The Indirect Estimation of Breathing Rate through Wearables: Experimental Study and Uncertainty Analysis through Monte Carlo Simulation

# The Indirect Estimation of Breathing Rate through Wearables: Experimental Study and Uncertainty Analysis through Monte Carlo Simulation

Gloria Cosoli
*Dept. of Industrial Engineering and Mathematical Sciences*
*Università Politecnica delle Marche*
Ancona, Italy
g.cosoli@staff.univpm.it

Luca Antognoli
*Dept. of Industrial Engineering and Mathematical Sciences*
*Università Politecnica delle Marche*
Ancona, Italy
l.antognoli@pm.univpm.it

Luna Panni
*Dept. of Industrial Engineering and Mathematical Sciences*
*Università Politecnica delle Marche*
Ancona, Italy
l.panni@pm.univpm.it

Lorenzo Scalise
*Dept. of Industrial Engineering and Mathematical Sciences*
*Università Politecnica delle Marche*
Ancona, Italy
l.scalise@staff.univpm.it

***Abstract*—Breathing Rate (BR) is a fundamental physiological parameter and wearable sensors can indirectly estimate it through the measurement of electrocardiogram (ECG). Indeed, they are widely employed in several application fields thanks to their multiple advantages, such as user-friendliness, availability in different quality and cost segments, and capability to acquire multidomain physiological signals. This study aims at applying an approach based on respiratory sinus arrhythmia to the ECG signals acquired by a cardiac belt (Zephyr BioHarness 3.0) and a smartwatch (Samsung Galaxy Watch3), evaluating the measurement accuracy as well as performing a Monte Carlo simulation to analyze the uncertainty propagation along the measurement chain, from the wearable sensors to the estimated BR value. The results show that both the wearable sensors provide an accurate estimation of BR (almost null bias), with good precision (standard deviation of residuals: 3 bpm for both sensors), and moderate-high correlation with reference values (Pearson's correlation coefficient: 0.77 for Zephyr BioHarness 3.0 and 0.63 for Samsung Galaxy Watch3). Considering an uncertainty of ±1 bpm and ±2 bpm on heart rate for Zephyr BioHarness 3.0 and Samsung Galaxy Watch3, respectively, the Monte Carlo simulation provided expanded uncertainty values on the estimated BR of ±6 bpm and ±8 bpm, respectively, evidencing a relevant impact of physiological variability.**

***Keywords*—*wearable sensors, breathing rate, uncertainty analysis, Monte Carlo simulation***

## I. INTRODUCTION

Breathing rate (BR) is one of the most significant physiological parameters that can be measured on a subject, being indicative of pathological instabilities like lung disease and cardiopulmonary arrest [1]. Indeed, through the respiratory pattern analysis it is possible to evaluate the risk of different potential illnesses linked to heart, lungs, blood vessels, or red blood cells [2], [3]. The clinical decision-making processes are often based on the examination of (normal or abnormal) breathing patterns [4]. Furthermore, the prediction of BR covers a relevant role as a marker for a plethora of phenomena: labour pain [5], anxiety [5], respiratory diseases (e.g. chronic obstructive pulmonary disease and asthma) and respiratory infections [6], driving safety [7], treatment of thoracic and abdominal tumours [8], just to cite some examples.

However, the measurement of BR is generally not straightforward, especially when a continuous assessment of BR is desired; Massaroni et al. [9] reviewed the state-of-the-art methods, dividing them into contact-based and contactless ones. In the former case, the sensing element is in contact with the body of the subject to be monitored and the measurement can be based on different working principles:

