Breathing Rate Estimation from the Electrocardiogram and Photoplethysmogram: A Review

Peter H. Charlton, Drew A. Birrenkott, Timothy Bonnici, Marco A. F. Pimentel, Alistair E. W. Johnson, Jordi Alastruey, Lionel Tarassenko, Peter J. Watkinson, Richard Beale and David A. Clifton

***Abstract*—Breathing rate (BR) is a key physiological parameter used in a range of clinical settings. Despite its diagnostic and prognostic value, it is still widely measured by counting breaths manually. A plethora of algorithms have been proposed to estimate BR from the electrocardiogram (ECG) and pulse oximetry (photoplethysmogram, PPG) signals. These BR algorithms provide opportunity for automated, electronic and unobtrusive measurement of BR in both healthcare and fitness monitoring. This paper presents a review of the literature on BR estimation from the ECG and PPG. Firstly, the structure of BR algorithms and the mathematical techniques used at each stage are described. Secondly, the experimental methodologies which have been used to assess the performance of BR algorithms are reviewed, and a methodological framework for the assessment of BR algorithms is presented. Thirdly, we outline the most pressing directions for future research, including the steps required to use BR algorithms in wearable sensors, remote video monitoring, and clinical practice.**

***Index Terms*—breathing rate, respiratory rate, electrocardiogram, photoplethysmogram, biomedical signal processing**

I. Introduction

BREATHING rate (BR) is a key physiological parameter used in a range of clinical settings for identification of abnormalities. Despite this, it is still widely measured by counting breaths manually. This approach is both labour-intensive and unsuitable for use in unobtrusive monitoring devices for early detection of deteriorations. Recently, a plethora of algorithms have been proposed to estimate BR from the electrocardiogram (ECG) and pulse oximetry (photoplethysmogram, PPG) signals. Both the ECG and PPG are commonly acquired during clinical assessment, and also by many wearable sensors in healthcare and fitness monitoring. Therefore, BR algorithms could provide automated, electronic BR measurements without the need for additional sensors.

P. H. Charlton and J. Alastruey are with the Department of Biomedical Engineering, King's College London, London SE1 7EH, UK (e-mail: peter.charlton@kcl.ac.uk).

P. H. Charlton, D. A. Birrenkott, M. A. F. Pimentel, L. Tarassenko and D. A. Clifton are with the Department of Engineering Science, University of Oxford, Oxford OX3 7DQ.

T. Bonnici and R. Beale are with the Department of Asthma, Allergy and Lung Biology, King's College London, London SE1 7EH.

T. Bonnici is with the Nuffield Department of Medicine, University of Oxford, Oxford OX3 9DU.

A. E. W. Johnson is with the Laboratory for Computational Physiology, Massachusetts Institute of Technology, Cambridge, MA 02139, USA.

P. J. Watkinson is with the Kadoorie Centre for Critical Care Research and Education, Oxford University Hospitals NHS Foundation Trust, Oxford OX3 9DU, UK.

The aims of this paper are: to provide a comprehensive review of the literature on BR estimation from the ECG and PPG; to present a methodological framework for the assessment of BR algorithms; and, to highlight the most pressing directions for future research. The background to the problem is summarised in the remainder of the Introduction. In Section II we present the methodology and results of a review of the literature on the topic. The BR algorithms reported in the literature are reviewed in Section III. Section IV-A provides a critical review of the experimental methodologies used previously to assess the performance of BR algorithms. In Section IV-B we present a methodological framework for assessment of BR algorithms. Finally, in Section V we highlight the most pressing directions for future research. This review builds on the work presented in [1].

A. The Importance of Breathing Rate (BR)

BR is a valuable diagnostic and prognostic marker of health. In hospital healthcare, it is a highly sensitive marker of acute deterioration. For instance, elevated BR is a predictor of cardiac arrest [2] and in-hospital mortality [3], and can indicate respiratory dysfunction . Consequently, BR is measured every 4-6 hours in acutely-ill hospital patients [4]. BR is also used in emergency department screening. In primary care, BR is used in the identification of pneumonia [5] and sepsis [6], and as a marker of hypercarbia [7] and pulmonary embolism [8]. However, BR is usually measured by manually counting chest wall movements (outside of intensive care). This process is time-consuming, inaccurate [9], [10], and poorly carried out [7], [11]. Furthermore, BR monitoring is not widely incorporated into wearable sensors such as fitness devices [12]. Therefore, there is potentially an important role for an unobtrusive, electronic method for measuring BR, such as the estimation of BR from the ECG or PPG.

B. The Electrocardiogram (ECG) and Photoplethysmogram (PPG)

The ECG and PPG are easily and widely acquired by non-invasive sensors in both healthcare and consumer electronics devices, making them suitable candidates for BR measurement in a range of settings.

The ECG is a measure of the electrical current generated by the action potentials in the myocardium (heart muscle) each heart beat. It is acquired by measuring the voltage difference

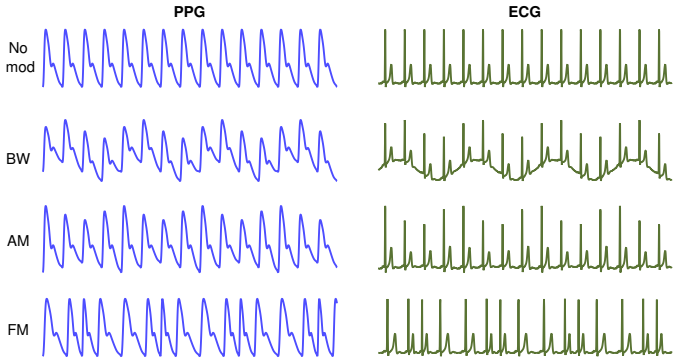

Fig. 1. The ECG and PPG are subject to three respiratory modulations: baseline wander (BW), amplitude modulation (AM) and frequency modulation (FM). Source: [27] (CC BY-NC 4.0).

between two points on the body surface over time caused by this current [13]. The ECG can be measured using low-cost circuitry and electrodes (typically applied to the thorax) [14]. Static monitors are used to obtain single ECG measurements during screening for heart disorders, and for continuous monitoring in critical care units. ECG monitoring is also incorporated into wearable sensors for use with ambulatory patients to identify changes in heart rate and rhythm [15], and in personal fitness devices.

The PPG is a measure of changes in blood volume over time in a bed of tissue [16]. It is measured by applying a sensor to the skin, or by non-contact imaging of a region of the skin using a camera [17]. A tissue bed is illuminated by either a supplementary light source (such as a LED) [18], or ambient light [19]. The intensity of light transmitted through or reflected from the bed is then measured by a photodetector [20]. Contact PPG measurements are commonly performed at peripheral sites (such as the finger or ear) using a low-cost pulse oximeter probe which can be quickly attached [6]. Non-contact measurements are performed by measuring the light reflected from areas of exposed skin, such as the face or hand [17], [21]. Smartphones and tablets can also be used to acquire contact and non-contact PPG signals [22], [23]. The PPG is routinely measured in a wide range of clinical settings to obtain peripheral arterial blood oxygen saturation (SpO_2) and pulse rate measurements. It is continuously monitored in critically-ill patients, and can be monitored in ambulatory patients using wearable sensors [24]. In addition, the PPG is used for continuous heart rate monitoring in fitness devices [25]. Further applications of the PPG are being developed, including blood perfusion assessment and pulse transit time measurement. These use PPG signals obtained simultaneously at multiple sites from a single non-contact imaging PPG [17].

C. Respiratory Modulation of the ECG and PPG

It is widely reported that the ECG and PPG both exhibit three respiratory modulations as illustrated in Fig. 1: baseline wander (BW), amplitude modulation (AM) and frequency modulation (FM) [5], [8], [12], [26]. BR algorithms estimate BR by analysing one or more of these modulations [5], [25].

The physiological mechanisms which cause respiratory modulations can be summarised as follows [28]. BW and AM of the ECG are caused by changes in the orientation of the heart's electrical axis relative to the electrodes, and changes in thoracic impedance [29]. BW of the PPG is due to changes in tissue blood volume, caused by: changes in intrathoracic pressure transmitted through the arterial tree; and, vasoconstriction of arteries during inhalation transferring blood to the veins [30]. AM of the PPG is caused by reduced stroke volume during inhalation due to changes in intrathoracic pressure, reducing pulse amplitude [31]. FM is the manifestation of the spontaneous increase in heart rate (HR) during inspiration, and decrease during exhalation, known as respiratory sinus arrhythmia (RSA) [32]. RSA is caused by at least three mechanisms [28]: (i) changes in intrathoracic pressure during inhalation stretch the sino-atrial node, increasing HR; (ii) increased vagal outflow during exhalation reduces HR; and (iii) reduced intrathoracic pressure during inhalation decreases left ventricular stroke volume, causing a baroreflex-mediated increase in HR [33].

The strengths of each modulation may differ between subjects and between patient groups [8]. Indeed, large inter-subject variations have been observed [28], [34]. Furthermore, particular modulations may be diminished in certain groups, such as FM in elderly subjects [28]. Consequently, many BR algorithms analyse multiple modulations, providing improved performance [5], [12].

II. Search Strategy and Results

A review of the literature was performed to identify publications describing BR algorithms for use with the ECG or PPG. Publications were identified through manual searches and searches of online databases (Google Scholar, IEEE Xplore ®, PubMed, Science Direct, and Scopus). Additional details of the search strategy are provided in Suppl. Section S1, allowing the search to be reproduced and updated.

A total of 196 publications describing BR algorithms were identified which form the basis for this review: [5], [6], [8], [12], [18], [22], [23], [25]–[27], [35]–[220]. The earliest publication was in 1971 [205], and only nine more were published between then and 1998. Since 1999, the rate of publication has risen steadily to the present rate of approximately 20 publications per year (Suppl. Fig. S2). This demonstrates the increasing interest in BR algorithms, and the importance placed upon the topic. Approximately half of the publications (101, 51.5%) were presented at conferences. The remainder were journal articles (88, 44.9%), theses (5, 2.6%) or book chapters (2, 1.0%).

III. BR Algorithms

BR algorithms can be considered to consist of up to five stages, as illustrated in Fig. 2. The role of each stage is as follows.

