Title: Estimating sleep parameters using an accelerometer without sleep diary

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Abstract

Wrist worn raw-data accelerometers are used increasingly in large scale population research. We examined whether sleep parameters can be estimated from these data in the absence of sleep diaries, which are common in sleep actigraphy. Our heuristic algorithm uses the variance in estimated z-axis angle and makes basic assumptions about sleep interruptions. Detected sleep period time window (SPT-window), was compared against sleep diary in 3752 participants (range=60-82years) and polysomnography in sleep clinic patients (N=28) and in healthy good sleepers (N=22). The SPT-window derived from the algorithm was 12.9 and 3.2 minutes longer compared with sleep diary in men and women, respectively. Average c-statistic to detect the SPT-window compared to polysomnography was 0.86 and 0.83 in clinic and healthy sleepers, respectively. We demonstrated the accuracy of our algorithm to detect the SPT-window. The value of this algorithm lies in studies such as UK Biobank where a sleep diary was not used.

Wrist-worn raw-data accelerometers are increasingly used for the assessment of physical activity in large population studies such as the Whitehall II study or mega-cohorts such as UK Biobank [1–3]. The decision to use raw-data accelerometers is motivated by the improved comparability of output across different sensor brands [4,5], and increased control over all steps in the data processing[6]. Accelerometers are commonly worn for 24 hours per day, thus providing information over the day and night; making them potentially valuable for sleep research.

A major challenge in accelerometer-based sleep measurement is to derive sleep parameters without additional information from sleep diaries [1,3,7]. Standard methods for sleep detection based on conventional accelerometers (actigraphy) involves asking the participant to record their time in bed, sleep onset and waking up time[8–10]. In a previous paper we developed a method to detect sleep guided by sleep diary records [11]. However, the increasing use of accelerometry in studies worldwide without sleep diaries necessitates the development of novel methods to derive indicators of sleep behaviour, in the absence of sleep diary records. A crucial step is the detection of the sleep period time window (SPT-window), which is the time window starting at sleep onset and ending when waking up after the last sleep episode of the night. Once the SPT-window can be detected without diary, our previously published method can be used to detect sleep episodes within this window [11]. Polysomnography (PSG) is considered the gold-standard measure of sleep parameters, making it an ideal methodology to validate sleep detection methods using an accelerometer algorithm. Additionally, experiments in real life can be used to establish concurrent validity with sleep diary.

This study aims to develop and evaluate a heuristic algorithm for the detection of the SPT-window from raw data accelerometers unaided by a sleep diary and to compare sleep parameter estimates (waking up, sleep onset time and SPT-window duration) with sleep diary records assessed in the daily life of a large cohort of older adults, and with PSG data collected in a sleep clinic and a group of healthy good sleepers.

Methods

Study population

Full details on data collection were previously described [11]. Briefly, data are drawn from the Whitehall II Study [12], where accelerometer measurement was added to the study at the 2012/2013 wave of data collection for participants seen at the central London clinic and for those living in the South-Eastern regions of England who underwent a clinical evaluation at home [2]. Of the 4879 participants to whom the accelerometer was proposed in the Whitehall II Study, 388 did not consent and 210 had contraindications (allergies to plastic or metal, travelling abroad the following week). Of the remaining 4281 participants who wore the accelerometer, 4204 (98.2%) had valid accelerometer data (a readable data file). Among them, sleep diary data were missing for 80 participants and 30 additional participants did not meet criteria for accelerometer wear time (at least one night defined as noon-noon with >16h of wear time). Of the remaining 4094 participants (jointly 27957 nights) 342 did not have complete demographic data (age, BMI and sex). Therefore, the main assessment of discrepancies between the accelerometer and the sleep diary was undertaken in 3752 participants (76.9.9% of those invited) with jointly 25644 nights [11]. The resulting participants (75.2% men) were on average 69.1 (standard deviation (SD) = 5.6) years old and had a mean body mass index (BMI) of 26.4 (SD = 4.2) kg/m^2.

We conducted a second study on sleep clinic patients in order to validate our sleep detection algorithm against polysomnography. These data come from 28 adult patients who were scheduled for a one-night polysomnography (PSG) assessment at the Freeman Hospital, Newcastle upon Tyne, UK, as part of their routine clinical assessment and were subsequently invited to participate in the study [11]. All 28 patients recruited for the polysomnography study (11 female) had complete accelerometer data for the left wrist and 27 had complete data for the right wrist and were aged between 21 and 72 years (mean±sd: 45±15 years). Diagnosed sleep disorders included: hypersomnia (N=2), insomnia (N=2), REM behaviour disorder (N=3), sleep apnoea (N=5), narcolepsy (N=1), sleep apnoea (N=4), parasomnia (N=1), restless leg syndrome (N=5), and sleep paralysis (N=1), and nocturnia (N=1). Three patients had more than one sleep disorder.

We conducted a third study on health good sleepers to validate our sleep detection algorithm against polysomnography using a different accelerometer brand. These data come from 22 adults who underwent a one-night PSG assessment at the University of Pennsylvania

Center for Sleep. Twenty-two participants recruited for the polysomnography study (68% female) had complete accelerometer data for the non-dominant wrist and were aged between 18 and 35 years (mean±sd: 22.8±4.5 years).

Ethics Statement

In both studies participants were provided with instructions and an information sheet about the study and were given time to ask questions prior to providing written informed consent. The studies were approved by the University College London ethics committee and the NRES Committee North East Sunderland ethics committee, and University of Pennsylvania ethics committee respectively.

Data availability

Whitehall II data, protocols, and other metadata are available to the scientific community. Please refer to the Whitehall II data sharing policy at https://www.ucl.ac.uk/whitehallII/data-sharing. Raw data from the polysomnography study has been made open access available in anonymized format on zenodo.org[13]. Data from the University of Pennsylvania are available through the National Institute of Mental Health data archive.

Instrumentation

Participants in the Whitehall II Study were asked to wear a tri-axial accelerometer (GENEActiv, Activinsights Ltd, Kimbolton, UK) on their non-dominant wrist for nine (24-h) consecutive days. They were asked to complete a simple sleep diary every morning which consisted of two questions: ‘what time did you first fall asleep last night?’ and ‘what time did you wake up today (eyes open, ready to get up)?’ The accelerometer was configured to collect data at 85.70 Hz with a ±8g dynamic range. A more complete description of the accelerometer protocol can be found in our earlier publication [2].

In the second and third study, polysomnography (Embletta®, Denver) was performed using a standard procedure, including video recording, a sleep electroencephalogram (leads C4-A1 and C3-A2), bilateral eye movements, submental EMG, and bilateral anterior tibialis EMG to record leg movements during sleep. Respiratory movements were detected with chest and abdominal bands measuring inductance, airflow was detected with nasal cannulae measuring pressure, and oxygen saturation of arterial blood was measured. Airflow limitation and changes in respiratory movement were used to detect increased upper-airway resistance. All respiratory events and sleep stages were scored according to standard criteria so that EEG determined total sleep time could be measured [9]. Participants in the second study (PSG in sleep clinic) were asked to wear the same brand of accelerometer as in the first study (GENEActiv, Activinsights Ltd, Kimbolton, UK) on both wrists throughout the one-night polysomnography assessment. Here, the accelerometer was also configured to record at 85.70 Hz. We collected accelerometer data on both wrist to assess the role of sensor location on classification performance, unfortunately no information on handedness was recorded. Participants in the third study (PSG in healthy good sleepers) were asked to wear an accelerometer of the brand Axivity (Axivity Ltd, Hoults Yard, UK) on the non-dominant wrist throughout the one-night polysomnography assessment. Here, the accelerometer was configured to record at 100 Hz.

