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How reliable is measurement of posture during sleep: real-world measurement of body posture and movement during sleep using accelerometers

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Title: How reliable is measurement of posture during sleep: Real-world measurement of body posture and movement during sleep using accelerometers

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Keywords

Sleep measurement

Body posture

Body movement

Accelerometer

Reliability

Abstract

Objective

Understanding sleeping behaviours could improve prevention and treatment of sleep problems and associated health conditions. This study aimed to evaluate a method to assess body posture and movement during sleep using trunk-worn accelerometers for 28 days.

Approach

Participants (50 adults with low back pain (66% female); aged 32(±9) years) wore two activPAL-micro sensors (thigh, trunk) during their normal daily life for 28 consecutive days. Parameters related to body posture (e.g., time spent lying supine or prone) and movement (e.g., number of turns) during sleep were calculated for each night. Average values for each parameter were identified for different periods, the Spearman-Brown Prophecy Formula was used to estimate the minimum number of nights required to obtain a reliable estimate of each parameter, and repeatability of measures between different weeks was calculated.

Main Results

Participants spent 8.1(±0.8) hours asleep and most time (44%) was spent in a supine posture. The minimum number of nights required for reliable estimates varied between sleep parameters, range 4-21 nights. The most stable parameters (i.e., requiring less than seven nights) were "average activity", "no. of turns", "time spent prone", and "posture changes in the first hour". Some measures differed substantially between weeks.

Significance

Most sleep parameters related to body posture and movement require a week or more of monitoring to provide reliable estimates of behaviour over one month. Notably, one week may not reflect behaviour in another week, and the time varying nature of sleep needs to be considered.

Introduction

Poor sleep quality has been associated with negative health outcomes such as obesity, pain, and stress (Grandner 2017). This relationship may be bidirectional as sleep problems are a common comorbidity with chronic health conditions, such as diabetes and depression (Appleton *et al* 2018). A better understanding of sleeping behaviours and how these are present in people with different conditions could help to improve the prevention and treatment of sleep problems and associated health conditions.

Measures of human sleep quantity and quality have been studied extensively using a variety of methods. Self-report measures of sleep remain the most practical method to monitor sleep over long periods, but these depend on participant recall and adherence (Smith *et al* 2018). Comprehensive objective assessment of sleep typically involves polysomnography (PSG) to measure a range of physiological parameters in a sleep laboratory. Although accurate, PSG is expensive, impractical to use to evaluate sleep for more than a few nights, and the unusual sleeping environment and intrusive equipment questions the extrapolation of results to daily life. The cabling and devices used for measurement are also likely to restrict body posture and movement during sleep (Smith *et al* 2018).

Assessment of posture and movement during sleep could provide information regarding sleep quality (Wrzus *et al* 2012) and has been applied by use of wrist-worn accelerometers. Although this method has reasonable validity and reliability for assessing sleep-wake patterns when compared to PSG in healthy populations with average or good sleep quality (Sadeh 2011, Conley *et al* 2019), these measures consistently overestimate sleep time and underestimate wake time compared to PSG, especially in people with chronic conditions (Conley *et al* 2019).

An alternative to wrist-worn accelerometers is the use of accelerometers fixed to the thigh or trunk to measure body posture. Thigh-worn accelerometry is a widely accepted method to quantify physical behaviour (e.g., sitting/lying, standing, walking) (Edwardson *et al* 2017, Stevens *et al* 2020). Because thigh-worn sensors are horizontal in both sitting and lying, and thus cannot distinguish these positions, Wrzus et al. (2012) used a combination of thigh- and trunk-worn accelerometers to measure body posture and postural changes during sleep and proposed this could provide additional insight into sleeping behaviour compared to a wrist-worn accelerometer. Sleeping postures (i.e., supine, side lying, prone) were identified from angular changes of body axes with 99.7% accuracy when compared to laboratory observation. Although promising, there are several limitations. First, measures were made for 24 hours, and it is unclear whether such data are representative of an individual's sleeping behaviour over a longer period (e.g., 1 week; 1 month). Second, as currently available movement sensors have limited battery life, when recording over long periods, it would be preferable for participants to be able to replace sensors at home rather than have them applied by trained staff. However, inaccurate placement could cause problems with classification algorithms (Wrzus *et al* 2012) and correction for inaccurate placement of accelerometers would be required.