- Respiratory airflow characterization in terms of both volume and velocity; flowmeters [10] and anemometers [11] can be exploited;
- Investigation of the respiratory sounds generated by the air flow through throat and airways. Acoustic sensors (microphones) sensitive to environment changes are employed [12];
- Air temperature/humidity variations with breathing cycles; indeed, the inhaled air is cooler than the exhaled one and the latter is vapour saturated. Both electric (e.g. thermistors, thermocouples, and resistance temperature detectors [13]) and fibre optics sensors (FOS) [14] can be used;
- Air chemical compositions changes (mainly in terms of oxygen, $O_2$, and carbon dioxide, $CO_2$) during inspiratory/expiratory phases. Infrared sensors [15] can be utilized, as well as FOS [16];
- Chest wall movements during breathing, since the chest walls expand during inspiration with a diameter increase up to 7 cm [17]. Different quantities are influenced by these movements: strain, transthoracic electrical impedance, inclination, acceleration, and velocity; hence, both traditional and FOS sensors can be exploited to assess these variations [18], [19];
- Cardiac activity modulation, investigated through electrocardiographic (ECG) or photoplethysmographic (PPG) signals [20].

Indeed, considering cardiac-related signals, different algorithms for the indirect estimation of BR have been developed in the last decades. In particular, the respiratory sinus arrhythmia (RSA) has been considered; in fact, the RR intervals (i.e. the temporal differences between consecutive R peaks in ECG signal) are shorter when the subject inhales (hence heart rate, HR, is higher) and longer when exhales (lower HR) [21], and this phenomenon can be analysed to derive BR. For example, this information was exploited by Schäfer et al. [22], who correlated HR variability (HRV) to

breathing cycles; another study combined RSA with the amplitude of R peaks, also on single-lead ECG signals [23]. HRV data were analysed also through fast Fourier transform (FFT) based methods [24] and wavelet transform [25]. Recently also artificial intelligence (AI) based technologies have been exploited for BR prediction; Bian et al. [26] employed a residual network (ResNet) architecture to estimate BR from PPG data, achieving a final mean absolute error of 2.5 bpm. Raji et al. [27] introduced a pattern-based prediction system based on an artificial neural network (ANN) fed with data gathered through a smart chest band; they obtained a classification accuracy of 98%.

At present, wearable sensors can play a relevant role in this field, since their spreading has made the physiological monitoring easier [28]. They are leading the way in many application fields and this is attributable to their multiple advantages: user-friendliness, non-intrusivity, ease of use, and capability to monitor many physiological quantities in near real-time. This represents a huge advantage in terms of remote monitoring and can be pivotal in the field of telemedicine, provided that the measurement accuracy of the sensors is adequate to the target application requirements. For this reason, the metrological characterization of wearable sensors, intended as the analysis of their performance when compared to a reference device, should be always performed according to rigorous procedures, to provide measurement results together with the related measurement uncertainty.

The aim of this work is to perform an experimental study for the indirect estimation of BR through ECG data acquired by means of wearable sensors, as well as to evaluate the measurement uncertainty propagation along the measurement chain. Indeed, the uncertainty on the HR values will affect the estimated BR, hence the metrological performance of the exploited hardware should be considered together with the goodness of the estimation algorithms.

The paper is organized as follows: Section II presents the materials and methods used in the study, Section III reports the obtained results for both BR indirect estimation and uncertainty analysis, which are discussed in Section IV; the final conclusions are provided in Section V.

## II. Materials and Methods

### A. Experimental campaign

The experimental campaign was performed at Università Politecnica delle Marche, whose Research Ethics Committee certified that the research study was compliant with the university Research Integrity Code. All the tests were conducted in accordance with the WMA Declaration of Helsinki and healthy volunteers were recruited; before starting the tests, the study methodologies and objectives were clearly explained to the participants, who signed an informed consent module. All the gathered data were managed according to the General Data Protection Regulation (GDPR).

### B. Acquisition devices

The subjects participating to the study simultaneously wore two wearable sensors, namely:

- Zephyr BioHarness 3.0, a cardiac belt with accuracies of ±1 bpm and ±2 bpm for HR and BR, respectively;
- Samsung Galaxy Watch3, a smartwatch capable to measure the ECG at wrist; data on measurement accuracy are not provided by the manufacturer.

The test setup is reported in Fig. 1.

