Turtle Shell Publications

Contactless Monitoring of Respiration Cycles

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Continuous monitoring of body vitals is poised to be one of the key elements of future healthcare including monitoring critical illnesses, personalized therapeutics and predictive medicine. Continuous monitoring of patients by a team of healthcare professionals in a hospital setting has proven to be extremely effective over traditional (and sparsely) periodic manual measurements by an attendant [1]. Such manual monitoring, apart from being prone to inefficiency and human error, is also not feasible due to already stressed healthcare systems, especially in developing countries where healthcare needs are already at severe odds with their fast growing ageing populations and an increasing shortage of trained professionals -- a projected deficit of 14 million healthcare workers globally by 2030 [2].

Technique for Contactless Respiration Monitoring

Ballistocardiography (BCG) detects any physiological parameter that produces a motion -- including breathing, snoring and limb movements [3]. However, BCG has its own set of challenges. BCG is prone to undesired noise from the setup environment. This could be mechanical vibrations or movement near and around the setup. Even heavy body movements can overpower the cardiac and respiratory signals resulting in a lower detection rate. Apart from these noises, BCG raw signal is a superimposition of respiratory effort, cardiac contractions and vibrations due to snoring; effective signal conditioning is required to segregate these signals for high fidelity analysis. Additionally, the signal can vary for different people and with different mattresses. It can even vary for the same subject in different postures and body positions. In this paper, we propose a novel unsupervised algorithm that is effectively able to identify each respiratory cycle from an unconstrained BCG signal.

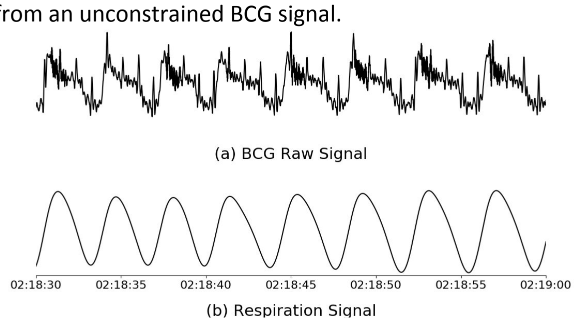

Figure 1: (a) Raw BCG signal, (b) Respiration signal

A normal respiration signal comprises alternate inhales and exhales, and is typically a sinusoidal waveform. The same is true for respiration effort as captured through BCG. Figure 1(a) shows raw BCG signal in comparison with airflow signal from the nasal thermistor acquired simultaneously.

Dozee - Contactless Patient Vitals Monitor

Placed under the mattress, Dozee monitors micro-vibrations produced by the body during sleep. Proprietary algorithms convert muscular, respiratory and cardiac movements into useful biomarkers to monitor heart, respiration, stress levels, restlessness, and sleep.

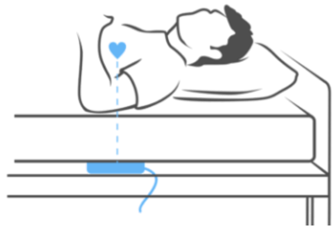

Fig. 2. Dozee in use

Methodology

The algorithm was validated for 13 full-night PSG recordings on 10 subjects. During each PSG recording, Dozee was also placed under the mattress. The raw BCG data was processed through our proposed algorithm to identify each respiration cycle and respiration rate for each 30s epoch. Respiration rate for each epoch as computed by the proposed algorithm was then compared against the same extracted from each of the nasal airflow signal, chest respiratory effort and abdomen respiratory effort. The nasal thermistor to monitor airflow is placed inside the nostrils of the subject and is susceptible to getting dislodged while the subject is asleep. The sleep expert conducting the study manually identified such instances and removed the faulty data for them. 732 epochs (6.3% of total data) of nasal thermistor data was dropped. Similarly, incorrect data for the respiratory efforts from both chest RIP belt and abdomen RIP belt was dropped when these belts got loose and didn't have enough tension to monitor the respiratory effort. 866 epochs (7.5% of total data) of respiratory effort data from chest RIP was dropped. Compared to these, in the pre-processing stage of the proposed algorithm, after pre-processing, 3130 epochs of BCG data (27.2% of total data) was not usable due to movements.

