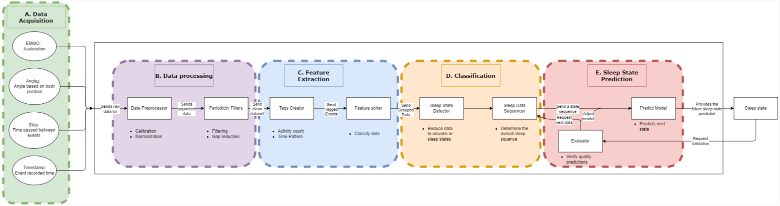


Figure 2: Architecture diagram

Sleep system approach: Data Extraction

- ENMO: Euclidean Norm Minus One, a measure of physical activity.
- Anglez: Angle of the wrist, which can indicate the position of the wrist.
- Step: step identifier.
- Timestamp: Measurement time. ENMO and Anglez are normalized

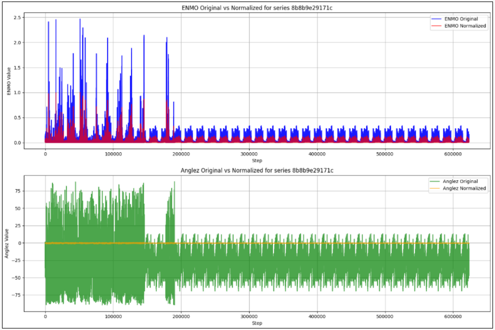
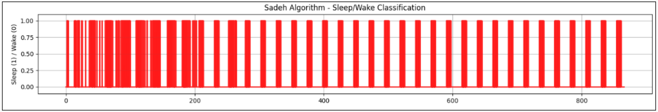
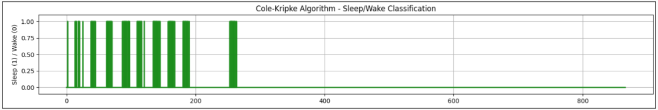


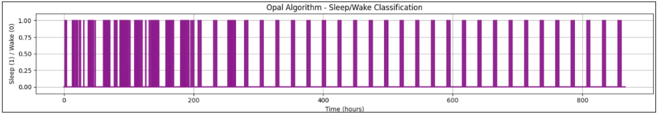
Figure 3: Data normalized

Sleep system approach: Data Transformation

- Sadeh algorithm Activity-based sleep-wake identification: an empirical test of methodological issues
- Cole-Kripke Algorithm automatic sleep/wake identification from wrist activity
- OPAL Algorithm for sleep/wake classification using activity and posture. This version uses a logistic regression-inspired approach to combine features

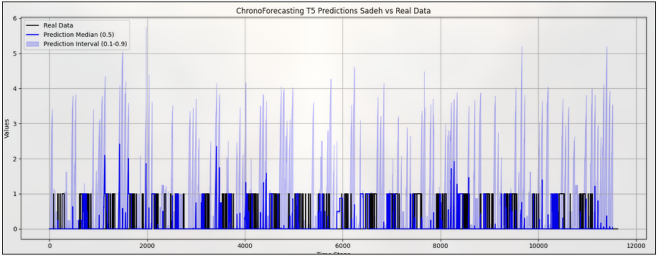




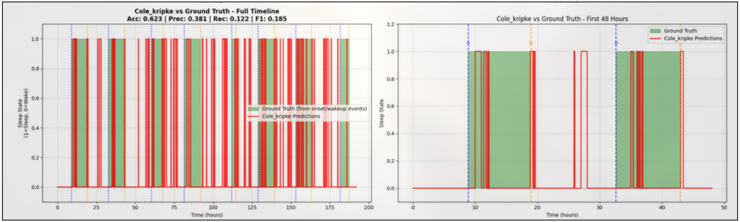


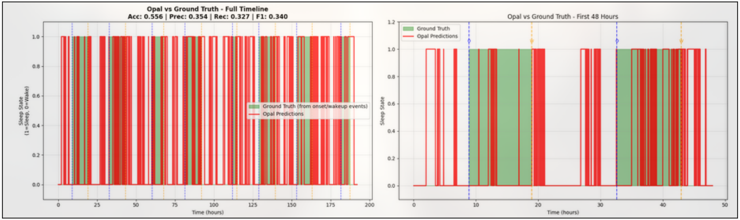
Sleep system approach: Data Consumers

- The data from every algorithm is divided by 180 in order to get 15 minutes intervals to, which 10 minutes are used to train the model and 5 minutes to predice and comparate to analyze the model precision.



Quality metrics





Results

Algorithm Performance Comparison - Code Execution Example

- This example demonstrates the actual performance metrics obtained from our compiled code implementation
- Performance evaluation is based on ground truth comparison from sleep event annotations

Algorithm	Accuracy	Precision	Recall	F1-Score
Sadeh	0.7040	0.1579	0.1390	0.1479
Cole-Kripke	0.7043	0.1784	0.1667	0.1723
OPAL	**0.5902**	**0.2105**	**0.4429**	**0.2853**

- **Best performing algorithm: OPAL (F1-Score: 0.2853)**
- OPAL demonstrates superior balance between precision and recall
- Higher recall indicates better sleep event detection capability

OPAL Algorithm - Detailed Event Analysis

Real-time Event Detection Performance (Code Execution Sample):

Event	Step	Epoch	Predicted	Ground Truth	Expected	Match
onset	25548	2129	1	1	1	✓
wakeup	31932	2661	1	1	0	×
onset	43488	3624	1	1	1	✓
wakeup	49224	4102	1	1	0	×
onset	59580	4965	0	1	1	×
wakeup	67272	5606	0	1	0	✓
onset	77640	6470	1	1	1	✓
wakeup	83844	6987	0	1	0	✓

- **Event Detection Rate:** 62.5% correct predictions (5/8 events)
- **Sleep Onset Detection:** 75% accuracy (3/4 onsets correctly detected)
- **Wake Detection:** 50% accuracy (2/4 wakeups correctly detected)
- This demonstrates the algorithm's preference for sleep state detection over wake transitions

Implementation Notes

- **Important:** These results represent a specific execution example of our compiled code
- The performance metrics may vary depending on the dataset and individual sleep patterns
- This example illustrates the methodology rather than following the sequential diagram flow
- OPAL's superior F1-score indicates better overall balance for clinical applications requiring sleep event detection
- The modular architecture allows for independent algorithm optimization and real-time performance evaluation

Conclusions

Conclusions

- The system is linear and deterministic, with modular components depending on the correct functioning of previous stages and a feedback loop that reinitializes processing to resolve errors and enhance reliability.
- A built-in validation module ensures error tolerance by detecting anomalies and reprocessing data from the point of failure to maintain result integrity.
- A data filtering mechanism restricts invalid or irrelevant input under certain conditions to ensure only valid data is processed.

Conclusions

- The architecture follows a modular and structured pipeline: raw data is processed (normalization, filtering, smoothing), features are extracted, and relevant data is sent to a deep learning model for event detection.
- Detected events go through validation and are then formatted and exported; this modular flow supports scalability, reuse, and adaptability to changing data or models.
- Components can be tested and upgraded independently, improving system robustness, fault tolerance, and resilience to data variability and randomness.
- Limitations include sensitivity to chaotic inputs (e.g., sleep disturbances from medication), environmental randomness, and sensor failures, requiring continuous adaptation and relying on advanced validation and pre-trained LLMs to reduce false outcomes.