

1 Article

2 **A study on the effect of contact pressure during** 3 **physical activity on photoplethysmographic heart** 4 **rate measurements**

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17 **Abstract:** Heart rate (HR) as an important physiological indicator could properly describe global
18 subject's physical status. Photoplethysmographic (PPG) sensors are catching on in field of wearable
19 sensors, combining the advantages in costs, weight and size. Nevertheless, accuracy in HR readings
20 is unreliable specifically during physical activity. Among several identified sources that affect PPG
21 recording, contact pressure (CP) between the PPG sensor and skin greatly influences the signals. In
22 this study, the accuracy of HR measurements of a PPG sensor at different CP was investigated when
23 compared with a commercial ECG-based chest strap used as a test control, with the aim of
24 determining the optimal CP to produce a reliable signal during physical activity. Seventeen subjects
25 were enrolled for the study to perform a physical activity at three different rates repeated at three
26 different contact pressures of the PPG-based wristband. The results show that the CP of 54 mmHg
27 provides the most accurate outcome with a Pearson correlation coefficient ranging from 0.81 to 0.95
28 and a mean average percentage error ranging from 3.8% to 2.4%, basing on the physical activity
29 rate. Authors also found that changes in the CP has greater effects on PPG-HR signal quality than
30 those deriving from the intensity of the physical activity and specifically, the individual best CP for
31 each subject provided reliable HR measurements even for a high intensity of physical exercise with
32 a Bland-Altman plot within ± 11 bpm. Despite future studies on a larger cohort of subjects are still
33 needed, this study could contribute a profitable indication to enhance accuracy of PPG-based
34 wearable devices.

35 **Keywords:** Photoplethysmography (PPG), PPG sensor, wearables, contact pressure, contact force,
36 heart rate, heart rate signal (HR), PPG accuracy, heart rate reliability.

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39 1. Introduction

40 Wearable and portable technologies have recently spread in everyday life [1–3], and this trend is
41 expected to reach higher percentages in the next years. The explosion of such interest in wearable
42 technologies depends on their potential to provide continuous physiological information in real-time
43 via an affordable and noninvasive device for health applications such as the monitoring of chronic
44 diseases and aging populations [4,5].

45 Moreover, thanks to recent advances in technology and in miniaturized chips, it is now possible for
46 a single wearable device to integrate a wide range of different sensors [6] to health awareness.

47 The high request from the market for innovative wrist-worn devices is moving many companies in
48 introducing new functionalities and new sensors in their devices and a continuous academic research
49 concerning wearable sensors have been carried forward during the last 10 years [5,7,8]; the expected
50 result is a continuous growing in quality and quantity of functionalities and reliability of wearable
51 devices aimed in enhancing the quality of life through the monitoring and maintenance of personal
52 physiological parameters.

53 Among different technologies, optical sensors based on photoplethysmography (PPG) have become
54 increasingly popular [9,10] and nowadays have been adopted and integrated in wrist-worn products
55 of several companies. PPG technology relies on a light emitting diode and a photo detector which is
56 able to monitor changes in the light intensity which are associated to changes in perfusion of the
57 portion of tissue underneath the sensor.

58 The PPG signal is composed by two components, a direct current (DC) component and an alternating
59 component (AC). The DC component depends on the characteristics of the tissues and on the average
60 of blood volume and it maintains a constant absorption characteristic during the measurement. The
61 AC component reflects the changes in blood volume and can be extracted from the DC component,
62 to which is superimposed, and used to calculate physiological parameters, such as the heart rate (HR).
63 Since its amplitude is only 1% to 2% of that of the DC component [11], it is susceptible to the presence
64 of movements and electrical noises. Indeed, one of the major issue in using PPG-based wrist-worn
65 devices is their poor capability in tracking a reliable PPG signal during daily routine activities and
66 physical exercises due to motion artifacts caused by hand movements [12].

67 Despite the susceptibility to motion artifacts, PPG technology is able to provide several physiological
68 parameters associated to the cardiovascular system, such as HR, heart rate variability [13–15], blood
69 oxygenation saturation [11,16,17], blood pressure [18–20] and arterial stiffness [21,22]. In particular,
70 HR is one of the first parameters observed in order to monitor subject's health in a wide range of
71 situations, such as patient monitoring [23], training of athletes [24], and worker's safeness [25].

72 The electrocardiogram (ECG) has been used for many years as the principal HR monitoring
73 technology. It detects the heart electrical activity by using several bio-electrodes that should be placed
74 at certain body locations. Despite this technology offers a very good accuracy [26], it does not offer
75 sufficient user portability and user flexibility. In comparison, PPG-based wristband-type device, are
76 wearable, comfortable, inexpensive and well accepted by its users still providing reliable
77 cardiovascular parameters, thanks to many improvements that are continuously proposed [27–34].
78 Therefore, PPG devices represent an excellent potential solution to replace ECG in monitoring
79 cardiovascular parameters during daily activities.

