2021 43rd Annual International Conference of the
IEEE Engineering in Medicine & Biology Society (EMBC)
Oct 31 - Nov 4, 2021. Virtual Conference

# Simultaneous Estimation of Instantaneous Heart and Respiratory Rates using Image Photoplethysmography on a Single Smartphone

Eduardo Hernandez-de la Cruz, Sonia Charleston-Villalobos, Tomas Aljama-Corrales, Bersain Reyes

***Abstract*— Heart rate (HR) and respiratory rate (RR) are very important physiological variables useful to evaluate the cardiorespiratory system. At present, there is a great interest by the general population in knowing their health status, quickly and easily. Accordingly, several approaches have been proposed to achieve that goal. In this study, the simultaneous estimation of the instantaneous HR and RR values was achieved by the image photoplethysmography (iPPG) technique, in the contact mode directly implemented in a smartphone. iPPG results were compared with those obtained using specialized biomedical sensors such as the electrocardiogram and the respiratory effort band. Performance evaluation included three different respiratory maneuvers in five healthy volunteers. The absolute mean error for instantaneous HR and RR estimations reached 0.94 ± 0.28 beats per minute and 0.40 ± 0.11 breaths per minute, respectively. The mean correlation index was 0.69 ± 0.14 between the iPPG-derived respiratory signal and the respiratory effort reference signal.**

***Clinical Relevance*— These results appear to indicate that the contact iPPG method implemented directly on the smartphone is a good option, accessible to the common population to estimate the instantaneous HR and RR values outside specialized clinical environments, e.g., in the point-of-contact office.**

***Keywords*—***iPPG, heart rate**,** respiratory rate, smartphone.*

## I. Introduction

There are different methods to obtain heart rate (HR) and respiratory rate (RR) values, ranging from simple observation and auscultation with stethoscopes, to those using biomedical devices, e.g., electrocardiography (ECG) to estimate HR or capnography to estimate RR [1]. In the case of the latter, although individual advantages, a common disadvantage of these devices resides in not being easily applied outside of clinical and research settings for everyday use by the general population, mainly because their high costs, discomfort, and specialized use.

Nowadays, technological advances have allowed the smartphones to perform complex computational processes, in such a way that there are mobile applications (apps) available in the market that innovatively estimate the average HR and RR. However, their instantaneous values are not provided. In such case, image photoplethysmography (iPPG) technique [2] may be used as an alternative to more established photoplethysmography (PPG). The iPPG technique basically consists in acquiring video signals from a region of the body to analyze the absorption and backscattering of light by living tissue. There are two modes of iPPG: 1) contact iPPG, where the lens of the video camera and the LED are located on the same region of the body, mainly on the index finger, 2) remote or non-contact iPPG, where the video camera is located at a distance from the subject to detect color changes in a region of the body, e.g. face, due to blood flow [2], [3].

It is known that ECG and iPPG signals are frequency modulated by the respiratory signal, which allows the estimation of average RR from the analysis of the HR or the pulse rate (PR) time series [4], [5]. The fluctuation in the cardiac cycle synchronized with respiration is known as respiratory sinus arrhythmia (RSA), which is described as a cardiac acceleration during inspiration and cardiac deceleration during expiration [6]. Taking advantage of RSA, various efforts have estimated the average values of HR and RR from iPPG signals [1]–[3]. However, most of these efforts do not handle the simultaneous estimation of the HR and RR time series, e.g., the one using two cameras of a smartphone and offline estimation [2]. Consequently, knowing the dominant frequency of HR and RR in any time instant was not possible, neither to observe the temporal dynamics of these two parameters during a given experimental maneuver.

This work focuses on the application of contact mode iPPG directly on a smartphone device to estimate both, the instantaneous HR and instantaneous RR values. To this end, the smartphone device was used to collect iPPG signals, via an Android app developed by our research group, from healthy volunteers performing different experimental breathing maneuvers. The smartphone-based estimation results were quantified in terms of performance indices and considering the information from specialized biomedical sensors as reference.

