Proceedings of the 2012 IEEE 12th International Conference on Bioinformatics & Bioengineering (BIBE), Larnaca, Cyprus, 11-13 November 2012

Combining Unobtrusive Electrocardiography and Ballistography for more Accurate Monitoring of Sleep

Antti Vehkaoja, Mikko Peltokangas, Jarmo Verho, and Jukka Lekkala
Department of Automation Science and Engineering
Tampere University of Technology
Tampere, Finland
firstname.lastname@tut.fi

Abstract— **We propose an unobtrusive bed integrated system for monitoring physiological parameters during sleep. Our system uses textile electrodes attached on the bed sheet for measuring multiple channels of electrocardiogram from which one at a time is selected for RR-interval detection and force sensors located under a bed post for detecting breathing and movements. The movement information is also used to assist in heart rate detection. We tested the system with six subjects in one hour recordings and achieved an average of 94 % detection coverage and 99 percentile absolute error of 2.86 ms for the RR-interval signal. Mean absolute error of the detected respiration cycle lengths was 0.24 seconds.**

Keywords—Bed integrated ECG (EKG), Heart rate, Respiration rate, Unobtrusive physiological measurement, Night-time monitoring

I. INTRODUCTION AND RELATED WORK

Automatic monitoring of night-time physiological information especially the heart rate, the respiration rate and movements can be used in various applications. Examples include screening of medical disorders like sleep apnoea [1, 2] and monitoring of sleeping quality [3] or psychophysiological stress [4]. While polysomnography is used as a standard method for collecting reliable data from a sleeping person, the strength of the methods that do not require effort from the person being measured, is that they can be used to collect longitudinal data thus enabling a more comprehensive view of the person's sleep being formed. Also the effect of the measurement equipment on the sleep is minimized when using these unobtrusive techniques.

Ballistography, which means the measurement of the mechanical signal produced by the heart beat or pulsatile blood movement and breathing is able to provide all the desired physiological parameters; the heart rate (HR), respiration rate (RR), and movements. Recent studies that have focused on the night-time HR detection based on the ballistocardiographic (BCG) signal have reported average HR errors between 0.34 % [5] and 1.79 % [6]. We obtained an average error percentage of 0.45 % in an earlier yet unpublished study by using force sensors under all four bed posts. Also the detection coverage of the HR is important for reliable sleep analysis. Long continuous beat-to-beat-interval (BBI) series enable more reliable calculation of heart rate variability (HRV) parameters, which are commonly used in sleep staging and sleep quality evaluation. We achieved approximately 91 % average recognition coverage with the ballistographic method in unsupervised recordings while Kortelainen *et al.* reported 88 % coverage in [5]. Brüser *et al.* [6] reported 95 % coverage but they had instructed the test persons to stay still during the measurements.

Even though fairly good accuracy and high recognition coverage of BBI data can be achieved with ballistographic sensors, it still may not be the optimal method for gathering the heart rate information. We achieved 95 % recognition coverage and 0.22 – 0.85 beats per minute (bpm) absolute HR error with a system that measures contact ECG using textile electrodes sewn on a bed sheet [7]. Other studies [8, 9] have reported detection coverage between 82 % and 93 % with large sized textile electrodes that have been located on a pillow and to the foot of the bed. These electrode locations allow the user to wear pajamas as long as the electrodes are in contact with the skin. In our system, the electrodes are attached horizontally to the bed sheet approximately to the height of the chest, which causes a requirement of naked upper body. The accuracy of the detected RRI data has not been defined in [8] or [9] but probability of erroneously detected R-peaks is obviously higher than when using regular ECG electrodes. Also bed integrated non-contact capacitive ECG monitoring has been studied [10–12]. The benefit of these systems is that the user is allowed to wear pajamas but they are much more prone to movement artifacts and electrical interferences and therefore do not necessarily provide benefits when compared with the ballistographic technique.

