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Monitoring Sleep with Force Sensor Measurement

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Monitoring Sleep with Force Sensor Measurement

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Abstract

This thesis presents methods for comfortable sleep measurement at home. Existing medical sleep measurement systems are costly, disturb sleep quality, and are only suited for short-term measurement. As sleeping problems are affecting about 30% of the population, new approaches for everyday sleep measurement are needed. We present sleep measurement methods that are based on measuring the body with practically unnoticeable force sensors installed in the bed. The sensors pick up forces caused by heartbeats, respiration, and movements, so those physiological parameters can be measured. Based on the parameters, the quality and quantity of sleep is analyzed and presented to the user.

In the first part of the thesis, we propose new signal processing algorithms for measuring heart rate and respiration during sleep. The proposed heart rate detection method enables measurement of heart rate variability from a *ballistocardiogram* signal, which represents the mechanical activity of the heart. A heartbeat model is adaptively inferred from the signal using a clustering algorithm, and the model is utilized in detecting heartbeat intervals in the signal. We also propose a novel method for extracting respiration rate variation from a force sensor signal. The method solves a problem present with some respiration sensors, where erroneous cyclicity arises in the signal and may cause incorrect measurement. The correct respiration cycles are found by filtering the input signal with multiple filters and selecting correct results with heuristics. The accuracy of heart rate measurement has been

validated with a clinical study of 60 people and the respiration rate method has been tested with a one-person case study.

In the second part of the thesis, we describe an e-health system for sleep measurement in the home environment. The system measures sleep automatically, by uploading measured force sensor signals to a web service. The sleep information is presented to the user in a web interface. Such easy-to-use sleep measurement may help individuals to tackle sleeping problems. The user can track important aspects of sleep such as sleep quantity and nocturnal heart rate and learn how different lifestyle choices affect sleep.

Computing Reviews (1998) Categories and Subject Descriptors:
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Helsinki, Jan 17th, 2014

Joonas Paalasmaa

Contents

Original papers

This thesis consists of an introductory part and the following publications, which are referred to as Papers I–V in the text. These publications are reproduced at the end of the thesis. They have not been used as part of other doctoral theses.

I. J. Paalasmaa. A respiratory latent variable model for mechanically measured heartbeats. *Physiological Measurement*, 31(10):1331-1344, 2010.

Author's contribution: Design and implementation of the method, collection of reference data, statistical analyses, writing the article.

II. J. Paalasmaa and M. Ranta. Detecting heartbeats in the ballistocardiogram with clustering. In *Proceedings of the ICML/UAI/COLT 2008 Workshop on Machine Learning for Health-Care Applications*, Helsinki, Finland, 2008.

Author's contribution: Design and implementation of the method, collection of reference data, statistical analyses, writing most of the article.

III. J. Paalasmaa, H. Toivonen, and M. Partinen. Beat-to-beat heart rate measurement for ballistocardiograms. Submitted for publication.

Author's contribution: Design and implementation of the method, management of the clinical trial, statistical analyses, writing most of the article.

IV. J. Paalasmaa, L. Leppäkorpi, and M. Partinen. Quantifying respiratory variation with force sensor measurements. In *33rd Annual International Conference of the IEEE Engineering in Medicine and Biology*

Chapter 1

Introduction

This thesis is about sleep measurement methods that do not disturb sleep. The methods developed here are based on an unnoticeable force sensor that is placed in the bed. This is a significant improvement over mainstream sleep monitoring systems since they require the use of wearable sensors that can degrade the quality of sleep. The unobtrusive measurement approach is particularly attractive for long-term use at home — even months or years — because the sensors are not expensive and no discomfort is caused to the user. The body of this thesis deals with the scientific challenges of providing accurate measurements in such setting. First, however, I give an overview of the motivation and context of this work.

1.1 Motivation and goals

Long-term sleep measurement allows new possibilities for improving sleep, which in turn has positive health effects. We have identified two primary means of such sleep improvement: self-tracking of sleep and long-term sleep measurement as part of medical sleep disorder treatment. With self-tracking, the user measures sleep over long terms, learns from the measurement what is wrong with their sleep, and acts to remove the possible causes of the sleeping problems. The measurement can be likened to a scale in weight loss — the problem (obesity, sleep deficit) is easier to solve when progress can be measured. With medical sleep disorder treatment, long-term sleep measurement data is provided to the sleep doctor, for following up the efficacy of treatment and monitoring the course of the sleep disorder.

New approaches for improving sleep can have a big impact on public health, because insufficient sleep quality and quantity are common health problems in the Western world. It has been estimated that about 30% of

the population have the symptoms of insomnia, the most prevalent sleep disorder [73]. Another sleep disorder with major health effects, sleep apnea, has a prevalence of 3% – 8% in men (depending on the population sample) and 2% in women in the most affected age group of 40 to 65 years [73]. Obesity significantly increases the risk of sleep apnea [32]. With overweight increasing globally [79], sleep apnea will become more and more prevalent. In year 2000 in the U.S. alone, sleep apnea-related traffic accidents cost 1400 lives and $15.8 billion, making it a serious public-health concern [84]. The new methods presented in this thesis have the potential of making sleep measurement more commonplace, which improves the chances of getting treated.

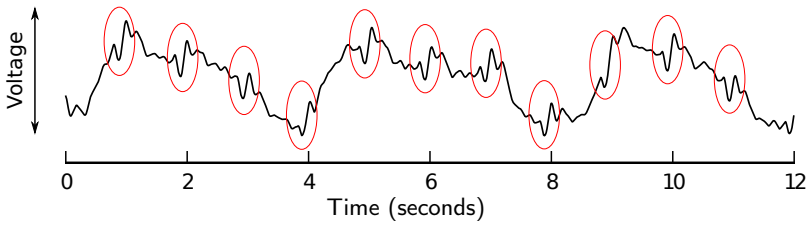
The established practice of medical sleep monitoring, polysomnography, involves wearing multiple electrophysiological sensors for a single night, at a sleep laboratory or at home [41]. It provides clinically valuable information, but is expensive and uncomfortable. More long-term and comfortable measurements can be done with actigraphy [69], where the overall sleeping patterns of a patient are measured with a wrist-worn movement sensor.

We have chosen to measure sleep with unobtrusive force sensors. The idea is to measure the forces caused by the body on the bed with a flexible film sensor that is placed below the bed sheet (Figure 1.1). These measurable forces are mainly caused by respiration, heartbeats and movements. While various force sensors have been used for sleep measurement for over 35 years [4], our aim is to make long-term sleep measurement practical by developing novel signal analysis methods for convenient and economical sensor technology. Alternative unobtrusive measurement methods include e.g. Doppler radars that measure the movements of the body, including respiration and heart activity [111, 98, 110].

The chosen measurement methodology poses scientific challenges, because physiological information (heart rate, respiration, etc.) cannot be readily extracted from the signal, but require sophisticated signal analysis methods. This thesis provides solutions to those challenges. From a practical point of view, the main novelty of our work is that the measurement and signal analysis methods have been integrated into systems that enable measuring sleep conveniently at home. These systems belong to the field of e-health, which includes, among others, the use of interactive technologies for improved health care [31, 1].

The ultimate aim of this research work is to develop practical and novel methods for sleep monitoring. They should be validated with reference measurements in realistic scenarios, so that their applicability and usefulness can be evaluated. As of January 2014, two products have been released that in-

(a)



(b)

Figure 1.1: The piezoelectric film sensor (a) and a recorded 12-second signal excerpt (b). The sensor is covered with a bed sheet to conceal it and make it more comfortable to sleep on. The cyclic low-frequency phenomenon with around four-second period in the signal is respiration. The heartbeat is the fluctuation that recurs around every second (red ellipses).

corporate adaptations of the algorithms described in this thesis: Beddit Pro (in early 2012) and Beddit (in late 2013)[1].

In the rest of this chapter, I summarize the contributions of this thesis and of the original papers. After that, Chapter 2 gives a brief overview of sleep physiology. Chapters 3 and 4 describe the contributions of the thesis in detail, with signal analysis methods presented in Chapter 3 and an e-health system in Chapter 4. These chapters also contain sections on previous work related to their specific topics. Finally, conclusions are presented in Chapter 5.

1.2 Contributions of the thesis

The contributions of this thesis are

a) signal processing methods for measuring heart rate based on a force sensor signal (Papers I-III)

b) signal processing methods for measuring respiration rate variability based on a force sensor signal (Paper IV)

c) an e-health system for long-term sleep measurement (Paper V).

How the contributions and Papers I-V are related to each other is shown in Figure 1.2, which presents the flow of information in the e-health system of Paper V. The outputs from the signal processing methods are presented to the user in the e-health system and also used as inputs to high-level analyses like sleep staging. Such cardio-respiratory sleep staging [51, 80, 21, 66, 25] has been one of the motivations for the research on the signal processing methods, although the actual sleep staging methods are left outside the scope of this thesis. The contributions have been presented in the five original papers, as described below.

Paper I We introduce a linear latent variable model for the respiratory variation of the heartbeat shape. The model describes the effect of respiration on the shapes of individual heartbeats. Having a precise model for this known source of variation helps distinguish it from other variation sources such as artifacts. Potential uses for the method are heart rate detection as well as diagnostic applications, where the shape of the heartbeat needs to be further analyzed.

[1] http://www.beddit.com/

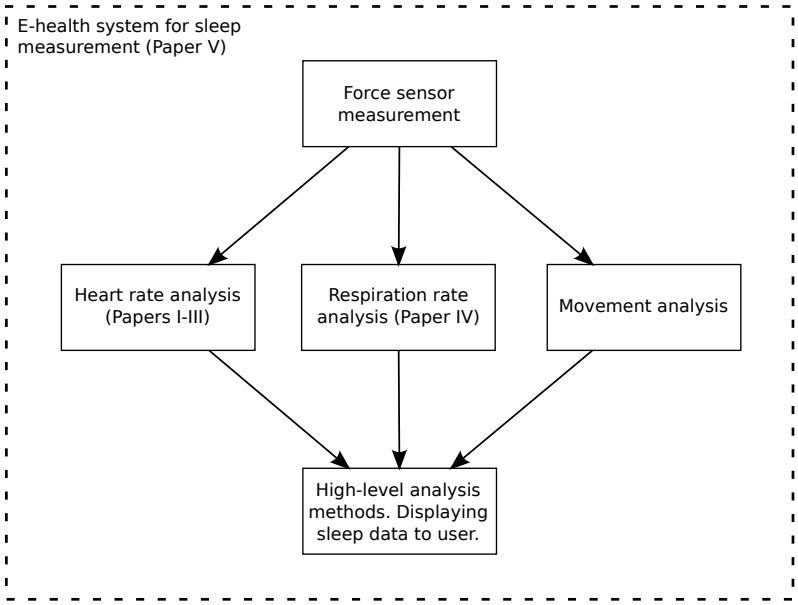


Figure 1.2: Flow of information in the e-health system.

Paper II We propose a clustering method for detecting heartbeats from a force sensor signal. The method has two uses: detection of heart rate and learning a model for the heartbeat shape. Such unsupervised learning functionality is utilized in the beat-to-beat heart rate measurement method described in Paper III. Learning the heartbeat shape is difficult, due to the shape's variability across different subjects and different sleeping positions. The clustering method provides an efficient solution to the variability problem.

Paper III We propose a method for measuring beat-to-beat heart rate from force sensor signals. The clustering method of Paper II is used to learn a model for the heartbeat shape. The model thus learned is then applied to detecting individual beat-to-beat intervals from the signal. Clinical trials consisting of 60 subjects were carried out to validate the precision of the method. The beat-to-beat heart rate detection method is a component of the e-health system described in Paper V.

