# Development and Preliminary Validation of Heart Rate and Breathing Rate Detection Using a Passive, Ballistocardiography-Based Sleep Monitoring System

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***Abstract*—Techniques such as ballistocardiography (BCG) that can provide noninvasive long-term physiological monitoring have gained interest due to a growing recognition of adverse effects from poor sleep and sleep disorders. The noninvasive analysis of physiological signals (NAPS) system is a BCG-based monitoring system developed to measure heart rate, breathing rate, and musculoskeletal movement that shows promise as a general sleep analysis tool. Overnight sleep studies were conducted on 40 healthy subjects during a clinical trial at the University of Virginia. The NAPS system's measures of heart rate and breathing rate were compared to ECG, pulse oximetry, and respiratory inductance plethysmography (RIP). The subjects were split into a training dataset and a validation dataset, maintaining similar demographics in each set. The NAPS system accurately detected heart rate, averaged over the prescribed 30-s epochs, to within less than 2.72 beats per minute of ECG, and accurately detected breathing rate, averaged over the same epochs, to within 2.10 breaths per minute of RIP bands used in polysomnography.**

***Index Terms*—Ballistocardiography (BCG), home health care, long-term monitoring, sleep.**

## I. Introduction

BALLISTOCARDIOGRAPHY (BCG) is a technique for quantifying the forces generated by the beating heart that was used primarily in the middle of the twentieth century [1]. It has fallen out of wide use since then, due to its impracticality at the time, and was usurped by the development and application of ECG. However, researchers can now take advantage of computational tools that make applying the basic principles of BCG more practical. One of the first technologies to do this was the static charge sensitive bed (SCSB) [2]–[4]. With a growing recognition of adverse effects from poor sleep and sleep disorders, there has been more interest in developing physiologic monitoring techniques that can provide long-term monitoring of patients' health conditions. This is evident from recent studies that attempt to monitor vital signs and/or sleep with alternative methods [5]–[16], the majority of which use some form of BCG [5], [7], [9]–[12], [14]. Additionally, several researchers are developing approaches to use monitoring technology in eldercare that could benefit from BCG. Wearable technologies are reviewed by Korhonen *et al.* [17], and Alwan *et al.* [18] present a method using sensors embedded in the user's environment, in addition to reviewing similar such systems.

Though ECG is in common clinical use, there are advantages of measuring BCG data, particularly in monitoring sleep. BCG-based technology can collect information without disturbing sleep, which is advantageous considering that many current sleep monitoring technologies can interfere with normal sleeping habits. BCG-based systems minimize noncompliance because the BCG-based system can be built into the patient's environment, such as in a seat cushion or a mattress pad. Though BCG systems lack the capability to provide 24-h data, a feature found in some wearable technologies, this aspect is less important in monitoring sleep than for other applications, such as tracking activity. Monitoring sleep using validated BCG-based assessment and screening tools has the potential to become useful in longitudinal sleep analysis and may provide predictive data for the development of sleep-related disorders. It could also fill the gap between the highly detailed, single-night assessments conducted in a sleep laboratory and single-variable wearable technology, such as wrist-worn technology used to monitor movement known as an actigraphy.

The noninvasive analysis of physiological signals (NAPS) system is a BCG-based monitoring system developed to measure heart rate, breathing rate, and musculoskeletal movement (Fig. 1). It uses a combination of analog signal processing and automated postprocessing algorithms to generate usable data from the acquired waveforms. Preliminary data [19], [20] have shown strong correlations between the heart rate passively measured using the NAPS system and conventional clinical techniques, including pulse oximetry and ECG. This system has already proven useful as a qualitative sleep assessment tool in an assisted living environment [18], [21], and shows promise as a general sleep analysis tool [22].

Before any attempts at quantitative sleep analysis can be made, the fundamental parameters of heart rate and breathing

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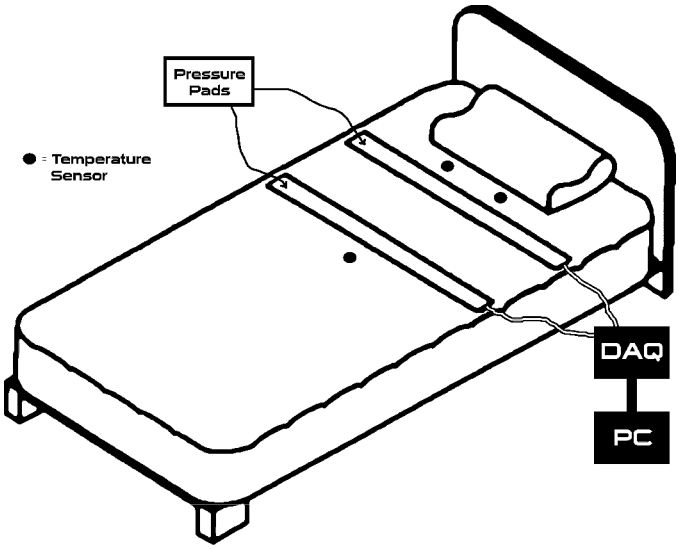


Fig. 1. NAPS system illustration.

rate need to be tested against the existing standard technologies to identify and minimize sources of error. To quantify the NAPS system's ability to report heart rates and breathing rates, the NAPS system was compared to standards of heart rate (ECG) and breathing rate [respiratory inductance plethysmography (RIP)] measurements. In addition, the effects of three factors were examined to determine how they influenced the accuracy of the NAPS system. First, we compared wake epochs to sleep epochs as defined by standard polysomnography methods. Second, we looked at the subject's average movement, a measure of restlessness during sleep. Last, we looked at the presence and severity of sleep apnea.