Many authors who have developed ballistographic methods for night-time physiological parameter detection have developed besides HR detection, also methods for RR detection. Paalasmaa *et al.* [13] used multiple low-pass filters suited for different respiration rates for filtering the original ballistographic signal and then selected the filter that produces the most consistent breathing amplitudes. Wang *et al.* used a single component of the wavelet transformed BG signal and an adaptive threshold to count the breathing cycles [14]. Breathing rate can also be detected as the frequency of the respiratory sinus arrhythmia seen in the RRI data but more reliable result can be calculated using the signal of the force sensors located under the bed post. Therefore we are combining the two measurement modalities in order to increase the overall accuracy of the received parameters.

There exist examples of commercialized eHealth systems intended for monitoring night-time physiological activity. A Finnish company Beddit.com Ltd. has brought to the market a monitoring system for sleep quality assessment [15]. Emfit Ltd. is another provider of a bed installable, unnoticeable vital sign monitoring system [16]. Beddit's system is primarily intended for the wellness related self-monitoring of sleep through a web service while Emfit's system is targeted for larger units like care centers and nursing homes. Both these systems are based on measuring ballistographic signals with sensors placed between or under the mattresses.

II. Materials and Methods

A. Measurement System

We used a custom made data acquisition (DAQ) device for collecting the data. Our low noise DAQ device contains 16 measurement channels, which can be used in the measurement of amplified ECG or other voltage signal. Also signals produced by piezoelectric sensors can be directly measured with the device. The input voltage range of the device is ± 2.18 V with a resolution of 67 µV.

The DAQ is capable of transmitting the measurement data either through USB or by a wireless Bluetooth link. We used the USB mode in these tests because the application at hand does not require mobility. The maximum sampling rate with the wired connection is 1 kHz per channel but 250 Hz was found high enough for the ECG recording because the low-pass cut-of the measurement amplifiers was set to 40 Hz.

1) Bed sheet ECG measurement electronics

The electrodes we are using are manufactured by embroidering from silver coated polyamide yarn. The size of the oval shaped electrodes is 32 mm × 22 mm. A moisture insulating layer is used under the electrodes in order to slow down the drying of the electrodes after they are first moistened by the moisture of the skin. In earlier tests, we used 9.8 cm inter-electrode distance but in the current setup we decreased the inter-electrode distance to 5 cm. Shorter inter-electrode distance enables combining several ECG channels, which increases the signal-to-noise ratio (SNR) of the ECG as well as the amount of choices for channel selection.

Our ECG amplifier contains eight measurement channels, seven of them for the bed sheet ECG channels and the remaining one for the reference signal recorded with conventional disposable Ag/AgCl electrodes manufactured by Ambu. All channels are identical, having two amplifier stages. The first stage is an instrumentation amplifier and the second is a non-inverting gain stage. Between the amplifier stages there is a first order high pass filter and after the second stage a second order 40 Hz Butterworth low-pass filter. The amplifiers used for the sheet ECG measurement are arranged so that each of them amplifies the potential difference between two adjacent electrodes. Fig. 1 shows the schematic of the amplifier connection of the first stage.

The eight electrodes placed 5 cm apart cover a 38 cm wide area in the middle of the bed. In order to maximize the ECG signal quality, the pillow should be located so that the electrodes are approximately 10-25 cm below the edge of the pillow. Even larger variation in the axial electrode location is tolerable in most cases but especially when sleeping on the right side, the ECG signal quality starts to decrease when the electrodes are located more than 20 cm below the arm pit.

2) Ballistography

We use two force sensitive film sensors made of Electro Mechanical film (EMFi) material to measure ballistography and movement signals. Both sensors are located under one bed post. The size of the sensors is 10 mm x 20 mm and their approximate voltage sensitivity is 1 V/N with the high-pass cut-off frequency of 0.01 Hz. The ballistographic sensors are used for two purposes: firstly, for measuring the respiratory information and secondly, for assisting in ECG signal processing by providing movement information.

B. Signal Processing

The two sensor modalities, bed sheet ECG sensors and bed post force sensors, are otherwise processed separately but the movement information provided by the force sensor is used to assist in processing the sheet ECG signals.

