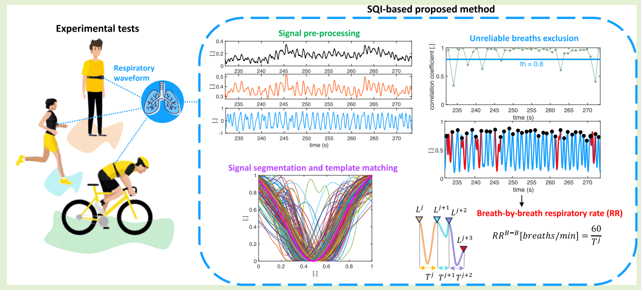
A Signal Quality Index for Improving the Estimation of Breath-by-Breath Respiratory Rate During Sport and Exercise

Chiara Romano, *Student Member, IEEE*, Lorenzo Innocenti, *Student Member, IEEE*, Emiliano Schena, *Senior Member, IEEE*, Massimo Sacchetti, Andrea Nicolò, *Member, IEEE*, and Carlo Massaroni, *Senior Member, IEEE*

***Abstract*—The breath-by-breath measurement of respiratory rate (RR) plays a pivotal role in sports and exercise. The accurate estimation of RR values on a breath-by-breath basis with wearable sensors has several open challenges during training, including motion artifacts and other breathing-unrelated events. This article presents a novel method based on a signal quality index (SQI) for identifying and excluding unreliable breaths from breathing waveforms. The method analyses the morphological characteristics of the respiratory signal, comparing each breath with an average breath template calculated as an average of all individual breaths. The comparison is made using a template matching without the need of a reference signal. Experimental tests have been carried out at rest and during walking, running, and cycling activities to assess the method's performance in estimating breath-by-breath RR by comparison with reference values collected with a flowmeter. The comparison between the RR values has been performed with an ad hoc developed method able to accomplish this task, even when the number of breaths identified by the two devices is different. The obtained results showed that our SQI-based method improves the accuracy of RR estimation by reducing the mean absolute percentage error (MAPE) values in all the tested conditions (18.5%, 22.2%, 2.8%, and 14.1% of MAPE improvement rate during rest, walking, running and cycling, respectively). Pilot tests during high-intensity interval training (HIIT) also demonstrated a 30.7% MAPE improvement rate. The promising findings demonstrated that using SQI-based algorithms can lead to more accurate RR estimations during exercise by using comfortable wearable sensors.**

***Index Terms*— Respiratory rate (RR), sensors, signal quality index (SQI), template matching, wearable device.**



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Chiara Romano is with the Research Unit of Measurements and Biomedical Instrumentation, Department of Engineering, Università Campus Bio-Medico di Rome, 00128 Rome, Italy (e-mail: c.romano@unicampus.it).

Lorenzo Innocenti, Massimo Sacchetti, and Andrea Nicolò are with the Department of Movement, Human and Health Sciences, University of Rome "Foro Italico," 00135 Rome, Italy (e-mail: lorenzo.uniroma4@gmail.com; massimo.sacchetti@uniroma4.it; andrea.nicolo@uniroma4.it).

Emiliano Schena and Carlo Massaroni are with the Research Unit of Measurements and Biomedical Instrumentation, Department of Engineering, and Fondazione Policlinico Universitario Campus Bio-Medico, 00128 Rome, Italy (e-mail: e.schena@unicampus.it; c.massaroni@unicampus.it).

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I. Introduction

PHYSIOLOGICAL monitoring in sports is increasingly important for improving training methodology, optimizing athletes' performance, reducing the risk of injuries, and protecting the well-being of athletes [1], [2]. As technology advances, monitoring different physiological parameters has become increasingly accessible and useful for professional and recreational athletes. Furthermore, cardiac and respiratory variables are among the most relevant physiological variables that can be monitored during sports and exercise [3], [4].

Respiratory monitoring during exercise has gained growing interest in recent years [5], [6]. However, most studies have been conducted in the laboratory, while only a few attempts have been made so far to monitor ventilatory variables in real-world sports settings [7]. Nevertheless, a reversal of this trend is expected considering the importance of respiratory rate (RR) for exercise monitoring and the increasing availability of unobtrusive wearable devices recording respiratory waveforms [8], [9], [10]. Indeed, the time course of RR provides information on physical effort and is associated with changes in exercise tolerance in a variety of exercise conditions [3],

[7], [11], [12]. Numerous technologies are available to support athletes and researchers in measuring ventilatory variables, and some of them can be used outside the laboratory setting. For instance, solutions based on the indirect measurement of respiratory flow using temperature or humidity sensors integrated into facial masks provide accurate measurements of RR [9]. Besides, the fact that RR can be extracted from the photoplethysmogram (PPG) and electrocardiogram (ECG) signals may facilitate RR measurement in a variety of healthcare and sports settings, since these signals can be obtained by noninvasive electronics devices (e.g., smartwatches). For this reason, several algorithms have been proposed to estimate RR from the respiratory modulation of ECG and PPG signals. However, despite the high comfort of the devices in the sports contexts, they may not be suitable for estimating RR at a breath-by-breath basis because they are often corrupted by motion artifacts during exercises [13]. On the other hand, a practical and effective solution for most sporting activities is the indirect measurement of chest wall deformation or movements caused by respiratory activity. Several sensors based on different working principles can be used for this purpose, such as piezoresistive [14], capacitive [15], and inductive strain elements [16], or magneto-inertial (IMU) sensors [17], [18], [19] embedded or attached to sports bands, garments, t-shirts, tops worn around the athlete's chest or abdomen area [9]. This integration allows athletes to perform their sports without discomfort or hindrance while collecting valuable data. In this context, the accuracy of the respiratory signal is crucial in interpreting this useful information.

