Report :

# Method of estimation of heart rate and respiratory rate from the under resting state

## 1. Introduction

The heart has been considered the source of courage, emotion, and wisdom for centuries [1]. Essentially, it appeared that the heart could affect our awareness, perceptions and intelligence. Numerous studies have since shown that heart coherence is an optimal physiological state associated with increased cognitive function, self-regulatory capacity, emotional stability and resilience [3]. Heart rate variability (HRV), defined as changes in the beat-to-beat interval or in the instantaneous heart rate, is a widely used marker of autonomic activity and is a very crucial parameter for evaluation of human health, both physical and mental. Heart rate variability, or heart rhythms that stood out as the most dynamic and reflective indicator of ones´ emotional state and healthy well-being [3]

Resting Heart Rate (RHR) is one of the most important biomarkers indicating the health condition of a subject. RHR is the number of heart beats per minute while the subject is at rest. Usually, the lower the RHR, the higher the level of physical fitness and vice versa. High RHR could be an indicator of elevated probability of cardiac uncertainty. In some cases, a low RHR may result occasional giddiness and fatigue [3]. In this report, I only present a summary of the method to determine RHR based on seism cardiogram (SCG), without regard to complex mathematical or medical details. The conclusion will be an analysis of the similarities and differences in the conclusions of the articles.

## 2. Method

The estimation of HR and RR may be obtained by the spectrum analysis of SCG signal. SCG possesses the advantages of lower sensor cost and relatively less complicated measuring procedures.

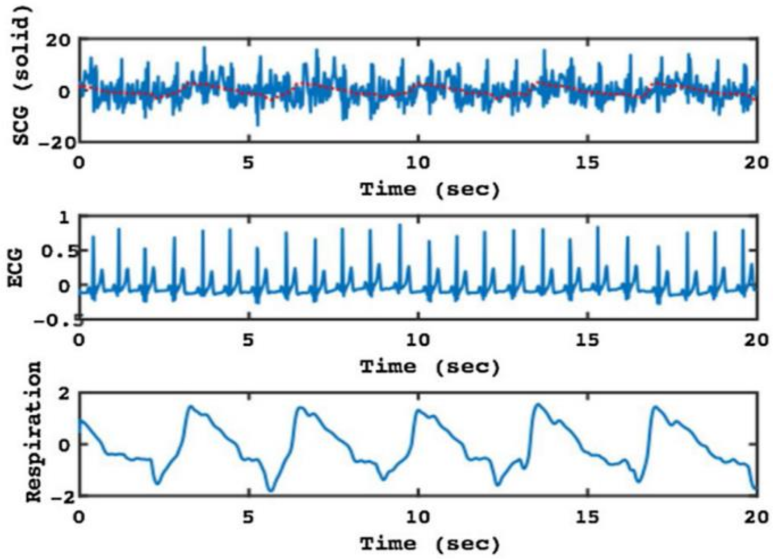



*Fig 1* *Time-domain patterns of twenty-second length recorded simultaneously for SCG, ECG and respiratory signal from the data*

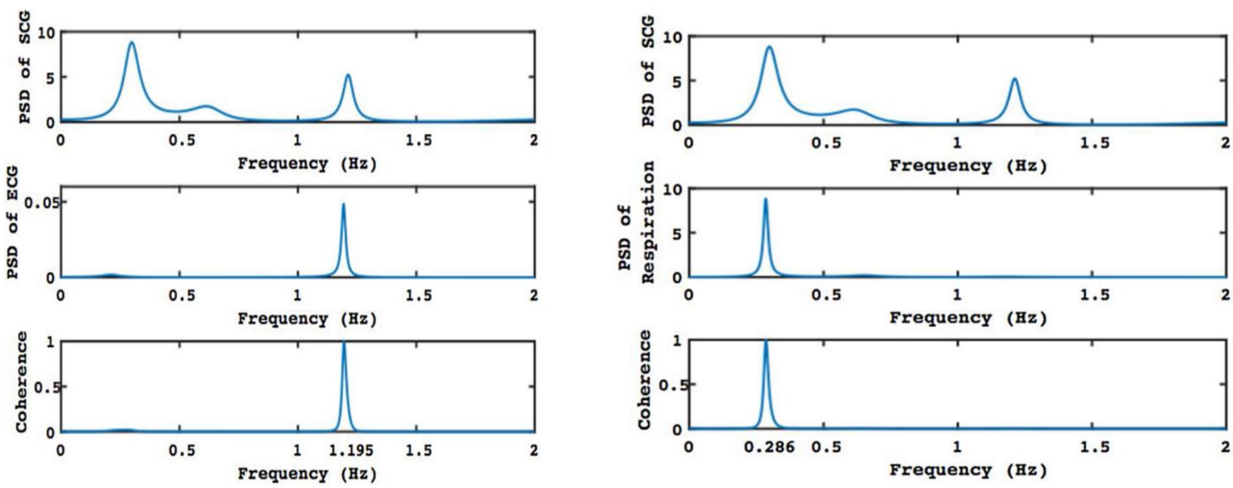



**Fig. 2 : (Left)** *The power spectral density (PSD)for SCG and ECG, and their coherence for the data Top : PSD of SCG ; middle : PSD of ECG; bottom: the coherence between the PSD of SCG and ECG*

