



RESEARCH ARTICLE

Sleep monitoring with the Apple Watch: comparison to a clinically validated actigraph [version 1; peer review: awaiting peer review]

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Abstract

Background: We investigate the feasibility of using an Apple Watch for sleep monitoring by comparing its performance to the clinically validated Philips Actiwatch Spectrum Pro (the gold standard in this study), under free-living conditions.

Methods: We recorded 27 nights of sleep from 14 healthy adults (9 male, 5 female). We extracted activity counts from the Actiwatch and classified 15-second epochs into sleep/wake using the Actiware Software. We extracted triaxial acceleration data (at 50 Hz) from the Apple Watch, calculated Euclidean norm minus one (ENMO) for the same epochs, and classified them using a similar algorithm. We used a range of analyses, including Bland-Altman plots and linear correlation, to visualize and assess the agreement between Actiwatch and Apple Watch.

Results: The Apple Watch had high overall accuracy (97%) and sensitivity (99%) in detecting actigraphy-defined sleep, and adequate specificity (79%) in detecting actigraphy defined wakefulness. Over the 27 nights, total sleep time was strongly linearly correlated between the two devices ($r=0.85$). On average, the Apple Watch over-estimated total sleep time by 6.31 minutes and under-estimated Wake After Sleep Onset by 5.74 minutes. The performance of the Apple Watch compares favorably to the clinically validated Actiwatch in a normal environment.

Conclusions: This study suggests that the Apple Watch could be an acceptable alternative to the Philips Actiwatch for sleep monitoring, paving the way for larger-scale sleep studies using Apple's consumer-grade mobile device and publicly available sleep classification algorithms. Further study is needed to assess longer-term performance in natural conditions, and against polysomnography in clinical settings.

Keywords

Apple Watch, Sleep Study, Actigraphy

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Introduction

Good sleep is vital for our health and wellbeing. Without it, our body and mind function poorly, with consequences that include risk of obesity¹, diabetes² and cardiovascular disease³. Polysomnography (PSG) is currently the gold standard method to monitor sleep. During PSG, subjects spend a night in a dedicated sleep lab, hooked up to a range of devices to measure physiological signals. However, information-rich PSG is expensive, laborious and intrusive. Because subjects are attached to many electrodes, sleep is disturbed by the recording, so that it is better at looking at qualitative abnormalities such as sleep apnea or narcolepsy.

Widespread adoption of smartphones, smartwatches and fitness devices opens up new opportunities for monitoring sleep and physical activity. Many of these consumer devices come with a built-in accelerometer, gyroscope, magnetometer, and in some cases, a heart rate sensor—more sensors than wrist-worn actigraphs, which only use an accelerometer to measure movement to infer sleep and wake states. Nevertheless, actigraphs are regarded as useful tools in clinical practice when measuring sleep and wakefulness in normal living environments, especially in the context of assessing regularity and overall diurnal fluctuations^{4–7}.

The affordability of consumer-grade mobile devices has driven their popularity and the abundance of applications (“apps”) available—including apps for health and sleep. These devices have the potential to be used in sleep studies and to inform clinical diagnosis. However, their performance needs to be properly validated in comparison to accepted methodologies such as actigraphy and PSG. This is difficult because the sleep classification methods (e.g., algorithms and analysis techniques) used in consumer-grade devices are proprietary, so the relationship between the underlying physiological measurements and the sleep state reported by an app is unclear.

We chose to investigate the feasibility of the Apple Watch as a sleep monitoring device because the manufacturer allows software developers to access the device’s triaxial accelerometer data. To the best of our knowledge, this is the first study to compare the Apple Watch against an actigraph.

Methods

Evaluation framework

Figure 1 sets out the framework for validating the Apple Watch against an actigraph. First, raw acceleration measurements are collected from each device and transformed into activity counts for the actigraph, and the “Euclidean Norm Minus One” (ENMO) for the Apple Watch. We then explore statistical relationships between activity counts and ENMO. Next, we determine a threshold to classify each epoch of ENMO values as “sleep” or “wake” and evaluate the sleep outputs of the two devices using Pearson correlation and Bland-Altman plots.

