DIY Wrist-Worn Device for Physiological Monitoring: Metrological Evaluation at Different Band Tightening Levels

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Abstract. Wearable devices are currently employed in several application fields, especially in the healthcare context, thanks to the advent of IoT technology in the global market. However, there are few studies focused on the reliability of collected data depending on the best wearing conditions, e.g. the band tightness in the case of wrist-worn devices, necessary to optimise the quality of the measured data. The aim of this study is to evaluate the variability of heart rate (HR) and tightening force data measured with a *Do-It-Yourself* (DIY) wrist-worn device, considering three different band tightening levels: loose, medium and tight. Results show that the increasing tightening levels produce an increasing tightening force, as expected; interestingly, the coefficient of variation is minimum (i.e., 0.16%) when the band tightening level is medium.

Keywords: Photoplethysmographic sensor · Wearable device · Health monitoring · Reliability · Metrological characterization · Data variability

1 Introduction

Wearable devices are currently employed in many different application fields, such as individual activity monitoring, rehabilitation and fitness/sport performance assessment [31,37], sleep quality evaluation [22,36], health tracking of elderly people in Ambient Assisted Living (AAL) scenario - also to improve their Quality of Life (QoL) - [2,3,35], monitoring of physiological parameters for the treatment and diagnosis of different diseases [20], early diagnosis of viruses

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symptoms (e.g., in COVID-19 pandemic [10,33]), Industry 4.0 [9], etc. Hence, wearable technologies are catching on in the healthcare context, thanks to multiple reasons: smartwatch-like devices are in fact user-friendly, relatively low-cost (with respect to standard equipment for the monitoring of physiological parameters) and available in distinct forms, several cost and quality segments, capable to satisfy different customer types, also thanks to user-experience oriented design of these tools. Also miniaturised devices, promoting comfort and user-friendliness of such systems, are topics of interest for the current research [12]. Moreover, it is worthy to underline that nowadays a single device can provide many different physiological/activity-related parameters, such as heart rate (HR) [27], heart rate variability (HRV) [19], energy expenditure [17], blood oxygen saturation [4], respiratory rate [14], number of steps [8], walked distance, etc. [15,30]. An additional success of wearable devices is attributable to the possibility of remote health monitoring thanks to the fact that, with a proper Internet-of-Things (IoT) architecture, they are capable to connect with other devices and share individual data e.g. on a Cloud platform, making them remotely available and safely stored. This is particularly relevant in health monitoring applications, also to support the healthcare providers in decision-making processes [6]. On the other hand, there are aspects requiring particular attention when using the data gathered by wearable devices; in fact, such systems are capable to provide data 24 hours a day, seven days a week. This generates a huge amount of data, the so-called "big-data" [16], potentially useful to train Artificial Intelligence (AI) algorithms for different purposes: well-being assessment [7], personal comfort measurement [13,26], stress level quantification [21,23], just to cite some. However, privacy-related issues should be properly considered, managing these individual data fulfilling the national and international regulations [5]. On the other hand, the evaluation of accuracy and reliability of these smartwatches are aspects still needing a lot of research [11,24]. It is beyond doubt that the hardware characteristics of the device influence the quality of measurement results [28]; also the correct positioning is of utmost importance to collect reliable data. When wearing a smartwatch, the band tightness obviously influences the measurement results, since sensors are susceptible to the contact pressure with skin. In particular, the functioning of the photoplethysmographic (PPG) sensor, commonly used to acquire the signal related to cardiac activity (indeed, it measures the changes in the blood volume, caused by the pumping activity of the heart [25]), is generally based on a light emitting diode (LED) and a photodetector [34]; hence, the measured signal depends on the quantity and quality of light received by the photodetector after being emitted by the LED and having crossed the skin tissues. Given that PPG sensor is very prone to motion artefacts, it would be necessary to optimise its positioning in order to maximise the signal-to-noise ratio (SNR), while minimising the environmental light that can reach the photodetector, and maximising the capture of the light reflected/transmitted by the skin (depending on the type of the PPG sensor, which can be based on reflection or transmission, respectively [29]). In order to take these aspects into account, it is fundamental to guarantee an optimal contact between the PPG sensor and the subject's wrist skin, maintaining a constant and stable position during the whole daily activities. In fact, different tightness values determine a different vibration in wrist-worn devices, turning into a different signal quality. In particular, a loose band would make output data not reliable if compared to the reference electrocardiographic (ECG) signal [18]. However, to the best of the authors' knowledge, concerning the consumer wearable devices, neither manufacturers provide specific indications on the optimal band tightening level value that should be achieved in order to maximise the signal quality, nor data related to this type of investigation are available in literature. Therefore, it would be interesting to add this evaluation during the smartwatch design phase, in order to give customers indications useful to obtain reliable results. Some of the authors performed a study to identify the optimal contact pressure capable to optimise the accuracy in the measurement of HR, considering a chest-strap device as gold standard instrument [32]. In the present study, the authors have realised a prototype of wrist-worn device including both a PPG sensor and a load cell, in order to quantify the effect of different tightening levels of the band on the recorded signal, evaluating in particular its variability. Ten healthy volunteer subjects have been enrolled to collect data for the evaluation of the measurement repeatability, as well as the effect of different band tightening levels and, consequently, of different tightening force values on the measurement of the HR. The paper is organised as follows. Section 2 provides details on the wrist-worn device developed in this study, the signal acquisition methodology and the post-processing of data. Section 3 reports and discusses the obtained results. Finally, Sect. 4 contains the authors' conclusions, with final considerations on the study and future work.

