Real time Heart Rate Variability Assessment from Android Smartphone Camera Photoplethysmography: Postural and Device Influences

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Abstract— **The aim of this paper is to present a smartphone based system for real-time pulse-to-pulse (PP) interval time series acquisition by frame-to-frame camera image processing. The developed smartphone application acquires image frames from built-in rear-camera at the maximum available rate (30 Hz) and the smartphone GPU has been used by Renderscript API for high performance frame-by-frame image acquisition and computing in order to obtain PPG signal and PP interval time series. The relative error of mean heart rate is negligible. In addition, measurement posture and the employed smartphone model influences on the beat-to-beat error measurement of heart rate and HRV indices have been analyzed. Then, the standard deviation of the beat-to-beat error (SDE) was 7.81 ± 3.81 ms in the worst case. Furthermore, in supine measurement posture, significant device influence on the SDE has been found and the SDE is lower with Samsung S5 than Motorola X. This study can be applied to analyze the reliability of different smartphone models for HRV assessment from real-time Android camera frames processing.**

I. Introduction

There is evidence that heart rate variability (HRV) is regulated by sympathetic and parasympathetic branches of the autonomic nervous systems (ANS). In recent years, there has been an increasing interest in HRV as broad indicator of overall health and fitness. In fact, it has been found that HRV is a good index of stress, depression and endurance of physical exercise [1]–[3].

Nowadays, many smartphones have high speed data transmission capabilities (e.g., 3G, WiFi) and external sensors connectivity via Bluetooth. Moreover, they have high resolution built-in camera, powerful processors and large storage capacities. Besides, most people wear their smartphones all the day long while performing their daily activities, so smartphones can be considered as non-invasive measurement devices.

Recently, researchers have shown an increased interest in pulse rate variability (PRV) because it can be used as a surrogate of HRV during non-stationary conditions, at least during the tilt table tests [4], [5]. Previous studies of smartphone-based systems measure pulse rate with an external sensor [6]. On the one hand, previous studies have been demonstrated the feasibility of smartphone camera sensor for HRV index estimation. However, most of them are based on off-line post-processing of raw video recordings with smartphone camera [7]. On the other hand, most studies of online frame-to-frame image processing have only focused on obtaining the pulse signal which is further analyzed for pulse detection and HRV [8].

This paper will focus on a smartphone-based system for real time frame-to-frame camera image processing in order to obtain pulse-to-pulse (PP) interval time series. In addition, this paper aims to investigate the influence on the error measurement of heart rate and HRV indices due to the measurement posture and the smartphone model employed.

II. Methods

A. Data Collection.

Eleven healthy people between 21 to 45 years old were recruited to participate in this study. Polar H7 band has been used to acquire ECG-derived RR interval time series in order to assess the accuracy of Pulse-to-Pulse (PP) interval time series obtained from developed application. Polar band has been used because it provides accurate RR series and it is widespread in sports field [9]. Therefore, subjects were asked to wear Polar band around the chest and simultaneously they held the smartphone in their hand and put index finger over smartphone camera lens and flash led. The experiments were conducted under supervision to ensure that smartphone remained well placed during the measurement. This study was performed in accordance with principles of the Declaration of Helsinki (2000).

Moreover, two different android smartphone models have been used to evaluate device influences. In fact, Motorola Moto X (MX) and Samsung S5 (S5) have been employed because both of them have different camera flash LED system, as shown in Fig. 1. On the one hand, MX rear camera resolution is 13 Mpx and it has dual-LED ring flash; on the other hand S5 camera has 16 Mpx resolution and traditional LED flash. The main features of both smartphones are similar: Snapdragon-801 2.5GHz quad-core CPU, Adreno-330 578MHz GPU, 2GB of RAM and Android OS (v. 4.4).

Furthermore, the participants were instructed to remain as still as possible in three different postures in order to assess postural influences. These postures were: supine with arms down, seated keeping the hand elevated to heart level, and seated keeping down arms. Each participant was asked to be measured four times: twice in the supine posture and once for each other posture.

*Research supported by Recercaixa 2013 and MINECO project PSI2011-29807-C02-02.