1) Combining and selecting the bed sheet ECG channels

Before combining the bed sheet ECG signals they are first low-pass filtered digitally using a 10^{th} order filter with 30 Hz cut-off and Butterworth like response. Combining the signals of adjacent bed sheet ECG channels increases the signal quality in two ways. Firstly, the noise caused by the measurement electronics and the interferences in the skin-electrode interfaces are independent between the channels if at least three channels are combined whereas the ECG signal is not independent. This increases the SNR by the square root of the number of combined channels. The more important source of improvement is the increased span of the measuring electrodes, which according to lead field theory, increases the measurement sensitivity deeper in the torso where the signal source, the heart, is located [17]. Fig. 2 shows an example of the improvement of the sheet ECG quality when the signals of three channels are combined.

As seen from the Fig. 1, the channels can be combined simply by adding the adjacent bed sheet channels together. All possible combinations of one, two, three, etc. adjacent bed sheet channels, altogether 28 channel combinations are thus formed. The final preprocessing step is the high-pass filtering the signal with the non-linear method proposed by Keselbrener *et al.* in [18], which subtracts a 100 ms sliding median from the signal thus efficiently removing low frequency components but leaving the R-peaks untouched.

The signals are then fed to the channel selection algorithm, which chooses the channel with the best signal quality to be used in R-R interval detection. The best channel is selected by

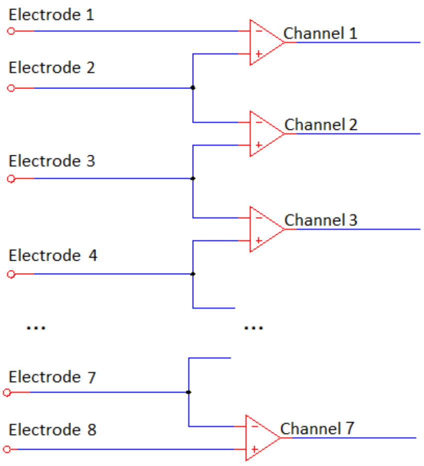

Fig. 1. Schematic of the input gain stage of the ECG amplifier. Summing the signals of channel 1 and channel 2 provides the ECG signal between the electrodes 1 and 3.

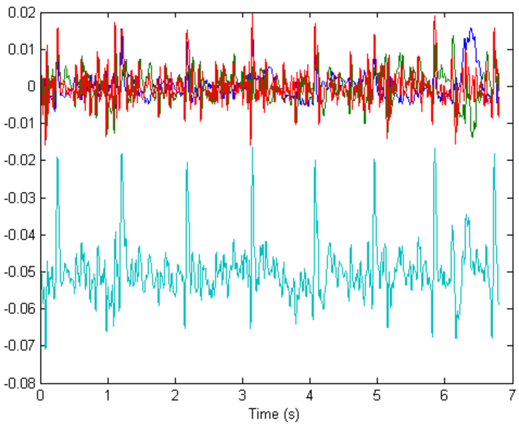

Fig. 2. An example of low quality bed sheet ECG signals from three measurement channels (upper traces). The R-peaks become more distinguishable when the signals are combined (bottom trace).

taking a 10-second sample of all the channels, then detecting R-peaks (all peaks with distinctive amplitude and steep enough rising and falling edges), and finally selecting the channel with the highest ratio between the average peak amplitude and the variance of the remaining baseline signal. If none of the signals fulfill the minimum requirements of the signal quality, then no channel is used and the channel selection is tried again after one second. The minimum requirements are that the found R-peak candidates or RR-intervals should be physiologically reasonable and their amplitude as well as the SNR should be within predefined limits. Depending on the sleeping posture, R-peaks may be negative or positive and both cases need to be considered. A more detailed description of the algorithm is found from [7]. The channel selection procedure is repeated if the quality of the ECG on the currently used channel decreases too much.

Fig. 3 shows the RRI recognition result of one recording and the number of the measurement lead selected for the bed sheet RRI detection. As seen from the Fig. 3 a), an ECG lead formed by only a single measurement channel has been used most of the time in this recording but also channel combinations have been used. For example a lead formed by six channels has been selected and used between 4000–4200 seconds.

