Watching over sleep: does co-assessment of skin temperature improve accuracy of actigraphic sleep estimates?

Based on:

Abstract

Actigraphy is widely used as a low cost, easily implementable alternative to polysomnography (PSG) for the assessment of sleep. Estimating sleep from wrist activity is however far from perfect. In particular the detection of wakefulness during immobility is problematic. Skin temperature is an easy accessible physiological variable that contains information on the state of the autonomic nervous system. The release of sympathetic vasoconstriction of the skin vasculature that occurs during sleep increases skin blood flow and consequently skin temperature. We argued that a relatively cool skin could indicate wake-related sympathetic activation and here investigated whether skin temperature could disambiguate false from true actigraphic sleep classifications during immobility. Actigraphy, wrist skin temperature and a routine PSG were simultaneously recorded in 52 participants, including people with a variety of sleep disorders and people without sleep disorder. Epoch-by-epoch (30-sec) actigraphic sleep-wake estimates were obtained using standard procedures and labelled as false vs. true sleep and wake classifications by comparison with PSG. Indeed, on average a lower skin temperature was recorded during false sleep classifications than during true sleep classifications. Also, a higher skin temperature was recorded during false wake classifications than during true wake classifications. Mixed effect logistic regression was therefore applied to obtain discriminant functions based on two temperature thresholds: (1) the temperature below which an actigraphic sleep classification has a higher probability to be false than true according to PSG and (2) the temperature above which an actigraphic wake classification has a higher probability to be false than true according to PSG. Leave-one-out crossvalidation was applied to obtain the accuracy of actigraphic sleep-wake estimates recoded according to the application of these temperature thresholds. Actigraphy alone incorrectly classified 8.1% [95% CI 8.1 – 8.2] of all epochs as sleep while PSG indicated wake and incorrectly classified 6.1% [95% CI 6.1 – 6.2] of all epochs as wake while PSG indicated sleep, resulting in an overall accuracy of 85.7% [95% CI 85.7 - 85.8]. The additional use of skin temperature thresholds did not significantly increase the accuracy. The results suggest that the use of skin temperature to improve the accuracy of actigraphic sleep estimates may require a temperature sensor with a shorter time constant, like an infrared sensor, or may even require direct assessment of changes skin perfusion in order to overcome the sluggishness of the resulting changes in skin temperature.
It is increasingly recognized that sufficient sleep is important for health. To screen for inadequate sleep, polysomnography (PSG) is the gold standard: electroencephalography, electrooculography and electromyography have to be recorded all night. Although ambulatory PSG devices have become available, the recording is still burdensome, as for example evidenced by the fact that an adaptation night is required because the first night often has a non-representative sleep architecture (Le Bon et al., 2001).

Due to its much lower invasiveness and cost, actigraphy is widely used as an alternative to polysomnography to estimate sleep. However, although actigraphy detects the sleep state reasonably well with PSG during sleep (Ancoli-Israel et al., 2003), the detection of wake during immobility is problematic (Pollak et al., 2001). Comparative studies have demonstrated that the accuracy of actigraphic sleep estimates in healthy volunteers and in clinical practice ranges between 60% to 85% and may be insufficient to detect small but clinically relevant abnormalities or treatment responses (Weiss et al., 2010). Alternatives to wrist activity assessment have therefore been proposed, for example ambulatory assessment of heart rate variability. However none of the proposed alternatives are as easy to implement as actigraphy.

We here propose and demonstrate that the addition of skin temperature recording to actigraphic assessment provides a solution that preserves long-term unobtrusive wearability and ease of recording and analysis, while dramatically improving the accuracy of sleep estimates. Skin temperature is a physiological variable that is easy to access and, like heart rate variability, contains information on the state of the autonomic nervous system, for instance sympathetic regulation of blood flow (Rubinstein & Sessler, 1990). During sleep, a release of sympathetic activation has been measured (Takeuchi et al., 1994). Combining this with the finding that skin blood flow is enhanced during sleep, which consequently raises skin temperature (Sindrup et al., 1995), we argued that a relatively cool skin could indicate wake-related sympathetic activation during immobility. Therefore, we investigated whether skin temperature could disambiguate false from true actigraphic sleep classifications. To investigate this hypothesis, polysomnography, actigraphy and skin temperature were simultaneously assessed in a heterogeneous sample of 52 volunteers, including people with a sleep disorder. Mixed effect logistic regression was applied to obtain discriminant functions to disambiguate false from true actigraphic sleep classifications by use of the skin temperature that was simultaneously recorded during each 30-second epoch. The a leave-one-out crossvalidation (LOOCV) methodology was used to estimate the sleep-wake classification accuracy of combined actigraphy and temperature recordings. The results indicate that a dramatic and robust improvement in actigraphic sleep estimate accuracy is feasible by the simple addition of wrist temperature, which could be assessed without any additional burden by integrating a temperature sensor in the bottom plate of an actigraph.
Watching over sleep

