

Analysis of Heart Rate Variability to Detect Changes Associated with Stress Using Cardiac Information Obtained via a Smartphone

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Abstract—In this study, the contact image photoplethysmography (iPPG) technique was used through a smartphone video camera, and its usefulness was explored under baseline conditions, stress induced by Stroop test and recovery, taking as reference the heart rate variability (HRV) extracted from the electrocardiography (ECG) in two conditions: 1) spontaneous breathing, and 2) controlled breathing at a fixed rate of 6 breaths per minute. Thanks to the use of smartphones, the measurements were made in the homes of the volunteers, who were provided with the measurement systems. Linear temporal and spectral, as well as nonlinear indexes (Poincaré plot and binary symbolic dynamics) were explored for HRV and pulse rate variability (PRV). Similar results were found for ECG-based HRV and iPPG-based PRV, corroborating the usefulness of iPPG via smartphones in HRV studies, providing an interesting alternative to perform HRV analysis outside research and clinical settings.

Clinical Relevance— This study shows the use of a smartphone to extract iPPG-based PRV time series and their linear and nonlinear indexes as a surrogate for ECG-based HRV during stress and a controlled breathing maneuver.

I. INTRODUCTION

Stress is a universal phenomenon that negatively impacts most people and can be defined as the physiological response to a threat, whether physical or psychological, that an organism faces, so that stress is actually a necessary mechanism of survival. However, when this response is forced to maintain itself for a prolonged period, the body loses the ability to regain homeostasis which can have short- or long-term effects depending on its duration and intensity. Thus, stress has been linked to various problems and disorders [1].

The level of stress can be assessed using indicators such as heart rate variability (HRV) or pulse rate variability (PRV) obtained from electrocardiography (ECG) or photoplethysmography (PPG) signals, respectively [1]. LF could be mostly related to sympathetic activation, however, parasympathetic activation is also present. Words with zero variations based on symbolic dynamics have been related to sympathetic activation during stress conditions, compared with a baseline state. The indexes of high frequencies, the mean and standard deviation, as well as the patterns with one variation based on symbolic dynamics, have been reported

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lower during stress. This is due to sympathetic activation and parasympathetic withdrawal during stress [2], [3].

Cardiorespiratory information is generally obtained using specialized biomedical devices, such as ECG, PPG, and spirometers, limiting stress studies outside of clinical or research settings that are not readily available to the general population. Recently, the use of smartphones has been proposed since they are ubiquitous devices that have various cost-effective sensors already incorporated, which allows them to be used in monitoring applications of vital signs, mainly for the estimation of the heart rate (HR) [4], accordingly called pulse rate (PR), but also to estimate PRV via contact or remote modalities of contact image photoplethysmography (iPPG) [2]. Although being comfortable, the use of remote iPPG has limitations related to user privacy due to the acquisition of video sequences focused on the face, as well as being highly susceptible to motion artifacts. In the contact iPPG approach, the smartphone video camera is used analogously to the photoreceptor in traditional PPG, while the light-emitting diode (LED) of the flash is used as the light source [5]. Currently, most people have access to smartphones allowing to obtain and process information from the outside in real time, which makes smartphones an attractive option to use them as physiological monitors, e.g. to assess stress in everyday conditions, where you do not have access to sophisticated equipment, e.g. in confinement due to the SARS-Cov-2 pandemic.

In this study, the contact iPPG technique via a smartphone to obtain information on PRV during maneuver involving induced stress, using the Stroop test, taking HRV information derived from ECG as a reference, was explored. To this end, the iPPG-based PRV time series were compared to ECG-based HRV ones. Then, their corresponding linear and nonlinear indexes were extracted and compared.