2) Heart rate detection and RRI post processing

After the best channel is selected, R-peaks are searched from it. The R-peak detection algorithm is based on finding all distinctive peaks similarly as in the channel selection phase. The algorithm is based on the method published by Zhengzhong *et al.* in [19] with some modifications. After finding the R-peaks, we used a second order polynomial fitting to find the exact peak location with sub-sample interval accuracy. The polynomial was fitted to three data points by taking one sample from the both sides of the original R-peak sample.

After the whole recording has been analyzed and potential R-peaks have been found, the resulting RRI series is processed in order to find possible false positive detections caused noise peaks by investigating the peak interval signal. Earlier we also developed an ectopic peak detector that finds and removes possible "not sinus node"-originated peaks based on their different morphology. These ectopic peaks should be removed before using the RRI signal in HRV analysis because they are not controlled by the autonomous nervous system.

The RRI post processing algorithm also combines the RRI segments computed before and after the channel reselections if it concludes that no R-peaks have been missed during the reselection.

3) Movement detection with force sensor

We have used a variance of a 4 second sliding window for detecting the amplitude level of the force signals. Adaptive threshold level is empirically defined as ten times the median variance of the whole recording. This approach suits well for the offline analysis but for a real time application, another method for finding the threshold has to be used.

The movement detector's output should not be used as such in excluding the sheet ECG data because in most cases the sheet ECG quality is adequate for the HR detection also during small movements. We have used the movement detector to assist in the decision of launching the channel reselection process. When the sheet ECG's SNR is so small that the channel reselection would normally be initiated, the movement detector is used for checking whether the small SNR is a result of the increased movement artifacts. We have noticed that smaller SNR can be tolerated if no movement is present, without compromising the HR detection accuracy. Therefore the HR detection can be continued without reselecting the channel if the deterioration of the SNR is caused by something else than movements. In this case the limit of the minimum allowable SNR is lower.

4) Breathing rate detection

Besides the heart rate, also the breathing rate is an important and widely used physiological parameter in sleep analysis. Our breathing rate detection is based on finding ascending and descending zero crossings as well as local maximums and minimums from the ballistographic sensors' signals filtered with different pass-bands and calculating the repetition intervals of each parameter. Then all the interval signals are interpolated into 1 second sample interval and breathing rate is voted as the median of all the suggested intervals. Filtering the ballistogram signal with different pass-bands for respiration detection was earlier used by Paalasmaa *et al.* in [13].

5) Reference sensors

Reference ECG signal was recorded using regular disposable electrodes attached to the chest. The electrode locations were selected so that they did not interfere with the sheet electrodes. The heart rate was calculated using the same algorithm than with the sheet ECG signals.

The reference breathing rate was measured using an NTC thermistor placed inside a breathing mask. The resistance was measured with a voltage division connection. The respiration rate was calculated from the smoothed and detrended thermistor voltage by finding the maximum of each signal segment on the positive side. We found short sections where the amplitude of the reference breathing signal was significantly decreased from the recordings of two test subjects. We interpreted these sections as breathing obstructions and discarded them from the analysis.

C. Test Measurements and Subjects

We made test measurements with five male and one female subject. The subjects were 23-32 year old, normal weight and had no history of cardiovascular or breathing related problems. The measurements were made in laboratory settings using an 80 cm wide spring mattress bed. The subjects were allowed to change their sleeping posture freely. The length of the recordings was approximately one hour and most of the subjects fell asleep during this time.

III. RESULTS AND DISCUSSION

A. RRI detection results

Table 1 shows the heart rate detection coverage and the 99 percentile error limits of the detected R-R intervals when the force sensor is used to assist in the decision of initiating the channel reselection. As seen from the Table 1, using the force sensor information improved the average RRI detection coverage by 1.1 % from 92.9 % to 94 %. While the improvement of the coverage provided by the force sensor is fairly small, a more important aspect is that because the channel is not changed so easily, there are overall less channel changes and the segments of continuously detected RRI data become longer. This benefits especially the calculation of frequency domain HRV parameters, which are usually calculated in sleep analysis from 30 or 60 second long data segments.