## II. Materials and Methods

### *A. Data Acquisition and Experimental Maneuvers*

In this study, data was acquired from five ($N = 5$) healthy volunteers with ages ranging from 22 to 27 years (mean ± standard deviation) 23.8 ± 1.64 years, weight 73.2 ± 11.96

*Research partially supported by a CONACyT-Mexico graduate scholarship (grant number: 726320).

E. Hernandez-de la Cruz was a graduate student in the master's degree program of Electrical Engineering at the Faculty of Science, Universidad Autónoma de San Luis Potosí, San Luis Potosi, 78295, Mexico (e-mail: A302346@alumnos.uaslp.mx).

S. Charleston-Villalobos and T. Aljama-Corrales are with the Electrical Engineering Department, Universidad Autónoma Metropolitana - Iztapalapa, Mexico City, 09340, Mexico (e-mail: schv@xanum.uam.mx; alja@xanum.uam.mx).

B. Reyes is with the Faculty of Science, Universidad Autonoma de San Luis Potosi, San Luis Potosi, 78295, Mexico (corresponding author phone: +52-1-444-8262300 ext. 5676; e-mail: bersain.reyes@uaslp.mx).

kg and height 1.68 $\pm$ 0.11 m, who were previously informed about the acquisition protocol and provided their informed consent to participate in the study according to Helsinki Declaration. The protocol involved the simultaneous acquisition of the iPPG signals, directly from a smartphone, and ECG and respiratory effort signals, which were considered as a reference for the estimation of HR and RR time series, respectively. The BiosignalPlux wireless device (PLUX Wireless Biosignal S.A., Lisboa, Portugal) was used to acquire reference signals at a sampling rate of 1000 Hz. The recording of ECG lead I was done via regular adhesive Ag/AgCl disposable electrodes. The respiratory effort signal was obtained from a piezoelectric band sensor placed around the chest of the volunteer. On the other hand, an app was developed with the IDE *Processing for Android* to extract the iPPG signals, from the videos of the rear camera of the smartphone at 30 frames-per-second (fps) and compute their respective HR and RR time series. The smartphone-based results were saved in the internal memory of the device in .csv format. A Huawei smartphone model P9 Lite 2017 with 3 GB RAM memory and a 64-bit octa-core processor at 2.1 GHz was used for all recordings.

Each volunteer was asked to perform three experimental maneuvers, with the purpose of modifying their heart and respiratory rates, as described below.

- *Spontaneous breathing*, in which the volunteer breathed naturally in a resting condition for three minutes.
- *After exercising*, where the volunteer was asked to perform squats for 30 s prior to data acquisition, which lasted three minutes.
- *Sudden changes in metronome breathing*, with the help of an audiovisual metronome, the volunteers breathed at a fixed rate for one minute and then suddenly switched their breathing to another fixed rate. Each one followed the sequence 6, 18, 24, 12 and 6 breaths-per-minute (bpm), equivalent to 0.1, 0.3, 0.4, 0.2, and 0.1 Hz, respectively. This maneuver lasted five minutes.

The last two maneuvers were intended to evaluate the ability of our app to estimate HR and RR with a significant temporal variation, i.e., the ability to track these parameters. In each maneuver, the volunteers remained seated and with their left arms resting on a flat surface. They were asked to hold the smartphone in such a way that their left index finger covered both the camera lens and the flash, avoiding movements during the recording, as shown in Fig. 1. Although the developed app allows obtaining all the temporal series of the iPPG, HR and RR, the acquired data was processed offline in MATLAB (R2017a, The MathWorks, MA, United States) for comparison purposes with reference signals.