- *Extract Respiratory Signal(s):* consists of extracting one or more signals dominated by respiratory modulation.
- *Fusion of Respiratory Signals:* multiple respiratory signals can be fused to give one respiratory signal (optional).
- *Estimate BR(s):* consists of estimating a BR from a window of a respiratory signal.

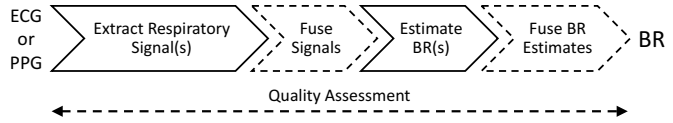

Fig. 2. The stages of a breathing rate (BR) algorithm. Dashed stages are optional.

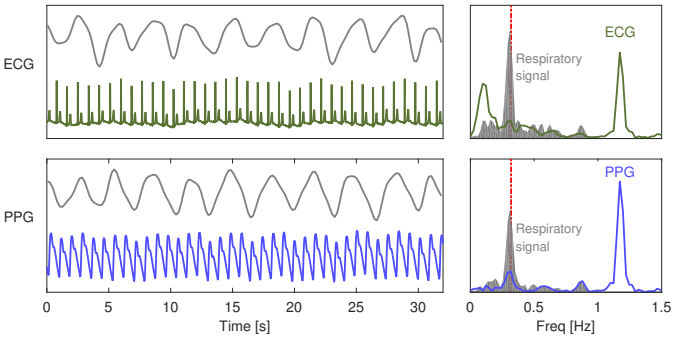

Fig. 3. Extraction of exemplary respiratory signals: ECG (upper plot) and PPG (lower plot) signals and extracted respiratory signals (grey) are shown on the left. The corresponding frequency spectra are shown on the right. The frequency spectra of the raw ECG and PPG signals are dominated by cardiac frequency content at 1.2 Hz. In contrast, the extracted respiratory signals are dominated by respiration at 0.3 Hz, which is approximately the BR provided by a reference respiratory signal (shown by the dashed line).

- *Fuse BR(s):* multiple BR estimates can be fused to obtain one final estimate (optional).
- *Quality Assessment:* used to reject or mitigate against imprecise estimates (optional).

The mathematical techniques which have been used at each stage are summarised in this section. Some of the content in this section has been adapted from [12], [28] (CC BY 3.0) and [1] (CC BY 4.0).

A. Extraction of Respiratory Signals

ECG and PPG signals are primarily cardiac in origin, with secondary respiratory modulations of much lower magnitudes. Therefore, the first stage of a BR algorithm is the extraction of a signal dominated by respiratory modulation from which BR can be more easily estimated, as demonstrated in Fig. 3. Techniques for extraction of a respiratory signal fall into two categories: filter-based or feature-based [8]. Filter-based techniques consist of filtering the raw signal to attenuate non-respiratory frequency components (*e.g.* band-pass filtering the PPG to extract a respiratory signal exhibiting BW). Feature-based techniques consist of extracting beat-by-beat feature measurements (*e.g.* the amplitude of each QRS complex). The individual processing steps used for extracting a respiratory signal are now described.

1) Elimination of very low frequencies: The first step is the elimination of very low frequency (VLF) components of the PPG and ECG, *i.e.* those at sub-respiratory frequencies. VLFs have been eliminated through high-pass filtering using: a median filter [68], [168], [173]; subtraction of a baseline trend calculated using a linear or polynomial fit [6], [142]; or measurements of the baseline at a specific point in the cardiac cycle (*e.g.* shortly before the QRS complex [141], or at midpoints between successive R waves [41] in the ECG). A cut-off frequency between 0.03 - 0.05 Hz is typically chosen [142], [190], [191], [199]. This step is beneficial regardless of whether a filter- or feature-based technique is being used, unless VLFs are removed during data acquisition, for instance by some commercial monitors [20].

TABLE I
FILTER-BASED TECHNIQUES FOR EXTRACTION OF RESPIRATORY SIGNALS

- Band-pass filter to eliminate frequencies outside the range of plausible respiratory frequencies [126].
- Use (ensemble) empirical mode decomposition to extract a respiratory signal as either one particular oscillation mode (intrinsic mode function, IMF), or the sum of the IMFs indicative of respiration [164], [187].
- Decompose signal using the discrete wavelet transform to reconstruct the detail signal at a predefined decomposition scale [53], optionally with automated selection of the mother wavelet [71].
- Extract respiratory oscillation using principal component analysis (PCA) [138] or singular spectrum analysis [128] after identifying the periodicity using singular value decomposition. The use of PCA has been refined using Multi-Scale PCA [131], and Modified Multi-scale PCA [134], in which wavelet decomposition was combined with PCA. PCA has also been applied to intrinsic mode functions extracted using ensemble empirical mode decomposition [151], [152].
- Extract the instantaneous amplitudes or frequencies of cardiac modulation using the continuous wavelet transform [35], the Teager-Kaiser energy operator [198], variable frequency complex demodulation [22], [61], the Hilbert transform [123], or the synchrosqueezing transform [73].
- Filter using the centred-correntropy function [84].
- Decimate by detrending the signal, low-pass filtering to eliminate frequencies higher than respiration, and re-sampling at a reduced sampling frequency [79] of 1 - 2 Hz [6].
- Extract an electromyogram signal from the high frequency content ($>$ 250 Hz) of the ECG caused by the activation of the diaphragm and intercostal muscles during respiration [89].

2) Filter-based techniques: Filter-based techniques for extraction of a respiratory signal are performed in a single step. Several techniques have been proposed, as listed in Table I.

3) Feature-based techniques: Feature-based techniques involve several steps to extract a time series of beat-by-beat features. Examples of the use of feature-based techniques are shown in Fig. 4. The first step is the elimination of very high frequency (VHF) noise by low-pass filtering to improve the accuracy of beat detection and feature measurements. Higher cut-off frequencies are used for the ECG (*e.g.* 40, 75, or 100 Hz [55], [91], [191]) than the PPG (*e.g.* 10 or 35 Hz [91], [108]), to preserve the high frequency content of the QRS complex. In addition, the ECG is particularly susceptible to power-line interference, which may be eliminated using an additional band-stop filter [104]. Commercial monitoring devices typically remove VHFs internally, similarly to VLFs [20]. Next, individual beats are detected (see Suppl. Section S2-A for details of beat detectors used in the literature). Fiducial points (such as Q- and R-waves, shown as black dots in Fig. 4) are then identified for each beat. These are used to measure a feature which varies with respiration (such as the difference in amplitudes between Q- and R-waves for AM). The fiducial points identified and subsequent feature measurements are specific to the particular feature-based technique being used,

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/RBME.2017.2763681, IEEE Reviews in Biomedical Engineering

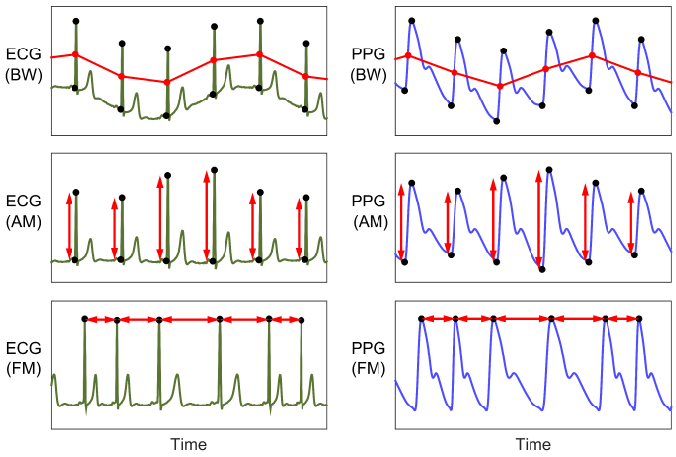

Fig. 4. Exemplary feature-based techniques for extraction of respiratory signals from ECG (left) and PPG (right) signals: measurements of baseline wander (BW), amplitude modulation (AM) and frequency modulation (FM) have been extracted for each beat from fiducial points (shown as dots). Adapted from: [27] (CC BY-NC 4.0).

TABLE II
FEATURE-BASED TECHNIQUES FOR EXTRACTION OF RESPIRATORY SIGNALS

- Extract BW as the mean amplitude of peaks and preceding troughs [12], or the mean signal value between consecutive troughs [174].
- Extract AM as the difference between the amplitudes of peaks and preceding troughs [5].
- Extract FM as the time interval between consecutive peaks [5].
- Extract peak amplitudes [5].
- Extract trough amplitudes [174].
- Principal component analysis of heart beats [175], [221].
- Extract the kurtosis between adjacent peaks [74].
- Extract the morphological scale variation of part of the signal (*e.g.* QRS complexes) by comparing the current beat to a template beat [39].
- Extract QRS durations [173].
- Extract QRS areas [190].
- Extract maximum Q-R or R-S slopes (using either a straight line fit [107] or 4th order central moments [179]), or QRS-wave angles from the difference between them [107].
- Extract PPG pulse widths [105].
- Extract the difference between the durations of the upslope and downslope of the PPG [201].
- Extract the direction or magnitude of the mean QRS vector axis using the arctangent of the ratio of QRS complex areas from two simultaneous ECG leads [189], [218].
- Extract rotation angles of vectorcardiogram loops using multiple ECG leads [47].
- Extract the main direction of the electric heart vector at a specific phase in the cardiac cycle (*e.g.* T-wave) [159].
- Extract the pulse transit time using the R-wave of the ECG and the subsequent PPG pulse onset [38], [91], peak [207], or upslope midpoint [104] .
- Extract the maximum upslope during diastole of a venous signal extracted from dual wavelength PPG signals [213].

as summarised in Table II (additional features are proposed in [34]). Several feature-based techniques use multi-lead ECG signals [29], or non-standard leads derived from them [107]. Lastly, the time series of beat-by-beat feature measurements is re-sampled at a regular sampling frequency of approximately 4-10 Hz. This is usually necessary since signals obtained from beat-by-beat feature measurements are irregularly sampled (once per beat), whereas subsequent processing often requires a regularly sampled signal. Often linear [5], [204] or cubic spline interpolation [104] is used. More complex methods include: Berger's algorithm, designed for use with an FM signal [222], used in [5], [95]; the Integral Pulse Frequency Modulation model, also designed for use with FM signals [223], used in [187]; and, the discrete wavelet transform [173].

