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Article

Assessment of ultra-short heart variability indices derived by smartphone accelerometers for stress detection

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Abstract: Body acceleration due the heartbeat-induced reaction forces can be measured as smartphone accelerometer (m-ACC) signals. Our aim was to test the feasibility of using m-ACC to detect changes induced by stress by ultra-short heart rate variability (USV) indices (SDNN and RMSSD). Sixteen healthy volunteers were recruited; m-ACC was recorded while in supine position, during spontaneous breathing (REST) and during one minute of mental stress (MS) induced by arithmetic serial subtraction task, simultaneous with conventional ECG. Beat occurrences were extracted from both ECG and m-ACC and used to compute USV indices using 60, 30 and 10s durations, both for REST and MS. A feasibility of 93.8% in the beat-to-beat m-ACC heart rate series extraction was reached. In both ECG and m-ACC series, compared to REST, in MS the mean beat duration was reduced by 15% and RMSSD decreased by 38%. These results show that short term recordings (up to 10 sec) of cardiac activity using smartphone's accelerometers are able to capture the decrease in parasympathetic tone, in agreement with the induced stimulus.

Keywords: ballistocardiography; seismocardiography; ultra-short heart rate variability; stress evaluation; smartphone; accelerometers.

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1. Introduction

Technology developments and device miniaturization have opened the possibility for hand-held devices such as smartphones to be used for physiological data collection. Through their embedded tri-axial accelerometers, the mobile phone is sensitive enough to record the vibrations generated by the beating heart (m-ACC), as accelerations of milligravity (mg) level. In this way, the movements along the lateral, the normal, and the longitudinal direction can be detected.

Depending on the accelerometers position, these signals usually resemble:

1) the ballistocardiogram (BCG), measuring the displacement of the mass of ejected blood from the ventricles through the aorta and then towards the peripheral circulation, represented by a series of systolic (I, J, K) waves describing the forces associated to the shifting of the center of body mass [1]–[10];
2) the seismocardiogram (SCG), capturing the sequence of mechanical cardiac events known as isovolumetric contraction (IVC), aortic valve opening (AO) and aortic valve closure (AC) relevant to the systolic period [4], [5], [11]–[15].

The heartbeat fiducial points on the m-ACC signal associated to the sharp cardiac vibration waves in concomitance to the systolic activity can be detected using an ECG-independent processing

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algorithm, and used to compute the cardiac interbeat interval, thus obtaining corresponding beat-to-beat time series. The feasibility and accuracy of measuring the beat-to-beat heart rate using smartphone accelerometers has been recently demonstrated [1], [3], [16]–[18].

Heart rate variability (HRV) analysis is usually applied to RR series, thus providing quantitative markers to evaluate the influence of autonomic nervous system (ANS) on the heart rate [19]–[22]. The HRV approach considers monitoring periods that may range from 5 min up to 24 h [20], providing information that may be related to physiological status such as diabetic neuropathy [22], myocardial dysfunction[23] or stress conditions[24], [25]. The feasibility of applying HRV analysis to beat-to-beat series obtained by accelerometric recordings of 5 minutes length has been already proven [26].

In the context of self-monitoring individual's health and well-being status, the interest in using shorter recordings (<5 minutes) in stationary conditions of real-life scenarios suitable for HRV analysis is emerging, thus increasing user compliance and reliability of measurement. To this purpose, the ultra-short heart rate variability (USV) time domain indices - the standard deviation of normal-to-normal intervals (SDNN) and the root mean square of successive differences (RMSSD) – have been proposed as a surrogate to assess the ASN influence on the heart rate [27]–[29].

We hypothesized that the USV analysis could be applied to assess the level of stress from the accelerometric signals acquired for short periods using a mobile phone, thus facilitating this self-assessment procedure without the need of other wearables or sensors, and overcoming the main limitation of keeping in position the device for longer periods.

Accordingly, our aim was to test the feasibility of detecting changes in the ANS state provoked by a mental task by using the beat-to-beat series from short recordings (<1min) extracted by mobile phone m-ACC signal. To attain that objective the USV indices were computed and compared with the indices obtained by the conventional ECG-RR series, considered the gold standard, simultaneously extracted. In addition, the ability to detect these changes using sub-segments of shorter durations (up to 10 sec) was explored.

2. Materials and Methods

2.1. Study population

A total of 16 subjects (age range 19-28, 6 females) were recruited, whose anthropometrics data are reported in Table 1. The experimental procedures described in this paper agreed with the ethics defined in the Helsinki Declaration of 1975, as revised in 2000. Each subject also provided voluntary written, informed consent to participate in the experimental protocol approved by the Ethical Committee of the Ospedale San Luca in Milan (ethical protocol code 2016_12_13_03).

Table 1. Anthropometric characteristics of the population in terms of age, weight, height and body mass index (BMI) expressed as median and (25^{th} - 75^{th} percentiles).

Age (y)	Weight (Kg)	Height (m)	BMI (Kg/m2)
22	67.5	180	21.5
(21-23)	(61-75.5)	(169-184)	(20.3-22.9)

2.2. Accelerometric signal acquisition

Each volunteer was studied in supine position using a smartphone (iPhone 6s, Apple), positioned directly on the navel, with the phone top towards the head (Figure 1). The 3-orthogonal axis accelerometric signals (m-ACC, fs = 100 Hz, accelerometer sensitivity of 0.001 g) were acquired using the app 'SensorLog' v.2.4, resulting in three oriented channels corresponding to lateral (X), longitudinal (Y) and normal (Z) directions, simultaneously with a 6-leads electrocardiogram (ECG, Nexfin HD monitor, BMEYE, Amsterdam; fs=1000 Hz). Despite the morphology of the m-ACC signal depends on the device position on the subject's body [16], Y and

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Z components showed a major informative content relevant to heartbeat occurrence. For this reason, they were chosen to be processed with the ECG-free heartbeat detection.