Although there are numerous validation studies concerning commercial devices such as Hexoskin[1] (Carre Technlogies Inc., Quebec, Canada) [20], [21], [22], [23], Zephyr Bioharness[2] (by Medtronic, USA) [24], [25], Equivital[2] EQ02 LifeMonitor[2] (Hidalgo Cambridge, U.K.) [26], LifeShirt[1] (Vivometrics, Inc., Ventura, CA, USA) [27], there is room for improvement in the validation methodology used in these studies. In most of the validation studies, the comparison between instrument and reference data is not performed on a breath-by-breath basis, thus leaving uncertainties on the suitability of the device for real-time respiratory monitoring. Also, validation studies often use the output of the company's algorithm, especially for commercially available sensors, although it is often unclear how RR values are extracted [28]. An alternative approach is to evaluate the performance of RR extracted from the raw respiratory signal using custom algorithms [28].

When dealing with wearable systems based on strain sensors, the biggest challenge is to accurately identify each breath to estimate RR (and other respiratory variables) on a breath-by-breath basis. A typical method to enhance parameter estimation from physiological signals involves the use of a morphology-based signal quality index (SQI) to locate segments with high-quality signals, thus enabling more accurate estimation of the parameters [29]. Although the use of SQIs is well consolidated in the estimation of cardiovascular variables even during exercise (e.g., heart rate estimation from the ECG signal [30], [31] or ballistocardiogram [32], pulse rate or stroke volume estimation from the PPG signal [33], [34]), limited research has been conducted on the development of an SQI for RR estimation. In this context, some techniques have been implemented; however, they have been especially used for clinical applications on impedance pneumography or PPG signals [35], [36]. Hence, no studies have attempted to implement SQIs to improve the accuracy of breath-by-breath RR estimation for real-world and sports applications by using data collected from wearable devices.

The challenge lies in recording respiratory data during exercise, which is considerably more problematic than collecting data from resting bedridden patients. Indeed, numerous sources of noise, such as torso movement, changes of direction, and coughs, make the identification of each breath challenging and may lead to underestimations or overestimations of RR during exercise. Furthermore, different sports activities may introduce various motion artifacts on the sensor signal due to the motion and vibrations experienced while combining movements of the legs, torso, and arms [37], [38]. Additionally, it is difficult to apply SQIs to identify and exclude abnormal RR values based on the breath duration [36], which may vary substantially during exercise. For example, athletes commonly exhibit apneas just before engaging in intense sporting actions and tend to rapidly increase their RR in response to vigorous exercise [39]. These factors affect the morphology of the respiratory waveform and the accuracy of RR estimation at a breath-by-breath level.

The aim of this study was to develop and evaluate a novel reference-independent SQI algorithm. The effect of using the developed SQI algorithm on the improvement in RR estimation was tested by comparison with a reference system under different conditions (i.e., at rest and during walking, running, and cycling). The proposed SQI allows for the identification of potentially unreliable (i.e., low-quality) breaths by comparing the morphology of the respiratory signal for each breath cycle with that of an average breath template. Only the reliable (i.e., high-quality) portions of the signal are then processed to evaluate RR over time on a breath-by-breath basis. In addition, a new method for validating measurement systems on a breath-by-breath basis was proposed.

This article is structured as follows. Section II describes the proposed SQI. Section III describes: 1) the experiments performed on athletes to assess the performance of the proposed SQI during different activities and 2) the custom-made method to compare RR values retrieved from two devices. Section IV reports the obtained results. Finally, Section V presents a feasibility assessment of the proposed algorithm on a signal collected during high-intensity interval training (HIIT), followed by the discussions and conclusions in Section VI.

[1]Registered trademark.

[2]Trademarked.

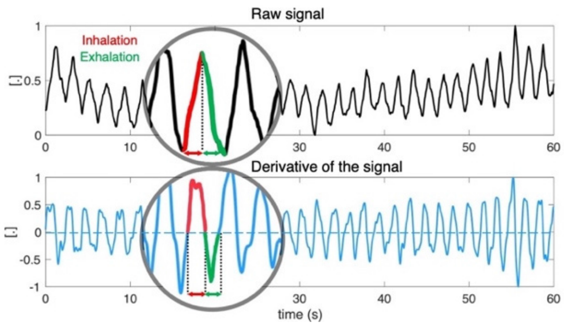

Fig. 1. Example of a raw respiratory signal and the related normalized derivative signal. The signal was collected during cycling with a strain-based chest strap.

