

Sustained Logging and Discrimination of Sleep Postures with Low-Level, Wrist-Worn Sensors

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Abstract

We present a study which evaluates the use of simple low-power sensors for a long-term, coarse-grained detection of sleep postures. In contrast to the information-rich but complex recording methods used in sleep studies, we follow a paradigm closer to that of actigraphy by using a wrist-worn device that continuously logs and processes data from the user. Experiments show that it is feasible to detect nightly sleep periods with a combination of light and simple motion and posture sensors, and to detect within these segments what basic sleeping postures the user assumes. These findings can be of value in several domains, such as monitoring of sleep apnea disorders, and support the feasibility of a continuous home-monitoring of sleeping trends where users wear the sensor device uninterruptedly for weeks to months in a row.

1. Introduction

Sleep is a natural and vital part of our daily lives, known to have a big effect on our memory [16], immune system, and metabolism [3], yet most people know very little about their particular sleeping habits. Even though the exact reasons for our sleep remain a mystery, it is known that many of the body's major organ and regulatory systems continue to work, with some parts of the brain actually increasing their activity dramatically. Sleep in mammals appears to be required for basic survival: Rats deprived of sleep die within two to three weeks, a similar time frame to death due to starvation [5].

Research into sleep focuses on a plethora of bio-physical signals, commonly called polysomnography (or *PSG*). A common setup to detect sleeping patterns, contains a set of 8 electrodes to the face of the patient, for EEG and EMG. An electrocardiogram (ECG) is recorded via two electrodes placed on the right side of the chest and on the left-lower side of the thorax. Around the chest and the abdomen, respiratory detectors are placed, and two EMG sensors are at-

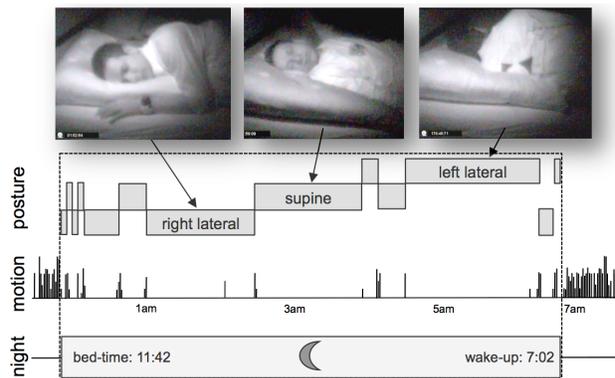


Figure 1. Users wear a watch-like sensor on the wrist, which records light, movements and orientation data, to detect the sleeping posture, amount of motion, and the night sleep segment. The sensor can be worn non-stop for weeks.

tached to each leg to measure the limb movement. A snoring detector is placed on the left cheek and a breathing tube right before the nostrils. All these sensors are wired, and take time getting used to. Patients often need to stay more than one night at sleeping labs for this reason.

This paper proposes an inherently wearable solution which allows a coarse but long-term perspective on the user's sleep. It does not intend to deliver a medical instrument for precise diagnostic purposes, but rather focuses on giving the user an insight into his or her sleeping patterns, at a low cost (especially in terms of deployment and usage, but also due to the system's cheap components).

The aim is to have descriptors that characterize the wearer's sleep during the night (Figure 1), with cheap low-power sensors. Central to this work are sleep postures, which are known to be an important parameter commonly applied in the detection of obstructive sleep apnea, but also utilized in general sleep studies [11, 2, 13, 14, 17, 8]. The time segment when the user is in bed, sleeping postures, and amount of motion during sleep are proposed as such cues for detection of sleep and sleep characteristics.

2. Related Work

There are dozens of commercial products and healthcare sensors that aim at providing the user with a similar type of low-fidelity information as put forward in this paper. What follows are several prolific examples, contrasted with our approach.

Actigraphy describes the measurement and logging of activity, and applications using actigraphy include sleep analysis. An actigraph consists usually of an accelerometer and a memory unit to store recorded sensor data and is often worn at the wrist or hip. Data can be recorded up to several years (depending on the type and frequency of readings) and uploaded via an interface to a host computer.