**Fig. 3 : (Right)** *The PSD for SCG and respiratory signal, and their coherence for the data Top: PSD of SCG; middle: PSD of respiratory signal; bottom: the coherence between the PSD of SCG and respiratory signal*

The 2 and 3 figure above demonstrate the PSD (Power Central Density) for SCG (left) and ECG (electrocardiogram) (right). In both Figs. 2 and 3, autoregressive (AR) PSD by Burg's method [24] is adopted for the spectral estimation with an order of ten and a frequency resolution of 0.001 Hz.

As we can observe, the results shown in Figs. 2 and 3 also represent that it is high potential for the simultaneous monitoring of HR and RR by SCG because it contains both coherence frequency of both ECG and RR. For these reasons, SCG has been adopted in much research [ 1]

# 3. Proposed algorithm

The algorithm includes three parts. The first part is the utilization of wavelet for the decomposition of SCG signal to extract the components related to heartbeat and respiration. The second one is the so-called envelogram which is used for the decomposed SCG signal that is related to heartbeat component. The purpose of envelogram is to make the shape of extracted heartbeat component like that of ECG signal such that the computation of heartbeat frequency could be more precise. The last part is the scalogram by complex Morlet wavelet which is used to derive the frequencies of heartbeat and respiration and the values of HR and RR could then be computed.[1]

### 3.1 Wavelet decomposition

In this study, dyadic tree-structured wavelet decomposition is conducted to extract the information related to heartbeat and respiration from SCG signal. Among miscellaneous types of wavelets, the Daubechies wavelet is selected for the sake of its potential in the implementation of fast algorithm. Another reason is that the oscillating pattern of db6 wavelet is similar to the shape of heartbeat and respiration pattern buried in SCG under different scales.

In this paper, Daubechies 6 wavelet (db6) is adopted for the reason of the m smooth shape on wavelet function.

In dyadic tree-structured wavelet decomposition, the signal is firstly split into low- and high-frequency components in the first level. s. This first low-frequency subband component is then downsampled by a factor of 2 and again decomposed into low- and high-frequency subbands. The primary purpose of downsampling by factor of 2 is to make the data length unchanged before and after the decomposition process and this implies the computation results could be saved in the same memory space. This process can be continued to J levels as desired [1]

### 3.2 Envelogram

As the heartbeat component acquired from SCG (denoted as HB from SCG) contains high-frequency oscillation, the envelope detection is required to derive a precise estimate on the heartbeat frequency (Figure 4). The envelogram proposed by Sarkady et al. was adopted to obtain the envelope of HB from SCG in this study.