Earlier we received 95.1 % average recognition coverage in overnight measurements using 9.8 cm inter-electrode distance and not combining the channels [7]. Because the measurement conditions in the current study are different (the measurement time is shorter and the portion of the time spent awake is longer), we also calculated the coverage with the current data by using only the 10 cm inter-electrode distance. The coverage achieved was 83.2 %, which shows that the improvement of the coverage is significant when the channel combinations are used. 10 cm distance was selected because it is close to the distance used in the earlier study. The difference still is that the combinations of two 5 cm channels provide also interlaced 10 cm ECG leads in addition to the 10 cm leads, which are next to each other.

Fig. 3 shows the RRI detection result from the recording of subject 6 (subfigure b) along with the information of the selected ECG lead (subfigure a). ECG leads numbered as 1-7 are the original ECG channels measured between two adjacent electrodes. Leads 8-12 are leads where two adjacent channels have been coupled by summing up their signals. Leads 13-17 are formed by three channels, and so on. An average of 41.8 %

TABLE I. THE EFFECT OF THE FORCE SENSOR AND THE CHANNEL COMBINATION ON THE RRI DETECTION COVERAGE AND THE UNCERTAINTY OF THE RRI DETECTION.

Subject number	**Performance characteristics**					
	Cov. Force[a]	***99 per***[b]	***Cov. no force***[a]	***99 per***[b]	***Cov. 10 cm***[a]	***99 per***[b]
1	97.27	1.71	97.19	1.64	96.67	1.30
2	97.18	2.63	97.09	3.06	96.57	2.27
3	92.00	3.42	90.72	3.21	83.85	3.89
4	88.78	3.87	86.53	3.80	82.07	3.46
5	96.78	2.50	96.75	2.63	75.47	3.49
6	92.07	3.01	89.13	2.90	64.41	3.06
Mean	94.01	2.86	92.90	2.88	83.16	2.91

a. RRI detection coverage when the force sensor information is applied (column 2), not applied (column 4), and when using only 10 cm inter-electrode distances.

b. 99 percentile of the absolute error in milliseconds with force sensor, without force sensor, and with only the 10 cm inter-electrode distance.

TABLE II. RESPIRATION CYCLE LENGTH DETECTION COVERAGE AND ERROR.

Subject number	**Respiration detection performance characteristics**				
	Detection coverage	***MAE***[a]	***e < 0.25***[b]	***e < 0.5***[b]	***e < 1***[b]
1	72.8	0.06	99.4	100.0	100.0
2	75.6	0.46	84.3	93.9	96.9
3	73.5	0.42	87.1	93.4	96.2
4	66.6	0.13	93.8	99.5	100.0
5	69.6	0.13	96.3	99.4	99.8
6	87.9	0.23	93.4	97.5	98.7
Mean	74.3	0.24	92.4	97.3	98.6

a. Mean absolute error (MAE) of respiration cycle length in seconds per breath.

b. Percent of the detected respiration cycle lengths where the error is smaller than 0.25 s, 0.5 s, and 1 s.

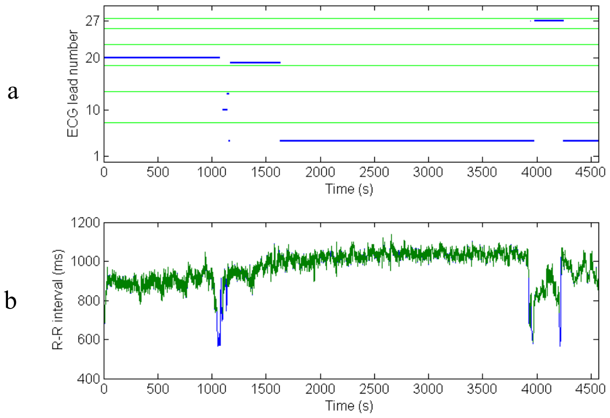

Fig. 3. A one hour recording showing the measurement leads used for sheet RRI calculation in a). Leads 1-7 below the lowest green horizontal line are the single measurements channels, leads 8-13 between the two lowest horizontal lines are augmented channels formed from two adjacent channels etc. The green line in b) is the RRI signal calculated from the sheet ECG signals and the blue line is the reference RRI. The sections of shorter RR-interval in b) are results of larger movements and sleeping posture changes and are therefore not detected from the sheet ECG.

of the total measurement time of all subjects, the channel selection algorithm had selected a measurement lead formed by one channel as the best. A lead formed by two channels was used 21.8 % of the time, three channels 12.7 %, four channels 16.2 %, five channels 1.6 %, and six channels 5.8 % of the time. The measurement lead formed by all seven channels was not selected in any of the recordings.