Paper IV We propose a method for the detection of respiration rate variability from force sensor signals. The force signal is filtered with multiple parallel filters to extract the respiration cycles from other fluctuations in the signal. Respiration variability measurement can be used in cardio-

respiratory sleep staging and in the measurement of sleep-related respiratory issues. The method is a component of the e-health system described in Paper V.

Paper V We describe an online e-health sleep measurement system. Sleep is automatically measured with force sensors and the resulting sleep information is presented to the user with a web interface. The system integrates the above heart rate and respiration signal analysis methods. For example, the variability of heart and respiration rates are used as inputs to a sleep staging method, and heart rate information is provided to the user in the form of a resting heart rate reading. The aims of the system are two-fold: self-tracking and improvement of sleep for consumer use as well as long-term medical sleep monitoring.

Chapter 2

Sleep physiology

2.1 Sleep stages

Sleep is a physiologic phenomenon that is controlled by the central nervous system (CNS). Sleep is characterized by decreased mobility, lack or decrease of consciousness and diminished sensory sensitivity.

It has been known for a long time that sleep is vital to both humans and animals. Based on *electroencephalographic* (EEG) measurement, it was found in the 1930s that the depth of sleep varies throughout the night, from wakefulness to light sleep to deep sleep [27]. Rapid eye movement sleep (REM) was discovered in 1953 [5], which established the still-valid classification of CNS activity into three fundamentally distinct states: REM sleep, non-REM sleep (NREM) and wakefulness. There is no physiological clear-cut boundary between being awake and asleep, so it is natural to treat wakefulness as one of the sleep stages, as I do in the following discussion.

REM sleep has also been called *paradoxical sleep*, because the neuronal activity of the brain resembles the waking state, unlike in NREM sleep. A peculiar feature of REM sleep is muscle paralysis, which blocks the neuronal connection between the brain and most muscles. Muscle paralysis prevents the awake-like brain activity from causing movement of the body during sleep. Dreaming is more frequent and vivid during REM sleep, although dreaming does occur also during NREM sleep [36, 92].

According to established guidelines of clinical sleep measurement [41], NREM sleep is further categorized into three levels, with increasing sleep depth: N1, N2 and N3. Stage N1 represents the drowsy state between wakefulness and sleep, and the depth of sleep is progressively increased in stages N2 and N3.

A typical night of a healthy young adult consists of about five *sleep*

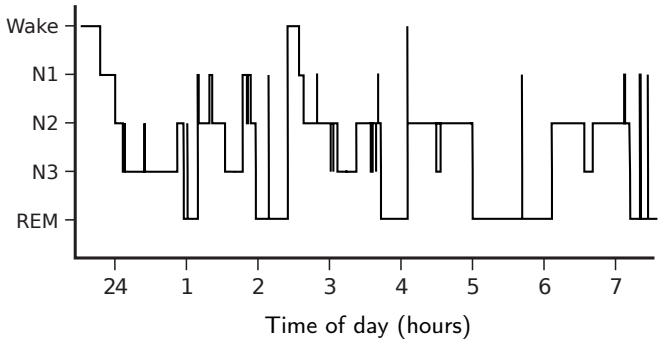


Figure 2.1: Sleep stages across a typical night. (Adapted from [62].)

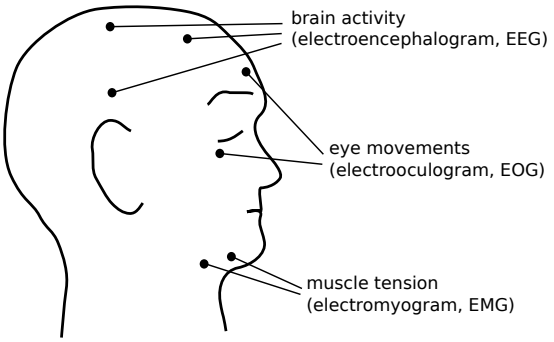


Figure 2.2: Measurement sites of the electrophysiological signals for sleep staging.

cycles, where sleep alternates between NREM and REM sleep in around 90-minute periods. In the first third of the night, the cycles contain relatively more of the deepest N3 sleep, whereas REM sleep dominates in the last third. An exemplary plot (*hypnogram*) showing the sleep stages for a single night is shown in Figure 2.1.

In addition to EEG, a few other electrophysiologic signals measured in the head region are needed for detecting sleep stages: *electrooculography* (EOG, eye movement electrical activity) and *electromyography* (EMG, electrical muscle activity measured from the chin). The sites of measurement are shown in Figure 2.2. The electrophysiological features of each sleep stage are given in Table 2.1.

Sleep stage	**EEG, EMG, EOG features**	**Movement, cardiac and respiratory features**
Wake	EEG: Alpha activity (8-13 Hz) for $\geq$50% of the epoch.	Much movement. Increased HRV. Stable respiration.
N1	EEG: Alpha activity for $<$50% of the epoch. Low-voltage mixed-frequency activity. Vertex sharp waves. EOG: Slow eye movements.	Little movement. Decreased HRV. Instability in respiration amplitude.
N2	EEG: Slow-wave activity (0.5-2 Hz) for $<$20% of the epoch. Sleep spindles or K-complexes.	Little movement. Decreased HRV. Stable respiration.
N3	EEG: Slow-wave activity for $\geq$20% of the epoch.	Little movement. Decreased HRV. Very stable respiration.
REM	EEG: Low-voltage mixed-frequency activity. Saw-tooth waves (2-6 Hz). EMG: Low activity. EOG: Rapid eye movements.	Movements during phasic REM. Increased HRV. Unstable respiration.

Abbreviations EEG: electroencephalography; EOG: electrooculography; EMG: electromyography; HRV: heart rate variability

Table 2.1: The electrophysiological features of sleep stages, according to the American Association of Sleep Medicine (AASM) standard [41], are given in the middle column. Sleep is classified into sleep stages in 30-second epochs based on these features. How sleep stages affect movement, heart rate and respiration is shown in the right column. See text for a more detailed description.

2.2 Movement, heart rate and respiration during sleep

The effects of the different sleep stages can be seen in heart rate, respiration and movement activity (see Table 2.1 for a summary). These observable effects form the basis of force sensor sleep measurement, because heart rate, respiration and movement can be measured with force sensors, as will be described in Chapter 3.

The interaction between sleep stages and cardio-respiratory-movement phenomena is mainly such that sleep stages *cause* the phenomena and not vice versa. However, some respiratory phenomena such as sleep apnea can indeed affect sleep stages (by causing awakenings).

Movement Compared to wakefulness, healthy NREM sleep consists of a very low level of motility, because voluntary movements are absent. Most of the duration of a REM episode is *tonic*, which means that muscle paralysis is effective and no movement activity is present. However, the paralysis mechanism is occasionally interrupted, causing involuntary *phasic* movement events (mostly transient muscle twitches) of the body.

In summary, the level of movement activity is much smaller in sleep than in wakefulness, although there is somewhat more movement in phasic REM periods than in the rest of sleep.

As sleep correlates with a low level of motility, circadian rhythmicity can be estimated with a method called *actigraphy* [69]. An accelerometer sensor is worn on the wrist 24 hours a day, which allows estimating the daily alternation between sleep and wakefulness. Due to its limited accuracy, actigraphy is typically used for the overall characterization of sleeping patters over a period of at least a week.

Heart rate and respiration Marked changes can be seen in heart rate and respiration across different sleep stages. These changes are caused by various physiological mechanisms. For example, the autonomic coordination between heart rate and respiration is strong in NREM sleep (heart rate varies steadily in the phase of respiration) and weak in REM sleep (heart rate is more erratic).

Various mathematical models have been proposed for describing heart rate and respiration processes and their interactions in different sleep stages. A convenient way to describe heart rate variability in different sleep stages is to compute the variability in standard frequency bands: high frequency (HF, 0.15–0.40 Hz), low frequency (LF, 0.04–0.15 Hz), very low frequency (VLF,

0.003–0.04 Hz) and ultra low frequency (ULF, 0.0001–0.003 Hz) [12, 97]. The ratios between the frequency bands markedly change across sleep stages. Another method for quantifying heart rate variability changes across sleep stages is *detrended fluctuation analysis* [17, 100, 75] that estimates long-range correlations and randomness of the heart rate time series. In addition, arousal to a lighter sleep stage has been found to trigger transient increases in heart rate [7].

The above models for measuring heart rate variability are indirectly also measuring heart rate–respiration interaction. For example, spectral power in the HF band is mainly caused by synchronization of heart rate with respiration. However, some models quantify the interaction between heart rate and respiration more explicitly, by directly modeling such interaction [42, 80, 95, 24, 76].

The properties of breathing alone (without mention of heart rate) change by sleep stage. In general, ventilation is reduced and respiration frequency increased in sleep compared to wakefulness [29]. The variability of respiration is high both at sleep onset [101] and in REM sleep [22, 63], with NREM sleep being less variable. Comparing different NREM sleep stages, N1 and N2 have more respiratory variation than N3 [61]. Similar to heart rate, long-range correlations of respiration are present in REM but absent in NREM [50].

Chapter 3

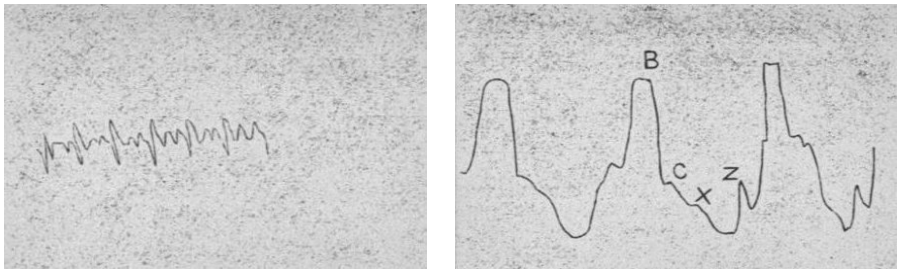
Unobtrusive cardiac and respiratory measurement

This chapter describes the signal analysis methods proposed in Papers I-IV. First, however, a compact review of unobtrusive cardiac and respiration measurement sensors is given. Then, our signal analysis contributions for cardiac measurement (Section 3.2) and respiration measurement (Section 3.3) are presented. Those sections also contain brief reviews of previous signal analysis methods for the respective tasks.

3.1 Unobtrusive sensors

Sensors that cause no discomfort are often called "unobtrusive". One way to draw the line between unobtrusive sensors and others is to require that sensing must not involve electrodes or any other wearable parts. Unobtrusive sensors measure the body either in the platform supporting the body (beds, chairs, weighing scales) or remotely, using e.g. radar technology. Heart rate and respiration can be measured unobtrusively, because respiration and the beating of the heart cause small movements of the body. Although wearable sensors may became very comfortable in the near future (e.g. rings or sensor garments), I exclude them from the following discussion, because current wearable technology does not yet provide a fully unobtrusive experience.

In the following, I give a short review of measurement methods that are applicable to unobtrusive sleep monitoring in the home environment. Various sensors exist and a detailed evaluation of their strengths and weaknesses is outside the scope of this thesis. A practical evaluation takes place commercially: the most appropriate sensors for unobtrusive measurement are likely to be found in successful products.



(a) (b)

Figure 3.1: Early BCG recordings by Gordon [37], measured with a weighing machine, (a), and a bed suspended with ropes, (b). The labels in (b) correspond to different features of a single heartbeat, as identified by Gordon.