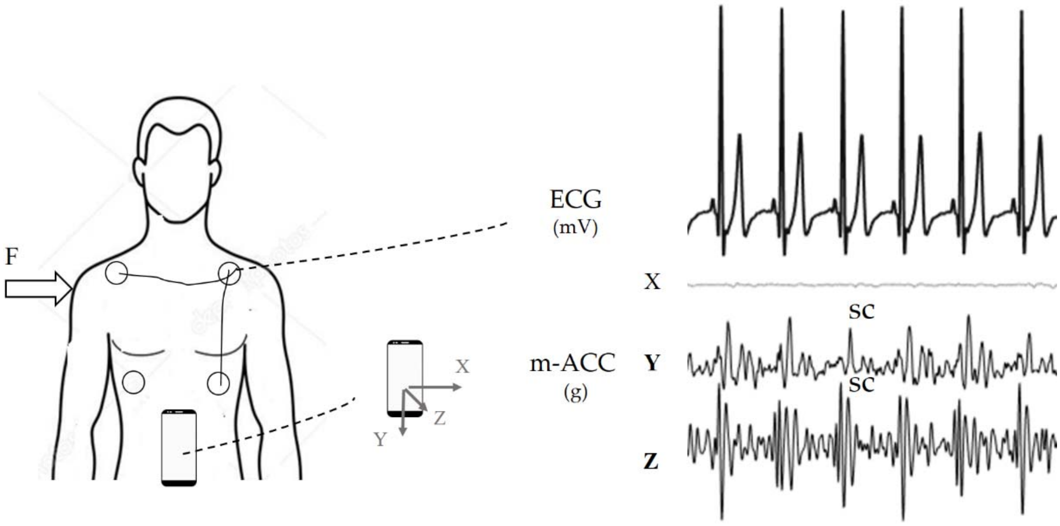

Figure 1. The ECG electrodes and a smartphone were positioned on the subject: signals were acquired simultaneously and synchronized by a motion artifact caused by an impulsive force (F) impressed on the subject' shoulder. The ECG and the simultaneously acquired tri-axial accelerometric signals (m-ACC) are shown: while the lateral (X) component does not project any heartbeat vibration, the longitudinal (Y) and normal (Z) components show a clear periodic complex (SC) related to cardiac heartbeat activity.

The signals were synchronized by applying a lateral impulsive force stimulus applied on to the subject's shoulder, which was detected both by the smartphone's accelerometers and by the ECG electrodes (as a movement artifact). After a 10 min of acclimation period in supine posture, the experimental protocol included two acquisitions performed sequentially (see Fig.2): the former, lasting 3 minutes with the subject breathing normally (REST) and, after 1 minute of readjustment, the latter lasting 1 minute where a mental stress (MS) condition. As mental arithmetic is one of the most commonly utilized laboratory psychological stressors able to increase HR [30]–[32], stress was provoked by asking the subject to properly answer after performing (silently) seven arithmetic serial subtractions starting from a 4-digit number.

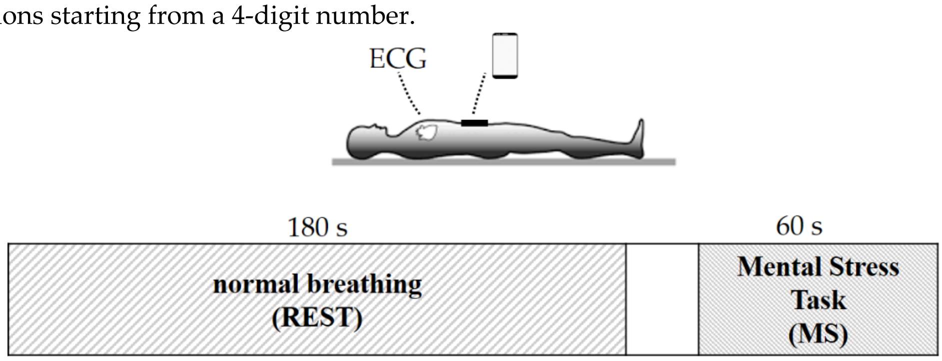

Figure 2. Schematic representation of the experimental protocol, where the subject was acquired in supine posture with a smartphone positioned on the belly above the navel. The protocol consisted in two steps: normal breathing (REST) and Mental Stress task (MS) where the subject was asked to perform arithmetic serial subtractions starting from a 4-digit number.

2.3. Signal processing

2.3.1. Pre-processing

To synchronize the smartphone signals with the ECG, the spike motion artifact introduced during the measurement was identified on the X component of the m-ACC signal and on the ECG lead I.

After this step, the Y and Z components of the m-ACC signal were both band-pass filtered (4th order Butterworth filter): cut-off frequencies of 5 and 25 Hz were used for Z, while 1 and 30 Hz for Y. This approach removed the out-of-band noise and breathing activity-related motion artifacts. The chest wall vibrations and the body acceleration due to the heartbeat-induced recoil forces were thus retained considering these different band-pass ranges [3].

2.3.2. Heartbeat detection and algorithm performance

On the ECG signal, R peaks were detected using Pan-Tompkins algorithm [33], [34] and used to derive the RR series for comparison purposes with smartphone-derived series.