## II. Methods

### A. Study Design

This study was reviewed and approved by the University of Virginia's Institutional Review Board (IRB) and the General Clinical Research Center (GCRC) Committee. All subjects were educated to the study specifics, and informed consents were obtained prior to their participation. An overnight sleep analysis was conducted at the University of Virginia Health System's GCRC Sleep Laboratory for each of the 40 healthy adults who enrolled in the study. Both conventional polysomnography and a NAPS system, outfitted with two resilient force-coupling pads and four temperature sensors, were used to simultaneously monitor the subjects during the studies.

We studied 32 males and eight nonpregnant females aged between 18 and 79 years who met our inclusion/exclusion criteria. Subjects were excluded if they had a history of cardiopulmonary disease, were a member of a vulnerable population (pregnant females, prisoners, or cognitively impaired), had seizures or epilepsy, used prescription sleeping pills, tranquilizers, stimulants, or antidepressants, or within seven days prior to the study had used over-the-counter sleeping aids, or stimulant diet aids. The subjects' demographics and apnea–hypopnea index (AHI) are noted in Table I. The subject population's racial demographic reflected that of the surrounding geographical area obtained from recent census data [23]. For purposes of NAPS system algorithm development and testing, the 40-subject population was divided into two groups of 20, a training set and a test set, respectively. There were no statistically significant differences between the groups in apnea severity, height, weight, age, and race; this ensures that the algorithms developed using the training data are not biased by any of these variables.

TABLE I
Subject Demographics and Apnea Severity

| Parameter | Mean | Standard Deviation | Minimum | Maximum |
|---|---|---|---|---|
| Height (cm) | 176.3 | 10.8 | 154.9 | 182.3 |
| Weight (kg) | 95.1 | 22.6 | 63.9 | 143.1 |
| Age (yrs) | 46.1 | 18.2 | 18 | 71 |
| AHI[a] | 24.8 | 31.0 | 0.8 | 95.6 |

[a]AHI = Apnea-Hypopnea Index

Polysomnography was performed throughout the night using conventional techniques as previously described [24]. Sleep was monitored with EEG, electrooculograms (EOGs), and electromyograms (EMGs). Breathing was monitored with nasal airflow detected by nasal pressure, oral airflow with a thermistor, and thoracic and abdominal movement with RIP. RIP is a method that consists of resistive bands that change electrical properties based on the chest wall movements during breathing. Heart rate was measured by ECG and pulse oximetry. The oximeter also monitored oxygen saturation. All data were recorded on a SANDMAN Computerized Sleep System [25]. Apneas were defined as a decrease in respiratory flow to between 0% and 20% of normal that lasts for at least 10 s. Hypopneas were defined as a decrease in flow from 20% to 60% below normal that lasts for at least 10 s and is accompanied by at least a 4% decrease in oxygen saturation [25]. Sleep was scored as described by Rechtschaffen and Kales [26]. The same technician performed the sensor hookups for all 40 subjects and scored each of the datasets, which were verified by one of the authors, Dr. Suratt. Raw data from each of the channels were provided for analysis. We also evaluated files containing information about sleep stage epochs, apneas, arousals, bad data, etc.

The NAPS acquisition system consisted of two resilient force-coupling pads, each 2 in wide and 3 ft long; each pad was pneumatically connected to an individual pressure sensor. These pads were fastened to a 3-ft square bed pad that was then secured under the normal bed linens to the twin mattress on a standard hospital bed; this ensured consistent relative spacing of the pads throughout the study. From this system, BCG signals were obtained and processed to yield heart rate, respiratory effort, and musculoskeletal movement data from both the upper chest area, at the approximate level of the heart, and the abdomen area above the waist. Positional pad placement adjustments were made at the beginning of the study to provide proper positioning of the pad with respect to the height of study participants, if necessary.

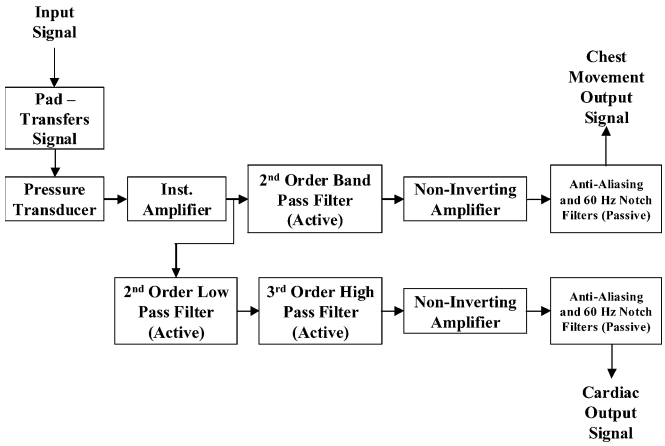


Fig. 2. NAPS analog signal processing block diagram.

There were no restrictions on the subject's sleeping position or orientation following the initial adjustment. The signal from each pressure sensor was preamplified, and then split into respiration and heart rate signals using analog filters. The respiration signal filter had approximate corner frequencies of 25 and 514 mHz with 40 dB/decade roll-off on either side. The two heart rate signal filters combined to form a fifth-order band-pass filter that had approximate corner frequencies of 785 mHz and 18 Hz. The high-pass portion has a 60 dB/decade roll-off while the low-pass portion has a 40 dB/decade roll-off. A block diagram of the analog circuitry appears in Fig. 2, and the full details have been described previously [22]. The two output signals from each pad were digitized using a USB data acquisition (DAQ) system connected to a laptop for data storage. This DAQ sampled each of the four channels (two cardiac and two respiration signals) at 150 Hz, and converted the analog signals to a 12-bit digital output. The data were transferred 30 s at a time to a computer database where it was stored for later analysis.