Participants

In total, 14 healthy participants (9 males, 5 females) were recruited by word of mouth and direct approach. Data were recorded from April to May 2018, participants wore the two devices for

two consecutive nights at home. The inclusion criterion for participants was age of at least 18 years old. Exclusion criteria were a previously diagnosed sleep disorder, or any condition that would lead to difficulty/discomfort while wearing the devices. The Queensland University of Technology Human Research Ethics Committee (#1800000242) approved all procedures, and all participants gave their signed consent prior participating the study. They were asked to wear both the Apple Watch and Actiwatch on their non-dominant wrist for two consecutive nights and sleep as they normally would. All wearable devices were then returned for data extraction. One participant forgot to charge the Apple Watch, so we lost one night of data and were left with 27 nights from 14 participants.

This study was designed as a proof of concept for whether it is possible to use the Apple Watch for sleep monitoring. Power calculations are appropriate when the distribution of the underlying data is known (and ideally, normal). At that point in time, this was not applicable given that there was no prior study for us to confidently characterize the distribution of the differences between the measurements obtained using different platforms. Sample size was therefore determined pragmatically⁸.

Wrist-worn devices

Table 1 shows specifications of the two wrist-worn devices used in this study: the Apple Watch Series 1 (Apple Inc., California, United States) and the Actiwatch Spectrum Pro (Philips, Bend OR). The Apple Watch has limited data storage, so data was downloaded to an iPhone via Bluetooth. We used the Core Motion Framework to develop an app to record triaxial accelerometer data at 50 Hz. The Actiwatch Spectrum Pro is a clinical-grade actigraph used for sleep and activity monitoring. It samples accelerometer data at 32 Hz and we set a 15-second epoch for processing this raw data. Processed data were downloaded using Philips’ Actiware Software (version 6.0.9). Outputs were activity counts and sleep/wake stage at each epoch.

Data processing and analysis

Accelerometer. Raw acceleration data from the Apple Watch was downloaded and processed using R statistical software. We calculated ENMO, the Euclidean Norm (magnitude) of the triaxial acceleration vector $A = (A_x, A_y, A_z)$ minus 1 gravitational unit. ENMO is used widely in physical activity and sleep monitoring^{9–13} and defined as:

$$\text{ENMO}(A) = \sqrt{A_x^2 + A_y^2 + A_z^2} - 1$$

We compared the mean ENMO of each 15-second epoch against activity counts from the actiwatch. We ensured that the clocks of both devices were synchronized and compared recordings of vigorous movement applied simultaneously to both devices to check that each devices’ timestamps were in sync.

Sleep algorithm. Philips’ Actiware software computes the total activity counts at epoch e using a weighted sum:

$$\text{Total_counts}(e) = 0.04 \sum_{i=-8}^{i=-5} a_{e+i} + 0.2 \sum_{i=-4}^{i=-1} a_{e+i} + 4a_e + 0.04 \sum_{i=1}^{i=4} a_{e+i} + 0.2 \sum_{i=5}^{i=8} a_{e+i}$$