II. METHODS

A. Acquisition protocol

For this study, twelve ($N=12$) volunteers were recruited (6 men and 6 women), with an age of 18 to 25 years and a normal body mass index ($18.5 - 24.9 \text{ kg/m}^2$). Before starting the measurements of any volunteer, their informed consent was provided and obtained according to the Declaration of Helsinki. ECG and PPG signals were acquired with the Biosignalsplux® system (PLUX Wireless Biosignals, Lisboa, Portugal) with the same sampling rate of 1000 Hz, where the iPPG signal was used to align the acquired ECG signal with the smartphone-based iPPG one. Lead CM5 was used for the ECG, and the pulse signal was acquired in the left

hand, with the sensor placed on middle finger. The video sequences, from which the iPPG signals are extracted, can be acquired with any commercially available mid-range smartphone and in this study, the Galaxy S4 smartphone (Samsung Inc. Seoul, Korea) with Android operating system (Android 4.2.2.) was used. The left index finger covered both the camera and the smartphone flash. The acquisition was carried out simultaneously with the two acquisition systems for 45 minutes in which the volunteer remained seated in front of a monitor. The processing was performed in MATLAB (The Mathworks, Natick, MA, USA). An example of data acquisition is shown in Fig. 1. Each volunteer performed four training sessions to maintain controlled breathing, with a frequency of 6 breaths-per-minute (bpm). The protocol consisted of performing two tests (A and B), following a random order. Test A and B consisted of three phases, each one of 5 minutes: baseline, stress and recovery. The Stroop test was used to induce stress in both tests. In the test B, during baseline and recovery phases, the volunteer breathed at 6 bpm, while at test A the volunteer breathed in a spontaneous fashion. The Stroop test phase consisted of selecting (clicking with opposite hand of the one with sensors was used) the name of the color that appeared on the stimulus screen in the response screen. The background color of the response screen and the response time varied, speeding from 3 to 1 s, as the test progressed. An example of the stroop test is shown in Fig. 1. On the other hand a self-report was prepared where it was asked “How much did you feel mentally stressed?” and a visual analogue scale was provided with values from zero (no stress) to ten (high stress) to assess the level of perceived stress. All signal acquisition was performed in regular house rooms without noise, without distractions, with the regular ambient light conditions, between 10 am and 1 pm. It is worth mentioning that thanks to the usefulness of the mobile solution, all signal acquisition was done during pandemic lockdown, at the respective home of the volunteers.

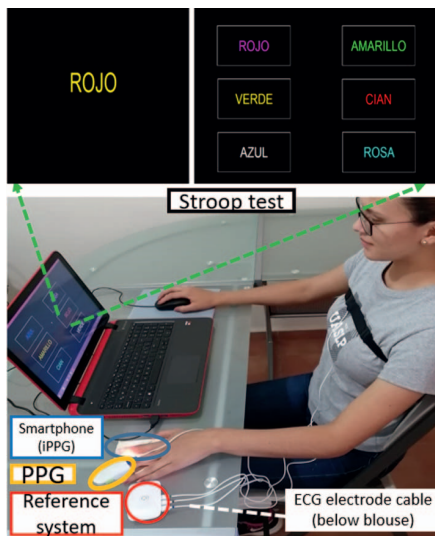


Figure 1: Stroop test and acquisition setup.

B. Signal processing

The iPPG signal was extracted from the videos acquired at 30 fps, using a 320x240 pixels resolution, inside a rectangular pixel region of interest (ROI) of 40% resolution, centered on each frame. The iPPG signals were extracted for the RGB video channels, by means of the spatial average of the intensity (i) the ROI at each instant.

$$iPPG_G(t) = \frac{1}{MN} \sum_{m,n \in ROI} i_G(t, m, n) \quad (1)$$

where G denotes the green channel, t is the instant of the current frame, M and N are the number of rows m and columns n of the ROI, respectively. The green channel was used because it provides a better signal for the iPPG, in agreement with previous studies [5]. After the signal was normalized, the obtained iPPG signal was resampled at 1000 Hz, for comparison purposes with reference signals. Finally, a 5th-order Butterworth bandpass filter with cutoff frequencies of 0.3 and 3.5 Hz was used. The cross-correlation function between the PPG and iPPG signal was used to synchronize acquired signals with the two different systems. R wave peaks from ECG were automatically detected using the Pan-Tompkins algorithm [8]. On the other hand, to detect the local maxima of iPPG signals, first a derivative filter was used. Subsequently, a 1.5-second moving window was used to find the local maximum points. Minimum and maximum duration thresholds of 0.2 and 2 s, respectively, between one peak and the next were considered. Artifacts were eliminated by taking two thresholds; one at 3 times the variance plus 30% of the maximum and another at $\pm 50\%$ of the mean. Finally, we proceeded to manual correction, if required, for ECG R peak and iPPG maxima.