Synchronization of the data from the two systems was achieved by asking the subjects to sit up and lie down in bed three times following the biocalibration of the polysomnography equipment at the beginning of the study. This created movement artifacts in both systems' data that could be reconciled easily. Data were recorded for the entire night, delineated by the "lights off" and "lights on" times of the polysomnography study.

### *B. Data Analysis*

All heart rate and breathing rate data were reported in 30-s epochs for the duration of the night. This approach was taken since these fundamental data from the NAPS system will be used to help derive sleep architecture and sleep apnea severity, two important variables typically reported from sleep laboratory data collected in 30-s epochs. Epoch boundaries were established based on the synchronized start time of the NAPS system data collection. The polysomnography data were fit to these epochs for appropriate comparison on an epoch-by-epoch basis. Only data recorded between the "lights off" and "lights on" times were considered for analysis.

Heart rate data were recorded by a pulse oximeter (NELLCOR, N-1000, Pleasanton, CA), ECG, and the NAPS system. The heart rate from the pulse oximeter was reported directly, initially being sampled at 4 Hz and reported at an up-sampled rate of 128 Hz. These values were then averaged over the 30 s of each epoch. The ECG waveform was initially sampled at 256 Hz and reported at a down-sampled rate of 128 Hz. Both of these sampling procedures were a function of the standard SANDMAN exporting mechanism to obtain the raw data [25]. In conducting the analysis to compare the heart rate measurements, ECG was used as the gold standard, though it was also susceptible to error. Breathing rate data were recorded by two RIP bands (thoracic and abdominal) and the two similarly placed NAPS pads. RIP was used as the gold standard for breathing information from the polysomnography data (instead of airflow) because it measures respiratory effort, like the NAPS system.

*1) ECG and Pulse Oximetry Heart Rate Algorithm:* Though the ECG information was used as a standard for comparison to the NAPS system, the heart rate data were not directly reported by the polysomnography system. Benitez *et al.* have developed a reliable algorithm [27] using the Hilbert transform to analyze the raw ECG signal. Slight modifications to this algorithm had to be made to adjust it to the specific ECG signal acquired by the SANDMAN system. This included increasing the window size from 1024 points to 1280 points (10 s), and adjusting the threshold and noise parameters to accommodate the characteristics of the signals detected by the polysomnography system. Additionally, the smoothing used the same cutoff frequencies as referenced in [27], but used the technique described in the NAPS algorithm shortly.

Once a reliable detection of the ECG R-waves was confirmed using data in the training set, the data from both ECG and pulse oximetry were grouped into the 30-s epochs required for comparison. Then, the noise levels in the ECG data for each epoch were computed based on the method described by Benitez *et al.* Two standard ECG lead configurations with different reference points were reported. Both of these waveforms were analyzed using this algorithm. Epochs that had noise levels greater than 30% for both of the ECG configurations or contained data marked as movement artifact were labeled for further examination. After these epochs were labeled, the heart rate differences from epoch-to-epoch were calculated. Readings for epochs that were found to be adversely influenced by movement artifact or signal noise were removed from the analysis, as described previously [22]. Only 2.9% of the ECG heart rate epochs (1057 out of 35 841) and 1.3% of the pulse oximeter heart rate epochs (450 out of 35 841) were removed using this technique.

There were significant disagreements between ECG and the pulse oximetry for some parts of the data in three subjects (two training, one test). This was due to a noisy or weak ECG signal for portions of the night. Since the pulse oximetry data were reported directly, it was taken as the gold standard, and areas of significant disagreement were removed from the analysis [22]. This occurred only in 2.2% of the total epochs analyzed (780 out of 35 841).

*2) NAPS Heart Rate Algorithm:* The raw data acquired by the NAPS system were analyzed in groups of six epochs by an

automated algorithm. After analyzing a group of epochs, the algorithm advanced by three epochs to provide a second reading for all but the first and last three epochs, all of which were outside the established "lights off" and "lights on" times. This provided redundancy to minimize the impact of movement artifacts on surrounding epochs. The NAPS data were preprocessed using bidirectional recursive filtering so that no phase shift was introduced into the acquired data as a result of smoothing. Once the data were smoothed, peaks and troughs of each waveform were found. Average peak amplitude over each epoch was used as a basis for signal presence, while positions of local minima and maxima and the difference between them were examined to label movement artifacts. Null signals for an entire epoch, such as when a person was not present in bed, were flagged, and movement percentages for each epoch were calculated from the amount of movement detected. Once the sections of BCG data free from significant movement were labeled, two different methods were used to detect the position of the HIJK portion of each BCG wave. The HIJK portion of the BCG wave represents the main systolic contraction of the heart in the same way as the QRS wave does for the ECG.

The first technique isolated individual BCG waves by examining changes in the relative positions of any local minima in the waveform. This technique was performed nine times with different imposed upper limit levels for the heart rate, starting with a beat-to-beat period of one-third of a second (corresponding to 180 beats per minute) and continuing by consistently incrementing the period by one-twentieth of a second to a final upper limit corresponding to approximately 80 beats per minute. This iterative technique also varied the minimum difference required for recognition between local minima and maxima (ignoring any combinations below this value, cutting down on fluctuations from noise) until consistent data were reported across the majority of the nine readings. Provisions were made, including checking for large drop-off in values of heart rate or consistency throughout the upper half of readings, to prevent heart rates above 80 beats per minute from being incorrectly reported. The reverse was done in the case of extremely low heart rates.

The second technique, which was simpler, involved using the derivative of the NAPS BCG waveform in combination with variable threshold peak detection. The threshold for detecting the HIJK BCG peak was initially set to a default value and then refined based on the results of the first pass through the waveform data. The default value and subsequent refinements were established based on preliminary data collected previously [19]. Possible BCG HIJK peaks were then selected using the threshold previously established. Instantaneous beat-to-beat heart rates were initially calculated from these detected peaks, with a minimum time difference of one-third of a second (180 beats per minute) between the peaks. After the initial calculation, the waveform was reexamined to eliminate outliers using the initial median calculated from the data, or to fill gaps where some peaks fell below the threshold by examining relative position of local minima (a component of the first technique) to isolate possible HIJK peaks.