Methods

Acquisition
Participants were recruited through the sleep disorders outpatient clinic at the VU Medical Center in Amsterdam with approval of the local medical ethics committee. Participants gave their written informed consent to wear, in addition to the routine ambulatory EEG recorder, an actigraph and a temperature logger for one night. The actigraph (Actiwatch, CamNtech ltd., Cambridge, UK) was worn on the wrist of their non-dominant hand. Self-reported ambidextrous subjects were treated as righthanded. Activity counts were aggregated in 30 second intervals. An iButton Thermochron temperature logger (type DS1922l, Maxim/Dallas, USA, 0.0625 °C resolution) was worn on the dorsal side of the dominant wrist, sampling skin temperature every 30 seconds with a resolution of 0.0625 °C. Ambulatory EEG was obtained using an EMBLA A10 recorder (EMBLA, Flaga hf, Reykjavik, Iceland) to record polysomnography and subsequently sent home with the request to follow their habitual sleep pattern, without any further restrictions. Self-reported time of lights-out and final awakening were logged using a sleep diary. A neurologist and clinical neurophysiologist diagnosed sleep disorders according to ICSD-2 criteria (American Academy of Sleep Medicine, 2005).

Analysis
Polysomnographic recordings were subjected to sleep staging according to the Rechtschaffen & Kales standard (Rechtschaffen & Kales, 1968) with the aid of visualization software (Somnologica, Flaga hf, Reykjavik, Iceland). Sleep stages reflected consensus between an experienced sleep technician and a clinical neurophysiologist. Only data between lights-out and final awakening were used. Consequently, each participant had a different number of 30-second epochs.
Actigraphic sleep estimates were obtained using proprietary Actiwatch software (version 5.57.0006, Philips Respironics, Murrysville, USA). The algorithm used to estimate wake and sleep from activity counts has been described earlier (Kushida et al., 2001). In short, the activity of the measured epoch and its surrounding 4 min period (±2 min) was summed according to the following equation: \[ A = 0.04E_x + 0.04E_{-x} + 0.20E_{-3} + 0.20E_{-1} + 2E + 0.20E_{+1} + 0.20E_{+2} + 0.04E_{+3} + 0.04E_{+4}, \]
where \( A \) = sum of activity counts for 30-s scored epoch and surrounding epochs. \( E = \) activity counts recorded during scored epoch; \( E_n = \) activity counts recorded during each previous (-1,-2,-3,-4) or following (1,2,3,4) successive epochs. If the summed activity count (A) is above a defined threshold (T), the epoch is scored as wake (i.e. \( A > T = \text{wake} \)), otherwise, it is scored as sleep (i.e. \( A \leq T = \text{sleep} \)). The default medium sensitivity level was used, where \( T = 40 \). The procedure yields Sleep or Wake scores for each interval between lights-out and final awakening (figure 1a).
To correct for possible desynchrony between the PSG and actigraphy recordings, the data for each subject were subjected to cross-correlation analysis, and if necessary actigraphy data were delayed or advanced to insure optimal synchronization. Desynchrony is a known issue with the Actiwatch: while the initiation clock time is read out from the host PC during the startup procedure, it starts running only after removal of the device from the interface. Subsequently, using PSG sleep scores as the gold standard, every single actigraphically classified sleep- or wake- epoch was labelled as either true (congruent with the PSG score), or false (incongruent with the PSG score) (figure 1a). For each subject the percentage by which each of these four classes (true wake, false wake, true sleep, false sleep) was represented in their recording was thus initially obtained based on actigraphy only. The subsequent step was to evaluate whether the percentage of false classifications could be reduced by addition of information on skin temperature in these epochs.