80 To fully exploit this potential, it is essential that the accuracy of PPG sensor [35] keeps adequate even
81 during physical activity and in free living conditions. Among several sources that affect PPG
82 recording (e.g. measurement site, specific biological and physiological characteristics of the subject,
83 breathing, ambient light and temperature), contact force between the sensor and the skin greatly
84 influences the PPG signal [36–41] and causes motion artefacts, which are known to be a limiting factor
85 that prevents the straight-forward usage of PPG and are considered to result from sensor-tissue
86 motion and internal tissue movement [42]. Specifically, contact force influences both the relative
87 motion between the sensor and the measuring site (especially during physical activities) and the
88 arterial geometry which can be deformed by compression [43]. The contact force between the sensor
89 and the skin can alter the sub-cutaneous perfusion and eventually it can obstruct microcirculatory
90 blood flow. These perturbations and alterations lead to a distortion of the peak points of the PPG
91 waveform and can lead to errors in detecting and calculating the HR, limiting all the practical
92 applications of PPG-based devices in physiological monitoring. With an increasing contact pressure
93 between the sensor and the skin (Fig. 1) the DC amplitude increase, whereas the AC component
94 increases first, with a maximum in the range of the optimal contact pressure and then it decreases to
95 the point that it is no longer possible to recognize the pulsation.

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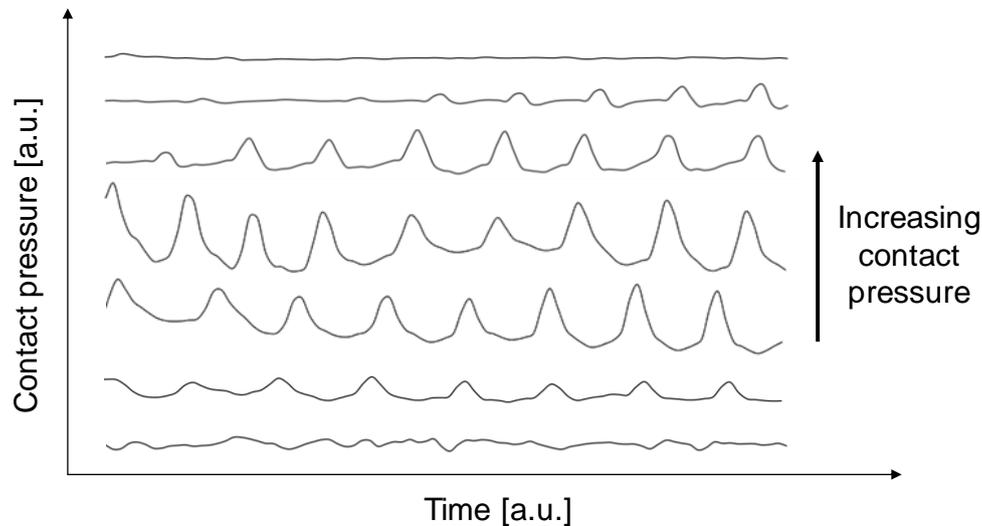


Figure 1. Qualitative representation of the variation of the AC signal for different contact pressures. With an increasing contact pressure, the amplitude initially increases up to a maximum and then it starts decreasing.

The best PPG signal with the highest amplitude, can theoretically be obtained under conditions of transmural pressure, defined as the pressure difference between the inside and outside of the blood vessel [9]. Consequently, insufficient or excessive contact pressure (CP) leads to low signal amplitude, to a poor signal to noise ratio, as well as distorted waveforms. Santos and colleagues [44] developed a stand-alone pulse oximeter based on PPG technology and equipped with a contact force sensor and found that contact force has influences also in SpO₂, which was found to decrease as the CP was increasing. Nevertheless, assessing the optimal range of contact force is still challenging due to the wide variability of the subjects in terms of age, gender and arterial stiffness [43,45].

Despite the effect of contact force in PPG signal quality has been investigated mainly during resting conditions, a deeper knowledge of this interaction is needed during physical activity and from a measurement site which is widely used by commercial products (i.e. wrist) so that it is possible to take into account all the different potential sources which affect signals in a likely daily life case scenario. With this aim, in this study we considered a PPG device in reflectance mode operation, as this approach is more likely to provide comfort and more daily usability for end users.

An integrated PPG-based system was developed for measuring the HR at different CP between the sensor and the skin to determine the quality of the PPG based HR measurement at different physical activities over a cohort of seventeen subjects. By applying three different levels of CP (i.e. 12, 33 and 54 mmHg; the different acquisitions shown in Fig. 1 were acquired before performing the experimental protocol in order to identify the target range of CP), the goal was to assess the optimal values of CPs to achieve a reliable estimation of HR measurements during different physical activities.

