

# Assessment of Sleep/Wake Patterns Using a Non-Contact Biomotion Sensor

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**Abstract**— We evaluate a contact-less continuous measuring system measuring respiration and activity patterns system for identifying sleep/wake patterns in adult humans. The system is based on the use of a novel non-contact biomotion sensor, and an automated signal analysis and classification system. The sleep/wake detection algorithm combines information from respiratory frequency, magnitude, and movement to assign 30 s epochs to either wake or sleep. Comparison to a standard polysomnogram system utilizing manual sleep stage classification indicates excellent results. It has been validated on overnight studies from 12 subjects. Wake state was correctly identified 69% and sleep with 88%. Due to its ease-of-use and good performance, the device is an excellent tool for long term monitoring of sleep patterns in the home environment in an ultraconvenient fashion.

## I. INTRODUCTION

To date, sleep medicine researchers have primarily focused on measurement of sleep in the relatively artificial environment of the sleep laboratory, using polysomnography. Despite the many technical advantages of polysomnography in capturing detailed physiological measurements over the course of one or two nights, it is not well suited as a research tool to tracking sleep over prolonged periods in so-called “free-living” conditions. However, there are a variety of applications in which it is useful to track sleep patterns over multiple nights, weeks or even months. For example, researchers might be interested in the effect of a pharmaceutical or behavioral intervention on sleep parameters. In [1], the authors use home polysomnography to identify changes in sleep efficiency, sleep onset and sleep duration in response to pharmaceutical or behavioral intervention. Similarly, in [2], the authors compare the changes in sleep efficiency due to either pharmaceutical intervention or behavioral therapy, by objectively measuring three nights of sleep before and after therapy, using a device which tracks head and eyelid movement. In both cases, the number of study nights was limited by the technical challenges of carrying out the assessment of sleep.

A more suitable technology for the assessment of sleep patterns is actigraphy. Actigraphy is a method of measuring the movement of subjects using sensitive accelerometers, typically worn on either the wrist or ankle. Actigraphy has

been widely used for measurement of sleep patterns over multiple nights of recording [3-8], and has been used for diverse applications such as (a) demonstrating differences in sleep due to Attention-Deficit-Hyperactivity-Disorder, (b) demonstrating disruption of sleep due to Alzheimer's disease, and (c) objective measurements of sleep in chronic insomniacs. However, there is still some debate concerning the potential utility of actigraphy; for example, Pollak et al. [8] contend that low accuracies of sleep/wake differentiation disqualify actigraphy as a valid sleep/wake indicator. In a rebuttal, Tryon [9] argues that differences between the gold standard (polysomnography) and actigraphy should be expected, and have a predictable error which can be accounted for. Based on the evidence to date, the American Academy of Sleep Medicine Practice Guidelines [10] indicate that actigraphy does provide a reliable method of measuring sleep in a normal healthy adult population, but that its use in routine diagnosis, assessment of severity, or management of any of the sleep disorders is not yet indicated (though there is evidence of its potential utility).

Regardless of the achievable levels of accuracy for sleep-wake classification using actigraphy, it can be safely said that actigraphy provides limited physiological information, as it only reflects movement.

Other technologies which have been considered for ongoing assessment of sleep in the home environment include reduced channel electroencephalogram systems (e.g., the Biosomnia system from Oxford Biosignals) or head and eye movement sensor systems (such as the Nightcap system, [11]).

Finally, the mainstay of clinical assessment of sleep in the home environment still remains the subjective sleep diary, in which the patient themselves is asked to record events such as “time to bed”, “lights out”, “sleep onset latency”, etc. The Pittsburgh sleep diary is one example of a well-accepted standard for recording such observations in a written format [12]. In general, however sleep diary estimates of sleep parameters such as duration, onset latency etc. correlate quite poorly with objective measurements of the same parameters.

In this paper, we introduce a new method for monitoring sleep in the home environment which may provide additional benefit to the sleep research community. Specifically, we describe a non-contact sensor which tracks a person's movement and respiration patterns while in their bed. Based on these signals, sleep/wake estimation is

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generated.