To do so, as schematically indicated in figure 1b, mixed effect logistic regression analysis (MLwiN, Centre for Multilevel Modelling, University of Bristol, Bristol, UK) was used to obtain two discriminant functions. First, if a low temperature during immobility is a signature of wakefulness, a temperature threshold can be determined below which an actigraphic sleep classification is more likely to have been scored as wake by PSG and may thus better be recoded as wake. At this temperature threshold, an epoch originally classified as sleep has a probability of 0.5 to indeed be sleep. Below it, it is more likely to be in fact wake, and above it to be sleep indeed. Second, if a high temperature, maintained over a period with some activity, is a signature of sleep, another temperature threshold can be determined above which an actigraphic wake classification is more likely to have been scored as sleep by PSG and may thus better be recoded as sleep. At this temperature threshold, an epoch originally classified as wake has a probability of 0.5 to indeed be wake. Above it, it is more likely to be in fact sleep, and below it to be wake indeed.

A leave-one-out crossvalidation (LOOCV) approach was applied to repeatedly estimate the optimally discriminant temperature thresholds in n-1 participants and obtain the temperature-optimized actigraphic sleep/wake classifications in the remaining participant. LOOCV excludes data of one subject at a time, until the temperature-optimized actigraphic sleep/wake classifications is obtained for each subject. These new classifications are then compared with PSG to obtain temperature-optimized percentages of true wake, false wake, true sleep, false sleep for that subject (figure 1c). The averaged accuracy over all subjects provides a conservative estimate of the predictor’s true accuracy (Kohavi, 1995).
**Figure 1** Re-classification and leave one out crossvalidation

(a) The dataset of each participant consists of a sequence of epochs classified by the actiwatch algorithm (Acti) as either wake (white squares) or sleep (grey squares). Each epoch may be classified as correct or incorrect wake (black or red letter w, representing congruent or incongruent score with polysomnography (PSG), respectively), or as correct or incorrect sleep (black or red letter s, representing congruent or incongruent score with PSG, respectively). The percentages of these 4 categories are determined and averaged across all subjects. (b) Mixed effect logistic regression analysis over n-1 participants can be applied to find the temperature threshold that best discriminates (p=0.50) epochs that represent true sleep from those that are falsely classified as sleep epochs. (c) This threshold temperature is then used to re-classify the epochs that were scored as sleep by the actiwatch algorithm for the participant that was not included in the regression (p(i)). Epochs of participant i that were originally classified as sleep but during which the wrist temperature is lower than the threshold temperature, will be re-classified as wake. Accuracy of the re-classified epochs is obtained by comparison with the golden standard PSG-based sleep scores of this participant. The leave one out crossvalidation (LOOCV) process is repeated 51 times, leaving out a different participant each time. The same procedure as described sub b) and c) were also used to re-classify epochs that were originally scored as wake by actigraphy.
Assessments were made in 52 participants aged 45.4 ± 15.0 (mean ± SD) years, half of which were male. Table 1 summarizes participant characteristics. Of the 52 participants, 10 were diagnosed with obstructive sleep apnea syndrome, 9 with periodic limb movement disorder, 8 with psychophysiological insomnia, 4 with circadian rhythm disorder, 3 with narcolepsy, 2 with epilepsy and 2 with REM sleep behaviour disorder. There were single cases of sleep state misperception, sleep terror, vasovagal collapse. Furthermore, there was one participant diagnosed with restless legs, with a possibility of both depression and obsessive compulsive disorder. Lastly, there were 10 participants not diagnosed with any disorder of sleep or otherwise.

An overview of the PSG sleep parameters can be found in Table 2. Participants switched off the lights on average at 23:34 ± 01:24 (mean ± SD) and woke up at 07:39 ± 00:48. On average, total sleep time was 406 ± 100 minutes.

Of the 52 datasets, 20 required a resynchronization of the actigraphic and PSG timeseries. Out-of-sync assessment occurred by omitting to take the actiwatch from its computer interface immediately after startup. The median absolute shift of these 20 datasets was 3 minutes (range: 1-135 minutes). Even after optimizing the synchronization with PSG, actigraphy-based sleep-wake classifications without information on skin temperature were inaccurate for 14.3% [95% CI 14.2 – 14.3], i.e. accurate for 85.7% [95% CI 85.7 – 85.8] of the epochs (Table 2). In detail, 8.5% [95% CI 8.5 – 8.6] of all epochs was congruently classified as wake by both PSG and actigraphy (true wake) whereas 6.1% [95% CI 6.1 – 6.2] of all the epochs were scored as sleep by PSG, yet incorrectly scored as wake by actigraphy (false wake). Furthermore, 77.2% [95% CI 77.1 – 77.3] of the epochs was congruently classified as sleep by both PSG and actigraphy (true sleep), whereas 8.1% [95% CI 8.1 – 8.2] of the epochs were scored as wake by PSG, yet incorrectly scored as sleep by actigraphy (false sleep).
Table 1 Participant characteristics and frequency of diagnosed sleep disorders.