The beat-to-beat intervals (BBI) were obtained from the ECG and iPPG as HRV and PRV time series, respectively. The mean was subtracted and the trend was eliminated. The time series were resampled at 4 Hz to estimate their Power Spectral Density (PSD) using the Welch method using 2048 frequency bins, and 8 Hamming windows with a 50% overlap between them. An example of the HRV and PRV time series, obtained from the ECG and iPPG, respectively, and their corresponding PSD, is shown in Fig. 2.

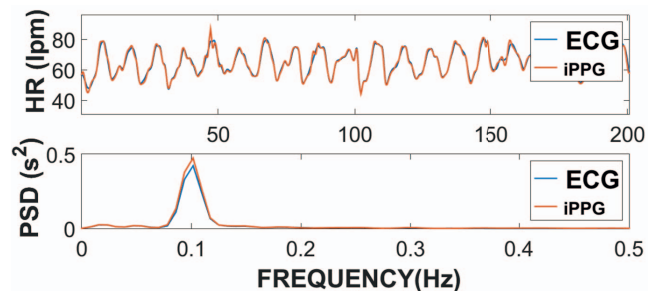


Figure 2: Example of time series and PSD of HRV and PRV in the baseline phase of test B (metronome breathing).

C. Heart rate variability indexes

The following indexes of the HRV and PRV time series were calculated:

- Temporal indexes: BBI_{mean}, standard deviation (SDNN), the squared root of the averaged sum of squared length differences between BBI (RMSSD) and the percentage of consecutive BBI that differ by more than 50 ms from each other (pNN50).
- Spectral indexes: TP (total power, 0-0.4 Hz), LF (low frequency, 0.04-0.15 Hz), HF (high frequency, 0.15-0.4 Hz), LF/HF, LFnu and HFnu.
- Non-linear indexes: *Poincaré plot*: The duration of the current beat is plotted on the x-axis, while the duration of the next beat is plotted on the y-axis, so that each point corresponds to two successive beats: SD1 is the standard deviation of the orthogonal intervals of the points BBI_n, BBI_{n+1} to the transverse diameter of the ellipse, it is also related to RMSSD [6]. SD2 is the standard deviation of the orthogonal intervals of the points BBI_n, BBI_{n+1} to the longitudinal diameter of the ellipse [7]. *Symbolic dynamics*: The series of intervals BBI_i ($i = 1, \dots, N$) is transformed into a binary symbolic series by two different approaches. In the first approach, the series of differences $\Delta BBI_i = BBI_i - BBI_{i-1}$ ($i = 2, \dots, N$) is calculated and the symbolic sequence is created according to the sign of each difference: $S_i = 0$ if $\Delta BBI_i \geq 0$ or $S_i = 1$ if $\Delta BBI_i < 0$. In the second approach, the difference series ΔBBI_i is transformed into a binary series according to a predefined threshold. The binary encoding represents whether the absolute value of the difference ΔBBI_i is below or above an empirically determined threshold τ . Tests of 5 to 50 ms were performed in steps of five and it was found that the value of $\tau = 15$ ms is the one that provides the most information about the changes in the signal: $S_{\tau,i} = 0$ if $|\Delta BBI_i| < \tau$ or $S_{\tau,i} = 1$ if $|\Delta BBI_i| \geq \tau$. All subsequences of length $k = 3$, are classified as follows: 0V, 1V and 2V sequences (with zero, one and two variations between successive symbols, respectively). Subsequently, the relative frequency of each pattern category is calculated for both symbolic sequences, i.e. $P0V\%$, $P1V\%$, $P2V\%$ and $P0V_{\tau}\%$, $P1V_{\tau}\%$ and $P2V_{\tau}\%$ [3].

D. Comparison between HRV and PRV

The performance of the smartphone-based PRV was compared against the ECG-based HRV by means of Bland-Altman graphical analysis, the mean absolute error (MAE), the root mean square error (RMSE) and the correlation coefficient (r). Although different number of beat were considered for each subject, in the Bland-Altman analysis no one seemed to contribute predominately over the others.

