

## Heart Rate Variability analysis using a Seismocardiogram signal

J. Ramos-Castro, *Member, IEEE*, J. Moreno, H. Miranda-Vidal, M.A. García-González, Mireya Fernández-Chimeno, *Member, IEEE*, G. Rodas and Ll. Capdevila

**Abstract**— Seismocardiography is a simple and non invasive method of recording cardiac activity from the movements of the body caused by heart pumping. In this preliminary study we use a smartphone to record this acceleration and estimate the heart rate. We compare the heart rate variability parameters from the seismocardiogram and ECG reference signal. The results show a great similarity and are strongly influenced by the instability in the sampling frequency of the device. The differences between RR series are lower than 10 ms.

### I. INTRODUCTION

The analysis of heart rate variability (HRV) has been established during the past few decades as a valuable non-invasive tool to assess the status of the cardiovascular autonomic function and it has been frequently used in the analysis of physiological signals in different clinical and functional conditions [1, 2]. In sports medicine, HRV has been considered useful both to assess the current physical state [3] and to identify anaerobic threshold in athletes [3]. In terms of time and frequency domain analysis, it has been proven useful for evaluating the adaptation of the autonomic nervous system to different loads of physical effort involved in both training and competition. Over recent years, there has been interest into using unobtrusive methods to monitoring heart rate without electrodes. The seismocardiogram (SCG) is the study of body vibrations induced by the heart beat. This term was popularized in the 90s by Salerno and Zanetti [4]. However, the recording of body movements associated with cardiac activity is much older [5]. The ballistocardiogram (BCG) records the movements of the body as an effect of the blood mass ejected by the heart with

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J. Ramos-Castro is with the Group of Biomedical and Electronic Instrumentation of the Department of Electronic Engineering of the Universitat Politècnica de Catalunya (UPC), Barcelona, 08034 Spain (phone: +34 93 401 67 63; Fax: +34 93 401 67 56 e-mail: [jramos@eel.upc.edu](mailto:jramos@eel.upc.edu)).

J. Moreno is with the Laboratory of Sport Psychology, Universitat Autònoma de Barcelona, Bellaterra,

Ll. Capdevila is with the Laboratory of Sport Psychology, Universitat Autònoma de Barcelona, Bellaterra,

H. Miranda-Vidal is with the Group of Biomedical and Electronic Instrumentation of the Department of Electronic Engineering of the Universitat Politècnica de Catalunya (UPC), Barcelona, 08034 Spain

M. A. García-González is with the Group of Biomedical and Electronic Instrumentation of the Department of Electronic Engineering of the Universitat Politècnica de Catalunya (UPC), Barcelona, 08034 Spain

M. Fernández-Chimeno is with the Group of Biomedical and Electronic Instrumentation of the Department of Electronic Engineering of the Universitat Politècnica de Catalunya (UPC), Barcelona, 08034 Spain

G. Rodas is with F. C. Barcelona, Medical Services F. C. Barcelona, Spain.

each contraction. Usually the BCG is recorded in a supine position over a mobile platform that moves with each beat. The SCG usually records the sternal acceleration and has higher frequency content than BCG. Recently, the interest in SCG has been revitalized by the availability of low cost MEMS sensors and portable devices that include them (smartphones, PDA, etc.)

Some authors have proposed the SCG signal to study changes in the cardiovascular system [6,7,8]. To the authors knowledge the SCG has not been used to analyze HRV so far. Friedrich et al [9] have estimated the RR intervals from the ballistocardiogram and compared them with the ECG RR intervals.

Our goal is to compare the HRV indexes estimated from the SCG signal with the ones calculated using the RR series obtained from the ECG. The SCG will be acquired with a smartphone. There are multiple choices in the market. However, very few of them meet the required specifications (low noise and a sampling frequency in the order of 100 Hz). We have tested several of them and at the end the iPhone 4 and iPhone 4s (Apple Inc) were the only available to meet the requirements. The RMS noise of the accelerometer is  $0.2 \cdot 10^{-3} \text{ m/s}^2$  approximately for each axis and the peak to peak amplitude of the SCG signal ranges from  $1 \cdot 10^{-3} \text{ m/s}^2$  to  $10 \cdot 10^{-3} \text{ m/s}^2$ . The signal bandwidth is below 50 Hz in most cases due to the mechanical low pass filter due to the mass of the phone.