## B. iPPG Signal Extraction

The channel averaging algorithm was implemented in the app used for the acquisition [5]. This algorithm allows iPPG signals to be extracted immediately after reading and converting a video frame to RGB format, i.e., it takes as input the sequence of frames where the $n$-th frame consists of the pixels, with coordinates $[\mathrm{i},\mathrm{j}]$, given by a vector $\boldsymbol{c}_{i,j}[n] = [r_{i,j}[n], g_{i,j}[n], b_{i,j}[n]]^{\mathrm{T}}$ where $r_{i,j}[n]$, $g_{i,j}[n]$ and $b_{i,j}[n]$ are the red, green y blue channels, respectively [7]. The information from the green channel (G) was used to extract the iPPG signals since it has been reported to be less susceptible to motion noise and to present greater uniformity in different mobile devices [1], [3]. The first step of the algorithm consists of selecting the region of interest (ROI) as the pixels that mainly contain pulse information, and calculating the average of the color intensities using


Figure 1. Mobile app developed for smartphones with Android operating system. Example of iPPG signal acquisition.

$$iPPG[n] = \frac{1}{|ROI|} \sum_{[i,j] \in ROI} g_{i,j}[n] \tag{1}$$

where $|ROI|$ denotes the number of pixels in the iPPG signal $iPPG[n]$. ROI averaging is known to reduce noise and preserve iPPG signal morphology. In this work, a ROI close to the camera flash of 50 x 50 pixels was considered, according to our pilot tests and information from a previous study [1].

## C. Estimation of HR and RR Time Series

Before estimating the HR and PR time series, the iPPG and reference signals were conditioned as described below [5]. First, the iPPG signals were resampled to the same sampling frequency of the reference signals, i.e., 1000 Hz, using cubic *spline* interpolation. Then, the resampled signals were digitally filtered with 4th order Butterworth IIR bandpass filters, with passbands of 0.05-40 Hz for ECG signals, 0.05-1.50 Hz for respiratory efforts, and 0.3-5.0 Hz for iPPG signals. Then, R-peaks detection in ECG signals was done via BioSig library [8], while the local maxima in iPPG signals were detected via a custom algorithm developed by our research team.

To estimate the instantaneous HR from the iPPG signals, the time intervals between the consecutive local maxima were interpolated at 4 Hz using cubic *splines* [2]. Some of the main problems of iPPG signals are slight baseline oscillations, the presence of sudden changes by movements of the subject or the effect of variations in the intensity of ambient light. To ensure a correct estimation of the instantaneous values of HR, and consequently of RR, an algorithm for automatic correction of local maximums was implemented as recommended in [5]. A similar procedure was applied to R-peaks to obtain ECG-based HR time series, considered as reference. It is worth mentioning that due to different starting times, the ECG-based and iPPG-based HR time series were automatically aligned using a cross-correlation approach.

Finally, the instantaneous RR values were estimated using a time-frequency representation by taking advantage of the frequency modulation of the ECG and iPPG signals, and consequently in the HR and PR series, respectively, as an effect of the RSA [6]. To this end, we employed the spectrogram (SP) to determine the time instants where a given frequency component was present in the cardiac signals. The SP for a signal of interest $s[n]$, representing HR or PR in our case, was computed accordingly to

$$SP[n,\omega] = \left| \sum_{n=0}^{L-1} s[\,m]h[m-n]e^{-j\omega m} \right|^2 \qquad (2)$$

where $h[n]$ denotes the analysis window of length $L$, $m$ denotes the current time, and $n$ and $\omega$ represent the variables of discrete time and digital angular frequency, respectively. The SP is known to exhibit a compromise in temporal and spectral resolution, for a given window length. In this work, a 12 s *Hamming* window was used, with 10 s overlapping between adjacent windows, based on previous findings of the working group [5]. Since only respiratory rate estimates in a normal range were considered, an SP sub-matrix was considered in the frequency range of $f_{Resp} \in [0\,,1]$ Hz. Then, the RR series was estimated by finding the maximum value in each instant of time (columns) of the SP sub-matrix, for each PR and HR time series. An example of the computed SP and extracted maxima value (instantaneous RR) obtained directly in the smartphone app is shown in Fig. 2.