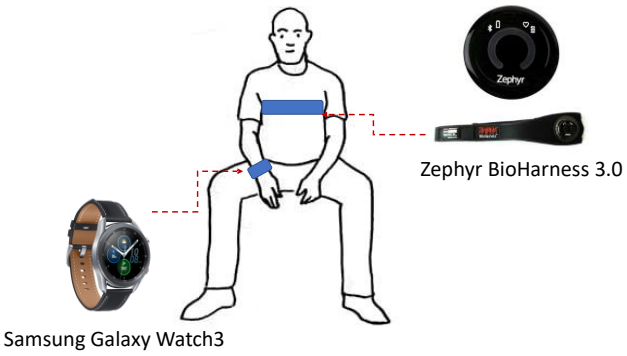


Fig. 1 Experimental test setup: the subject simultaneously wear the cardiac belt (Zephyr BioHarness 3.0) and the smartwatch (Samsung Galaxy Watch3).

### C. Test protocol

Tests were performed on 30 volunteer healthy subjects (22±3 years old, body mass index: 22.5±2.3 kg/m$^2$). Each subject participating to the campaign performed 6 tests: 3 at rest, the remaining 3 immediately after having performed physiological activity (namely 2 minutes walking/running on a treadmill at 3, 8, and 10 km/h (0-slope). All the ECG recordings lasted 30 s (since the ECG recording duration on the smartwatch cannot be modified) and the subject was asked to remain as still as possible throughout the entire test duration, in order to minimize the motion artifacts. In this way, a total of 180 trials were recorded.

### D. Data processing for BR estimation

The starting signals for the BR estimation were the ECG acquired by Zephyr BioHarness 3.0 and Samsung Galaxy Watch3. The algorithm used for the estimation was that proposed by Schäfer et al. [22], with the modifications proposed in [29] (where all the processing details are available); in addition, the ECG signals were at first filtered through a 3$^{rd}$ order band pass Butterworth filter (0.5-40 Hz, i.e. the frequency range typical of a monitor-quality ECG [30]). The tachogram signals derived from the R peaks detected through the Pan-Tompkins algorithm [31] were cleaned from artifacts before being used as input to the algorithm for the BR indirect estimation; in particular, RR intervals were considered as erroneous when their absolute value was greater than the RR mean value plus 1.5 times the related standard deviation. The reference BR values were obtained from the breathing waveform measured by the Zephyr BioHarness 3.0 (accuracy: ±2 bpm), considering the pressure changes on the breathing sensor installed on the cardiac belt; before peaks identification and, hence, BR computation, the signal was filtered through detrend function and moving median (window size of 15 samples, experimentally chosen based on visual verification). We have not considered the BR values directly provided by the sensors since abnormalities in the first seconds were present. To evaluate the estimation accuracy of BR, the measurement differences between the estimated values and the reference ones were computed, considering the average BR on the 30-s recordings; it is worthy to underline that the obtained differences were rounded up to the unit. Hence, the distribution of measurement differences was evaluated and their mean and standard deviation values were computed, being related to measurement accuracy and precision, respectively. Also Bland-Altman plot [32] was made to

evaluate the agreement between test and reference measurement results. Finally, the linear correlation between estimated and reference BR values was evaluated through the Pearson's correlation coefficient (ρ); the correlation strength was considered low if ρ was lower than 0.30, moderate when lying in the range 0.30-0.70 and strong for ρ above 0.70 [33]. In these evaluations, the measurement differences lying beyond the 95% confidence interval (covering factor k=2) was deleted, being considered as outliers.

### *E. Uncertainty analysis*

The measurement uncertainty in the estimation of BR was evaluated through the Monte Carlo simulation method, in compliance with the Guide to the Expression of Uncertainty in Measurement (GUM) [34]. The simulation was iterated $10^6$ times, in order to deliver a 95% coverage interval for the output (i.e. 95%) according to the GUM recommendations. The input to the BR estimation algorithm, i.e. tachogram, was perturbed according to a Gaussian distribution with a standard deviation (i.e. input uncertainty, u(x)) equal to 0.017 s for Zephyr BioHarness 3.0 (corresponding to 1 bpm on HR values, as declared in the user manual) and to 0.042 s (corresponding to 2.5 bpm on HR values – cautionary conditions, given that the mean absolute percentage error acceptable for HR monitors is 5 bpm according to the ANSI/AAMI/IEC 60601-2-27:2011/®2016 [35]) for Samsung Galaxy Watch3, for which no accuracy data are provided by the manufacturer. Two diverse analyses were performed, namely:

- Simulation performed on a unique trial (randomly selected) used as input, perturbed as described above, iterated $10^6$ times;
- Simulation performed on 100 random trials selected as input to the algorithm, perturbed as described above, iterated $10^4$ times. In this way, a total of $10^6$ BR predictions were simulated.