4) Elimination of non-respiratory frequencies: Non-respiratory frequencies should be removed from respiratory signals to avoid erroneously identifying spurious frequency content as the BR. Band-pass filtering has been used, with cut-offs at either end of the range of plausible respiratory frequencies [44], [68], [104], [108], [165]. There is no consensus on the optimal range of plausible respiratory frequencies. Furthermore, it may need to be adjusted according to the patient population, particularly for children [224]. Indeed, some BR algorithms use a range which adapts to the HR [79], [122], [153], [154], [203]. As a guideline, Karlen *et al.* used a conservative range of 4 - 65 breaths per minute (bpm) [5].

TABLE III
TECHNIQUES FOR FUSION OF RESPIRATORY SIGNALS

- Spectral-averaging: calculate the individual power spectra of multiple respiratory signals, and then find the average spectrum [104], [108], [190].
- Peak-conditioned spectral-averaging [104], [108]: only sufficiently *peaked* spectra are included in calculation of a *peak-conditioned* average power spectrum. To qualify a spectrum must have a certain proportion of its power within an interval surrounding the frequency corresponding to the maximum power [45], or the previous BR estimate [108].
- Cross-power spectral analysis: calculate the individual power spectra of multiple respiratory signals, and then multiply the spectra [111].
- Cross time-frequency analysis [162]: use the smoothed pseudo Wigner-Ville distribution to estimate time-frequency spectra between two signals.
- Time-frequency coherence [162]: used to measure the degree of coupling between two signals.
- Vector auto-regressive (AR) modelling [132]: the poles of multiple AR models (one for each respiratory signal) are calculated. Only those poles which are common to both models, and which fall within the range of plausible respiratory frequencies, are used to extract a respiratory signal.
- Point-by-point multiplication of signals [103].
- Use of a neural network with multiple input signals to identify periods of inhalation and exhalation [26], [38].

B. Fusion of Respiratory Signals

The second stage is the fusion of multiple respiratory signals to provide one respiratory signal from which BR can be estimated. Multiple respiratory signals can be obtained either by extracting multiple signals simultaneously (*e.g.* by using both the ECG and PPG [38], or by using multiple extraction methods [103]), or by segmenting a respiratory signal into several (often overlapping) windows and treating these as individual signals [45]. Techniques for fusion of multiple respiratory signals are listed in Table III. This stage is optional, and is intended to increase the accuracy and robustness of BR estimates [38].

Techniques for fusion of simultaneous respiratory signals result in a single respiratory signal with enhanced respiratory content and reduced spurious frequency content. These techniques, such as spectral averaging, can improve BR algorithm accuracy even beyond that achieved by using the respiratory signal with the strongest respiratory modulation [104], [108]. This is beneficial since the relative strengths of different modulations are often unknown, since it can vary between individuals and with BR [34]. The contribution of spurious frequencies, such as Traube-Hering-Mayer waves at $\approx$ 0.1 Hz [126], is reduced since these are unlikely to be manifested consistently across all respiratory signals. Fusion of spectra obtained from short segments of a single respiratory signal reduces variance and increases robustness [104]. This is particularly advantageous during exercise, when there is significant motion artifact [47]. Fusion techniques often incorporate quality assessment which excludes signals from the calculation which exhibit little respiratory modulation [104]. This can prevent a BR from being calculated if there is insufficient respiratory modulation [108], which is appropriate when monitoring BR continuously to detect abnormalities.

C. Estimation of Breathing Rates

The third stage of BR algorithms is the estimation of BR. The input to this stage is a window of a respiratory signal, and the output is a BR estimate. The techniques used for this stage, listed in Table IV, act in either the time or frequency domain. Time domain techniques involve detecting individual breaths, followed by calculation of the BR as the mean breath duration. Time domain techniques have the advantage of not requiring a quasi-stationary BR, although they are susceptible to spurious breath detection due to abnormal respiratory signal morphology [12]. Frequency domain techniques involve identifying the frequency component related to respiration, typically through spectral analysis or identification of the instantaneous dominant frequency. One aspect of using auto-regressive frequency domain techniques is the selection of an model order, detailed in Suppl. Section 2-B. The BR estimation stage may be the last in a BR algorithm. However, two further stages can optionally be used, and are now described.

D. Fusion of Breathing Rates

Techniques for fusion of multiple BR estimates can be used to improve the robustness of a final BR estimate. Several approaches have been used to fuse simultaneous BR estimates derived from different respiratory signals. Firstly, BRs can be fused by averaging using the mean, median, or mode [5], [58], [170], optionally after exclusion of outliers [58], [107]. The quality of the final estimate can then be assessed from the standard deviation of the individual estimates [5]. Secondly, BRs can be combined by weighting them according to their variances [8], [220]. Thirdly, a Kalman filter can be used to fuse BRs, which can be weighted according to confidence metrics [122], [157]. Fourthly, candidate BRs obtained through auto-regressive modelling can be fused using the Pole Magnitude Criterion [163] or the Pole Ranking Criterion [165]. Finally, BRs derived from a single respiratory signal at different time points can be fused using temporal smoothing [108] or particle filtering [116].

TABLE IV
TECHNIQUES TO ESTIMATE BR FROM A RESPIRATORY SIGNAL

Frequency-based techniques
• Spectral analysis: identify the respiratory frequency from a power spectrum calculated using either: the fast Fourier Transform [5] (which can operate on unevenly sampled signals [81]), auto-regressive spectral analysis using Burg or Yule-Walker algorithms [193], the Welch periodogram [105], the short-time Fourier transform [186], the Lomb-Scargle periodogram (which can operate on unevenly sampled signals) [46], or sparse signal reconstruction (which can be applied to multiple respiratory signals) [216], [217]. The BR is usually identified as the frequency corresponding to the maximum spectral power in the range of plausible respiratory frequencies, although other approaches have been proposed [218].
• Identify the respiratory frequency as the dominant frequency of a scalogram calculated using the continuous wavelet transform [35].
• Identify the common frequency component in multiple respiratory signals using the weighted multi signal oscillator based least mean square algorithm [86].
• Estimate instantaneous BR [86] using an adaptive notch filter [100], [167], or an adaptive band-pass filter [149].
• Find periodicity using the autocorrelation function [178].
• Estimate the instantaneous BR from either a single signal or multiple signals using a bank of notch filters [147], [148].
• Auto-regressive all-pole modelling, with BR estimated from the frequency of either the highest magnitude pole [6], or the lowest frequency pole [79]. The (order reduced) modified covariance method has also been used [130], [133]
• Use Gaussian process regression to estimate periodicity [171].
Time domain breath detection techniques
• Detect breaths using peak detection.
• Detect breaths by identifying zero-crossings with a positive gradient (after de-trending) [26].
• Detect breaths from peaks and troughs using (adaptive) thresholding to identify those breaths which have been reliably detected [68], [141], [178]

E. Quality Assessment

Quality assessment techniques are optional, and fall into two categories: signal quality indices (SQIs) and respiratory quality indices (RQIs).

SQIs are used to identify segments of ECG or PPG data of low quality, which are typically rejected based on the assumption that BRs derived from them are likely to be inaccurate [5]. SQIs based on template matching involve constructing a template of average beat morphology, and calculation of the correlation between individual beats and the template [225]. A signal segment is deemed to be of high or low quality by comparing the average correlation coefficient for that segment to an empirically-determined threshold. Hjorth parameters have also been used, quantifying the strength of an oscillation in a signal [170]. Furthermore, signal quality can be assessed using multiple beat detectors, with agreement between detectors indicating high quality [155]. Beat-by-beat characteristics have also been analysed to identify low quality input signals, including beat-to-beat intervals, pulse amplitudes and clipped pulses [5].

In addition to SQIs, a relatively recent development in the quality assessment of BR algorithms has been the derivation of RQIs [50], [59], [95], [157], [226]. RQIs are used to assess the quality of extracted respiratory signals. RQIs are an important development since the presence or absence of respiratory modulations of the ECG or PPG is independent of the overall quality of those signals and instead varies based on factors such as gender, age, pre-existing health conditions, level of hydration, body position and the value of the BR itself [34], [157], [227]. Presently, RQIs assess the quality of respiratory signals based on the regularity of breathing peaks and the periodicity of the respiratory waveform. Time and frequency domain techniques have been used including: statistical analysis of the variations in the respiratory peaks [59], Hjorth descriptors, Fourier transform, auto-regression, and autocorrelation [50], [157]. Because RQIs return a range of values (often between 0 and 1) as opposed to a binary outcome, one of the important considerations in RQI implementation is the compromise between data retention and improved estimation accuracy. Recent results using RQIs to fuse BR estimates from multiple ECG and PPG modulations have shown that RQIs both increase data retention and decrease estimation error compared to existing fusion methods [226]. Further work is required to investigate the performance of RQIs in the presence of diseases which cause irregular or shallow breathing, such as in premature infants at risk of apnoea.

IV. Assessment of BR Algorithms

A. Assessment Methodologies Used in the Literature

A wide range of methodologies were used to assess the performance of BR algorithms in the 196 publications. These are summarised in Table V, and critically reviewed in this section. The methods used to obtain Table V are described in Suppl. Section S3.

The literature has focused on the development of novel BR algorithms, rather than comparisons of existing algorithms. This is shown by approximately half (49.5%) of publications assessing the performance of only one algorithm, without any comparator. Furthermore, only 8 publications (4.1%) compared more than 10 algorithms. Several issues make it difficult to compare the reported performance of algorithms between different publications: the use of different statistical measures, the use of data from different subject populations, and the lack of standardised implementations of algorithms (with the exception of [221]), to name but a few [12]. Consequently, it is not possible to determine from the literature which algorithms perform best. The RRest Toolbox (http://peterhcharlton.github.io/RRest) has been designed to address these issues [12], [27], [28]. It provides standardised implementations of several algorithms, as well as code to assess their performance using a range of statistics across multiple publicly available datasets. Further comparisons of algorithms would provide equipment designers with much needed evidence to determine which algorithms are most suitable for implementation.