Accelerometer data preparation

A previously published method was used to minimize sensor calibration error [14] and to detect and impute accelerometer non-wear periods [2,15]. Arm angle was estimated as follows: $angle = \left(\tan^{-1}\frac{a_z}{{a_x}^2+{a_y}^2}\right)\cdot 180/\pi$, where a_x, a_y, and a_z are the median values of the three orthogonally positioned raw acceleration sensors in gravitational (g) units (1g = 1000 mg) derived based on a rolling five second time window. Here, the z-axis corresponds to the axis positioned perpendicular to the skin surface (dorsal-ventral direction when the wrist is in the anatomical position). Next, estimated arm angles were averaged per 5 second epoch and used as input for our algorithms for detecting sleep period time (SPT-window) and sleep episodes.

Heuristic algorithm to detect the SPT-window

There are several challenges in the development of an algorithm to detect the SPT-window: absence of hard data labels to train a classifier under real life conditions (not in a clinic), consideration of real life behaviour, e.g. how to handle sleep scattered across the full 24-hour day and ensuring that the algorithm is not over fitted to a specific population or accelerometer brand. Thus an algorithm was built by visually inspecting twenty random accelerometer multi-day recordings from different studies and accelerometer brands (ten from the Whitehall II Study as reported in this paper and ten from UK Biobank study [1]) while iteratively enhancing the algorithm to best detect the visible data segment of no movement without using or looking at sleep diary data.

The resulting heuristic algorithm, which we will refer to as Heuristic algorithm looking at Distribution of Change in Z-Angle (HDCZA), applied per participant is illustrated in Figure 1 and works as follows. *Step 1-2:* Calculate the z-angle per 5 seconds. *Steps 3-5:* Calculate a 5-minute rolling median of the absolute differences between successive 5 second averages of the z-angle. This step makes the algorithm invariant to the potentially unstandardized orientation of the accelerometer relative to the wrist. *Step 6-7:* Calculate the 10th percentile from the output of step 5 over an individual day (noon-noon), and multiply by 15. This is used as a critical individual night derived threshold to distinguish periods of time involving many and few posture changes. Detect the observation blocks for which the output from step 5 was below the critical threshold, and keep the ones lasting longer than 30 minutes. *Step 8:* Evaluate the length of the time gaps between the observation blocks identified by step 7, if the duration is less than 60 minutes then count these gaps towards the identified blocks. *Step 9:* The longest block in the day (noon-noon) will be the main SPT-window, defined as the time elapsed between sleep onset (start of the block) and waking time (end of the block).

Our motivation for the design of the algorithm is as follows. By visually inspecting the angle-z values over a day some individuals seemed inactive or sleeping throughout the day with minimal variation in angle, while other individuals had more distinct inactive (night time) and active (daytime) periods. These differences presumably reflect the degree of sedentary lifestyle and amount of sleep in a day. Using a percentile as part of the threshold calculation allows the threshold to account for between individual differences in z-angle distribution. The factor 15 in step 6 of the algorithm was derived iteratively using visual inspection of the classification. The 30-minute time period is motivated by the assumption that people are typically not in bed for less than 30 minutes for their nocturnal time in bed, as opposed to daytime napping, and the 60-minute time period is motivated by the assumption that sleep separated by awake periods greater than 60 minutes ought to be treated as two distinct sleep episodes to avoid adding early evening naps or afternoon naps to the SPT-window.

Second algorithm for reference

When comparing our algorithm to the sleep diary we also considered a second, but more naïve heuristic algorithm, which we will refer to as L5±6. The algorithm is based on the

the raw signal metric Euclidian Norm (vector magnitude) Minus One with negative values rounded to zero (ENMO), which in formula corresponds to $max\left\{(\sqrt{acc_x{}^2 + acc_y{}^2 + acc_z{}^2} - 1), 0\right\}$, with acc_x, acc_y, and acc_z referring to the three orthogonal acceleration axes pointing in the lateral, distal, and ventral directions, respectively [15]. Metric ENMO has previously been demonstrated to be correlated with magnitude of acceleration as well as human energy expenditure in the present generation of wearable acceleration sensors[15]. L5±6 takes the 12 hour window centred around L5 (least active five hours in the day based on metric ENMO) and then searches within this window for sustained inactivity periods which were previously described [11]. In short, sustained inactivity periods are calculated as the absence of change in arm elevation angle (same angle-z as used above) larger than 5 degrees for more than 5 minutes [11]. Next, the SPT-window is defined from the start of the first to the end of the last occurrence of a sustained period of inactivity in the 12-hour window.

Sleep episodes within the SPT-window

Sleep episodes were defined as the sustained periods of inactivity within the SPT-window, as defined in the previous section [11]. From this, the number of sleep episodes within each SPT-window detected (HDCZA, L5±6) was calculated as well as sleep efficiency within the SPT-window calculated as the percentage of time asleep within the SPT-window [11].

Statistical analysis

Comparison with sleep diary

The SPT-window derived from both the HDCZA and L5±6 were compared separately with sleep diary records with a multi-level regression to account for the variation in availability of night time data and to include both night and person level predictors. For SPT-window duration (difference between sleep onset and waking time), sleep onset and waking time, the difference between diary and accelerometer-based detection was used as the dependent variable, while population demographics (sex, age, BMI), season (winter or summer) and weekend versus weekday were used as predictors. Here, we used function lme from R package nlme. Further, correlation coefficients and mean absolute error (MAE) between sleep onset, waking time, and SPT-window duration were calculated. Additionally, the c-statistic, also known as the Area Under the Curve (ROC), was calculated from the epoch-level binary classifications of SPT-window <1> or not <0> by diary and the HDCZA and L5±6, first calculated per day and then aggregated as average per participant. Additionally, to investigate whether more wakefulness time within the SPT-window corresponds to a larger HDCZA-sleep diary difference in SPT-window duration we calculated the amount of wakefulness categorised as [0-1), [1-2), [2-3), [3-4), and at least 4 hours, and compared this with the difference in SPT-window duration between sleep diary and the HDCZA. The notation [a-b) is used to denote an interval that is inclusive of 'a' but exclusive of 'b'.