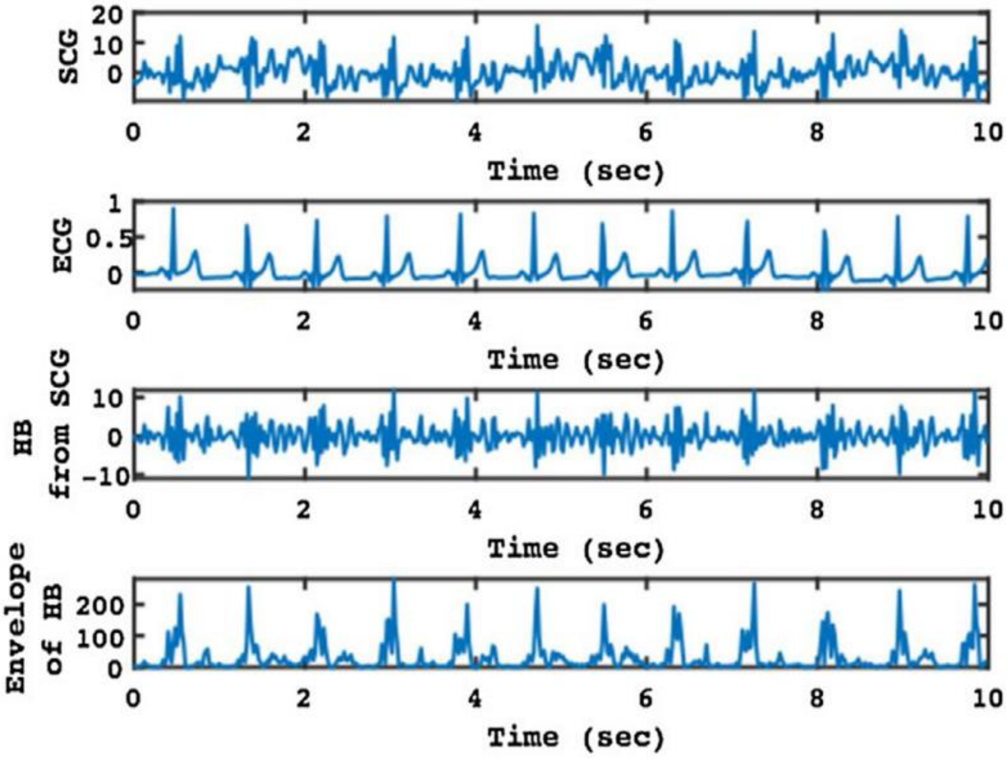



***Fig 4:*** *The patterns related to heartbeat (HB) information acquired from SCG with the synchronously recorded ECG for the data numbered b017. Top : SCG; the second from top: ECG; the second from bottom: the HB pattern acquired from SCG; bottom: the envelope of HB.*

By inspecting the pattern of SCG with respective to that of ECG (refer to the top and middle sub-figures of Fig. 1), it can be observed that SCG is an oscillated signal that contains higher harmonics (more than 7) of the fundamental heartbeat component. This implies that the frequency range of heartbeat component acquired from SCG (denoted as HB from SCG) covers at least seven times of the fundamental heartbeat frequency which can be acquired by the beat-to-beat interval from ECG signal.

The bottom subfigure of Fig. 4 demonstrates the envelope of HB from SCG, and it can be observed that the pattern becomes smoother and the timing for peaks is also synchronous to that of QRS complexes in ECG.

### 3.3 Scalogram

The spectrum must be estimated for the envelope of HB and for the respiratory component to derive the heartbeat frequency and the respiratory frequency such that HR and RR could be estimated respectively [1] Among various approaches for obtaining PSD, the scalogram by complex Morlet wavelet is adopted in this study. This approach can be implemented by FFT, and the PSD can also be conducted for the interested frequency range.

Mathematical transformations are complex and need not necessarily be mentioned here.

The heartbeat frequency and respiratory frequency are obtained from the local maxima of time-averaged PSD for the range 0.05∼0.73 and 0.75∼1.7 Hz, respectively. Multiplying these frequencies by 60, HR (in unit of beats per minute, bpm) and RR (in unit of respirations per minute, rpm) can then be derived.

As one purpose of this study is to propose the potential algorithm that is feasible to be implemented in the embedded system, the above algorithm is evaluated sequentially by a mode of segment-by-segment estimation. For the estimation of HR, a 10- second length of SCG (totally 500 points of data) is utilized for computation in the procedure each time. And then shift a certain time index with the same length of data for the next estimation of HR. Such procedure is repeated till the end of signal. The procedure for the estimation of RR is conducted in an equivalent way. As the cycle of respiration is longer than heartbeat, it is a length of 20 s (totally 1000 points of data) adopted for RR estimation each time. The shifted time index is 50 (that is an interval of 1 s) for the sequential HR and RR estimation. In addition, another goal of this study is to evaluate the feasibility of the proposed algorithm by comparison with the results acquired from the gold standard approach. To reduce the bias induced by different approaches, the values of HR (and RR) are also derived from the time-averaged PSD of ECG (and respiratory signal) by the same procedure mentioned above.