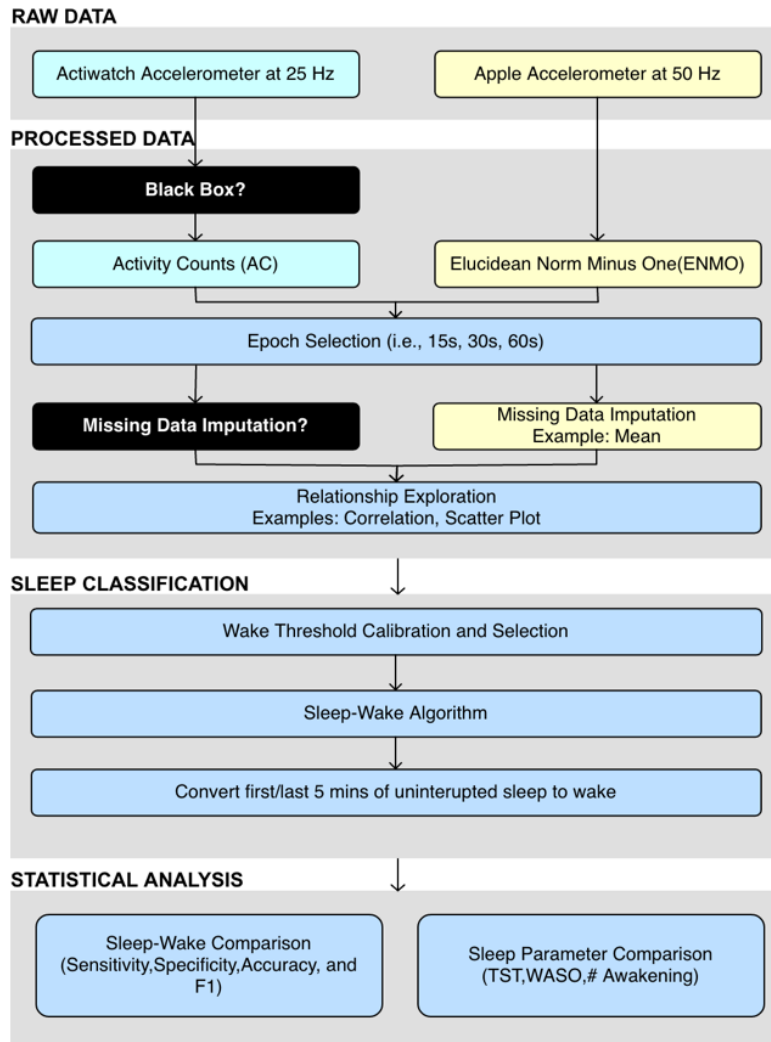


Figure 1. Evaluation framework for wrist-worn accelerometer devices.

Table 1. Device specifications.

Specification	Apple Watch	Actiwatch
Model	Series 1	Spectrum Pro
Price	\$AU 359-559	\$AU 3470
Battery life	1 day	50 days
Sensor	Accelerometer, Gyroscope, Heart rate	Accelerometer, Light sensor
Accelerometer sampling rate	50 Hz	32 Hz
Recording Time (Accelerometer)	3 days	50 days

where a_e is the activity count of epoch e . We used the shortest (15-second) epoch so that data could be converted to longer epochs if required. Each epoch was classified as sleep if its total activity counts were less than or equal to a threshold; epochs with counts above the threshold were classified as wake. Our

study used a low and medium threshold (20 and 40, respectively) derived from Actiware 6.0.9 software.

Statistical analysis. The R program (version 3.3.2) is used for statistical analysis and visualization. To measure agreement between Apple Watch and Actiwatch, we used a range of statistical methods including:

- Calculating the Pearson Correlation between total activity counts and ENMO.
- Using a receiver operating characteristic (ROC) analysis, taking the Actiwatch as ground truth.
- Using Bland-Altman plots to measure the agreement between two measurements by quantifying the mean bias and constructing an agreement interval.
- Computing the overall accuracy and performance the devices' sleep/wake classifications using a confusion matrix, again taking the Actiwatch as ground truth.

The confusion matrix of sleep-wake classifications has four outcomes: true positive (TP), true negative (TN), false positive (FP), and false negative (FN), with sleep positive, and wake negative. Using these outcomes, we calculated accuracy, sensitivity, specificity, and F1 score as defined in Table 2¹⁴.

Table 2. Classification performance statistics.

Measure	Formula
Accuracy	$(TP + TN) / (TP + TN + FN + FP)$
Sensitivity or Recall	$TP / (TP + FN)$
Specificity	$TN / (TN + FP)$
Precision	$TP / (TP + FP)$
F1 Score	$2 * \text{Precision} * \text{Recall} / (\text{Precision} + \text{Recall})$

We also calculated measures of sleep quality of interest in sleep studies: total sleep time (TST), wake after sleep onset (WASO), and number of awakenings. TST is the total duration of epochs classified as sleep; WASO is the total duration of wake epochs. Number of awakenings is the number of wake events of at least 30 seconds duration¹⁵.

Results

Sleep-wake agreement

Figure 2 displays measurements over the first night of randomly selected participant: overall patterns of Actiwatch and Apple Watch are very similar with clearly aligned periods of movement. For example, around 22:10, both activity counts and ENMO were quite active with high peaks, then both signals gradually declined. During a sleep period from 02:00–02:30, both features remained steady with no obvious movements. Raw measurements are available as *Underlying data*¹⁶.