On both Y and Z components of the m-ACC signal, to detect the systolic complex (SC), an ECG-free algorithm based on template matching technique was applied [35], performing the following steps:

- signals were divided into 30s segments (Figure 3, a);
- for each segment, a template of 400 ms duration centered at the absolute maximum within the first 10s was extracted (Figure 3, b);
- computation of the cross-correlation between the identified template and the 30 s signal segment (Figure 3, c);
- searching windows centered at each maxima of the cross-correlation function (Fig. 3 c), dashed red) were defined and used to precisely locate each SC (red dot) as the wave with the maximum absolute amplitude on the m-ACC signal (black) (Fig. 3 d). The length of the search window is calculated taking into consideration the mean of the previous three heart beats durations.

Then, beat-to-beat duration series were calculated as the distance between two consecutive peaks.

Once the beat-to-beat series were obtained for both Y and Z components, the optimum time series (OPT) was selected as the one associated to the minimum mean square deviation with respect to a polynomial (5^{th} order) that fits the data. This step allowed to automatically selecting the series with less outliers in presence of possible artifacts and missed or wrong detections, thus obtaining at least a beat-to-beat series for each subject and condition, from which to proceed for the USV indices computation.

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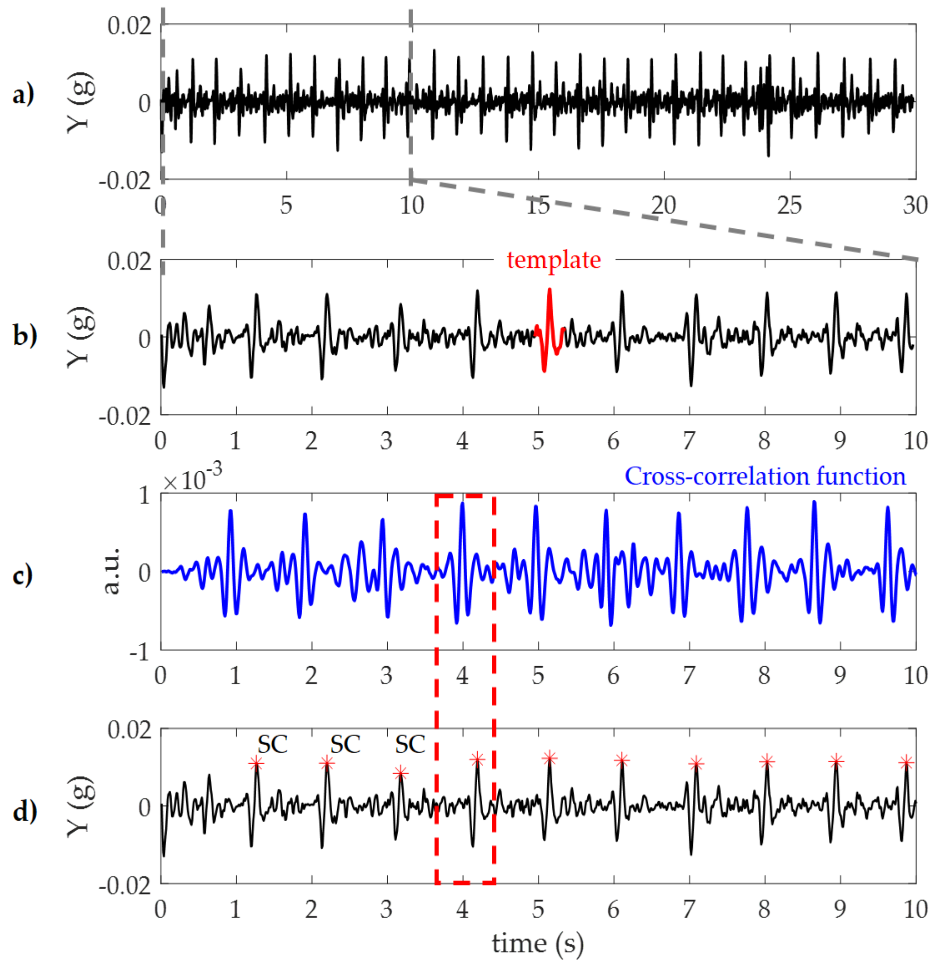

Figure 3. Schematic representation of the ECG-free heartbeat detection algorithm. a): 30s segment of the m-ACC signal recording (black); b) within the first 10 s segment, a template (red) is automatically selected; c) the cross-correlation function (in blue) was obtained using the template with the 30s signal (black) and the position of maximum values of cross-correlation were used to identify a search window (dashed red) for each heartbeat; d) the windows were thus used to detect the systolic complex (SC, red dots) on the m-ACC signal (black).

2.3.3. Ultra-short heart rate variability indices

The SDNN and RMSSD were computed as USV time domain indices. The SDNN estimates overall HRV, while RMSSD is actually an estimate of high frequency variation in HR led by the vagal tone activity of the ANS [20], [27], [36]–[39]. They were calculated using the most central 60 s, 30 s and 10 s signal segments of the REST and MS recordings, from both RR and OPT series.

2.4. Statistical analysis

Results are presented as median (25th-75th percentile).

The algorithm’s feasibility was computed as the number of acquisitions in which at least one optimal series for the ultra-short heart rate variability analysis was obtained, with respect to the total number of acquisitions. The sensitivity was calculated as the percentage ratio between the SC complex detected with respect to the corresponding R-ECG peaks. To evaluate the accuracy (Acc) of the applied ECG-free detection algorithm, all the peaks were visually inspected together with ECG annotations: the misdetections, as double detection or incorrect peaks, were identified and categorized as false positive (FP), while the missing detections were considered as false negative (FN), where the true positive (TP) corresponded to a detection in the correct position (see Eq. 1).