An example of a long-term actigraphy unit is the Actiwatch [12], which is used to measure sleep quality of individuals suffering from sleeping disorders and monitor circadian rhythms. The different types of Acti-watches can be equipped with light sensors or a real time clock for time stamping. The current versions' memories go up to 64Kb and the battery lifetime is 180 days. The information that is stored contains solely the level of activity.

The SenseWear Body Monitoring System [1] is targeting activity and sleep detection applications. It records acceleration in 2 axes, skin temperature, heat flux and galvanic skin response. The platform consist of an armband worn on the upper arm collecting the sensor data, a watch-like display unit on the wrist to display real-time feedback and software for analyzing uploaded data on a host computer. The SenseWear system senses and records far more than the prototype in this paper, but is also larger and less well suited for long-term logging of data.

The aXbo [6] is an example of a sleep phase alarm clock which senses body movements and builds up a model for the sleep phases, so that it can wake up the user during an optimal sleeping phase. The sensing unit is worn at the wrist and data is sent wireless to the aXbo nightstand unit. The aXbo unit can be used with a rechargeable battery for seven days and has a USB interface. Only limited information about the hardware and the algorithm running on it is public however, which rules out a comparison to our Porcupine unit and approach.

Other solutions include non-wearable deployments, such as the Dream Recorder software on OSX [4] which can use the built-in camera from an Apple MacBook to detect motion via pictures during the night, and the microphone to detect snoring.

Most of these state-of-the-art approaches either record the activity level on an energy efficient device that is worn continuously, or record more precise data on a device that is built to be active for one night. Our approach combines elements of these two: a long-term logging of motion *and* posture, using imprecise, but energy-efficient sensors.

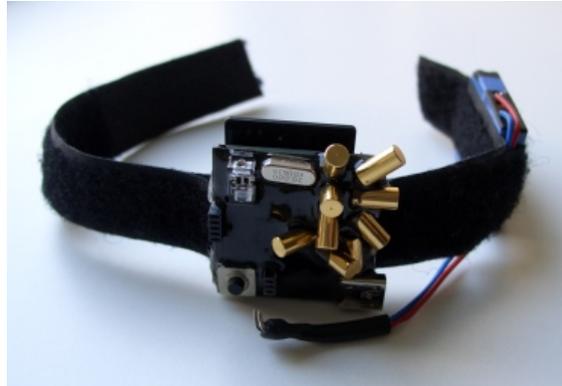


Figure 2. The Porcupine wearable platform measures 32x37x15mm, and was configured to log data from 2 light sensors and 9 tilt switches to a 1GB SD card for this paper's experiments. In this mode it can run continuously for almost 2 weeks on a light-weight 3.7V battery.

3. Hardware Description

A substantial part of this work relies on a sensing platform that is wearable and efficient enough to do sustained logging of data by using a set of light-weight sensors. The following describes the developed hardware and, key to this work, the proposed sensing method for postures.

The Porcupine [9] (Figure 2) was developed as a prototype device for the logging of human physical activities. It was built to be a small, cheap, yet robust device that would be worn by subjects for long periods of time, in order to acquire highly realistic data in mobile settings.

The components of the Porcupine were chosen for both their small footprint and low energy consumption:

Light Sensors. Two sensitive photodiodes in perpendicular directions detect ambient light.

Tilt Switches. A set of 9 mechanical ball tilt switches, placed at 45° between each other, provides a coarse degree of tilt and movement.

Temperature Sensor. A high-resolution thermistor is placed on the bottom side of the board.

3D Accelerometer. The ADXL330 is a commonly used three-dimensional MEMS acceleration sensor.

PIC microcontroller. The 18F4550 is a low-power microcontroller, with USB connection and the ability to switch between operating speeds with internal RC oscillators. This enables it to go into an efficient power mode for different modalities, e.g., slow when processing the tilt switches, and fast when processing the accelerometers' data¹.

Realtime Clock. A Clock and Calendar IC can keep the correct date and time so that the data can be time-stamped.

¹Note that for this paper, the Porcupines had their accelerometer and temperature sensors turned off, and ran in a low-power 32kHz sensing mode.

SD card slot. The Porcupine has an SD card slot so that plenty of storage can be used (≤ 4 GB).

There is also an LED and a button present on the board for basic debugging and user interaction, as well as a USB connector and a charging circuitry, so that the attached battery can be recharged from USB. The 5-pin programming connector can be re-used for extra modules. Both hardware design and embedded software are publicly accessible via <http://porcupine2.sf.net>.