Using simultaneously recorded polysomnogram (PSG) and our non-contact biomotion sensor we compare two-state (sleep/wake) hypnograms obtained from the two modalities.

## II. METHODS

### A. Non-contact Sensor

The non-contact sensor employed in this study is a patented multi-channel biomotion sensor. It employs 5.8GHz Doppler radar using a patented modulation system that limits both the maximum and minimum range. Quadrature operation eliminates range-dependent sensing nulls. The baseband *inphase* (I) and *quadrature* (Q) signals are filtered using analog active filters with bandwidths (0.05-1.6) Hz and (1-5) Hz. The emitted power is very low - less than 10mW.

### B. Non-contact Sensor Data Logger

The design of the non-contact biomotion logger shares some of the benefits of existing actimeters. These include convenience of use, light weight, portability, cheap, low power usage, non-intrusive, and the capacity to record for several days or even for weeks.

The non-contact biomotion data logger incorporates all of the aforementioned characteristics. It can be mains or battery powered. It is a standalone device which records data from an internal non-contact sensor to an SD flash card for easy transfer to a PC for analysis. It is capable of logging continuously for weeks with standard off-the-shelf SD cards (up to 4GB), as used in digital cameras. It contains an independent battery-powered clock which tags the movement data with accurate time information and digitizes the sensor channels at 50Hz with 10-bit resolution.

Figure 1 depicts the non-contact biomotion data logger. The user places it no more than 1 meter from the bed, between 0.25 to 0.5 meters above the height of the mattress, and facing towards the torso of the subject. For the detection of movement (actimetry), positioning of the logger has been found not to be crucial. For detection of breathing, the data logger is more sensitive to positioning however, experiments show that if placed within the above limits, good signals are obtained.



Fig. 1. The BiancaMed non-contact biomotion data logger unit for recording of activity and respiration patterns.

### C. Test Corpus

The test site was at University College Dublin and was

performed on 14 normal volunteers. These studies were approved by the University College Dublin Human Ethics Approval committee and all participants provided informed consent.

For the study we modified a non-contact biomotion data logger so that its signals were acquired simultaneously with regular PSG signals using contact sensors.

Table 1: Demographic information

<i>Number (M/F)</i>	<i>Age (yrs)</i>	<i>BMI</i>	<i>Sleep Efficiency (PSG)</i>
<b>14 (11/3)</b>	<b>27±5</b>	<b>27±5</b>	<b>75±16%</b>

The regular PSG signals acquired are shown in table 2. The EEG, EOG, ECG, ribcage respiratory effort and non-contact biomotion sensor signals were all acquired simultaneously using the Biopac MP100 data acquisition system.

In addition we recorded the following extra signals but did not use them in this study.

- Tri-axial actimetry (10 Hz)
- Holter-oximeter (NorthEast Monitoring, Maynard, MA) - this records a modified lead 5 ECG, SpO<sub>2</sub>, and a pulsephotoplethysmogram signal.
- Continuous blood pressure (Portapres, Finapres, The Netherlands)

Subjects were requested to refrain from caffeine in the day prior to the study, and to report to the laboratory approximately 1 hour before their normal bed-time (to allow time for set-up and acclimatization). The subjects had no known sleep disorders.

After acquisition the data was converted to the EDF format for further processing.

Subsequent signal analysis was carried out using MATLAB 6.5 (The Mathworks, Natick, MA)

Table 2: Signals recorded

<i>Sensor</i>	<i>Signal</i>	<i>SR (Hz)</i>
<b>Biomotion</b>	<b>I</b>	<b>100</b>
	<b>Q</b>	<b>100</b>
<b>EEG</b>	<b>C4/A1</b>	<b>125</b>
	<b>C3/A2</b>	<b>125</b>
<b>EOG</b>	<b>ROC/A1</b>	<b>125</b>
	<b>LOC/A1</b>	<b>125</b>
<b>EMG</b>	<b>Chin</b>	<b>250</b>
<b>ECG</b>	<b>modified II</b>	<b>100</b>
<b>Respiratory</b>	<b>Ribcage</b>	<b>10</b>

### Expert Scoring

Objective scoring of the sleep study signals, was achieved by using the Somnolyzer software (The Siesta Group Schlafanalyse GmbH, Vienna, Austria ([www.thesiestagroup.com](http://www.thesiestagroup.com)) to score the recorded PSG signals. Information on Somnolyzer's validity can be found at: <https://www.thesiestagroup.com/index.php?id=50>.