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$$Acc = \frac{TP}{FP + FN + TP} \qquad Eq. 1$$

In order to test if the OPT series could represent a valid surrogate for electrodes-free heart beat duration extraction, linear correlation and Bland-Altman analysis were applied, such that the OPT series were compared to the corresponding RR series globally.

Mann-Whitney unpaired test (*p<.05) was applied to compare the OPT versus RR series parameters (cardiac cycle median duration and USV indices) to support the hypothesis that the obtained parameters represent the same information, both in CTRL and MS.

Friedman test (*p<.05) was applied for testing whether heartbeat mean duration and USV indices obtained from different length recordings (60 s, 30 s and 10 s) were representative of the same distribution, to support the hypothesis of using the shortest possible acquisition length. In case of different distributions among groups, the multi-comparison group by Bonferroni test was also applied (*p<.05/n, where n=3 groups).

Non-parametric Wilcoxon paired test (*p<.05) was used to test significant differences in ANS sympatho-vagal status evidenced by the USV parameters between REST and MS, separately for the ECG and OPT series.

3. Results

3.1. Algorithm perfomance

The m-ACC signals from one subject in REST and one in MS were discarded due to poor signal-to-noise ratio thus resulting in a feasibility of the beat-to-beat heart rate series extraction of 93.8%. The algorithm automatically selected the Z component as the best component for heartbeat detection in 10/15 subjects for REST and in 11/15 subjects for MS.

Compared to the 1784 R-ECG peaks in REST and 1271 in MS, the ECG-free detection algorithm detected correctly 1754 beats in REST and 1246 beats in MS, thus resulting in an algorithm sensitivity of 98.3% and 98%, respectively, with high accuracy (98%) reached.

In addition, due the presence of ectopics beats in both REST and MS OPT series that could result in erroneous USV indices, another subject was discarded. Accordingly, to allow paired comparison, 13 subjects were considered for further analysis.

3.2. Cardiac cycle duration

High R^2 value (0.99) and narrow confidence interval (CI=±33 ms, ±2SD) were obtained with Bland-Altman analyses. The algorithm globally was able to detect heart beat duration in a range from 447 ms up to 1337 ms.

No statistical difference (Mann-Whitney and Friedman test) was found between heart beat duration and USV indices obtained from RR and OPT, for each measurement, in both conditions.

Table 2 reports the results obtained considering different duration of signal segments. For all segment durations, a significant decrease in heart beat duration was induced by MS compared to REST, as evident in both RR and OPT series. In particular, for a 60 s segment, both the RR and OPT were found reduced in absolute values by 16% (10%-26%); by considering a 30 s segment, the RR and OPT were reduced by 17 % (10% - 27%), while using 10 s portion the RR and OPT were reduced by 20 % (9%-27%). In Fig. 4, the corresponding trends for each subject are represented.

Table 2. Heart beat duration (ms) obtained from the ECG (RR) and the optimal (OPT) series by smartphone's accelerometer expressed as median (25^{th}-75^{th} percentiles), for 60 s, 30 s and 10 s signal segments, in control (REST) and mental stress (MS) conditions. * Wilcoxon p<0.5 REST vs MS.

RR (ms)		OPT (ms)	
REST	MS	REST	MS

60s	887 (780-985)	740 * (580-827)	887 (780-987)	741 * (584-830)
30s	888 (779-992)	748 * (570-832)	888 (779-993)	747 * (571-832)
10s	886 (774-982)	737 * (575-822)	887 (774-982)	740 * (576-822)

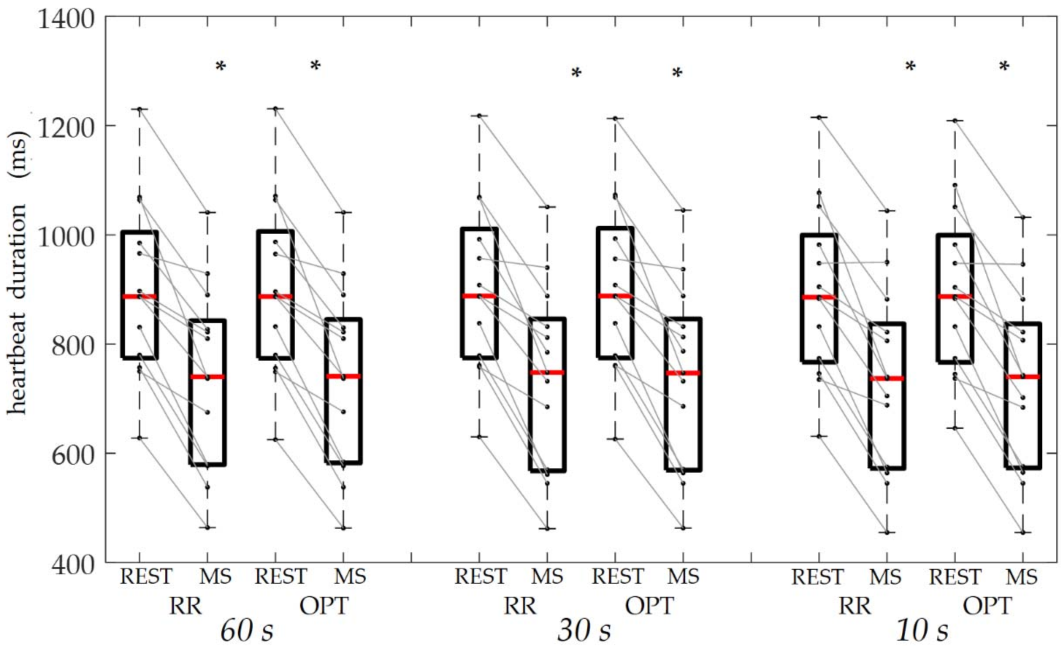

Figure 4. Distributions and individual data of RR and OPT series, in control (REST) and mental stress (MS) conditions, using 60 s, 30 s and 10 s signal segments. * Wilcoxon p<0.5 REST vs MS

3.3. Ultra-short heart rate variability indices

In Table 3, the results of USV indices obtained considering different duration of ECG and OPT signal segments are reported.