This paper uses tilt switches to record both motion and posture, by combining them in a cluster where 9 tilt switches are placed together. By placing them at 45° angles between each other, a coarse-grained 3d posture sensor is assembled. Figure 3 shows the basic principle in one plane using 4 tilt switches. By adding tilt switches for the other two orthogonal planes, a total of 9 switches is required.

The cluster of tilt switches provides very low-resolution information compared to the accelerometer – which has some similarities in design but provides a more exact and fine-grained output. However, the prime advantage of using this sensing method is that it requires less battery power to run for extended periods, and it additionally provides output that is much simpler and faster to process. In previous studies and experiments [9], it was shown that the Porcupine typically runs up to 10 times longer when using the tilt switches instead of the accelerometers.

The tilt switches are read at 130 Hz in this paper’s experiments, and their nominal position and hamming distance are stored as features at approximately 3Hz in memory. The two light sensors are sampled once every 50 seconds, accompanied by a time stamp from the realtime clock. All other components are turned off in software.

The experiments in this paper will study the feasibility of inferring the sleeping posture of the user, just by reading the states of these nine switches. This assumes that the wrist position is distinct for different postures, and that the output of the cluster of tilt switches is accurate enough to capture these distinctions.

4. Night Segmentation

As we propose to have the logging device worn by its user during the day *and* night, a first challenge is the detection of the nightly sleep intervals within the data when the user went to bed and woke up again. Although this can be done by the user, by for instance pressing a button on the Porcupine before and after sleeping, this would be tedious and could introduce errors.

Here we explore similar techniques to some from the related work section, by combining time, motion and readings from ambient light sensors. An additional benefit of acquiring these night segments is that they provide direct information on the user’s circadian rhythm.

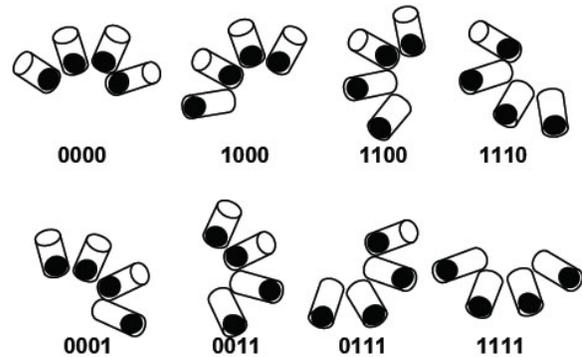


Figure 3. A sketch of the tilt switches’ principle: a single tilt switch outputs a 0 when the conductive ball inside its cylindrical case hits two terminals at the bottom (i.e., ‘closes the switch’) or a 1 otherwise.

In an experiment, data was recorded from 11 subjects, between 26 and 61 years old, of which 7 male and 4 female, with none of them knowingly suffering from a sleeping disorder. The subjects were asked to wear the Porcupine sensor on their dominant wrist for at least 24 hours, though most wore it for a longer period. Some of the subjects annotated the times of their going to sleep and awakening by pressing the button on the Porcupine, but most recalled these times after the recording. For this they had a tool to their disposal, which uploaded the data to their PC and visualized the past 24-hour period in a set of time series plots.

It is important to note that time by itself did not provide much information for estimating the night segment. The 11 subjects had different lifestyles, some started their night early (around 10pm) and others late (around 3am). Time in combination with the presence of light and motion did well for estimating the waking up event, while a combination with light achieved the best performance for the bed-time event.

Since the light sensors are chosen and positioned to be sensitive to ambient light, it is not surprising that this type of sensor was found to be the most effective for detecting the start of the night segments. Even though the datasets were taken during winter, with all subjects regularly wearing long-sleeved clothing, drops in the light sensors’ values allowed accurate detection of bed-time. Even though many datasets displayed significant periods of darkness during the day (due to the Porcupines being covered or the users being in a dark environment such as a movie theatre), every night started with the light sensors’ data going from brightness to an extensive period of darkness. The waking up time was harder to detect, and relied on mainly motion and light. The importance of the light data might be biased here by the winter season, since most subjects were forced to turn on the light immediately after waking up.