In both methods, a heart rate was computed in a way similar to counting R–R intervals of ECG by establishing beat-to-beat heart rates based on the detected HIJK BCG waves. These instantaneous heart rates were reported for both methods and from each of the two sensor pads present (chest and abdomen), generating four different heart rate datasets. The medians for each of the four sets of data were reported as possible heart rates for that epoch. Once these readings were established, the algorithm generated a quality score based on: 1) instantaneous heart rate consistency on a beat-by-beat basis; 2) clustering of data near the median; and 3) the percentage of actual beats obtained out of the total possible based on the heart rate recorded during the epoch. The algorithm then selected the heart rate with the highest score for each epoch. The selected heart rate data were then subsequently examined in an effort to further eliminate outliers, based on 1) and 2) from the quality score. The median for this data was then recalculated and reported as the heart rate for the epoch. Once completed for all six epochs in the group, these readings were examined together for consistency. If high variance was reported among these reported readings, the data were reexamined by both methods, with adjustments made to the initial parameters (such as the threshold and expected range of heart rates) based on the first readings. Additionally, if excessive movement was present, excessively low quality data were reported, or there was no signal detected during a specific epoch, no heart rate data were reported.

To prevent large errors within a group of six epochs, an automated correction method was employed. This correction scheme was applied only in cases where one of the heart rates was significantly different than the average. This automated correction occurred only in 2% of the epochs in the preliminary data (10 out of 480), with this process being established from a previous dataset [19]. This algorithm is summarized in Fig. 3.

Before the heart rates could be finally established for each epoch, the redundant readings for each epoch needed to be resolved. This was mainly done by selecting one of them if no data were reported for the other, or averaging the two if they were similar. However, if the two measurements had a difference greater than 10% of their collective average, and that difference was greater than 5, the algorithm had to resolve this difference by examining surrounding epochs [22]. This automated correction occurred only in 2.3% of the epochs in the overall dataset (825 out of 35 841) and was established based on data from the training set. Heart rates that were adversely affected by movement artifact were removed from the analysis, as previously described [22]. This automated, rule-based process eliminated only 2.6% of the epochs recorded in the overall dataset and was established based on data from the training set.

*3) Breathing Rate Algorithm:* The analysis of the respiration signals is significantly simpler than the heart rate analysis, as it was a much easier signal to detect. Automated algorithms were developed to detect and align breaths recorded by the two compliant force-coupled pads of the NAPS system as well as the breaths detected by the RIP bands. Though some adjustments needed to be made between the two systems because of how the sensors responded to movement, the basic principles remained the same. Just like the heart rate data, the breathing rates were analyzed in groups of six epochs, advancing by three epochs to

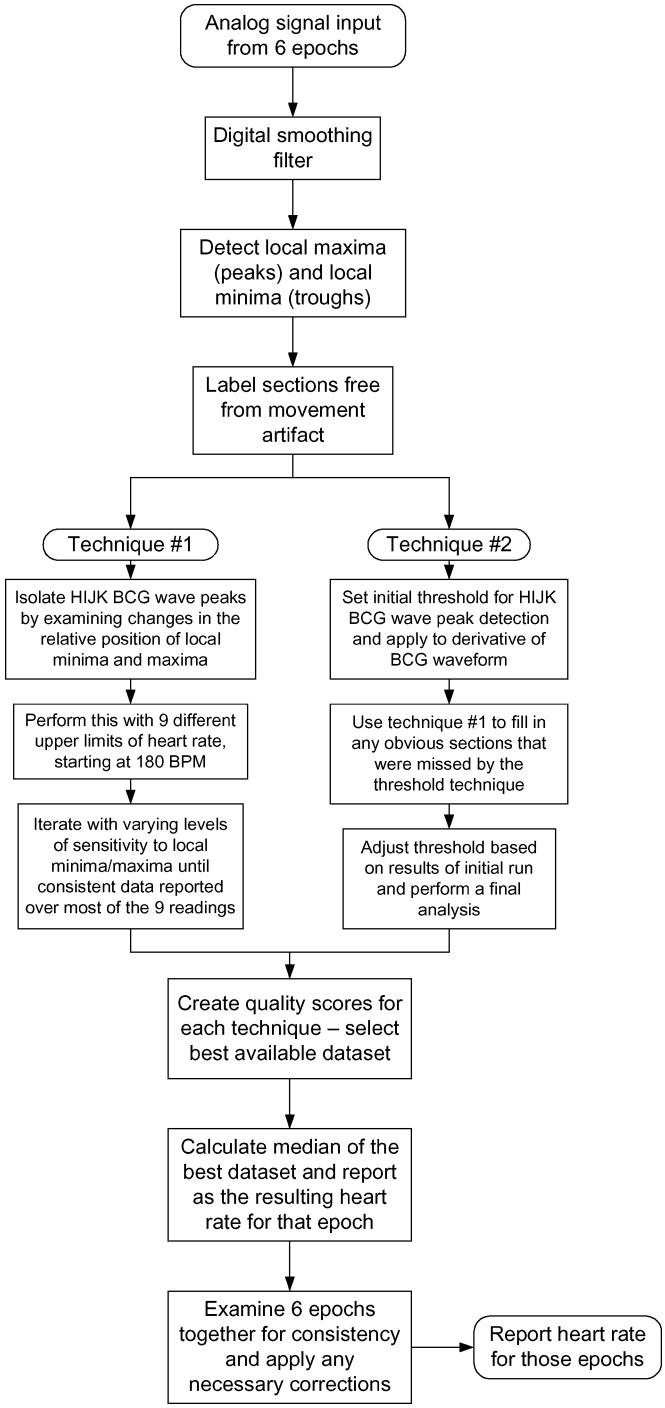


Fig. 3. High-level block diagram of the heart rate algorithm.

produce the redundant datasets. However, due to the simplicity of the signal, no use of iteration or multiple methods were required.