E. Statistical analysis of HRV and PRV indexes

The criterion of normality of the HRV and PRV indexes results was evaluated using the Kolmogorov-Smirnov test.

Accordingly, the differences between the phases (baseline, stress and recovery) were evaluated using the Kruskal-Wallis test and the tukey-kramer post hoc rank test was used. Multiple comparison tests were made based on the Bonferroni test. The difference between tests (A: spontaneous breathing, B: metronome breathing) was evaluated with the two-sided Wilcoxon rank sum test.

III. RESULTS

The aim of the paper was to test if the iPPG-based PRV series and indexes are a surrogate of ECG-based HRV ones during stress and a controlled breathing maneuver. Table I shows the comparison between the time series of HRV based on ECG and PRV based on iPPG (smartphone). Results for RMSE in beats-per-minute (BPM), MAE, r and Bland-Altman bias and limits of agreement (LoA) are shown for each phase of each test. The correlation coefficient shows a strong positive association between the values obtained by HRV and PRV. Both RMSE and MAE were lower in test A compared to test B, and lower during the baseline stages with respect to the stress phase of both tests.

Table II summarizes the results of HRV and PRV that have statistically significant differences with respect to the stress phase. The statistically significant differences between test A and test B are also shown in Table II. Regarding comparison results between HRV and PRV, LF index showed similar significant differences in test A for HRV and PRV, while in test B, the indexes with similar significant differences were LF , $LFnu$, $HFnu$, LF/HF and $P1V\%$ during baseline and recovery phases. On the other hand, the indexes $SDNN$ (baseline), $SD2$ (baseline), $POV\%$ (recovery), $P1V_{\tau}\%$ (recovery) and $P1V_{\tau}\%$ showed statistical differences between phases or tests by HRV, but not by PRV.

IV. DISCUSSION

Given that the correlation coefficient between the PR and HR time series shows a strong linear relationship and the Bland-Altman bias was close to zero, the results shown in Table I were expected to provide similar information on the HRV and PRV indexes. Due to the influence of controlled breathing on Test B, Test A (phases performed at spontaneous breathing) can be differentiated from this test in most indexes in the baseline and recovery phases. Although the stress phase was the same for both tests, the index $P1V\%$ shows a significant difference between test A and test B, which could be due to the influence of controlled breathing before the phase of stress in test B. The above shows of how nonlinear indexes provide information that cannot be obtained with linear indexes. $P1V\%$ is related to the parasympathetic, but it acted differently than expected, since under stress conditions it showed a higher value compared to baseline and recovery. However, when a non-zero threshold ($P1V_{\tau}\%$) was used, in test B, it was lower in stress compared to baseline and recovery with HRV, and lower in stress than in baseline with PRV. This result could be due to greater vagal activity during baseline and recovery phases in comparison with stress. Because the LF band contains

the frequency corresponding to the controlled breathing, it increased in the corresponding phases, in the same way as $LFnu$ and LF/HF . As expected, $P1V_{\tau}\%$ and $SDNN$, were lower in the stress with respect to the baseline and recovery phases of test B. This may be because breathing at 6 bpm promotes synchronization of the respiratory and cardiac system. During inhalation there is more blood available and the oxygen concentration in the alveolus is maximum, improving gas exchange. This helps to improve the subject's adaptation to stress by promoting greater respiratory efficiency and higher HRV [9].

In the future, we are considering causing a higher level of stress, improving monitoring of controlled breathing, increasing the studied sample size, and taking into account the respiratory signals also estimated from the iPPG signal.

V. CONCLUSIONS

In this work, a smartphone was used to obtain information from the contact iPPG-based PRV time series and compared with the ECG-based HRV time series. Thanks to the usefulness of the mobile solution, it could be done during pandemic lockdown, at home. Linear and non-linear indexes of HRV and PRV were calculated and compared in order to differentiate the stress phase from the baseline and recovery phases. It was expected to find more significant differences between the baseline and recovery phase with respect to stress during test A (spontaneous breathing), as happened with test B (controlled/metronome breathing). Although, some indexes show unexpected behavior most of the indexes

showed similar results for both methods, suggesting that the use of contact iPPG via a smartphone could provide similar information to the ECG.