Ballistocardiography Measurement of mechanical cardiac activity from the platform supporting the body is called *ballistocardiography* (BCG). The term comes from the Greek word *ballein*, to throw. The heart throws, or pumps, blood to the artery, which causes the body to move during each cardiac cycle.

The first documented measurements on how the beating of the heart causes the body to move have been traced back to the late 19th century [37]. J. W. Gordon measured cardiac activity by tracing the movements of the index of a weighing machine (Figure 3.1a) and by measuring the footward movements of a light bed that was swung with four ropes (Figure 3.1b). It was not until the work of Isaac Starr from the 1930s that the method started to gain medical prominence [91, 87]. Starr's key contribution was the introduction of *high-frequency BCG*, where it was not the actual displacement of the body that was measured, but rather the force that the displacement exerted on the supporting platform. Previous experimenters had measured displacement directly, and did not get good results as the low-frequency respiratory phenomenon interfered with the cardiac activity. One such device measuring displacement is shown in Figure 3.2. Measurement of force effectively acts as a high-pass filter and thus diminishes the respiratory artifact. Ballistocardiography was to become a clinically significant tool, but the development of other methods such as electrocardiography led to a drastic lessening of BCG research activities from late 1950s [87, 34, ch. 2].

One of the reasons for the decline of BCG was that the recording apparatus was expensive and cumbersome. That is no longer the case. Recently, various convenient and inexpensive sensors have been developed for mea-

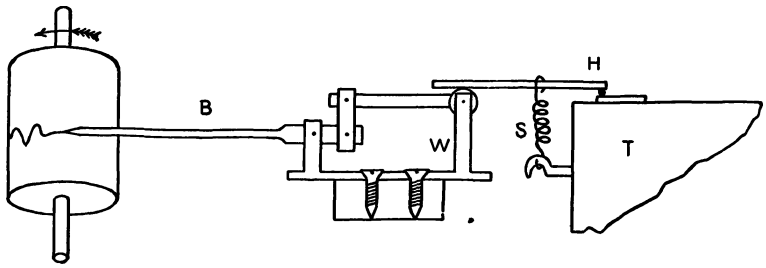


Figure 3.2: Henderson's device [40] is based on measuring the displacement of the bed, "T", by amplifying the footward movement (horizontal movement in the figure) of the bed with levers and graphing it on a revolving drum. The bed is suspended so that it can move freely in the footward direction.

suring the mechanical activity of the heart. Chair sensors [56] are designed to be used as diagnostic devices, so that cardiac diagnoses can be performed while the patient sits on the chair. Similarly, a sensor embedded in a conventional weighing scale [43] enables making diagnostic cardiac measurements whenever the patient visits the scale.

Various sensors for measuring the BCG of a sleeping person have been developed, including bed post sensors [13], a pillow sensor [18], different kinds of mattress sensors [46, 19, 58, 39, 57] and an infrared sensor placed under the mattress [14]. A notable example is the *static charge-sensitive bed* [4], developed in the late 1970s, to measure sleep quality using unobtrusive measurement of respiration, heart rate and movement. The bed sensors do not strictly match the original definition of BCG as force measurement along a defined axis (e.g. head-to-foot), because the subject changes sleeping posture during the night. For convenience, all these measurement methods are called BCG here.

Bed electrocardiography Although conventional electrocardiography requires wearing adhesive electrodes, there are ways to measure the ECG during sleep without disturbance. Textile ECG electrodes [45, 28, 74] measure the electrical activity by using conducting sheet material as the electrode. A drawback of the method is that only limited parts of the skin area can be covered in cloth, to avoid insulating the electrodes from the skin.

Capacitive ECG avoids the insulation problem by measuring electrical displacement currents caused by the changing potential distribution of the heart [99, 108]. These currents can be measured with an electrode that is close to the skin, but not in direct contact.

Radar measurement The movements of the chest caused by respiration and heart can be measured with radio frequency radar sensors [67, 68, 110, 25]. The radar is positioned close to the bed so that radiation can be directed towards the body of the sleeping person. Radar measurement has been used in consumer products that measure sleep quality (GEAR4 Renew SleepClock[1], Omron Sleep Design HSL-101[2]).

Force sensor respiration measurement Most of the BCG and radar sensors mentioned above are also capable of measuring respiratory activity, because respiration causes the chest to move measurably. However, some systems have been developed for the unobtrusive measurement of just respiration and movement activity [9, 8, 11]. Respiration events such as *central sleep apneas* can be detected with such measurement, which could be used in sleep disorder diagnosis.

The primary sensor used in this thesis is of the ballistocardiography type and also measures breathing activity. The sensor (Figure 1.1) is made of flexible piezoelectric material, measures 4 cm by 70 cm and is 0.2 mm thick. It is attached to the mattress with adhesive tape, just beneath the bed sheet. The micro-movements of the body caused by heartbeats and respiration are detected by the sensor, enabling physiological measurement. Obviously, gross movements of the sleeper are also detected. This "bed film sensor" type has been used by many researchers [46, 57, 106, 78, 16, 3] and provides a good cardiorespiratory signal without causing discomfort.

It is natural to compare bed film sensors to two alternatives for measuring heart rate, respiration and movements: radar sensors and load cells. Radar sensors [67, 68, 110, 25] measure movement of the body from a distance and the signal contains information on heart rate, respiration as well as movements. Load cells are force sensors that are installed to the support of the bed (e.g. bed post) [13, 21, 23, 9]. Most load cells measure movement and respiration, and some are sensitive enough for detecting heart rate. These three similar modes of measurement (bed film sensor, radar, load cell) all have their advantages and drawbacks. The main difference between bed film sensors and load cells is that film sensors have a more localized area of measurement (subject needs to be on the sensor) than load cells (subject is measured anywhere on the bed). Thus, load cells are not suitable for double beds, where both subjects' signals would get mixed, but measure a single subject well. The radar signal is similar to those from bed film sensors

[1] http://renewsleepclock.com/
[2] http://www.healthcare.omron.co.jp/product/hsl/hsl-101.html

and load cells, but the setup of measurement differs. Radars are normally positioned above the bed, pointing at the subject, whereas bed film sensors and load cells are installed to the bed.

In Papers I, II and IV, we used a different ballistocardiographic sensor, which is placed under the bedpost (see Figure 3.10a on page 31). The switch to the current sensor was made in late 2011, to better measure respiration activity. The main difference between the sensors is that in the current sensor the amplitude of the respiration waveform is 5 to 10 times the heartbeat amplitude, whereas in the old sensor they are about equal. The signal analysis methods presented in this thesis are applicable to both sensor types due to the similarity of the signals. In fact, the method presented in Paper III has been validated with measurements from both sensor types. This illustrates the power of adaptive methods in generalizing to different settings.

3.2 Heart rate measurement signal analysis methods

There are three main contributions for heart rate measurement: a model for respiratory variation of heartbeats (Paper I, Section 3.2.2), a clustering method for learning the heartbeat shape (Paper II, Section 3.2.3) and a method for measuring beat-to-beat heart rate (Paper III, Section 3.2.4). The clustering method is a component of the beat-to-beat heart rate measurement method.

3.2.1 Background and related work

Measuring the heart rate from BCG or similar mechanical signals is a much more difficult task than *electrocardiogram* (ECG) heart rate measurement, the most commonplace cardiac measurement method. Individual heartbeats can be detected in an ECG signal relatively easily, by locating a clear spike (called the *QRS complex*, from the consecutive named spikes Q, R, S of the ECG heartbeat) that accompanies each heartbeat. However, with BCG, the cardiac impulses are less pronounced and more variable than the salient shape of the QRS complex. The relation between BCG and ECG is shown in Figure 3.3. Each ECG heartbeat signal consists of a clear spike (the QRS complex), which is followed by an impulse in the BCG around 80 ms later [30]. The ECG spike precedes the impulse in the BCG, because electrical activity causes the mechanical contraction of the heart. Various methods have been proposed for the measurement of beat-to-beat heart rate in BCG signals. They are reviewed next.

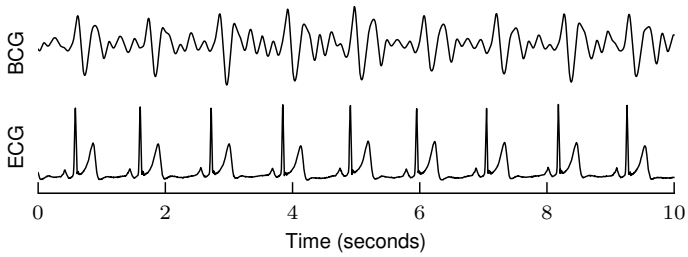


Figure 3.3: A 10-second excerpt of synchronized ballistocardiography (top) and electrocardiography (bottom) signals.

Many algorithms are based on pre-processing the BCG signal with digital filters such as wavelets, and detecting peaks [111, 13, 49, 71, 35] or slightly more complex features [2, 88, 109, 66, 33] (typically a "W" shape) in the signal. The problem with these methods is that they make strong assumptions about the shapes of the heartbeats in the signal. The properties of the BCG signal vary in practice so much that no simple filtering rule can be devised for accurate and reliable heartbeat detection.

Not all methods make equally strong assumptions about the shapes of heartbeats in the BCG signal. The clustering method proposed in Paper II detects the heartbeats directly with little prior information about the heartbeat shape. A similar approach has been employed by Rosales et al. [81]. The problem with these methods is that they do not model the region between the detected heartbeat positions. Therefore, it is difficult to infer if two consecutive detected heartbeat positions form a genuine beat-to-beat interval or if there is a heartbeat between them that was missed by the clustering procedure. One promising method uses k-means clustering to extract a template for the heartbeat shape and detects heartbeats and beat-to-beat intervals with the template [15].

One group of methods does not try to detect beat-to-beat intervals by first finding heartbeat positions, but estimates a "fundamental frequency" of short segments and infers beat-to-beat intervals that way [58, 103, 16]. The method by Brüser et al. [16] has been validated with 33 test subjects and can be considered to represent the state of the art.

The contributions of Papers I-III will be summarized in the following three sections.

3.2.2 Respiration variation model for the heartbeat shape

The model for the respiratory variation of heartbeat shape described below has originally been presented in Paper I.

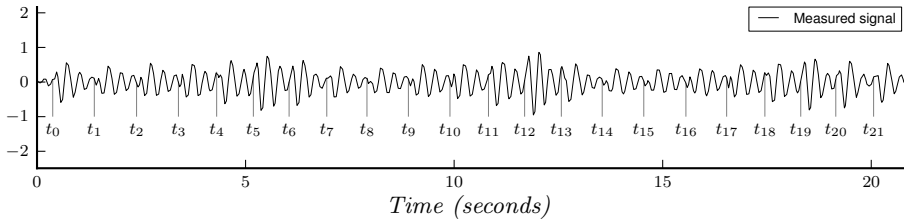


Figure 3.4: A BCG signal segment containing three respiration cycles. Each t_i denotes the onset of the ith heartbeat (x-axis, time in seconds). The signal has been acquired with the bedpost sensor (Figure 3.10a) and has been high-pass filtered to remove the low-frequency trend caused by respiration.

Various beat-to-beat heart rate measurement methods [48, 15, 86, 93] are based on quantifying the difference between signal segments and a heartbeat shape model. Heartbeats are detected where the model fits the signal well. The quantification will be more precise if the physiological variation in the heartbeat shape can be taken into account when matching the heartbeat shape to the signal.