Most algorithms assessed in the literature take either the ECG or PPG as the input signal (used in 50.0 and 57.7% of publications respectively). Very few publications reported

TABLE V
Methods used to assess BR algorithm performance

Category	No. publications (%)
Application of BR algorithms	
Number of algorithms assessed	
1	97 (49.5)
2-5	75 (38.3)
6-10	16 (8.2)
11-15	5 (2.6)
$\geq$ 16	3 (1.5)
Input signal(s)	
ECG	98 (50.0)
PPG	113 (57.7)
Fusion of ECG and PPG	3 (1.5)
Pulse Transit Time	8 (4.1)
Window duration [s]	
$<$ 30	8 (4.1)
30-59	47 (24.0)
60-89	49 (25.0)
$\geq$ 90	11 (5.6)
unknown	79 (40.3)
Datasets	
Age(s) of subjects [years]	
0 - 0.1: Neonate	5 (2.6)
0.1 - 17: Paediatric	26 (13.3)
18 - 39: Young adult	121 (61.7)
40 - 69: Middle-aged adult	72 (36.7)
$\geq$ 70: Elderly adult	51 (26.0)
unknown	57 (29.1)
Level(s) of illness	
Healthy	128 (65.3)
Sick in community	25 (12.8)
Acutely-ill	14 (7.1)
Critically-ill	52 (26.5)
unknown	8 (4.1)
Type(s) of breathing	
Spontaneous	154 (78.6)
Metronome	44 (22.4)
Ventilated	38 (19.4)
Simulated	3 (1.5)
unknown	20 (10.2)
Number of datasets used	
1	168 (85.7)
2	27 (13.8)
3	1 (0.5)
Comparison with reference BRs	
Reference BR equipment	
Air flow or pressure	46 (23.5)
Impedance pneumography (ImP)	48 (24.5)
Capnography	32 (16.3)
Inductance plethymography (InP)	13 (6.6)
Piezoelectric	8 (4.1)
Strain gauge	17 (8.7)
Metronome	9 (4.6)
Other	20 (10.2)
None	5 (2.6)
unknown	29 (14.8)
Common statistical measures	
Error statistic	111 (56.6)
Breath detection statistic	31 (15.8)
Bias	30 (15.3)
Limits of agreement (LOAs)	29 (14.8)
Correlation	23 (11.7)
Proportion of windows	6 (3.1)

algorithms using both ECG and PPG [38], [132], [164], or pulse transit time [38], [63], [75], [91], [104], [105], [108], [207]. It may be beneficial to use multiple input signals when they are available, such as in wearable sensors [164].

There are pros and cons to the use of shorter and longer window durations with BR algorithms. Most studies used durations of between 30 and 90 s, although durations of 5 to 300 s have been used [178], [210]. Several studies have investigated the impact of window duration on performance [5], [25], [49], [65], [102], [178], [200], [210]. A (non-significant) trend towards lower errors at longer window durations has been reported [5], [25], although there is not yet a consensus as to the optimal window length. The optimal length is likely to differ between populations and applications [49]. On the one hand, using shorter windows reduces both the time required to measure BR, and the computational requirements of BR algorithms [5]. It also increases the likelihood that the BR is stable throughout the window, and allows variations in BR to be tracked more accurately, both of which are concerns during exercise [45]. On the other hand, longer windows may improve the accuracy of algorithms, and increase the range of detectable BRs [25]. Consequently, a duration of 32 s was chosen as a compromise in [5], [200].

The datasets used were often not representative of target populations, and not publicly available. Datasets were often acquired from young, healthy subjects. Fewer publications used data acquired from elderly adults (26.0%), patients suffering from chronic diseases in the community (12.8%), or acutely-ill patients in hospital (7.1%), who are more representative of target patient populations. In addition, few publications used ambulatory data (15.3%). Some publications used data from ventilated patients (19.4%) or subjects breathing in time with a metronome (22.4%). It is not yet clear whether the respiratory mechanics of these subjects can be presumed to be similar to those of spontaneously breathing patients [12]. Consequently, it is not clear whether the performance of BR algorithms reported in these studies is truly indicative of expected performance in target populations. A total of 13 publicly available datasets have been used to assess BR algorithms (Table VI). However, only one publication has used more than two datasets [51]. The range of available datasets makes it possible to assess algorithms across multiple datasets, which is important as performance may differ significantly between datasets [25].

A range of techniques have been used to acquire reference BRs. Typically, a respiratory signal such as impedance pneumography (ImP) was acquired from which reference BRs were estimated using a bespoke algorithm. Many bespoke algorithms were used, although often there was no assessment of the performance of these algorithms. This makes it difficult to know whether errors in BR estimates derived from the ECG and PPG were solely due to poor BR algorithm performance, or contributed to by inaccuracies in reference BRs. Notable exceptions are [149], [178] and [12]. In [149] eight methods were used to obtain reference BRs, and the final estimate was calculated as the mean of the three estimates closest to the median. In [178] several algorithms for obtaining reference BRs were compared, and time domain breath detection methods were found to be *"the only serious candidates"*, with frequency domain spectral methods and an autocorrelation method performing poorly. In [12] a time domain breath detection algorithm was also used, and its performance was quantified by comparing the reference BRs provided by the algorithm to those obtained from manual annotations of a subset of the data. An alternative approach is to manually annotate individual breaths in the entire dataset [5], [25]. Regardless of the approach chosen, it is important that reference BRs are accurate for robust assessment of BR algorithms.

A wide range of statistics have been used to assess BR algorithm performance. Statistics were most commonly calculated from the errors between reference and estimated BRs (used in 56.6% of publications), including the mean (absolute) error, root-mean-square error, and the percentage error. The related limits of agreement (LOAs) method, consisting of the systematic bias and LOAs within which 95% of errors are expected to lie, was used less often (14.8%), even though this has the advantage of quantifying both accuracy and precision [12]. This method is useful because certain applications require greater accuracy (such as identification of pneumonia indicated by BR $>$ 40 bpm [5]), whereas others require greater precision (such as detection of acute changes in BR indicative of deterioration [12]). Statistics indicating the reliability with which individual breaths are detected were used in 15.8% of publications. These included statistics such as sensitivity, specificity, false negative and false positive rates. Correlation coefficients were used in a minority of publications (11.7%). The wide range of statistics reflects the difficulty of quantifying the performance of algorithms using one single metric.

B. A Methodological Framework for Algorithm Assessments

We now present a general methodological framework for assessment of BR algorithms. The reader is referred to [1, ch. 6-7] for examples of BR algorithm assessments conducted in line with this framework.

1) Purpose of Assessment: It is important to identify the purpose of an algorithm assessment: either exploratory analysis, or validation of a BR algorithm. Exploratory analyses are used to determine the performance of a novel algorithm, often in comparison to existing algorithms [25], [84]. They provide evidence to inform the direction of algorithm development, and can be used to identify candidate algorithms for validation studies. Validation studies assess BR algorithms to determine whether they are suitable for a particular application [37]. The purpose of the assessment informs the study design.

2) Dataset(s): The dataset required for an assessment differs according to its purpose. In a validation study, the dataset should be as representative as possible of the intended application, to ensure the results indicate the expected performance. The subject population should be closely matched to the intended users, including: age, level of illness, range of BRs and type of breathing. Signal acquisition equipment should be similar to that which will be used, considering: transducers, signal fidelity (sampling frequency and resolution), and any signal filtering. The recording setting, including the presence or absence of subject movement, should also be similar. If

TABLE VI
PUBLICLY AVAILABLE DATASETS USED TO ASSESS BR ALGORITHMS.

Dataset	Ref	No Subjs	Age	ECG	PPG	Resp Sigs	Type of Breathing	Level of Illness
Datasets containing breath annotations								
CapnoBase	[5]	42	paed, adult	Y	Y	CO_2	spont, vent	surgery, anaesthesia
BIDMC	[25]	42	adult	Y	Y	ImP	spont, vent	critical
Datasets without breath annotations								
MIMIC-II	[228]	23,180	paed, adult	Y	Y	ImP	spont, vent	critical
MGH/MF	[229]	250	paed, adult	Y	N	ImP, CO_2	spont, vent	critical
MIMIC	[230]	72	unk	Y	Y	ImP	spont, vent	critical
VORTAL	[12]	57	adult	Y	Y	ImP, Press	spont	healthy
Fantasia	[231]	40	adult	Y	N	unk	spont	healthy
UCD Sleep Apnea	[232]	25	adult	Y	N	flow	spont	healthy, apnea
CEBS	[233]	20	adult	Y	N	piezo	spont	healthy
ECG and resp	[234]	20	adult	Y	N	flow, pleth	spont	healthy
MIT-BIH Polysomnographic	[235]	18	adult	Y	N	flow	spont, vent	healthy, apnea
Apnea-ECG	[236]	8	adult	Y	Y	InP, flow	spont	healthy, apnea
Portland State	[237]	1	paed	Y	Y	unk	unk	critical

Definitions: Age - paediatric (paed); Respiratory signals (Resp Sigs) - capnometry (CO_2), piezoresistive thoracic band (piezo), oral or nasal flow (flow), oral-nasal pressure (Press), inductance plethysmography (InP), impedance pneumography (ImP), body plethysmography (pleth); Breathing - spontaneous (spont), ventilated (vent); unknown (unk)

any publicly available datasets (Table VI) meet these criteria then they can be used. Otherwise, a novel dataset should be acquired. The requirements for datasets in exploratory analyses are less stringent. In fact, variation within a dataset can allow a greater range of hypotheses to be tested, such as: multiple heart rhythms [210]; young and elderly subjects [163]; multiple input signals (both ECG and PPG) [12]; and, the presence and absence of movement [165]. An assessment's generalisability can be increased by using multiple datasets.

The methodology used to obtain reference BRs is highly important (see Section IV-A). If possible, reference BRs should be obtained indepedently from the input signals (ECG or PPG). For instance, ImP signals are often acquired using the same electrodes as the ECG. In contrast, gold standard spirometry signals are measured from air flow at the mouth (and nostrils) avoiding dependencies with input signals. Methods for estimating BRs from a reference signal should be carefully chosen, and preferably evaluated. The reliability of manual breath annotations can be improved by using two independent annotators, particularly when signal periods containing disagreements between annotators are discarded [25]. Reliability can be assessed using inter-annotator agreement. When using an automated algorithm, its performance can be evaluated using manual annotations on a subset of the data [12].

3) BR Algorithm(s): The choice of BR algorithm(s) is straightforward in validation studies. The performance of one or a few algorithms is evaluated, without the need for additional comparator algorithms, to determine whether the proposed algorithm(s) perform sufficiently well for the chosen application.

