Application of Machine Learning to Improve Time-in-Bed Detection by Leg-Worn Actigraphy

Thomas Ferree, PhD, Martin Moynihan, and Shai Gozani, MD, PhD; NeuroMetrix Inc., Waltham, MA, USA

INTRODUCTION

- Actigraphy is used widely to analyze human sleep.
- Time in Bed (TIB), is critical as it defines the temporal frame for sleep/wake classification.
- Placement on the leg offers unique advantages for determining TIB automatically.
- We report an algorithm that combines a Bayesian classifier and a decision tree to detect TIB.
- We used machine learning techniques to optimize the algorithm in one cohort and validated its performance in a second cohort.

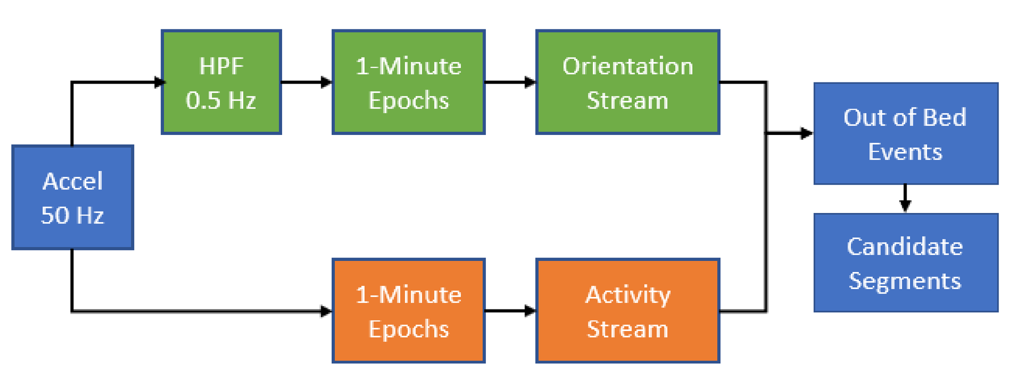
METHODS

Training Cohort. 155 nights of actigraphy data from 42 subjects with presumed normal sleep patterns.

Testing Cohort. 20 nights of actigraphy data from 9 subjects with presumed normal sleep patterns.

Study Device. Quell® (NeuroMetrix, Inc.) is a TENS device worn on the calf for the treatment of chronic pain. It contains a 3-axis accelerometer and algorithms for analyzing sleep.

Study Protocol. Subjects wore the actigraphy device from one afternoon to the next morning for an average 710 minutes, and recorded TIB Start and TIB End in their diary.



Study Data. Three-axis accelerometer data were acquired at 50 Hz, and processed as Orientation and Activity data streams in 1-minute epochs. These were used to detect Out-of-Bed (OOB) events. Sets of epochs between OOB events are called Segments (SEG).

METHODS, CONT'D

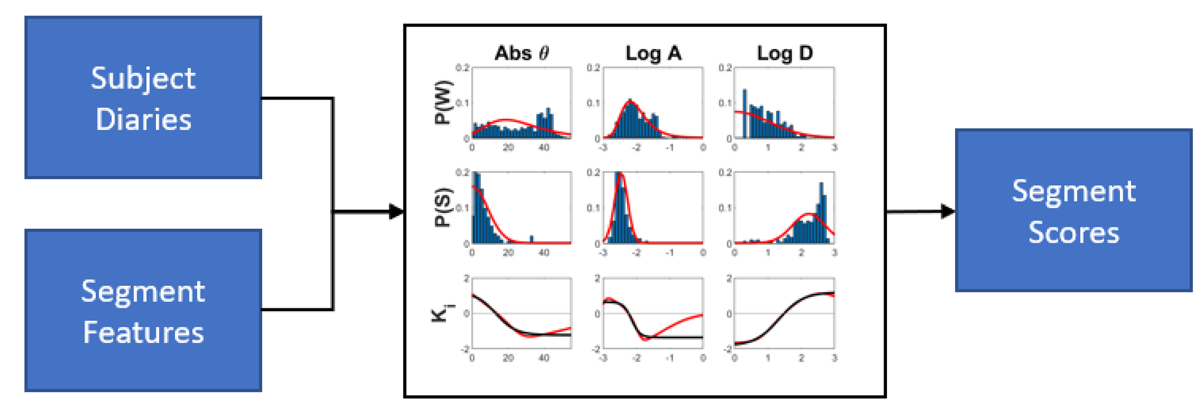
Bayesian Classifier. Let S denote sets of epochs within TIB and W denote sets of epochs outside TIB. Each segment has Features F = {Angle θ, Activity A, Duration D}. A naïve Bayesian classifier has the form

$$\frac{P(S)}{P(W)} = \frac{P_0(S)}{P_0(W)} \prod_{i=1}^{3} \frac{P(S|F_i)}{P(W|F_i)}$$