Evaluation with polysomnography

The recording time of PSG is typically constrained to the time in bed window, which means that our heuristic algorithm (HDCZA) may not detect sufficient data corresponding to time out of bed to derive its critical threshold and accurately detect the SPT-window. We addressed this concern by adding simulated wakefulness data to the beginning and ending of the accelerometer and PSG recording. The PSG and accelerometer data were expanded with 90 minutes of simulated data at the beginning and ending that would not trigger the SPT-window detection: simply the class wakefulness for PSG, and a sine wave with amplitude 40 degrees and period 15 minutes complemented with random numbers (mean=0, standard deviation=10) for accelerometer-based angle-z. Note that the specific shape of the simulated values is not critical as long as it does not trigger the detection of sleep and the 10th percentile of all the data (step 6 of HDCZA) reflects real and not simulated data. The addition of simulated data is needed because the heuristic detection algorithm effectively searches for the beginning and end of a large time period without body movement, if the full PSG represents sleep then the algorithm would not be able to detect such a transition in movement level. Additionally, the algorithm's threshold that scales with the variance in the data was constrained to a range corresponding to the 2.5th and 97.5th percentile of the distribution of the threshold value observed in a sample of real life accelerometer recordings, 0.13 and 0.50, respectively. This was done because the in-clinic PSG does not provide a full 24-hour cycle of body movement to derive this threshold. In the PSG evaluation we did not evaluate L5±6, because it requires more than 12 hours of (non-simulated) data, which most PSG recordings do not offer. After sleep classification with HDCZA and before running the comparison between HDCZA and PSG, 60 minutes of simulated data were removed at the beginning and end.

The following performance metrics for SPT-window detection were used: Difference in onset, waking time, and duration, accuracy, c-statistic, t-test, and mean absolute error (MAE). Performance estimates accuracy and c-statistic were derived from both the data, as well as from the data expanded with wakefulness time to simulate performance estimates in a 24 hour recording. Sleep classification within the SPT-window was evaluated as difference in duration (t-test) and as the percentage of time spent in sleep stages REM, and non-REM stages 1, 2, and 3 (N1, N2, and N3) correctly classified by the algorithm as part of SPT-window. Sleep efficiency within the SPT-window by PSG and algorithm was compared via t-test and MAE. A *P*-value of < .005 was considered significant[16]. Further, method agreement was evaluated with modified Bland-Altman plots[17] with PSG criterion values on the horizontal axis.

Code availability

Both SPT-window detection algorithms are implemented and available in open source R package GGIR version 1.5-16 (https://cran.r-project.org/web/packages/GGIR/)[18], see the software's documentation on input arguments 'loglocation' and 'def.noc.sleep' for further details on the use of L5±6 and HDCZA. The R code used for our comparisons with sleep diary can be found at: https://github.com/wadpac/whitehall-acc-spt-detection-eval. The R code used for our comparisons with polysomnography can be found at: https://github.com/wadpac/psg-ncl-acc-spt-detection-eval, with the code used for the Newcastle data in the *master* branch of the repository and its adaptation for the differently formatted Pennsylvanian data in the *psg-penn* branch.

Results

Comparison between accelerometer results and that from sleep diary

Demographics of the three study cohorts are described in Table 1. The probability density distribution for the difference between sleep parameter estimates from algorithm and sleep diary is more symmetrical around zero compared with the L5±6 approach, see Figure 2. The heuristic algorithm HDCZA estimates sleep onset on average 13.8 and 7.7 minutes earlier than that reported in the sleep diaries by men and women, respectively, and 3.5 minutes per ten years of age relative to mean age, see Table 2. Difference between sleep diary estimates and HDCZA estimates in waking time were associated with sex, age, and BMI, while differences in SPT-window duration were associated with sex and age, see Table 2. The L5±6 method estimates sleep onset on average 86 and 78.2 minutes earlier than that reported in the sleep diary for men and women, respectively, see Table 2. Difference between sleep diary and L5±6 estimates of SPT-window, sleep onset, and waking time were all associated with sex and BMI. Additionally, an association was found with weekend day for SPT-window duration and sleep onset, see Table 2. The Pearson's correlation coefficients and c-statistics between accelerometer derived sleep parameters, and sleep diary, are higher for HDCZA compared with L5±6, see Table 3. The combined MAE from onset and waking time was 35.7 and 76.7 minutes for HDCZA and L5±6, respectively.

For nights with [0-1), [1-2), [2-3), [3-4), and at least 4 hours of accumulated wakefulness an average difference in SPT-window duration between sleep diary records and our heuristic algorithm (HDCZA) was observed as 27, 4, -53, -136, and -147 minutes corresponding to 57.8, 32.0, 7.6, 1.7, and 0.8% of 27,957 recorded nights, respectively. Here, the last two categories, corresponding to at least 2 hours of accumulated wakefulness, reflect 8.9% of the participants.

Comparison between accelerometer results and that from polysomnography

In the PSG study in sleep clinic patients, on average 9.4 (standard deviation 1.6) hours of matching data from PSG and accelerometer were retrieved per participant, with no difference in recording duration between left and right wrist (P = 0.75). Sleep onset time, waking time, SPT-window duration, and sleep duration within the SPT-window derived from the HDCZA algorithm differed all non-significantly from polysomnography and MAE ranged from 31 minutes for sleep onset to 71 minutes for SPT-window duration, see Table 4. The combined MAE from onset and waking time was 38.9 and 36.7 minutes for the left and right wrist, respectively. SPT-window duration was estimated for the left wrist within 2 hours for the majority of individuals (75 %) but deviated by more than 2 hours in seven individuals, six of which had a sleep disorder, as shown in Figure 3 (right wrist: 81%, five, and four, respectively). On average, the accuracy and c-statistic for SPT-window classification were 87% and 0.86 in the PSG recording window, and 94% and 0.94 when expanded with simulated wakefulness as an estimate of 24 hour performance, see Table 4. Further, the average sensitivity to detect sleep as part of the SPT-window was above 91% in both wrists, see Table 4. Results for the PSG study carried out in healthy good sleepers indicated better overall performance as shown in Table 5 and Figure 4. The classifications of the HDCZA algorithm in comparison with the PSG sleep stage classification for all participants are provided in the Supplementary material 1 and 2 to this manuscript.

Discussion

In this paper we present a heuristic algorithm, referred to as HDCZA, for detecting the Sleep Period Time-window (SPT-window) from accelerometer data. Raw data accelerometers are increasingly used in population research, and the value of this algorithm lies in studies such as the UK Biobank where a sleep diary was not used [1]. Although the focus of our analysis is sleep, the present findings are equally valuable for physical activity research as it will help to split observation period between night sleep and daytime inactivity.

In our comparison with sleep diary records in a large cohort of older adults (60-83 years) a small systematic difference was found in sleep duration and sleep onset time, with significant but small associations with sex and age, and no association with BMI. Here, the average difference and the Akaike Information Coefficients indicated that the algorithm is better than our naïve reference method L5±6. Furthermore, the c-statistic was on average 95% for HDCZA. We acknowledge that the sleep diary cannot be considered a gold standard criterion method, but it is reassuring to see that differences between algorithm and sleep diary in a large cohort of elderly individuals are on average within a quarter of an hour.

An important limitation of the sleep diary study data is that no information is available on daytime sleep or daytime inactivity behaviour to help better understand the misclassifications in SPT-window by our algorithm. To facilitate such research future studies are warranted to consider implementing daytime sleep diaries, and possibly additional sensor technologies such wearable cameras[19], RFID proximity sensors[20] or additional wearable movement sensors to better capture a lying posture[21,22].