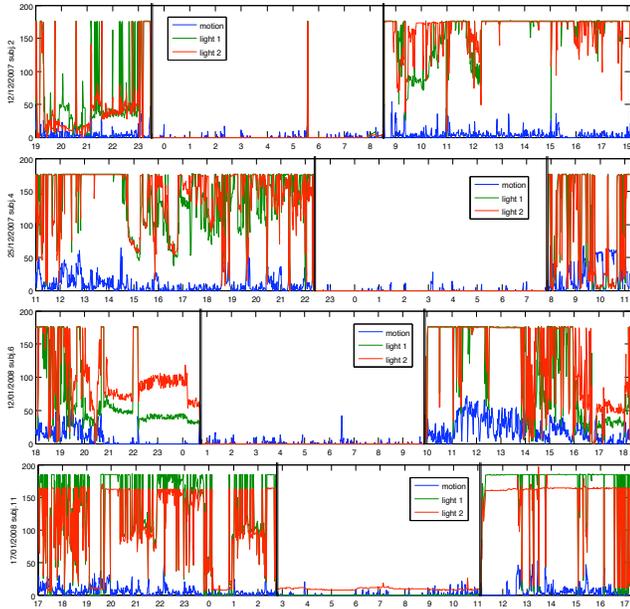


Figure 4. Four examples of data for which the nightly sleep segments have been marked. Note that the method is robust against small light changes (top), low light levels (bottom), as well as high amounts of motion and dimmed light before the bed-time event (middle).

Several types of algorithms, including HMMs and Bayesian nets, were tried out to accurately detect these bed-time and waking up events, using leave-one-out cross-validation over all data sets. The best results were obtained from a combination of two simple rules: One which marked 'bed-time' by a falling edge signal for both light sensors followed by a sustained average below 10% for a window of 6 hours, and one which marked 'wake-up' by a rising edge in light and motion, preceded by the same window. The methods performed with near-100% accuracy for all but one dataset, where the ambient light was consistently low.

In summary, it is feasible to segment the night period, from when the wearer goes to bed till the waking up time, with data from mainly the light sensors, tilt switches and the on-board realtime clock. Figure 4 shows some examples.

5. Preliminary Study: Sleeping Lab Data

After the detection of the night segment, it is possible to analyze its data further to reveal more fine-grained information. As a preliminary study, rich PSG data from a sleeping lab is compared with data from the Porcupine's tilt switches to investigate the feasibility of sleep phase or sleep stage detection.

One of the most common types of sleep pattern information, using PSG, is to represent the night as a series of sleeping stages. It is known that methods relying on traditional

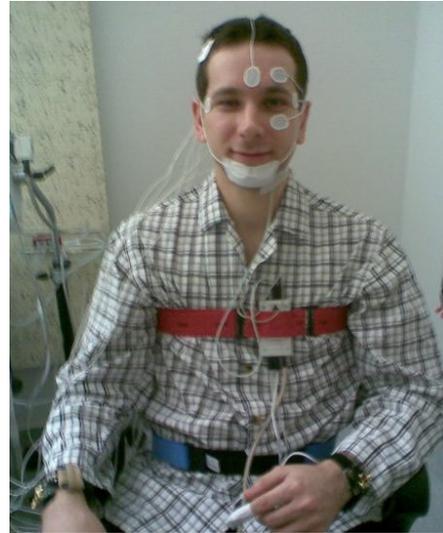


Figure 5. Close-up of PSG sensors, wired to equipments next to the bed. Porcupines are worn on both wrists.

actigraphy, such as the ones discussed in the related work section, cannot compete with the reliability of PSG. Accuracies of up to 75% are reported for the approaches that use body motion, given that the subject is "an adult between 15 and 55 years old, without sleep disorders" [4].

Several cues could be detected from the subject's motions during the sleep. The Rapid Eye Movements, or REM, period occurs periodically and in conjunction with a number of other physiological changes: Brain waves exhibit a fast, low voltage activity, heart- and pulse rates tend to speed up, and there is rarely any body motion present in this phase. REM is especially known as the period when vivid dreams occur, and are a key phase in characterizing a subject's sleep. REM is usually followed by several stages, called deep sleep, where sleep is the most restorative. Knowledge about the typical duration of the REM stage, its 90 minute cycle that reoccurs during sleep, and the lack of body motion during REM sleep, can be used to model the probability that the user is in the REM stage.