2. Materials and Methods

The measurement devices, the protocol for human subjects and the data analysis are described below:

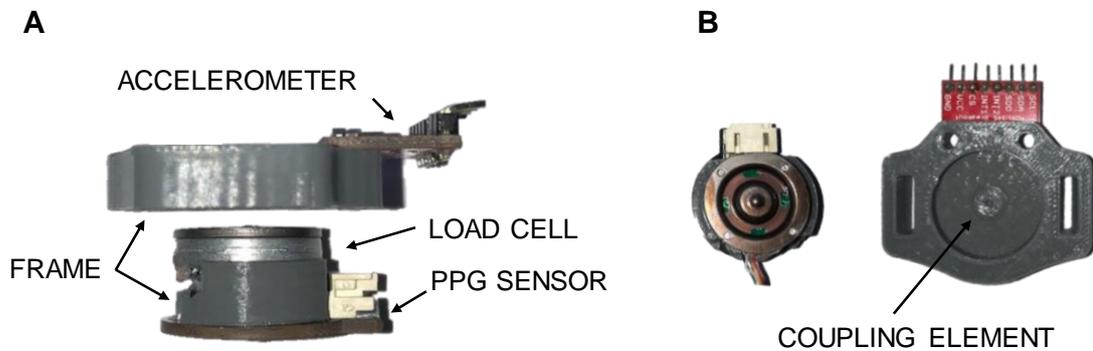
2.1. Measurement device

Two different devices were used to collect simultaneously an ECG R-R interval from the chest and a PPG waveform from the wrist of participants who took part in the protocol. The ECG data, as a reference, were collected by using a Polar chest strap (H9, Polar Electro, Kempele, Finland) and

133 recorded via mobile app (Elite HRV Inc., Asheville, U.S.) which provides an array containing all the
 134 R-R intervals.

135 The PPG data were collected by using a custom made wrist-wearable device shown in Fig. 2.

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 139 **Figure 2.** Lateral view of the prototypal measurement device configuration (A) and coupling elements for
 140 the load transmission (B)
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143 The PPG system consists of: i) a commercial PPG sensor (DFRobot, Beijing, China) equipped with a
 144 wavelength of 520 nm, ii) a 3 axis ADXL 345 accelerometer (Sparkfun Electronics, Colorado, U.S.), iii)
 145 a load button cell (FX1901, Meas. Spec., Fremont, U.S.) and iv) a PLA frame where all the components
 146 are mounted together.

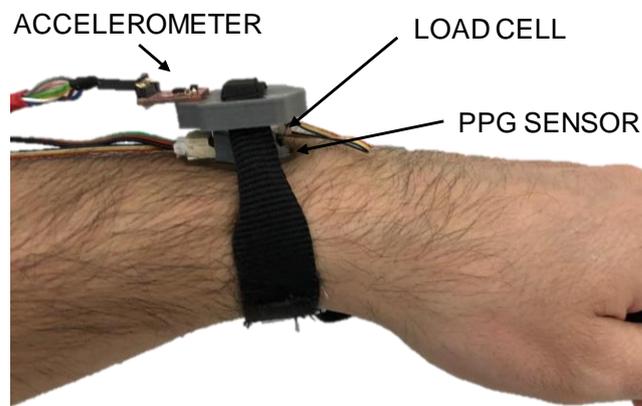
147 As the load cell was placed right above the PPG sensor that allowed to quantify the CP between the
 148 skin and the PPG sensor (contact area = 473 mm², a value close to that of many commercial products)
 149 in order to investigate its influence on the reliability of the HR acquisitions during physical activity.
 150 Specifically, three different contact pressures were identified (i.e. CP1 = 12 mmHg, CP2 = 33 mmHg
 151 and CP3 = 54 mmHg) which correspond to the three tightening levels commonly used by smartwatch
 152 users.

153 The accelerometer, which is exposed to the same acceleration of the PPG sensor, was used to monitor
 154 the orientation of the arm over subjects and the effective rate of the exercise.

155 The system was finally fastened on the wrist by using a 20 mm wide nylon strap, as shown in Figure 3.
 156 All wires were then fixed onto the arm to prevent any unwanted displacement of the system during
 157 physical activity.

158 All data were acquired by using an Arduino Mega 2560 board (Arduino, Turin, Italy), recorded with
 159 a sampling frequency of 250 Hz and then analyzed off-line using a dedicated Matlab® algorithm
 160 (MathWorks, Inc., Natick, Massachusetts, U.S.).

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Figure 3. Prototypal measurement system in operation

2.2. Human study protocol

Seventeen subjects ranging from 22 to 55 years old (Male = 12, Female = 5; age = 36 ± 11 years, height = 173 ± 6 cm, weight = 73 ± 9 kg) were enrolled for the experimental protocol. None of them took stimulants or drugs before the tests that could have influenced HR variations. Sixteen subjects presented a skin colour classification of Type II, basing on the Fitzpatrick scale and one subject presented a skin classification of Type III. As the skin pigmentation affects the PPG signal [33,46,47], a sample of subjects with the same colour was selected to reduce the influence of this parameter.

Subjects were asked to wear simultaneously the Polar H9 chest strap and the prototypal wristband and stand still in front of a step 22,5 cm high. After the study coordinator settled the wristband to one of the three predefined CP, participant went up and down the step for 60 seconds at three different intensities of physical activity (i.e. low = 90 bpm, medium = 120 bpm and high = 140 bpm) for a total of 9 exercise sequences for each subject (3 tightening level of the wrist bracelet at three different activity intensities executed in a random order). A metronome was used as a guide for participants during each exercise and 10 s of signal at rest were recorded before the execution of each physical activity. The CP data were monitored both online and offline at the start and end of the test to ensure that the chosen CP had not changed during the physical activity.

2.3. Data analysis

ECG and PPG data were processed offline with Matlab® and in figure 4 it is possible to observe the principal steps of the signal conditioning. To reduce noise, a low pass filter with a cutoff frequency of 5 Hz was applied to the digitized PPG waveform as well as an Hampel filter to detect and remove any outliers as it has been already tested as an effective algorithm for the detection and removal of false peaks [48,49].