Authors have used a lot of different metrics to describe the performance of their measurement systems and the uncertainty of the results. Commonly used values are mean absolute error (MAE) as in [5] and [6] or RMS error as in [11]. Another suitable figure for reporting uncertainty or result is using percentile units, which tells about the uncertainty of the true positive detections and is not affected by possible false positives. We selected 99 percentile of the RRI signal's absolute error as the metrics of the RRI uncertainty. The average 99 percentile limit for the error when using all channel combinations and the force sensor information was 2.86 ms, which is less than one sample interval, 4 ms. As seen from the Table 1, using the force sensor does not have a clear effect on the RRIs' 99 percentile error in either way and neither has the use of only 10 cm inter electrode distance.

We also calculated the RMS and MAE error figures for the measurements. The RMS error varied between 0.87 ms and 11.04 ms between the recordings, the average RMS error being 4.94 ms. The average RMS error converted to the beats per minute was 0.27 bpm (0.06 – 0.48 bpm). The problem of using the RMS error is that few erroneously detected R-peaks in a recording may have a large effect on the result even when most of the RRIs are really close to the reference. Mean absolute error is less disturbed by random large errors. The RRI MAE of our recordings varied between 0.48 ms and 1.07 ms. The average was 0.91 ms. Conversion to the percentage units yielded 0.050 % and 0.103 % as the min and max, and 0.088% as the average MAE percent from reference RRI. As one could