There are additional considerations when choosing BR algorithms for exploratory studies. Firstly, additional comparator algorithms should be included to contextualise the results, particularly if using a novel dataset since no comparative results will be available. Comparator algorithms should include leading algorithms from the literature (the Smart Fusion algorithm [5] is often used for this purpose [25], [100], [217], [220]). It may also be beneficial to include algorithms created by varying the technique used at a particular stage of the algorithm to identify techniques which improve performance [12], [220]. Secondly, the BR algorithms can be optimised in a preliminary analysis prior to assessment (ideally using a separate dataset). Aspects suitable for optimisation include: window duration, whether or not to use a fusion technique [5], choice of beat detector, which respiratory signals to use, and the threshold for quality assessment [1]. For instance, the simulated dataset in [12] is suitable for verifying algorithm implementations. Thirdly, the range of BRs which can be outputted by an algorithm should be fixed.

4) Statistical Analysis: The nature of the statistical analysis differs between exploratory and validation studies. In exploratory studies a wide range of statistics should be used to quantify different aspects of algorithm performance (such as errors, the proportion of windows for which a BR estimate is provided, power requirements, and the time delay betwen the start of signal acquisition and a BR estimate being outputted). The analysis need not identify the best algorithm. Rather, it should identify algorithm techniques which lead to improved performance. This may be aided by sub-group analyses of algorithms which use different techniques, and of different subject populations. In validation studies a primary statistic should be identified a priori with which to determine whether the algorithm performs sufficiently well. Ideally, a threshold value of this statistic, indicating sufficient performance, should be chosen a priori (such as a mean absolute error, MAE, of < 2 bpm). Although there are no standardised performance thresholds, further guidance on selecting primary endpoints is provided in Section V-C. Additional statistics can also be used to quantify secondary aspects of algorithm performance.

The following should also be considered: (i) whether a statistical test is required to identify improved performance

(such as the Wilcoxon signed rank test for paired data, or the Wilcoxon rank sum test for unpaired data [28]); (ii) the expected distribution of errors, since parametric statistics such as LOAs are influenced more by non-normal error distributions than non-parametric statistics such as coverage probability [12]; (iii) whether statistics are required to assess ability to detect apnoea [194], [197].

5) Reproducibility: It is helpful to decide at the outset whether study resources will be made publicly available (including datasets, BR algorithms, and evaluation code) [12], particularly if ethical approval is needed. One should also decide whether the analysis should be reproducible [27].

V. Future Research Directions

A. Areas for Algorithm Development

There are several promising areas for BR algorithm development. Firstly, little research has been conducted into the use of models of respiratory modulations in BR algorithms. Womack presented a model relating respiratory sinus arrhythmia to respiration [205]. If mathematical models such as this were incorporated into BR algorithms then this could improve performance, particularly if they exploit relationships between the different respiratory modulations. Secondly, it has recently been proposed that the BRs provided by many different BR algorithms could be fused to improve performance [58], by both reducing the errors, and increasing the proportion of windows for which a BR estimate is provided [220]. Further work is required to determine which BR algorithms should be used in this approach. Thirdly, as the availability of annotated data increases, there is opportunity to use machine learning techniques in BR algorithms. Fourthly, the utility of BR algorithms would be greatly enhanced if the uncertainty associated with a BR estimate was quantified since unreliable BR estimates could be easily discarded [8]. Fifthly, further research is required to identify BR algorithms with low computational requirements which are suitable for use in miniaturised devices such as wearable sensors [82], [215]. Finally, BR algorithms which use a breath detection technique could be used to estimate breathing rate variability, which may have utility as a marker of mental state and disease progression [204].

B. Equipment

Research into BR algorithms has mostly used ECG and PPG signals acquired from routine equipment to assess the performance of algorithms. Some research has investigated alternative equipment for acquiring ECG and PPG signals, to either improve the performance of BR algorithms, or to increase their utility.

Design considerations when using PPG signals include: (i) the anatomical site for PPG measurement (such as finger, ear, forehead, forearm, shoulder, wrist, sternum), which may influence the strength of respiratory modulations [28], [62], [238]–[240]; (ii) the wavelength of emitted light [22], [241]; and (iii) the use of transmission or reflection mode PPG [239]. Each of these factors may influence algorithm performance. Recent research indicates that low-fidelity PPG signals can be used with BR algorithms, such as those acquired at low sampling frequencies [28], or from smart phones or tablets [22], [23], [96], [109], [110]. This will potentially increase the utility of BR algorithms since they could be used in ubiquitous devices such as smart phones in resource-constrained settings [23], [96], [109], [110].

Design considerations when using ECG signals include: (i) whether suitable signals can be acquired without needing electrodes to be attached at several anatomical sites; and (ii) whether multi-lead signals confer a significant benefit over single-lead signals. Klum *et al.* proposed that ECG electrodes positioned as little as 24 mm apart can be used to acquire respiratory signals [242]. This is promising for the implementation of BR algorithms in patch-style wearable sensors [243]. The use of textile-based systems to acquire ECG signals has also been investigated [168], [192], [209]. This could allow BR to be monitored by incorporating sensors into bed sheets [209] or a specialised T-shirt [122]. It has also been proposed that ECG signals could be acquired at locations other than the thorax such as the wrist [76] when a FM-based BR algorithm is used. Some studies have investigated the relative merits of single and multi-lead ECG signals [191], [244], or fusion of respiratory signals acquired from single and multi-lead signals [111]. It is not yet clear whether multi-lead signals provide improved performance, and therefore whether this should be considered when designing ECG acquisition equipment.

C. Applications

BR algorithms may have utility in a range of clinical and personal settings, with each setting having different requirements. The benefits and challenges of using algorithms in each setting are now described.

1) Clinical Assessment: At present, BR is usually measured manually in clinical assessment in both hospitals and the community (as described in Section I-A). In contrast, BR algorithms could provide automated BR measurements. The key design challenges in this setting are to: (i) provide an accurate and precise BR, (ii) for most windows of input signal, (iii) preferably using the PPG since pulse oximeters can be attached quickly and easily, without any additional disposables. In particular, BR algorithm designs often include a trade-off between performance and the proportion of windows for which BR estimates are provided [5]. The latter is likely to be more important since the present manual BR measurements have been reported to have poor performance (*e.g.* LoAs of -8.6 - 9.5 bpm [9]). An attractive case can be made for the use of BR algorithms in 4-6 hourly assessment of hospital inpatients, since the time saved by using an automated method could reduce healthcare costs, and if BR algorithms provide improved performance then this could improve patient safety.

2) Clinical Monitoring using Wearable Sensors: It is important that wearable sensors are capable of monitoring BR, since BR is a sensitive marker of physiological deterioration preceding adverse events (see Section I-A). However, existing approaches for monitoring BR using wearable sensors are not ideal [12]. Many use impedance pneumography [245]. This is unobtrusive, involving measurement of variations in

thoracic impedance with respiration through injection of a high frequency current into the thorax at ECG electrodes [246]. However, it is prone to errors caused by posture changes and motion [245], and has been observed to be imprecise (*e.g.* LoAs of -9.9 - 7.5 bpm [9] and -11.1 - 11.9 bpm [247]). Inductance plethysmography has also been used to monitor BR, although this requires cumbersome chest bands [245] which may be too uncomfortable for prolonged monitoring [248]. More recently accelerometers have been used for BR monitoring [24], although this is still an ongoing area of research [249].

An alternative approach is to estimate BR from the ECG or PPG signals already acquired by many wearable sensors. This would allow BR to be monitored relatively unobtrusively, without an additional transducer. Wearable sensors can acquire ECG and PPG continuously, whereas clinical deterioration usually occurs over several hours. Therefore, one has the luxury of being able to discard data from which a BR cannot be confidently estimated. The key challenge is to provide accurate BR estimates, since erroneous estimates may trigger false alerts, which are resource-consuming and can erode trust in the wearable sensor [250]. Fusion techniques can reduce the frequency of erroneous estimates [12]. An additional challenge arises due to ambulatory data being highly susceptible to artifact, caused by poor sensor contact or movement [8], [192]. Methods for improving BR algorithms for use with wearable sensors include: (i) using SQIs to identify (and discard) artifactual data [225]; (ii) using techniques to reduce the influence of motion artifact [49], [82], [101], [129], [138], [192]; and, (iii) fusing BRs according to the uncertainties associated with each determined by either deriving features from extracted respiratory signals (such as variation in breath-to-breath intervals) [59], or analysing the respiratory signals using Gaussian processes [8]. Furthermore, wearable sensors often acquire more than one signal from which BR could be estimated to improve robustness to artifact, such as ECG and PPG [38], [164], or ECG and accelerometry [59], [122]. The impact of motion on BR algorithms should be investigated further [53], as it is important both in clinical settings (such as during mobilisation after surgery), and for fitness applications. Such a study would require reliable reference respiratory monitoring (such as spirometry), and would benefit from incremental increases in the level of motion (such as on a treadmill).

3) Exercise Monitoring: It has been proposed that BR algorithms could be used in exercise monitoring. In healthcare BR algorithms could be used during stress tests, which otherwise require a device (such as a spirometer) which is uncomfortable and may interfere with breathing [45]. Typically the ECG signal would be used, since it is already monitored during exercise tests. This is a particularly challenging setting because: (i) input signals are greatly contaminated with motion artifact; and (ii) ideally BR would be provided continuously, making it difficult to reject periods of low quality data. Temporal filtering has been widely used in this setting to increase BR algorithm performance [45], [47], [106]. In addition, multi-lead ECG signals have been used to improve performance, involving deriving cardiac rotation angles, including correction and rejection of outlying measurements [47].

BR algorithms could also be used in fitness devices. Many fitness trackers do not measure BR, but do acquire PPG for heart rate monitoring [25]. The ability to measure BR would be a valuable addition. This setting is less challenging than that of exercise tests, since continuous BRs are not required, but could be provided only when expected to be reliable. In addition, BRs do not need to be as accurate as in healthcare. However, in this setting the PPG is likely to be highly corrupted by motion artifact [8].