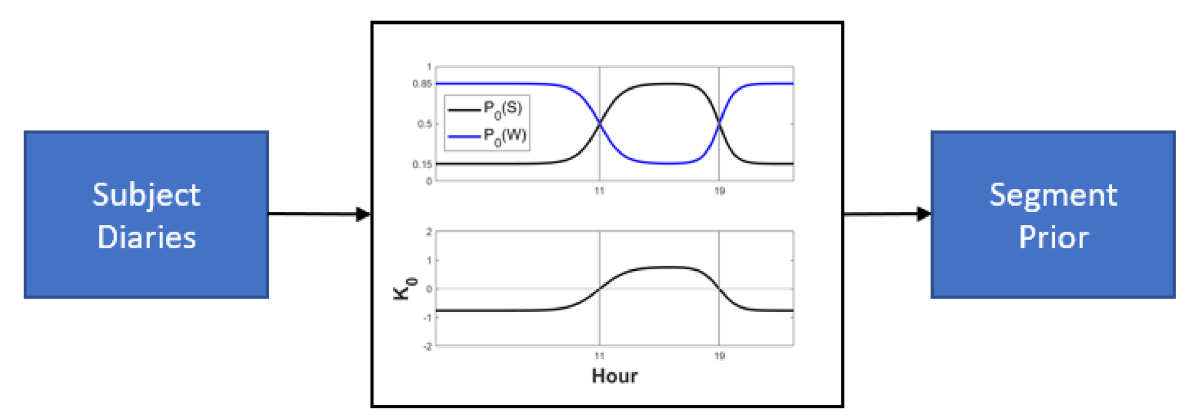
or equivalently

$$K = K_0 + \sum_{i=1}^{3} K_i$$

Segment Features. Analytical distributions were fit to P(S|F) and P(W|F) for each Feature F. In order to insure sensible monotonic behavior beyond the Training data, each ratio was fit to a sigmoid.



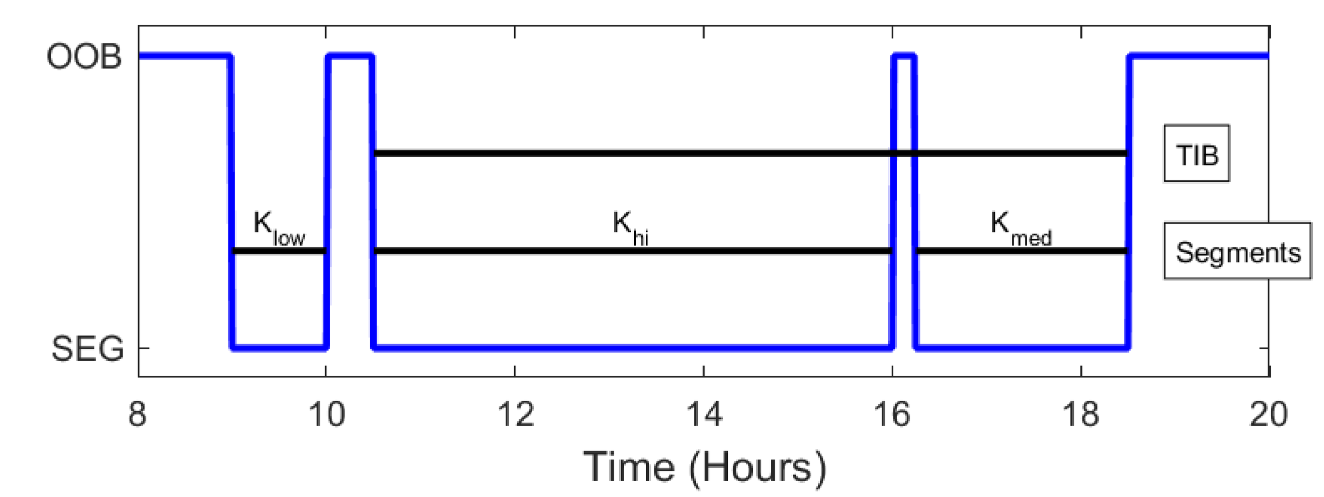
Prior Probability. A prior probability function $P_0(S)$ was defined



Time in Bed. Sleep is a temporal process lasting hours. We define TIB as a contiguous set of epochs spanning the main sleep episode in a given night. We assume that sleep is monophasic but accommodate OOB events during the night.

Decision Tree. A decision tree was built that takes as input the Segment features and their temporal order, and outputs the first and last Segments within TIB. Parameters in those rules were optimized using Simulated Annealing. The error function was set to Infinity if TIB was not found for every night, otherwise was set to the total absolute error in TIB Start and TIB End.

RESULTS



Classifier Performance. In the 155 training files there were 843 Segments, and 97% were classified correctly. In the 20 validation files there were 94 Segments, and 99% were classified correctly.

N = 843	Bayesian Classifier	Decision Tree
Accuracy	92.9	96.8
Sensitivity	93.6	92.6
Specificity	92.5	98.9

N = 94	Bayesian Classifier	Decision Tree
Accuracy	87.5	98.9
Sensitivity	100	96.9
Specificity	0.75	100

SUMMARY

- We applied machine learning to develop algorithms that combine activity, orientation, and time to estimate TIB for leg-worn actigraphy.
- The Bayesian model and decision tree yielded 97% accuracy in the Training Cohort and 99% Accuracy in the Testing Cohort.
- Limitations on Accuracy are due primarily to restful behaviors before the actual TIB.
- Future work will explore new segment features, different classifiers, and using within-night data to further improve estimates of TIB.

ACKNOWLEDGEMENTS

This work was funded by NeuroMetrix, Inc.

Presented at 32nd Annual Meeting of the APSS (June 8-12, 2019, San Antonio, TX)
Contact: tom_ferree@neurometrix.com