II. Proposed Algorithm for the Detection and Exclusion of Potentially Unreliable Breaths and RR Calculation

In this section, the SQI-based algorithm for detecting and excluding unreliable breaths is described. The algorithm has been developed by considering raw signals collected with strain-based wearable sensors, showing an increasing trend during inhalation and a decreasing trend during exhalation, as reported in Fig. 1. The proposed method consists of five major stages.

A. Signal Pre-Processing

A first-order Butterworth bandpass filter with 0.01 and 2 Hz cut-off frequencies was first applied. This filtering process allows the exclusion of frequencies in the signal that are not related to respiratory activity [3]. Then, the derivative of the respiratory signal was calculated and normalized in the range $\{-1, 1\}$ (i.e., x). Hence, the latter results in a positive signal during inhalation and a negative signal during exhalation (see Fig. 1). This processing centers the signal around zero, avoiding any rising or falling trends in the baseline. At this stage, there are not any baseline wander. However, it may show amplitude variations that make detecting respiratory peaks difficult. Hence, the upper (e_{superior}) and lower (e_{inferior}) root mean square envelope were computed [see Fig. 2(a)] and the min-max normalization was applied to obtain x', as in the following equation:

$$x'(t) = \frac{x(t) - e_{\text{inferior}}(t)}{e_{\text{superior}}(t) - e_{\text{inferior}}(t)}. \quad (1)$$

B. Detection of Breaths in Sliding Windows

The signal was segmented into consecutive 12 s - windows, each overlapping by 2 s. Subsequently, the power spectral density (PSD) of the windowed signal was calculated, and the frequency corresponding to the maximum PSD was picked out. The dominant peak obtained by the PSD of the signal was used to determine the temporal threshold for peaks detection [see Fig. 2(b)].

C. Breaths Segmentation

Each breath was segmented as the signal between two consecutive maxima. Then, both the amplitude and duration of each breath were normalized between 0 and 1. Finally, the average breath template was computed as the mean of all the individual breaths [see Fig. 2(c)].

D. Similarity Analysis and Exclusion of Unreliable Breaths

To quantify the similarity of breath morphologies, the Pearson correlation coefficients (ρ) were calculated between all the individual breaths and the average breath template. Therefore, assuming the variable A^i as the breathing waveform of ith breath and the variable B as the average breath template, each consisting of N samples (i.e., the length of the two vectors), the ρ values were calculated as below

$$\rho\left(A^i, B\right) = \frac{1}{N-1}\sum_{j=1}^{N}\left(\frac{A_j^i - \mu_A}{\sigma_A}\right)\left(\frac{B_j - \mu_B}{\sigma_B}\right) \quad (2)$$

where μ_A and σ_A are the mean and standard deviation of A^i and μ_B and σ_B are the mean and standard deviation of B. Then, the correlation coefficient matrix (R_i) was calculated as the matrix of ρ for each pairwise variable combination. Since A and B are always directly correlated to themselves, the diagonal entries are just 1, as in the following equation:

$$R_i = \begin{pmatrix} 1 & \rho\left(A^i, B\right) \\ \rho\left(B, A^i\right) & 1 \end{pmatrix}. \quad (3)$$

Then, all breaths with a correlation below a set threshold were excluded. The algorithm was implemented to optimize the performance in estimating RR, by setting the ρ threshold to 0.6, 0.7, 0.8, or 0.9 [see Fig. 2(d)].

E. Breath-by-Breath RR Assessment

After excluding unreliable breaths considering the different thresholds, the breath-by-breath RR values were calculated. Thus, the respiratory periods (T) were computed as the time elapsed between successive peaks. Using these values, the RR was determined by calculating the ratio of 60 and T. In calculating the breath-by-breath RR, a condition was imposed whereby if a breath was previously excluded, then the related RR is disregarded. A schematic representation of the main steps involved in the new algorithm is shown in Fig. 2.

III. Experimental Tests and Proposed Method to Compare Reference and Wearable-Extracted Breath-by-Breath RR Values

A. Population and Experimental Setup

Experimental tests were carried out on 33 volunteers to evaluate the performance of the proposed algorithm during both motionless condition (i.e., at rest) and three different activities: walking, running, and cycling. Those data were collected in our previous experiments [40], [41]. The experimental setup during rest, walking, and running consists of a treadmill (RHC500 Treadmill, Air Machine S.r.l., Cesena, Italy) on which tests were performed at different walking/running speeds, the Zephyr Bioharness[2] (hereinafter, BH) wearable chest strap, and a flowmeter (SpiroQuant P from