4) Telemonitoring in the home: Telemonitoring can be used to conduct frequent assessment of physiology in patients with chronic diseases living at home [251]. Telemonitoring setups often include a pulse oximeter, which patients use to assess their own heart rate and SpO_2 [25]. However, it is difficult to measure BR remotely. A simple solution would be to incorporate a BR algorithm into a pulse oximeter. Indeed, Shah *et al.* recently found that BRs estimated from telemonitoring PPG data were predictive of exacerbations in chronic obstructive pulmonary disease [252]. The design challenges in this setting are similar to those for clinical assessment, although greater importance should be placed on obtaining an accurate BR than obtaining the measurement quickly. Ideally, a telemonitoring device would estimate BR in real-time, continuing until an estimate with a high degree of confidence was available. The user would then be prompted to remove the device. Furthermore, if an abnormal BR was detected then the user could be prompted to repeat the measurement to reduce the likelihood of false alerts.

5) Remote video monitoring: The applications presented so far require sensors to be attached to the subject [253]. This requires manual intervention, may be poorly tolerated [254], and may cause discomfort and skin irritation [253], particularly when used over prolonged time periods. It has recently been proposed that BR algorithms could be applied to imaging-PPG signals acquired using non-contact video cameras [17]–[19], [21], [146]. Additional pre-processing steps are required to extract PPG signals from imaging-PPG videos for use with BR algorithms [17]: automatic detection of a region of interest (such as the face); synthesis of spatial information to extract a signal from the region; and, colour channel selection (using information from either a single or multiple colour channels). Heart rate and SpO_2 can also be estimated from imaging-PPG signals, increasing their utility [19], [21]. Further work is required to determine whether BR measurements are best extracted from the cardiac-synchronous component of imaging-PPG signals, or from the changes in reflected light caused by the motion of breathing.

D. Translation into Clinical Practice

Three key areas for future work to translate BR algorithms into clinical practice are now considered.

Firstly, it is not clear whether different patient populations and clinical settings require different BR algorithms. This may arise due to differences in the requirements of algorithms (*e.g.* precision versus the proportion of windows for which an estimate is provided), or differences in respiratory physiology

between patient groups (such as breathing patterns or the strength of respiratory modulations). Therefore, the first area for future work is to assess the performance of BR algorithms in the patient populations in which they are intended to be used. This will provide evidence for the expected performance of a BR algorithm in a particular target population (such as children [119], [183], [203]), and it will allow the most suitable BR algorithm for that population to be identified. For instance, Addison *et al.* have conducted several studies to assess the performance of BR algorithm performance across a range of populations (low-acuity hospitalised patients [37], [48] and patients in the post-anaesthesia care unit [145]), and in the presence of several pathophysiologies (respiratory disease [66], congestive heart failure [144] and chronic obstructive pulmonary disease, COPD [143]). This provides an understanding of the performance of the Medtronic Nellcor ™ BR algorithm (found to have LoAs of 0.07 ± 3.90 bpm in hospitalised patients [48]), and how its performance may be affected by pathophysiologies. Further investigation of the impact of cardiac arrhythmias on performance is much needed [210], since arrhythmias may affect the physiological mechanisms responsible for respiratory modulation of the ECG and PPG [255].

Secondly, BR algorithms must be implemented in clinical monitors to be widely used in clinical practice. This review identified one clinical monitor in which a BR algorithm has been implemented: the Nellcor ™ bedside patient monitoring system, with reported LoAs of 2.25 ± 10.60 bpm when assessed against capnography-derived BRs in patients undergoing procedural sedation and analgesia for endoscopy procedures [194]. This clinical implementation of a BR algorithm marks the beginning of a new phase in the use of BR algorithms, since research into the potential clinical benefit of BR algorithms can be conducted with greater ease after clinical implementation. The process of implementing BR algorithms in monitors is likely to benefit from collaboration across multiple disciplines.

The third key area for future work is to conduct clinical trials to determine how BR algorithms can be used to deliver benefit to patients. These are likely to consist of two stages: an observational trial to determine whether a BR algorithm could be expected to be beneficial, followed by an interventional trial in which clinicians respond to the BRs, prompting changes in treatment. The first stage could be conducted using retrospective analysis of ECG or PPG signals, whereas the second is likely to require a clinical monitor in which a BR algorithm has been implemented. For example, Shah *et al.* used a PPG-based BR algorithm to perform a retrospective analysis of the utility of BR for prediction of exacerbations in COPD patients [252]. They observed that BRs derived from the PPG were predictive of exacerbations, although the clinical utility of this approach needs to be assessed in an interventional trial.

E. Novel Physiological Insights

Novel insights into respiratory physiology can be gained by using BR algorithms in settings where it would otherwise not be practical to either measure BR, or to monitor it continuously. In [189], [256] an ECG-based BR algorithm was used to study changes in BR in the days following an acute myocardial infarction through secondary analysis of Holter ECG monitoring. This led to the insight that an elevated nocturnal BR (of ≥ 18.6 bpm) was associated with an increased risk of non-sudden cardiac death. It has also been suggested that BR algorithms can be used to investigate changes in breathing patterns due to pathology. In [179] an ECG-based BR algorithm was used to study changes in inspiration time, exhalation time, and the ratio of inspiration to exhalation time (as well as BR), associated with schizophrenia. In this particular study no respiratory signal was available, so the BR algorithm provided additional insights.

VI. Conclusion

A wide range of algorithms to estimate BR from the ECG and PPG have been reported in the literature. These mostly conform to a standardised structure, with many different mathematical techniques proposed for each stage. BR algorithms are now being incorporated into clinical devices, with encouraging initial studies of their performance and utility in both hospitals and the community. Further work is required to identify the most suitable BR algorithms for use in different settings, and to determine how BR algorithms can be used to deliver patient benefit. The great potential of BR algorithms is only likely to be realised through close collaboration between researchers, clinicians and industrial partners.

Acknowledgment

This work was supported by the UK Engineering and Physical Sciences Research Council (EPSRC, Grant EP/H019944/1); the Oxford and King's College London Centres of Excellence in Medical Engineering funded by the Wellcome Trust and EPSRC under Grants WT88877/Z/09/Z and WT088641/Z/09/Z; the National Institute for Health Research (NIHR) Biomedical Research Centre based at Guy's & St Thomas' NHS Foundation Trust and King's College London; the NIHR Oxford Biomedical Research Centre Programme; a Royal Academy of Engineering Research Fellowship (RAEng) awarded to DAC; an EPSRC Challenge Award to DAC; and the Rhodes Trust The views expressed are those of the authors and not necessarily those of the EPSRC, Wellcome Trust, NIHR, NHS, Department of Health, RAEng or Rhodes Trust.

Data Access Statement

The data and code used in this research are provided in the Supplementary Material (available at *[url to be inserted]*). Further information about the data and conditions of access can be found by emailing research.data@kcl.ac.uk.

References

[1] P. H. Charlton, "Continuous respiratory rate monitoring to detect clinical deteriorations using wearable sensors," PhD Thesis, King's College London, 2017.

[2] R. M. Schein *et al.*, "Clinical antecedents to in-hospital cardiopulmonary arrest," *Chest*, vol. 98, no. 6, pp. 1388–92, 1990.

[3] R. W. Duckitt *et al.*, "Worthing physiological scoring system: derivation and validation of a physiological early-warning system for medical admissions. An observational, population-based single-centre study." *British Journal of Anaesthesia*, vol. 98, no. 6, pp. 769–74, 2007.

[4] Royal College of Physicians, "National Early Warning Score (NEWS): Standardising the assessment of acute-illness severity in the NHS," Report of a working party. London: RCP, 2012.

[5] W. Karlen *et al.*, "Multiparameter respiratory rate estimation from the photoplethysmogram," *IEEE Transactions on Biomedical Engineering*, vol. 60, no. 7, pp. 1946–53, 2013.

[6] S. Fleming *et al.*, "Non-invasive measurement of respiratory rate in children using the photoplethysmogram," in *Conf Proc Eng Med Biol Soc.* IEEE, 2008, pp. 1886–9.

[7] M. A. Cretikos *et al.*, "Respiratory rate: the neglected vital sign," *The Medical Journal of Australia*, vol. 188, no. 11, pp. 657–9, 2008.

[8] M. A. F. Pimentel, P. H. Charlton, and D. A. Clifton, "Probabilistic estimation of respiratory rate from wearable sensors," in *Wearable Electronics Sensors*, S. C. Mukhopadhyay, Ed. Springer International Publishing, 2015, vol. 15, pp. 241–62.

[9] P. B. Lovett *et al.*, "The vexatious vital: neither clinical measurements by nurses nor an electronic monitor provides accurate measurements of respiratory rate in triage," *Annals of Emergency Medicine*, vol. 45, no. 1, pp. 68–76, 2005.

[10] K. E. J. Philip *et al.*, "The accuracy of respiratory rate assessment by doctors in a London teaching hospital: a cross-sectional study," *Journal of Clinical Monitoring and Computing*, vol. 29, no. 4, pp. 455–460, 2015.

[11] K. Philip, R. Richardson, and M. Cohen, "Staff perceptions of respiratory rate measurement in a general hospital," *British Journal of Nursing*, vol. 22, no. 10, pp. 570–4, 2007.

[12] P. H. Charlton *et al.*, "An assessment of algorithms to estimate respiratory rate from the electrocardiogram and photoplethysmogram," *Physiological Measurement*, vol. 37, no. 4, pp. 610–26, 2016.

[13] A. T. Reisner, G. Clifford, and R. G. Mark, "The physiological basis of the electrocardiogram," in *Advanced methods and tools for ECG data analysis*, G. D. Clifford, F. Azuaje, and P. E. McSharry, Eds. London: Artech House, 2006, ch. 1, pp. 1–25.

[14] G. Clifford and M. B. Oefinger, "ECG acquisition, storage, transmission, and representation," in *Advanced methods and tools for ECG data analysis*, G. D. Clifford, F. Azuaje, and P. E. McSharry, Eds. London: Artech House, 2006, ch. 2, pp. 27–53.

[15] J. A. Walsh, E. J. Topol, and S. R. Steinhubl, "Novel wireless devices for cardiac monitoring," *Circulation*, vol. 130, no. 7, pp. 573–81, 2014.

[16] J. Allen, "Photoplethysmography and its application in clinical physiological measurement," *Physiological Measurement*, vol. 28, no. 3, pp. R1–39, 2007.

[17] Y. Sun and N. Thakor, "Photoplethysmography Revisited: From Contact to Noncontact, from Point to Imaging," *IEEE Transactions on Biomedical Engineering*, vol. 63, no. 3, pp. 463–477, 2016.