In order to investigate the feasibility of detecting these sleep stages with our own sensors, a preliminary one-subject study was undertaken in an academic sleeping lab. The ground truth in this experiment was taken from the actual sleeping lab PSG data (see Figures 5 and 6). From this data, the sleep stages were extracted and used as annotations for the information recorded by two Porcupine sensors, one attached at each wrist. A tool called Harmonie-S [15] was used by medical staff to analyze the PSG data, offering synchronization between the sleep lab's night vision video and the body data. The lab's video footage was used for annotating detailed sleeping postures, since the lab's chest sensor provides the basic postures only.



Figure 6. PSG data from the sleeping lab recordings.

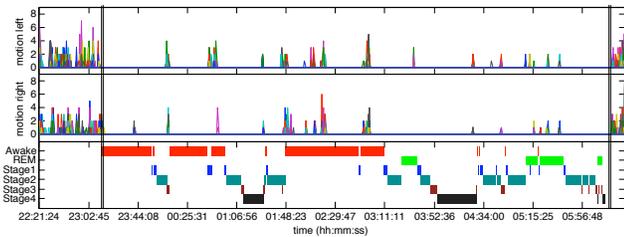


Figure 7. The top two plots show the presence of motion during the night (for each wrist), while the annotations from the sleeping lab’s PSG data are plotted below.

Figure 7 shows the plot from the two wrist-worn Porcupines, annotated by the various sleep stages that were extracted from the raw PSG data. Both the motion plots and the annotations show a large amount of ‘awake’ stages during the night, mainly to be attributed to the unfamiliar environment. As a consequence, there occurred only a small amount of REM and deep sleep stages.

From visual inspection of the data however, it is not clear that several of the rules of thumb for detecting candidate periods of REM and non-REM sleep with motion are valid for our data. First of all, as can be seen in the second and third REM stages in Figure 7, motion does occur even though in normal sleep, by passing through sleep stages 1 to 4 and after that reaching REM, the muscle tone is decreasing and movement should cease to occur. Cues for the relaxing of the body were observed, but both the PSG and the Porcupine data included motion during several REM stages. Due to the high amount of awake stages in our data, any timing information on cycles that we could use as a prior for detecting likely next REM stages was not present in the data.

For these reasons, no attempt was made to detect of sleep stages or phases from the motion data. The most likely explanation is that this study’s data is limited and taken under unusual circumstances (in a sleeping lab rather than at home).

6. Body Postures: Experiment Setup

From several studies involving patients with sleeping disorders [11, 2, 13, 14, 17, 8], a set of basic sleeping posture categories was extracted for a next experiment. These categories are commonly applied in the detection of obstructive sleep apnea, but are also mentioned in general sleep studies as an important parameter.

The following types are the basic sleep postures considered in this experiment, with the latter two categorized further to reflect finer-grained body postures, to come to four basic and eight extended sleep body postures:

- **‘Left lateral’** and **‘Right lateral’**. The left lateral posture has the left shoulder down, while the right lateral posture has the right shoulder down. In anatomical terminology: the left lateral posture has the ventral side left and dorsal side right, while the right lateral posture has the ventral side right and the dorsal side left.
- **‘Supine’**. The supine posture has the subject lying down with the face up, or the dorsal side being down, and the ventral side being up. When the body is slightly tilted towards one side, for instance when supported by an arm or leg, we use the combined **‘Left supine’** or **‘Right supine’**.
- **‘Prone’**. The prone posture is defined by lying with the face down, or the dorsal side being up, and the ventral side down. When the body is slightly tilted towards one side, for instance when supported by arm or leg, we use the combined **‘Left prone’** or **‘Right prone’**.

These categories are used as the target classes and annotations of the data sets: from video footage, these sleep posture categories are identified by the subject and used to label the synchronized data from the Porcupine, via the time stamps in both data streams. The objective of the experiment is to compare the sensor data recorded during the different sleeping postures. This allows an evaluation of how well the tilt switches’ data can distinguish between body postures.