In the former case, the obtained uncertainty (i.e. output uncertainty, u(y)) can be related to the input signal uncertainty (i.e. sensor uncertainty), whereas in the latter also intra- and inter-subject physiological variability comes into play. This is particularly relevant, given that its contribution cannot be neglected [36].

## III. Results

In this section the results related to the indirect estimation of BR along with the Monte Carlo method-based uncertainty analysis are reported.

### *A. Indirect estimation of breathing rate*

The distribution of measurement differences between estimated BR (from ECG data coming from Zephyr BioHarness 3.0 and Samsung Galaxy Watch3, respectively) are reported in Fig. 2 (top and bottom, respectively). A mean difference of approximately 0 bpm was obtained for both the sensors, with a standard deviation describing their dispersion about the mean difference equal to 3 bpm in both the cases. Instances are more centred on the mean value in the case of Zephyr BioHarness 3.0, resulting in a more sharpened distribution.

Considering the Bland-Altman plot (Fig. 3 top and bottom for Zephyr BioHarness 3.0 and Samsung Galaxy Watch3, respectively), it is possible to observe that the agreement between estimated and reference BR values is quite good.

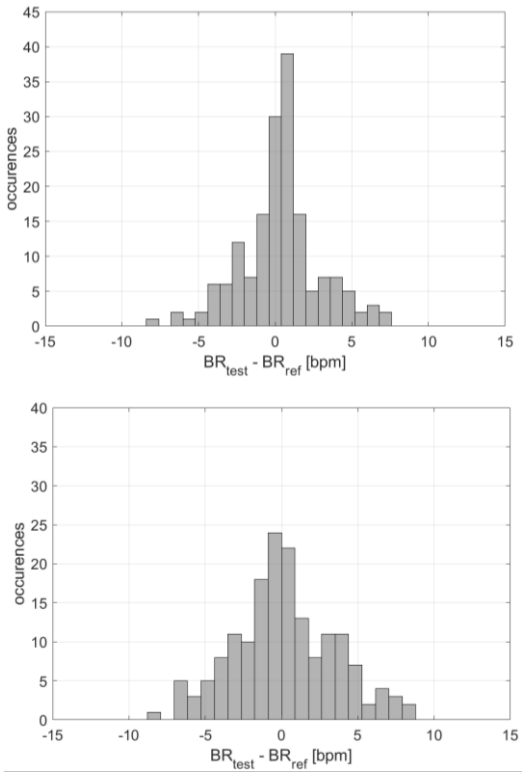


Fig. 2 Distribution of the measurement differences between the BR estimated through Zephyr BioHarness 3.0 ECG (top) and Samsung Galaxy Watch3 (bottom), respectively, and the reference values obtained through the respiratory signal provided by Zephyr BioHarness 3.0 (mean value: 0 bpm; standard deviation: 3 bpm – for both the sensors).