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Figure 1. Employed smartphones' rear camera and flash led system

Then, during the experiment, participants were asked to remain in the above mentioned postures while they were holding a different smartphone model in each hand. 100 seconds recording for each posture were taken; the Polar band and smartphone measurements were synchronized.

B. *Smartphone camera-based Photoplethysmography*

The PPG is an optical technique used to detect blood volume changes in the microvascular bed of tissue. Then, finger PPG is a non-invasive method to measure changes in capillary bed of finger. Therefore, PPG signal can be obtained with a smartphone-based system, where flash camera is the light emitting diode and the CMOS camera sensor is the photodetector [10]. Measuring green light intensity detected, the pulse wave can be obtained [7].

An Android smartphone application has been developed to acquire pulse PPG signal from image camera sensor. The pulse wave has been obtained from green light intensity [11]. Particularly, the developed smartphone application acquires frames with 640x480 pixel resolution to 30 frames per second sampling rate. Although higher resolution can be used, this resolution has been chosen because it is enough for our purposes and it reduces the computational cost. By other hand, the frames have been acquired to 30 frames per second because this is the highest sampling rate supported by the smartphone devices employed.

C. *Renderscript Frame-by-Frame Processing*

Renderscript API is an Android programming framework for running computationally intensive task. It enables write script code in C99-based language, which is called in native at runtime and it communicates with Android Virtual Machine. Portability is one advantage of Renderscript because smartphone application can be written in Java but some scripts can be written to be executed in Renderscript. Moreover, Renderscript provides a high performance computation because it takes care of parallelizing and scheduling work efficiently across all processors available on a device, such as multi-core CPUs, GPUs, or DSPs. Furthermore, it remains platform independent because the code is compiled and cached on the device at runtime [12]. Then, the developed application has used Renderscript API to process frame-by-frame camera image for PPG signal obtaining and HR detection.

D. *Smartphone Application Frame Processing*

The main blocks of the developed smartphone application that extracts PPG signal from processing frame-by-frame image camera for heart rate detection are shown in Fig. 2.

Firstly, smartphone application acquires frame image in YUV format with NV21 encoding that provides easy and effective compression. Then, a script is executed for converting the Android YUV buffer to RGB pixel array. The memory allocation and parallelization is performed by Renderscript API.

Secondly, the green component of pixel array is averaged to obtain PPG waveform. This part of application is parallelized by pixel rows for faster computing.

Thirdly, an algorithm to detect and recover lost frames has been developed because of Android camera does not guarantee stable frame rate. The lost frame detection algorithm is based on the analysis of frame timestamp variability between consecutive frames. In addition, when algorithm detects a lost frame, it is recovered by linear interpolation.

Finally, the designed algorithm for PPG signal conditioning and heart rate detection can be divided into three main sub-blocks:

1) *Signal smoothing & interpolation*: the obtained PPG is filtered to reduce random noise with a 2nd order Butterworth low-pass filter with cut off frequency of 4Hz. Then, it is used a 2nd order Butterworth high-pass filter with cut off frequency of 1.5 Hz for baseline filtering and derivate analysis of PPG signal. After that, the PPG signal was resampled to 1 kHz by three-point cubic spline interpolation to increase the temporal resolution. Finally, the interpolated signal is low-pass filtered at 10 Hz to reduce noise that can be introduced by interpolation.

2) *Adaptive Threshold*: the initial value of threshold is obtained from the 70% of the standard deviation of the first 5 seconds of filtered PPG. Then, adaptive threshold is calculated from 0.5 times the mean of the five last detected PPG peaks. Additionally, a reduction coefficient is applied when the peak detected is 2.5 times higher than current for avoiding abrupt changes.

3) *Peak Detection:* the peaks are detected from adaptive threshold upward crossing of PPG signal. The peak is detected looking for PPG interpolated maximum during next 12*N (N=33 interpolation factor, ~400 ms) samples from threshold crossings. Then, pulse-to-pulse (PP) arrivals at the finger time series have been obtained.