Short-term changes in BCG heartbeat shape have been found to be caused mostly by respiration [90, p. 191]. See Figure 3.4 for an example of the respiratory effect in the signal. A common model for the variation is that the heartbeat shape varies by amplitude [48, 44, 15, etc.]. However, with some measurement setups, amplitude variation is not an adequate model for the respiratory variation. For example, with seismocardiogram measurement, a specific feature of the seismocardiogram heartbeat (called the *S1-S2 interval*) has been found to vary by respiration [72].

Our model describes an individual heartbeat shape $\mathbf{x}_i$ as a weighted sum of a mean heartbeat vector $\boldsymbol{\mu}$ and a respiratory component vector $\mathbf{w}$. Vector $\mathbf{w}$ represents the direction of the respiratory variation and is weighted by a respiration phase variable z_i, which describes the magnitude of the respiratory effect and normally follows the phase of respiration [89]. The formal description of the model is

$$\mathbf{x}_i = \mathbf{w}z_i + \boldsymbol{\mu} + \epsilon \tag{3.1}$$

where ϵ is a noise term. Compare that to the amplitude variation model,

$$\mathbf{x}_i = z_i\boldsymbol{\mu} + \epsilon,$$

where the heartbeat vector is simply a scaled mean heartbeat vector.

The result of applying the model to test signals is shown in Figure 3.5. Our model was found to describe the respiratory variation better than the

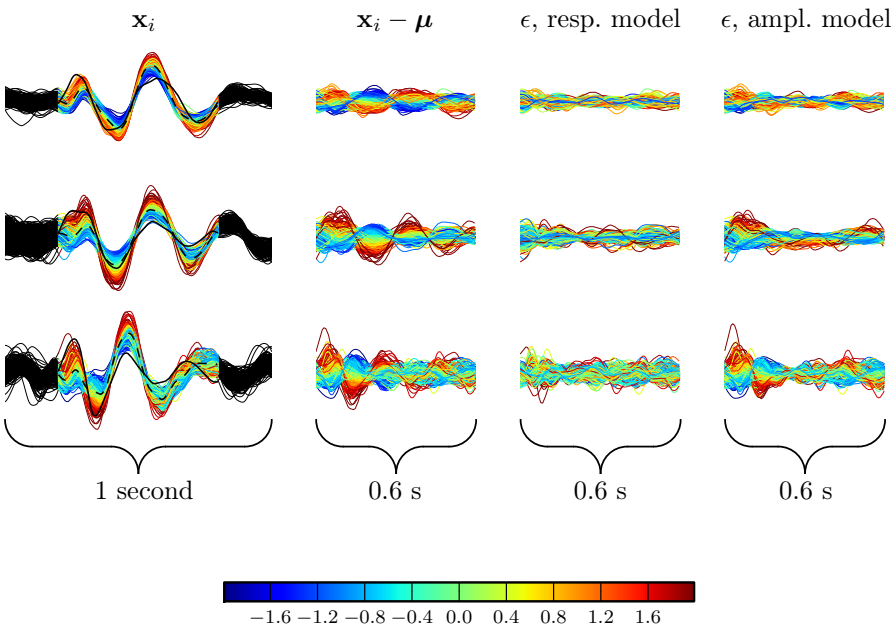


Figure 3.5: N heartbeat waveforms $(\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_N)$ are plotted in the first column, with the context before and after each $\mathbf{x}_i$ shown in black. The mean heartbeat $\boldsymbol{\mu}$ (- - -) and variation vector $\mathbf{w}$ (——) are shown as black lines. The second column contains the heartbeat waveforms minus the mean heartbeat $(\mathbf{x}_1 - \boldsymbol{\mu}, \mathbf{x}_2 - \boldsymbol{\mu}, \ldots, \mathbf{x}_N - \boldsymbol{\mu})$. The error terms ϵ of the respiratory model and amplitude model are in the third and fourth columns, respectively. The color of each line shows the value of the respiratory latent variable z_i of each heartbeat (see colorbar) in all the four columns. The vertical dimension is in arbitrary units and is identical for all the plots in the figure.

amplitude variation model, as measured with Bayesian information criterion [54] (see Paper I for details). The criterion gives an estimate of how suitable a model is for describing observed data, in this case heartbeat vectors.

3.2.3 Inferring the heartbeat shape with clustering

The following clustering method was originally presented in Paper II and its details have been refined in Paper III.

The heartbeat impulses in a BCG signal vary across subjects and within a measurement night across different sleeping postures. One strategy for detecting heartbeats in a flexible manner is to first learn the shape of the heartbeat and then use the shape for detecting heartbeat positions.

We have developed a clustering method for the learning task. The clus-

tering method is applied on a segment of the signal: within the segment, we look for clusters of short signal windows that are similar to each other. Windowing and clustering are performed as follows. First, the segment is divided into overlapping 0.4-second windows so that each window is centered at an extremum of the derivative of the signal. Figure 3.6 illustrates this process. The window center positions are shown as upward lines in Figure 3.6a and all the 0.4-second signal windows are overlaid in Figure 3.6b.

In our implementation, the clustering method is applied to a 15-second signal segment at a time, and the densest four-item cluster is selected to represent the heartbeat shape. A longer segment would contain more heartbeats and thus improve the estimation of the shape, while a shorter segment would make the estimation of the shape more rapid (useful in real-time monitoring applications).

The signal windows are clustered using complete-link agglomerative clustering. Figure 3.6c shows the densest (smallest complete-link distance) four-item cluster of signal windows (these window positions are in Figure 3.6a as downward lines). If the complete-link distance of the densest four-item cluster is below a fixed threshold, the heartbeat shape is estimated with the technique described below. Otherwise, the above procedure is repeated after 15 seconds.

The heartbeat shape is now estimated as follows. First, 2.5-second signal windows (*shape windows*) centered at the four cluster signal windows are extracted (Figure 3.6d). To estimate the length of the heartbeat shape, a *heart valve signal* (HVS) is calculated [15]. This is done by taking the pointwise average of squared and low-pass filtered shape windows (Figure 3.6e). The local minima of the HVS around the center of the segment (vertical lines in Figures 3.6e-f) determine the length of the heartbeat shape (Figure 3.6f).

The heartbeat learning method is used in measuring beat-to-beat heart rate, as will be described below.

3.2.4 Measuring beat-to-beat heart rate

The beat-to-beat heart rate measurement method described below has originally been proposed in Paper III.

The purpose of the method is to extract heart rate variability information by finding time intervals between consecutive heartbeat positions (beat-to-beat intervals). The algorithm has to accomplish two tasks: find heartbeat positions for the start and end of each interval, and assure that the start and end positions are consecutive heartbeats, i.e., that there are no missed heartbeats between them.

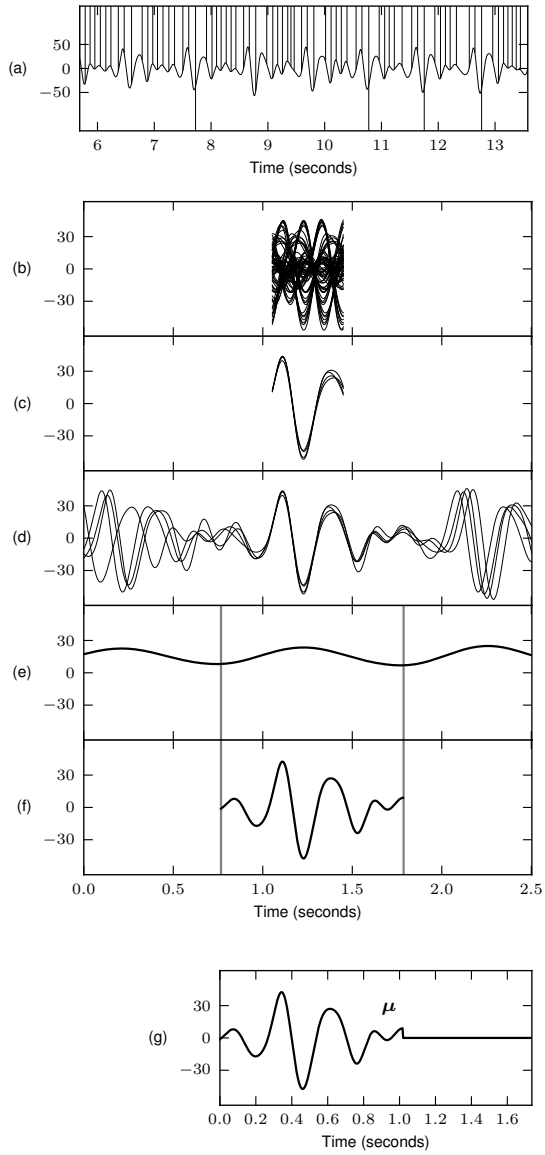


Figure 3.6: (a): A 8-second signal segment (shown for improved clarity, although the method uses 15-second segments). The center positions of the signal windows are shown as vertical upward lines, and of the densest cluster as downward lines. (b): All 0.4-second signal windows overlaid. (c): The signal windows of the densest cluster of four windows. (d): 2.5-second shape windows that are used for extracting the heartbeat shape model. (e): The computed heart valve signal (HVS). (f): The heartbeat shape is extracted by taking the point-wise mean of the shape windows between the local minima of the HVS. (g): The vector $\boldsymbol{\mu}$ is formed by taking the computed heartbeat shape and filling the rest of the vector with zeros.

First, the heartbeat model parameter $\boldsymbol{\mu}$ is estimated with the clustering method described in Section 3.2.3. The model is then used for detecting beat-to-beat intervals and periodically updated based on the detected beat-to-beat intervals.

The detection of heartbeat positions is limited to a set of candidate positions. They are found by locating local maxima of the cross-correlation between the observed signal and the heartbeat shape mean vector $\boldsymbol{\mu}$.

Beat-to-beat intervals are detected by finding pairs of consecutive heartbeat positions that match the signal well. A potential interval-start heartbeat position t_a is fixed to a candidate position and different candidate positions are tried for the interval-end heartbeat position t_b. If a t_b candidate results in a plausible beat-to-beat interval (small-enough residual, see (3.3) below) and the amplitudes of the two heartbeats are similar enough (the larger amplitude is less than 2 times the other), the beat-to-beat interval $(t_\mathrm{a}, t_\mathrm{b})$ is output. A large amplitude difference between consecutive heartbeats is physiologically unlikely, so such cases are discarded as probable false detections.

How well the two heartbeat positions match the signal is calculated by constructing a synthetic signal segment based on the positions and the heartbeat model, and computing the difference between the observed and synthetic signals. This computation is visualized in Figure 3.7 with two cases. The residual is much higher in the case where the heartbeat interval does not match the signal well.

First, synthetic heartbeat vectors $\mathbf{x}_\mathrm{a}$ and $\mathbf{x}_\mathrm{b}$ are constructed by fitting the heartbeat vector model (3.1) to the signal at positions t_a and t_b. The fitting is done by minimizing the mean-square error between the model (3.1) and the observed signal $\mathbf{s}$, by adjusting only parameter z_i in (3.1). The mean-square error for the heartbeat position t_a is given by

$$\text{average}\left(\left(s_j - (z_\mathrm{a}\boldsymbol{\mu})\,[j - t_\mathrm{a}]\right)^2\right) \tag{3.2}$$

where j goes from 0 to the length of the heartbeat shape. Parameter z_a is optimized to minimize the mean-square error, which gives the synthetic heartbeat vector $\mathbf{x}_\mathrm{a} = z_\mathrm{a}\boldsymbol{\mu}$. The heartbeat vector for position t_b ($\mathbf{x}_\mathrm{b}$) is constructed in the same way. The reconstructed two-beat region is then obtained as a superposition of $\mathbf{x}_\mathrm{a}$ and $\mathbf{x}_\mathrm{b}$.