### D. *Performance Indices*

The similarity between the iPPG-based HR and RR time series and their counterparts derived from the references, was analyzed with three performance indices: 1) the correlation coefficient ($\rho$), 2) the relative error, and 3) the mean absolute error (MAE). In addition, the agreement between the measures was studied via Bland-Altman analysis. Finally, paired $t$-test was used to analyze statistical differences, considering a value of $p < 0.05$ as statistically significant.

## III. Results

An example of the time series of HR, obtained from ECG, and PR, obtained from the smartphone, is shown in Fig. 3 for a maneuver after physical activity. It can be seen that both signals exhibit big oscillations around a high HR value, reaching even 90 beats-per-minute (BPM), and that this keeps decreasing until reaching a resting frequency of around 60 BPM after one minute. The high oscillations around the trend HR were due to the big respiratory efforts to recover after exercising. Table I summarize the results obtained for the instantaneous estimation of HR for each respiratory

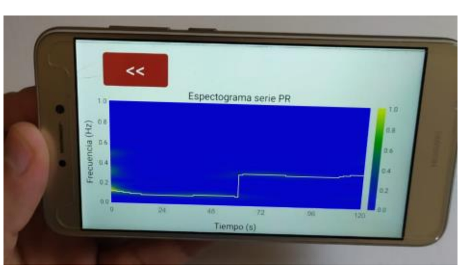


Figure 2. Example of spectrogram and instantaneous RR estimation obtained directly in the developed Android app, for the first two minutes of a maneuver with sudden changes in breathing.

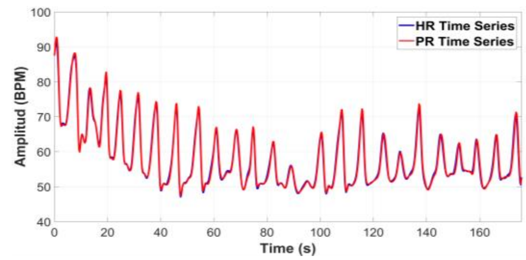


Figure 3. Example of computed time series for HR (from ECG) and PR (from iPPG, smartphone) corresponding to a respiratory maneuver after physical activity.

maneuver. In general, the similarity between the HR and PR series was very high (coefficient $\rho$ close to 1), the errors reached a very low value, and the limits of agreement (LoA) were narrow, e.g., in the maneuver after physical activity, an MAE of $0.97 \pm 0.52$ BPM was found, and a bias of 0.01 BPM with LoA of -2.91 and 2.91 BPM. For the instantaneous estimation of HR, no statistically significant bias was found for any maneuver.

Regarding the instantaneous estimation of RR, TableII summarizes the results obtained for each respiratory maneuver, where the time series of ECG-derived RR and iPPG-derived RR (smartphone), are compared to RR computed from respiratory effort signal. In general, similar results were obtained between both RR-derived estimates. For example, for the spontaneous maneuver, an MAE of $0.53 \pm 0.25$ bpm and LoA of -2.45 and 2.03 bpm were obtained from ECG, while from the iPPG a MAE of $0.51 \pm 0.21$ bpm and LoA of -2.18 and 1.91 bpm, were found. In this maneuver, correlation coefficients and the relative error percentages were practically the same with both estimation methods. Only the ECG-derived RR time series reported a statistically significant non-zero bias. It can be seen that the maneuver with sudden changes in metronome breathing presented the worst performance indices. We consider that this could be due to the limitations in the temporal estimation while using the SP to obtain instantaneous estimates, i.e. the window length used. It is worth mentioning that the SP parameters used for the ECG and respiratory effort signals were the same as those implemented in the app for the iPPG signal.

Finally, we started to explore the feasibility of estimating a surrogate respiratory signal derived from the iPPG signal. To this end, we found a correlation index $\rho$ equal to $0.69 \pm 0.14$, for all maneuvers. Fig. 4 shows a spontaneous respiratory effort signal (reference) together with the corresponding HR (from ECG) and PR (from iPPG) time series. Despite the difference between their amplitudes, the similarity between the oscillations of the derived signals appears to point out the feasibility to continue exploring the iPPG, as an alternative to ECG, to follow changes in respiratory efforts reflecting the RSA.