2 Materials and Methods

2.1 Wrist-Worn Acquisition Device

The PPG data were recorded by using a *Do-It-Yourself* (DIY) wrist-worn wearable device. The device consists of a PPG sensor (Keyestudio XD-58C Pulse Sensor, with a 515 nm green light LED), a button load cell (FX1901, Meas. Spec., Schaffhausen, Switzerland), an amplifier board HX711 and an Arduino ATmega2560 with a sampling rate of 9600 Hz as acquisition board. The assembled device is shown in Fig. 1, whereas the separate components in Fig. 2.

Concerning the employed sensors, the PPG sensor was fixed in place by means of glue on a custom 3D-printed watch case, whereas the load cell was placed on a 3D printed casing, in order to be held in position every time the wrist band is worn. The CAD models and the overall assembly with both the PPG and load cell sensors are shown in Fig. 3.

The wrist band support was connected to a 3D-printed load cell presser, as it can be seen in Fig. 4.

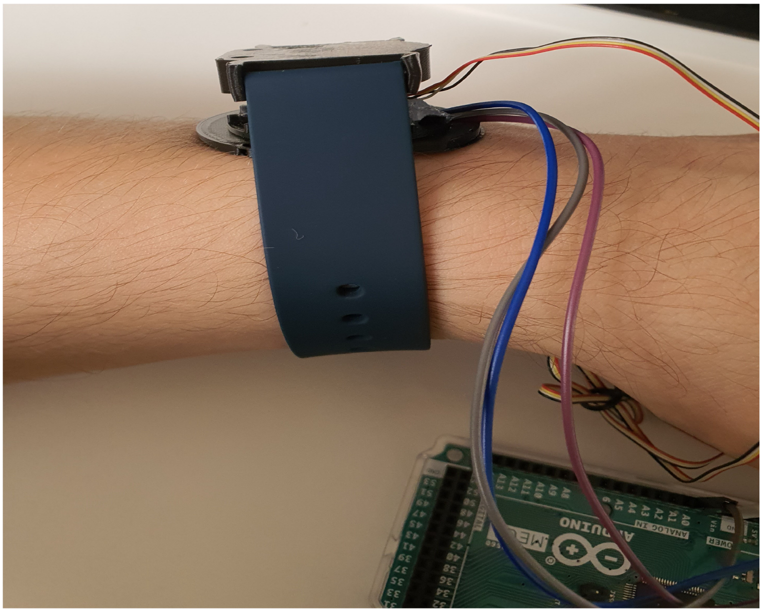

Fig. 1. Wrist-worn wearable device assembly.