<table>
<thead>
<tr>
<th></th>
<th>mean</th>
<th>±</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>n</td>
<td>52</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age (years)</td>
<td>45.4</td>
<td>±</td>
<td>15.0</td>
</tr>
<tr>
<td>Male / female</td>
<td>26 / 26</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Right-handed / left-handed / ambidextrous</td>
<td>43 / 6 / 3</td>
<td></td>
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</tbody>
</table>

Reason for diagnostic recording
- Apnea-related complaints: 30
- Hyper- or insomnia-related complaints: 21
- Other: 1

Classification
- Sleep apnea: 10
- Leg movement: 9
- Insomnia: 8
- Circadian rhythm disorder: 4
- Narcolepsy: 3
- Epilepsy: 2
- REM sleep behaviour disorder: 2
- Sleep state misperception: 1
- Sleep terror: 1
- Vasovagal collapse: 1
- Restless legs + depression + obsessive compulsive disorder: 1
- No disorder: 10

Age presented as mean ± standard deviation (SD).
Table 2 Polysomnographically determined sleep parameters.

<table>
<thead>
<tr>
<th>Sleep parameters</th>
<th>mean (median)</th>
<th>SD (range)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bed Time (hh:mm ± hh:mm)</td>
<td>23:34 (01:23)</td>
<td>01:23</td>
</tr>
<tr>
<td>Get Up Time (hh:mm ± hh:mm)</td>
<td>07:38 (00:48)</td>
<td>00:48</td>
</tr>
<tr>
<td>Sleep onset latency (minutes)</td>
<td>23 (1 - 100)</td>
<td></td>
</tr>
<tr>
<td>Sleep duration (minutes)</td>
<td>406</td>
<td>100</td>
</tr>
<tr>
<td>WASO</td>
<td>59 (0 - 327)</td>
<td></td>
</tr>
<tr>
<td>S1</td>
<td>63</td>
<td>41</td>
</tr>
<tr>
<td>S2</td>
<td>155</td>
<td>63</td>
</tr>
<tr>
<td>S3</td>
<td>76</td>
<td>40</td>
</tr>
<tr>
<td>S4</td>
<td>38</td>
<td>30</td>
</tr>
<tr>
<td>R-lat</td>
<td>129 (11 - 395)</td>
<td>38</td>
</tr>
<tr>
<td>R-dur</td>
<td>81</td>
<td></td>
</tr>
</tbody>
</table>

Group measures are presented as mean ± standard deviation (SD) for normally distributed variables and as median (range) for not-normally distributed variables.

Figure 2 indicates that the wrist temperatures measured over epochs of true wake, false wake, true sleep and false sleep show pronounced differences. Of importance for the disambiguation of false and true actigraphic estimates of the sleep state, a lower temperature is on average found for the false classification (33.3 °C [95% CI 33.2-33.3] for false sleep vs. 33.8 °C [95% CI 33.8-33.8] for true sleep, p<3*10^-6). Of importance for the disambiguation of false and true actigraphic estimates of the wake state, a higher temperature is on average found for the false classification (33.8 °C [95% CI 33.8-33.8] for false wake vs. 33.2 °C [95% CI 33.2-33.2] for true wake, p<9*10^-5).