The two datasets (ECG and PPG) were synchronized by means of minimum bpm error by using the 10 s rest-condition signal to find starting points with maximum correlation values [24] and then PPG signal was used to extract waveform features as the peaks.

The HR was quantified both for every single pairs of consecutive peaks and by using a moving average from a variable subset of data ranging linearly from 5 at 60 bpm up to 13 at 150 bpm.

ECG and PPG derived HR were finally compared (17 subjects, 9 different tests for each person) and the parameters of interest were assessed.

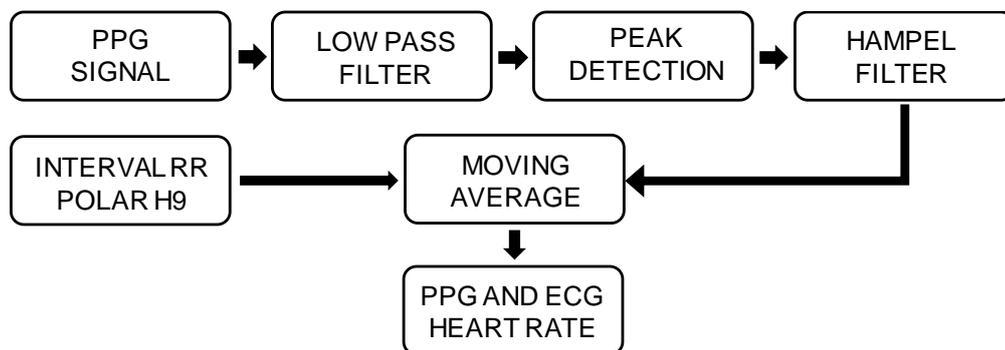
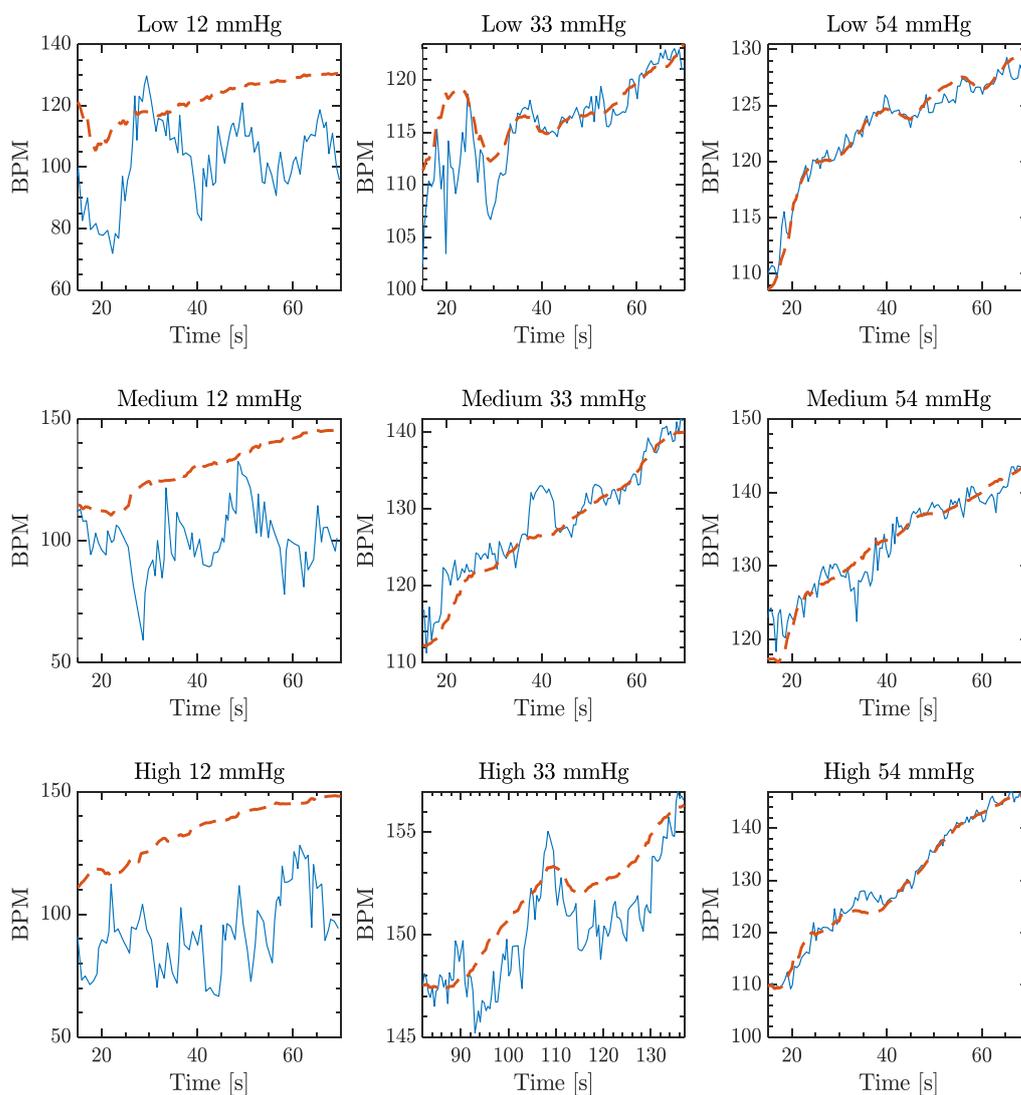