Regarding SDNN, for 60 s and 30 s signal segments, no statistical difference was found between REST and MS, both using ECG and OPT. However, for 10 s segments the SDNN was significantly reduced from CTRL to MS only for RR series.

In case of RMSSD obtained from both RR and OPT series, significant differences were found for each signal segment length between REST and MS. In particular, for 60 s segment the RMSSD from RR was reduced in absolute values by 38% (26%-71%), and by 40% (8%-68%) from OPT; from 30 s segment it was reduced by 45% (27%-72%) from RR, and by 46 % (22%-64%) from OPT, while for 10 sec segments it was reduced by 53% (13%-73%) from RR, and by 49% (8%-66%) from OPT.

Friedman test resulted significant for SDNN indices both for RR and OPT series during MS, and from the multi-comparison Bonferroni test the distribution differed between the 60 s segments indices with respect to the 30 s and 10 s indices. On the other hand, the RMSSD obtained from different signal segments (60 s, 30 s and 10 s) resulted to belong to the same distribution.

In Fig. 5 the corresponding results for each subject are presented, from which it is possible to observe the decrease in the RMSSD for both RR and OPT series, at each signal segment duration.

Table 3. SDNN and RMSSD values (ms) obtained from the ultra-short heart rate variability analysis using RR and optimal (OPT) series. SDNN and RMSSD are expressed as median (25^{th}-75^{th}

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percentiles), for 60 s, 30 s and 10 s signal segments duration, both in control (REST) and mental stress (MS) conditions. * Wilcoxon p<0.05 REST vs MS; # Friedman p<0.05 vs 60 s.

	RR		**OPT**	
	REST	**MS**	**REST**	**MS**
		SDNN (ms)		
60s	48 (41-64)	42 (27-72)	54 (43-66)	45 (32-72)
30s	42 (35-68)	39 # (19-47)	47 (40-65)	39 # (27-51)
10s	39 (28-61)	26 * # (16-42)	38 (35-66)	31 # (21-44)
		RMSSD (ms)		
60s	39 (30-65)	23 * (14-31)	48 (38-76)	36 * (25-48)
30s	40 (24-67)	22 * (10-30)	51 (38-73)	36 * (24-45)
10s	41 (27-61)	20 * (11-30)	47 (36-78)	27 * (20-35)

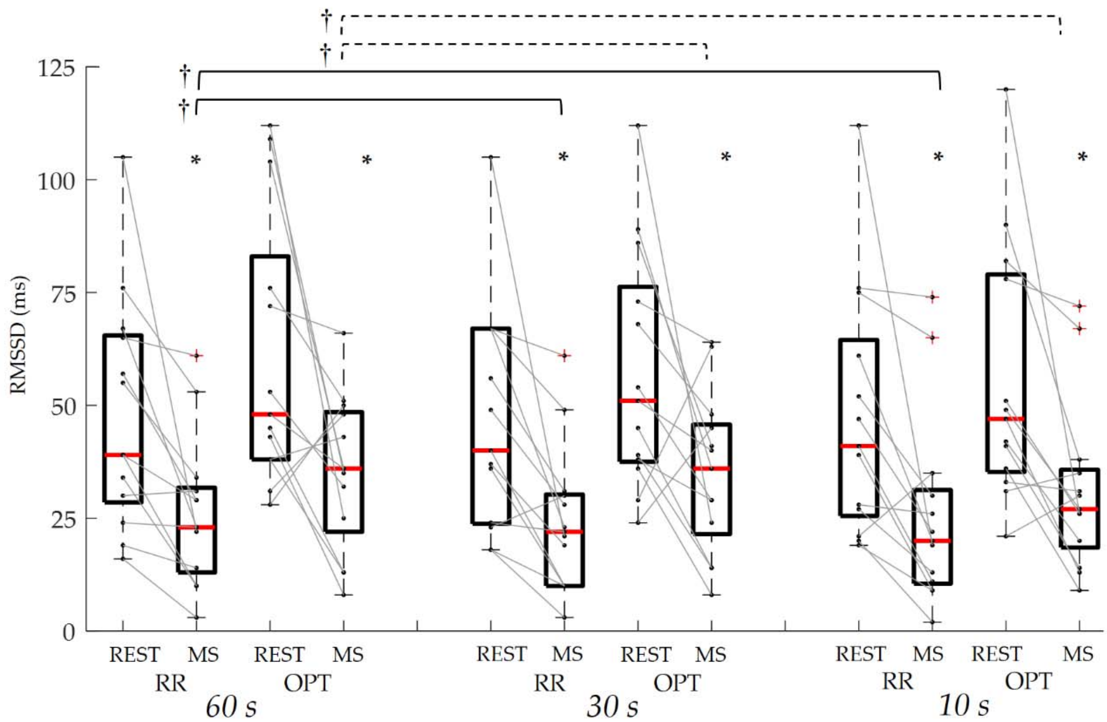

Figure 5. Distributions and individual data of RMSSD values obtained from RR and OPT series, in control (REST) and mental stress (MS) conditions, considering 60 s, 30 s and 10 s signal segments. * Wilcoxon p<0.05. REST vs MS; † Friedman and multicomparison with Bonferroni correction p<0.016 vs 60 s.