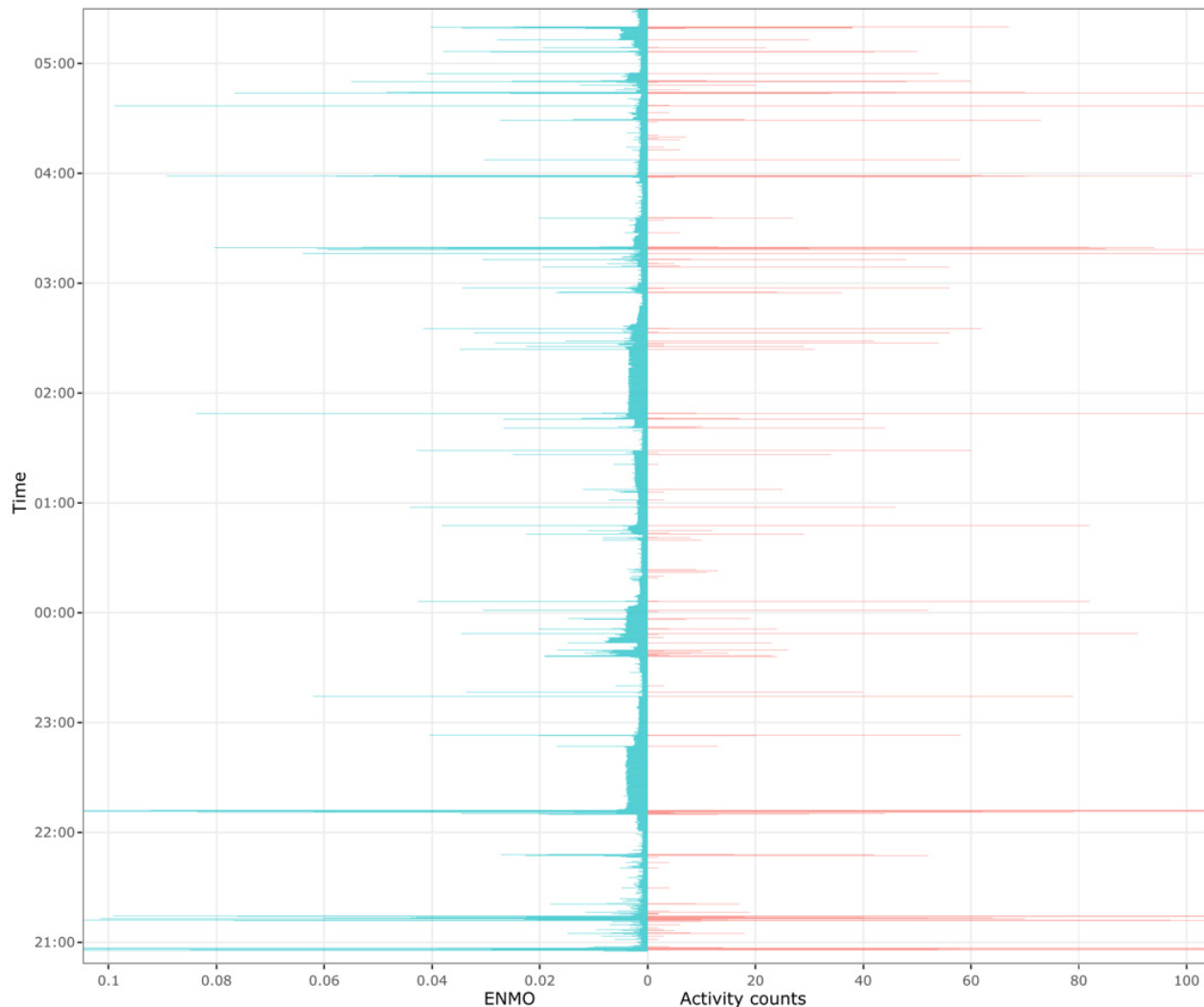


Figure 2. One night of measurements at 15 second epochs. ENMO is shown in turquoise (left) and Activity Counts in pink (right).

Pearson correlation was computed to assess the relationship between activity counts and ENMO shown in [Figure 3](#). Overall, there was strong, positive correlation between activity counts and ENMO ($r = 0.85$, nights = 27, $p < 0.001$). There were similar patterns across 15-second, 30-second, and 60-second epochs. We used 15-second-epochs in the remainder of this analysis.

Optimal wake threshold

Unlike the Actiwatch, there is no pre-established wake threshold for the Apple Watch ENMO data. To identify an optimal threshold, we isolated 11 nights without any missing data, and created all the possible training sets containing k nights, where k varies from 1 to 10. For instance, for $k = 1$ or $k = 10$ there are 11 such training sets, while for $k = 5$ or $k = 6$ there are 462 sets. In total, we considered 2046 distinct training sets. For each of these sets, we identified the threshold that maximized the F1 score on the nights not used for training. [Figure 4](#) shows how this threshold converges to 0.0608 when comparing against the medium Actiwatch threshold. This ‘optimal’ threshold was used for the rest of our analysis. A similar pattern was observed for the low Actiwatch threshold, with the Apple Watch threshold converging to 0.0523. We also measured the impact of the threshold choice through a ROC curve for the medium Actiwatch setting ([Figure 5](#)).