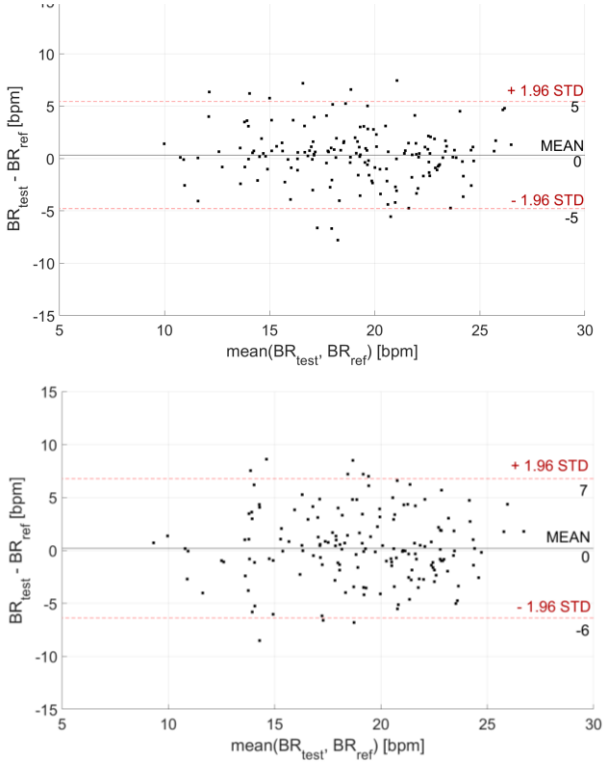


Fig. 3 Bland-Altman plot related to Zephyr Bioharness 3.0 (top, confidence interval at 95% of the level of agreement: [-5, 5] bpm) and Samsung Galaxy Watch3 (bottom, confidence interval at 95% of the level of agreement: [-7, 7] bpm).

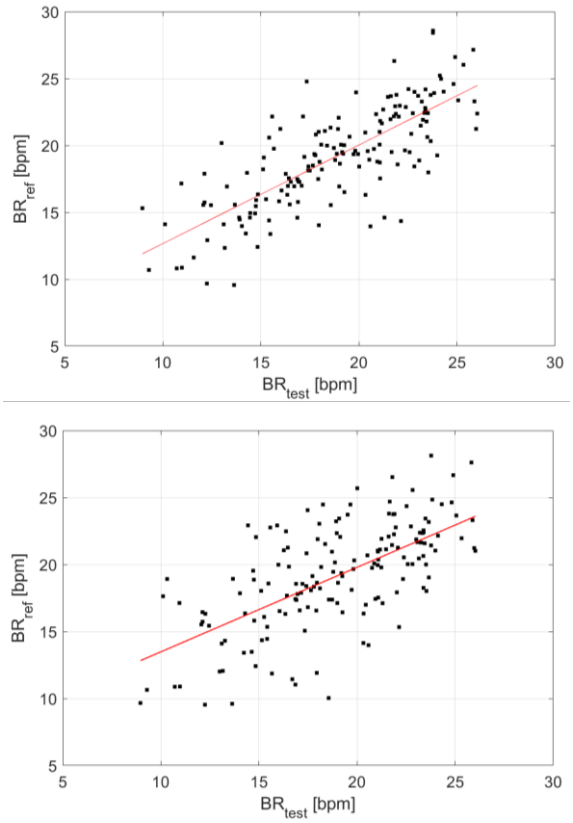


Fig. 4 Correlation between the BR estimated through Zephyr BioHarness 3.0 ECG (top) and Samsung Galaxy Watch3 (bottom), respectively.

Indeed, the bias is almost null and the confidence interval results to be narrow, acceptable for monitoring purposes.

Finally, the Pearson's correlation coefficient was estimated at 0.77 and 0.63 for Zephyr BioHarness 3.0 and Samsung Galaxy Watch3, respectively, indicating a moderate and strong correlation with the reference BR values. The related scatter plots are reported in Fig. 4 (top and bottom for Zephyr BioHarness 3.0 and Samsung Galaxy Watch3, respectively).

### *B. Uncertainty analysis*

In relation to the uncertainty analysis, the results are reported in Table I. It is possible to observe that the input uncertainty of 0.017 s reflected into an uncertainty of 1 bpm on the output (i.e. estimated BR) for Zephyr BioHarness 3.0. Concerning Samsung Galaxy Watch3, the input uncertainty of 0.042 s caused an uncertainty of 2 bpm on the estimated BR. Therefore, the expanded uncertainty (coverage factor k=2) on the estimated BR is equal to ±2 bpm and ±4 bpm for Zephyr BioHarness 3.0 and Samsung Galaxy Watch3, respectively. The probability distribution of the estimated BR obtained with the Monte Carlo simulation related to the two wearable sensors is reported in Fig. 5 (top and bottom, respectively). Both the distributions are centred around 22 bpm, which was the value of BR predicted on the original signal. When perturbing 100 (random) trials, the probability distributions (Fig. 6 – values are centred around o, since the mean value for each trial was removed and only the uncertainty was taken into account) were characterized by a u(y) of 3 bpm and 4 bpm for Zephyr BioHarness 3.0 and Samsung Galaxy Watch3, respectively.