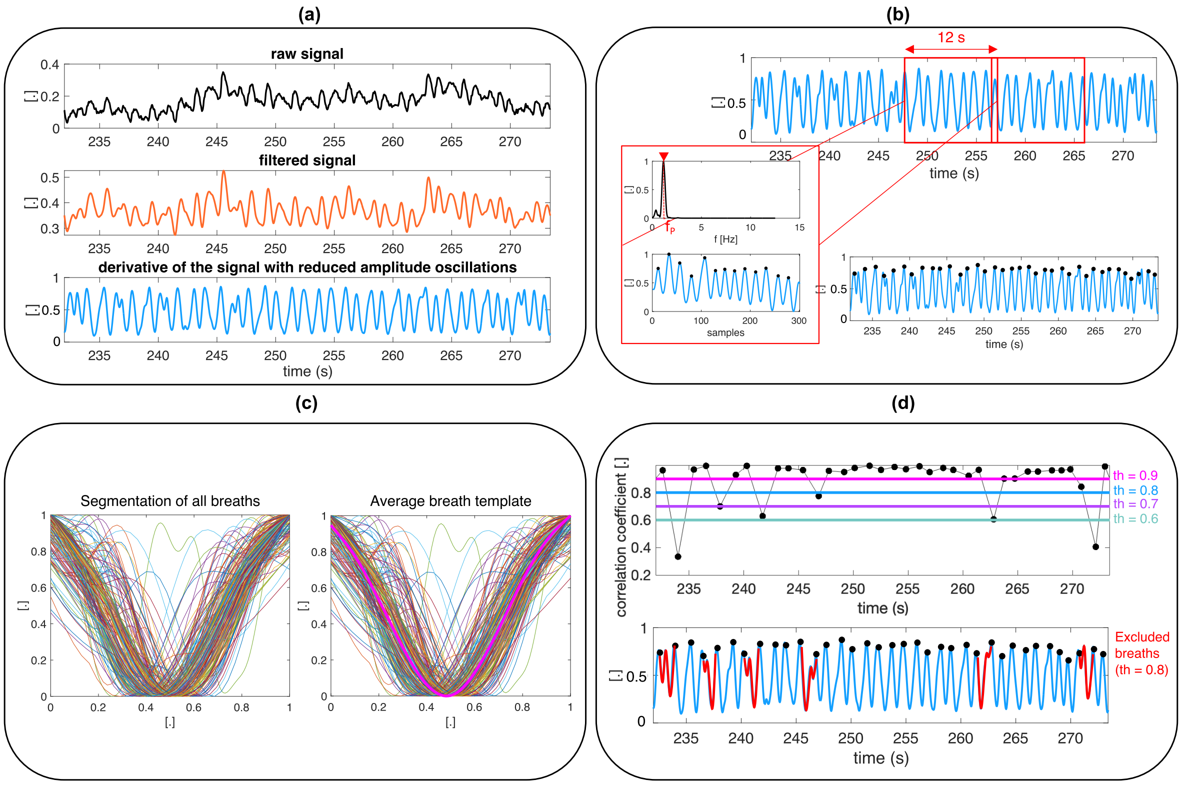

Fig. 2. Schematization of the main steps of the novel SQI-based algorithm developed for the exclusion of unreliable breaths. (a) Signal preprocessing. (b) Detection of breaths. (c) Breaths segmentation and average template signal assessment. (d) Similarity analysis and exclusion of unreliable breaths.

EnviteC, Honeywell, North Carolina, USA), used for recording the reference respiratory airflow signals. On the other hand, the experimental setup for cycling tests consists of a cycle-ergometer (WattBike Pro, model WAT-1W51-015-15), the BH chest strap, and a flowmeter (Quark PFT, COSMED S.r.l., Rome, Italy) used as reference device. An example of the experimental setups is shown in Fig. 3(a).

B. Experimental Protocol

The experimental protocol is extensively described in [40] and [41], and consists of an initial familiarization phase and a 3 min of warm-up, then participants were encouraged to perform a synchronization sequence consisting of three deep breaths followed by apnea [see Fig. 3(b)]. This procedure was used to synchronize the respiratory signals collected with the BH and the reference systems. Then, they were asked to perform four different activities.

1) *Motionless Trials (i.e., at Rest):* The volunteers were asked to remain upright and breathe quietly for 60 s.
2) *Trials During Walking:* The volunteers were asked to walk at 3 and 6 km/h on a treadmill. Each of the two stages lasted 60 s.
3) *Trials During Running:* The volunteers were asked to walk at 9 and 12 km/h on a treadmill. Each of the two stages lasted 60 s.
4) *Incremental Trial During Cycling:* The volunteers were asked to cycle at a self-selected pedaling cadence and to replace spontaneous breathing with the RR paced by a metronome. This test lasted 300 s, and the RR increased from 20 to 75 bpm in an exponential fashion.

The study was approved by the Institutional Review Board of the University of Rome “Foro Italico” (CAR 112/2021) and by the Ethical Committee of University Campus Bio-Medico di Rome (code: 27.2(18).20 dated June 15, 2020). The principles of the Declaration of Helsinki were followed in all steps of the study and written informed consent for study participation was signed by all volunteers.

C. Comparison Between Reference and Wearable-Extracted Breath-by-Breath RR Values: Proposed Method

Reference signals were used to retrieve reference RR values and evaluate the performance of the proposed SQI.

