Sleep State Prediction Using Accelerometry Data: A Systematic and Computational Approach

Juan Carlos Quintero Rubiano, Juan Felipe Wilche Gomez, Juan Nicolas Diaz Salamanca
jcquinteror@udistrital.edu.co, jfwilchesg@udistrital.edu.co, jndiazs@udistrital.edu.co
UNIVERSIDAD DISTRITAL FRANCISCO JOSÉ DE CALDAS

Introduction

Sleep disorders affect a significant portion of the population, manifesting as disruptions to normal sleep patterns. Accurate identification of sleep states is crucial for diagnosing these disorders and evaluating treatment efficacy. Traditionally, sleep monitoring relies on polysomnography (PSG) however due to cost and specialized laboratories, accelerometers is shown as a low-cost alternative for sleep state prediction, this paper addresses the central question: How can accelerometer data be used to accurately predict sleep state.

Input data analyzed

Wrist movement: Intensity and temporal patterns of movement, as measured by the accelerometer.
Movement speed: Changes in velocity over time, derived from the raw acceleration data.
Timestamp: Mark the exactly time which the data was recorded, useful to identify between data.
No environmental or physiological data are available in this analysis.

Models

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 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), con- volutional neural networks (CNNs), and hybrid models are increasingly used to capture temporal dependencies and complex patterns in accelerometry data.

Conclusion

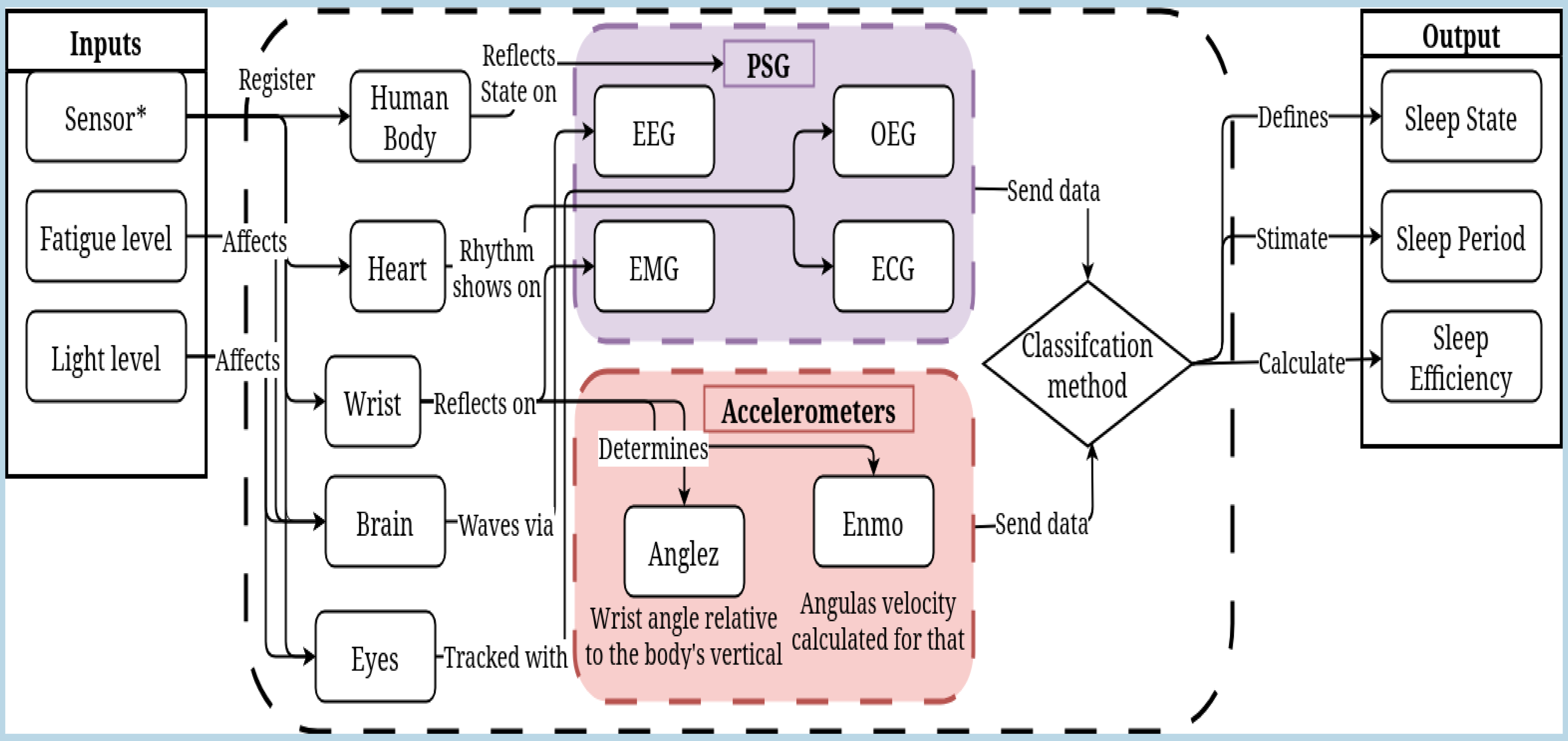
Accelerometers measures present a low-cost and non-invasive alternative with consistent accurate reported sensitivity values of 91-93 percent for actigraphy compared to PSG and advanced machine learning techniques, particularly sequence models like LSTMs, achieve the best accuracy in binary sleep/wake classification. However, several limitations over distinguish between all sleep stages (e.g., REM vs. non-REM) with high accuracy, and it may misclassified periods of quiet wakefulness as sleep. Also the absence of environmental and physiological data constrains the precision of accelerometry based model.

Sleep state systematic approach

Sleep stages are divided by biophysiological changes during sleep on the parameters: **EEG (Brain activity)**, **EOG (Eye movements)**, **EMG (Muscle tone)**, **ECG (Heart rate)**. According to American Academy of Sleep Medicine (AASM) guidelines, these measurements allow classification of sleep into five distinct stages (Wake, N1, N2, N3, and REM):

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 activity	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 STAGES MEASUREMENTS SYSTEM DIAGRAM



Sleep state computational approach

The computational model processes raw accelerometry data to extract features such as:
•Activity counts: The sum of absolute acceleration changes over fixed time epochs (typically 30-second or 1-minute windows), providing a measure of overall movement intensity.
• Movement variability: Standard deviation and entropy of accelerometer signals, which can distinguish between different sleep states.
• Frequency-domain features: Spectral power in different frequency bands, extracted using Fourier transforms, capturing rhythmic movements characteristic of different sleep states.
• Temporal patterns: Sequences of activity/inactivity, du- rations of inactive periods, and transitions between active and inactive states.
These features are input to classify each time segment as sleep or wake period.