### II. METHODS

We recorded the data in two groups of 6 subjects each. In all cases the subject was in supine position and the recording took 5 minutes. The first group was to compare the RR series from the SCG and ECG signals in the best conditions. We acquired simultaneously both of them with a sampling frequency of 1 kHz. The second group recordings were taken in the Futbol Club Barcelona premises with basket players from the junior team. In this case the RR was recorded with a commercial device and the SCG was recorded with an iPhone 4.

#### A. Data Acquisition

In the first group the ECG, chest acceleration and respiration were recorded. The ECG circuit is based on AD627 instrumentation amplifier and an isolation amplifier ISO124 to avoid electrical hazards. The total gain is approximately 2000. The signal is high pass filtered at 0.5 Hz with a first order filter and low pass filtered to 100 Hz with a second order Butterworth filter. The chest acceleration was measured with a triaxial accelerometer (ADX1330, Analog Devices) with a low pass frequency of

100 Hz. The respiration was measured with an inductive band and a chest inductive interface from SleepSense. The respiratory signal is further amplified with a gain of 200 with an instrumentation amplifier. The three signals were acquired with a data acquisition board (DAQPad6016, National Instruments) with a range of  $\pm 5V$  and 16bit resolution and sampling frequency of 1 kHz.

In the second group the ECG was recorded with a commercial system, Omega Wave Sport System (OWS; Eugene, OR) and the RR intervals, calculated by the system software, exported to a file. The chest acceleration was acquired simultaneously with the internal accelerometer of a smartphone (iPhone 4, Apple Inc). We developed an application that records the raw data to an internal file and sends it by e-mail after stopping the recording. The sampling frequency was programmed to 100 Hz, the maximum value the iOS APIs supports.

### B. Signal Processing

In the first group the ECG signal was used to estimate the RR. The raw R peak locations were calculated with a Hamilton-Tompkins QRS detector [10]. After this, a cross-correlation procedure was used in order to improve the QRS complex locations by using the first QRS of each ECG as a template. Finally, the RR time series were obtained by digital differentiation of the R time series.

The z axis of the accelerometer data (normal component to the chest) was used to detect the heartbeat. The acceleration signal was filtered with 4<sup>th</sup> order Butterworth band pass filter with cutoff frequencies of 6 Hz and 25 Hz respectively. After filtering, the signal energy was estimated and compared with a threshold. The algorithm finds the maximum amplitude and position of the signal energy between two consecutive crossings with different slopes. With the position of the maximum the algorithm searches for a minimum in the acceleration signal that corresponds to the isovolumetric contraction, (Fig. 1).

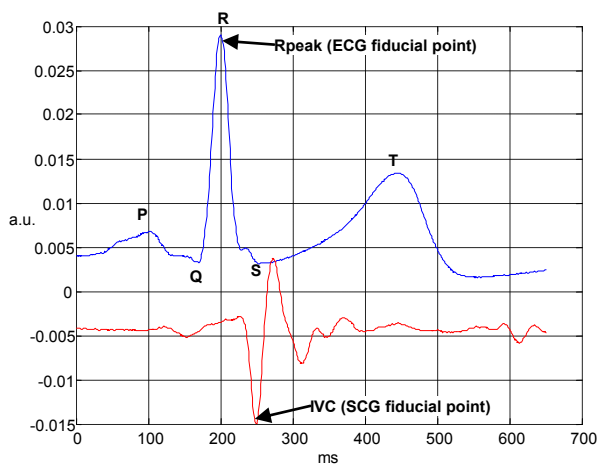


Figure 1. A cycle of ECG (top) and SCG (bottom) signals

In the second group the RR data was imported directly from the Omega Wave System. The accelerometer data recorded with the smartphone was resampled to 1 kHz with

cubic spline interpolation to increase the temporal resolution. The algorithm for the heartbeat detection was the same as in the first group.