As stated above, the estimation of breath-by-breath RR values requires the identification of inspiration (or expiration) peaks in the signal. As a result, the number of breaths (and therefore the RR values) may be different between two or more devices, particularly when low-quality breath signals are analyzed. This introduces complication to the performance assessment between the two measuring instruments, often leading researchers to perform analyses by interpolating breath-by-breath RR values at 1 s intervals. Hence, a breath-by-breath comparison requires the number of breaths identified on the reference and BH signals to be the same. To tackle this issue, in this article, we suggest a method for comparing RR values extracted from two different respiratory signals, even

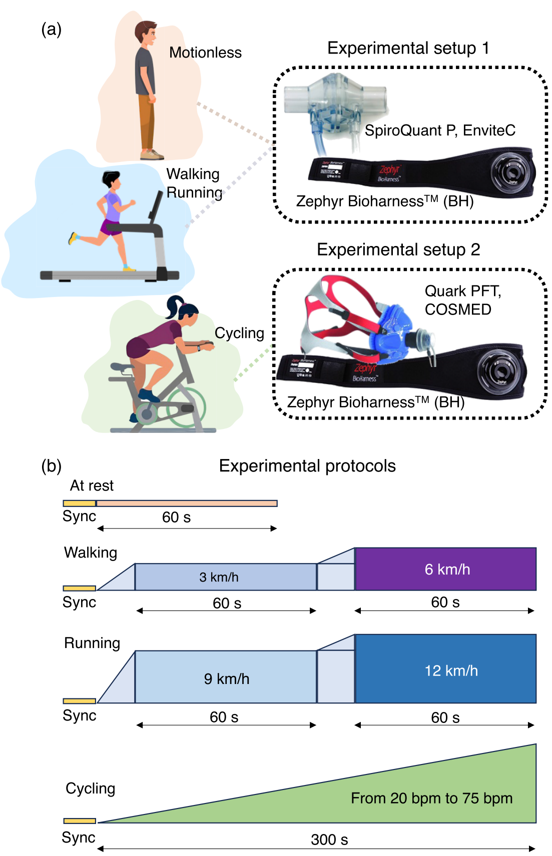

Fig. 3. (a) Schematization of the experimental setups and (b) protocols that were carried out during four different types of sports activities (i.e., at rest, walking, running, and cycling).

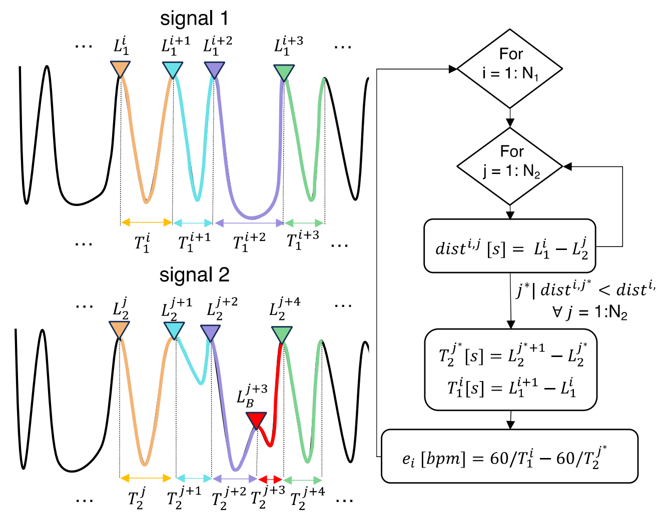

Fig. 4. Schematization of the method used for comparing the reference breath-by-breath RR values and those extracted by using the proposed algorithm applied on the signal 2 (in our study, the signal collected with the BH). T_1^i: ith breath period identified on the signal 1 (i.e., reference signal); L_1^i: location of the ith maximum identified on signal 1; $T_2^{j^*}$: jth breath period identified on signal 2; $L_2^{j^*}$: location of the jth maximum identified on the signal 2; N_1: number of all breaths identified on signal 1; N_2: number of all breaths identified on the signal 2; $\text{dist}^{i,j}$: distance between the position of the ith maximum and the jth maximum; and e_i: error between the RR of the ith breath and that of the j^*th breath.

when the number of breaths identified by the two devices is different.

The method workflow is reported in Fig. 4. Let consider the reference airflow signal as the signal provided by one of the measuring reference devices (denoted as device 1 and related signal 1) while the BH a generic device (denoted as device 2 and related signal 2). The BH signal was preprocessed as described in Fig. 2(a), while the reference signal was first inverted to obtain a signal with the same trend as the derivative of the BH signal. Then, it was filtered with a first-order Butterworth bandpass filter with cut-off frequencies of 0.01 and 2 Hz [3]. Subsequently, on both signals, all the inspiratory events were identified by using sliding windows, as described in Section II [see Fig. 2(b)]. To compare the same number of events, the following steps were performed: considering each event identified in the signal 1 (denoted as L_1^i with $i = 1, \ldots, N_1$), the time distance ($\text{dist}^{i,j}$) between this event and all the events identified in signal 2 (i.e., L_2^j, with $j = 1, \ldots, N_2$) were calculated. Then, the event in signal 2 that exhibited the lowest distance value ($j^* | \text{dist}_{(i,j^*)} < \text{dist}_{(i,j)} \forall j = 1 : N_2$) was selected to be compared with L_1^i. Subsequently, the respiratory periods from both device 1 ($T_1^i = L_1^{i+1} - L_1^i$) and device 2 ($T_2^{(j^*)} = L_2^{(j^*+1)} - L_2^j$) were used to calculate the related RR values as the ratio of 60 to the estimated T. Finally, the difference (e_i) between the RR values provided by the two devices was calculated.