When compared against polysomnography in 28 sleep clinic patients, accuracy and c-statistic values indicate good agreement on an epoch by epoch level. Estimated SPT-window duration by HDCZA deviated by more than 2 hours from PSG in seven individuals (six of which has a sleep disorder) as shown in figure 3. Inspection of the PSG results indicated that poor classification typically occurs in patients with absence of deep sleep or who have long periods of wakefulness (> 1 hour) in the middle of the night, e.g. pages 10 and 26 in the Supplementary material, respectively (see Supplement 1). However, the interpretation of the results was complicated in case of SPT-window split into several periods separated by long waking periods. For example, one particular individual had a short sleep episode at the beginning of the PSG recording followed by several hours of wakefulness, see page 9 of the Supplementary material (Supplement 1), indicating a possible ambiguity in the correct definition of the SPT-window by both PSG and HDCZA.

To investigate the extent to which the larger differences in individuals with long periods of wakefulness observed in the PSG study occur in the general population we went back to the free-living data. In the free-living data, more wakefulness during the night corresponded to larger differences between sleep diary and algorithm derived SPT-window duration, indicating that more wakefulness time is indeed a challenge in a daily life recording setting. However, it was reassuring to see that only a small fraction (2.5%) of all the nights scattered across 8.9% of the participants were affected by one hour or more. Differences and mean absolute error were better in the evaluation with healthy good sleepers (Pennsylvania), indicating that SPT-window detection primarily forms a challenge in those with sleep disorders. The expansion of PSG data with daytime wakefulness to simulate algorithm performance in a full day has to our knowledge not been done before. We think this can help the comparison and interpretation of the c-statistic between the night time only PSG and full day sleep diary studies. A downside of this approach is that it comes with the assumption that daytime is always correctly classified. Therefore, we presented both performance estimates with and without the additional simulated data.

In the absence of a gold standard criterion method that can be applied in a representative part of the population under daily life conditions to train and test a classifier, we consider the heuristic approach the most promising for detecting the SPT-window. The heuristic approach comes with the following advantages: (i) It is not optimized with subjective and therefore potential erroneous sleep diary records, (ii) It avoids potentially overfitting towards a small patient population in a PSG study unrepresentative for the general population, (iii) It does not make assumptions about the timing or duration of the SPT-window, and (iv) It is computationally simple which will facilitate easy replication.

Only one other study was found in the literature that compared SPT-window extracted from accelerometry (or actigraphy) unaided by sleep diary and sleep diary to facilitate further interpretation of our current findings. Recently, O'Donnell and colleagues also investigated possible approaches to SPT-window detection [23]. To compare algorithm performance, we replicated their main performance metric: the mean absolute error (MAE) in sleep onset and waking time. Our HDCZA algorithm has a MAE of 35.7 minutes when compared against sleep diary (N=3752), which is slightly higher and equal compared with the 33.3, 34.4, and 35.9 minutes reported for the three algorithms investigated by O'Donnell (N=14)[22]. Although the age range is similar between the studies, the substantial difference in sample size and unknown differences in the prevalence of disturbed sleep warrants a future standardized comparison between the algorithms. Further, the MAE estimates in our PSG studies are 38.9, 36.7, and 26.9 minutes in the left- and right wrist sleep clinic patient data, and health good sleepers, respectively. When we consider the design of our and their approach, we observe a couple of differences: Their change-point and random forest approaches were optimized on a trained data set with sleep diary data as criterion, which our approach avoids following aforementioned point (i). Further, O'Donnell's thresholding approach relies on the assumption that the average SPT-window duration is 8 hours, which our approach also avoids following aforementioned point (iii). Other strengths of our approach are the evaluation with sleep diary in much larger cohort than theirs and we evaluated our approach against PSG in sleep clinic patients arguably a challenging subpopulation to classify sleep in. Neither our nor their approach currently uses the available temperature or light sensor information, in our case because of concerns about measurement bias from environmental conditions. Therefore, future research is needed to explore the potential of temperature and light information to enhance the SPT-window classification.

It should be noted that the historical studies like the one by Cole-Kripke[24] and later studies [25,26] focussed on automatic distinction of sleep and wakefulness aided by the boundaries of time in bed, lights off, or diary records of the SPT-window. These studies then focussed on correct classification of Wake After Sleep Onset (WASO), Total Sleep Time (TST), and Sleep Efficiency. Therefore, these historical studies represent a different methodological challenge than discussed in the present work and can therefore not be used as a reference point.

Our algorithm does not facilitate the detection of sleep latency. To derive sleep latency, one would need diary records of time in bed or the lights out period. Future research is warranted to investigate how sleep latency, time in bed, and the lights out period may reliably be detected from wearable accelerometer data without asking the participant to record their sleep behaviour using a diary or marker button.

The analysis presented in this paper will facilitate feasible large-scale population research on sleep and physical activity. In addition to the proof of validity as provided in this paper additional support for the credibility of the algorithm was found in our separate study identifying genome wide associations with sleep parameters derived from our algorithm in UK Biobank [REF: Lane et al. bioRxiv 2018, REF Jones et al. bioRxiv 2018], replicating signals previously associated with self-reported sleep duration and chronotype [27–30]. Our algorithm can be applied to data from the three most widely used accelerometer brands: Actigraph, Axivity, and GENEActiv, and is available as part of open source R package GGIR (https://cran.r-project.org/web/packages/GGIR/).

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Author contributions

V.T.v.H. ‘contributed to’ conception and design of the work, data analysis and interpretation, article drafting, and critical revision of the article. S.S. and K.N.A. ‘contributed to’ data collection, and critical revision of the article. S.E.J., M.K., T.F., D.R.M., P.G., M.B., B.A.S.M., M.N.W, A.I.P ‘contributed to’ critical revision of the article.

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Figures

Figure 1: Steps of the heuristic algorithm HDCZA for SPT-window detection.

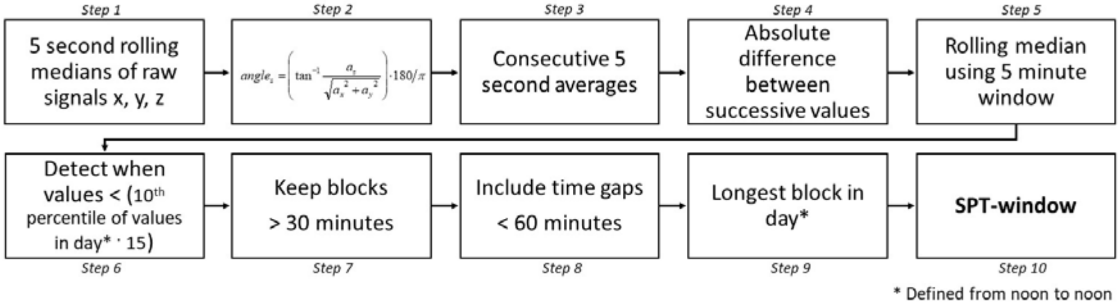

Step 1
5 second rolling medians of raw signals x, y, z
Step 2
$angle_z = \left(\tan^{-1}\frac{a_z}{\sqrt{a_x^2+a_y^2}}\right)\cdot 180/\pi$
Step 3
Consecutive 5 second averages
Step 4
Absolute difference between successive values
Step 5
Rolling median using 5 minute window
Detect when values < (10th percentile of values in day* · 15)
Step 6
Keep blocks > 30 minutes
Step 7
Include time gaps < 60 minutes
Step 8
Longest block in day*
Step 9
SPT-window
Step 10
* Defined from noon to noon

Figure 2: Probability density distributions for accelerometer-based estimates of sleep duration, sleep onset, and waking up time using dots to indicate the 5th, 25th, 75th and 95th percentile.