## IV. Conclusion

The results presented in this study contribute not only to corroborate that contact iPPG signals provide a surrogate of ECG-based HR estimates, but also that they allow estimating instantaneous RR with a low level of error. The former was achieved directly in smartphones via a mobile app, for

TABLE I. RESULTS FOR INSTANTANEOUS HR ESTIMATION USING SMARTPHONE, CONSIDERING ECG AS REFERENCE.

| Maneuver | *ρ (unitless)* | *Error (%)* | *MAE (BPM)* | *Bias (BPM), p* | *LoA (BPM)* |
|---|---|---|---|---|---|
| **Spontaneous** | 0.99 ± 0.01 | 1.28 ± 1.73 | 0.94 ± 0.28 | 0.04, 0.18 | -3.03, 3.10 |
| **After exercise** | 0.99 ± 0.01 | 1.34 ± 1.34 | 0.97 ± 0.52 | 0.01, 0.94 | -2.91, 2.91 |
| **Sudden changes** | 0.99 ± 0.01 | 1.41 ± 1.28 | 1.03 ± 0.45 | 0.03, 0.06 | -2.73, 2.80 |

ρ: correlation coefficient; LoA: limits of agreement; MAE: mean absolute error; BPM: beats per min

TABLE II. RESULTS FOR INSTANTANEOUS RR ESTIMATION USING ECG AND SMARTPHONE, CONSIDERING RESPIRATORY EFFORT AS REFERENCE.

| Maneuver | ECG | | | | | RR (smartphone) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | *ρ (unitless)* | *Error (%)* | *MAE (bpm)* | *Bias (bpm), p* | *LoA (bpm)* | *ρ (unitless)* | *Error (%)* | *MAE (bpm)* | *Bias (bpm), p* | *LoA (bpm)* |
| **Spontaneous** | 0.99 ± 0.01 | 4.44 ± 7.33 | 0.53 ± 0.25 | -0.21, 0.01 | -2.45, 2.03 | 0.99 ± 0.01 | 4.41 ± 6.66 | 0.51 ± 0.21 | -0.13, 0.10 | -2.18, 1.91 |
| **After exercise** | 0.99 ± 0.01 | 3.10 ± 3.36 | 0.37± 0.08 | -0.05, 0.01 | -1.17, 1.06 | 0.99 ± 0.01 | 3.24 ± 3.22 | 0.40 ± 0.11 | -0.01, 0.21 | -1.15, 1.12 |
| **Sudden changes** | 0.98 ± 0.01 | 6.78 ± 11.67 | 0.74 ± 0.25 | -0.19, 0.01 | -3.38, 2.99 | 0.98 ± 0.01 | 7.09 ± 15.11 | 0.73 ± 0.23 | 0.03, 0.06 | -3.24, 3.31 |

different breathing maneuvers in healthy volunteers.

According to Bland-Altman analysis, the most challenging breathing maneuvers to estimate instantaneous HR and RR directly from the smartphone correspond to spontaneous breathing, and with sudden changes in metronome breathing. It is worth mentioning that some of the acquired respiratory effort signals (references) presented irregularities in their waveform caused by instabilities of the band sensor, i.e., oscillations that do not correspond to the respiratory effort of the volunteer, which contributed to estimation errors. We considered that the performance of RR estimation can improved if the reference signals are obtained from differential flow sensors or turbine, or using hot wire anemometers, as recommended in the protocols related to the estimation of respiratory parameters [9]. Unfortunately, such type of sensors was not available in our laboratory at the time of this study. Another limitation is the small size of the studied population, and we are currently working to increase this size.

Even though the implemented app allowed the successful calculation of the HR and RR time series, its main limitation is its high sensitivity to user's motion. Therefore, we are currently implementing robust methods to extract iPPG signals in the app, e.g., ICA (Independent Component Analysis), that allow to contend with motion artifacts. More complex algorithms could also be implemented in the app to estimate instantaneous RR, e.g., the synchrosqueezing transform which reached RR estimates with LoA of −3.62 and 4.17 bpm using 8-minute conventional PPG records from pediatric and adult patients under anesthesia [10].