Figure 4. Schematic block diagram of the signal conditioning

208 3. Results

209 The data from the three axis accelerometer showed no substantial differences between subjects at
 210 each physical activity. The mean and standard deviation values of the acceleration peaks during the
 211 test were 0.34 ± 0.08 g and 0.21 ± 0.04 g, respectively in Y-axis and X-axis (i.e. longitudinal and sagittal
 212 axis). Moreover, a qualitative inspection of the acceleration data in the frequency domain confirmed
 213 that all subjects respected the physical rhythm agreed for each test.

214 Similarly, data acquired from the load cell varied slightly during the execution of the test but returned
 215 to its initial value at the end of the physical activity demonstrating that all the variations were due to
 216 muscular movements while the buckle stayed stuck in place without loosening up. Synchronized
 217 PPG and ECG signals recorded from a single subject which reflects the averaged results are shown,
 218 as example, in Fig. 5.
 219



220 **Figure 5.** Filtered and synchronized PPG (continuous line) and ECG (dashed line) acquisition at each physical
 221 activity and for every CP, to evaluate qualitatively the correlations between ECG and PPG

222

223 From a qualitative point of view, it is possible to observe that for a contact pressure of 12 mmHg
 224 (CP1) the PPG signal does not follow the trend of ECG signal and this was found to be true for almost
 225 all subjects. It is also possible to observe that at 54 mmHg (CP3) the PPG signal follows the trend very
 226 well, tracing even the small variations in heart rate detected by the ECG chest trap.

227

228 **Table 1.** Pearson correlation coefficient of ECG-HR and PPG-HR at each physical activity rate and for each
 229 contact pressure (i.e. CP1 = 12 mmHg, CP2 = 33 mmHg and CP3 = 54 mmHg).

230

Exercise rate	Pearson correlation coefficient		
	Pc= 12 mmHg	Pc= 33 mmHg	Pc= 54 mmHg
90 bpm	0.56	0.93	0.95
120 bpm	0.32	0.89	0.94
140 bpm	0.28	0.76	0.81

231

232

233 To establish the accuracy of PPG-based device with respect to the gold standard (i.e. ECG device) it
 234 has been calculated the Pearson Correlation coefficient (r) and the mean-average-percentage-error
 235 (MAPE) for all subjects, which are shown in Tab.1 and 2.

236

237 **Table 2.** Mean average percentage error of ECG-HR and PPG-HR at each physical activity rate and for each
 238 contact pressure (i.e. CP1 = 12 mmHg, CP2 = 33 mmHg and CP3 = 54 mmHg).

239

Exercise rate	MAPE (σ)		
	Pc= 12 mmHg	Pc= 33 mmHg	Pc= 54 mmHg
90 bpm	8.9% (4.4)	2.4% (2.7)	2.4% (3.2)
120 bpm	10.3% (4.9)	3.5% (3.5)	2.7% (3.0)
140 bpm	11.8% (6.2)	4.6% (5.3)	3.8% (3.8)

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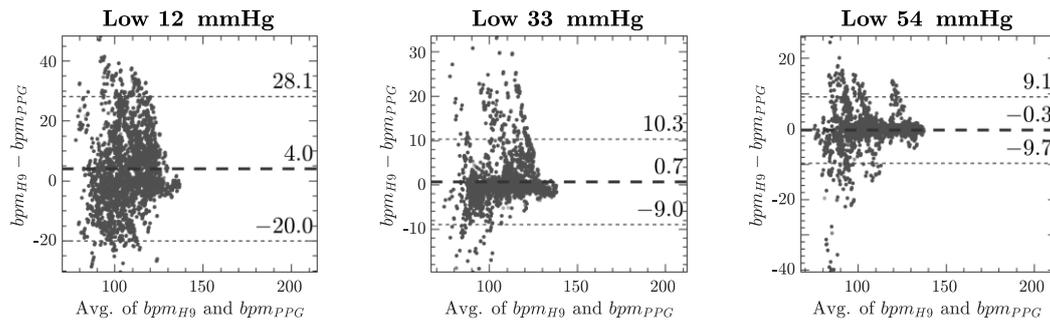
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242 It is possible to observe, as expected, that for every contact pressures, the Pearson coefficient
 243 decreases for higher rate of the physical exercise while the MAPE increase. The comparison of PPG
 244 and ECG-based devices was furtherly tested by using Bland-Altman technique [50] that has been
 245 widely used [25,51,52] to evaluate physiological parameters and results are show in Fig. 6.