This study is a secondary analysis of a larger study (Costa *et al* 2021a, 2021b) and aimed to evaluate a method to assess body posture and movement during sleep over longer periods in the real-world. The study addressed five aims. First, we developed and evaluated a method to correct for potential errors that could be induced if participants inaccurately positioned the accelerometers. This correction was then used for the analyses in this study. The second aim was to characterise posture and movement during sleep over 28 days. The third was to investigate the minimum number of nights needed to provide a reliable estimate of an individual's sleep behaviour over 28 days. Fourth, the measures made over different combinations of nights (number of nights and combinations of weekday/weekend-days) were compared against the average of the entire 28 nights. The fifth aim was to study the repeatability between measures made in the first and fourth week.

Methods

Ethical Statement

The Institutional Medical Research Ethics Committee of the University of Queensland, Brisbane, Australia, approved this study (Approval #: 2010000045). The study was conducted according to the principles of the Declaration of Helsinki and in conformity with local statutory requirements. All participants gave written informed consent to participate in the study. This research does not involve identifiable human participants. Data was anonymized prior to analysis and publication. This study is not based on a registered clinical trial.

Participants

This study involved data of the first 50 participants (33(66%) female; 17(34%) male; mean (SD) age of 32(9) years) from a larger ambulatory monitoring study of adults aged 18-50 years with low back pain (LBP), recruited from the general population (Costa *et al* 2021a, 2021b). Participants were included if they had a history of LBP of longer than three months and if they expected to continue to experience pain during the study. Participants were excluded if they had undergone spinal surgery, had another primary source of pain, were unable to undertake activities of daily living, or if they had any major medical condition.

Activity monitoring

Participants wore two activPAL^{3TM}-micro sensors at all times during their normal daily life activities (for the larger study) and during sleep (for the current study) for 28 consecutive days. The activPAL is a small and lightweight (23.5 x 43 x 5 mm; 10 g) device that contains a tri-axial accelerometer to detect static and dynamic accelerations (Figure 1a). The sensors were initialized (activPAL™ software v7.2.32), waterproofed (using Tegaderm and a vacuum-seal packaging) and attached to participants by trained staff, in the first instance, using a hypoallergenic adhesive (Tegaderm, 3M^{TM} or Fixomull, BNS medical). As participants would be required to remove and reattach sensors during the period of recording, they were trained in the procedure and provided with written instructions at this visit. One sensor was attached to the midline of the right thigh, midway between the hip and the knee (Figure 1b).

This is the standard wear location for the activPAL to measure activity (e.g., sitting, standing, walking) during the day (Edwardson *et al* 2017). To measure body posture and movement during sleep (Wrzus *et al* 2012), a second sensor was attached to the trunk, over the lower right rib cage (Bassett *et al* 2014). The trunk sensor was placed approximately in line with the thigh-sensor, so that the front of both sensors was facing the same direction when standing. With a fully charged battery, the sensor can record data for approximately ten consecutive days, and each participant used three pairs of sensors during the study. In addition, participants were asked to record their bed and wake up time every day using a smartphone application (RealLife Exp, LifeData, USA).

Correction for errors in trunk sensor position

A study was undertaken in a different set of participants to evaluate methods to identify and correct for errors in placement of the sensor on the trunk. Data were collected in four pain-free adults (2 male, 2 female) with mean (SD) age of 30 (3) years and BMI between 21 and 24. Participants wore one activity sensor on the thigh and four on the trunk to represent possible “incorrect” placements of the trunk sensor (Figure 1b). They were instructed to adopt a range of pre-determined lying positions (supine, prone, right, and left side), which were confirmed by direct observation. Participants spent three minutes in each of the four postures. For correction, the thigh sensor was used as a reference. The following steps were implemented. First, it was assumed that when the thigh is in a “supine posture” (knee pointing upwards) the trunk should also be in a supine posture. We identified periods with the thigh in this posture and the angle recorded by the trunk sensor was adjusted based on the rotation information of the thigh sensor. Estimates of body postures (supine, prone, left/right side) were calculated with the uncorrected and corrected estimations and compared to the observed body posture to evaluate the accuracy of the described procedure. Percentage of correctly identified postures was determined for each sensor location.

Data analysis

Data analysis required identification of the periods of sleep and then, within those periods, calculation of a range of postures and movement. For these two elements, algorithms and criteria were refined or developed as follows.