After obtaining the RR series from the ECG and accelerometer, signal artifacts were identified and corrected automatically prior to analysis. In short, if the change from one R-R interval to the next exceeds the interquartile range of the differentiated R-R time series ten-fold then it is decided that an artifact is present. The artifact is then classified as a missing beat, extra beat or ectopic like beat. For an extra beat, the corrected R-R interval is obtained by adding as many consecutive R-R intervals to obtain a value close to the mean of the previous ten R-R intervals. A missing beat is split in as many R-R intervals with equal value as needed to be close to the mean of the previous ten R-R intervals. An ectopic like beat is substituted with two equal R-R intervals corresponding to the mean of the two R-R intervals involved in the ectopic like beat (Fig. 2).

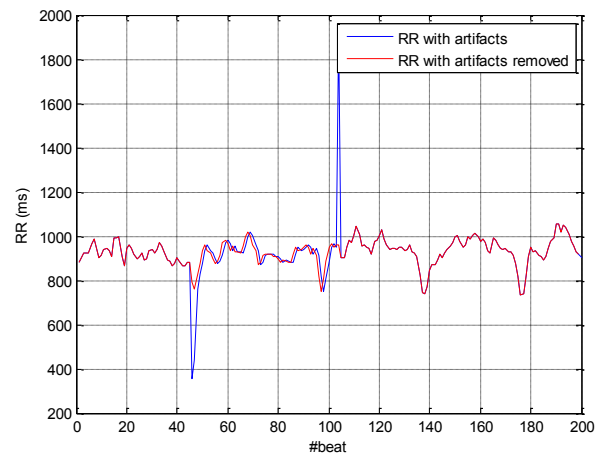


Figure 2. RR artifact removal

The RR intervals from the accelerometer and OWS were synchronized for further analysis using temporal “event” markers. Then fine alignment of the series was carried out using the cross-correlation function between both series and visual inspection.

### C. HRV Time and Frequency Domain Analysis

Time domain analysis was done in accordance with the current recommendations [11]. The mean NN interval, the standard deviation of all NN intervals (SDNN) and the root mean square of differences (RMSSD) of successive NN intervals were calculated. For frequency domain analysis, all RR series were re-sampled at 3 Hz using a cubic spline prior to the HRV analysis. The power spectrum of the re-sampled time series was estimated using the Fast Fourier Transform after removing the mean of the time series and multiplying the time series by a Hann window. The power of the very low frequency band (PVLf) was estimated by integrating the power spectrum for frequencies lower than 0.04 Hz. Accordingly, the power of the low frequency band (PLF) was computed in the band 0.04 – 0.15 Hz and the power of the high frequency band (PHF) was computed in the band

0.15 – 0.4 Hz. Moreover, the LF/HF was computed as the ratio PLF / PHF. The calculation of these indices is consistent with the recommendations of the Task Force of the European Society of Cardiology and the North American Society of Pacing and Electrophysiology [11].

### III. RESULTS

In the first group the RR series from the ECG and SCG signals were compared for each subject. The mean RMS error between both RR series was lower than 3 ms and was comparable to results achieved in previous works when comparing two commercial devices based on the ECG [12]. The position of the accelerometer was important to get good results. We found empirically that sternum is the best place. Fig. 3 shows the comparison between the ECG and SCG RR series. The lower trace is the difference in the estimated RR intervals. It shows an absolute error lower than 1% of the mean RR value.