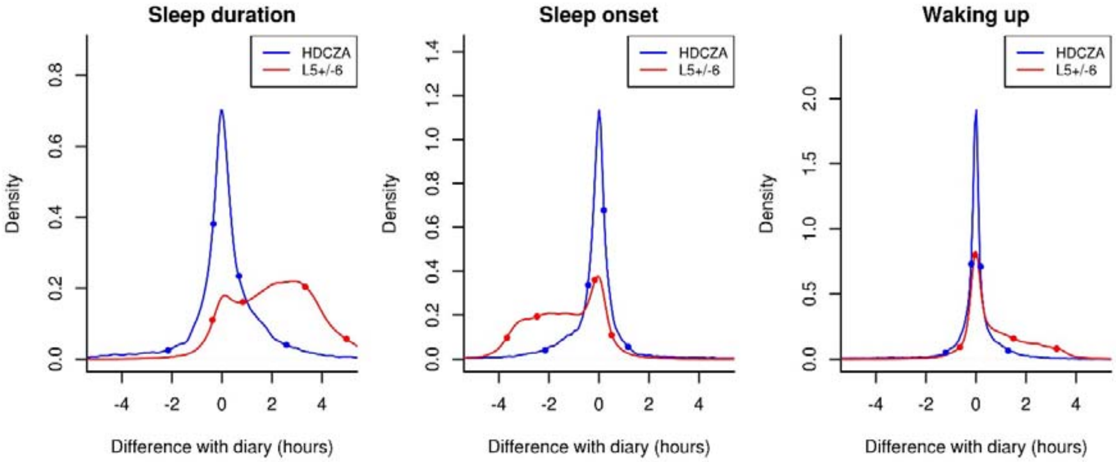


Figure 3: Modified Bland-Altman plots with 95% limits of agreement (LoA) for SPT-window duration and sleep duration relative to polysomnography (PSG) in sleep clinic patients, with dashed lines indicating LoA and straight line indicating the mean. Open bullets reflect individuals with a sleep disorder, while closed bullets reflect normal sleepers.

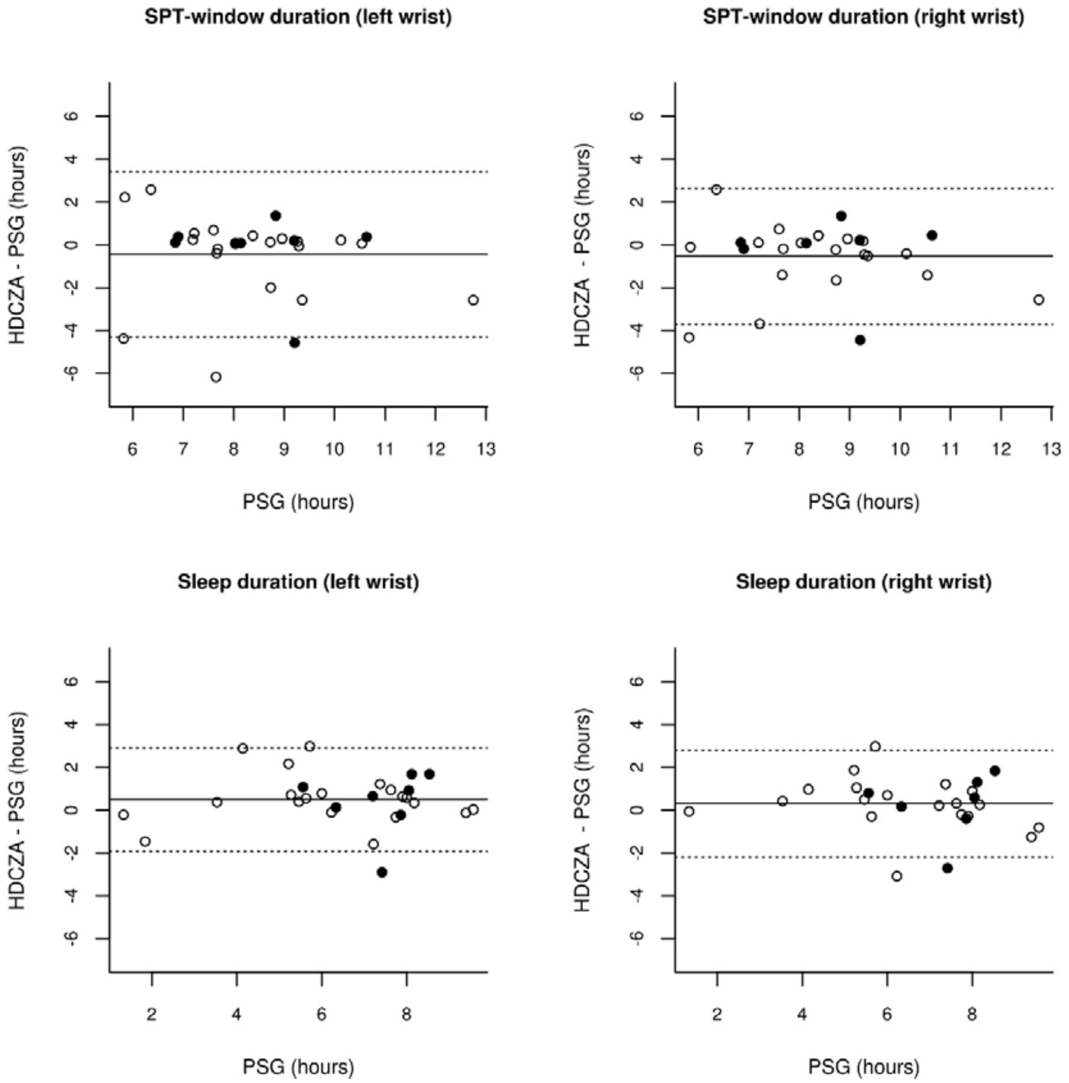
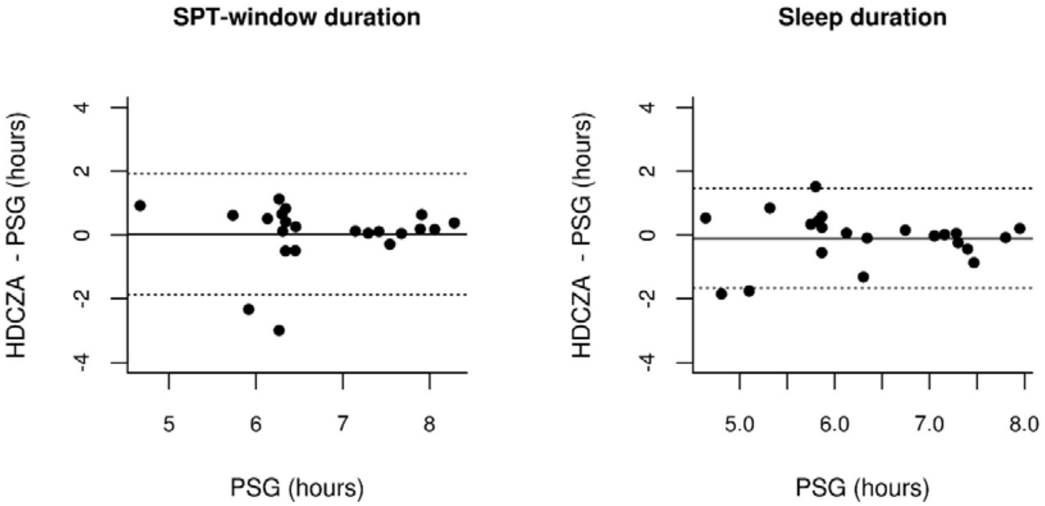