IV. Results

This section deals with the first step of selecting a correlation threshold to exclude unreliable breathing cycles. This evaluation involves the use of a reference system for a comprehensive comparison, thereby quantifying the extent of improvement that the algorithm provides. To determine the adequate trade-off between performance in estimating breath-by-breath RR and the number of excluded breaths, the mean absolute percentage error (MAPE) between the BH RR values and those obtained from the reference signal was calculated, as in the following equation:

$$\text{MAPE}\,[\%] = \frac{1}{N} \sum_{i=1}^{N} \left| \frac{\text{RR}_{\text{BH}}^i - \text{RR}_{\text{ref}}^i}{\text{RR}_{\text{ref}}^i} \right| \times 100 \tag{4}$$

where N represents the total number of breaths. MAPE values were calculated in two conditions: first, when the novel SQI algorithm for excluding unreliable breaths was applied (MAPE_{ex}); and second, when no breaths were excluded ($\text{MAPE}_{\text{noex}}$). In all the comparisons against the reference system, the method described in Section III-C has been applied. To quantify the performance of the proposed SQI, we investigated the MAPE improvement rate as ($\text{MAPE}_{\text{noex}} - \text{MAPE}_{\text{ex}}/\text{MAPE}_{\text{noex}}$) $\times$ 100 expressed in %, together with the ratio between the percentage of excluded breaths on the N value ((# excluded breaths/# total breaths) $\times$ 100). This analysis was performed considering each correlation threshold (i.e., 0.6, 0.7, 0.8, and 0.9). The results, which include individual activities as well as the average across all subjects, are presented graphically in Fig. 5.

The results show that the MAPE improvement rates remain constant between 0.6 and 0.7 during at-rest condition and

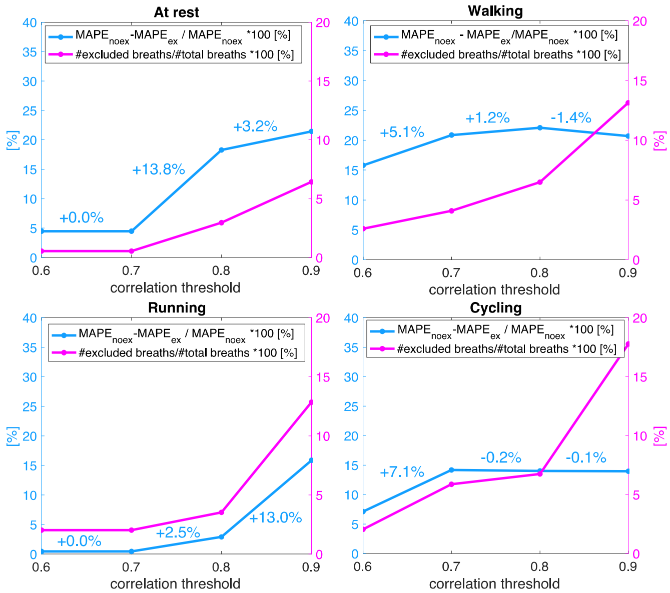

Fig. 5. MAPE improvement rates (in blue) and percentage of excluded breaths compared to the total number of breaths performed during the trials (in magenta). Values were calculated considering the average value between subjects.

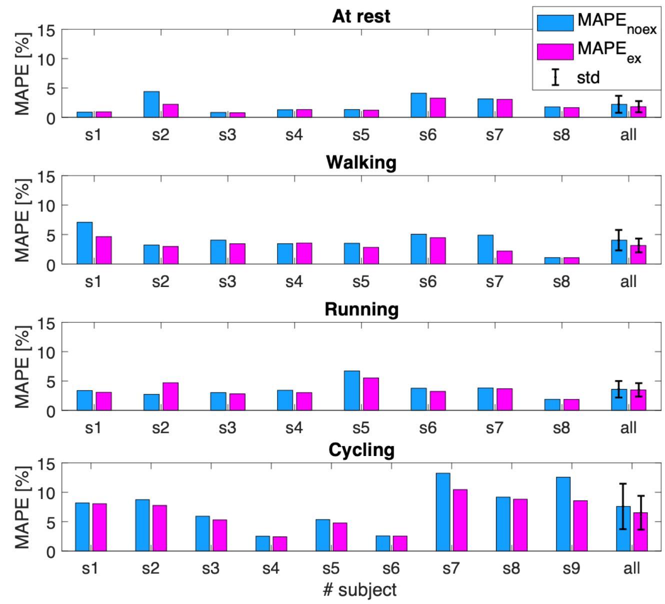

Fig. 6. MAPE values calculated for each activity and each subject, considering MAPE_{ex} and $\text{MAPE}_{\text{noex}}$. std: standard deviation.

running. In contrast, there is an increase in performance in the walking and cycling activities of 5.1% and 7.1%, respectively. Also, between the 0.7 and 0.8 correlation threshold, there is a wider increase in the percentage of MAPE improvement rate for all activities, except cycling. Specifically, there is an improvement of 13.8%, 1.2%, and 2.5% in the case of rest, walking, and running, respectively. On the other hand, in cycling, there is a minor decrease in the MAPE improvement rate of 0.2%. Concerning these thresholds, in all the activities, the percentage of excluded breaths compared to total breaths is always less than 2.2%. Finally, the use of 0.9 correlation threshold at rest and during running, result in an improvement in performance with respect to the 0.8 correlation threshold of 3.2% and 13.0%, respectively. However, in the case of walking and cycling, performance worsens by 1.4% and 0.1%, respectively. The percentage of excluded breaths in relation to the total number of breaths increases from a correlation threshold of 0.8–0.9 up to a maximum of 10.9% and 6.7% in the case of cycling and walking, respectively.