Using the same method as a component of the heart rate waveform analysis, the algorithm detected the peaks and troughs of the smoothed waveform, while also separating out movement epochs and epochs with no signal from actual breathing waveform data. The average amplitude of the breathing data was used to discern the expected amplitudes for breathing, setting a variable amplitude threshold for detecting breaths based

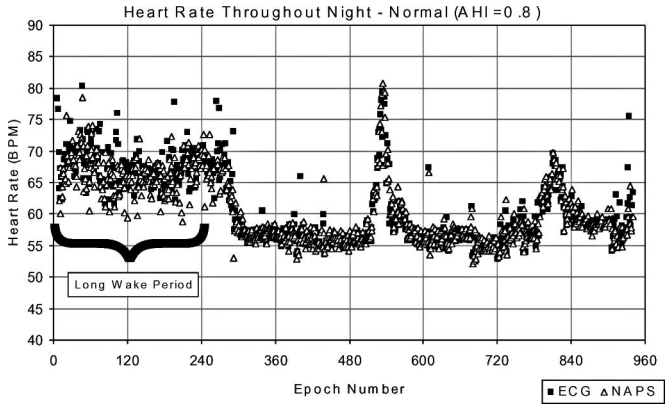


Fig. 4. Epoch-by-epoch comparison of NAPS and ECG heart rates for subject 2011, normal.

on the results. In cases where there were signals from slight movement artifacts or changes in breathing patterns, the signal amplitude was examined to clarify what was considered a full breath. The default value and subsequent refinements for these thresholds were established based on preliminary data collected previously [19], and then scaled as necessary for the RIP bands.

For both the RIP bands and the NAPS pads, the breathing rates were calculated on a breath-by-breath basis just like the heart rate data. The breathing rates obtained for an epoch from either system were averaged separately so that two readings each for both the NAPS and RIP were produced (one upper and one lower). Since the smoothing of the data eliminated a larger section of data at the beginning and end of the epoch, the redundant sets of readings from the moving window were combined to provide a more complete dataset for a single epoch. Thus, for the breathing, the resolution required was between the upper and lower data rather than the redundant readings for each epoch. Any readings from either the NAPS or the RIP that were not between 6 and 30 breaths were eliminated as influenced by apneas and movement artifact, respectively.

As with the heart rate data, the vast majority of readings were either close enough to just average together to generate the breathing rate for that epoch or one was selected when the other produced no data. However, if there was a difference between the upper and lower readings greater than five breaths per minute, an additional review was required for resolution [22]. For the RIP data, these corrections occurred in 4.7% of the epochs in the overall dataset (1727 out of 36 868). For the NAPS data, these corrections occurred in only 0.3% of the epochs in the overall dataset.

*4) Excluded Data:* Once the algorithms were established, for both the parameters recorded by standard polysomnography and by the NAPS system, an adequate comparison could be made between the two systems. To do this properly for the heart rate data, only the epochs with all three measures present were included in the overall comparison. This excluded 14.53% of the 18 291 epochs recorded across all subjects in the test set. Just over 10% of these epochs were excluded solely due to the NAPS system missing data, mostly caused by a subject's excessive movement during a given epoch. Additionally, one 79-year-old subject had an extremely irregular heart rate (rms

TABLE II
HEART RATE SUMMARY FOR THE NAPS SYSTEM

| Description | Number of Epochs Included | Predicted Mean Discrepancy | 95% Confidence Interval | p-value | Std. Dev. of Discrepancies (within subjects) | 95% Confidence Interval | p-value |
|---|---|---|---|---|---|---|---|
| Overall | 15633 | -0.314 | (-0.652, 0.024) | 0.067 | 2.72 | (2.69, 2.75) | < 0.001 |
| Sleep | 12184 | -0.327 | (-0.856, 0.202) | 0.211 | 2.65 | (2.61, 2.68) | < 0.001 |
| Sleep: No Apnea | 9500 | -0.198 | (-0.680, 0.283) | 0.399 | 2.56 | (2.52, 2.60) | < 0.001 |
| Sleep: Contains Apnea | 2684 | -0.682 | (-1.174, -0.190) | 0.009 | 2.92 | (2.85, 3.00) | < 0.001 |

Column descriptions (left to right; applies to all similar tables): 1) epochs Include: the number of epochs counted in the analysis for the corresponding set of data; these include only epochs where data were present for all three measurements; 2) predicted mean discrepancy: model-based prediction for the mean measurement discrepancy; 3) 95% confidence interval: for the true mean measurement discrepancy; 4) *p*-value: for the null hypothesis that the true mean measurement discrepancy is equal to zero; 5) standard deviation: the estimated standard deviation for within-subject measurement discrepancy; 6) 95% confidence interval: for the true standard deviation for within-subject measurement discrepancy; 7) *p*-value: the *p*-value for the null hypothesis that the true standard deviation for the within-subject measurement discrepancy is equal to zero.