In most studies mentioned in the review in [10], the sensor for sleep posture was strapped to the abdomen or chest. Note that, as the porcupine was worn around the dominant wrist instead of the abdomen/chest, this is not a trivial task. However, the size and wrist placement of the Porcupine arguably do offer a more comfortable setup (see [10]).

Figure 8 shows the home setup. An inexpensive webcam was modified by removing its infrared filter and replacing it with strips of photo negatives. In our experiments, the annotation of data was done manually (recording start and stop times for all sleep postures) using visual inspection of these 15 fps infrared camera recordings. A separate IR LED array

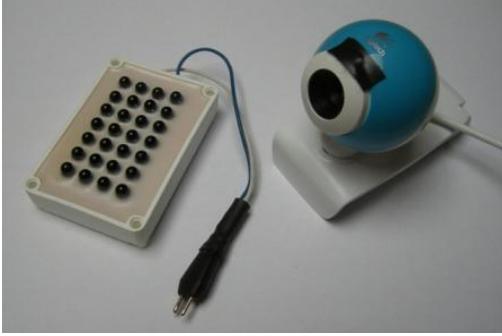


Figure 8. The IR LED array (left) and modified webcam (right) for ground truth recording at home.

was positioned a few meters away from the subject so that most of the bed area would be illuminated by infrared light, and subsequently picked up by the camera in total darkness.

The data set contains annotated sleep posture data from 9 nights, monitoring regular sleep from 4 subjects (2-3 nights each), one female and three males, ranging in age from 20 to 50, with no known sleeping disorders. The strenuous task of browsing through the infrared video and annotating the body postures’ start and stop times proved to be very time-consuming, which is the primary reason for the reduced set of data for this experiment.

7. Body Postures Experiment

The data from the Porcupines in the experiments were uploaded and converted to a comma-separated text file, after which they were analyzed and visualized by Matlab scripts. This section reports on our findings for using the proposed Porcupine data body posture detection, after the segmentation of the night period.

One of the recorded nights, taken from approximately 2 am till 9 am, is depicted in Figure 10. It shows the Porcupine’s light data in the top plot, the on-board calculated hamming distances of the Porcupine’s tilt switches in the plot below that, and the tilt switch states below that (with each tilt switch a separate time plot). The lower plots show the annotations from the video data, and video frames from each posture. Correlation can be seen between periods when the subject remained in the same posture and the annotations. The light sensor values can be seen to fluctuate to moderate levels during the night due to the IR-light emitted from the IR beacon. The subjects for this experiment were asked to press the Porcupine’s button before going to sleep and when getting up, these events were encoded in the motion plot as the spikes with a value of 15.

Figure 9 shows all unique tilt switch patterns on the left, with their occurrences for all postures combined in the stacked bar plot in the middle. The right plot shows the

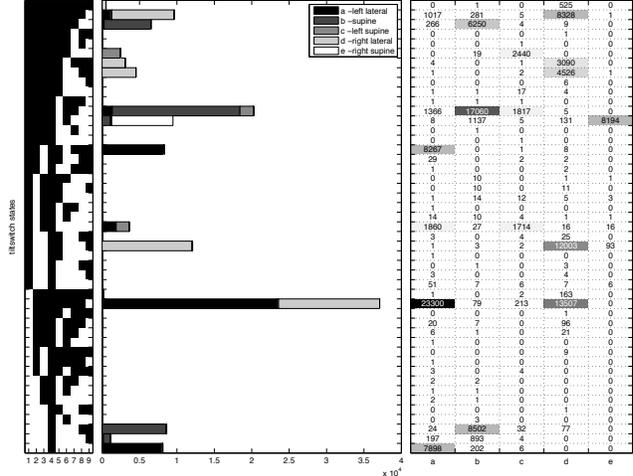


Figure 9. left: visualization of all tilt switch patterns present in a dataset (black squares for 1, white ones for 0), middle: per tilt switch pattern, the number of occurrences for all associated postures as a stacked bar plot, right: the same occurrences in a matrix. The last row in this plot shows for instance that the pattern ‘000100000’ occurred 7898 times for posture a - left lateral and 202 times for posture b - supine.

number of samples per tilt switch pattern that were counted per body posture. For instance, row 11 depicts the pattern ‘111101100’ which occurred during four postures (visualised by left lateral: 1366 times, supine: 11060 times, left supine: 1817, and right lateral: 5 times). This figure also shows that there is no one-to-one mapping between tilt patterns and body postures, but that there are typically multiple tilt switch patterns possible per body posture. This is not surprising, since the placement at the wrist measures the upper arm’s posture instead of the torso’s posture, and since slight motions can easily result in different tilt switch patterns.