Based on the results obtained from this preliminary analysis, the correlation threshold of 0.8 is the most beneficial considering the MAPE improvement rates and the percentage of excluded breaths. Employing this threshold, errors were assessed considering the RR values extracted from the reference signals in terms of MAPE for each subject and each activity, as reported in Fig. 6.

The results show that using the algorithm results in MAPE_{ex} values lower than $\text{MAPE}_{\text{noex}}$ values in almost all subjects, with a maximum decrease in MAPE of 4.0% in subject 9 during cycling. Also, considering the average value among the subjects, the $\text{MAPE}_{\text{noex}}$ is always higher than MAPE_{ex}, with a difference of at least 0.1% (2.8% of improvement rate) for running up to 1.1% (22.2% of improvement rate) for walking.

V. Feasibility on HIIT Tests

Experimental tests were carried out on one healthy volunteer to test the proposed algorithm on signals collected during HIIT. This section focuses on evaluating the performance of the novel algorithm in the context of activities characterized by sudden changes in RR. The aim is to assess the robustness of the algorithm in scenarios where abrupt fluctuations in RR occur. Such instances tend to make the respiratory signal less reliable due to motion artifacts resulting from the shift in activity intensity, as illustrated in Fig. 7.

The experimental setup consists of a cycle-ergometer (WattBike Pro, model WAT-1W51-015-15), the BH chest strap, and a flowmeter (Quark PFT, COSMED S.r.l., Rome, Italy) used to collect reference respiratory airflow. After an initial synchronization phase, the subject was asked to perform eight repetitions of 20 s of work and 40 s of recovery. The cyclist self-selected the work-phase power output to reach approximately a value of 19 of the Borg's 6–20 ratings of perceived exertion scale on the last of the eight repetitions.

Thus, the algorithm proposed in Section II was applied to the BH signal to select each breath and exclude the unreliable ones. In addition, breaths were identified on the reference signal and compared to the previous ones, as described in Section III-C. Subsequently, to assess the performance of the proposed method at a breath-by-breath level, $\text{MAPE}_{\text{noex}}$ and MAPE_{ex} were evaluated by considering a correlation threshold of 0.8. Hence, the percentage of excluded breaths compared to the total breaths performed during the trials was evaluated.

Results show that using the proposed method decreases the MAPE value from 6.5% to 4.5% (30.7% of improvement rate), by excluding only 4.4% of the total breaths.

VI. Discussion and Conclusion

This study focused on the development of an algorithm for assessing the quality of respiratory signals through an SQI

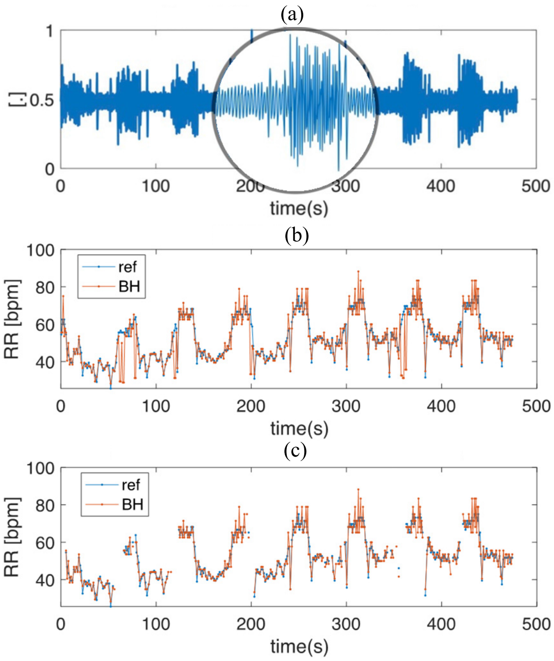

Fig. 7. (a) Raw signal collected with the BH chest strap during HIIT. A zoom is shown in which there is a transition from the recovery phase to the work phase. (b) RR trend over time, considering all breaths identified in the BH signal (in orange) and the reference signal (in blue). (c) RR trend over time when unreliable breaths were excluded using the novel algorithm.