Figure 4: Modified Bland-Altman plots with 95% limits of agreement (LoA) for SPT-window duration and sleep duration relative to polysomnography (PSG) in healthy good sleepers, with dashed lines indicating LoA and straight line indicating the mean.



Tables

Table 1: Participant characteristics used for the analyses

Study	**Daily life (diary)**	**PSG sleep clinic**	**PSG healthy good sleepers**
N	3752	28	22
Age (mean ± standard deviation in years)	69.1 ± 5.6	44.9 ± 14.9	22.8 ± 4.5
Sex	2822 males, 930 females	17 males and 11 females	7 males and 15 females
SPT-window duration (mean ± standard deviation)	7.6 ± 0.9 hours	8.4 ± 1.6 hours	6.7 ± 0.9 hours
Sleep onset time (mean in hh:mm ± standard deviation)	23:49 ± 59 minutes	22:32 ± 69 minutes	23:24 ± 54 minutes
Waking time (mean in hh:mm ± standard deviation)	7:28 ± 58 minutes	06:58 ± 76 minutes	06:09 ± 32 minutes

Table 2: Sleep parameter differences (minutes) between estimates from sleep diary and two accelerometer-based methods (N=25,644 nights)

Sleep parameters	**HDCZA**			**L5±6**		
Method	**Sleep onset time**	**Waking time**	**SPT-window duration**	**Sleep onset time**	**Waking time**	**SPT-window duration**
Y-intercept (SE)	-13.8 (0.9) **	-0.9 (0.7)	12.9 (1.1) **	-86 (1.0) **	48.0 (0.9) **	134 (1.2) **
Betas (SE)						
Women	6.1 (1.1) **	-3.6(0.9) **	-9.7 (1.3) **	7.8 (1.3) **	-9.7 (1.2) **	-17.5 (1.6) **
Ten years of age †	3.5 (0.8) **	-2.2 (0.7) *	-5.7 (1.0) **	0.4 (1.0)	-0.3 (0.9)	-0.7(1.2)
Five BMI index points ‡	0.1 (0.5)	-1.3 (0.5) *	-1.4 (0.7)	-3.1 (0.7) **	1.9 (0.6) **	5.0 (0.8) **
Weekend	3.3 (1.0) **	1.9 (0.9)	-1.3 (1.2)	6.1 (1.2) **	0.0 (1.1)	-6.1 (1.4) **
Winter	0.6 (0.9)	-1.6 (0.8)	-2.2 (1.1)	-1.0 (1.1)	0.9 (1.0)	1.8 (1.4)
Within individual residual SD	25	18.7	30.9	17.8	13.3	20.7
Between individual residual SD	66.6	58.4	82.4	86.1	76.5	102.6
AIC	81583	73985	92467	92440	86067	101364

[Degrees of freedom=25,632; † relative to mean age of 69.4 years; ‡ relative to mean BMI of 26.4 kg / m^2; SE: Standard Error; SD: Standard Deviation; AIC = Akaike information coefficient, * P < .005, ** P < .0005]

Table 3: Correlation, mean absolute error, and concordance between sleep diary and accelerometer estimates (N=4,094)

Parameter	**Metric**	**HDCZA**			**L5±6**		
		Value	**t; DF**	**P**	**Value**	**t; DF**	**P**
sleep onset time	Correlation in timing	0.76 (95% CI: 0.74 – 0.77)	74; 4092	**	0.68 (95% CI: 0.67 – 0.70)	60; 4092	**
	MAE (min)	29.9			85.3		
waking time	Correlation in timing	0.80 (95% CI: 0.79 – 0.81)	86; 4092	**	0.74 (95% CI: 0.72 – 0.75)	69; 4092	**
	MAE (min)	22.1			50.5		
SPT-window	Correlation in duration	0.51 (95% CI: 0.49 – 0.54)	38; 4092	**	0.25 (95% CI: 0.22 – 0.28)	17; 4092	**
	MAE (min)	41.0			131.2		
	c-statistic	0.95 (IQR: 0.94 – 0.98)	-	-	0.92 (IQR: 0.90 – 0.94) †	-	-

[DF: Degrees of freedom; MAE: mean absolute error; min: minutes; * P < 0.005; ** P < 0.0005; † -0.03 difference (95% CI for difference: -0.032; -0.029), t=47, DF=4,093, P < .0005]

Table 4: Comparison algorithm with polysomnography in sleep clinic patients (Newcastle study)

Parameters	Metric	Left wrist (N=28)			Right wrist (N=27)		
		Value	**t; DF**	**P**	**Value**	**t; DF**	**P**
Sleep onset	Difference (min)	-10 (95% CI: -30; -9)	-1.08; 27	0.29	0 (95% CI: -27; 27)	0.02; 26	0.98
	MAE (min)	30.8	-	-	40.2		
Sleep wake	Difference (min)	-37 (95% CI: -75; 1)	-2.00; 27	0.06	-31 (95% CI: -57; -6)	-2.54; 26	0.02
	MAE (min)	47.1	-	-	33.2		
SPT-window	Difference in duration (min)	-27 (95% CI: -73; 19)	-1.21; 27	0.23	-32 (95% CI: -71; 6)	-1.72; 26	0.10
	MAE (min)	70.9	-	-	63.5	-	-
	c-statistic	0.86 (IQR: 0.81-0.98)	-	-	0.87 (IQR: 0. 81-0.95)	-	-
	c-statistic 24 hour†	0.93 (IQR: 0.94-0.99)	-	-	0.94 (IQR: 0.94-0.99)	-	-
	Accuracy (%)	87 (IQR: 81-98)	-	-	88 (IQR: 84-97)	-	-
	Accuracy 24 hour† (%)	94 (IQR: 92-99)	-	-	94 (IQR: 93-99)	-	-
Sleep within SPT	Difference in duration (min)	30 (95% CI: 1; 58)	2.11; 27	0.04	18 (95% CI: -12; 48)	1.24; 26	0.23
	Sensitivity (%)	92 (IQR: 97-100)	-	-	91 (IQR: 98-100)	-	-
Sleep efficiency within SPT	Difference (percent point)	8.7 (95% CI: 3.63 – 13.82)	3.51; 27	*	9.4 (95% CI: 3.76 – 15.06)	3.42; 26	*
	MAE (percent point)	10.1	-	-	10.6	-	-