Then, the modeling error ϵ_j concerning the pair of heartbeat positions t_a and t_b is calculated, as

$$\epsilon_j = s_j - (\mathbf{x}_\mathrm{a}[j - t_\mathrm{a}] + \mathbf{x}_\mathrm{b}[j - t_\mathrm{b}]) \tag{3.3}$$

over the region $t_\mathrm{a} \le j \le t_\mathrm{a} + (t_\mathrm{b} - t_\mathrm{a}) \times 2$, that is, over a region that consists of both heartbeats. The heartbeat interval $(t_\mathrm{a}, t_\mathrm{b})$ is accepted if the average

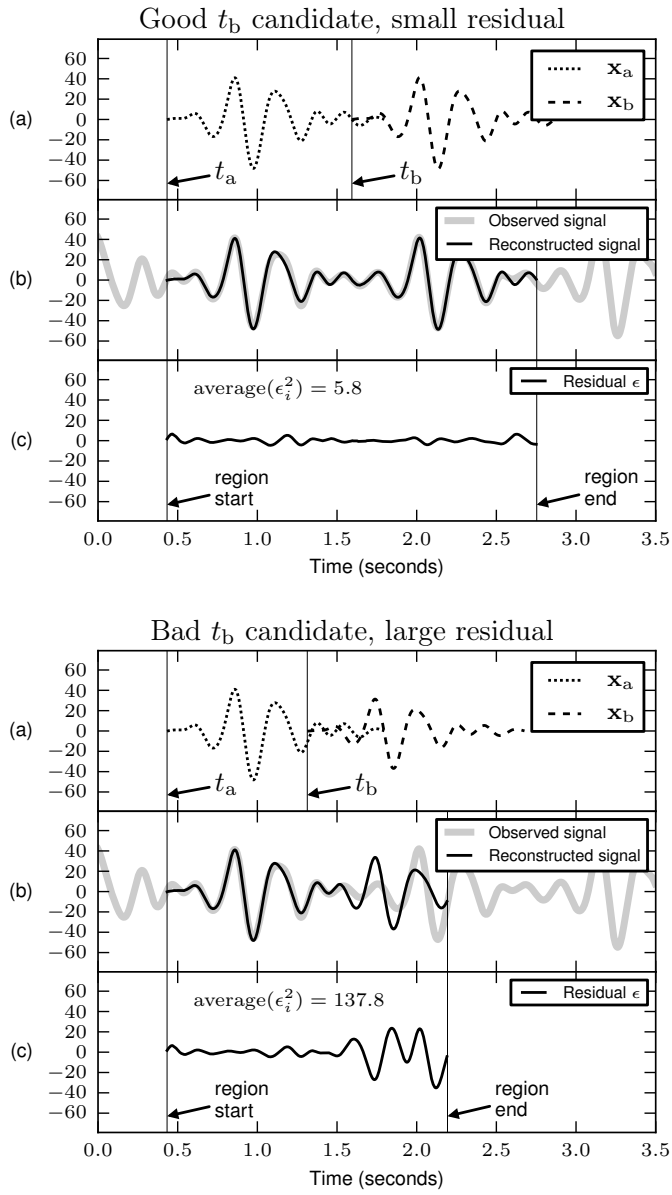


Figure 3.7: Beat-to-beat interval evaluation in cases where the residual is low (a, b, c in the upper panel) and high (a, b, c in the lower panel). (a): Candidate heartbeat vectors $\mathbf{x}_a$ (dotted line) and $\mathbf{x}_b$ (dashed line). (b): The reconstruction of the beat-to-beat interval (black) and the observed signal (gray). (c): The computed residual (3.3).

of the square residual ϵ_j^2 over the region is below a fixed threshold and the amplitude comparison criterion given above is satisfied.

The vector $\boldsymbol{\mu}$ is re-estimated every 20 new beat-to-beat interval detections, using the latest 100 detected beat-to-beat interval start positions. The model is updated continuously, because the shape of the heartbeat can drift slowly, for example due to changes in average heart rate. Vector $\boldsymbol{\mu}$ is estimated with the method by Inan et al. [44], by taking an ensemble average so that the interference of adjacent heartbeats is cancelled. The ensemble averaging method produces heartbeat vectors where the effect of the preceding and following heartbeats have been cancelled.

Updating $\boldsymbol{\mu}$ as described above handles cases where the heartbeat shape changes slowly. However, changes e.g. in sleeping posture can alter the heartbeat shape so much that it needs to be fully re-initialized. To account for such changes, four "instances" of the beat-to-beat interval detection method described above are run in parallel. Every 20 seconds, the instance with fewest heartbeat detections in the preceding 20-second period is re-initialized with the clustering method. The instance with most detections in that 20-second period is set to be the "active" instance. The beat-to-beat intervals are taken from the active instance for each 20-second period.

The beat-to-beat intervals produced by the above method are post-processed by removing probably incorrect beat-to-beat intervals from the data. The median m of the previous 15 detected beat-to-beat intervals is calculated for each new interval. If the new beat-to-beat interval is in range $m/1.6 \ldots m \times 1.6$ it is accepted and rejected otherwise. These limits have been chosen as a suitable trade-off between 1) detecting as many beat-to-beat intervals as possible and 2) detecting as few incorrect beat-to-beat intervals as possible.

3.2.5 Evaluation

The model for the respiratory variation of heartbeat shape (Section 3.2.2) has been evaluated with Bayesian information criteria (see Paper I for details). The beat-to-beat heart rate measurement methods described in Papers II and III have been evaluated as part of a clinical study in Paper III. Results from the study will be described next.

The performance of the method was tested with overnight recordings from 60 people: 40 patients were measured at a local sleep clinic and 20 volunteers in their homes. At the clinic, the BCG signal was measured from a standard consumer bed with the bedpost sensor, and the film sensor was used at home. In total 46 overnight recordings had a successfully acquired ECG reference and those were used in the validation. A relatively high

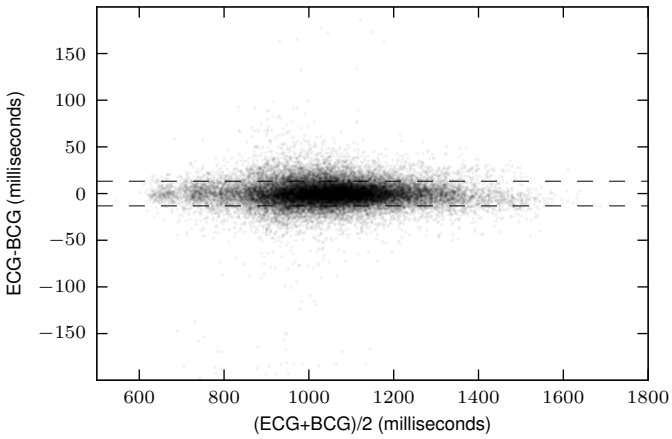


Figure 3.8: Bland-Altman plot of the difference between detected BCG beat-to-beat intervals and ECG reference. Out of the 770676 detected beat-to-beat intervals, 30000 have been randomly selected to make the plot easier to read. The upper dashed horizontal line denotes the average E_{mean} statistic across all subjects (the other line is its negation).

number of failed measurements was caused by an experimental measurement setup that was required due to the new sensor technology.

For each beat-to-beat interval detected from the BCG signal, a corresponding reference beat-to-beat interval was sought from the reference ECG signal. The resulting differences between BCG and ECG beat-to-beat intervals from the whole study are visualized in Figure 3.8.

The performance of the method was evaluated with various statistics, computed separately for each test subject (see Table I in Paper III for full results). For example, *coverage*, *precision* and mean beat-to-beat interval error (E_{mean}) were calculated. Coverage is the ratio between the number of detected BCG and ECG intervals. Precision is the ratio $correct/(correct + incorrect)$ where correct and incorrect beat-to-beat interval detections are separated with a 30 ms threshold.

The performance of the method varies strongly by test subject. The subjects have different degrees of cardiac problems and sleeping disorders. This causes the signal quality to vary: the signals are very clear in some cases and full of movements and other distortion in other cases. However, the demographic parameters (age, BMI (body mass index), and sex) do not have a strong effect on the results. With the signals measured at home (film sensor), the bed types and measurement setups vary, with some subjects sleeping in double beds with a partner and some sleeping alone. These

measurement differences likely explain some of the variability in the results.

The two key accuracy parameters are coverage and E_{mean}. There is large variability in coverage. In the best case, 94.0% of the heartbeats have been detected, whereas in the worst case, only 8.19% have been detected. Average coverage is 54.07%, so on average over half of the heartbeats are detected. The cause for the lowest coverage value 8.19% is not completely clear. However, based on inspection of the signal, the primary cause is probably that the sensor has not been placed properly under the subject, as the signal quality is not optimal.

The average of the mean error (E_{mean}) across all test subjects is 13.2 ms. The sensor used seems to have an effect on accuracy. Out of the 46 subjects, the 16 worst measurements by mean error (E_{mean}) have been acquired with the bedpost sensor. The largest E_{mean} statistic with the bedpost sensor is 33.9 ms but only 12.8 ms with the film sensor.

3.2.6 Discussion

We have proposed methods for modeling the respiratory variation of heartbeat shapes and detecting beat-to-beat heart rate from BCG signals. The respiratory variation model could potentially be used in heart rate analysis methods or diagnostic applications, because it allows modeling the heartbeat shape with improved precision. Although the Bayesian information criterion analysis shows that the model is suitable for heartbeat modeling, its real utility can only be tested in real use, such as a diagnostic application. Until then, it remains open what the true benefits of such heartbeat modeling are.

The proposed method for beat-to-beat detection has been validated with a clinical study (see Table I in Paper III for full results) and is in use in the e-health system described in Chapter 4.2. The clinical validation shows that the beat-to-beat detection method has fairly good precision despite the large variation in the test subjects and measurement setups. The method measures beat-to-beat intervals with around 13 ms precision. In the best cases, over 90% of the heartbeats have been detected with good precision, which should be enough for detailed heart rate variability (HRV) analyses, whereas in the worst cases, the number of detected heartbeats is sufficient for estimating only the overall trend of resting heart rate. The average error in resting heart rate is less than 1 BPM with most subjects, which enables sufficiently precise average HR measurement for many applications. In the e-health system described in Chapter 4.2, both HRV and resting heart rate measurement are utilized. If coverage is sufficient, stress reactions of the user are estimated based on HRV, whereas only the resting heart rate number

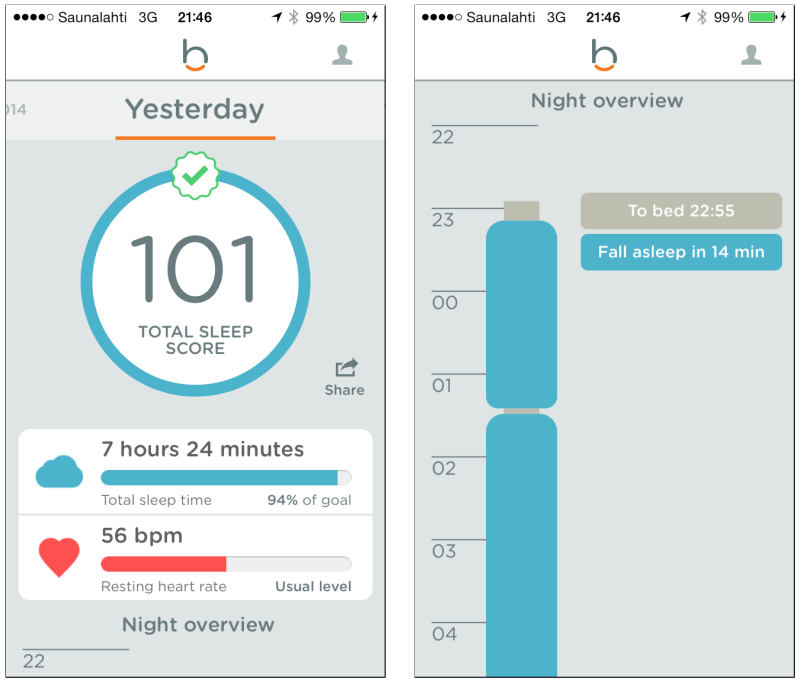


Figure 3.9: Screenshots from the Beddit smartphone app. The summary of a single night's sleep information is shown.

and curve are given if coverage is low.