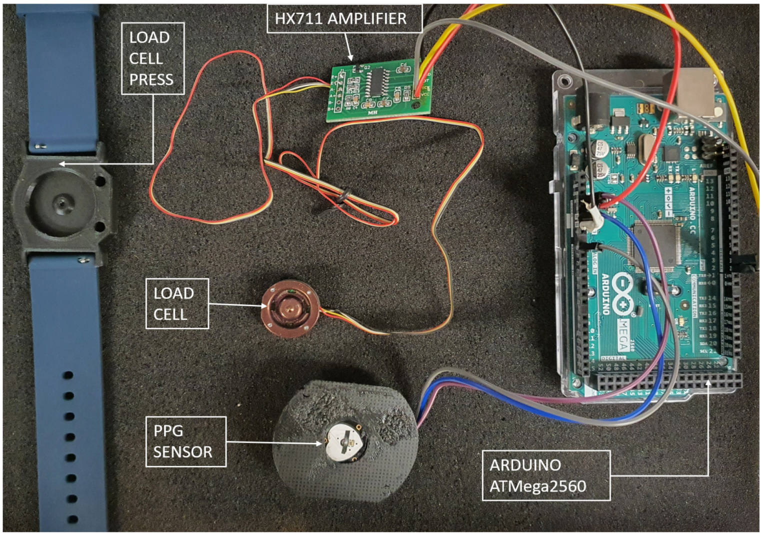

Fig. 2. Wrist-worn wearable device components.

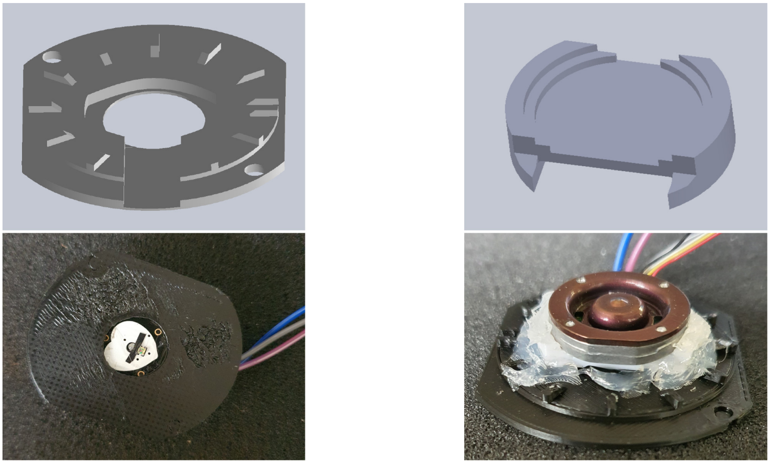

Fig. 3. CAD models and overall assembly of PPG (left) and load cell (right) casings.

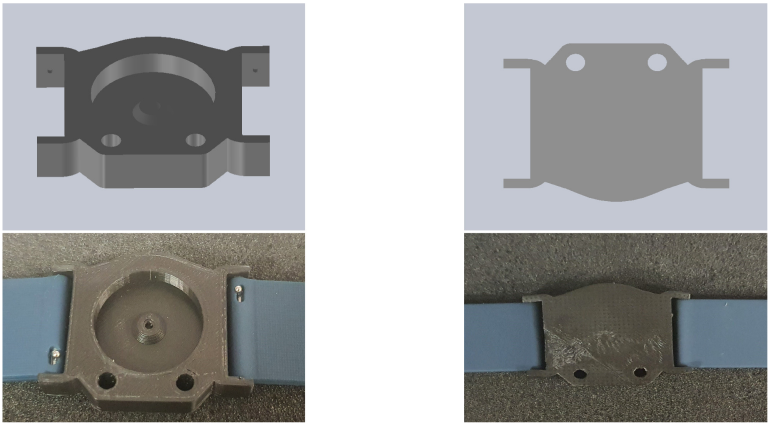

Fig. 4. 3D-printed load cell presser and wrist band assembled: front (left) and back (right) views.