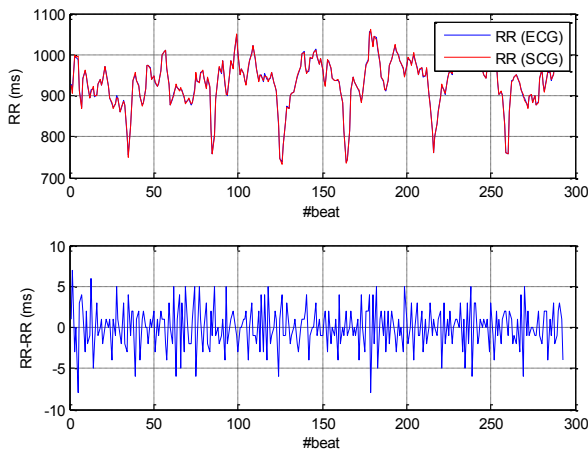


Figure 3. RR series obtained from the ECG and SCG signals in the same subject (top trace), Difference between both series (bottom trace)

The second step was to compare the OWS RR series and the RR series from the accelerometer recorded with the smartphone. Fig. 4 shows an example of the good agreement between both signals. However, the differences between both series are higher (bottom trace). The RMS error for the best case was 5.1 ms. The origin of this discrepancy with the previous group is mainly due to the uncertainty in the timing of the sampling frequency of the accelerometer data in the smartphone. The sampling period is controlled in the phone operating system by events, it is not a real time system. The number of samples in a second was fluctuating between 98 and 100.

The HRV parameters were calculated for both series in the second group and the mean and standard deviation was calculated for each parameter and in each case (ECG and SCG, Table I). The discrepancies are lower for temporal parameters. The frequency domain indexes are more sensitive to the noise introduced by the jitter in the sampling frequency. The PLF and PHF have the lower correlation and statistical significance (Table II).

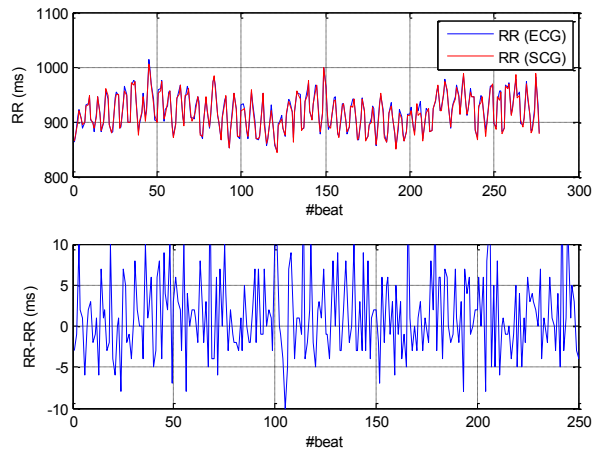


Figure 4. RR series from ECG and SCG recorded with the OWS and iPhone respectively (top trace). Difference between both series (bottom trace)

TABLE I. MEAN AND STANDARD DEVIATION FOR THE HRV TIME AND FREQUENCY INDEXES, FOR THE SECOND GROUP

| Parameter               | OWS    |        | iPhone |        |
|-------------------------|--------|--------|--------|--------|
|                         | mean   | std    | mean   | std    |
| RR <sub>mean</sub> (ms) | 1104.8 | 159.9  | 1097.0 | 151.3  |
| SDNN (ms)               | 109.3  | 50.2   | 127.3  | 64.5   |
| RMSSD (ms)              | 131.7  | 70.3   | 155.6  | 89.1   |
| Pnn50 (%)               | 59.6   | 24.8   | 59.9   | 23.9   |
| PVLF (ms <sup>2</sup> ) | 1653.1 | 1330.7 | 1920.4 | 1435.4 |
| PLF (ms <sup>2</sup> )  | 1515.6 | 1160.7 | 2117.3 | 2018.4 |
| PHF (ms <sup>2</sup> )  | 7211.6 | 5800.1 | 8615.3 | 6217.9 |
| LF/HF                   | 0.2    | 0.1    | 0.2    | 0.1    |
| Duration(s)             | 259.6  | 14.8   | 258.1  | 16.5   |

TABLE II. PEARSON'S CORRELATION COEFFICIENT FOR HRV PARAMETERS FORM OWS AND IPHONE RR SERIES TABLE TYPE STYLES.

| HRV param. | r       |
|------------|---------|
| RRmean     | .999*** |
| SDNN       | .972*** |
| RMSSD      | .929**  |
| Pnn50      | .994*** |
| PVLF       | .987*** |
| PLF        | .782*   |
| PHF        | .976*** |
| LF/HF      | .684    |

\*\*\* p<.001 \*\* p<.005 \* p<.05

#### IV. CONCLUSION

In this paper we have presented the feasibility to obtain a good estimation of the common HRV parameters from a SCG signal. The time indexes are more robust to errors produced by a misdetection or timing uncertainty.