The method contains some parameters, such as modeling residual threshold (see (3.3)), amplitude difference threshold as well as the parameters of the post-processing step. How those parameters should be set depends on the needs of the application and qualities of the signal. Some applications require as many detections as possible, whereas in other cases precision is more important.

The precision of the method is similar to the two state-of-the-art methods by Brüser et al. [15, 16]. Their reported mean absolute errors are 16.6 ms and 7.1 ms, respectively. The errors are similar to the mean absolute error 13.2 ms of the method proposed here. Exact comparison is difficult, because the test subjects' physiology and measurement environment have a large effect on the result.

Future work in the development of the method should study how the inter-subject variability in the method's performance is related to different measurement setups (bed type, sensor position, sensor installation) and physiological differences between people. Moreover, the simple post-processing step should be replaced with a more physiologically justified

model. The utility of the method for HRV analysis should be studied by measuring how well BCG and ECG measurements agree on computed HRV parameters.

An example application of BCG heart rate measurement is in the "Beddit" sleep monitoring product, which acquires a BCG signal from a film sensor over Bluetooth, and displays the sleep measurement results in a smartphone app. Heart rate measurement is utilized in the app by displaying the resting heart rate (average over the night) in each night's overview (see Figure 3.9). Changes in resting heart rate correlate e.g. with stress [104, 64, 10], alcohol consumption [82] and overtraining [105], which helps the user to understand what kind of lifestyle choices affect health.

3.3 Respiration signal analysis methods

This section describes the respiration signal analysis method proposed in Paper IV. The aim of the method is to quantify respiratory variation based on force sensor measurement. The variation information can be used e.g. in sleep staging [80, 22] and an adaptation of the method is indeed a component of the e-health system described in Section 4.2.

3.3.1 Background and related work

There are three main motivations for measuring respiration unobtrusively during sleep. First, respiration conveys information about the general condition of the patient, so the deterioration of health can be detected with respiration monitoring [94, 47]. Second, *sleep-related breathing disorders* (SRBD) such as sleep apnea represent a major share of sleeping problems. Sleep apnea is underdiagnosed and new unobtrusive measurement methods have a potential to help that, as was recently demonstrated by Beattie et al. [9]. Third, the structure of sleep can be analyzed based on respiration, because sleep stages have differing effects on respiration (see Section 2.2).

Respiration rate analysis methods detect respiration rate either as an average respiration cycle length over a time window, or by finding the length of each individual respiration cycle. The average respiration cycle length can be detected using autocorrelation [6] or by taking a discrete Fourier transform (DFT) of the signal and finding a peak corresponding to the respiration frequency [107]. The methods for finding individual respiration cycle lengths are typically based on filtering the signal to emphasize the respiration frequency and detecting the respiration cycles by zero-crossing or peak detection [38, 58, 111, 26].

An alternative way to quantify respiration variability is not to detect individual respiration cycles but process the whole signal with DFT [52].

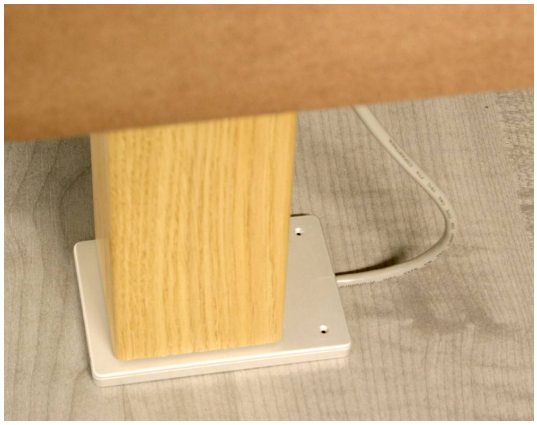
3.3.2 Methods for detecting respiration cycles

We have proposed a method for extracting individual respiration cycle lengths from a force sensor signal (Paper IV). The difference to existing methods is that the force sensor signal is filtered in a special way, which allows detecting the respiration cycles correctly in signals that do not have a single near-sinusoidal pattern at the respiratory frequency, but have a more complex morphology. A problematic signal morphology is visualized in Figure 3.10, where, in addition to the respiration phenomenon at 4-second intervals, there is a positive deflection between consecutive respiration cycle peaks. We have noticed the phenomenon with the two types of force sensors used by us: flexible film sensor (Figure 1.1) and the bedpost sensor (Figure 3.10a). Various previously presented methods [80, 26, 59] might detect twice the real respiratory frequency when the disturbing deflections are strong enough.

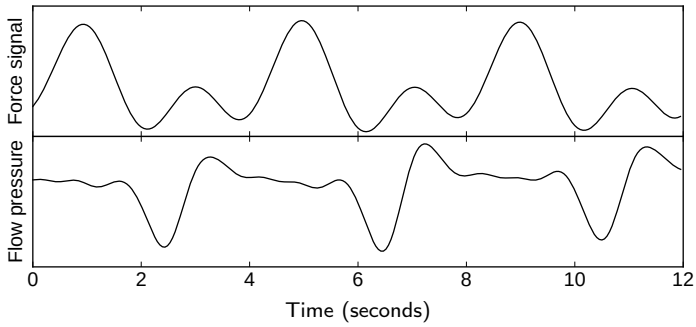
The method we proposed addresses the challenging respiration cycle morphology of force sensor signals by low-pass filtering the signal at different cut-off frequencies and, at consecutive time instants, selecting one of them to be used for the determination of respiration cycle lengths. The method can be described with the four successive steps below. The steps are visualized with a flowchart in Figure 3.11.

Step 1: Removal of movement sections Before the respiration cycles are analyzed, parts of the signal that contain gross movements are discarded from further processing. This is done by discarding those 30-second signal regions that have a peak-to-peak value over twice the average.

Step 2: Low-pass filtering the signal The respiration signal is low-pass filtered at four cut-off frequencies: 0.154 Hz, 0.22 Hz, 0.33 Hz and 0.5 Hz. Each frequency is the previous multiplied by 1.5. That is based on the assumption that the signal contains a respiration frequency at f Hz and potentially a disturbing phenomenon at around $2 \times f$ Hz. Therefore, at least one of the filters will result in an output signal that has the respiration frequency intact but the disturbance removed. For example, when the force signal of Figure 3.10 is filtered with the four filters, cut-off frequencies 0.33 Hz and 0.5 Hz retain the respiratory frequency but suppress the higher-frequency artifact.



(a)



(b)

Figure 3.10: (a) The bedpost sensor used in Paper IV. (b) A signal excerpt showing three respiration cycles of a low-pass filtered force signal and an airflow pressure reference signal. The force signal is in practice more difficult to analyze for respiration cycles than the airflow signal. It contains two deflections per respiration cycle, compared to the single clear dip per respiration cycle in the airflow signal.

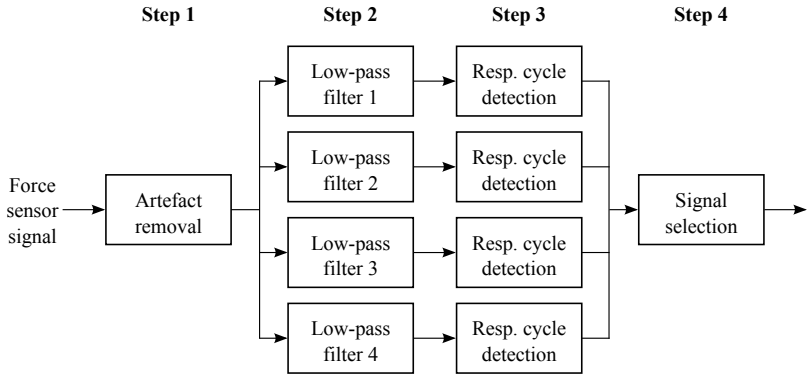


Figure 3.11: A flowchart description of the respiration cycle detection method.

The assumption that there may be a disturbing phenomenon at $2 \times f$ Hz is motivated by the physiological fact that each respiration cycle has two events causing a deflection in the signal: inspiration and expiration.

Step 3: Detection of respiration cycles The respiration cycles are detected from each filtered signal. A respiration cycle begins at a local maximum and ends at the next local maximum in the signal. In addition, the amplitude of each respiration cycle is calculated by taking the difference between the signal value of the local maximum that starts the cycle and the minimal signal value in the cycle.

Step 4: Choosing correct respiration cycle lengths A final sequence of respiration cycle lengths is compiled from the four signals based on the stability of respiration cycle amplitudes in each signal.

The measurement time is divided into three-second intervals. For each three-second interval in the measurement period, the respiration cycle lengths are selected from the filtered signal whose respiration cycle amplitudes exhibit least variability. The variability is calculated as the maximal absolute difference between two successive log-amplitudes, among the last five respiration cycle amplitudes before the interval.

The correct signal is typically selected, because the signal that contains frequencies up to the respiratory frequency is more stable in its amplitude than a signal that also contains higher-frequency disturbing phenomena. When the cut-off frequency is below the respiratory frequency, only unsystematic low-frequency phenomena remain. They have a high amplitude

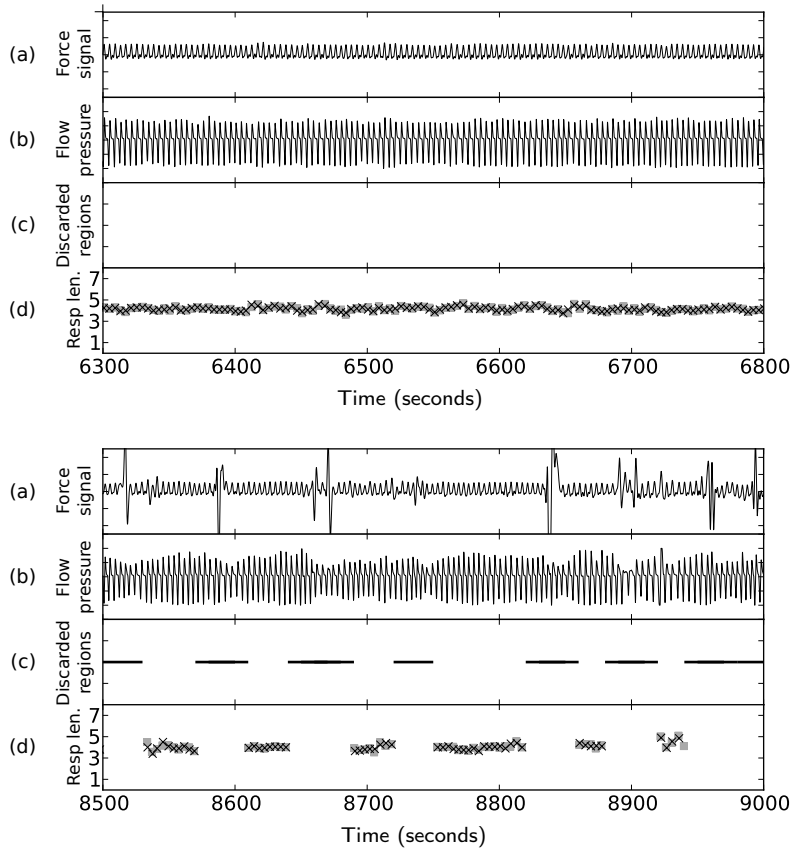


Figure 3.12: Two signal excerpts acquired at the sleep clinic. (a) The force sensor signal. (b) The reference airflow signal. (c) Regions discarded because of movements. (d) Reference respiration cycle lengths are shown as gray squares and the calculated cycle lengths as diagonal crosses. In the top example, the measurement is practically uninterrupted, whereas there are occasional movements in the bottom example.

