# Applying Kalman Filtering to Model Circadian Rhythms: A Novel Approach to Analyzing Wearable Sensor Data

Asya Akkus[1], Siddharth Khadkikar[1], Ashley Sah[1], Ritika Devarakonda[1], Maisoon Rahman[1], & Noah Henriques[1]

[1]Department of Computer and Data Sciences, Case Western Reserve University, Cleveland, Ohio 41106

## Abstract

## Introduction

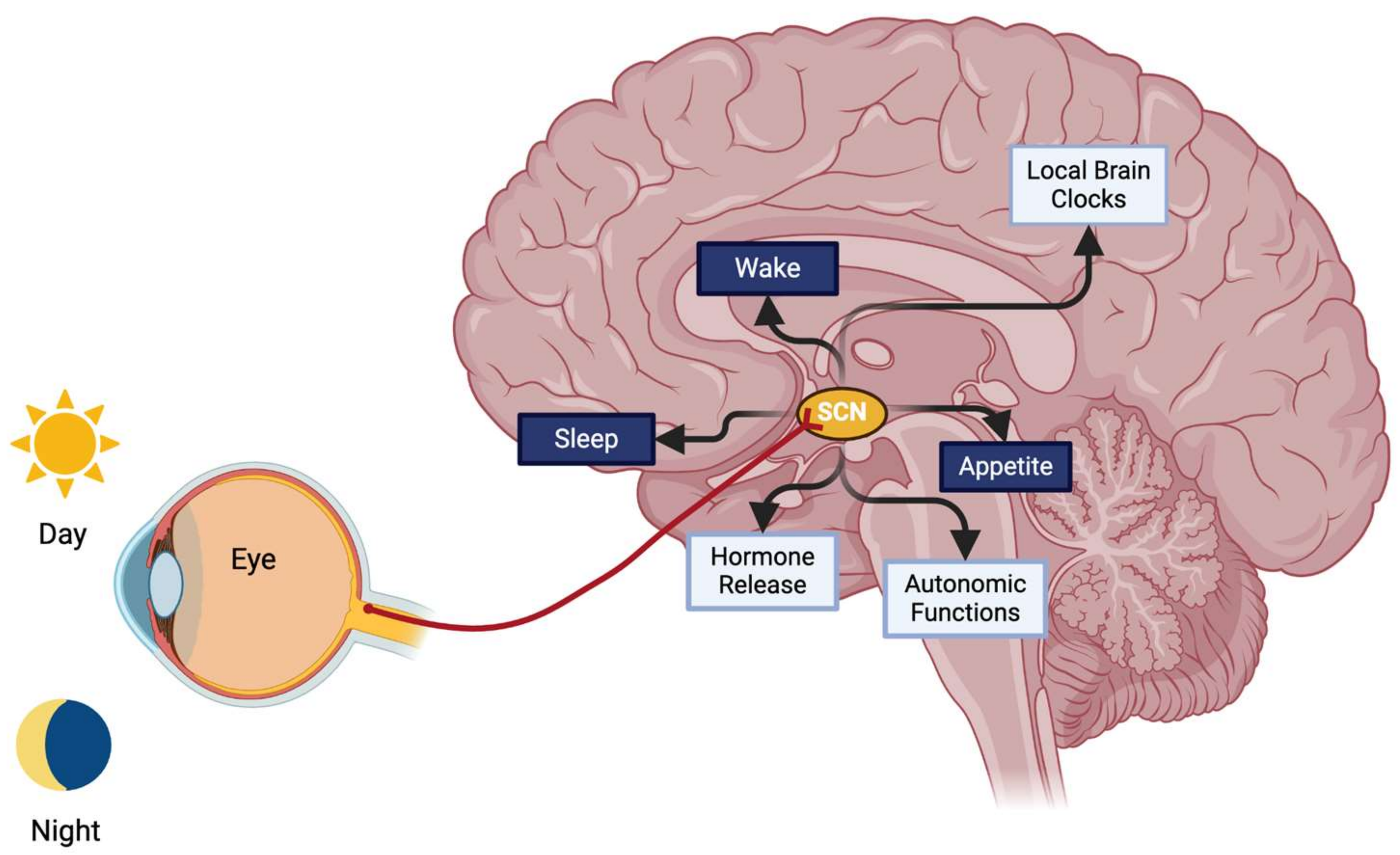


**Fig 1. The suprachiasmatic nucleus (SCN), located in the hypothalamus, functions as the master circadian pacemaker, orchestrating the timing of biological processes throughout the body.** It synchronizes local clocks in various brain regions and peripheral tissues to ensure alignment of physiological and behavioral rhythms, such as sleep-wake cycles, hormone release, appetite regulation, and autonomic nervous system activity.