Identification of estimated sleep time

A multistep automated approach was used to identify sleep time. First, using activPAL proprietary software, events from each 24 hours of recording of the thigh sensor were exported, which indicate the start and end of each continuous period spent "sedentary (i.e., sitting/lying)", "standing" and "walking". Further data processing and analysis were performed using MATLAB software (MATLAB R2018b, The MathWorks, Inc., Natick, MA). For this analysis periods unlikely being part of waking hours were identified as *in-bed* or *non-wear* based on previously published algorithms (Winkler *et al* 2016, Berg *et al* 2016). *In-bed* periods were identified using a 2-step algorithm: In step 1, "long sedentary periods" (>5 hours) are identified and, in case none are found, the largest "short sedentary periods" (>2 hours) was selected. Then, step 2 searches within the time window of 15 minutes before and after the *in-bed* period for independent events that are probably part of the same continuous *in-bed* period: in case it finds another in bed period, or long (>2 hours) uninterrupted stationary events, these are then combined with the *in-bed* period previously identified (Winkler *et al* 2016). Raw acceleration data was visually inspected to ensure the complete *in-bed* period was found. For example, if a participant had been up and active (e.g., walking) in the middle of the night for more than 15 minutes and went back to bed for several hours after that, the algorithm described above may not have identified both *in-bed* periods (before and after being up for >15 min). For this reason, the data were visually inspected and the start and/or end of the *in-bed* period was adjusted if necessary. The Supplementary Material (S1) shows a flowchart and example data of the detection of *in-bed* periods. Periods of *non-wear* were identified as continuous "very long events" (<12 hours), or events of 7+ hours duration starting in unlikely periods of the day: sedentary periods starting between 8AM and 6PM, or standing/walking events starting between midnight and 6AM (Berg *et al* 2016). Periods identified as *in-bed* that were unexpected, e.g., when they occurred during the day, were verified against self-reported bed/wake times. All *non-wear* periods were checked against self-reported non-wear times, where possible (i.e., when the daily diary was completed).

Third, as the *in-bed* periods likely also contained time in bed but not asleep (Winkler *et al* 2016), the *time likely to be sleep* was estimated using raw accelerometer data from the trunk sensors: raw tri-axial acceleration signals from the trunk sensor were plotted over time, and the initial estimates (start and end-time) of *in-bed* periods obtained from the thigh sensor were indicated. These plots were visually inspected to identify moments of *sleep onset* and *wake up* based on the reasoning that, when the participant is sleeping, the trunk should be in horizontal position and trunk movement is negligible for extended periods. On this basis, *sleep onset* was estimated by visual inspection as the time when fluctuations in trunk acceleration stopped, which would indicate cessation of small movements that occur when awake and *wake up* time was identified using the converse criteria.

Identification of body posture and sleep parameters

Body postures were continually monitored using the angular orientation of the trunk-sensor during the identified sleep times and a series of parameters were defined according to the methods described by Wrzus et al. (Wrzus *et al* 2012) and some additional measures (Table 1). The activPAL sensor provides accelerations from three orthogonal axes which can be used to calculate angular position and motion (Lyden *et al* 2016), and thus, body postures and movements between postures. This involved several steps. The raw accelerations were calibrated to equivalent g-force values using specifications from the manufacturer (“Analog Devices: Product Overview ADXL345” 2021). These Cartesian coordinates were transformed to spherical coordinates, yielding an angle in the transverse plane (ZY for the activPAL, see Figure 1a) between ±180° (Figure 1c). When lying down, the angular orientation of the trunk sensor was used to estimate the body posture. Four body postures were identified using thresholds similar to those described by Wrzus et al. (2012), considering supine as the angle of 0°, the criteria for the four postures were: lying supine (-45° to 45°); lying on the right side (45° to 135°); lying prone (-135° to +135°); and lying on the left side (-45° to -135°) (Figure 1c).