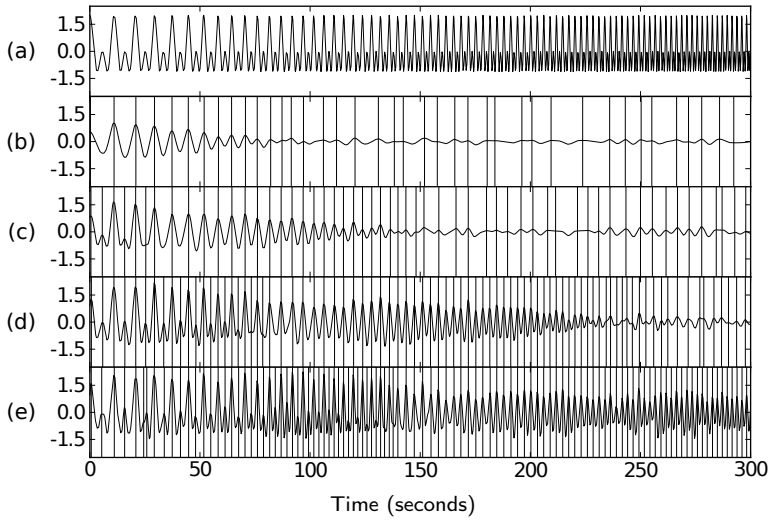


Figure 3.13: (a) 300-second synthetic respiration signal whose cycle length changes smoothly from 12 to 2 seconds. (b)-(e) The four low-pass filtered signals. In the beginning (0-80 sec) the first filter extracts the correct respiration cycles, in 30-120 sec the second filter, in 80-220 sec the third filter and in 150-300 sec the fourth filter.

variation, so the signal is not selected for the determination of the respiration cycle lengths.

An exemplary respiration cycle detection result of the algorithm in shown in Figure 3.12.

3.3.3 Evaluation

The method was evaluated both with synthetic data and reference signals measured at a sleep clinic.

A synthetic 300-second signal with the challenging signal morphology characteristics was created (Figure 3.13). In the signal, the cycle length of a sinusoidal signal changes smoothly from 12 to 2 seconds, and the artifact signal is added as a sinusoid with half the cycle length. The method succeeded to detect the correct respiration cycle lengths over the whole signal. This verifies the point that if the disturbing phenomenon is at double the respiration frequency, filtering will remove it.

In the evaluation with real data, a 5.5-hour airflow signal was acquired from a patient at a sleep clinic, and a simultaneous force sensor signal was acquired with a bedpost sensor. The movement suppression procedure

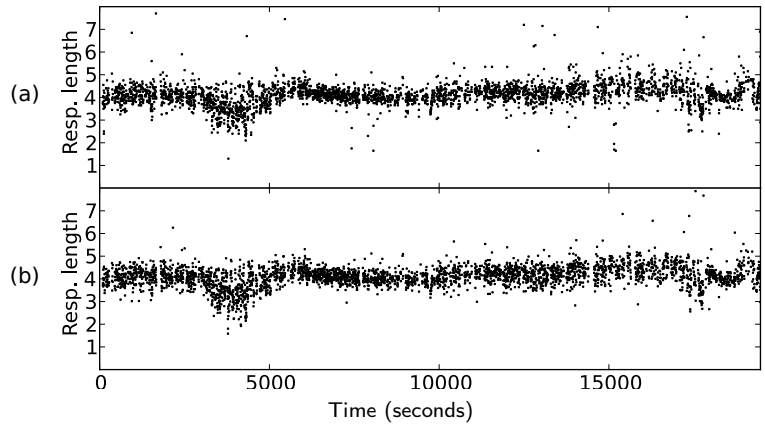


Figure 3.14: (a): Respiration cycle lengths detected from the force sensor signal with the proposed method. (b): Reference respiration cycle lengths.

discarded 27% of the recording time. Of the detected respiration cycles, 86.5% deviated less than 0.25 seconds from the reference and 98.5% less than 1 second. These signals and results are visualized in Figures 3.12 and 3.14.

3.3.4 Discussion

The proposed respiration cycle detection method makes it possible to quantify the variation of the respiration rate, as individual respiration cycles are detected. The empirical results show that the proposed method detects the respiration cycles of the reference rather accurately and with few incorrect values.

Breathing during sleep can become disturbed, for example, with sleep apnea, and it is unclear how the proposed method would work with disturbed breathing. The method does quantify respiratory variation precisely in the one tested case of healthy breathing. It is possible that the increased variability of respiration caused by sleep apnea can be detected with the proposed method, but more data is needed to investigate that further.

The variation of respiration changes by sleep stage, so the method can work as a building block for respiratory sleep staging methods. For example, the respiration variability features described by Redmond et al. [80] can be extracted from force sensor measurements with the proposed method.

The method solves the problem of having a disturbing phenomenon at about double the respiration frequency. The problem is present with both of the sensors used in the this research work and it is likely to arise

with other similar force sensors, too. In fact, this method does have some applicability for others, as it has been developed further by Vehkaoja et al. [102]. They improved the selection of the low-pass filtered signal from which the respiration cycle lengths are taken. While our method chooses a single filtered signal based on amplitude variation, they compute four respiration cycle candidates (intervals between successive maxima, successive minima as well as between successive rising and falling zero-crossings) for each filtered signal. At one-second intervals, the respiration cycle length candidates are clustered and the densest cluster is used as the result. Effectively, the most common interval across the total 16 candidates (4 candidates for each of the 4 signals) is sought. They tested the method with ten subjects and, on average, 82% of the respiration cycles were detected and 95.5% of them deviated less than 0.25 seconds from the reference.

Chapter 4

Long-term sleep measurement at home

An overview of the e-health system proposed in Paper V is described in this chapter. Adaptations of the signal analysis methods described in Chapter 3 are used in the system.

4.1 Background and related work

Recently, new devices for the measurement of sleep quality have emerged. These devices are usually based on actigraphy, they are not intended for diagnosis, and they have no medical device approval [55]. Instead, they are inexpensive and are sold directly to customers for self-help use. Zeo Sleep Manager measures both movement and EEG, and its accuracy has been validated using polysomnography reference measurement [85]. GEAR4 Renew SleepClock and Omron Sleep Design HSL-101 are based on a radar sensor and infer sleep quality based on movement and respiration measurement. Fitbit, Lark, BodyMedia FIT, Jawbone UP, SleepTracker, Misfit Shine, Withings Pulse, WakeMate and Polar Loop are based on wrist actigraph measurement. Many of these devices have a web application for viewing the measurements and a smartphone interface.

Some e-health telemonitoring applications for unobtrusive sleep monitoring exist [20, 60]. Sleep is measured with sensors installed in the mattress and the signals are sent over the Internet for physicians to analyze. The e-health system developed by us differs from previous work in that the sleep information is provided directly to the subject of measurement, without necessarily needing a healthcare provider for interpretation. An overview of the system is given next.

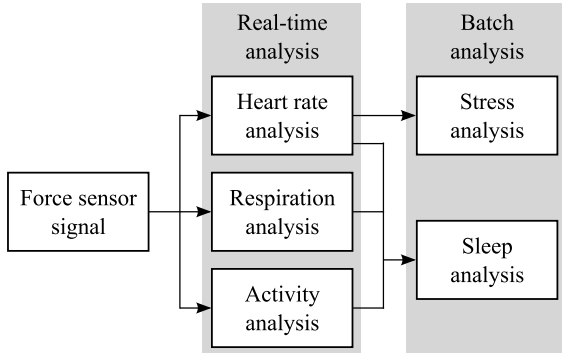


Figure 4.1: Analysis flowchart.

4.2 E-health system for unobtrusive sleep measurement

System overview The e-health system is a fully automated web application for sleep monitoring in the home environment. The novelty of the approach is that the sleep information produced by unobtrusive measurement is presented to the user with a web service, which also provides sleep coaching.

As an overview, the service works as follows. The force sensor (Figure 1.1), placed under the bed sheet or mattress topper, measures the mechanical vibrations of the person. These signals are automatically sent to a web server for analysis. The server first infers the heart rate (Papers I-III), respiration rate (Paper IV), and activity information from the signals, as the data is received. Based on this information, sleep is analyzed (as batch processing, typically in the morning). Finally, various aspects of sleep are presented to the user on a web site. A daily view shows features such as sleep stages, whereas a timeline view shows trends and long-term changes in sleep quality.

The force signal from the sensor is sampled at 140 Hz. Additionally, temperature, ambient noise level, and brightness are measured periodically. They are used to evaluate the quality of the sleeping environment. This information, about 300 kilobytes of compressed data per hour, is sent to the server as it is measured.

A flowchart of the analyses that follow is shown in Figure 4.1. When the server receives the signal from the sensor, heart rate variability and respiration rate variability information is extracted as explained in Sections 3.2.4 and 3.3.2, respectively. Movement information is analyzed by detecting dis-

crete events of movement from the BCG signal. That is done by dividing the high-pass filtered (cut-off frequency 5 Hz) signal into three-second windows. Each window is detected as movement if the difference between signal minimum and maximum in the segment is above a fixed threshold. Based on those results, the following sleep analyses are calculated in the morning:

- Sleep staging into the following phases: wakefulness, REM sleep, light sleep and deep sleep
- Stress reactions (based on heart rate variability) [83]
- Heart rate curve and average heart rate
- Restlessness index, calculated based on detected movement events

The sleep staging is carried out by an algorithm that utilizes heart rate variation, respiratory variation and activity information (cf. Sections 3.3 and 3.2, [80, 53, 22, 21, 65]). As no eye movement activity is measured, the exact detection of rapid eye movement sleep (REM) periods is not possible. Estimation of REM periods is based on quantifying the variation of respiration and heart rate as well as measuring movements.

As of November 2013, sleep staging is being further developed to a simpler system where sleep is classified into only two types: normal sleep and deep sleep. The simplification improves understanding of the measurements as well as classification accuracy.

Use case: Sleep discovery web application The primary use case for the sleep measurement system is a web application by which users may monitor their sleep and make discoveries about their sleep and lifestyle. Sleep information is presented so that the relevant features of sleep can be detected easily.

The sleep of a single night is presented with detailed structure (Figure 4.2b-c). The main feature is the hypnogram, where sleep is divided into wakefulness, REM sleep, light sleep and deep sleep. The overall restlessness of sleep is visualized with a plot that shows how much movement there is in different parts of the night, with 5-minute resolution. The heart rate information is shown as a trend curve and as a single resting heart rate number that corresponds to the lowest point on the curve. Stress reactions are estimated as the reciprocal of HF frequency band heart rate variability [83, 10] and stress is displayed as a relative number between 0% and 100%. Temperature, brightness and noise level measurements are shown as plots for the period of the whole night, to facilitate detecting sleeping environment problems.