#### D. Sleep Stage Classification Algorithm

A sleep stage classification system that processed the non-contact biomotion sensor data to produce sleep and awake classifications every 30 seconds was developed using the following observations:

1) Large movements (e.g., several cm in size) can be easily recognized in the non-contact signal (as shown in Figure 4). 2) Bodily movement provides significant information about the sleep state of a subject, and has been widely used in actigraphy to determine sleep/wake state.

3) The variability of respiration changes significantly with sleep stage. In deep sleep, it has long been noted that respiration is steadier in both frequency and amplitude than during wakefulness of REM sleep.

Accordingly, a first stage in processing of the non-contact biomotion signal was to identify movement and respiration information. To illustrate how this is possible, Figure 2 shows an example of the signal recorded by the non-contact sensor when there is a significant movement of the torso and arms due to the person shifting sleeping position. An algorithm based on detection of high amplitude and frequency sections of the signal was used to isolate the periods of movement [13]

For periods where there is no significant limb or torso movement, respiratory-related movement is the predominant recorded signal and estimates of breathing rate and relative amplitude are obtained using a peak and trough identifying algorithm. Figure 3 illustrates the signal recorded by the sensor during a period of Stage 4 sleep that demonstrates a steady breathing effort.

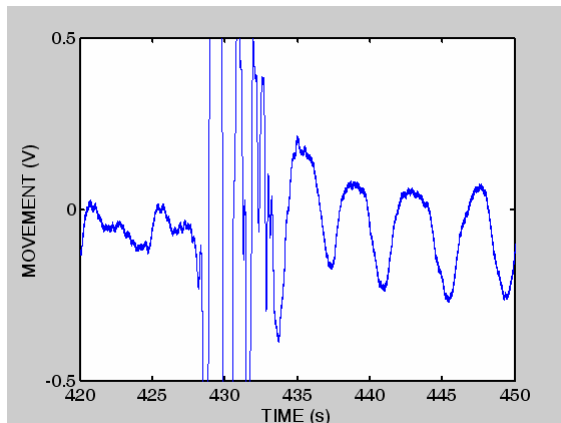


Figure 2: The non-contact biomotion sensor signal recorded over 30 seconds when the person turns over. Note that the change in body position will often result in a change of amplitude for the respiratory movement due to the new body position and reflection.

#### Classification Performance

We compare the sleep epoch annotations from the PSG and the non-contact biomotion sensor and report the overall classification accuracy, sleep sensitivity and predictivity, wake specificity and predictivity. The overall accuracy is the percentage of total epochs correctly classified. The sleep sensitivity is the percentage of sleep epochs correctly classified. The wake specificity is the percentage of wake

epochs correctly classified. Finally the sleep (wake) predictivity is the percentage of epoch's labeled sleep (wake) that is correctly labeled.

We also characterise the sensitivity of the system to the five standard sleep states (Stages I-IV and REM).

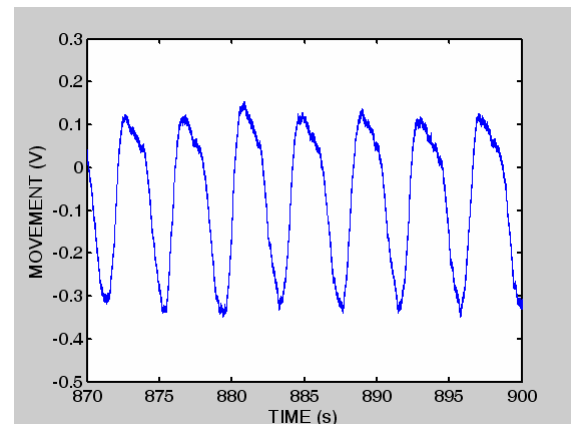


Figure 3: The non-contact biomotion sensor signal recorded over 30 seconds of deep sleep.