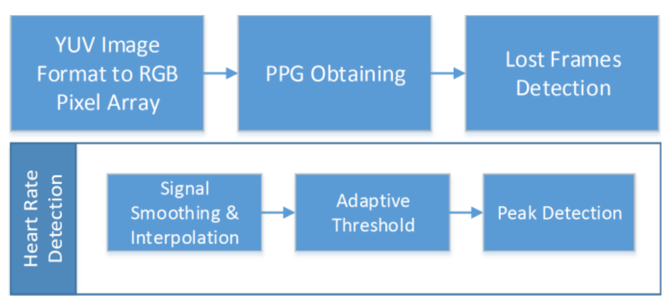

Figure 2. Block diagram of smartphone application frame processing

E. *Evaluation of Results.*

The accuracy of PP time series obtained from smartphone application has been assessed by comparing with RR time series derived from Polar band. In addition, these series have also been analyzed to assess postural and device influences in error measurement. Therefore, PP and RR time series must be beat-to-beat aligned, in fact, they have been aligned automatically by maximizing intra-class correlation coefficients (ICC). Then, time origin of one series relative to another has been shifted to left and right. After that, the standard deviation of the difference (SDE) has been used to quantify the error between time series.

For each smartphone model, the correlation between the PP and RR series was expressed as ICC coefficients. Instead of Pearson correlation coefficients, ICC was used because it doesn't ignore systematic bias, so it addresses not only correspondence but also agreement. Moreover, three indices of HRV have been computed in both time series to analyze differences in the HRV quantification: SDNN, RMSSD, and LF/HF [13].

Finally, three-way analysis of variances (ANOVA) tests have been employed to assess if SDE, ICC or HRV indices obtained were influenced by the smartphone model, measurement posture or measured subject. Additionally, a paired student's t-test was performed to compare SDE differences between MX and S5 devices by each posture ($p<0.05$ considered significant).

III. Results

A. Smartphone Application Performance

To profile the performance of the developed Android application running on smartphone, Trepn profiler app has been used. Trepn Profiler is a performance diagnostic tool designed by Qualcomm. Specifically, it has been used to profile the developed smartphone application CPU and GPU usage. Then, we have obtained on average S5 CPU load was 43.8 % ± 11.6 which is higher than MX 34.4% ± 6.3. Moreover, the average of S5 GPU usage was 15.3% ± 0.61, which is also higher than MX 6.21% ± 1.21. Despite CPU and GPU performance differences, the results show that both of smartphone models have enough computation capability to perform required tasks.

B. Heart Rate Time Series

The mean ± standard deviations of SDE and ICC for all tests conducted in each positon for each smartphone model are shown in Table 1. It is apparent from this table that PP and RR time series in all postures for two devices are highly correlated (ICC r >0.95).

Fig. 3 shows the SDE obtained with two devices in the three postures by subject. From the chart we can see that the influence of measurement posture in SDE is different for each person. In fact, three-way ANOVA shows that SDE depends on the subject under measurement ($p<0.001$), and the smartphone model ($p<0.05$) but there are no significant differences associated to subject posture.

TABLE I. Error Measuments of PP Time Series

Posture	SDE (ms)		ICC (.r)	
	MX	*S5*	*MX*	*S5*
Seated heart level	7.81 ± 3.81	5.67 ± 2.50	0.98 ± 0.011	0.99 ± 0.0093
Seated arms down	7.88 ± 2.48	7.08 ± 2.64	0.97 ± 0.024	0.96 ± 0.026
Supine	6.83 ± 2.32	5.20 ± 2.19	0.98 ± 0.026	0.99 ± 0.0093

In depth analysis, the paired Student-test did not show significant differences of SDE between S5 and MX in seated at heart level and seated keeping arms down. However, they have been found in supine posture ($p<0.05$) where the SDE is lower using S5 than MX.

C. Heart Rate Variability

The results of the relative error of mean RR and HRV indices between Polar band and those obtained from the smartphones are shown in Table 2. Three-way ANOVA shows that relative error of mean RR depends on smartphone model ($p<0.001$) but there are no significant differences associated to the subject under measurement and posture. Although, the Table 2 shows that this relative error is lower for MX than S5, both of them are low.