[18] M. van Gastel, S. Stuijk, and G. de Haan, "Robust respiration detection from remote photoplethysmography," *Biomedical Optics Express*, vol. 7, no. 12, p. 4941, 2016.

[19] M. Villarroel *et al.*, "Continuous non-contact vital sign monitoring in neonatal intensive care unit," *Healthcare Technology Letters*, vol. 1, no. 3, pp. 87–91, 2014.

[20] K. H. Shelley, "Photoplethysmography: beyond the calculation of arterial oxygen saturation and heart rate," *Anesthesia and Analgesia*, vol. 105, no. 6, pp. S31–6, 2007.

[21] L. Tarassenko *et al.*, "Non-contact video-based vital sign monitoring using ambient light and auto-regressive models," *Physiological Measurement*, vol. 35, no. 5, pp. 807–31, 2014.

[22] Y. Nam, J. Lee, and K. H. Chon, "Respiratory rate estimation from the built-in cameras of smartphones and tablets," *Annals of Biomedical Engineering*, vol. 42, no. 4, pp. 885–98, 2014.

[23] W. Karlen *et al.*, "Respiratory rate assessment from photoplethysmographic imaging," in *Conf Proc Eng Med Biol Soc.* IEEE, 2014, pp. 5397–400.

[24] P. Hubner *et al.*, "Surveillance of patients in the waiting area of the department of emergency medicine," *Medicine*, vol. 94, no. 51, p. e2322, 2015.

[25] M. A. Pimentel *et al.*, "Towards a robust estimation of respiratory rate from pulse oximeters," *IEEE Transactions on Biomedical Engineering [in press]*, 2016.

[26] A. Johansson, "Neural network for photoplethysmographic respiratory rate monitoring," *Medical & Biological Engineering & Computing*, vol. 41, no. 3, pp. 242–8, 2003.

[27] P. H. Charlton, M. Villarroel, and F. Salguiero, "Waveform analysis to estimate respiratory rate," in *Secondary Analysis of Electronic Health Records*. Springer International Publishing, 2016, ch. 26, pp. 377–90.

[28] P. H. Charlton *et al.*, "Extraction of respiratory signals from the electrocardiogram and photoplethysmogram: technical and physiological determinants," *Physiological Measurement*, vol. 38, no. 5, pp. 669–90, 2017.

[29] R. Bailon, L. Sornmo, and P. Laguna, "ECG-derived respiratory frequency estimation," in *Advanced methods and tools for ECG data analysis*, G. D. Clifford, F. Azuaje, and P. E. McSharry, Eds. London: Artech House, 2006, ch. 8, pp. 215–44.

[30] M. Nitzan, I. Faib, and H. Friedman, "Respiration-induced changes in tissue blood volume distal to occluded artery, measured by photoplethysmography," *Journal of Biomedical Optics*, vol. 11, no. 4, p. 040506, 2006.

[31] D. J. Meredith *et al.*, "Photoplethysmographic derivation of respiratory rate: a review of relevant physiology," *Journal of Medical Engineering & Technology*, vol. 36, no. 1, pp. 1–7, 2012.

[32] G. G. Berntson, J. T. Cacioppo, and K. S. Quigley, "Respiratory sinus arrhythmia: Autonomic origins, physiological mechanisms, and psychophysiological implications," *Psychophysiology*, vol. 30, no. 2, pp. 183–96, 1993.

[33] P. D. Larsen *et al.*, "Respiratory sinus arrhythmia in conscious humans during spontaneous respiration," *Respiratory Physiology & Neurobiology*, vol. 174, no. 1, pp. 111–8, 2010.

[34] J. Li *et al.*, "Comparison of respiratory-induced variations in photoplethysmographic signals," *Physiological Measurement*, vol. 31, no. 3, pp. 415–25, 2010.

[35] P. S. Addison and J. N. Watson, "Secondary transform decoupling of shifted nonstationary signal modulation components: application to photoplethysmography," *International Journal of Wavelets, Multiresolution and Information Processing*, vol. 2, no. 1, pp. 43–57, 2004.

[36] P. S. Addison *et al.*, "Developing an algorithm for pulse oximetry derived respiratory rate (RR(oxi)): a healthy volunteer study," *Journal of Clinical Monitoring and Computing*, vol. 26, no. 1, pp. 45–51, 2012.

[37] P. S. Addison *et al.*, "Pulse oximetry-derived respiratory rate in general care floor patients," *Journal of Clinical Monitoring and Computing*, vol. 29, no. 1, pp. 113–20, 2014.

[38] C. Ahlstrom *et al.*, "A respiration monitor based on electrocardiographic and photoplethysmographic sensor fusion," in *Conf Proc Eng Med Biol Soc.* IEEE, 2004, pp. 2311–4.

[39] I. Alikhani *et al.*, "Spectral data fusion for robust ECG-derived respiration with experiments in different physical activity levels," in *Conf Proc. Biomedical Engineering Systems and Technologies*, 2017, pp. 88–95.

[40] M. R. Ambekar and S. Prabhu, "A novel algorithm to obtain respiratory rate from the PPG signal," *International Journal of Computer Applications*, vol. 126, no. 15, pp. 9–12, 2015.

[41] S. P. Arunachalam and L. F. Brown, "Real-time estimation of the ECG-derived respiration (EDR) signal using a new algorithm for baseline wander noise removal," in *Conf Proc Eng Med Biol Soc.* IEEE, 2009, pp. 5681–4.

[42] S. Babaeizadeh *et al.*, "A comparison of three ECG-derived respiration techniques during cardiac magnetic resonance image acquisition," *Journal of Electrocardiology*, vol. 45, no. 6, p. 696, 2012.

[43] S. Babaeizadeh and P. Healthcare, "Cost-efficient accurate monitoring of respiration rate using ECG," in *Conf Proc CinC.* IEEE, 2015, pp. 1009–12.

[44] S. Babaeizadeh *et al.*, "Electrocardiogram-derived respiration in screening of sleep-disordered breathing," *Journal of Electrocardiology*, vol. 44, no. 6, pp. 700–6, 2011.

[45] R. Bailon *et al.*, "Robust electrocardiogram derived respiration from stress test recordings: validation with respiration recordings," in *Conf Proc CinC.* IEEE, 2004, pp. 293–6.

[46] R. Bailón *et al.*, "Robust estimation of respiratory frequency from exercise ECGs," in *Conf Proc CinC.*, vol. 30. IEEE, 2003, pp. 299–302.

[47] R. Bailón, L. Sörnmo, and P. Laguna, "A robust method for ECG-based estimation of the respiratory frequency during stress testing," *IEEE Transactions on Biomedical Engineering*, vol. 53, no. 7, pp. 1273–85, 2006.

[48] S. D. Bergese *et al.*, "Multicenter study validating accuracy of a continuous respiratory rate measurement derived From pulse oximetry: a comparison with capnography," *Anesthesia & Analgesia*, vol. 124, no. 4, pp. 1153–9, 2017.

[49] T. Berset *et al.*, "Robust heart rhythm calculation and respiration rate estimation in ambulatory ECG monitoring," in *Conf Proc Eng Med Biol Soc BHI.*, vol. 25. IEEE, 2012, pp. 400–3.

[50] D. Birrenkott *et al.*, "Robust estimation of respiratory rate via ECG- and PPG-derived respiratory quality indices," in *Conf Proc Eng Med Biol Soc.* IEEE, 2016, pp. 676–9.

[51] D. Birrenkott, "Respiratory quality index design and validation for ECG and PPG derived respiratory data," Report for transfer of status, University of Oxford, 2015.

[52] E. Bowers, A. Murray, and P. Langley, "Respiratory rate derived from principal component analysis of single lead electrocardiogram," in *Conf Proc CinC.* IEEE, 2008, pp. 437–40.

[53] J. Boyle *et al.*, "Automatic detection of respiration rate from ambulatory single-lead ECG," *IEEE Transactions on Information Technology in Biomedicine*, vol. 13, no. 6, pp. 890–6, 2009.

[54] L. F. Brown and S. P. Arunachalam, "Real-time estimation of the ECG-derived respiration (EDR) signal," in *Biomedical Sciences Instrumentation*, vol. 45, 2009, pp. 59–64.

[55] M. Campolo *et al.*, "ECG-derived respiratory signal using Empirical Mode Decomposition," in *Proc Int Symp Medical Measurements and Applications.* IEEE, 2011, pp. 399–403.

[56] A. Canu and M. Canu, "Embedded low-power system for respiration rate calculation," MSc. Thesis, Unviersity College Cork, 2010.

[57] A. Canu *et al.*, "Respiration rate calculation using low power DSP processor and SpO2 sensor," in *Proc Int Symp Medical Measurements and Applications.* IEEE, 2011, pp. 517–20.

[58] R. A. Cernat *et al.*, "Recording system and data fusion algorithm for enhancing the estimation of the respiratory rate from photoplethysmogram," in *Conf Proc Eng Med Biol Soc.* IEEE, 2015, pp. 5977–80.

[59] A. M. Chan, N. Ferdosi, and R. Narasimhan, "Ambulatory respiratory rate detection using ECG and a triaxial accelerometer," in *Conf Proc Eng Med Biol Soc.* IEEE, 2013, pp. 4058–61.

[60] P. Charlton *et al.*, "The influence of recording equipment on the accuracy of respiratory rate estimation from the electrocardiogram and photoplethysmogram," in *MEC Annual Meeting and Bioengineering14 Programme and Abstracts*. London: MECbioeng14, Imperial College London, 2014, p. 96.

[61] K. H. Chon, S. Dash, and K. Ju, "Estimation of respiratory rate from photoplethysmogram data using time-frequency spectral estimation," *IEEE Transactions on Biomedical Engineering*, vol. 56, no. 8, pp. 2054–63, 2009.

[62] S. S. Chreiteh *et al.*, "Estimation of respiratory rates based on photoplethysmographic measurements at the sternum," in *Conf Proc Eng Med Biol Soc.* IEEE, 2015, pp. 6570–3.

[63] C. P. Chua and C. Heneghan, "Pulse transit time-derived respiratory parameters and their variability across sleep stages," in *Conf Proc Eng Med Biol Soc.* IEEE, 2005, pp. 6153–6.