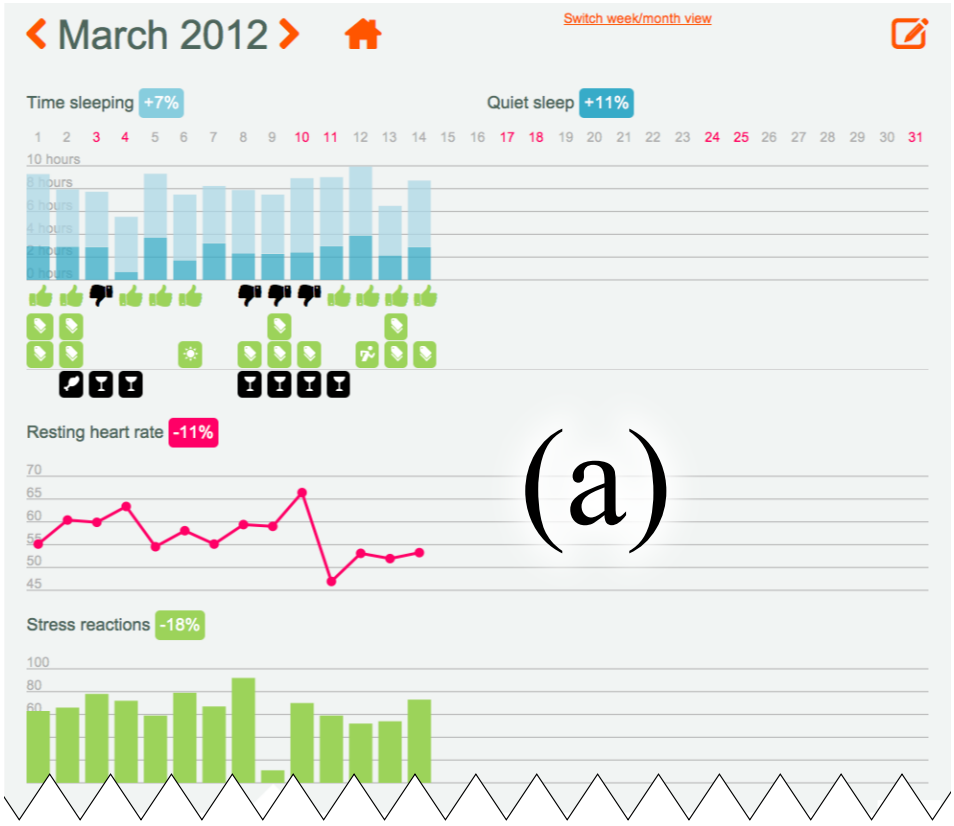


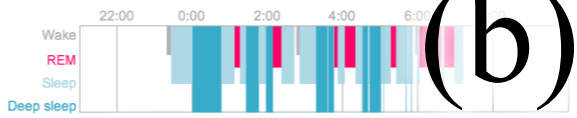
Figure 4.2: (a) The timeline and navigation view containing sleep times, user-entered tags, resting heart rates, and relative stress reaction values for each day. (b) Night summary figures. (c) Detailed night information, including sleep stages and a guide to their interpretation, actigraphy, heart rate, ambient noise, ambient luminosity, room temperature, relative stress reactions and resting heart rate figures. (d) Logged entries for the previous and following day along with their comparison to the intended goal.

Friday 9 March

7h 28min
Total amount of sleep ?
83% of your goal 9:00

2h 17min
Total amount of quiet sleep ?
76% of your goal 3:00

96%
Sleep efficiency ?
100% of your goal 75.0



(b)

Structure of sleep

- Number of bed exits
- Awakenings
- Sleep latency
- Sleep fragmentation
- Wake-up sleep stage

Close

3/5 Your sleep latency was very good, 7min

Sleep latency tells how fast you fall asleep. If falling asleep takes a long time, it might be a better idea to get out of the bed, maybe read or have some tea, and try to sleep a little later.

Previous Next

(c)

Movement

During sleep, there should be periods (more than 15 minutes) with no or few movements. Occasional movements are a part of normal, healthy sleep.

Heart rate

During sleep your heart rate gets lower as you are resting. If you have slept long enough, your heart rate starts to climb again before wake-up.

Ambient noise level

Ambient noise can affect your sleep. How disturbing the noise is depends, but usually noise level above 42 dB (quiet talking) can disrupt sleep.

Ambient light

Sleeping can be difficult when there is too much light in the environment.

Room temperature

Ideally, the temperature in bedroom should be quite low. Optimum temperature for sleep is below 20° Celcius.

24.6° C Average room temperature

40.6 dB Average noise level

Show all about environment

11% Stress reactions
You were significantly less stressed than usually ?

59 Heart rate
Your heart rate was higher than usually ?

Show/hide diary tips

Previous day: Thursday

2 p.m. Exercised for **30min**

There's still 30min to this weeks goal, keep going!

(d)

Friday

7:55 p.m. Had **2 drinks** of alcohol

1 drinks until todays limit

4 before hitting this weeks limit

The other way to visualize sleep is a timeline view (Figure 4.2a), where sleep information from a time period is summarized. In addition to displaying sleep amounts for each night in the period, summary figures and relevant cyclic phenomena are shown.

No self-help program can help if it is left unused. To make use as easy as possible, the measurement device is designed to work fully automatically and the user is reminded to check their sleep with daily emails. By clicking a link in the email, the user can tell whether they feel refreshed or tired, and describe the previous evening with simple tags (stress, alcohol, caffeine, television, exercise etc.). The logged information is shown in the timeline view along with sleep information (Figure 4.2a). This helps to recognize, for example, that alcohol consumption or stress in the evening leads to feeling tired in the daytime. Goals can be set for sleep time and for things that the user has logged (Figure 4.2d). We assume that the user can set sensible sleep time goals after some use of the system.

Use case: Long-term medical sleep monitoring The unobtrusive sleep measurement method makes it possible to monitor patients with sleep problems for months or even years in their normal sleeping environment.

The presentation of sleep information in medical use has different needs from the self-help application. In medical use, the users of the web application are sleep doctors who interpret measurements from their patients. The following information is visualized: time in bed, actigram, heart rate and respiration rate, as well as measurements of the sleeping environment. The actigram is shown instead of sleep stages, because sleep doctors are used to EEG-based sleep stages rather than the awake, REM, light sleep, deep sleep classification of cardio-respiratory sleep staging. For analysis of sleep-related breathing disorders (SRBD), the raw force sensor signal is provided to the sleep doctor. The measured signal is similar to a signal from a *static charge sensitive bed*, which have been used for preliminary apnea analysis [77].

The advantages of the presented approach over wrist actigraphy in medical use are: 1) measurement is unobtrusive, 2) respiratory and cardiac information is measured in addition to activity. The drawback compared to actigraphy is that daytime activity cannot be measured.

The method is likely particularly suitable for diagnosing periodic hypersomnias, where long measurement terms are required for characterizing the circadian patterns.

4.3 Discussion

The e-health system has been available for consumers since early 2012 (Beddit Pro). Although no comprehensive experimental data is available, user feedback has been collected actively. Positive feedback has been received about the unobtrusive measurement that does not disturb sleep. A minority of users have had difficulties setting up the Internet connection for the system, as it does require some level of computer literacy.

The overall aim of the system in consumer use is to motivate improving lifestyle habits with the help of sleep measurement. More research would be needed to determine how exactly the system is being used and how the users utilize the sleep measurement in their lives.

The system has already been in medical use in clinical studies. It has been integrated in a commercial research data analysis system VivoSense® by Vivonoetics, Inc., which makes the research use easier[1]. In one study, the treatment of obesity-related sleeping disorders was studied with the e-health system [96]. The patients in the study were given exercise and diet interventions, whose effect on the sleep disorders was then measured. The results from the study remain to be published.

Utilizing the e-health system in the follow-up of sleep disorder patients is being piloted. The sleep doctor has access to the patient's sleep measurements with a web application tailored for clinical use. The physician can follow the overall status of the patient, such as long-term circadian rhythms.

[1] http://vivonoetics.com/products/vivosense/

Chapter 5

Conclusions

The contributions of this thesis are fundamental building blocks for systems that measure sleep with force sensors. The signal analysis methods have been evaluated with reference recordings from clinical studies and the e-health system has been adapted into two commercial products. I next discuss the significance of the methods developed here and possibilities for future work.

The proposed heart rate and respiration rate detection methods allow monitoring during sleep with comfortable bed sensors. The heart rate method has been validated with a 60-person clinical study. Because of a fairly large number of subjects, it is likely that the method's accuracy in real use corresponds to the results of the study. The respiration rate method was tested with only a single subject, so its accuracy in real use is more uncertain. However, a 10-subject independent validation has been carried out with a modification of the method, showing good accuracy [102].

As the heart and respiration rate measurement methods are building blocks in e-health systems, their accuracy should eventually be tested from a viewpoint of the end user of the system. For example, if heart rate measurement is used for deriving a resting heart rate reading for each night, it should be evaluated whether heart rate measurement accuracy is suitable for that purpose. These system-level evaluations are left for future work and are not part of this thesis.

The broader theme of this thesis is long-term sleep measurement. Short-term medical sleep measurement (days or weeks) for diagnostic purposes is an established field, while consumer products for sleep tracking have become available just in recent years. Today, the tracking of health-related information (heart rate and speed during exercise, daily movement activity, weight, diet) is popular, but sleep measurement has not yet established a mainstream position. Self-tracking of sleep is likely to become popular in

the near future, because its measurement can help people improve their sleep. When sleeping problems are objectively quantified, the motivation for solving them is likely to improve.

The methods proposed in this thesis allow unobtrusive sleep measurement, where the primary measured parameter is the movement of the body, and where higher-level parameters such as respiration, heart rate, sleep stages and sleep-related breathing disorders are inferred from the movement signal. Unobtrusive sleep measurement techniques will likely have a prominent role in the near future. Currently, most sleep self-tracking consumer devices are based on wearable sensors such as wristbands, watches or headbands. With unobtrusive measurement, the user of the device has the benefit that absolutely no disturbance to sleep is caused. Such comfort of use is an important factor, as it improves the chances that the habit of measuring sleep becomes long-lasting.

Some ideas from the research have been picked up by other researchers. The respiration rate variability method described in Paper IV has been developed further by Vehkaoja et al. [102]. The clustering method from Paper II seems to have been influential, because a few heartbeat detection methods utilizing clustering in a similar way have recently been proposed [15, 81].

Research on unobtrusive sleep measurement is fertile ground. There is potential for major public health impacts in the development of systems that help people improve their sleep and become aware of potential sleep disorders. One clear direction based on the work in this thesis is to study how to best get people to improve their sleeping. The e-health system for sleep measurement presented in Chapter 4 has the potential to motivate sleep improvement, but its efficacy should be studied quantitatively. It would be good to know what kind of sleep coaching mechanisms are most effective and if established behavioral treatment approaches for insomnia [70] could be used with an e-health sleep coaching system.

This research continues as a commercial enterprise. So far, two sleep monitoring products have been brought to the market: Beddit Pro and Beddit. In total 5031 Beddit devices were sold in a 10-week crowdfunding campaign in 2013[1], which shows that there is customer interest for unobtrusive sleep measurement products. The products are based on the sensor in Figure 1.1 and provide the sleep information to the user with a web interface and smartphone app. The aim is to make sleep monitoring a convenient and commonplace activity and that way improve the sleep and well-being of people. The methods developed in this thesis help reach that goal.

[1] http://igg.me/at/beddit-sleep-tracker

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