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TABLE I: Performance analysis between HRV (ECG) and PRV (iPPG) time series

Index	Test A			Test B		
	Baseline	Stress	Recovery	Baseline	Stress	Recovery
RMSE (BPM)	2.17 ±1.9	2.49 ±2.4	2.43 ±2.0	5.33 ±5.0	6.31 ±7.3	5.64 ±6.4
MAE (BPM)	1.34 ±1.3	1.70 ±2.0	1.23 ±1.1	3.60 ±4.1	4.30 ±5.7	3.70 ±4.7
r	0.89 ±0.15	0.91 ±0.12	0.91 ±0.14	0.83 ±0.26	0.75 ±0.34	0.83 ±0.24
Bland-Altman analysis (bias(LoAInf, LoASup))	-0.019 (-4.50, 4.46)	-0.004 (-5.10, 5.09)	0.023 (-4.12, 4.13)	0.179 (-9.92, 10.37)	0.240 (-11.86, 12.32)	0.251 (-9.91, 10.40)

Data are expressed as a mean ± SD for RMSE, MAE and r and mean of bias(LoAInf, LoASup) for Bland-Altman analysis.

TABLE II: Comparison of HRV/PRV indexes between both methods (ECG and iPPG).

Index	comparison between phases - ECG			comparison between phases - iPPG		
	Baseline	Stress	Recovery	Baseline	Stress	Recovery
Test A (spontaneous breathing)						
BBImean(s)	0.80 (0.70, 0.91)	0.71 (0.69, 0.87)	0.78 (0.71, 0.92)	0.80 (0.71, 0.90)	0.72 (0.69, 0.87)	0.78 (0.69, 0.92)
RMSSD (s)	0.05 (0.03, 0.06)	0.04 (0.03, 0.06)	0.05 (0.04, 0.08)	0.04 (0.03, 0.07)	0.04 (0.03, 0.05)	0.05 (0.03, 0.08)
SDNN (s)	0.05 (0.04, 0.08)	0.06 (0.04, 0.07)	0.07 (0.05, 0.09)	0.05 (0.04, 0.08)	0.06 (0.04, 0.07)	0.08 (0.05, 0.10)
LF (s^2)	0.21 (0.11, 0.48)	0.18 (0.11, 0.23)	0.47 (0.27, 1.06) ^o	0.25 (0.12, 0.50)	0.20 (0.11, 0.24)	0.50 (0.30, 1.07)*
HF (s^2)	0.22 (0.16, 0.66)	0.24 (0.15, 0.30)	0.26 (0.13, 0.71)	0.20 (0.18, 0.75)	0.23 (0.16, 0.32)	0.33 (0.15, 0.69)
LF/HF	0.75 (0.45, 0.92)	0.83 (0.45, 1.34)	1.36 (0.54, 3.22)	0.69 (0.48, 1.09)	0.80 (0.54, 1.17)	1.28 (0.72, 3.03)
LFnu (%)	43.1 (31.2, 47.2)	45.2 (31.2, 57.0)	57.25 (35.6, 74.84)	40.8 (32.7, 51.5)	44.5 (35.0, 53.3)	55.7 (42.0, 72.75)
HFnu (%)	56.8 (52.7, 68.7)	54.7 (42.9, 68.7)	42.7 (25.1, 64.3)	59.1 (48.4, 67.2)	55.4 (46.6, 64.9)	44.2 (27.2, 57.9)
SDI (s)	0.03 (0.02, 0.04)	0.02 (0.02, 0.04)	0.03 (0.02, 0.05)	0.03 (0.02, 0.05)	0.03 (0.02, 0.04)	0.03 (0.02, 0.05)
SD2 (s)	0.07 (0.05, 0.11)	0.08 (0.06, 0.10)	0.10 (0.07, 0.12)	0.07 (0.06, 0.11)	0.08 (0.06, 0.10)	0.14 (0.07, 0.13)