2.2 Data Acquisition Protocol

Ten healthy subjects, 4 males and 6 females aged between 21 and 31 years, with a Body Mass Index (BMI) between 19 and 26 kg/m^2 and a wrist circumference between 14 and 19 cm, with a skin colour classification of Type II (Fitzpatrick scale), were involved in the experimental tests. Before starting the data collection, all the subjects signed an informed consent, providing adequate information about the study objectives and test modalities.

In order to evaluate the metrological characteristics of the PPG sensor, the participants were submitted to nine sessions: three repetitions, lasting 30 s per each, for the three levels of band tightness (i.e., *loose*, *medium* and *tight*). The band tightening levels were defined as shown in Table 1, according to the subject's wrist size. The wrist size was considered as the *loose* level (starting point), i.e. with the band length equal to the wrist circumference (L_0, tightening of 0.00 cm).

Table 1. Tightening levels of the band - (L_0 is the subject's wrist circumference)

Tightening level	Band length
Loose	L_0 - 0.00 cm
Medium	L_0 - 0.50 cm
Tight	L_0 - 1.00 cm

The DIY wrist-worn device was placed on the same wrist as the one where each of the subjects usually wears her/his watch (5 subjects on right wrist and 5 subjects on the left one). An automatic oscillometric digital blood pressure monitor was employed to collect subjects' data related to blood pressure (BP) and HR before starting the acquisitions; this device was positioned on the left arm, as generally recommended. Furthermore, the measurements were repeated after having changed the band tightness. In particular, the prototype wearable device worn at the *loose* level was tested according to the subject wrist circumference. After 30 s, the band was unfastened and then braced again to test the PPG measurement repeatability. The same procedure, repeated for three times, was adopted for the *medium* and *tight* levels, with +0.50 cm and +1.00 cm of band tightening, respectively. During the tests, participants were required to avoid hand and/or arm movements to reduce the motion artefacts potentially compromising the measurements. Moreover, data collected by using both the PPG sensor and the load cell were graphically displayed with the Telemetry software [1] to have a preliminary signals visual inspection. Indeed, data from the load cell helped to verify that the reached tightening level was comparable, over all the subjects, irrespective of the personal wrist circumference.

2.3 Data Processing

The data gathered with the DYI wrist-worn device were processed in MATLAB environment. At first, both PPG and load-cell signals were resampled at 1 kHz, by using the modified Akima piecewise cubic Hermite interpolation. Then, the signal peaks were searched for the computation of HR from PPG signal. Once the HR series were obtained, the statistical quantities were derived, namely the mean (μ), the standard deviation (σ) and the coefficient of variation (c_{v}, also known as relative standard deviation) computed as follows:

$$c_{\mathrm{v}} = \sigma/\mu \tag{1}$$

Similarly, data collected through the load cell was processed in order to obtain the μ, the σ and the c_v during each acquisition, hence verifying that the band tightening system was effective and that the contact pressure levels among different subjects were compatible, as well as repeatable on the same subject. Histograms were plotted to describe the distribution of the measurement results; the number of bins (K) was computed by means of the Sturges' rule formula, as follows:

$$K = 1 + \frac{10}{3} log_{10}(N), \tag{2}$$

where N is the numerosity of the sample.

3 Results and Discussions

In this section, the authors report the results related to the intra-subject repeatability of both HR and tightening force data measured with the three different band tightening levels (i.e., *loose*, *medium* and *tight*), as well as the inter-subject variability. It is worthy to highlight that a high repeatability is desired for what concerns tightening force (in order to give recommendations on the optimal wearing conditions), whereas HR variability is mainly due to the individual physiological state. However, HR related variability should be rather low in short acquisitions and considering resting conditions.

3.1 BP and HR Data Measured with the Oscillometric Method

Before changing the band tightening level, both HR and BP data were measured on each subject, including the maximum and minimum pressure values (named systolic and diastolic, respectively) with the oscillometric method by means of an automatic digital blood pressure monitor. The related measurement accuracies are ± 3 mmHg, and $\pm 4\%$ of the reading, for BP and HR, respectively. Resulting data, along with the subject's wrist circumference (accuracy of $\pm$ 0.1 cm), are reported in Table 2.