In order to reflect how well the tilt switch data support the model of a posture in a measure, we use cluster precision [7] by treating the different possible tilt patterns as the cluster centroids: We first define the ratio for different body postures j for each tilt switch pattern i as the number of samples that are labelled as posture j , divided by the total number of labeled samples with the tilt switch pattern i :

$$p_{i,j} = \frac{|C_{i,j}|}{\sum_j |C_{i,j}|} \quad (1)$$

In this notation, $C_{i,j}$ stands for the set of tilt switch patterns i labelled with posture j . The tilt switch pattern i would in this paper be a 9-bit binary string such as ‘001110101’ or ‘110010111’. The body posture j would be as earlier defined, attached to a label such as ‘left lateral’, ‘prone’ or ‘right supine’.

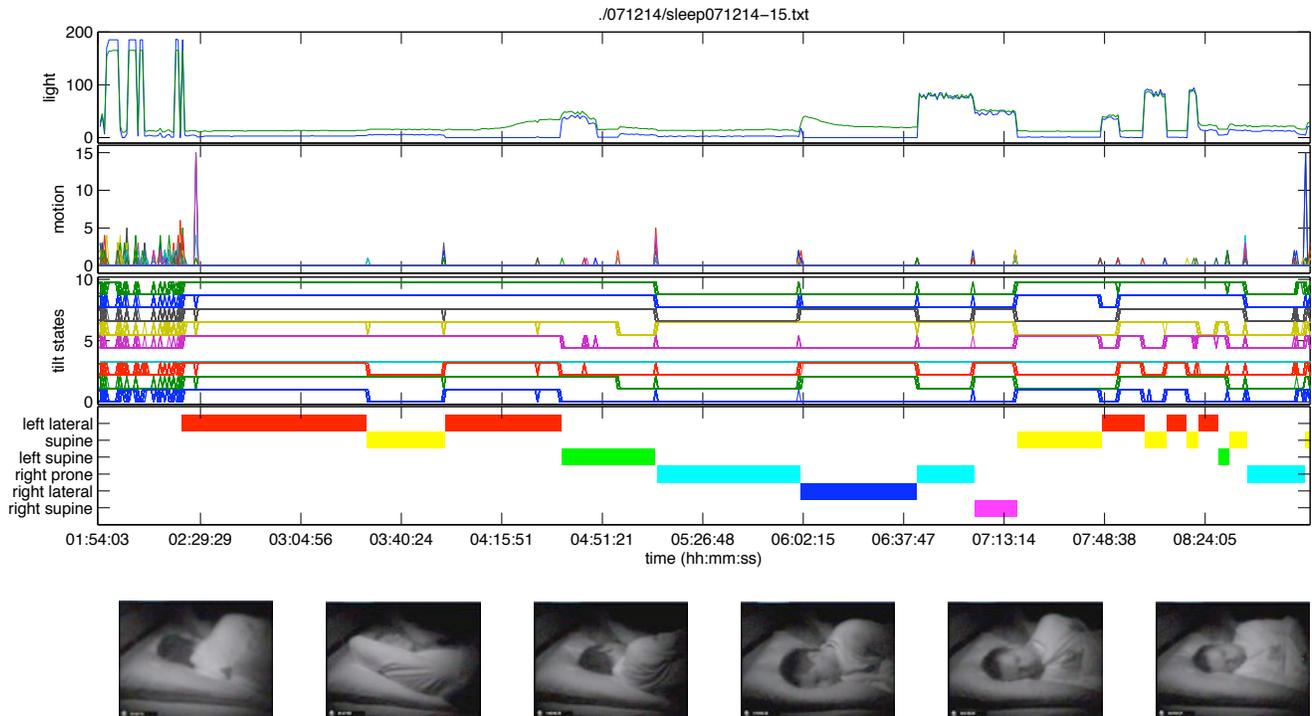


Figure 10. Time series and snapshots from one of the datasets, taken from approximately 2am till 9am. The colored bars in the bottom plot are the annotations from the video. Below the plots are frames from the video footage for each of the body postures (in order of appearance) used as ground truth.