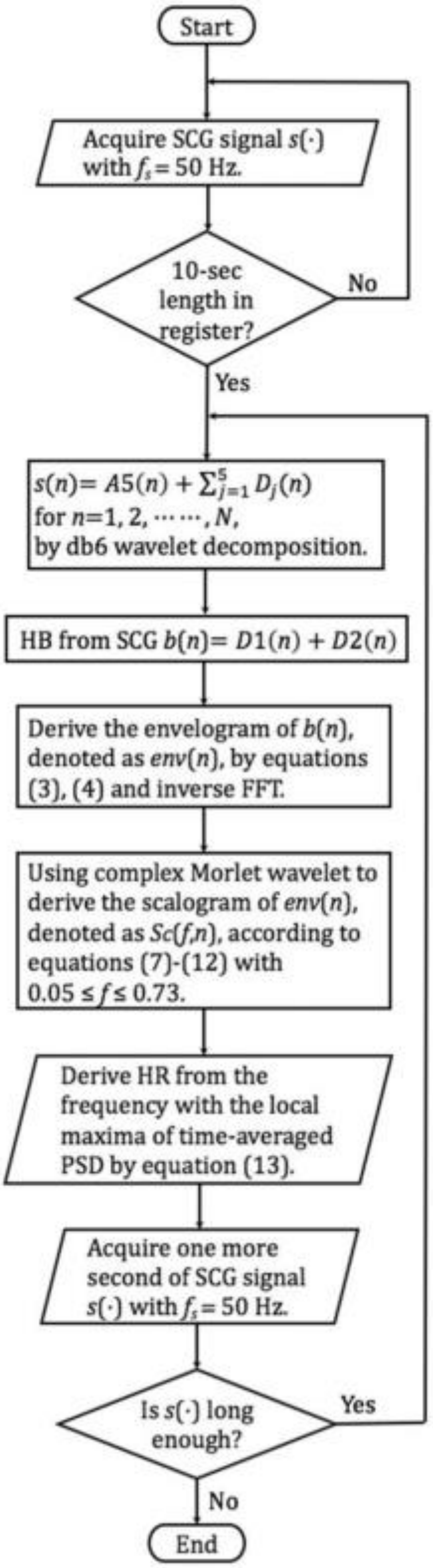



***Fig. 5.*** *Flowchart of the proposed algorithm.*

# 4. Statistical analysis

In this study, two kinds of statistical analysis (ICC [38,39] and Bland-Altman agreement analysis [40]) were adopted to evaluate the feasibility of HR and RR acquired from SCG via the comparison with those obtained by conventional standard approaches. ICC was originally proposed by R. Fisher to quantify the degree of relatedness for the case of paired measurements. In this study, the MATLAB code developed by A. Salarian [49] was utilized for the estimation of ICC and 95 % confident intervals (C.I.). Salarian's MATLAB code is developed according to the literature by McGraw and Wong

The lower and upper bounds of ICC were estimated under 0.05 level of significance. According to the guideline given by Koo and Li, a value of ICC below 0.50 represents poor agreement, 0.50 to 0.75 a moderate level, between 0.75 and 0.90 a good score, and it is excellent correlation for ICC above 0.90.

The method proposed by Bland and Altman [40] is adopted to serve this purpose in this paper. Let the mean value for the differences between two measurement data be denoted as md and the standard deviation for the differences as sd. A mean difference close to zero denotes a very high agreement between two measurements. The value of sd can be used for a reference to see the variation between paired measurement data. The limits of agreement (with 95 % C.I.) are also derived to see the scattering characteristics in the measurement. The limits of agreement are given by md−2·sd (lower) and md+2·sd (upper)

According to ANSI/AAMI EC13: 2000, the minimal allowable HR meter range is 30–200 bpm, with an allowable error of no greater than ±10 percent of the input rate or ±5 bpm. For this reason ±5 bpm is selected to be the specification for HR estimation in this study . These specific values (±5 bpm for HR and ±2 rpm for RR) are used as an index to see whether the limits of agreement are within the defined ranges.

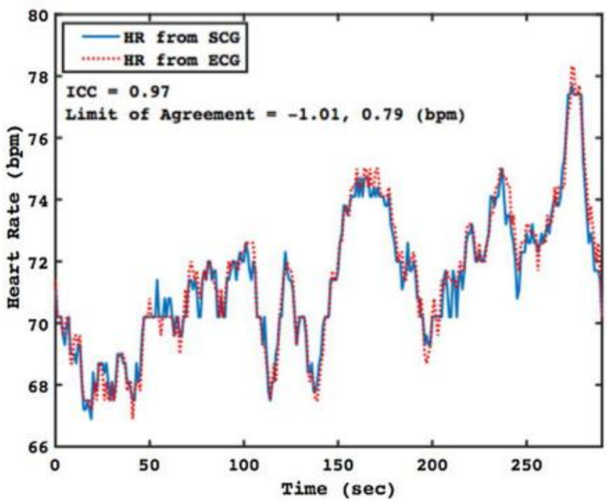



***Fig 6:** The traces of HR estimation acquired from SCG (solid line) and ECG (dotted line) for the data numbered b017. The ICC and the lower and upper limit of agreement are also shown in the figure.*