Overall, there is good agreement between the Apple Watch and Actiwatch for both medium and low setting thresholds.

Significantly, the ability to detect sleep (sensitivity) are higher than 98%. However, the ability to detect awake ranges from 60% to 79% for both thresholds. The overall accuracy and F1 score were consistent for both settings. The results are summarized in [Table 3](#).

Bland-Altman plots

[Figure 6](#) plots the difference versus the mean of TST, WASO and numbers of awakenings for Apple Watch and Actiwatch. We used a 15-second epoch and medium threshold for our main analysis. For TST, most nights were within the limits of agreement and close to perfect agreement (the black line, [Figure 6a](#))—three nights of TST were in perfect agreement. Only one night was outside the agreement intervals and was overestimated TST by 30 minutes. The overall bias of TST was 6.31 minutes.

In terms of WASO, differences fall mostly within the levels of agreements ([Figure 6b](#))—two nights were in perfect agreement. One night stood outside the agreements which an underestimation of WASO by 30 minutes. This night was the same night that we found in TST. The overall bias of estimating WASO was -5.74 minutes.

For the total number of awakenings, the overall bias was -4.56. Only one night was in perfect agreement but all nights lie within the upper and lower agreement levels ([Figure 6c](#)).

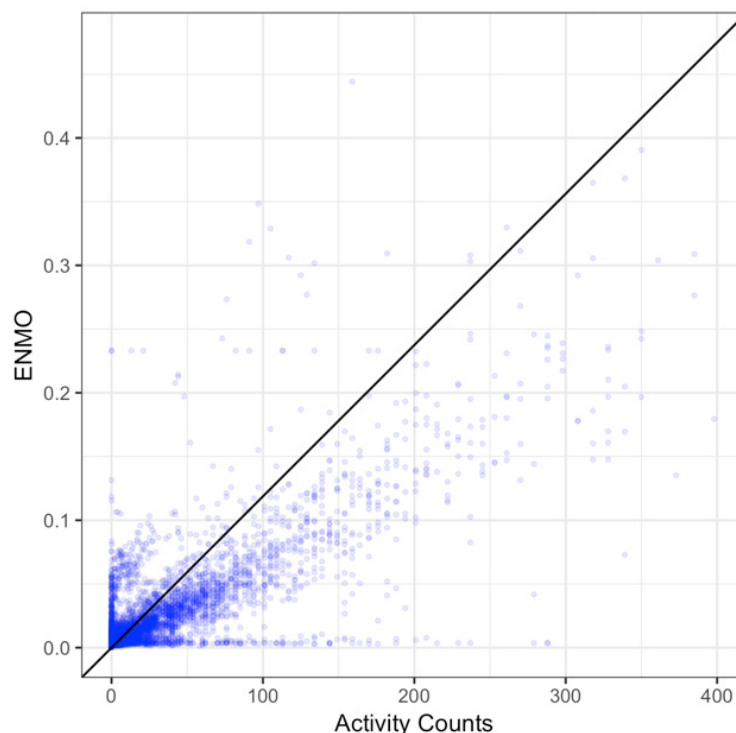


Figure 3. Apple Watch mean ENMO versus Actiwatch activity counts for all 15s-epochs over 27 nights of data. The diagonal line is the standardized major axis fit¹⁷ of activity counts and mean ENMO, constrained to pass through the origin.