[* P < .005; MAE: mean absolute error; min: minutes; SPT-window: Sleep period time window; CI: Confidence Interval; DF: degrees of freedom; t: t-statistic; IQR: Inter quartile range; † recording expanded with simulated data of wakefulness to resemble 24 hours]

Table 5: Comparison algorithm with polysomnography in healthy good sleepers (N=22, Pennsylvania)

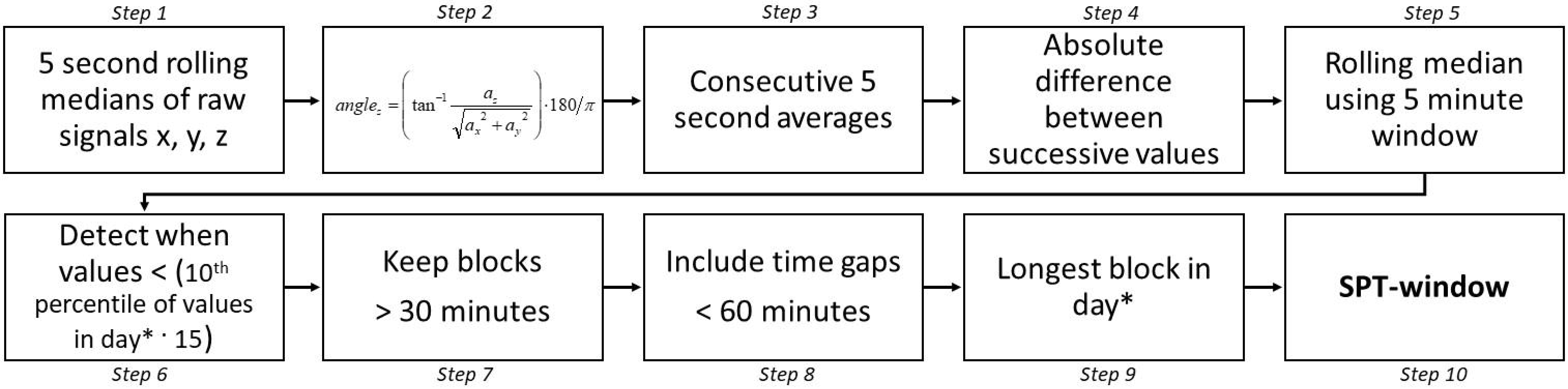
Parameters	Metric	Value	t; DF	P
Sleep onset	Difference (min)	-20 (95% CI: -39; -2)	-2.30; 21	0.03
	MAE (min)	32.9	-	-
Sleep wake	Difference (min)	-17 (95% CI: -39; 4)	-1.67; 21	0.11
	MAE (min)	21.0	-	-
SPT-window	Difference in duration (min)	2 (95% CI: -24; 27)	0.14; 21	0.89
	MAE in duration (min)	37.7	-	-
	c-statistic	0.83 (IQR: 0.80-0.90)	-	-
	c-statistic 24 hour†	0.95 (IQR: 0.95-0.99)	-	-
	Accuracy (%)	89 (IQR: 86-97)	-	-
	Accuracy 24 hour† (%)	96 (IQR: 95-99)	-	-
Sleep within SPT	Difference in duration (min)	-6 (95% CI: -27; 15)	-0.59; 21	0.56
	Sensitivity (%)	93 (IQR: 94-100)	-	-
Sleep efficiency within SPT	Difference (percent point)	-1.74 (95% CI: -4.46; 0.98)	-1.33; 21	0.20
	MAE (min)	4.8	-	-

[* P < .005; MAE: mean absolute error; min: minutes; SPT-window: Sleep period time window; CI: Confidence Interval; DF: degrees of freedom; t: t-statistic; IQR: Inter quartile range; † recording expanded with simulated data of wakefulness to resemble 24 hours]