Table 1. The precision values for all body postures from Figure 9.

ext. posture	P_j	basic posture	P_j
left lateral	0.7185	left lateral	0.7553
supine	0.8584	supine	0.8862
left supine	0.5424		
right supine	0.8523	right lateral	0.7845
right lateral	0.7622		

Finally, we obtain the cluster precision measure P_j for every body posture j by summing these distributions $p_{i,j}$ above weighted by the number of tilt switch patterns i labelled as j , and normalized over the total number of patterns i labelled as j :

$$P_j = \frac{\sum_i p_{i,j} |C_{i,j}|}{\sum_i |C_{i,j}|} \quad (2)$$

This results in a value that reflects how much the samples from different postures overlap: if there is no overlap in tilt switch data between postures, perfect classification can be achieved by a simple lookup table and the measure for the dataset would be 1; in worst-case scenarios, such as when the data would overlap for all postures, the measure would go to zero as the number of postures increases.

Table 1 shows the results for body postures in the dataset from Figure 9. Most body postures have high precision values, indicating that they are characterized well by their data. Two postures, however, have precisely the same tilt switch pattern, namely 'right lateral' and 'right supine'. Similarly, there is a large overlap between 'left supine' and 'supine'. By considering in this particular dataset the basic body postures only, the precision would rise above 0.75 for all body postures.

By combining all cluster precision values in a dataset, it is finally possible to calculate two values for that dataset: one overall cluster precision over the basic body postures, and one overall cluster precision over all body postures introduced in that same section. For both values, a sum is taken over all P_j , weighted by the number of samples per posture j .

Table 2 displays these results per dataset, showing that restricting to the basic postures provides overall more distinct tilt switch patterns. The results remain close to those when combining all datasets per subject. This results on average in 80% for basic postures and 73% for extended postures. We have not calculated the precisions across all subjects, however, but expect that these results will be worse due to left-handed and right-handed wearing positions, as well as person-specific postures.

Table 2. Overall precision values for sleep postures from tilt switch data.

Date and subject	Basic postures	Extended postures
06/12/2007, 1	0.9490	0.8303
14/12/2007, 1	0.9274	0.7262
16/12/2007, 1	0.8012	0.7468
18/12/2007, 2	0.8667	0.8787
19/12/2007, 2	0.6042	0.5207
21/12/2007, 3	0.6665	0.5552
22/12/2007, 3	0.9418	0.9334
27/12/2007, 4	0.7316	0.7100
28/12/2007, 4	0.7894	0.8032

8. Conclusions and Future Work

This paper investigated and presented techniques to perform night segmentation and sleep posture detection, with a light-weight monitoring device which can thus assist in monitoring sleeping trends. Simple energy-efficient sensors make it possible to wear the wrist-worn sensor and record motion data over weeks continuously.

It was observed in a first study that it is relatively easy to estimate the night segments in continuous data. From a sleeping lab study, we concluded that investigating the detection of sleep phases by monitoring motion alone would require much more extensive PSG data to be conclusive. This paper's main study focused on adding body posture recognition during the sleep, on top of the motion and light readings, using video from a cheap infrared setup for establishing ground truth in the evaluation. The results from this last study are promising: the basic body postures result in very different tilt switch patterns, as measured using precisions averaging around 80%.

The experiment concludes that sufficiently accurate estimation of basic sleep postures can be done by a single power-efficient wrist-worn sensor. Together with light and motion, we propose body postures as a low-cost modality for sleeping characteristics, with a wide potential use in for instance sleep apnea and spinal conditions. This sensing can be done over long intervals (weeks to months), enabling other applications that analyze sleeping trends to easily access and explore this information.

More long-term studies are required to investigate how this information over long spans of time can be represented, and how users would provide training data. Additionally we are studying other modalities we might incorporate in the current sensor setup. The Porcupine platform is being revised continuously to make it smaller and more energy efficient by adjusting both hardware components and processing algorithms in the Porcupine's microcontroller. The current version for instance uses microSD cards for memory, reducing the size and weight significantly.

9. Acknowledgments

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