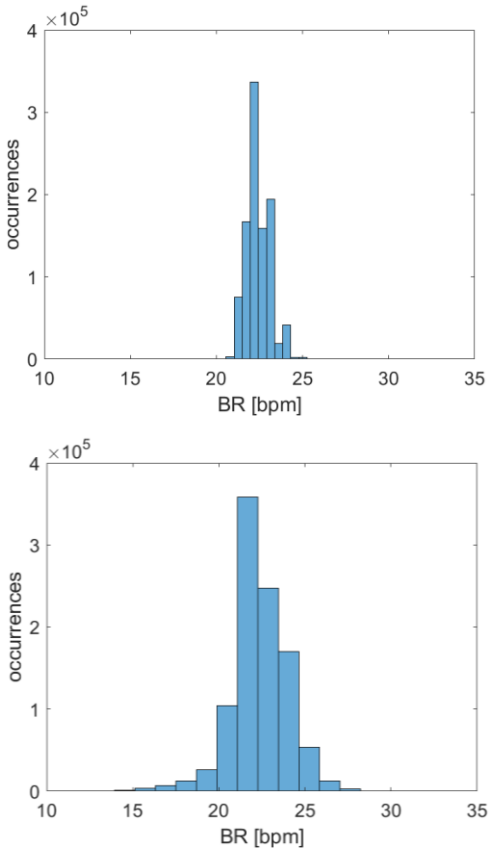


Fig. 5 Probability distributions of the estimated BR for Zephyr Bioharness 3.0 (top) and Samsung Galaxy Watch3 (bottom) when data from a unique (random) trial were perturbed (Gaussian distribution, σ=0.017 s and σ=0.042 s, respectively, on the tachogram used as input to the algorithm for the indirect estimation of BR) - $10^6$ iterations in total.

TABLE I. RESULTS FROM MONTE CARLO SIMULATION

| Wearable sensor | Perturbed trials | u(x) | u(y) |
|---|---|---|---|
| Zephyr BioHarness 3.0 | 1 ($10^6$ iterations) | ±17 ms | ±1 bpm |
| | 100 ($10^4$ iterations) | ±17 ms | ±3 bpm |
| Samsung Galaxy Wacth3 | 1 ($10^6$ iterations) | ±42 ms | ±2 bpm |
| | 100 ($10^4$ iterations) | ±42 ms | ±4 bpm |

## IV. DISCUSSION

The indirect estimation of BR through the proposed method resulted to be equally accurate and precise with the two tested wearable sensors; the almost null mean residual (observable both in the measurement differences distribution, Fig. 2, and in the Bland-Altman plots, Fig. 3) means that measurement accuracy is high, with an acceptable statistical confidence. The measurement differences were rounded up to the unit, however the cardiac belt provided less dispersed residuals, as it can be inferred from the narrower confidence interval at 95%; indeed, 95% of the measurement differences is expected to fall in the confidence intervals of [-5, 5] bpm and [-7, 7] bpm for Zephyr BioHarness 3.0. and Samsung Galaxy Watch3, respectively. This is confirmed through the uncertainty analysis performed according to the Monte Carlo simulation method. In fact, considering just a (random selected) trial, the output uncertainty is actually doubled for the smartwatch with respect to the cardiac belt, accounting for a higher sensor uncertainty on the electrocardiographic