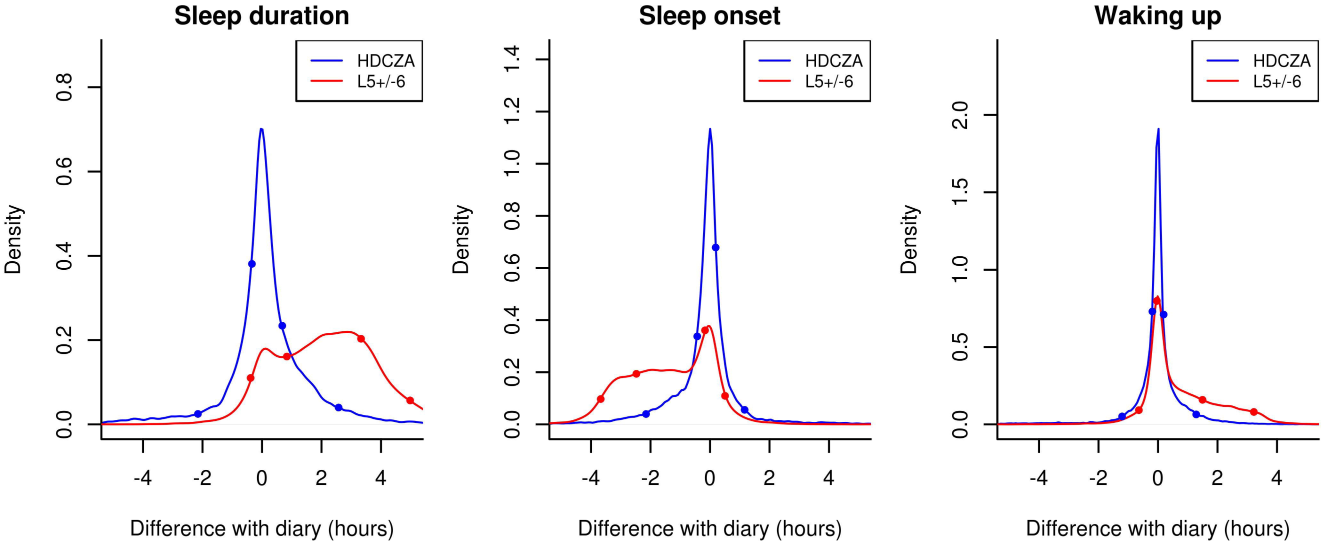
Supplementary materials

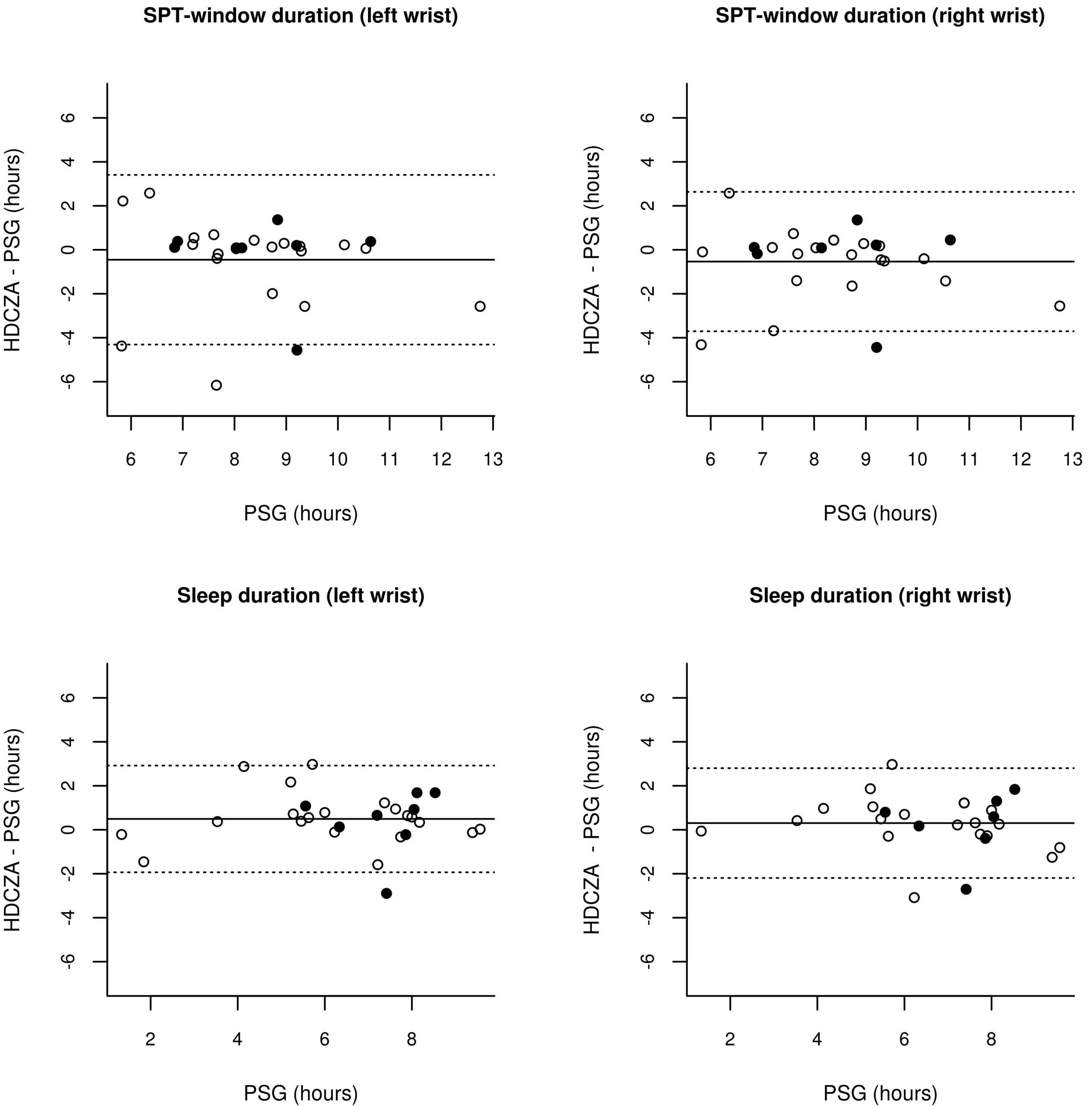
Supplement 1 sleep clinic - shows classifications of the algorithm (blue line) in comparison with the PSG sleep stage classification for all participants in the sleep clinic study (Newcastle).

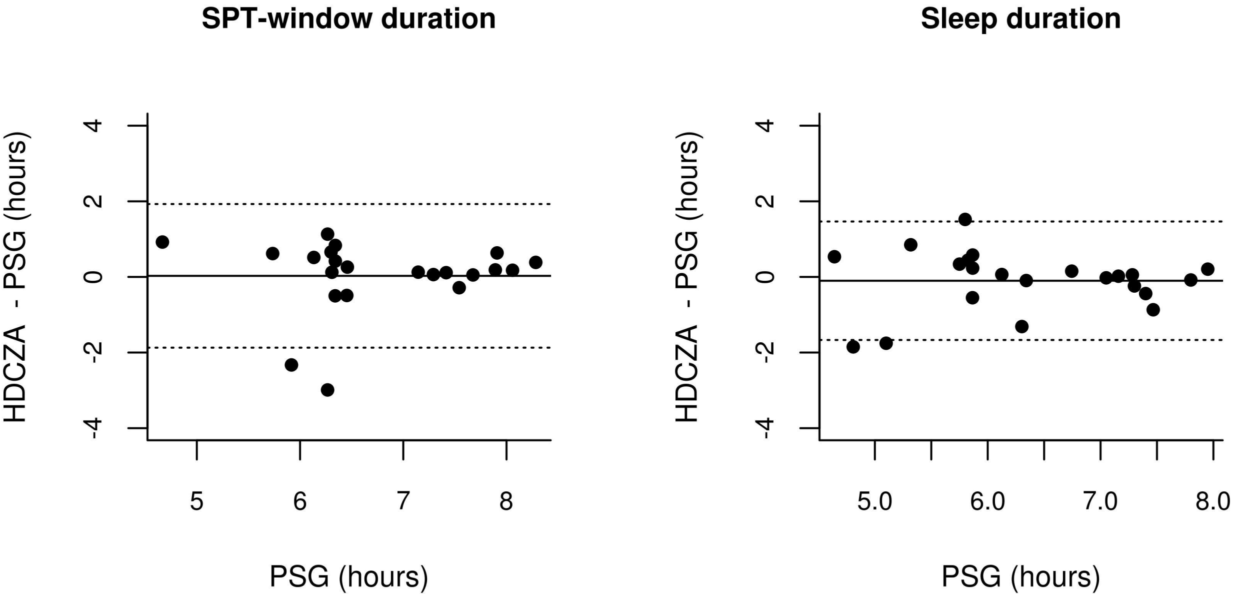
Supplement 2 healthy good sleepers - shows classifications of the algorithm (blue line) in comparison with the PSG sleep stage classification for all participants in the health good sleepers study (Pennsylvania).


Step 1
5 second rolling medians of raw signals x, y, z
Step 2
$angle_z = \left(\tan^{-1} \frac{a_z}{\sqrt{a_x^2 + a_y^2}} \right) \cdot 180/\pi$
Step 3
Consecutive 5 second averages
Step 4
Absolute difference between successive values
Step 5
Rolling median using 5 minute window
Step 6
Detect when values < (10th percentile of values in day* · 15)
Step 7
Keep blocks > 30 minutes
Step 8
Include time gaps < 60 minutes
Step 9
Longest block in day*
Step 10
SPT-window

* Defined from noon to noon


Sleep duration
Sleep onset
Waking up
HDCZA
L5+/-6
Density
Difference with diary (hours)
0.0
0.2
0.4
0.6
0.8
1.0
1.2
1.4
0.5
1.5
2.0
-4
-2
0
2
4


SPT-window duration (left wrist)
SPT-window duration (right wrist)
Sleep duration (left wrist)
Sleep duration (right wrist)
HDCZA - PSG (hours)
PSG (hours)
6
4
2
0
-2
-4
-6
6
7
8
9
10
11
12
13
2
4
6
8


SPT-window duration
HDCZA - PSG (hours)
4
2
0
-2
-4
5
6
7
8
PSG (hours)
Sleep duration
HDCZA - PSG (hours)
4
2
0
-2
-4
5.0
6.0
7.0
8.0
PSG (hours)