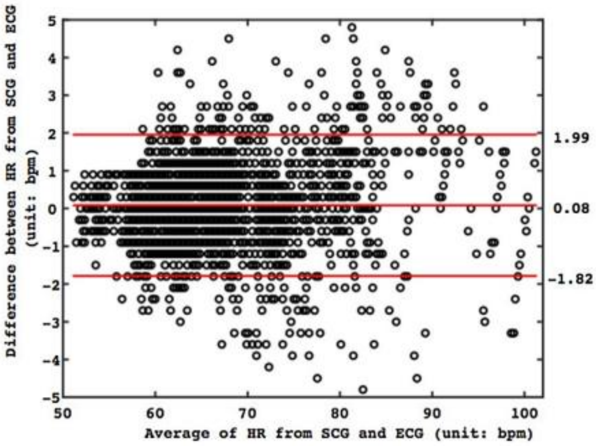
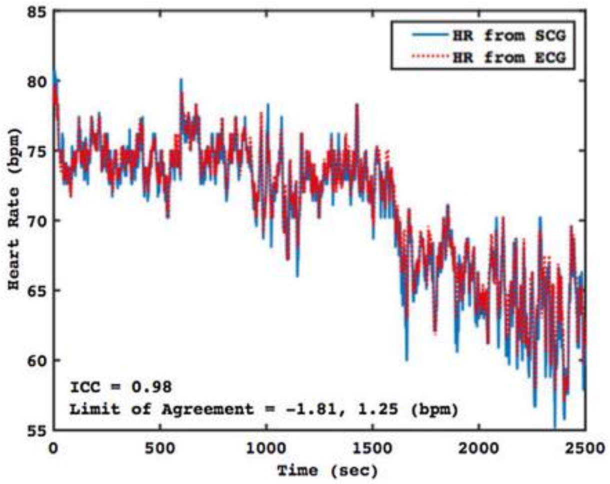



*Fig 7.* Bland-Altman plot for HR estimation acquired from SCG and from ECG. Center solid line: mean difference between the two approaches. Upper and lower solid lines: md ±2·sd (95 % limits of agreement).



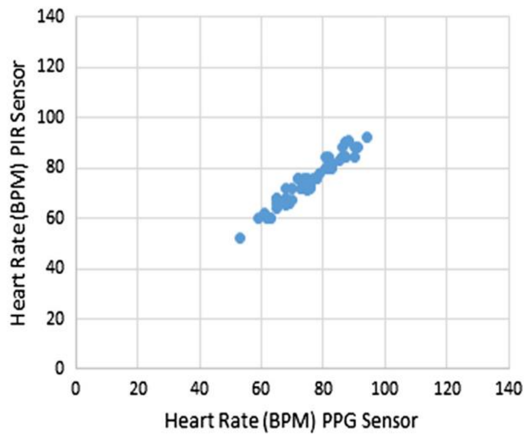




*Fig 8 and 9.* The long-term traces of HR estimation acquired from SCG (solid line) and ECG (dotted line (left) and scatter plot of the PIR sensor and the industry standard PPG sensor RHR values using PIR method (right)

According to figure 14, the estimation of HR using **SCG analysis gives results in the range 57 - 80 bpm** and gradually stabilize around 65; On the other hand, with the method determined **by pyroelectric infrared sensor, the result is in range 56 -96 bpm** [3]

In the report on PIR sensor, the cumulative distribution function (CDF) shows that 95% of values have deviation less than 4 beats per minute. Our results further show that the mean values of the 60 RHR (30 subjects, two measurements per subject) measurements using the PPG and the PIR sensors are 75.5 BPM (beats per minute) and 74.7 BPM (beats per minute), respectively.

# 5. Conclusion

This paper presents an algorithm to estimate HR and RR simultaneously from SCG. The proposed algorithm can be coded in an efficient way and is feasible to be implemented in an embedded system.

For HR estimation, the minimal ICC value is 0.80 and the 95 % C.I. is at least 0.75. These statistical values indicate good to excel lent correlation between the approaches by SCG and ECG, even the worst limits of agreement for HR estimation (which is −4.08 bpm, 2.43 bpm) satisfy the requirement of the maximal allowable error, ±5 bpm.

The above results indicate that HR can be estimated from SCG. At present time, the proposed algorithm is only focused on the usage under resting state. In clinical settings, the proposed technology may be potential for the patients under quiescent status such as those in vegetative state, in ICU, during the surgery or in sleep monitoring, and so on. Such approach can be incorporated in a unique embedded device to make the estimation of HR and RR in a simpler way than ever.

# 6. Reference


### [1] Estimation of heart rate and respiratory rate from the seismocardiogram under resting state

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### [3] Resting heart rate estimation using PIR sensors Hemanth Kapu

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## [4] Resting-state high-frequency heart rate variability is related to respiratory frequency in individuals with severe mental illness but not healthy control 2016

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