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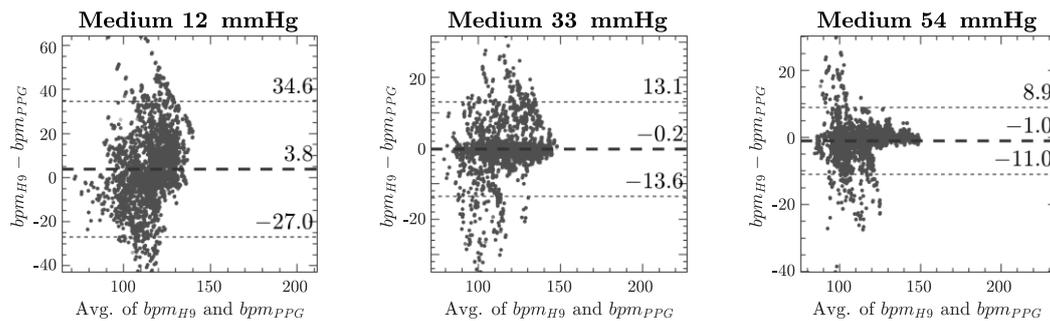
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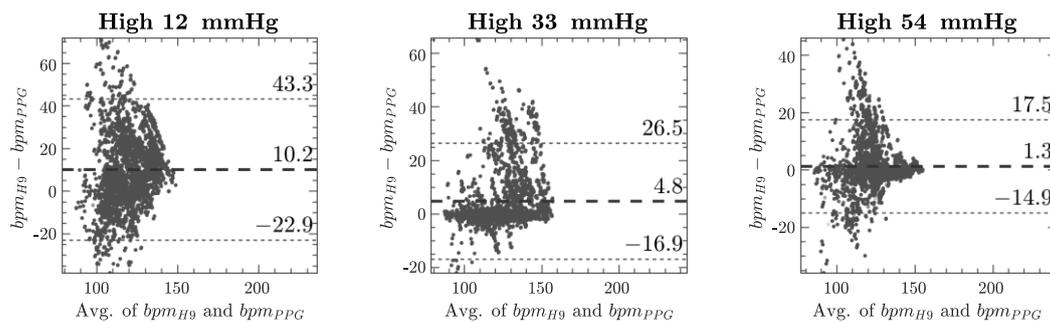
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257 **Figure 6.** Bland Altman plot of PPG and ECG acquisition at each physical activity and for every CP, to better
 258 evaluate the correlation correlations between ECG and PPG acquisitions

259

260 As it is possible to observe from Tab.2, the MAPE was found to be particularly low at CP3, the
 261 maximum contact pressure (i.e. 54mmHg), which provided the best results for any exercise rate and
 262 represents the optimal CP when taking into account all the subjects. However, it is worth noting that
 263 the standard deviation associated with the MAPE suggests that the optimal CP depends on the
 264 specific characteristics of each participant of the study due to the subjective variability. Indeed, the
 265 actual force exerted at the artery wall would be different for each subject since the arterial depth may
 266 vary from subject to subject. This, together with the thickness of the fat layer, the hydration and the
 267 specific characteristics of the biological tissues, including the skin colour, may contribute for the inter-
 268 subject variability in the recording of the HR.

269

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271

272 Subsequently, we considered the best MAPE results of every single subject for each single physical
 273 activity (Tab.3), to obtain a deeper analysis of the inter-subject variability.

274

275 **Table 3.** Number of subjects (n) which presented the individual optimal contact pressure (Optimal CP) at
 276 every physical activity intensity

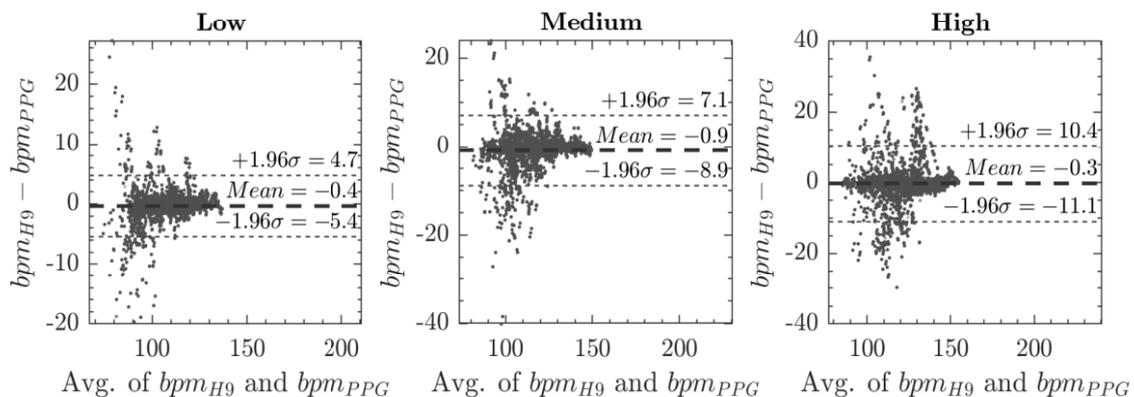
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Exercise rate	Lowest individual MAPE		
	12 mmHg	33 mmHg	54 mmHg
90 bpm	n = 0	n = 9	n = 8
120 bpm	n = 1	n = 4	n = 12
140 bpm	n = 0	n = 6	n = 11

278

279 It is possible to observe from Table 3 that for the lowest CP, only one subject presented its lowest
 280 MAPE at a physical activity of 120 bpm and no one at an intensity of 90 and 140 bpm. At the two
 281 higher physical activities (i.e. 120 and 140 bpm) the majority of subjects presented the lowest personal
 282 MAPE at a CP of 54 mmHg. Only for the low level of physical activity a uniformity of results was
 283 observed, in which almost an equivalent number of subjects presented the lowest MAPE at the
 284 contact pressures of 33 and 54 mmHg.