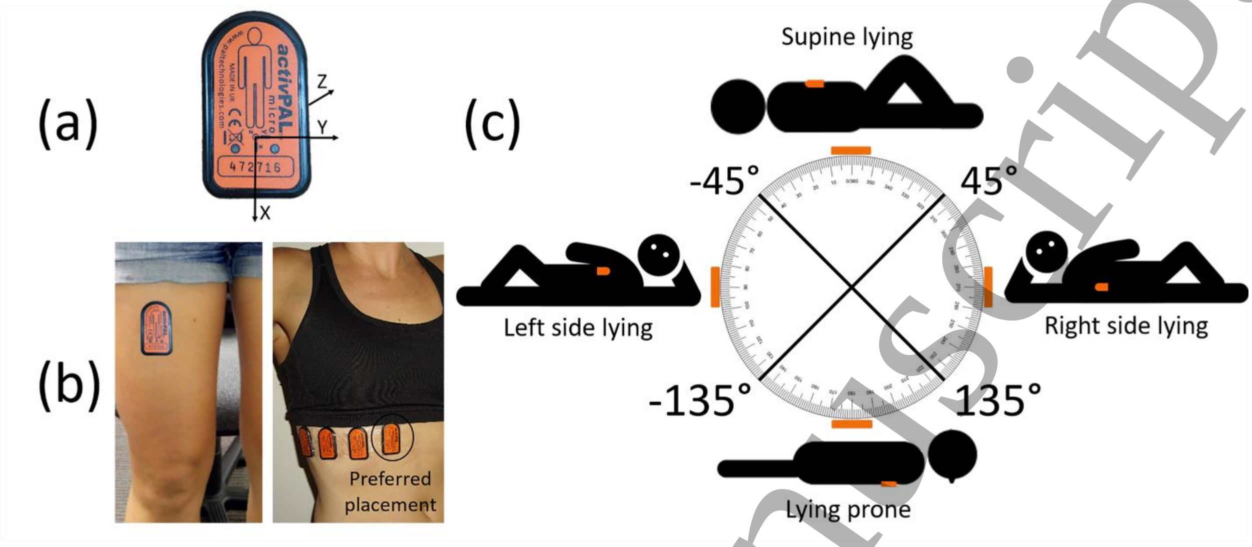

Figure 1. (a) Axis system of the activPAL tri-axial accelerators; (b) placement of the activPAL thigh sensor and possible placements of the trunk sensor when attached by participants (the most medial/anterior placement is the preferred placement); (c) body postures while lying and classification thresholds for the activPAL sensor attached to the trunk.

To identify the body postures and movement behaviour for each sleep period, a sliding circular mean was calculated across a 5-second window. When the orientation differed more than 30° from the preceding window, it was considered as a "posture change" and a boundary was set. The time between boundaries consists of a single body posture and was defined as a *segment* of data. The posture during each segment was recorded as the mean angular orientation across that segment. The total duration of time in each posture during the episode of sleep was recorded (i.e., in case of multiple segments, the *total duration* was the sum of durations across all segments). We also recorded the total number of posture changes and the number of segments that had a duration of 15 minutes or longer ("long posture"). Similarly, we calculated the number of *changes of 10°,* which may be an indication of "tossing and turning" during restless sleep. As the identified body posture before a boundary was not always different from the body posture after a boundary (boundary was defined by change of 30° but may not cross a threshold for a different posture), we separately counted the boundaries that involved a change in body posture as a "*turn*". Furthermore, if the average gravitational force of the trunk-sensor across one segment in the longitudinal axis was <-0.66 g, the corresponding segment was considered a "*rise*" (i.e., stand up from lying down). *Total number of rises* was counted as well as the number of *rises in the first hour*. *Total time upright* was defined as the sum of the duration across all rise segments. Finally, *average activity over the night* was derived by taking the average change in the resultant acceleration vector of the trunk-sensor (Table 1) (Wrzus *et al* 2012).

Table 1. Description of posture and sleep parameters

Parameter	**Description**	**Unit**
Sleep time	Time between start and end of sleep events	Hours
Time Upright	Total time upright during the period defined as sleep	Minutes
Lying time	Time defined as sleep minus time upright	Hours
Average activity	Average change in resultant acceleration vector of trunk-sensor	g (m/s^2)
Rises	Postures with trunk longitudinal gravitational force > -0.66	Count
Rises first hour	Rises in first hour	Count
No. Turns	Number of changes in body postures	Count
Posture duration	Average duration in a posture	Minutes
Long postures	Postures maintained longer than 15 minutes	Count
Time "supine"	Trunk angle: -45° to +45°	Minutes
Time "right side"	Trunk angle: +45° to - 135°	Minutes
Time "prone"	Trunk angle: -135° to +135°	Minutes
Time "left side"	Trunk angle: -45° to -135°	Minutes
Posture changes >30°	Number of posture changes of 30 degrees or more	Count
Posture changes >30° in first hour	Number of posture changes of 30 degrees or more for first hour	Count
Posture changes >10°	Number of posture changes of 10 degrees or more	Count
Posture changes >10° in first hour	Number of posture changes of 10 degrees or more for first hour	Count

Statistical analysis

For each participant, all sleep parameters were calculated for each night. Nights containing missing data were excluded from analysis. Nightly averages for each sleep parameter were calculated for different numbers of nights (1-7 nights), selected randomly from the first week of monitoring. The nightly average of each sleep parameter was also calculated for the entire 28 nights. This value was used as the reference for comparison of the validity of the shorter periods of measurement. Finally, averages were also generated based on combinations including one or two weekend-days.