3.2 Results from Wrist-Worn PPG Sensor and Load Cell

Concerning the tightening force values obtained from the load cell, it is possible to notice that the same band tightening level resulted in different tightening force values (see Fig. 5). This is probably due to the different subjects' wrist circumference and morphology (i.e., physiological diversity), which means a different contact condition between the band, consequently the load cell, and the skin. However, considering the whole test population along with all the acquired force signals, the variability (quantified with the standard deviation, St. dev.) among the subjects is quite low (c_v <1%, see Table 3).

Table 2. BP and HR values measured on the test population with the oscillometric method: results obtained in the test sessions performed with different band tightening levels.

Subject	Wrist circumference [cm]	Tightening level	Systolic BP [mmHg]	Diastolic BP [mmHg]	HR[bpm]
1	15.0	Loose	115	74	87
		Medium	103	65	85
		Tight	108	63	79
2	14.0	Loose	110	77	91
		Medium	112	71	76
		Tight	113	68	78
3	17.0	Loose	122	76	75
		Medium	117	70	78
		Tight	116	69	81
4	14.0	Loose	118	86	63
		Medium	121	90	62
		Tight	85	51	63
5	16.0	Loose	119	76	90
		Medium	114	69	90
		Tight	113	70	89
6	16.0	Loose	115	62	58
		Medium	140	78	71
		Tight	128	78	72
7	15.5	Loose	113	61	80
		Medium	105	68	80
		Tight	96	57	80
8	19.8	Loose	107	62	50
		Medium	115	61	52
		Tight	-	-	-
9	17.0	Loose	116	71	60
		Medium	111	72	64
		Tight	106	64	64
10	15.5	Loose	101	66	69
		Medium	103	57	73
		Tight	95	59	69

On the other hand, considering the variability within the same subject (i.e., intra-subject variability), higher standard deviation values are reported for some subjects with respect to others (e.g., subject no. 5). However, considering all the tightening levels, it is possible to observe a homogeneous increasing trend (from *loose* to *tight* level) for all the subjects, even if different absolute values of force are reported, as it can be seen in Fig. 5.

The force distributions related to the data acquired with different band tightening levels are reported in Fig. 6: the force distribution is unimodal (not normal), with a positive skew (i.e., the tail is on the right).

Table 3. Inter-subject variability related to tightening force values obtained from the load cell, with the three different tightening levels (i.e., *loose*, *medium* and *tight*).

Tightening level	Tightening force		
	Mean [N]	St. dev. [N]	c_v [%]
Loose	0.49	0.15	0.30
Medium	1.07	0.17	0.16
Tight	2.51	0.62	0.24

Table 4. Inter-subject variability related to HR obtained from PPG sensor, with the three different tightening levels (*loose*, *medium* and *tight*).

Tightening level	HR		
	Mean [bpm]	St. dev. [bpm]	c_v [%]
Loose	81	15	18
Medium	80	13	16
Tight	81	14	17

Regarding the inter-subject variability of PPG results, the values obtained with the three different band tightening levels are compatible (see Table 4), considering that HR parameter shows an intrinsic physiological variability, irrespective of the band tightness. Moreover, the distributions of HR values are approximately Gaussian-like, as it can be observed in Fig. 7.

However, it is worthy to underline that the device wearing conditions undoubtedly influence the quality of the acquired data and, consequently, the reliability of the measurement results.

In particular, the measured tightening force is different depending on the wearing conditions of the device. It is possible to see that the mean value increases with tightening level, as expected (see Table 3 and Fig. 5). However, the coefficient of variation shows a trend not coherent with the tightening level, suggesting that it is possible to obtain more stable results with a higher tightening level of the band. The lowest variation is obtainable with the medium tightening level (corresponding to a tightening of 0.50 cm with respect to the subject's wrist circumference).