285



286 **Figure 7.** Bland Altman plot between ECG and the best individual subset of PPG acquisitions

287

288

289 Then, we created a subset of these data (i.e. best individual results), assessing a Bland Altman plot,
 290 showed in figure 7. We furtherly compared the MAPE and Bland Altman of this subset (Tab.4) with
 291 the best results of the whole dataset (i.e. 54mmHg). From the comparison between the optimal contact
 292 pressure and the best results of the whole dataset (i.e. 54 mmHg), it is possible to notice that the
 293 MAPE decreased of -47% for the low level of physical activity, -23% for the medium and -38% for the
 294 high level of physical activity.

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299 **Table 4.** Bland Altman and MAPE comparison between the best individual subset and whole dataset at CP3
 300 (i.e. 54 mmHg)
 301

Exercise rate	Bland-Altman mean ($\pm 1.96 \sigma$)		MAPE err % (σ)	
	54 mmHg	Optimal CP	54 mmHg	Optimal CP
90 bpm	-0.3 (± 9.4)	-0.4 (± 5.0)	2.4% (3.2)	1.3% (1.9)
120 bpm	-1.0 (± 10.0)	-0.9 (± 8.0)	2.7% (3.0)	2.1% (2.5)
140 bpm	1.3 (± 16.2)	0.3 (± 10.7)	3.8% (3.8)	2.3% (2.6)

302

303 Finally, no statistical significance was found focusing the analysis on the Body Mass Index or on the
 304 circumference of the wrist of the population sample examined. A comparison was assessed using
 305 Bland-Altman analysis between the 5 female subjects and 5 male subjects randomly chosen. Observed
 306 average standard deviation in the female sample was 48% lower. However, given the limited number
 307 of female subjects, this analysis has no statistical relevance and detailed results are not reported.

308

309 4. Discussion

310 The current study investigated the influence of CP in the reliability of the PPG-based device for HR
 311 evaluation during different intensities of physical activity. The gold standard device for the
 312 comparison was a Polar ECG-based chest strap, which was found to have a good validity during
 313 body movements in previous studies [25,52].

314 To the best of the authors' knowledge, in the literature there are studies which conduct CP tests with
 315 a PPG sensor placed on the fingers or in any case during static experiments [36,37,39,40,43], but an
 316 extremely limited number of them is focused on the relation between physical activity and CP in
 317 PPG-based measurements [53]. However, during static tests, it is not possible to observe all the
 318 possible influencing quantities acting during physical activity. The purpose of this study was to
 319 evaluate the influence of CP on HR measurements acquired at different physical exercise rates on a
 320 sample of 17 subjects.

321 The authors found that CP between the PPG sensor and the skin influenced the signal recorded on
 322 the wrist of the participants who took part in the experiment. Specifically, results have demonstrated
 323 that different contact pressures provide significant differences in signal quality and reliability. While
 324 the PPG-HR at a low CP (i.e. 12mmHg) has shown a very weak correlation with ECG-HR, in
 325 accordance with our previous study [41], CP2 and CP3 (i.e. 33 and 54 mmHg respectively) provided
 326 the most accurate results.

327 In previous HR comparison tests, the results have been regarded as reliable as MAPE keeps under
 328 5% [24,25,54] and Pearson correlation coefficient ranges from $0.7 \leq r \leq 0.9$ for a very large correlation
 329 and $r > 0.9$ for an excellent correlation [55,56]; Hwang and colleagues [25] investigate the accuracy
 330 of a PPG sensor embedded in a wristband-type tracker to be used by construction workers. They
 331 concluded that PPG-based HR monitoring system has a potential to be applied at construction sites
 332 for monitoring construction workers' HR on a real-time basis as it showed a MAPE of 4.79% and a
 333 Pearson correlation coefficient of 0.85. However, authors specify that the accuracy needs to be
 334 further improved, particularly during heavy works.

335 Our findings showed that the MAPE (Tab.2) ranges from 2.4% to 4.6% for a CP of 33 mmHg and
 336 from 2.4% to 3.8% at 54 mmHg. It is worth noting that, at a fixed CP, MAPE grows as the intensity