Data were analysed in four ways:

(i) *General sleep description:* Means and standard deviations were calculated for each sleep parameter for the total 28-day period and for week 1 and week 4.

(ii) *Number of nights needed to reliably estimate sleep parameters over a month:* The Spearman-Brown Prophecy Formula was used to estimate the minimum number of nights required to obtain a reliable estimate of each sleep parameter. This formula is based on the intraclass correlation (ICC) and is as follows: N=[ICCd/(1-ICCd]*[(1-ICCe)/ICCe], where N = the number of nights needed, ICCd = desired level of reliability (0.8), and ICCe = estimated level of reliability (McGraw and Wong 1996, Trost *et al* 2005). The estimated level of reliability of the sleep parameters was examined by calculating single-measure (single-night) ICCs (consistency; two-way random model). The single-measure ICC is used when the actual (future) application will be based on a single measurement. Calculation of this ICC considers all available data (multiple measurements) (Koo and Li 2016). In this study, the reliability of sleep parameters for a single measurement (night) was then used in the Spearman-Brown Prophecy Formula to assess the minimum number of nights required to obtain a reliable estimate of each sleep parameter. To check the accuracy of the estimate, for each sleep parameter, we then used the number of nights (derived from the Prophecy Formula) to calculate the average-measures ICCs. The average-measure ICC is a type of ICC that provides the reliability for the mean of multiple measurements (nights, in this case) (Koo and Li 2016).

(iii) *Comparison of different combinations of nights:* The averages of the sleep parameters based on the different combinations of nights were compared with the reference (average of entire 28 nights) using correlation coefficients (Pearson if normally

distributed, otherwise Spearman) and Bland-Altman methods to assess mean biases and limits of agreement.

(iv) *Between week repeatability:* To determine the repeatability of the sleep parameters between weeks of measurement, ICCs (two-way random model, average measures) between the nightly average of week 1 and week 4 were calculated. This was undertaken for both the nightly average based on one random night in each period and the nightly average based on seven nights of both periods.

Results

Evaluation of correction of trunk-sensor data

Using the uncorrected signal, classification for the best placed sensor (most medial/anterior placement, see Figure 1b) was accurate for 98.1% of the measures. For the placement that was most lateral on the chest (i.e., rotated approximately 90° relative to the “correct” placement), the classification was accurate for 13.9% of the measures. After correcting the rotation angle, the classification was 100% accurate for the best placed sensor and 95.9% accurate for the least ideal placement.

General sleep description

Twenty-two participants (42%) provided valid (i.e., nights without any missing data) data for the full 28 nights and for the other 28 participants there were on average four nights of missing data (range 1-14 nights) over the 28 days. Based on the activity sensors, participants slept for an average (SD) of 8.1 (0.8) hours per night. Overall, 44% of the time lying down was spent in a supine position, 23% on the right side, 21% on the left side, and 9% in prone. For each of the 18 sleep parameters, the nightly average for the whole 28-day period and for data of weeks 1 and 4 are presented in Table 2.

Table 2. Nightly average of each sleep parameter (mean (SD)) for different recording periods

	28-days	**7 days (Week 1)**	**7 days (Week 4)**
Total valid nights (%)	92.4%	96.0%	89.7%
No. of valid nights	25.9 (3.3)	6.7 (0.7)	6.3 (1.3)
Sleep time (h)	8.1 (0.8)	8.2 (1.0)	8.1 (0.9)
Time Upright (min)	6.4 (8.4)	6.0 (10.2)	5.4 (8.8)
Lying time (h)	7.9 (1.0)	8.1 (1.0)	8.0 (1.0)
Average activity (g)	1.1 (0.1)	1.1 (0.0)	1.1 (0.1)
Rises	0.9 (0.7)	1.0 (1.0)	0.9 (0.8)
Rises first hour	0.1 (0.2)	0.1 (0.2)	0.2 (0.3)
No. Turns	17.0 (7.1)	17.2 (8.2)	17.2 (7.3)
Posture duration (min)	22.2 (9.6)	22.9 (12.7)	22.9 (13.2)
Long postures (>15 min)	9.7 (1.8)	10.0 (2.0)	9.8 (2.2)
Time “supine” (min)	214.3 (69.8)	226.7 (74.5)	223.0 (79.9)
Time “right side” (min)	113.7 (41.2)	115.9 (52.3)	105.5 (44.0)
Time “prone” (min)	45.7 (42.2)	38.3 (37.6)	48.0 (49.8)
Time “left side” (min)	102.8 (44.3)	107.0 (49.6)	104.3 (55.0)
Still position latency (min)	1.1 (1.4)	1.0 (1.7)	1.0 (1.1)
Posture changes >30°	28.5 (11.1)	28.6 (13.2)	29.3 (11.9)
Posture changes >30° in first hour	3.9 (1.5)	4.0 (1.9)	4.2 (1.9)
Posture changes >10°	51.2 (16.0)	52.3 (19.7)	51.9 (16.7)
Posture changes >10° in first hour	6.0 (2.8)	6.4 (3.5)	6.2 (3.0)