The relative error of SDNN is associated on the subject under measurement ($p<0.001$), and the smartphone model ($p<0.05$) but there are no significant differences associated to subject posture. Moreover, the relative errors of RMSSD and LF/HF are high. The relative error of RMSSD depends on the subject ($p<0.001$), and posture ($p<0.05$) but there are no

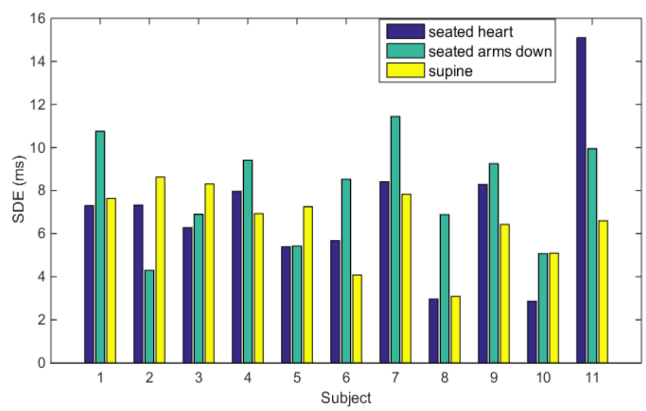

Figure 3. Mean of Pulse-to-Pulse SDE in each measurement posture by subject

TABLE II. Relative Error Measuments of RR Mean and HRV Indices between Polar Band and Smartphones

Posture	eRRmean (%)		eSDNN (%)		eRMSSD (%)		eLF/HF (%)	
	MX	*S5*	*MX*	*S5*	*MX*	*S5*	*MX*	*S5*
Seated Heart level	0.12 ± 0.10	0.18 ± 0.006	4.25 ± 1.28	2.68 ± 2.01	13.6 ± 8.02	11.4 ± 8.26	16.6 ± 14.0	11.9 ± 11.4
Seated keeping arms down	0.094 ± 0.04	0.15 ± 0.03	5.00 ± 2.73	5.24 ± 3.14	18.0 ± 20.2	39.3 ± 35.6	16.5 ± 9.38	27.2 ± 12.1
Supine	0.092 ± 0.06	0.18 ± 0.02	5.02 ± 2.99	3.31 ± 2.04	14.6 ± 10.9	9.4 ± 5.62	15.3 ± 11.6	16.07 ± 9.74

significant differences associated to smartphone model. For RMSSD, the best postures are arms at heart level and supine posture. Finally, the subject has significant effect in relative error of LF/HF ($p<0.001$) but there are no significant differences associated to subject posture and smartphone model.

IV. Discussion

The current study found significant differences of SDE associated to smartphone model and on average the SDE is lower with S5 than MX. Those results may be explained by the different arrangement of illumination. Although MX has two light emitters and S5 one, the S5 light emitter has higher intensity than the MX ones. In addition, other factors related with smartphone-camera specification such as sensitivity, embedded post-processing can affect.

By other hand, it has been found significant differences of the relative error of RMSSD associated to subject posture. However, the differences of the absolute error of RMSSD associated to subject posture weren't statistically significant. In addition, there is a significance difference associated to subject posture of RMSSD obtained from gold standard. Moreover, more subjects must be measured to explain postural influences in RMSSD quantification.

V. Conclusion

A smartphone application for real-time PP interval time series acquisition by frame-to-frame image processing has been developed. Moreover, the results of this study indicate that the relative error of RR mean is negligible and the SDE is around 7.81 ± 3.81 ms in the worst case. In addition, the smartphone model has significant influence on SDE and the relative error of SDNN, which are lower using S5 than MX. Then, these findings suggest that S5 can be more suitable than MX for this application.

Moreover, the relative errors of short term HRV indices have been obtained: the relative error of SDNN is acceptable, but RMSSD and LF/HF can be so high depending on usage scenario. Furthermore, it has been found that influence of subject under measurement on the relative error of HRV short time indices is significant, but the significance postural and device influences vary among the HRV indices.