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4. Discussion

Current smartphone technology and embedded sensors have the potential to acquire signals related to cardiac activity. In addition to the use of the on-board camera to derive the pulsation of the skin capillary blood flow in the fingertips from which to obtain pulse rate [16], micro-electro-mechanical systems technology embedded in smartphones potentially allows measuring heart mechanical activity by acquiring vibrational signals when positioned on the body [6]. The potential of these approaches in using the smartphone as source of vital parameters stands in the ability to acquire these signals anytime and anywhere, without the need of additional peripherals, thus improving patient empowerment through self-measurement.

However, in order to be accepted by the medical community, the potential value relevant to the use of these technologies needs to be proved. While the use of smartphone cameras using photoplethysmography for early detection of atrial fibrillation, based on the analysis of beat-by-beat duration variability series, has initially proved its value in a prospective two-center, international clinical validation study [40], the validation of using smartphone accelerometers is still limited and again focusing on beat-by-beat duration variability only [16], [17], [41], [42].

Our hypothesis was that the beat-to-beat heart rate series derived by smartphone without any peripheral were suitable for the USV analysis, potentially useful for stress evaluation from short time series. To this purpose, the feasibility of detecting changes in ANS sympatho-vagal state provoked by mental task in normal volunteers was tested.

The interest in ultra-short HRV measurements as a non-invasive marker of autonomic status is also emerging as training status marker to objectively measure stress levels in athletes [37], [38], [43].

In our work, the smartphone was used as a sensor for accelerometric data acquisition, showing a good feasibility (93.8 %). Signal quality allowed further analysis, including automatic parameters extraction at least in one component of the smartphone tri-axial accelerometers. Acceptable limits of agreement corresponding to ±10 bpm for the fastest heart rate analyzed (134 bpm) and to ±1 bpm for the lowest one (45 bpm) were obtained, in agreement with previous studies[2], [3], [35].

The different durations of considered signal segments were selected as a compromise, taking into consideration an acquisition as short as possible in a hypothetical user-driven scenario, but at the same time being able to record a reasonable amount of data to provide reliable measurements. As already stated, for mobile applications short-term measurements are desirable for USV analysis, since the conventional five minute long recordings might be inadequately long and prone to artifacts [36].

The results of this study are in agreement with our preliminary findings [35] obtained in only six subjects, thus confirming the feasibility of applying USV to SC beat-to-beat measurements derived by the smartphone accelerometers. From the obtained results, it was shown that median heart rate could be accurately estimated from very short segments (even from 10 seconds acquisition) of m-ACC signals, without differences when compared to the ECG results. Through the mental stress task, the median heart beat duration was found significantly shortened when compared to the rest condition, as physiological expected [44], and in line with what observed using the ECG derived series.

The obtained results for SDNN and RMSSD parameters showed a general decrease in RMSSD, and a trend of decrease, significant only for 10 seconds ECG, in SDNN. As mental stress is known to increase sympathetic activity, as revealed by the increased heart rate and reduced SDNN, the mental exercise induced a significant decrease in parasympathetic activation, in agreement with the induced stimulus, reflected by the significant decrease in RMSSD in both ECG and OPT series. These results highlight the potential to use the smartphone's accelerometers to derive cardiac beat-to-beat measurements, able to monitor a stress-induced situation as a decrease from a baseline value, using very short acquisitions (even from 10 seconds).

Once confirmed in a larger number of subjects, a 10 sec or 30 sec acquisition could be considered as an easy, non-invasive way for the self-evaluation of stress using accelerometers already embedded in the mobile phone. This technology could have potential benefits in both cardiac disease prevention and self-assessment of patients with chronic disease (such as diabetes

[22], [45], or in patients where an imbalance of cardiac autonomic activity plays an important role, such as in coronary heart disease [46][47]–[49]), where simple but effective monitoring tools are needed in order to have reliable at-home measurements, managed directly by the patient.

5. Conclusions

The beat-to-beat heart rate variability series derived by smartphone's accelerometers were able to detect the changes in ultra-short term HRV indices relevant to a change in the sympatho-vagal balance activation, induced by a stressor stimulus. In particular, the USV feature of RMSSD obtained by the m-ACC signal of up to 10 sec duration could be used as potential marker to estimate the stress level compared to a control value. This simple approach and its potential application in stress evaluation generate new value of using the embedded smartphone accelerometers as a new tool for self-tracking of cardiac activity.

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References

[1] F. Landreani *et al.*, "Feasibility study for beat-to-beat heart rate detection by smartphone's accelerometers," *2015 E-Health Bioeng. Conf. EHB 2015*, pp. 3–6, 2016.

[2] F. Landreani *et al.*, "Heartbeat Detection Using Three-Axial Seismocardiogram Acquired by Mobile Phone," *2018 Comput. Cardiol. Conf.*, vol. 45, p. 6, 2019.

[3] F. Landreani *et al.*, "Beat-to-beat heart rate detection by smartphone's accelerometers: Validation with ECG," in *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*, 2016, vol. 2016-Octob, pp. 525–528.

[4] A. Laurin, F. Khosrow-Khavar, A. P. Blaber, and K. Tavakolian, "Accurate and consistent automatic seismocardiogram annotation without concurrent ECG," *Physiol. Meas.*, vol. 37, no. 9, pp. 1588–1604, 2016.