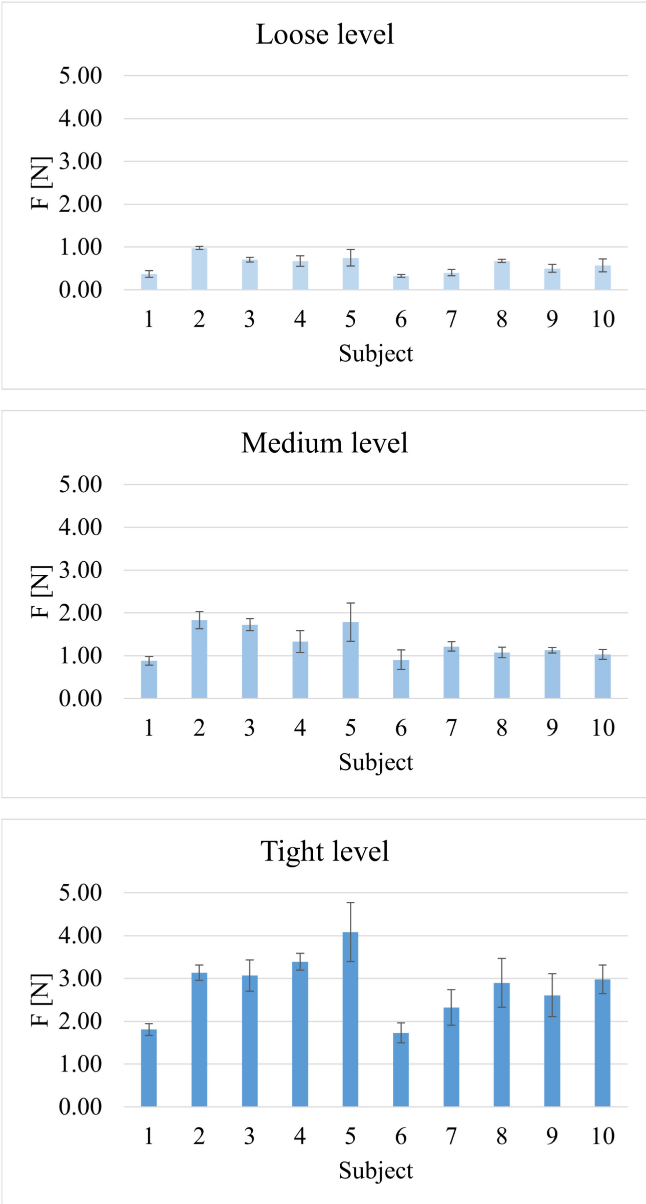

Fig. 5. Tightening force intervals (mean $\pm$ standard deviation) measured for *loose* (top), *medium* (centre) and *tight* (bottom) levels, for the whole population.