337 of physical activity increases, as expected. Similarly, we found a Pearson coefficient (Tab.1) ranging
338 from 0.76 to 0.93 for a CP of 33 mmHg and from 0.81 to 0.95 for a CP of 54 mmHg.
339 The PPG-based HR measurements comparison was furtherly tested by using the Bland-Altman
340 analysis (Fig.6), which has been intensively used in wearable devices performances assessment
341 [50,57]. In a physiological monitoring study, Gatti and colleagues [55], basing on previous sport
342 studies, selected a maximum acceptable limit of agreements (LoA) in the range of ± 11 bpm for HR.
343 In another study concerning device accuracy on HR measurements, Lee et al. [51] considered as
344 accurate a LoA in the range of ± 11.5 and less accurate as the LoA were found in the range of ± 13.8 . In
345 our study, the Bland-Altman analysis (Fig. 6) provided its best results for a CP of 54 mmHg. LoA
346 settled below ± 10 bpm for the low and medium physical activity rate, and in a less accurate range of
347 ± 16 bpm for the high intensity of physical exercises.
348 The measurement data suggest that the best results of the whole datasets (Tab.3) are achieved for a
349 CP of 54 mmHg. However, the MAPE (Tab.2) indicates that among different individuals and task
350 intensities there is a large individual-dependent variability which makes it difficult to assess a single
351 optimal CP for the whole sample at each physical activity.
352 Tab.4 shows that the best individual CP provides the lowest MAPE. Specifically, the Bland-Altman
353 analysis, shown in figure 7, provided LoA within ± 11 bpm (i.e. ± 10.7) even for the high intensity of
354 physical exercises, which is considered as reliable.
355 Moreover, the MAPE of the whole dataset calculated at the lowest physical activity (i.e. 90 bpm) and
356 for the lowest CP is 2.34 times higher than the MAPE obtained at the highest physical activity and for
357 the highest CP. Therefore, basing on the results of this study, there are two main considerations: i)
358 with an individual optimal CP it is possible to consider the PPG-based HR measurement reliable even
359 for high intensity of physical exercise (i.e. 140 bpm), ii) the CP has greater effects on PPG-HR signal
360 quality than those deriving from the intensity of the physical activity ranging from 90 bpm, to 140
361 bpm.
362 Although the individual optimal contact pressure can bring a potential benefit in term of
363 physiological measurements accuracy during physical activities, it is necessary to have a system that
364 can adapt the tightening pressure of the wrist-type device. Sim and colleague [36] proposed a PPG
365 platform integrated with a thermo-pneumatic type regulator to regulate the contact-force during the
366 measurement, adopting a target contact force of 0.6 N which showed the highest amplitude. Results
367 showed a significant improvement of PPG measurement in terms of amplitude, suggesting a
368 potential application of this approach to bio signals measurements in various field.
369 Despite numerous studies on the influence that CP has on the signal, no accepted standards have
370 been adopted for PPG measurements of this parameter. Most of them analyzed the AC and AC/DC
371 amplitudes of the reflected PPG signal [39]. Teng and colleagues [43] studied the change in pulse
372 amplitude (AC) of the reflective PPG signals with increasing contact force, from 0.2 N to 1.8 N. They
373 found that for different subjects, the pulse amplitude peaked at different contacting forces, from 0.2 N
374 to 1.0 N, concluding that the actual force exerted at the artery wall would be different for each subject
375 due to the inter-subject variability.
376 On these basis, the effects of CP should be carefully examined in the design of PPG-based health
377 monitoring devices as the careful control of it can bring a potential benefit in terms of accuracy and
378 reliability.

379

380 5. Conclusions

381 Wearable PPG sensors have become very popular in the last decade thanks to their low cost,
382 simplicity and huge potential in measuring important cardiovascular information.
383 Scientific interest has continued to find new physiological parameters beyond the pulse oximetry and
384 HR to be measured with a PPG sensor, trying to fully exploit their potential. Although recent progress
385 has been made in the hardware and signal processing to increase the accuracy of measurements, a
386 reliable PPG sensor device, able to accurately detect HR signal during physical activity, has yet to be

387 fully developed and this limits the application of this technology in different field. Among several
388 sources that affect PPG signal, CP between the sensor and the skin greatly influences the PPG signal
389 quality, compromising the overall reliability of the system and preventing its widespread use during
390 the typical daily activities. Optimal CP could contribute in reducing motion artefacts and ensuring a
391 good signal and to determine it, in vivo PPG acquisitions were obtained from a cohort of seventeen
392 subjects for different physical activity intensities.

393 The comparison between ECG and PPG signals showed the reliability and effectiveness of the
394 proposed approach. Specifically, results show that the CP has greater effects on PPG-HR signal
395 quality than those deriving from the intensity of the physical activity. Moreover, we observe that
396 with an individual optimal CP it is possible to measure reliable HR signals even at high exercise
397 intensity. With higher HR accuracy, a PPG-based HR sensor, integrated in a wristband, can be
398 effectively used for monitoring athletes, workers and in general, for the personal health management
399 for a safer and healthier lifestyle.

400 Despite future studies on a larger cohort of subjects are needed to furtherly strengthen our results,
401 this study could contribute in enhancing PPG-based devices accuracy in the monitoring of HR for an
402 easy personal health management.

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407 Colombarini; Investigation, Francesco Scardulla, Leonardo D'Acquisto, Raffaele Colombarini and Salvatore
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409 Leonardo D'Acquisto, Sijung Hu and Diego Bellavia; Visualization, Leonardo D'Acquisto, Francesco Scardulla
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418 **Abbreviations:**

419	PPG	PhotoPlethysmoGraphy
420	ECG	ElectroCardioGraphy
421	HR	Heart Rate
422	CP	Contact Pressure
423	MAPE	Mean Average Percentage Error
424	LoA	Limit of Agreement
425	AC	Alternating Component
426	DC	Direct Component
427	SpO ₂	Peripheral oxygen saturation
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