[5] P.-F. Migeotte *et al.*, "Ballistocardiography and Seismocardiography: A Review of Recent Advances," *IEEE J. Biomed. Heal. Informatics*, vol. 19, no. 4, pp. 1414–1427, 2014.

[6] E. Pinheiro, O. Postolache, and P. Girão, "Theory and Developments in an Unobtrusive Cardiovascular System Representation: Ballistocardiography," *Open Biomed. Eng. J.*, vol. 4, no. 1, pp. 201–216, 2010.

[7] O. Postolache, P. S. Girão, E. Pinheiro, and G. Postolache, "Unobtrusive and Non-invasive Sensing Solutions for On-Line Physiological Parameters Monitoring," Springer, Berlin, Heidelberg, 2010, pp. 277–314.

[8] O. T. Inan *et al.*, "Ballistocardiogram: Mechanism and Potential for Unobtrusive Cardiovascular Health Monitoring," *Sci. Rep.*, vol. 6, no. 1, 2016.

[9] E. J. Pino, J. A. P. Chavez, and P. Aqueveque, "BCG algorithm for unobtrusive heart rate monitoring," in *2017 IEEE Healthcare Innovations and Point of Care Technologies (HI-POCT)*, 2017, pp. 180–183.

[10] J. Alihanka, K. Vaahtoranta, and I. Saarikivi, "A new method for long-term monitoring of the ballistocardiogram, heart rate, and respiration," *Am. J. Physiol. Integr. Comp. Physiol.*, vol. 240, no. 5, pp.

R384–R392, 2017.

[11] D. M. Salerno, R. S. Crow, L. Hedquist, P. Hannan, and D. Jacobs, “Relationship between Seismocardiogram and Echocardiogram for Events in the Cardiac Cycle,” *Am. J. Noninvasive Cardiol.*, vol. 8, no. 1, pp. 39–46, 2017.

[12] M. Di Rienzo *et al.*, “A wearable system for the seismocardiogram assessment in daily life conditions,” in *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*, 2011, pp. 4263–4266.

[13] Z. Iftikhar *et al.*, “Multiclass classifier based cardiovascular condition detection using smartphone mechanocardiography,” *Sci. Rep.*, vol. 8, no. 1, p. 9344, Dec. 2018.

[14] M. Jafari Tadi *et al.*, “A real-time approach for heart rate monitoring using a Hilbert transform in seismocardiograms,” *Physiol. Meas.*, vol. 37, no. 11, pp. 1885–1909, 2016.

[15] T. Koivisto *et al.*, “Automatic detection of atrial fibrillation using MEMS accelerometer,” in *Computing in Cardiology*, 2015, vol. 42, pp. 829–832.

[16] F. Landreani and E. G. Caiani, “Smartphone accelerometers for the detection of heart rate,” *Expert Rev. Med. Devices*, vol. 14, no. 12, pp. 935–948, 2017.

[17] F. Landreani *et al.*, “Heartbeat Detection Using Three-Axial Seismocardiogram Acquired by Mobile Phone,” *2018 Comput. Cardiol. Conf.*, vol. 45, no. Ivc, 2019.

[18] F. Landreani *et al.*, “Respiratory Frequency Estimation from Accelerometric Signals Acquired by Mobile Phone in a Controlled Breathing Protocol,” *2017 Comput. Cardiol. Conf.*, vol. 44, 2018.

[19] J. Rodriguez *et al.*, “Poststroke alterations in heart rate variability during orthostatic challenge,” 2017.

[20] Task Force of The European Society of Cardiology and The North and S. of P. and Electrophysiology, “Guidelines Heart rate variability Standards of measurement, physiological interpretation, and clinical use,” *Eur. Heart J.*, vol. 17, no. 19, pp. 354–381, 1996.

[21] J. F. Thayer, S. S. Yamamoto, and J. F. Brosschot, “The relationship of autonomic imbalance, heart rate variability and cardiovascular disease risk factors,” *Int. J. Cardiol.*, vol. 141, no. 2, pp. 122–131, May 2010.

[22] M. Chessa *et al.*, “Role of heart rate variability in the early diagnosis of diabetic autonomic neuropathy in children,” *Herz*, vol. 27, no. 8, pp. 785–790, Dec. 2002.

[23] J. Nolan, A. D. Flapan, S. Capewell, T. M. MacDonald, J. M. Neilson, and D. J. Ewing, “Decreased cardiac parasympathetic activity in chronic heart failure and its relation to left ventricular function.,” *Heart*, 2007.

[24] Z. Jing and A. Barreto, “Influence of Mental Stress on Heart Rate and Heart Rate Variability,” *FLAIRS Conf.*, pp. 395–400, 2008.

[25] J. Taelman, S. Vandeput, A. Spaepen, and S. Van Huffel, “Influence of mental stress on heart rate and heart rate variability,” in *IFMBE Proceedings*, 2008.

[26] J. Ramos-Castro *et al.*, “Heart rate variability analysis using a seismocardiogram signal,” in *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*, 2012, pp. 5642–5645.

[27] M. L. Munoz *et al.*, “Validity of (Ultra-)Short recordings for heart rate variability measurements,” *PLoS One*, vol. 10, no. 9, pp. 1–15, 2015.

[28] H. J. Baek, C.-H. Cho, J. Cho, and J.-M. Woo, “Reliability of Ultra-Short-Term Analysis as a Surrogate of Standard 5-Min Analysis of Heart Rate Variability,” *Telemed. e-Health*, 2015.