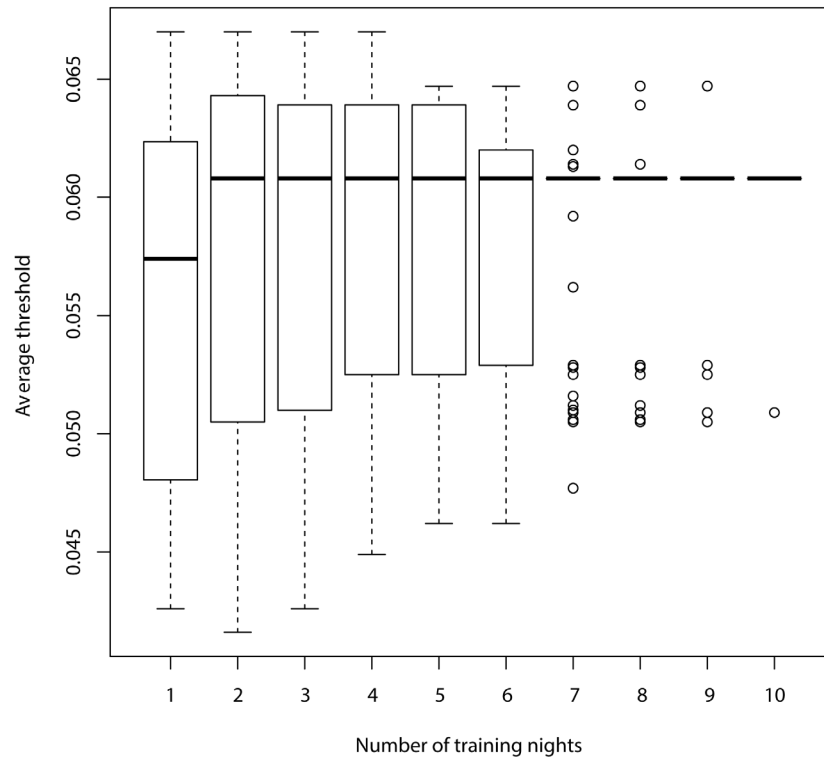


Figure 4. Box plot of the distributions of 'optimal' thresholds based on 1–10 nights of training data. As the number of training nights increase, the distributions converge around a value of 0.0608.

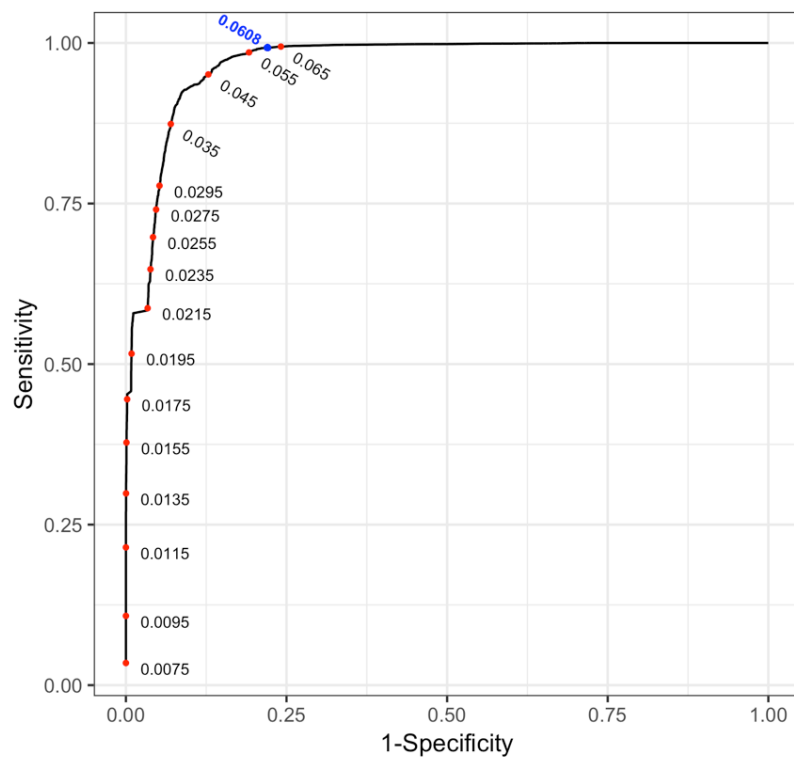


Figure 5. ROC curve for varying threshold, Apple Watch threshold taking the Actiwatch at a 15 s-epoch medium threshold as truth.

Discussion

This study compares measurements of sleep and wake obtained from Apple Watch, a consumer-grade device, and Philips Actiwatch Spectrum Pro, a clinically validated actigraphy device, in a set of healthy adults. We found that ENMO and activity counts were highly correlated. By using a combination of ten-night training data and ROC plot, we identified an

optimal threshold for Apple Watch ENMO data in comparison to the Actiwatch for both medium and low settings (Table 3).

In the medium threshold setting, the sleep parameters of TST, WASO, and number of awakenings were comparable to that of the Actiwatch with no significant differences. The discrepancy between the two measurements appeared to be clinically acceptable as a difference of TST and WASO did not exceed 30 minutes^{6,18}. The Apple Watch performs best in comparison to the Actiwatch at medium threshold, consistent with Quante's recommendation¹⁹.