This study can be applied to analyze the reliability of different smartphone models for HRV assessment from real-time Android camera frames processing. Then, this work can be used to find the most suitable smartphone model for health related applications based on HRV analysis.

Acknowledgment

This work has been supported by the Recercaixa 2013 project "Desenvolupament de marcadors d'estils de vida saludable per a gent gran basats en Smartphones" and MINECO project PSI2011-29807-C02-02.

References

[1] I. C. Jeong and J. Finkelstein, "Classification of cycling exercise status using short-term heart rate variability.," *Conf. Proc. ... Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. IEEE Eng. Med. Biol. Soc. Annu. Conf.*, vol. 2014, pp. 1782–1785, Aug. 2014.

[2] A. L. Wheat and K. T. Larkin, "Biofeedback of heart rate variability and related physiology: a critical review.," *Appl. Psychophysiol. Biofeedback*, vol. 35, no. 3, pp. 229–242, Sep. 2010.

[3] R. Reiner, "Integrating a portable biofeedback device into clinical practice for patients with anxiety disorders: results of a pilot study.," *Appl. Psychophysiol. Biofeedback*, vol. 33, no. 1, pp. 55–61, Mar. 2008.

[4] E. Gil, M. Orini, R. Bailon, J. M. Vergara, L. Mainardi, and P. Laguna, "Photoplethysmography pulse rate variability as a surrogate measurement of heart rate variability during non-stationary conditions.," *Physiol. Meas.*, vol. 31, no. 9, pp. 1271–1290, Sep. 2010.

[5] M. Bolanos, H. Nazeran, and E. Haltiwanger, "Comparison of heart rate variability signal features derived from electrocardiography and photoplethysmography in healthy individuals.," *Conf. Proc. ... Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. IEEE Eng. Med. Biol. Soc. Annu. Conf.*, vol. 1, pp. 4289–4294, 2006.

[6] J. A. J. Heathers, "Smartphone-enabled pulse rate variability: An alternative methodology for the collection of heart rate variability in psychophysiological research," *Int. J. Psychophysiol.*, vol. 89, no. 3, pp. 297–304, Sep. 2013.

[7] C. G. Scully, J. Lee, J. Meyer, A. M. Gorbach, D. Granquist-Fraser, Y. Mendelson, and K. H. Chon, "Physiological parameter monitoring from optical recordings with a mobile phone.," *IEEE Trans. Biomed. Eng.*, vol. 59, no. 2, pp. 303–306, Feb. 2012.

[8] J. B. Bolkhovsky, C. G. Scully, and K. H. Chon, "Statistical analysis of heart rate and heart rate variability monitoring through the use of smart phone cameras.," *Conf. Proc. ... Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. IEEE Eng. Med. Biol. Soc. Annu. Conf.*, vol. 2012, pp. 1610–1613, 2012.

[9] D. Nunan, G. Donovan, D. G. Jakovljevic, L. D. Hodges, G. R. H. Sandercock, and D. A. Brodie, "Validity and reliability of short-term heart-rate variability from the Polar S810.," *Med. Sci. Sports Exerc.*, vol. 41, no. 1, pp. 243–250, Jan. 2009.

[10] J. Allen, "Photoplethysmography and its application in clinical physiological measurement," *Physiol. Meas.*, vol. 28, no. 3, p. R1, 2007.

[11] J. Lee, K. Matsumura, K. Yamakoshi, P. Rolfe, S. Tanaka, and T. Yamakoshi, "Comparison between red, green and blue light reflection photoplethysmography for heart rate monitoring during motion.," *Conf. Proc. ... Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. IEEE Eng. Med. Biol. Soc. Annu. Conf.*, vol. 2013, pp. 1724–1727, 2013.

[12] Google Inc, "RenderScript | Android Developers." [Online]. Available: http://developer.android.com/guide/topics/renderscript/compute.html. [Accessed: 27-Mar-2015].

[13] Task Force of the European Society of Cardiology and North American Society of Pacing and Electrophysiology, "Heart Rate Variability: standards of measurement, physiological interpretation, and clinical use," *Circulation*, vol. 93, no. 5. pp. 1043–1065, 1996.