## Kalman Equations

Kalman filtering is an algorithm that estimates the state of a dynamic system by combining noisy measurements with predictions from a mathematical model to produce an optimal estimate. Kalman filtering relies on the following mathematical equations to predict a system's state:

State transition equation and measurement equation:

$$x_k = A_k x_{k-1} + Bu_k + n_k$$

$$z_k = Hx_k + v_k$$

A = state transition matrix
$B_{uk}$= set controls
$n_k$= process noise
H = measurement matrix
$v_k$= measurement noise

Step-Update Equations:

$$\hat{x}_k = Ax_{k-1}$$

$$P_k^{pr} = AP_{k-1}A^T + Q$$

A = state transition matrix
$x_k$= the next steps
$p^{pr}_k$= covariance in error of the state estimate
Q = matrix accounting for additional uncertainty

Measurement Update Equations:

$$K_k = P_k^{pr} H^T \left(HP_k^{pr} H^T + R\right)^{-1}$$

$$\hat{x}_k = \hat{x}_k^{pr} + K_k\left(z_k - H\hat{x}_k^{pr}\right)$$

$$P_k = \left(I - K_k H_k\right)P_k^{pr}$$

H = matrix relating the state to predicted measurements
R = measurement error
K = Kalman gain

## Materials & Methods

### Dataset Creation and Literature Review:

- Parsed XML Apple Watch Data from subject into CSVs.
- Read literature on Kalman filtering applications and modeling circadian rhythms.

### Kalman Filtering:

- Conducted initial data processing and interpolation.
- Initialized matrices based on literature review.
- Tuned state covariance matrices, state-transition matrices, process noise covariance matrices, and measurement noise covariance matrices.