There are already mobile phones (such as EPI Life) on the market that measure actual ECG for further analysis. However, the opportunity to record a SCG signal with a conventional smartphone and process the data inside the device broadens the scope of future medical applications. The subject has to remain motionless to reduce the artifacts in the SCG signal. We are working in the development of more robust detectors and signal quality estimators. Another limitation with some smartphones is the noise in the acceleration sensor. The improvements in the MEMS technology will solve it.

The increasing computing power in the smartphones on the market will allow implementing the entire signal processing inside the device in a near future.

#### REFERENCES

- [1] N. Montano, A. Porta, C. Cogliati, G. Costantino, E. Tobaldini, K.R. Casali, F. Iellamo "Heart rate variability explored in the frequency domain: A tool to investigate the link between heart and behavior" *Neurosci Biobehav Rev.*; 33(2):71-80. 2009
- [2] J. Pumplra, K. Howorka, D. Groves, M. Chester, J. Nolan. "Functional assessment of heart rate variability: physiological basis and practical applications." *Int J Cardiol.*; 84(1):1-14. 2002
- [3] Buchheit M, Gindre C. "Cardiac parasympathetic regulation: respective associations with cardiorespiratory fitness and training load." *Am J Physiol Heart Circ Physiol*; 291 : 451 – 458, 2006
- [4] J.M. Zanetti, D.M. Salerno, "Seismocardiography: a technique for recording precordial acceleration" *Computer-Based Medical Systems, 1991. Proceedings of the Fourth Annual IEEE Symposium*, pp. 4 – 9, 1991
- [5] I. Starr and F.C Wood, "Twenty-Year Studies with the Ballistocardiograph: The Relation between the Amplitude of the First Record of "Healthy" Adults and Eventual Mortality and Morbidity from Heart Disease," *Circulation*, vol. 23, no. May, pp 714-732, 1961
- [6] B. Ngai, K. Tavakolian, A. Akhbardeh, A.P. Blaber, B. Kaminska, A. Noordergraaf. "Comparative analysis of seismocardiogram waves with the ultra-low frequency ballistocardiogram." *Conf Proc IEEE Eng Med Biol Soc.* 2009;2009:2851-4.
- [7] P. Castiglioni, P. Meriggi, F. Rizzo, E. Vaini, A. Faini, G. Parati, G. Merati, M. Di Rienzo "Cardiac sounds from a wearable device for sternal seismocardiography" *Conf Proc IEEE Eng Med Biol Soc.* 2011;2011:4283-6.
- [8] C. Bruser, K. Stadhanner, A. Brauers, S. Leonhardt, "Applying machine learning to detect individual heart beats in ballistocardiograms." *Conf Proc IEEE Eng Med Biol Soc.* 2010;2010:1926-9.
- [9] D. Friedrich, X.L. Aubert, H. Fuhr, A. Brauers. "Heart rate estimation on a beat-to-beat basis via ballistocardiography - a hybrid approach." *Conf Proc IEEE Eng Med Biol Soc.* 2010;2010:4048-51.
- [10] P. S. Hamilton and W. J. Tompkins, "Quantitative Investigation of QRS Detection Rules Using the MIT/BIH Arrhythmia Database," *IEEE Transactions on Biomedical Engineering*, vol. 33, pp. 1157–1165, 1986
- [11] Task Force of the European Society of Cardiology and the North American Society of Pacing and Electrophysiology. Heart-rate variability: standards of measurement, physiological interpretation and clinical use. *Circulation*; 93 : 1043 – 1065, 1996
- [12] E. Parrado, M.A. García, J. Ramos, J.C Cervantes, G. Rodas, L. Capdevila. "Comparison of Omega Wave System and Polar S810i to detect R-R intervals at rest." *Int J Sports Med.* May;31(5):336-41, 2010