Number of nights needed to reliably estimate sleep parameters over a month

The Spearman-Brown Prophecy Formula showed that the number of nights required to estimate the behaviour over 28 nights varied between sleep parameters, ranging from four to 21 nights (Table 3). Reliable estimates of six parameters (i.e., “average activity”, “no. turns”, “lying supine”, “lying prone”, and “posture changes >30° in first hour” and “posture changes >10° in the first hour”), could be generated from seven or fewer nights of data. Features that required the greatest number of nights (and lowest single-measure(night) ICCs) were the number of rises and time upright, sleep time and average duration of postures. This finding indicates these measures vary considerably from night to night. Generally confirming our analysis, when the average ICC measures are calculated using the derived minimum number of nights, values were approximately 0.80 for all parameters (Table 3).

Table 3. Number of required nights to generate a reliable estimate of each of the sleep parameters based on the Intraclass Correlation [a] (ICC; single measures).

	Intraclass Correlation		No. of nights[a] needed for ICC[b]≥0.8	ICC[b] for no. of nights[c] needed
	Single measure	Average measure		
Sleep time (h)	0.19	0.87	18	0.82
Time Upright (min)	0.17	0.85	20	0.82
Lying time (h)	0.21	0.88	16	0.81
Average activity (g)	0.49	0.96	5	0.87
Rises	0.27	0.91	11	0.86
Rises first hour	0.16	0.84	21	0.78
No. Turns	0.51	0.97	4	0.86
Posture duration (min)	0.18	0.86	19	0.88
Long postures (>15 min)	0.26	0.91	12	0.84
Time “supine” (min)	0.39	0.95	7	0.83
Time “right side” (min)	0.22	0.89	15	0.85
Time “prone” (min)	0.42	0.95	6	0.73
Time “left side” (min)	0.30	0.92	10	0.79
Posture changes >30°	0.25	0.90	13	0.74
Posture changes >30° in first hour	0.44	0.96	6	0.93
Posture changes >10°	0.27	0.91	11	0.77
Posture changes >10° in first hour	0.39	0.95	7	0.91

[a] The number of nights is calculated using the Spearman-Brown Prophecy Formula based on a reference ICC of 0.8.

[b] Average-measures ICC

[c] This refers to the no. of nights displayed in the 3rd column of this table.

Comparison of different combinations of nights (28-night reference)

For most parameters (13 out of 17) the correlations between measures calculated from 7-nights and 28-night reference was >0.80. A few parameters (“no. turns”; “lying supine”; “lying prone”; “posture changes >30° in first hour”) reached high correlations (>0.90) when comparing the 7-night estimate with the 28-night reference. Addition of any day above five for the estimates made little further improvement in correlations (ranging from -0.01 to +0.06) with the 28-night reference. Overall, including a weekend day in the estimates did not change correlation coefficients. Similar to the impact on ICCs, mean biases and limits of agreements (LoA) showed small improvements (smaller bias;

narrower LoA) when using an estimate based on five or more nights. Correlations, mean biases and limits of agreement for all different combinations are provided in the Supplementary Material (S2).

Between week repeatability

When comparing the nightly average based on one night in week 1 and one night in week 4, the ICC ranged from -0.45 to 0.73. ICC was negative for two parameters ("Sleep time" and "Lying time"), which means that variability within a night (between participants) exceeded the variability between nights. Negative ICC estimates indicate that the variability within groups exceeds the variability across groups and is interpreted as a low true intraclass correlation (Taylor 2009). The ICCs increased when averages were generated over the seven nights of both weeks and ranged from 0.51 to 0.90 (Figure 2). Five sleep parameters reached an ICC >0.80: "number of turns", "time supine", "time prone", and movements (10 and 30°) in the first hour. It is important to note that low ICCs are more likely to represent differences in the individual's behaviour between nights rather than error in the measurement.