TABLE III
HEART RATE SUMMARY FOR PULSE OXIMETRY

| Description of Epochs Included | Number of Epochs Included | Predicted Mean Discrepancy | 95% Confidence Interval | p-value | Std. Dev. of Discrepancies (within subjects) | 95% Confidence Interval | p-value |
|---|---|---|---|---|---|---|---|
| Overall | 15633 | -0.289 | (-0.406,-0.171) | < 0.001 | 1.50 | (1.49, 1.52) | < 0.001 |
| Sleep | 12184 | -0.335 | (-0.479, -0.191) | < 0.001 | 1.33 | (1.31, 1.35) | < 0.001 |
| Sleep: No Apnea | 9500 | -0.289 | (-0.429, -0.149) | < 0.001 | 1.20 | (1.18, 1.20) | < 0.001 |
| Sleep: Contains Apnea | 2684 | -0.464 | (-0.613, -0.315) | < 0.001 | 1.71 | (1.67, 1.76) | < 0.001 |

sequential differences (RMSSD) value of $\sim$300 ms), and there was disagreement among all three heart rate methods. There was a negative bias for the entire night in the pulse oximetry as compared to ECG and a similar, but larger, negative bias in the NAPS system. The NAPS system had problems analyzing the data for this subject because the algorithm assumes relatively normal heart rate variability; this is a limitation of the current implementation of the NAPS system's algorithm. Such a case is rare and is considered an outlier due to both the age of the person and the high heart rate variability (the other 39 subjects individually averaged under 160 ms, with the vast majority under 100 ms—less by at least a factor of 2, if not 3). With this in mind, this subject's heart rate data were excluded from the analysis and is the reason for the difference in total epochs noted for the heart rate and breathing rate analyses.

Similar restrictions had to be placed on the respiration data. Due to the sensitivity of both the RIP bands and NAPS pads to movement artifacts, an epoch was excluded from the comparison if it contained more than 12.5% of movement as measured by the NAPS system and was considered awake, as reported by the polysomnography data. The NAPS system's movement measure was used because there is no convenient method of overall movement measurement implemented in the polysomnography system. Since the main purpose of breathing analysis during a sleep study is to detect sleep apnea, which is recorded only during sleep, this exclusion is not significant. In addition to the epochs removed due to movement artifact, only epochs with both measures present were included. Thus, 16.53% of the test set data (18 291 epochs) was excluded largely either due to movement artifact (just over 11%) or the NAPS system not reporting a reading (just under 5%).

*5) Statistical Methods:* To analyze the heart rate measurement agreement between ECG, the NAPS system, and pulse oximetry, we computed two sets of delta values that utilized the heart rate measurements from only those epochs in which all three measures of heart rate were available. The first set was computed by subtracting, epoch by epoch, the ECG-derived heart rate from the NAPS-system-derived heart rate, while the second set of delta values were computed by subtracting, epoch by epoch, the ECG-derived heart rate from the pulse–oximetry-derived heart rate. For both sets of delta values, the ECG-derived heart rate was considered as the gold standard.

The two sets of delta values were analyzed individually by way of random-effects and mixed-effects linear models. This was done in lieu of Bland–Altman testing because there were several hundred measurements from each individual that were not necessarily independent events. For the random-effects models, each subject's set of delta values were treated as a random cluster of data. For the mixed-effects models, each subject's set of delta values were once again treated as a random cluster of data, while the independent factor of interest [average movement, apnea status (present or absent), severity of apnea (AHI), or sleep status (awake or asleep)] was treated as a fixed effect. For both types of models, the estimation of the mean within-subject heart rate measurement discrepancy and the estimation of the within-subject variance component were based on the restricted maximum-likelihood principle. The 95% confidence interval for the mean within-subject heart rate measurement discrepancy was computed based on the $t$-distribution, while the 95% confidence interval for the within-subject variance component was computed based on the $\chi^2$-distribution, with the degrees of freedom of the $\chi^2$-distribution determined via the Satterthwaite approximation.

To analyze the breathing rate agreement between the NAPS system and the RIP bands, we computed a set of delta values by subtracting, epoch by epoch, the RIP breathing rate from the

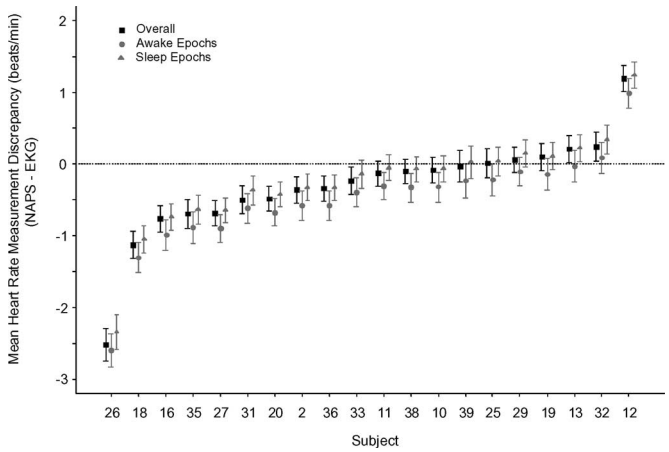


Fig. 5. NAPS predicted mean discrepancy from ECG for each subject. The points indicate the predicted mean discrepancy while the vertical lines indicate the 95% confidence interval for the predicted mean measurement discrepancy.

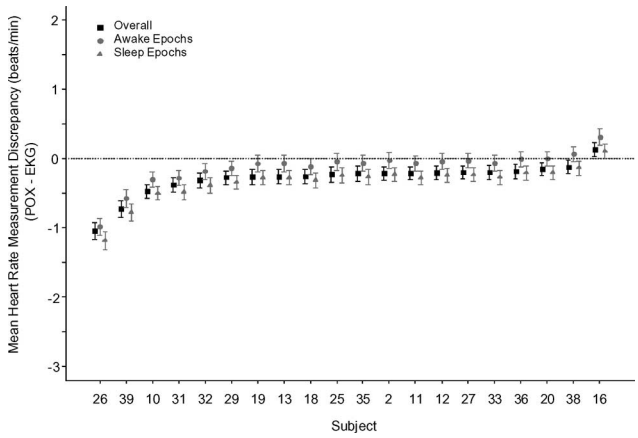


Fig. 6. Pulse oximetry predicted mean discrepancy from ECG for each subject. The points indicate the predicted mean discrepancy while the vertical lines indicate the 95% confidence interval for the predicted mean measurement discrepancy.