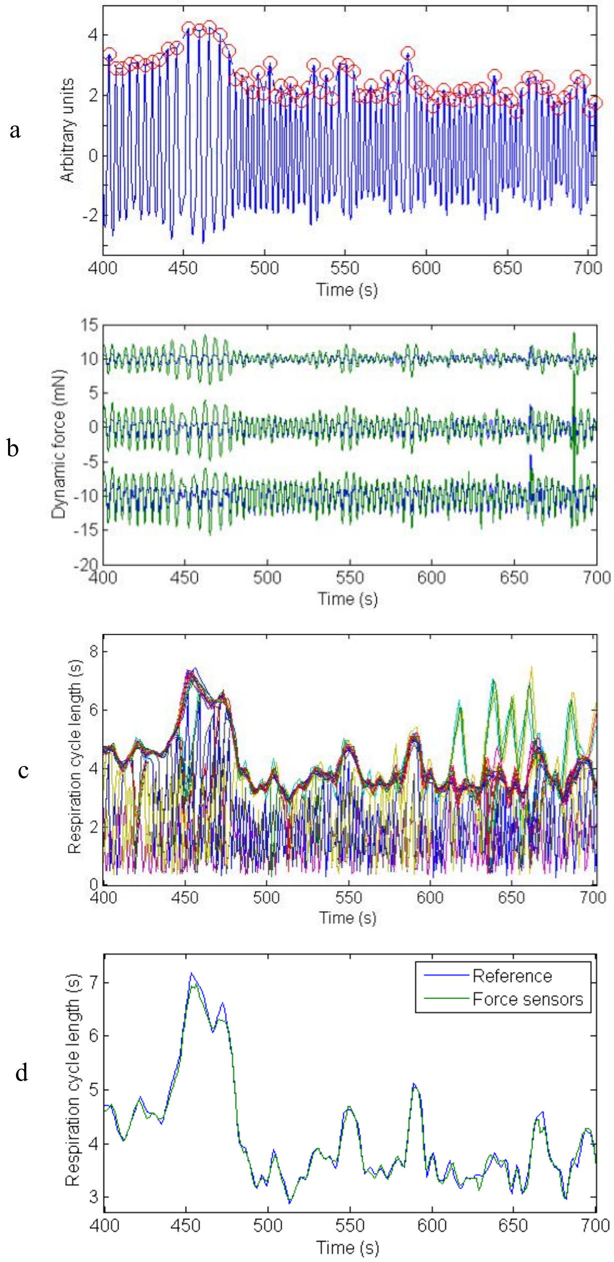

Fig. 4. A 300 second example of a respiration recording. Reference signal with the detected peaks is shown in a), signals of force sensors filtered with different pass bands in b), respiration cycle length suggestions based on the signals of b) are shown in c), and respiration cycle lengths detected with the reference sensor and force sensors in d).

assume based on the nature of the monitoring method, the 0.088 % MAE is clearly smaller than the smallest error reported for the ballistocardiographic method (0.34 % in [5]). Also the RMS error reported in [11] for a system using capacitive electrodes (0.66 ± 0.57 bpm is outperformed by our 0.27 bpm RMSE.

B. *Breathing rate detection results*

Table 2 shows the performance characteristics of the breathing rate detection. The average respiration detection coverage 74.3 % is significantly lower than what is achieved with the sheet ECG and what is usually achieved with ballistocardiographic methods for RRI detection [5-6]. The reason for this is the fairly long safety marginal before and after the detected movements, which is required because strong filtering causes fluctuation into the signal baseline after the impulse like movement artifacts. The detection coverage of the respiration rate could probably be improved by a more efficient pre-processing of the signal and by using a different filtering method. Also Paalasmaa *et al.* used fairly long safety marginal and received 73 % coverage in [13]. The average mean absolute error of detected respiration cycle length was 0.24 seconds. 97.3 % of the cycle lengths were less than 0.5 second apart from the reference, which is a similar result than what was reported in [13], 95.9 %. A 300-second example of respiration recording is shown in Fig. 4. As seen from the subfigure b), in this case the signal of the force sensor drawn in green has higher amplitude and less distorted waveform than in the other sensor whose signal is drawn in blue. This however varies and sometimes the other sensor offers better signal quality. The interferences cause a lot of erroneous respiration cycle length suggestions as seen in the subfigure c) but as seen in d), the median of the suggestion still follows the reference calculated from the signal in a) really well.

IV. Conclusions and Future Work

We have presented an unobtrusive system for monitoring physiological signals while the person is in bed. The novelty of our system is in the combination of two sensor modalities; contact ECG integrated into the bed sheet for measuring heart rate and heart rate variability parameters and force sensors for measuring movements and respiration and for providing additional information for the heart rate detection algorithm to improve its performance. The results received from one hour long recordings with young healthy adults show that the detection coverage and accuracy of the received physiological parameters are so good that this information can be used in evaluation of the sleep structure and quality.

Further testing and longer recordings are still required to verify the performance with the people including wider demographics or who suffer from sleeping related disorders. Improvement of the respiration rate algorithm is another target of the future work.

Acknowledgment

We would like to acknowledge the volunteers who participated in the study.

References

[1] F. Roche, J.-M. Gaspoz, I. Court-Fortune, M. Pascal, V. Pichot, D. Duverney, F. Costes, J.-R. Lacour, and J.-C. Barthélémy, “Screening of obstructive sleep apnea syndrome by heart rate variability analysis,” Circulation, vol. 100, no. 3, pp. 1411–1415, Sep. 1999.

[2] N. Ayas, S. Pittman, M. MacDonald, and D. White, “Assessment of a wrist-worn device in the detection of obstructive sleep apnea,” Sleep Med, vol. 4, no 5, pp. 435–442, Sep. 2003.

[3] A. Bulckaert, V. Exadaktylos, G. De Bruyne, B. Haex, E. De Valck, J. Wuyts, J. Verbraecken, and D. Berckmans, “Heart rate-based nighttime awakening detection,” Eur J Appl Physiol, vol. 109, no 2, pp. 317–322, May 2010.