The mixed effect logistic regression analyses, repeated according to the leave-one-out cross validation approach, resulted in the following discriminant functions. First, if a temperature lower than 24.2 °C [95% CI 24.2 – 24.2] is measured during an epoch originally classified by actigraphy as sleep, the epoch should be re-classified as wake. An actigraphically classified sleep epoch during which wrist temperature is below 24.2 °C has a probability $p>0.50$ to represent PSG-determined wakefulness. An actigraphically classified sleep epoch during which wrist temperature is above 24.2 °C has a probability $p>0.50$ to represent PSG-determined sleep indeed. Second, if a temperature higher than 34.7 °C [95% CI 34.7 – 34.7] is measured during an epoch originally classified by actigraphy as wake, the epoch should be re-classified as sleep. An actigraphically classified
Watching over sleep

An actigraphically classified sleep epoch during which wrist temperature is above 34.7 °C has a probability \( p > 0.50 \) to represent pSG-determined sleep. An actigraphically classified sleep epoch during which wrist temperature is below 34.7 °C has a probability \( p > 0.50 \) to represent pSG-determined wake indeed. By means of the LOOCV approach, ‘optimal’ temperatures of on average 24.2 °C and 34.7 °C were obtained for every subset of \( n-1 \) participants and used to obtain, for the remaining participant, the percentages of true wake, false wake, true sleep and false sleep after correcting the original actigraphic sleep and wake estimates accordingly. However, on average, as compared to uncorrected actigraphic sleep and wake estimates, the additional use of skin temperature thresholds did not significantly increase the overall accuracy from 85.7% [95% CI 85.7 – 85.8] to 86.0% [95% CI 85.9 – 86.1] (\( p = 0.49 \)). In detail, the percentage of true wake decreased from 8.5% [95% CI 8.5 -8.6] to 6.9% [95% CI 6.9 – 7.0] (\( p = 2 \times 10^{-6} \)), the percentage of false wake decreased from 6.1% [95% CI 6.1 – 6.2] to 4.3% [95% CI 4.2 – 4.3] (\( p = 3 \times 10^{-7} \)), the percentage of true sleep increased from 77.2% [95% CI 77.1 – 77.3] to 79.1% [95% CI 79.0 – 79.2] (\( p = 3 \times 10^{-7} \)) and the percentage of false sleep increased from 8.1% [95% CI 8.1 – 8.2] to 9.7% [95% CI 9.7 – 9.8] (\( p = 2 \times 10^{-6} \)). Overall inaccuracy did not significantly decrease from 14.3% [95% CI 14.2 – 14.3] to 14.0% [95% CI 13.9 – 14.1] (\( p = 0.49 \)) (Table 3).

**Figure 2** Mean and standard errors of the mean of wrist skin temperature in epochs where both actiwatch and polysomnography (PSG) both score wake (True Wake), in epochs where actiwatch scores wake while participants are asleep (False Wake), in epochs where both actiwatch and PSG both score sleep (True Sleep), and in epochs where the actiwatch scores sleep while subject are awake as indicated by PSG (False Sleep).
Table 3 Percentages of false and true sleep and wake classifications based on actigraphy only, and on actigraphy combined with wrist temperature.

<table>
<thead>
<tr>
<th>AW Score</th>
<th>PSG Score</th>
<th>Classification</th>
<th>Actigraphy only</th>
<th>Actigraphy combined with wrist temperature</th>
<th>Between method difference</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Percentage (%)</td>
<td>Percentage (%)</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>95% C.I.</td>
<td>95% C.I.</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Wake</td>
<td>8.5</td>
<td>6.9</td>
<td>2*10^{-6}</td>
</tr>
<tr>
<td></td>
<td></td>
<td>False Wake</td>
<td>6.1</td>
<td>4.3</td>
<td>3*10^{-7}</td>
</tr>
<tr>
<td></td>
<td></td>
<td>True Sleep</td>
<td>77.2</td>
<td>79.1</td>
<td>3*10^{-7}</td>
</tr>
<tr>
<td></td>
<td></td>
<td>False sleep</td>
<td>8.1</td>
<td>9.7</td>
<td>2*10^{-6}</td>
</tr>
</tbody>
</table>

Table 3 The distribution of percentages of false and true sleep and wake classifications based on actigraphy only (column 2) and after re-classification by means of the temperature threshold discriminant functions (column 3). The last column shows the significance, according to two-tailed paired t-tests, of the differences in accuracy and specificity between the standard actigraphic sleep estimates and the temperature-enhanced actigraphic sleep estimates. The addition of wrist temperature did not significantly increase the accuracy of wake and sleep estimates.