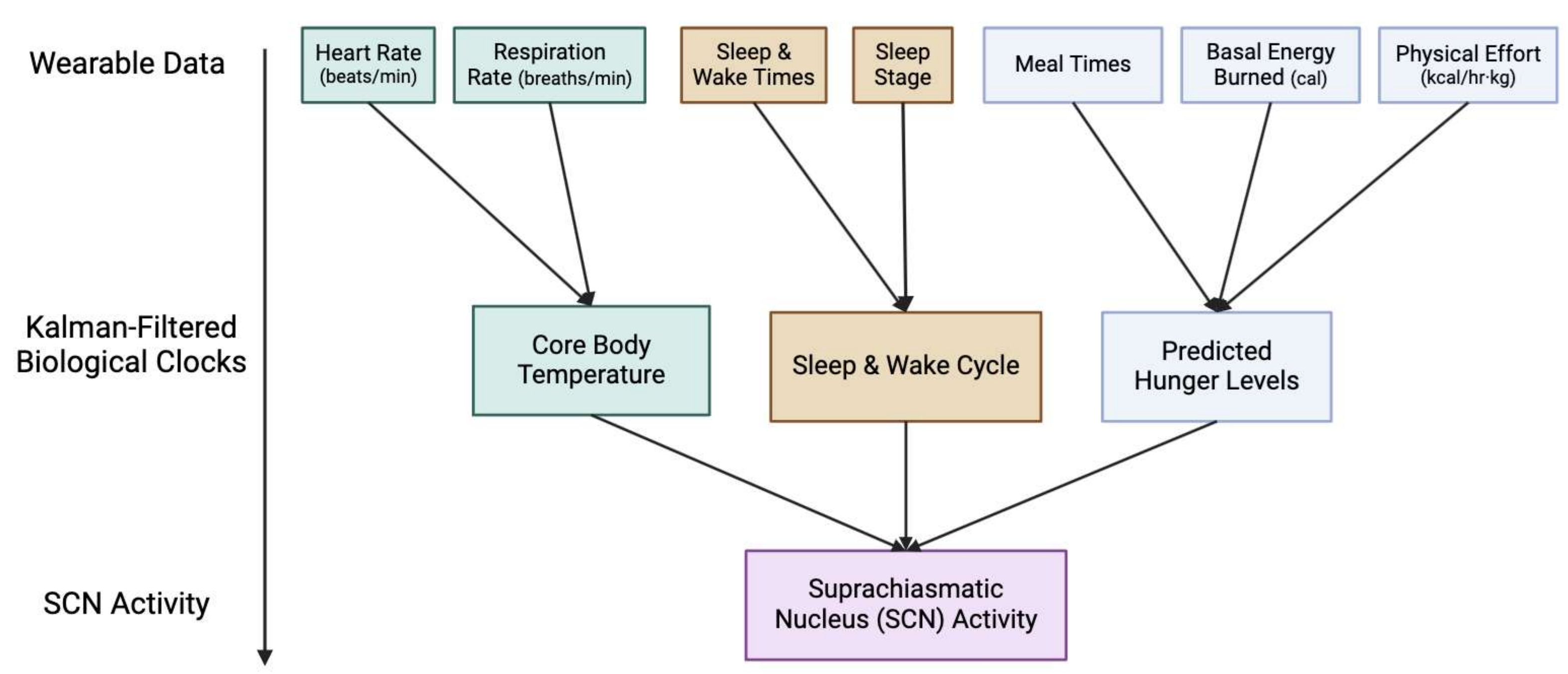


**Fig 2. Filtering process.** Wearable data is processed using Kalman filtering to model individual biological clocks, including basal body temperature, sleep/wake cycle, and feeding behavior. A higher-order Kalman filter combines these clocks to generate a model of SCN activity over time. The process ensembles signals from the Kalman-filtered biological clocks, which are complex biological rhythms synchronized and driven by the SCN.

## Future Research

### Improving the Model:

- Matrices can be tuned further to improve model accuracy and address overfitting by incorporating regularization techniques to prevent the model from overly relying on specific parameters or data trends.
- Modeling more circadian rhythms before ensembling the predicted SCN activity Kalman Filter.
- Incorporating additional measurements collected from Apple Watch (e.g basal metabolic rate).

### Long Term Applications of the Model:

- Modeling the circadian rhythm could aid in detecting anomalies and the early onset of illnesses.
- Useful for sleep disorder management–such as insomnia or sleep apnea–by providing detailed analysis of the sleep-wake cycle.
- This model has potential to be connected to a wearable device to get enhanced fitness tracking.
- Predict optimal times for administering medications (e.g., chemotherapy) to reduce side effects.