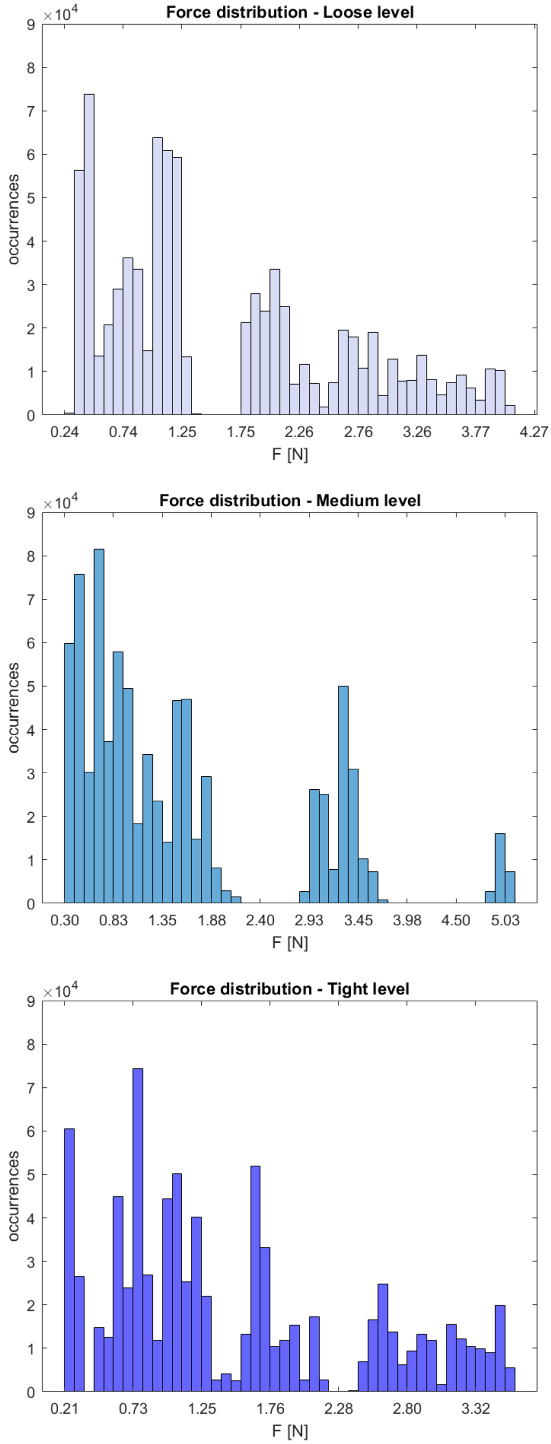

Fig. 6. Distribution of the measured tightening force in the tests with different tightening levels: *loose* (top), *medium* (centre) and *tight* (bottom), for the whole population.

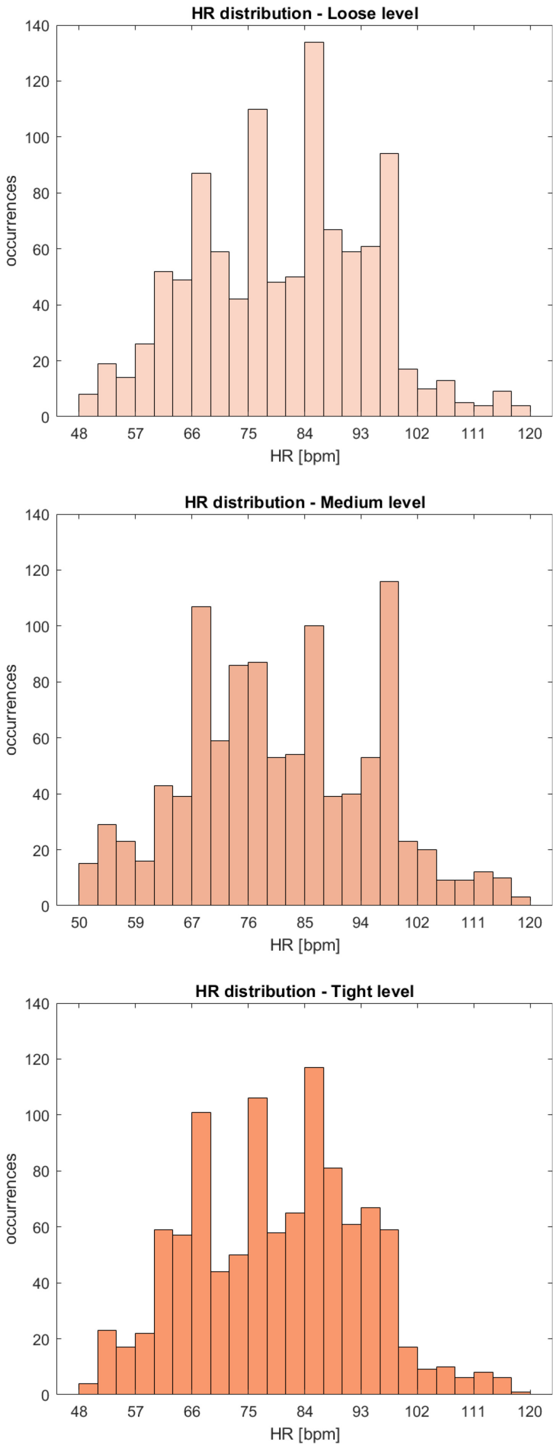

Fig. 7. Distribution of the measured HR in the tests with different tightening levels: *loose* (top), *medium* (centre) and *tight* (bottom), for the whole population.