Watching over sleep

Discussion

The findings of our study indicate that wrist temperature is lower during false actigraphic sleep estimates than during true actigraphic sleep estimates. Also, wrist temperature is higher during false actigraphic wake estimates than during true actigraphic sleep estimates. These differences suggested that the simple addition of wrist temperature to actigraphic estimates of sleep and wakefulness might result in an improvement of their accuracy, as compared to estimates based on wrist movement only. However, the application of discriminant functions, obtained by means of logistic regression and leave-one-out-cross-validation, did not result in any relevant improvement. The failure to improve actigraphic sleep estimates in spite of the systematic temperature differences between false and true sleep estimates is in our opinion most likely due to the sluggishness of recorded temperature changes. Firstly, the iButton Thermochron used in our study has a time constant of about 19 seconds and may take up to a minute to completely attain the true temperature of its environment (Van Marken Lichtenbelt et al., 2006). For brief periods of wakefulness during sleep, the response time could thus be too sluggish. Correct correction of an epoch may thus unfortunately be balanced by incorrect change of a subsequent epoch. Faster temperature sensors, notably infrared sensors, may be required to be able to exploit the skin temperature differences we demonstrated between true and false actigraphic sleep estimates (Figure 2). Such sensors have recently become available in miniaturized size. Secondly, the changes in skin temperature themselves may be too sluggish. Changes in skin temperature are secondary to the changes in skin perfusion that reflect changes in the output of the autonomic nervous system. This introduces another low-pass filter of the fluctuations that would ideally be recorded. Thus, if faster temperature sensors do not solve the sluggishness issue, it may be required to directly record skin perfusion rather than its secondary effect, on skin temperature. We are however not aware of robust miniaturized skin perfusion sensors that could easily be integrated in actigraphs.

The mechanisms underlying the association between sleep and skin temperature, evident from figure 2, most likely involves skin blood flow regulation by the autonomic nervous system. At the transition from wake to sleep a release of sympathetic activation has been measured (Takeuchi et al., 1994). This might account for increases in skin blood flow and consequently skin temperature, which have been observed during sleep (Sindrup et al., 1995). Nocturnal wakefulness will, even when immobility is maintained, increase sympathetic vasoconstriction, resulting in a decrease in skin temperature. Sleep and skin temperature may moreover be bidirectionally linked, because mild warming of the skin suppresses nocturnal wakefulness and shifts sleep to deeper stages (Fronczek et al., 2008; Raymann et al., 2008).
Chapter 6

We would like to give a brief methodological comment on the two-step approach of first classifying epochs as sleep or wakefulness by use of actigraphy only, and subsequently determining separate discriminant functions based on two temperature thresholds for re-classification of sleep and wake epochs. We evaluated this sequential use of wrist activity and wrist temperature based on the findings illustrated in figure 2 and after demonstrating that multiple logistic regression analysis that used temperature as regressor in parallel to activity did not improve the accuracy of sleep estimates as compared to the mere use of activity as single regressor. The reason for failure of the one-step approach may be collinearity: in general periods of sleep are characterized by both immobility and high skin temperature while periods of wakefulness are characterized by both mobility and low skin temperature. A sluggish temperature response may have induced the same collinearity in the two-step approach of re-classification. Only if faster tracking of temperature changes is available, a final judgment on the use of re-classification can be made.

The present validation and optimization study was on purpose performed in a heterogeneous population, including participants diagnosed with several sleep-related disorders. Ancillary analyses on more homogeneous subgroups did not result in more useful discriminant functions. It should also be mentioned that in addition to the use of a faster responding sensor, additional studies might also target specific disorders in which thermoregulation is affected, like the vasospastic syndrome (Gompper et al., 2011). A possible solution to individual differences in average skin temperature could be to use centered rather than raw temperature values. An ancillary analysis where we used centered temperatures did not result in more useful discriminant functions.

In addition to the mentioned specific subject-characteristics, environmental characteristics should be considered as well. Studies were performed throughout the seasons in the moderate climate of the Netherlands. Temperature thresholds and accuracy remain to be evaluated if sleep studies are to be performed in more extreme environmental temperatures. On the other hand, it should be noted that people tend to optimize the bedroom, bedding and clothing to create a sleep microclimate with a very limited temperature range (Goldsmith & Hampton, 1968; Muzet et al., 1984).

In summary, while our findings summarized in figure 2 suggest that the simple addition of wrist temperature to actigraphic recordings could be of use in discriminating false positive and false negative sleep estimates, discriminant functions did not significantly improve actigraphic sleep estimates. A faster sensor of either skin temperature or even skin perfusion may be required to exploit the finding of temperature differences between false and true classifications.
Acknowledgements

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References


Chapter 6