TABLE I
COMPARISON WITH PREVIOUS WORK

Author	Monitoring technique	Setting	SQI algorithm	Performance – Mean Absolute Error (MAE)
Charlton et al. [36]	Impedance pneumogra phy	Clinical setting	Morpholog y quality index	0.21 bpm (1st dataset) and 0.40 bpm (2nd dataset) (rest)
Papini et al. [42]	Photopletis mography	Clinical setting	Morpholog y quality index	1.24 bpm (rest)
Chen et al. [43]	Thermal camera	Occupation al setting	Dynamic time warping	0.49 bpm (rest)
Pereira et al. [44]	Thermal camera	Occupation al setting	Normalized power spectrum	0.59 bpm (rest)
Our work	Strain sensor	Sports	Template matching	0.35 bpm (rest); 0.78 bpm (walking); 1.02 bpm (running); 2.55 bpm (cycling)

based on respiratory signal morphology. This algorithm is primarily designed for sports contexts, where the recording of breath-by-breath RR values with wearable devices encounters inherent challenges. Indeed, motion artifacts can significantly undermine the signal quality providing incorrect information to athletes and coaches about the time course of RR values. Hence, the primary objective of the algorithm was to identify and exclude unreliable respiratory cycles.

The algorithm was devised to operate autonomously, devoid of any reliance on a reference signal and additional signals derived from other sensors (e.g., IMU sensors). Although these sensors could potentially improve the proposed method by providing information on the subject's movements, their integration would result in both an increase in the bulk of the wearable system and an increased computational burden during data acquisition and postprocessing. Hence, the evaluation of breath quality was solely based on the characteristics of the respiratory signal itself. This was achieved by comparing each breath to an average breath template derived from the average of all the respiratory cycles performed by the subject. Both the signal and the average breath template were normalized in both amplitude and frequency. As a result, the individual-specific dynamics of the signal were taken into consideration, and only those breaths deviating from the typical morphology of the subject's signal were excluded. In order to assess the performance of the algorithm in different sporting activities, we carried out experimental tests involving static positions, walking, running, and cycling. For these tests, reference signals were collected to establish the difference in performance between cases where no breath exclusions were performed, and cases where unreliable breaths were excluded by our algorithm. The results showed improvements in MAPE performance in all the investigated activities. In addition, HIIT tests were conducted to evaluate the behavior of the algorithm when fast alternation between work and recovery phases results in abrupt RR changes. The results showed that even under such dynamic conditions, the algorithm shows promising performance improvements, with only a marginal exclusion of approximately 4% of the total breaths.

There are studies in the literature proposing the use of SQI for performance improvement in RR estimation, as shown in Table I.

However, these are mainly used in environments such as clinical or occupational where subject movement is restricted. Also, some studies present techniques to exclude motion artifacts in the respiratory signal. For example, Gwak et al. [45] used an IMU sensor to clean a respiratory signal collected with piezoresistive sensors by implementing an algorithm in a frequency domain analysis. Furthermore, Nabavi and S. Bhadra [46] proposed a method for filtering motion artifacts on a respiratory signal extracted from a PPG signal using information provided by an IMU sensor. However, none of the methods were developed for a breath-by-breath RR estimation. Also, they usually require the use of an additional sensor that increases the overall system footprint. Moreover, while signal morphology analysis is commonly performed using ECG and PPG signals [31], [34], [47], its application to respiratory signals in sports has been overlooked. In this study, we extend the application of morphology-based analysis to respiratory signals, offering a novel approach to enhance the accuracy of respiratory signal processing. Additionally, we propose an easy-to-implement method to compare breath-by-breath RR values of a system under validation with those of a reference system, even in cases where the number of breaths identified by the two devices differs.

Although the results of the proposed method are highly encouraging in all tested sports activities, it is necessary to acknowledge some limitations of the current study. The main limitation pertains to the potential impact of differences in the inspiratory time (T_i) to total time (T_{tot}) ratio, which could affect the recognition of a signal with a T_i/T_{tot} ratio as an unreliable breath due to its different shape compared to that of the average breath template. However, the T_i/T_{tot} ratio may not change substantially during exercise, although it usually increases as exercise intensity rises [48], [49]. Abrupt variations in T_i/T_{tot} are sporadic but may occur, especially during intermittent exercise, where abrupt changes in RR are observed. Besides, we cannot exclude the possibility that some breaths identified as unreliable by our algorithm may contain interesting information from a pathophysiological perspective. Further research is needed to test this algorithm in different populations, including patients with pulmonary diseases, where variations in the morphology of the breathing cycle may reveal signs of the disease. An example is the identification of cough events. Another limitation is related to the number of sports activities and exercise modalities investigated.

In conclusion, the introduced methods address a critical issue in wearable device-based respiratory signal analysis, enhancing the assessment of RR, especially in sports contexts characterized by motion artifacts. The results obtained from our experiments underscore the effectiveness of the proposed algorithm, demonstrating a substantial improvement in performance across various activities. However, upcoming advancements in this research direction will focus on enlarging the sample size to enhance the overall generalizability of our findings. Also, our study could involve further refinement of the algorithm's parameters and exploration of its potential applications in different sports contexts and exercise modalities, e.g., outdoor sports where motion artifacts might be more pronounced. Additionally, the proposed method based on SQI computation could find applications in the identification of the so-called "errant breaths" (induced, for example, by coughing and swallowing while breathing during exercise) that should exhibit frequency components and breath shapes different enough from the characteristics of the template.

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