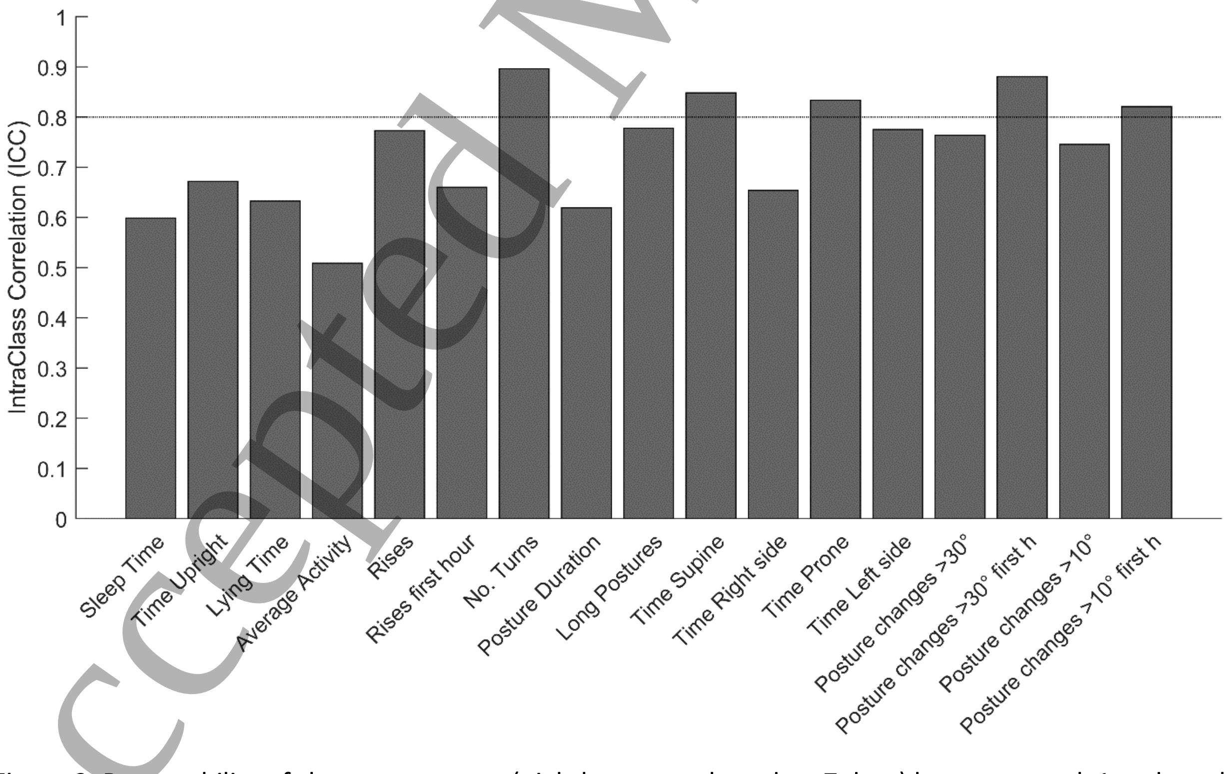

Figure 2. Repeatability of sleep parameters (nightly average based on 7 days) between week 1 and week 4. The horizontal dotted line shows an ICC of 0.8, which generally indicates good/acceptable reliability.

Discussion

This study evaluated a method to assess body posture and movement during sleep over multiple days or weeks in the real-world. This study confirms the feasibility of use of accelerometers to measure posture and movement during sleep for multiple days or weeks using a correction method to account for potential suboptimal placement of the accelerometers. Results showed that the minimum number of nights required for a reliable estimate (i.e., value that is representative of a measure made over 28 days) is different for each sleep parameter. Some parameters, including “average activity”, “no. turns”, “lying supine”, “lying prone”, and “posture changes first hour”, were relatively stable, and seven or fewer nights were sufficient to provide a reliable estimate. Other parameters were less stable, such as “Sleep time”, “time upright”, “Rises first hour”, “Posture duration”, and required more than 18 nights to provide a reliable estimate.

This is the first study to evaluate posture and movement of the whole-body during sleep using accelerometers for several weeks in free living contexts. Most of the parameters were calculated using methods based on those presented by Wrzus et al. (2012), for analysis of data over a single 24-hour period. Although other studies have used accelerometers to measure sleep position and body movements over multiple days (e.g. (Skarpsno *et al* 2017)), the focus has been on associations with demographics, lifestyle and insomnia symptoms. Wrist or ankle-worn accelerometers have also been used for multiple days or weeks in free-living contexts, but these sensors do not measure whole body movement or distinguish between different lying positions (Smith *et al* 2018, Zambotti *et al* 2019). Changes in body posture and movements during sleep could provide more insight into sleeping behaviour and sleep problems, with relevance for a range of conditions such as back pain.