To the best of our knowledge, this is the first study to evaluate the Apple Watch, a popular-consumer grade device, against a clinical-grade actigraph device for sleep monitoring. We have compared the two devices at high resolution (i.e., 15-second epochs) and low-resolution sleep parameters (i.e., TST, WASO, and number of awakenings). A similar study compared a consumer fitness tracking device (Fitbit charge HR) against Philips' Actiwatch 2: the accuracy of sleep parameters was good²⁰.

Table 3. Overall performance in accuracy, sensitivity, specificity and F1 in comparison with the Actiwatch in medium and low setting mode.

Variable	Medium threshold	Low threshold
Accuracy	97.11% $\pm$ 0.53%	93.53% $\pm$ 0.86%
Sensitivity	99.28% $\pm$ 0.21%	98.97% $\pm$ 0.35%
Specificity	78.94% $\pm$ 1.95%	63.50% $\pm$ 2.40%
F1 Score	98.35% $\pm$ 0.32%	96.16% $\pm$ 0.57%

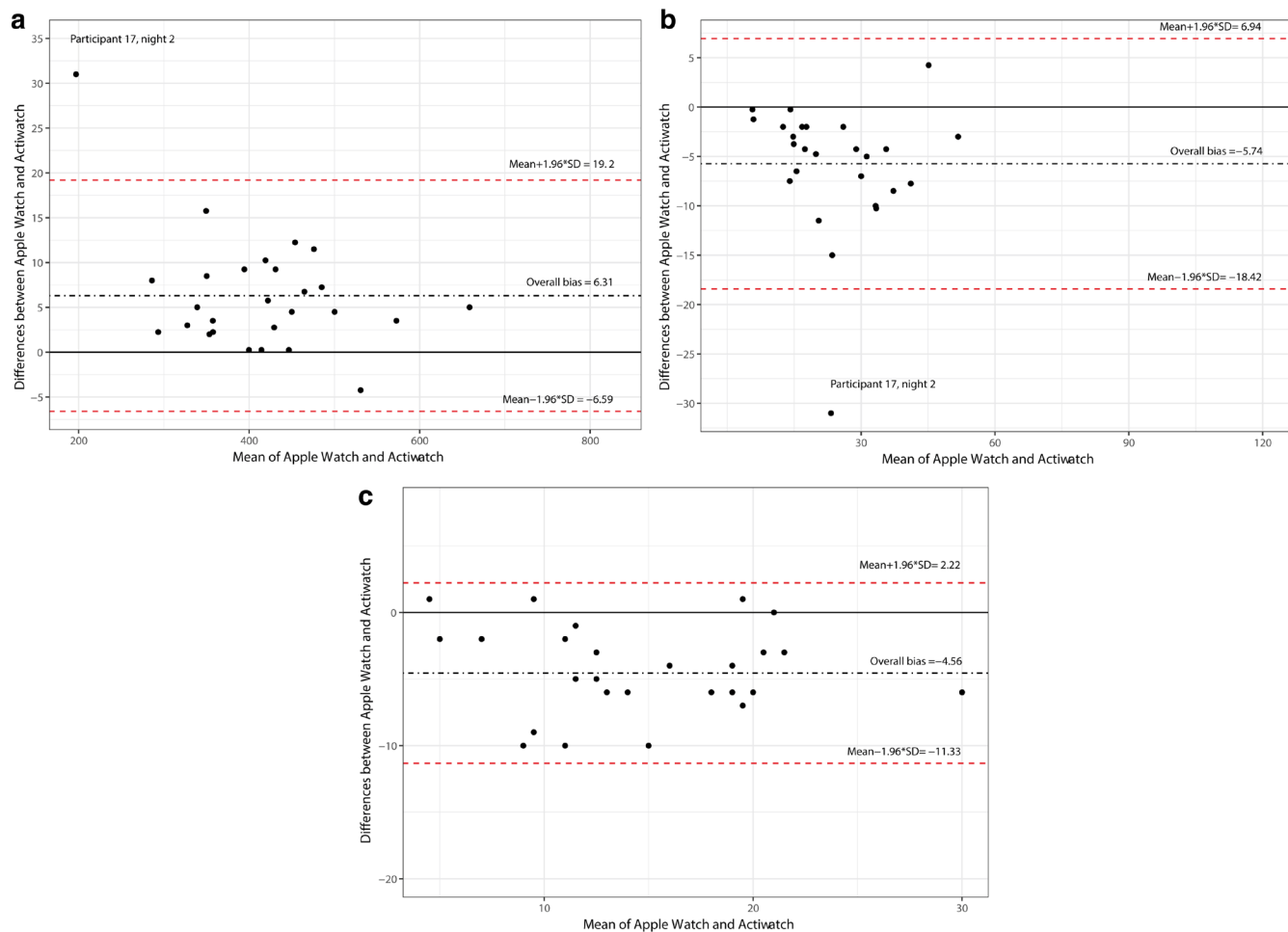


Figure 6. Bland-Altman plots show the agreement between Apple Watch and Actiwatch in medium threshold. The red dashed lines represent in the upper and lower agreement limits (95% confidence intervals). (a) Total sleep time (minutes). (b) Wake after sleep onset (minutes). (c) Number of awakenings.

However, Montgomery-Downs *et al.* suggested that both Fitbit and Actiwatch tended to have limited specificity²¹. Therefore, care must be paid in validation. Furthermore, both studies compared only low-resolution sleep parameters due to the limited information of the type of feature, and proprietary sleep algorithm²². Our study provides additional support for high-resolution data (i.e., ENMO), which could be further used in a sleep-wake algorithm validated against gold standard PSG.

We note that ENMO and activity counts are dominated by very small values (i.e., points near or at (0, 0)), as shown in Figure 3. This is a consequence of doing a study in which participants are moving very little for relatively long periods. While this is reasonable in assessing whether the Apple Watch produces comparable results to the Actiwatch for sleep monitoring, this study cannot draw conclusions about whether the Apple Watch is comparable to the Actiwatch across a broader range of activity levels (e.g., during exercise). The main benefit of assessing sleep using a well-known consumer-grade device lies in increasing the opportunity for longitudinal studies in a wider population. Over 30 million Apple Watches have been sold²³. The availability of advanced sensor technology in smart watches (e.g., heart-rate sensors) opens up possibilities for improved sleep monitoring with consumer wearable devices.