[4] M. Hall, R. Vasko, D. Buysse, H. Ombao, Q. Chen, JD. Cashmere, D. Kupfer, and JF Thayer, “Acute stress affects heart rate variability during sleep,” Psychosom Med, vol. 66, no 1, pp. 56–62, Jan-Feb 2004.

[5] J. Kortelainen, M. Mendez, A. Bianchi, M. Matteucci, and S. Cerutti, “Sleep staging based on signals acquired through bed sensor,” Information Technology in Biomedicine, IEEE Transactions on, vol. 14, no 3, pp.776–785, May 2010.

[6] C. Brüser, K. Stadlthanner, S. de Waele, and S. Leonhardt, "Adaptive beat-to-beat heart rate estimation in ballistocardiograms," Information Technology in Biomedicine, IEEE Transactions on, vol.15, no.5, pp.778–786, Sept. 2011.

[7] M. Peltokangas, J. Verho, and A. Vehkaoja, “Unobtrusive night-time EKG and HRV monitoring system,” in Proc. 10th International Workshop on Biomedical Engineering, , Oct. 2011, pp. 1–5.

[8] S. Devot, A. Bianchi, E. Naujokat, M. Mendez, A. Brauers, and S. Cerutti, “Sleep monitoring through a textile recording system,” in Proc. 29th Annual Int Conf of the IEEE Engineering in Medicine and Biology Society, EMBC, Aug. 2007, pp. 2560–2563.

[9] M. Ishijima, “Cardiopulmonary monitoring by textile electrodes without subject-awareness of being monitored,” Medical and Biological Engineering and Computing, vol. 35, no. 6, pp. 685–690, Nov. 1997.

[10] Y. G. Lim, K. K. Kim, and K. S. Park, “ECG recording on a bed during sleep without direct skin-contact,” Biomedical Engineering, IEEE Transactions on, vol. 54, no. 4, pp. 718–725, Apr. 2007.

[11] K.-F. Wu and Y.-T. Zhang, “Contactless and continuous monitoring of heart electric activities through clothes on a sleeping bed,” in Information Technology and Applications in Biomedicine, 2008. ITAB 2008. International Conference on, May 2008, pp. 282–285.

[12] S. Ishida, N. Shiozawa, Y. Fujiwara, and M. Makikawa, “Electrocardiogram measurement during sleep with wearing clothes using capacitively coupled electrodes,” in Proc. 29th Annual Int Conf of the IEEE Engineering in Medicine and Biology Society, EMBC, Aug. 2007, pp. 2647–2650.

[13] J. Paalasmaa, L. Leppakorpi, and M. Partinen, "Quantifying respiratory variation with force sensor measurements," in Proc. 33rd Annual Int Conf of the IEEE Engineering in Medicine and Biology Society, EMBC, Aug. 2011, pp. 3812–3815.

[14] F. Wang, M. Tanaka, and S. Chonan, “Development of a PVDF piezopolymer sensor for unconstrained in-sleep cardiorespiratory,” Journal of Intelligent Material Systems and Structures, vol. 14, no. 3, pp. 185–190, March 2003.

[15] Beddit.com Ltd, available: http://www.beddit.com/sleep

[16] Emfit Ltd. Non contact vital signs monitor, available: http://www.emfit.com/en/care/products_care/vitals-monitor-and-nurse-call/

[17] M. Puurtinen, J. Hyttinen, J. Viik, P. Kauppinen, and J. Malmivuo, “Estimation of ECG signal of closely separated bipolar electrodes using thorax models,” in Proc. 26th Annual Int Conf of the IEEE Engineering in Medicine and Biology Society, EMBC, Sept. 2004, pp. 801–804.

[18] L. Keselbrener, M. Keselbrener, and S. Akselrod, “Nonlinear high pass filter for R-wave detection in ECG signal,” Medical Engineering & Physics, vol. 19, no. 5, pp. 481–484, Jul. 1997.

[19] G. Zhengzhong, K. Fanxue, and Z. Xu, “Accurate and rapid QRS detection for intelligent ECG monitor,” in Measuring Technology and Mechatronics Automation (ICMTMA), 2011 Third International Conference on, Jan. 2011, pp. 298–301.