Results

The detection rate for the proposed algorithm varied from 47.4% to 87.7%, with an average of 72.8%. The detection rate for all the subjects was above the average barring one subject (Subject 3) who was extremely restless throughout the 3 recordings (detection rates of 47.4%, 50% and 53.8%). Without the 3 recordings for Subject 3, the average detection rate increases to 79.3% over roughly 8640 epochs of BCG data across 10 recordings. Figure 3 shows the respiration rate computed from the proposed algorithm for the whole night overlaid with each of the three validation sensors.

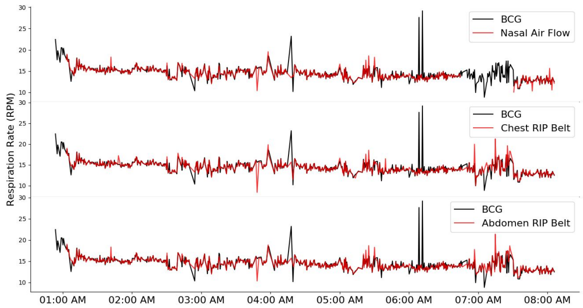

Figure 3: Whole night respiration rate comparison for Subject 2

Table 1: Overall results for the proposed algorithm

Subject	Time (h)	Detection Rate (%)	Accuracy w.r.t. Air Flow (%)	Accuracy w.r.t. Chest RIP belt (%)	Accuracy w.r.t. Abdomen RIP belt (%)
S1	7.2	74.2	95.06	94.81	94.34
S1	7.1	78.3	96.33	96.1	96.07
S2	7.3	80.4	98.45	98.14	98.35
S3	7.7	47.4	NA	93.88	94.21
S3	9	50.0	NA	94.04	94.61
S3	8	53.8	NA	94.29	94.55
S4	8.3	75.3	95.42	95.32	95.91
S5	8.8	79.4	97.3	96.7	97.26
S6	6.2	80.7	96.52	96.41	96.45
S7	6.8	75.9	92.31	95.14	91.28
S8	7.3	87.7	97.96	97.81	97.54
S9	6.5	82.1	96.63	96.63	96.83
S10	5.7	81.2	95.74	94.58	95.8
Total/ Avg.	**95.9**	**72.8**	**96.17**	**95.68**	**95.63**

Table 1 shows the recording duration, detection rate and accuracy of the proposed algorithm in comparison to all the 3 validation sensors. We are able to achieve an average accuracy of 96.17% as compared to the respiration rate from nasal airflow, 95.68% compared to respiratory effort from the chest RIP and 95.63% in comparison to the respiratory effort from the abdomen RIP. Further, when the respiration rate was computed with zero crossings in the BCG signal over the same dataset, the accuracy was 87.9% when compared to the respiration rate from chest respiratory effort signal, 87.68% when compared to respiration rate obtained from abdomen respiratory effort signal and 88.14% when compared to respiration rate obtained from nasal airflow signal.

Future Work

In this work we only focussed on detecting the respiration activity in an overnight setting. Further work and studies can help build systems for detecting apnea and hypopnea events, as well as other breathing abnormalities like Cheyne-Stokes, Biot's, etc. In fact, Subject 4 was diagnosed with sleep apnea based on the recording conducted in this study with an AHI of 25/hour. Figure 4 shows one apnea episode tagged in the recording.

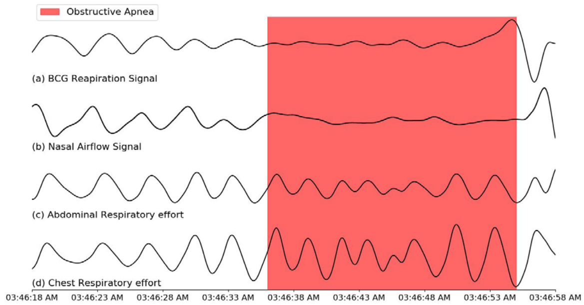

Figure 4: Apnea detection using BCG and proposed algorithm

Conclusions

A novel algorithm to identify respiration cycles and respiration rate in long-term BCG recordings with a high accuracy was presented. To overcome several challenges posed by the variable nature and quality of BCG data, the algorithm used unsupervised clustering methods focussed on the shapes of localized extremas in the respiration signal. Over a cumulative duration of about 96 hours, the proposed algorithm was able to achieve an accuracy of 96.17% for respiration rate for 30s epochs when compared to the respiration obtained from nasal airflow signal, 95.68% when compared to the respiration rate obtained from the chest respiratory effort signal and an accuracy of 95.63% for the respiration rate computed from abdominal respiratory effort signal.

References

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