Our results show that some sleep parameters are more robust than others across nights. Parameters related to movement (e.g., “average activity” and “turns”) and position (e.g., “lying supine” and “lying prone”) were most robust, but still required 4-7 days of monitoring to obtain a reliable estimate. Data from a study by Skarpsno et al. (2017) that was based on a working population in whom musculoskeletal pain was very common, reported little variation in sleep positions and body movement across six testing nights. Although this suggests that data from additional nights was not necessary, that study only included a single 6-night period, and according to our data, this might may not be representative for monitoring during another. Parameters related to the duration of sleep were more variable between days. Similar to our results, but using wrist worn actigraphy-measurements, Aili et al. (2017) found that more than seven nights were needed for a reliable measure of total sleep time.

The parameters “Sleep time”, “Time Upright”, and “Lying time” all required more than two weeks of monitoring to provide a reliable estimate. Although it is likely that this is explained by high variability of these parameters over time, the method used to calculate these parameters requires consideration. All parameters relate to *sleep time* and the method used to estimate *sleep time* in this study included manual selection of time-points based on visual inspection of the data. This may introduce some variation in data. The accuracy of this method requires evaluation, for example verification using other methods such as electroencephalography to identify sleep state (Fekedulegn *et al* 2020). Our method to estimate *sleep onset* and *wake up*, based on decreases and increases in trunk acceleration, respectively, could directly influence some parameters that are also based on trunk movement, such as “posture changes in the first hour”. Likewise, it is also important to note that such methods might lead to overestimation of total sleep time, as one may remain still for some time prior to falling asleep.

Notably, the present data showed that one week of monitoring may not reflect behaviour over a subsequent week for most parameters, even when values are averaged over 7 days (12 out of 17 with ICC <0.8). This suggests that long periods (e.g., several weeks) may be required if a single representative estimate is preferred. Alternatively, this observation implies that when sleep parameters are to be contrasted with other measures (e.g., pain intensity) it is likely that analysis that takes into account the time-varying nature of sleep parameters and the contrasting measure need to be considered. The availability of wearable sensors, in combination with the presented method to correct for inaccurate placement of sensors, make ambulatory assessment over a long period possible.

The sleep parameters used in this study were all derived from the trunk sensor, but the thigh sensor was used to correct for potential misplacement of trunk sensor. Wearing both sensors also enables differentiation between sitting and lying, which is especially useful for differentiating between these positions during the day (e.g. naps) (Smits *et al* 2018), and could be beneficial for monitoring 24-hour behaviour. Additionally, the thigh sensor can be used to measure leg movements during sleep, which could be useful to detect specific sleep problems, such as periodic limb movement disorder (Smith *et al* 2018).

Some methodological issues require consideration. First, these data are based on participants with LBP, and it is plausible that movement and posture during sleep might differ between individuals with and without pain. Previous work suggests a reciprocal relationship between sleep disturbance and pain (Finan *et al* 2013). Second, some of the sleep parameters included in this study are not independent of each other, for example as time lying in a supine posture increases, time in another posture (prone, left or right side) will decrease. Thus, in addition to time spent in each position separately, these measures may need to be considered as a composite (Dumuid *et al* 2018). Despite these limitations, this study has potential clinical implications. For instance, the methods presented here could be used in both clinical and research contexts to provide further insights on how sleep position in real-world contexts (i.e., sleeping at home) relates to clinical conditions such as low back pain (which may be provoked by specific postures, and could explain pain the following day) or sleep apnoea symptoms (which are affected by body position) (Ravesloot *et al* 2021). Likewise, our methods could be used to further understand the relationship between frequent body posture change and sleep, with relevance for conditions such as parasomnia (Fleetham and Fleming 2014). Whether sensors should be worn for short or long periods will depend on the purpose of the investigation. If the study aims to evaluate short term effects of a specific posture, then recording over a few days should suffice. However, if the aim is to characterize sleeping posture of an individual, then longer duration recording is required to capture the variation over time.

Conclusions

This study shows that most sleep parameters related to whole body movement and posture require a week or more of monitoring to provide a reliable estimate of behaviour over one month. Importantly, the results also showed that one week of monitoring does not always reflect behaviour in subsequent weeks, which suggests that multiple weeks of monitoring may be required, and this time varying nature of sleep might need to be considered in studies. The method used to correct the data for potential suboptimal placement of trunk-worn accelerometers facilitates longer periods of monitoring with reapplication of the sensor by the participants. Further research is needed to verify the accuracy of estimates of sleep onset and wake up times from trunk acceleration data.

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