PoV (%)	29.9 (12.2, 44.3)	17.8 (12.5, 29.1)	32.9 (16.9, 49.4)	28.2 (16.2, 44.9)	17.9 (13.7, 28.5)	31.7 (19.8, 47.7)
P1V (%)	62.4 (47.2, 69.8)	66.5 (55.4, 70.7)	54.8 (44.9, 64.3)	61.0 (50.3, 70.9)	66.8 (59.6, 72.1)	58.8 (46.6, 70.0)
P1V $\tau\%$	46.0 (39.4, 50.3)	37.6 (31.4, 45.6)	43.0 (35.0, 50.9)	28.5 (26.6, 42.2)	37.2 (27.2, 41.3)	41.0 (32.8, 47.7)
Test B (controlled / metronome breathing)						
BBImean (s)	0.83 (0.73, 0.91)	0.77 (0.70, 0.88)	0.81 (0.73, 0.92)	0.83 (0.73, 0.91)	0.76 (0.70, 0.88)	0.79 (0.72, 0.92)
RMSSD (s)	0.07 (0.05, 0.09)	0.04 (0.03, 0.06)	0.06 (0.05, 0.09)	0.08 (0.06, 0.10)*	0.05 (0.04, 0.09)	0.08 (0.07, 0.10)*
SDNN (s)	0.11 (0.08, 0.12) ^o ***	0.06 (0.05, 0.09)	0.11 (0.08, 0.13) ^o **	0.10 (0.08, 0.12)**	0.06 (0.05, 0.09)	0.11 (0.09, 0.13) ^o **
LF (s^2)	2.22 (1.53, 3.39)***	0.23 (0.15, 0.36)	2.46 (1.33, 3.40)***	2.26 (0.91, 2.78)***	0.30 (0.18, 0.49)	2.35 (1.12, 3.29)***
HF (s^2)	0.21 (0.10, 0.38)	0.20 (0.13, 0.25)	0.27 (0.10, 0.40)	0.32 (0.20, 0.65)	0.23 (0.13, 0.45)	0.44 (0.22, 0.57)
LF/HF	9.68 (7.36, 17.5)***	1.61 (0.68, 2.95)	10.1 (6.53, 13.6)***	6.84 (3.19, 12.9)***	1.26 (0.64, 2.08)	5.83 (2.95, 12.4)***
LFnu(%)	90.6 (88.0, 94.6)***	61.6 (39.0, 74.6)	91.0 (86.7, 93.1)***	87.24 (76.0, 92.6)***	55.1 (39.1, 67.4)	85.3 (72.9, 92.4)***
HFnu(%)	9.35 (5.39, 11.9)***	38.3 (25.3, 60.96)	8.95 (6.87, 13.2)***	12.7 (7.36, 23.9)***	44.8 (32.6, 60.9)	14.6 (7.51, 27.0)***
SDI (s)	0.04 (0.03, 0.06)	0.03 (0.02, 0.04)	0.04 (0.03, 0.06)	0.05 (0.04, 0.07)*	0.03 (0.02, 0.06)	0.06 (0.05, 0.07)*
SD2 (s)	0.14 (0.11, 0.16) ^o ***	0.08 (0.06, 0.11)	0.15 (0.10, 0.17) ^o **	0.14 (0.10, 0.15)**	0.08 (0.07, 0.12)	0.15 (0.11, 0.17) ^o ***
PoV (%)	59.8 (50.7, 62.4)***	24.6 (14.7, 40.2)	57.8 (51.2, 61.6)***	39.2 (24.3, 54.1) ^o	22.4 (7.87, 31.1)	39.1 (16.0, 57.3)
P1V (%)	38.2 (33.8, 43.2)***	54.1 (49.9, 60.2) *	39.2 (35.1, 42.0) ^o **	41.9 (37.3, 45.7)***	53.6 (50.7, 56.5)**	43.8 (36.6, 48.3)***
P1V $\tau\%$	55.8 (45.7, 60.5)***	40.7 (36.1, 45.4)	49.9 (47.4, 55.5) ^o **	51.7 (41.5, 56.3)*	29.6 (26.5, 42.6)	45.2 (31.6, 47.9)

Median (25, 75 percentiles). Significant differences vs the stress phase. ^o $p < 0.05$; * $p < 0.01$ and between test A and test B ** $p < 0.05$; *** $p < 0.01$