NAPS system breathing rate. The RIP breathing rate was considered as the gold standard. Random-effects and mixed-effects linear models were utilized to analyze the aforementioned set of delta values. The statistical analyses were carried out in exactly the same way as the previously mentioned heart rate measurement agreement analyses. The software of the PROC MIXED procedure of SAS version 9.1 (SAS Institute, Inc., Cary, NC) was use to conduct the statistical data analyses.

## III. Results

One example of heart rate data for an entire night, from a normal subject, is plotted in Fig. 4. The NAPS system's overall performance as compared to ECG is shown in Table II, while the same for pulse oximetry is shown in Table III. Though the NAPS system is more variable than the pulse oximeter, having higher percentages of discrepancies further away from zero, the NAPS data overall were unbiased ($p = 0.067$), more so during sleep ($p = 0.211$), while the pulse oximeter data showed

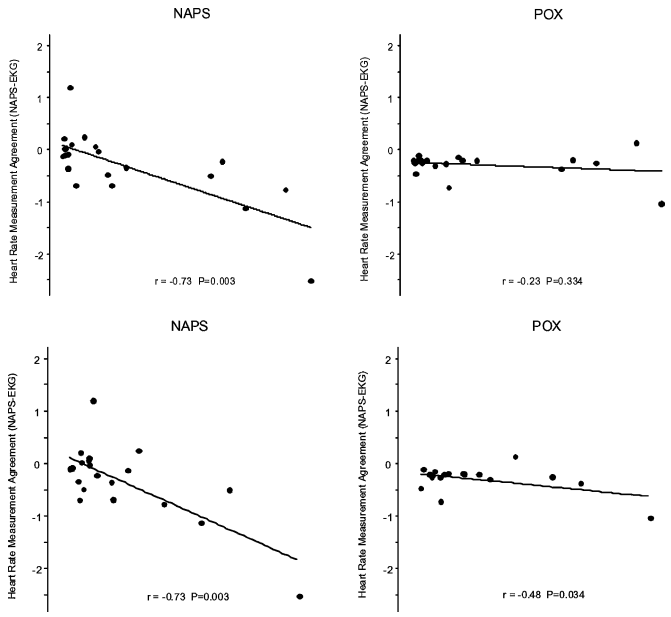


Fig. 7. (a) Correlation between the AHI and the NAPS system's predicted mean measurement discrepancy from ECG for the 20 subjects of the test set sample. (b) Correlation between the AHI and the pulse oximeter's predicted mean measurement discrepancy from ECG for the 20 subjects of the test set sample. (c) Correlation between the average epoch movement percentage and the NAPS system's predicted mean measurement discrepancy from ECG for the 20 subjects of the test set sample. (d) Correlation between the average epoch movement percentage and the pulse oximeter's predicted mean measurement discrepancy from ECG for the 20 subjects of the test set sample.

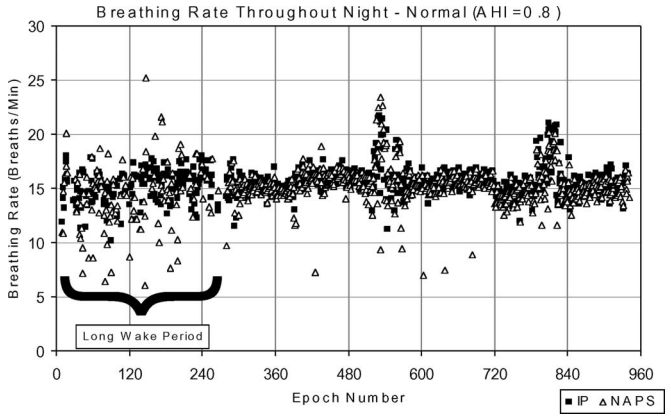


Fig. 8. Epoch-by-epoch comparison of NAPS and RIP breathing rates for subject 2011, normal.

a significant negative bias in both the overall analysis and during sleep ($p < 0.001$ for both). This bias is mostly caused by the pulse oximeter's algorithm, which is not that responsive to rapid changes in heart rates, and is generally not a large problem during sleep. Table II also shows that the performance of the NAPS system is influenced if only sleep epochs are counted and highlights the difference in variability within those sleep epochs that contain apneas versus those that do not. For each of the four datasets described in Tables II and III, the predicted mean discrepancies found from the NAPS and pulse oximeter are shown for each subject in Figs. 5 and 6.

TABLE IV
BREATHING RATE SUMMARY FOR THE NAPS SYSTEM

| Description | Number of Epochs Included | Predicted Mean Discrepancy | 95% Confidence Interval | p-value | Std. Dev. of Discrepancies (within subjects) | 95% Confidence Interval | p-value |
|---|---|---|---|---|---|---|---|
| Overall | 15267 | -0.290 | (-0.560, -0.020) | 0.037 | 2.10 | (2.08, 2.13) | < 0.001 |
| Sleep | 12602 | -0.299 | (-0.600, 0.002) | 0.052 | 2.03 | (2.01, 2.06) | < 0.001 |
| Sleep: No Apnea | 9775 | -0.170 | (-0.417, 0.078) | 0.167 | 1.59 | (1.57, 1.61) | < 0.001 |
| Sleep: Contains Apnea | 2827 | -0.653 | (-0.912, -0.393) | < 0.001 | 3.08 | (3.00, 3.17) | < 0.001 |

When each subject's individual overall predicted mean discrepancy was plotted against their average movement [Fig. 7(a)], a significant negative correlation was found using the NAPS data. The same was true when plotted against the reported apnea index—the number of apneas per hour of sleep [Fig. 7(c)]. A regression analysis that examined these factors simultaneously revealed that both the average movement ($p < 0.001$) and apnea index ($p = 0.005$) were important in predicting the measurement discrepancies. For the pulse oximetry data, only the average movement calculation showed a significant negative correlation. A regression analysis conducted for the pulse oximeter showed that only the average movement ($p < 0.001$) was important [Fig. 7(b)].