Table 5. Intra-subject repeatability related to HR obtained from PPG signals and tightening force values measured from the DIY wrist-worn device, with the three different tightening levels (*loose*, *medium* and *tight*).

Subject	Tightening level	HR			Tightening force		
		Mean [bpm]	St. dev. [bpm]	c_V [%]	Mean [N]	St. dev. [N]	c_V [%]
1	Loose	74	10	14	0.37	0.08	0.21
	Medium	73	10	14	0.88	0.10	0.11
	Tight	71	7	10	1.81	0.14	0.08
2	Loose	99	6	6	0.97	0.03	0.04
	Medium	94	7	7	1.83	0.20	0.11
	Tight	98	10	10	3.13	0.18	0.06
3	Loose	82	6	7	0.70	0.05	0.07
	Medium	81	6	7	1.73	0.14	0.08
	Tight	87	6	6	3.07	0.36	0.12
4	Loose	81	11	13	0.67	0.12	0.18
	Medium	79	8	10	1.33	0.26	0.19
	Tight	77	7	9	3.39	0.20	0.06
5	Loose	68	10	14	0.75	0.19	0.25
	Medium	75	8	11	1.78	0.44	0.24
	Tight	68	6	10	4.08	0.69	0.17
6	Loose	90	4	4	0.33	0.03	0.10
	Medium	93	4	4	0.90	0.23	0.24
	Tight	94	4	4	1.73	0.23	0.13
7	Loose	73	6	8	0.40	0.07	0.18
	Medium	76	9	11	1.21	0.11	0.09
	Tight	80	8	10	2.32	0.41	0.17
8	Loose	91	9	10	0.67	0.04	0.05
	Medium	79	5	6	1.07	0.12	0.11
	Tight	81	8	9	2.90	0.57	0.19
9	Loose	70	8	11	0.50	0.09	0.18
	Medium	65	19	29	1.13	0.06	0.06
	Tight	70	23	32	2.61	0.50	0.19
10	Loose	68	5	7	0.57	0.15	0.26
	Medium	67	4	7	1.03	0.11	0.11
	Tight	67	7	11	2.98	0.33	0.11

4 Conclusion

In this study, the authors investigated whether and how different tightening levels of a wrist-worn band can affect the variability of the collected data (from PPG and load cell sensors) and, hence, the reliability of the measurement results. In particular, for each data acquisition session, three band tightening levels were considered: *loose*, *medium* and *tight*. The results show that, over all the subjects, the different tightening levels produce an increasing tightening force when passing from *loose* to *tight* through *medium* level; however, the coefficient of variation is minimum (i.e., 0.16%) when the band tightening level is *medium*. This is compliant also to the subject's comfort conditions in wearing the DIY wrist-worn wearable device, since the *tight* level sometimes causes discomfort, particularly in those subjects having a higher wrist circumference (i.e., >17 cm). However, further interesting investigations can be conducted focusing on the optimal band tightening in real life, when the subjects perform activities of daily living. This means to evaluate the reliability of the HR measurements at both rest and dynamic conditions; indeed, motion artefacts could be reasonably more significant during free-living conditions. According to our findings, the load cell could be avoided and replaced with a commercial watch wristband, used at different predefined tightening levels, starting from the subject's wrist circumference (i.e., *loose* level). Such replacement can be performed after a dedicated calibration of the different tightening levels on a wide test population, properly including the physiological variability in wrist morphology and circumference; a wider test population should be involved also to collect data better fulfilling the normality condition. This statement is supported by the results that show an increase of force at every tightening level. Further studies can be conducted by including an inertial sensor (e.g., 3-axis accelerometer) to identify the potential motion artefacts corrupting the PPG measurement and, consequently, to improve the physiological monitoring. Moreover, it would be interesting to compare HR values obtained by means of PPG sensors with those measured by a gold-standard instrument (e.g., electrocardiograph), evaluating the different band tightening levels, in order to verify how the contact pressure influences the reliability of the wearable device measurement, hence contributing to provide a more accurate understanding of healthy subjects' and patients' conditions.

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