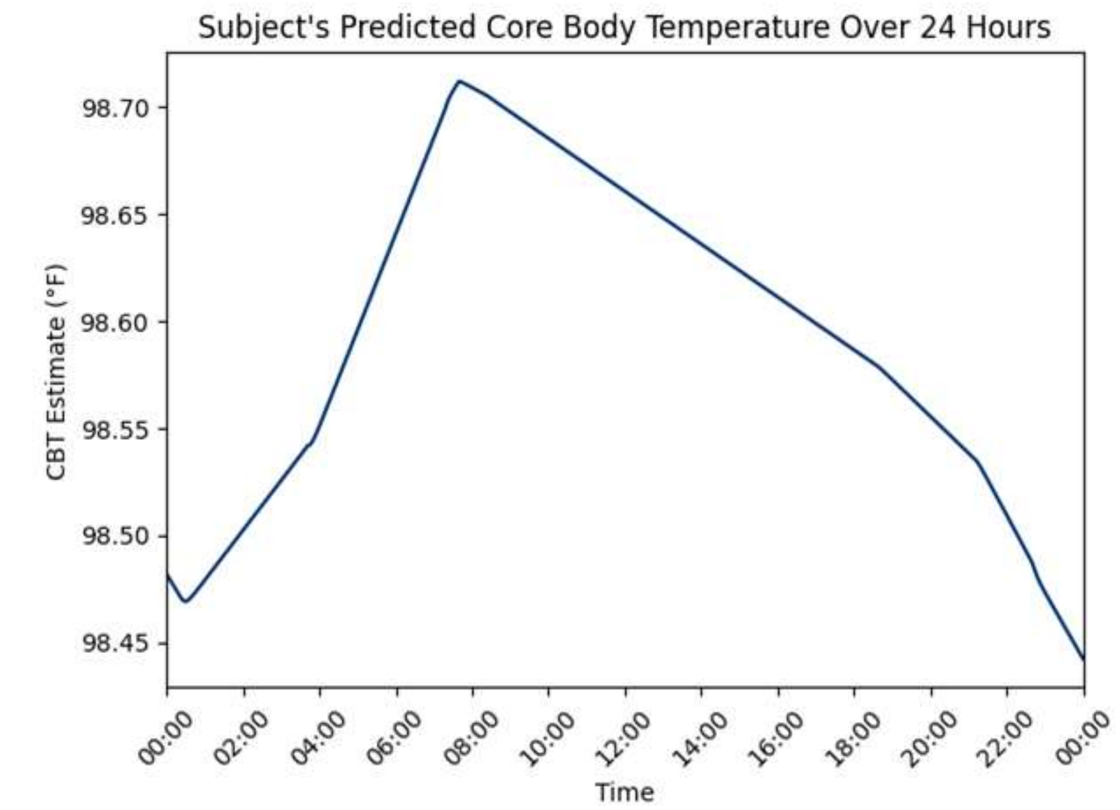


**Fig 3. Core Body Temperature (°F) modeled over 24 hours using Kalman Filtering.**

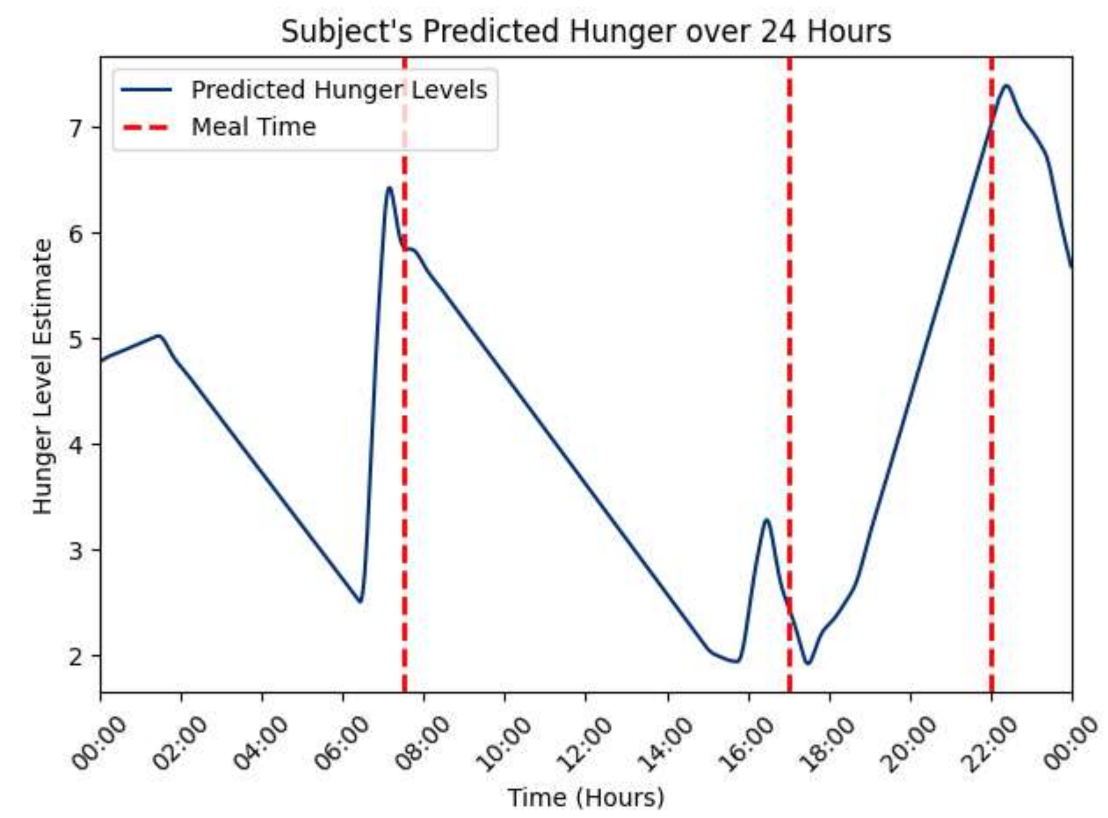


**Fig 4. Hunger levels (blue) modeled over 24 hours using Kalman Filtering.** Meal times are represented by red, dashed lines, and correspond with peaks in the hunger level.

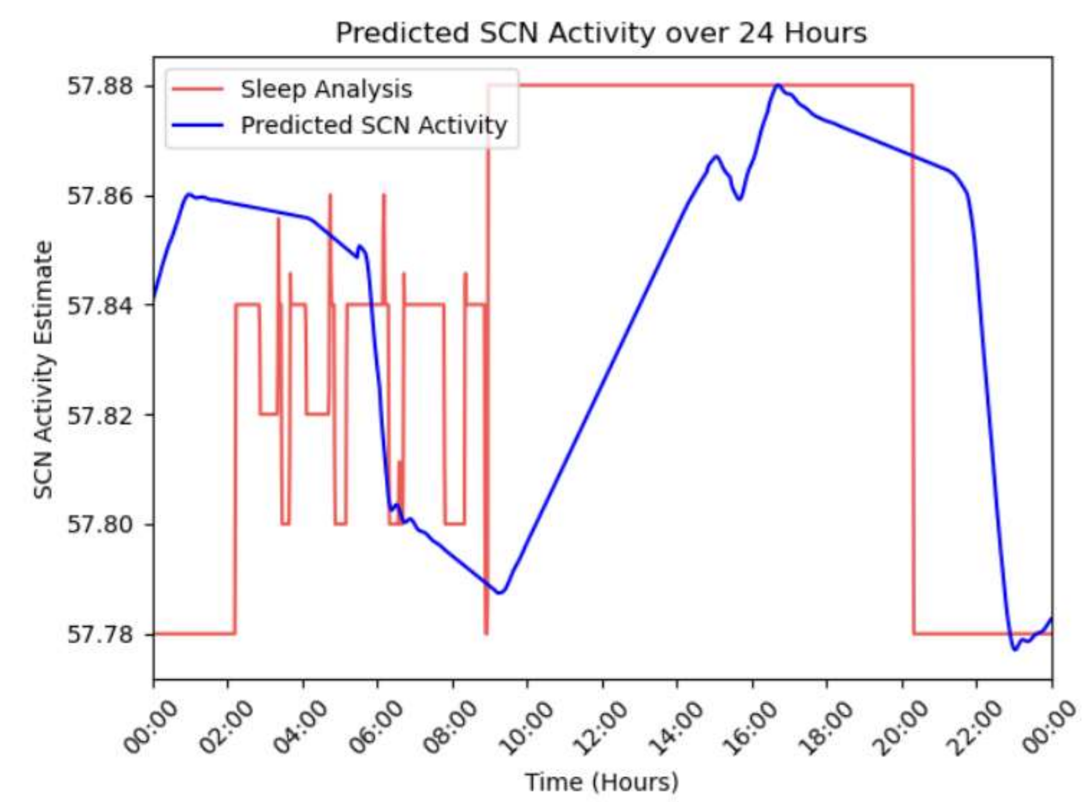


**Fig 5. Suprachiasmatic Nucleus activity (blue) and sleep-wake cycle (red)**. The SCN model uses core body temperature estimates (Fig. 3) and hunger level estimates (Fig. 4), over 24 hours. This model of SCN activity is a proof of concept that attempts to predict SCN activity levels based on biological clock activity that it synchronizes. Sleep-wake cycle is also shown, with higher levels indicating time awake and lower levels indicating deep sleep.

## Acknowledgements

Dr. Shuai Xu, Department of Computer and Data Sciences
Dr. Kevin Xu, Department of Computer and Data Sciences
Figure 2 created with BioRender.com