### III. RESULTS

Two records could not be scored due to faulty PSG sensors and were deleted from the study.

Figure 4 shows an example of the respiratory effort signals captured by the ribcage sensor and the biomotion sensor and demonstrates that the biomotion sensor successfully captures both the respiration interval and amplitude.

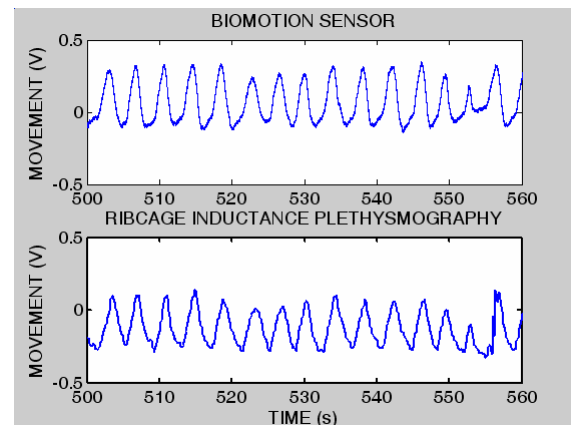


Figure 4: Simultaneously recorded respiratory movement signals from Subject 1 over a 60-second period. The top panel is the signal from the biomotion sensor; the bottom is from a ribcage respiratory inductance plethysmograph.

Table 3 shows the epoch-based classification performance results determined from the 12 subjects with good quality signals and Figure 5 shows an example hypnogram.

Table 3: Epoch classification results

Overall		By sleep state	
Awake	69%	Awake	69%
Sleep	87%	REM	82%
Pred. of Awake	53%	Stage 1	61%
Pred. of Sleep	91%	Stage 2	87%
Accuracy	82%	Stage 3	97%
		Stage 4	98%

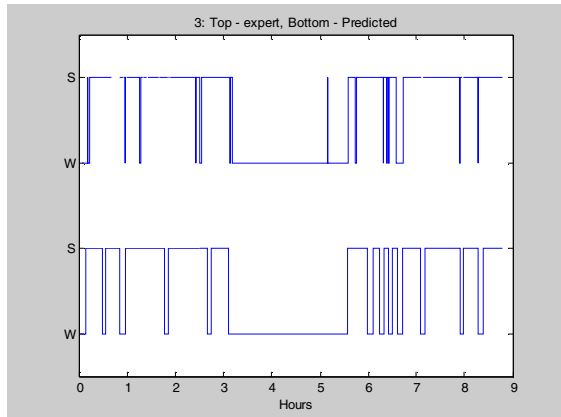


Figure 5: Example of the two-stage hypnogram determined from the PSG signals (top panel) and the hypnogram predicted by the biomotion sensor (bottom panel)

#### IV. DISCUSSION AND CONCLUSION

The results in Table 3 demonstrate that the stage 3 and 4 sleep are the easiest states to identify and that stage 1 sleep is the most difficult to identify. This is consistent with the observations that stage 1 sleep can be the most difficult to define.

It is useful to compare the sleep/wake classifications achieved using the non-contact biomotion sensor against those achieved using actigraphy in several representative publications. In [4], a group of 34 older adults being treated for chronic primary insomnia was studied using actigraphy. The overall accuracy of epoch classification was 83.1%, with most errors occurring due to wake being classified as sleep. Kushida et al. [14] evaluated wrist actigraphy in 100 sequentially presented subjects for suspected sleep apnea. The accuracy of sleep-wake classifications ranged from 77% (with watch on 'low' setting) to 77% (with watch on 'high' setting).

We conclude that the performance of the proposed non-contact biomotion sensor is comparable to existing actigraphy methods. As well as offering a highly convenient

ease-of-use, the device is an excellent tool for long term monitoring of sleep patterns in the home environment as once setup it can be left continuously monitoring the bedroom environment. Finally whereas actigraphy is a single modality signal capturing activity, the non-contact biomotion sensor is a richer source of physiological information capture both actigraphy and respiration information.

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