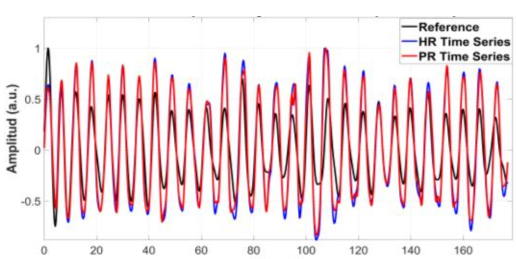


Figure 4. Reference respiratory effort signal (black line), and their respective HR (ECG, blue line) and PR (iPPG, red line) time series, corresponding to a spontaneous respiratory maneuver.

Nevertheless, it is important to keep in mind that, despite its simplicity, the spectrogram showed a good performance to estimate the RR time series, and that for devices with limited processing capabilities, such as mid-range smartphones, this type of algorithms with low computational cost is of particular interest. Finally, we consider that similar efforts to the one carried out in this study will continue to contribute providing alternatives for monitoring cardiorespiratory parameters to the general population on an anywhere and anytime fashion.

## REFERENCES


[1] Y. Nam, J. Lee, and K. H. Chon, "Respiratory rate estimation from the built-in cameras of smartphones and tablets", *Annals of biomedical engineering*, vol. 42, n.º 4, pp. 885-898, 2014.

[2] Y. Nam, Y. Kong, B. Reyes, N. Reljin, and K. H. Chon, "Monitoring of heart and breathing rates using dual cameras on a smartphone", *PloS one*, vol. 11, n.º 3, p. e0151013, 2016.

[3] N. V. Hoan, J.-H. Park, S.-H. Lee, and K.-R. Kwon, "Real-time Heart Rate Measurement based on Photoplethysmography using Android Smartphone Camera", *Revista Multimedia de Tesis*, vol. 20, n.º 2, pp. 234-243, 2017.

[4] P. H. Charlton *et al.*, "Breathing rate estimation from the electrocardiogram and photoplethysmogram: A review", *IEEE reviews in biomedical engineering*, vol. 11, pp. 2-20, 2017.

[5] E. Hernandez de la Cruz, S. Charleston-Villalobos, A. T. Aljama-Corrales, and B. A. Reyes, "Estimación de las Frecuencias Cardiaca y Respiratoria Instantáneas empleando Métodos de Fotopletismografía de Imagen en un Smartphone", en *Memorias del Congreso Nacional de Ingeniería Biomédica*, 2020, vol. 7, pp. 21-28.

[6] J. A. Hirsch and B. Bishop, "Respiratory sinus arrhythmia in humans: how breathing pattern modulates heart rate", *American Journal of Physiology-Heart and Circulatory Physiology*, vol. 241, n.º 4, pp. H620-H629, 1981.

[7] A. M. Unakafov, "Pulse rate estimation using imaging photoplethysmography: generic framework and comparison of methods on a publicly available dataset", *Biomedical Physics & Engineering Express*, vol. 4, n.º 4, p. 045001, 2018.

[8] C. Vidaurre, T. H. Sander, and A. Schlögl, "BioSig: The Free and Open Source Software Library for Biomedical Signal Processing", *Computational Intelligence and Neuroscience*, vol. 2011, mar. 2011, doi: 10.1155/2011/935364.

[9] C. Massaroni, A. Nicolò, D. Lo Presti, M. Sacchetti, S. Silvestri, and E. Schena, "Contact-based methods for measuring respiratory rate", *Sensors*, vol. 19, n.º 4, p. 908, 2019.

[10] P. Dehkordi, A. Garde, B. Molavi, J. M. Ansermino, and G. A. Dumont, "Extracting instantaneous respiratory rate from multiple photoplethysmogram respiratory-induced variations", *Frontiers in physiology*, vol. 9, p. 948, 2018.