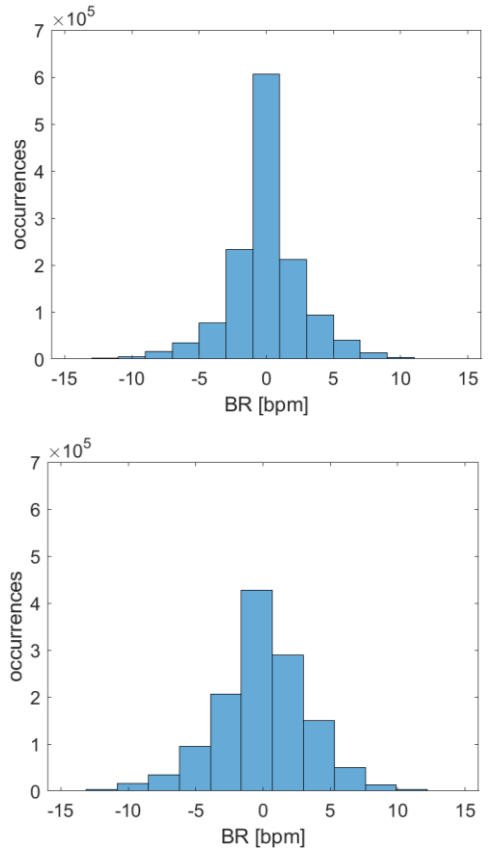


Fig. 6 Probability distributions of the estimated BR for Zephyr Bioharness 3.0 (top) and Samsung Galaxy Watch3 (bottom) when 100 (random) trials were perturbed (Gaussian distribution, σ=0.017 s and σ=0.042 s, respectively, on the tachogram used as input to the algorithm for the indirect estimation of BR) - $10^6$ iterations in total.

activity assessment. On the other hand, perturbing 100 trials acquired on different subjects, the output expanded uncertainty (k=2) resulted to be equal to ±6 bpm and ±8 bpm for Zephyr BioHarness 3.0 and Samsung Galaxy Watch3, respectively. This means that physiological variability plays a relevant role in the estimation of BR from ECG data, given that the uncertainty triples for the cardiac belt and doubles for the smartwatch. Hence, an increase of 2 bpm in the value of u(y) can be attributed to physiological variability characterizing the test population.

## V. Conclusions

In this work the authors exploited the ECG data measured by means of two wearable sensors, namely Zephyr BioHarness 3.0 and Samsung Galaxy Watch3, to indirectly estimate the average BR from 30-s ECG signals. Measurement accuracy and precision were evaluated analysing the distribution of the measurement differences between estimated and reference BR values; hence, an uncertainty analysis was performed through the Monte Carlo simulation method, also considering the physiological variability intrinsic of the test population.

The results showed that the indirect estimation of BR exploiting the ECG signals measured by means of wearable sensors provide accurate results. An almost null mean measurement difference was obtained for both Zephyr BioHarness 3.0 and Samsung Galaxy Watch3. Hence, it can be stated that the accuracy of the estimated BR is optimal and the results are in agreement with the reference values (confirmed by the Bland-Altman plot, showing zero bias and a narrow 95% confidence interval for both the sensors).

Since the application of wearable sensors is constantly growing also in medicine related fields, the evaluation of measurement accuracy and uncertainty is extremely relevant. In this work the authors performed an uncertainty analysis through a Monte Carlo simulation, to express measurement uncertainty according to the GUM. It resulted that an uncertainty of ±1 bpm and of ±2.5 bpm considered for Zephyr BioHarness 3.0 and Samsung Galaxy Watch3, respectively, causes an uncertainty of ±1 bpm and ±2 bpm, respectively, in the indirect estimation of BR when a single trial is perturbed. However, when more trials are perturbed, both the u(y) values increase of 2 bpm. Thus, physiological variability carries substantial weight in the output uncertainty.

In future, it would be interesting to optimize the whole measurement chain; the sensor hardware surely plays a relevant role, but also the measurement procedures have their own weight on the outcome. Among the sources of uncertainty, it is worthy to mention the sensor-skin contact and the subjective interferences that can alter the results (e.g. little movements due to the post-activity fatigue, impeding the subject to remain still). Also, different inputs to the BR estimation algorithm could be considered, such as the effect of diverse filtering techniques and options (e.g. filter order, types, and cut-off frequencies). Finally, also a deeper analysis of the reference sensor could be of interest, to investigate the sources of its intrinsic inaccuracy at the beginning of the acquisition.

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