We faced some practical challenges in implementing sleep monitoring on the Apple Watch, including constraints of power, memory management, data transfer, and sensor capabilities. In total, 16 nights had missing data from the Apple Watch. In each of these nights, data was missing in one contiguous block of 20–60 minutes in duration. We needed to impute data based on the average of previous and next available data. At this stage, the cause of the missing data is still to be determined.

Recording was limited to two consecutive nights per participant due to memory and data transfer constraints. With these limitations in mind, we suggest future studies are needed to carefully monitor and deal with data loss where more nights of recording are investigated. Lastly, our study assessed only one sleep-wake algorithm based on the Cole-Kripke algorithm¹⁷; future studies could assess other sleep-wake algorithms that use a combination of weighted sum activity with the cut-off wake threshold to classify sleep or wake stages¹⁵.

Conclusion

Our study lays down a foundation for using accelerometer data of consumer-grade devices for sleep monitoring. Our experiments show that Apple Watch provides sleep measures comparable to the Philips Actiwatch, a clinical gold standard, with greatest similarity at the medium threshold of activity counts. These findings increase our confidence in using the consumer grade Apple Watch for sleep monitoring and open up possibilities for much larger-scale sleep studies. We also hope this work will serve as a basis for sleep clinicians in the use of data extracted from this device in their patients.

To further our research, we now intend to compare the Apple Watch against PSG and consider incorporating other types of physiological sensors from consumer-grade devices (e.g. heart-rate sensor). These findings add to a growing body of literature on the use of consumer-based accelerometer for sleep studies and will assist other researchers in establishing validation parameters for the use of other types of consumer devices.

Data availability

QUT Research Data Finder: Sleep Data. <https://doi.org/10.25912/5cc28f62e81ad16>.

Underlying data are contained within SleepDataset.zip. There are 27 csv files in this archive, with each file corresponding to a single night of data. The files have four columns: timestamp, Actiwatch activity counts, Actiware classification (1 for wake, 0 for sleep), and ENMO value calculated from the Apple Watch data. Each row corresponds to the data for a 15-second epoch. Dates have been modified to preserve privacy, with times are unchanged.

Data are available under the terms of the [Creative Commons Attribution 4.0 International license](#) (CC-BY 4.0).

Grant information

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