One example of breathing rate data for an entire night, from a normal subject, is plotted in Fig. 8. The NAPS system's overall performance as compared to the RIP bands is shown in Table IV. The breathing rate data from the NAPS was only slightly negatively biased ($p = 0.037$), and this was mostly caused by the apneas present (no apnea: $p = 0.167$; apnea: $p < 0.001$). The same subsets explored for the heart rate data were also included in Table IV for the breathing rate analysis. The effects of these parameters on the predicted mean discrepancy, along with the overall measurement, are shown for each subject in Fig. 9. The average movement calculation and apnea indexes reported showed a similar relationship to the heart rate data as significant negative correlations were found using the NAPS data. A regression analysis that examined these same factors, as with the heart rate data, again revealed that both the average movement ($p < 0.001$) and the apnea index ($p < 0.001$) were important.

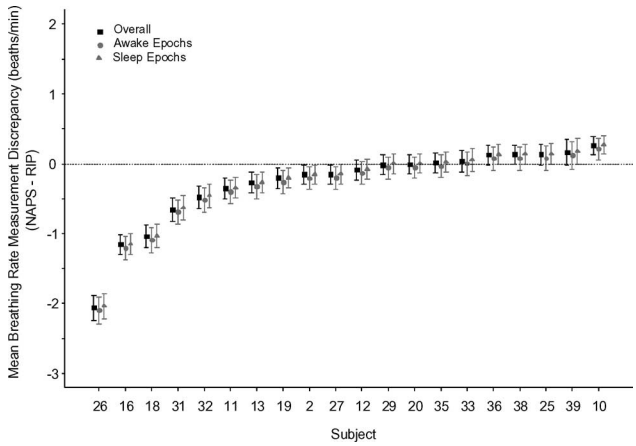


Fig. 9. NAPS predicted mean measurement discrepancy from IP for each subject. The points indicate the predicted mean measurement discrepancy while the vertical lines indicate the 95% confidence interval for the predicted mean measurement discrepancy.

## IV. DISCUSSION

The NAPS system accurately detected heart rate to within 2.72 beats per minute of ECG over the prescribed 30-s intervals with minimal impact from various factors. In addition, the NAPS system accurately detected breathing rate to within 2.10 breaths per minute of RIP bands used in polysomnography. Accurate quantitative analysis of heart rate and breathing rate over these 30-s epochs for an entire night will be very useful in developing subsequent algorithms that assess sleep architecture. In specifically examining the factors of average movement and apnea severity, the pulse oximeter readings were less influenced than the NAPS system's data. However, even though these effects were statistically significant for the NAPS data and indicate that with an increase in these parameters, the average discrepancy was also increased, the effect was minimal overall (less than 0.05 beats per minute). The breathing data also registered minimal impact as there was almost no change (less than 0.001 breaths per minute). Though these effects were small overall, they did have more significant impact when examining the individual subjects. Each of the subjects' readings showed general agreement across the board, as seen in Figs. 5 and 9, with a few exceptions. Subjects 26, 18, and 16 appear in both figures as the three largest negative discrepancies. These particular subjects had the three highest apnea indexes, ranging from 70 to 96/h, so one would expect them to have the most discrepancy. The main reason for the negative bias, indicating that the NAPS system is underestimating both heart rate and breathing rate, is due to the movement artifact usually associated with apneas. The movement that occurs after an apnea is the result of the subjects briefly waking themselves up to start breathing again, which is known as an arousal. These arousals can mask increases in heart rate and breathing rate, which will not be counted by the NAPS system during these epochs and is one reason why a separate algorithm for detecting apneas using the breathing waveform is under development. This is confirmed by the data in Tables II–IV, where influence of the presence of apneas across all subjects was measured. This effect also appeared similarly in the pulse oximetry data, but to a lesser degree. For the purpose of sleep analysis, the main clinical application of the NAPS system, this limitation is manageable. However, it does make the NAPS system less desirable for real-time applications over short periods of time, unless minimal movement artifact was present. On

the other end of the spectrum, one subject, number 12, showed a positively skewed average discrepancy in the heart rate data. Upon examination of the raw data in both the areas where good agreement between the NAPS and ECG occurred as well as the areas of overestimation, an interesting pattern was revealed. The areas of overestimation were characterized by extremely high amplitudes of respiratory effort that interfered with the isolation of the heart rate waveform. This effect is not as severe as the one caused by movement and apneas, and can be corrected in the future by employing a slightly modified set of filters to provide better separation in the extreme cases of very high breathing amplitudes.

## V. Conclusion

The NAPS system demonstrated strong agreement with the ECG and RIP standards of measurement for heart rate and breathing rate, and thus can accurately detect these parameters. The performance of the NAPS system was maintained over a wide range of heart rates and subject demographics. The results form a foundation and encourage further research. In particular, the use of these tested parameters of heart rate and breathing rate is an important step to establishing a simple, yet robust technique to quantify cardiac and respiratory parameters that, when combined with quantified movement data, is being developed to quantify sleep architecture without the use of EEG waveforms. This information, in addition to an apnea detection algorithm currently being developed, makes the NAPS system a promising candidate to conduct unattended home sleep monitoring and screen for sleep apnea.

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