[29] L. Pecchia, R. Castaldo, L. Montesinos, and P. Melillo, “Are ultra-short heart rate variability features good surrogates of short-term ones? State-of-the-art review and recommendations,” *Healthc. Technol.*

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Peer-reviewed version available at *Sensors* **2019**, *19*, 3729; doi:10.3390/s19173729

Lett., 2018.

[30] R. P. Sloan, J. B. Korten, and M. M. Myers, "Components of heart rate reactivity during mental arithmetic with and without speaking," *Physiol. Behav.*, vol. 50, no. 5, pp. 1039–1045, Nov. 1991.

[31] T. G. Brown, A. Szabo, and P. Seraganian, "Physical Versus Psychological Determinants of Heart Rate Reactivity to Mental Arithmetic," *Psychophysiology*, vol. 25, no. 5, pp. 532–537, Sep. 1988.

[32] C. F. Sharpley, P. Kamen, M. Galatsis, R. Heppel, C. Veivers, and K. Claus, "An Examination of the Relationship Between Resting Heart Rate Variability and Heart Rate Reactivity to a Mental Arithmetic Stressor," *Appl. Psychophysiol. Biofeedback*, vol. 25, no. 3, pp. 143–153, 2000.

[33] J. Pan and W. J. Tompkins, "A Real-Time QRS Detection Algorithm," *IEEE Trans. Biomed. Eng.*, 2007.

[34] Sedghamiz. H, "Matlab Implementation of Pan Tompkins ECG QRS detector," 2014. [Online]. Available: https://www.researchgate.net/publication/313673153_Matlab_Implementation_of_Pan_Tompkins_ECG_QRS_detector.

[35] F. Landreani *et al.*, "Ultra-short-term heart rate variability analysis on accelerometric signals from mobile phone," *2017 E-Health Bioeng. Conf. EHB 2017*, pp. 241–244, 2017.

[36] L. Salahuddin, J. Cho, M. G. Jeong, and D. Kim, "Ultra short term analysis of heart rate variability for monitoring mental stress in mobile settings," in *Annual International Conference of the IEEE Engineering in Medicine and Biology - Proceedings*, 2007, pp. 4656–4659.

[37] F. Y. Nakamura, A. A. Flatt, L. A. Pereira, R. Ramirez-Campillo, I. Loturco, and M. R. Esco, "Ultra-Short-Term Heart Rate Variability is Sensitive to Training Effects in Team Sports Players.," *J. Sports Sci. Med.*, vol. 14, no. 3, pp. 602–5, Sep. 2015.

[38] A. A. Flatt and M. R. Esco, "Validity of the ithletetm smart phone application for determining ultra-short-term heart rate variability," *J. Hum. Kinet.*, vol. 39, no. 1, pp. 85–92, 2013.

[39] J.-L. Elghozi and C. Julien, "Sympathetic control of short-term heart rate variability and its pharmacological modulation," *Fundam. Clin. Pharmacol.*, vol. 21, no. 4, pp. 337–347, Aug. 2007.

[40] N. Brasier *et al.*, "Detection of atrial fibrillation with a smartphone camera: first prospective, international, two-centre, clinical validation study (DETECTAF PRO)."

[41] R. Mohamed and M. Youssef, "HeartSense: Ubiquitous Accurate Multi-Modal Fusion-based Heart Rate Estimation Using Smartphones," *Proc. ACM Interactive, Mobile, Wearable Ubiquitous Technol.*, vol. 1, no. 3, pp. 1–18, 2017.

[42] S. Sieciński and P. Kostka, "Determining heart rate beat-to-beat from smartphone seismocardiograms: Preliminary studies," in *Advances in Intelligent Systems and Computing*, 2018, vol. 623, pp. 133–140.

[43] A. E. Aubert, B. Seps, and F. Beckers, "Heart Rate Variability in Athletes," *Sports Medicine*. 2003.

[44] L. Bernardi *et al.*, "Effects of controlled breathing, mental activity and mental stress with or without verbalization on heart rate variability," *J. Am. Coll. Cardiol.*, vol. 35, no. 6, pp. 1462–1469, 2000.

[45] U. Nussinovitch, O. Cohen, K. Kaminer, J. Ilani, and N. Nussinovitch, "Evaluating reliability of ultra-short ECG indices of heart rate variability in diabetes mellitus patients ☆," *J. Diabetes Complications*, vol. 26, pp. 450–453, 2012.

[46] P. K. Stein *et al.*, "Severe depression is associated with markedly reduced heart rate variability in patients with stable coronary heart disease," *J. Psychosom. Res.*, vol. 48, no. 4–5, pp. 493–500, Apr. 2000.

[47] M. T. La Rovere *et al.*, "Short-Term Heart Rate Variability Strongly Predicts Sudden Cardiac Death in Chronic Heart Failure Patients," *Circulation*, vol. 107, no. 4, pp. 565–570, Feb. 2003.

[48] R. M. Carney, R. D. Saunders, K. E. Freedland, P. Stein, M. W. Rich, and A. S. Jaffe, "Association of

doi:10.20944/preprints201907.0062.v1

Peer-reviewed version available at *Sensors* **2019**, *19*, 3729; doi:10.3390/s19173729

depression witk reduced heart rate variability in coronary artery disease," *Am. J. Cardiol.*, vol. 76, no. 8, pp. 562–564, 1995.

[49] M. Kupari, J. Virolainen, P. Koskinen, and M. J. Tikkanen, "Short-term heart rate variability and factors modifying the risk of coronary artery disease in a population sample," *Am. J. Cardiol.*, vol. 72, no. 12, pp. 897–903, 1993.