[64] A. Cicone and H.-T. Wu, "How mathematics can help in sensing instantaneous physiological information from photoplethysmography in a fast and reliable way," *arXiv:1701.02072*, 2017.

[65] D. A. Clifton *et al.*, "Home monitoring: breathing rate from PPG and ECG," Oxford, 2012.

[66] D. Clifton *et al.*, "Measurement of respiratory rate from the photoplethysmogram in chest clinic patients," *Journal of Clinical Monitoring & Computing*, vol. 21, no. 1, pp. 55–61, 2007.

[67] S. Cohen *et al.*, "Robust respiratory rate detection using alar photoplethysmography and a thermistor," in *American Society of Anesthesiologists*, 2013.

[68] D. Cysarz *et al.*, "Comparison of respiratory rates derived from heart rate variability, ECG amplitude, and nasal/oral airflow," *Annals of Biomedical Engineering*, vol. 36, no. 12, pp. 2085–94, 2008.

[69] S. Dabiri and M. A. M. Shirazi, "Estimation of respiratory rate from photoplethysmogram signal of sleep apnea patients: A comparative study of different methods," in *Conf Proc TSP.* IEEE, 2015, pp. 440–3.

[70] N. Daimiwal, M. Sundhararajan, and R. Shriram, "Respiratory rate, heart rate and continuous measurement of BP using PPG," in *Conf Proc CSP.*, 2014, pp. 999–1002.

[71] G. Dan, Z. Li, and H. Ding, "A mother wavelet selection algorithm for respiratory rate estimation from photoplethysmogram," in *IFMBE Proceedings*, D. A. Jaffray, Ed. Springer International Publishing, 2015, vol. 51, pp. 962–5.

[72] S. Dash *et al.*, "Estimation of respiratory rate from ECG, photoplethysmogram, and piezoelectric pulse transducer signals: a comparative study of time-frequency methods," *IEEE Transactions on Biomedical Engineering*, vol. 57, no. 5, pp. 1099–107, 2010.

[73] P. Dehkordi *et al.*, "Estimating instantaneous respiratory rate from the photoplethysmogram," in *Conf Proc Eng Med Biol Soc.* IEEE, 2015, pp. 6150–3.

[74] S. Ding *et al.*, "Derivation of respiratory signal from single-channel ECGs based on source statistics," *International Journal of Bioelectromagnetism*, vol. 6, no. 1, 2004.

[75] X. Ding *et al.*, "A pulse transit time based fusion method for the noninvasive and continuous monitoring of respiratory rate," in *Conf Proc Eng Med Biol Soc.*, 2016, pp. 4240–3.

[76] D. N. Dutta, R. Das, and S. Pal, "Automated real-time processing of single lead ECG for simultaneous heart rate and respiratory rate monitoring," *Journal of Medical Devices*, vol. 11, no. 2, p. 024502, 2017.

[77] A. Espiritu Santo and C. Carbajal, "Respiration rate extraction from ECG signal via discrete wavelet transform," in *2nd Circuits and Systems for Medical and Environmental Applications Workshop (CASME)*. IEEE, 2010, pp. 1–4.

[78] R. Firoozabadi, E. D. Helfenbein, and S. Babaeizadeh, "Monitoring respiration rate in sleep-disordered breathing patients using chest belts or ECG," *Journal of Electrocardiology*, vol. 47, no. 6, p. 908, 2014.

[79] S. G. Fleming and L. Tarassenko, "A comparison of signal processing techniques for the extraction of breathing rate from the photoplethysmogram," *International Journal of Biological and Life Sciences*, vol. 2, no. 4, pp. 233–7, 2006.

[80] J. Y. a. Foo and S. J. Wilson, "Estimation of breathing interval from the photoplethysmographic signals in children," *Physiological Measurement*, vol. 26, no. 6, pp. 1049–58, 2005.

[81] G. D. Furman *et al.*, "Electrocardiogram derived respiration during sleep," in *Conf Proc CinC.* IEEE, 2005, pp. 351–4.

[82] A. Fusco *et al.*, "On how to extract breathing rate from PPG signal using wearable devices," in *Conf Proc BioCAS.* IEEE, 2015, pp. 3–6.

[83] A. Garde *et al.*, "Empirical mode decomposition for respiratory and heart rate estimation from the photoplethysmogram," in *Conf Proc CinC.* Zaragoza: IEEE, 2013, pp. 799–802.

[84] A. Garde *et al.*, "Estimating respiratory and heart rates from the correntropy spectral density of the photoplethysmogram," *PLoS ONE*, vol. 9, no. 1, p. e86427, 2014.

[85] L. Guo, S. Lei, and M. Pan, "The methods and limitations of extracting respiratory rhythm utilizing photoplethysmographic signals," in *Conf Proc BMEI.* IEEE, 2010, pp. 1059–1062.

[86] S. Gupta and J. B. Sharma, "Estimation of respiratory rate from the ECG using instantaneous frequency tracking LMS algorithm," in *Conf Proc ICACCA.*, 2016, pp. 88–90.

[87] E. Helfenbein *et al.*, "Electrocardiogram/electromyogram-derived respiration in the presence of simulated respiratory disease," *Journal of Electrocardiology*, vol. 44, no. 6, pp. 751–2, 2011.

[88] E. Helfenbein *et al.*, "ECG/EMG-derived respiration during cardiac magnetic resonance imaging," *Journal of Electrocardiology*, vol. 45, no. 6, pp. 693–4, 2012.

[89] E. Helfenbein *et al.*, "Development of three methods for extracting respiration from the surface ECG: a review," *Journal of Electrocardiology*, vol. 47, no. 6, pp. 819–25, 2014.

[90] I. Isasi *et al.*, "Cerebral oximetry versus pulse photoplethysmography to monitor respiration rate," in *Conf Proc CinC.*, 2016, pp. 853–6.

[91] A. Johansson *et al.*, "Pulse wave transit time for monitoring respiration rate," *Medical & Biological Engineering & Computing*, vol. 44, no. 6, pp. 471–8, 2006.

[92] A. Johansson, P. A. Oberg, and G. Sedin, "Monitoring of heart and respiratory rates in newborn infants using a new photoplethysmographic technique," *Journal of Clinical Monitoring and Computing*, vol. 15, no. 7-8, pp. 461–7, 1999.

[93] W. S. Johnston and Y. Mendelson, "Extracting breathing rate information from a wearable reflectance pulse oximeter sensor," in *Conf Proc Eng Med Biol Soc.* IEEE, 2004, pp. 5388–91.

[94] T. Kagawa, A. Kawamoto, and N. Nakajima, "System for simultaneous measurement of breathing rate and heart rate using photoplethysmogram," in *Conf Proc Body Area Networks.* ICST, 2013.

[95] W. Karlen *et al.*, "Respiratory rate estimation using respiratory sinus arrhythmia from photoplethysmography," in *Conf Proc Eng Med Biol Soc.* IEEE, 2011, pp. 1201–4.

[96] W. Karlen *et al.*, "Estimation of respiratory rate from photoplethysmographic imaging videos compared to pulse oximetry," *IEEE Journal of Biomedical and Health Informatics*, vol. 19, no. 4, pp. 1331–8, 2015.

[97] S. A. Kazmi *et al.*, "Respiratory rate (RR) based analysis of PPG signal for different physiological conditions," in *Conf Proc. ICSSA*, 2015, pp. 166–71.

[98] V. Khambhati and M. B. Patel, "Extraction of a respiration rate from ECG signal using discrete wavelet transform during exercise," *Imperial Journal of Interdisciplinary Research*, vol. 3, no. 2, pp. 1238–41, 2017.

[99] A. Kikta and P. Augustyniak, "Comparing methods of ECG respiration signals derivation based on measuring the amplitude of QRS complexes," *Journal of Medical Informatics and Technologies*, vol. 11, pp. 155–63, 2007.

[100] H. Kim, J.-Y. Kim, and C.-H. Im, "Fast and robust real-time estimation of respiratory rate from photoplethysmography," *Sensors*, vol. 16, no. 9, p. 1494, 2016.

[101] V. Kumar and G. Singh, "Estimation of respiration rate from ECG using canonical components analysis and ensemble empirical mode decomposition," *International Journal of Bio-Science and Bio-Technology*, vol. 7, no. 3, pp. 139–46, 2015.

[102] H. H. Kuo *et al.*, "Using ECG surface electrodes in measurement of respiration rate for preterm infants," in *Proc ISBB*. IEEE, 2014, pp. 12–5.

[103] M. M. Lakdawala, "Derivation of the respiratory rate signal from a single lead ECG," MSc. Thesis, New Jersey Institute of Technology, 2008.

[104] J. Lázaro *et al.*, "Deriving respiration from the pulse photoplethysmographic signal," in *Conf Proc CinC*. Hangzhou: IEEE, 2011, pp. 713–6.

[105] J. Lázaro, "Non-invasive techniques for respiratory information extraction based on pulse photoplethysmogram and electrocardiogram," PhD. Thesis, University of Zaragoza, 2015.

[106] J. Lazaro *et al.*, "Electrocardiogram derived respiration from QRS slopes: Evaluation with Stress Testing Recordings," in *Conf Proc Eng Med Biol Soc.*, 2013, pp. 3913–6.

[107] J. Lázaro *et al.*, "Electrocardiogram derived respiratory rate from QRS slopes and R-wave angle," *Annals of Biomedical Engineering*, vol. 42, no. 10, pp. 2072–83, 2014.

[108] J. Lázaro *et al.*, "Deriving respiration from photoplethysmographic pulse width," *Medical and Biological Engineering and Computing*, vol. 51, no. 1-2, pp. 233–42, 2013.

[109] J. Lázaro *et al.*, "Respiratory rate derived from smartphone-camera-acquired pulse photoplethysmographic signals," *Physiological Measurement*, vol. 36, no. 11, pp. 2317–33, 2015.

[110] J. Lazaro *et al.*, "Smartphone-camera-acquired pulse photoplethysmographic signal for deriving respiratory rate," in *Conf Proc ESGCO*. IEEE, 2014, pp. 121–2.

[111] S. Leanderson, P. Laguna, and L. Sörnmo, "Estimation of the respiratory frequency using spatial information in the VCG," *Medical Engineering & Physics*, vol. 25, no. 6, pp. 501–7, 2003.

[112] E. M. Lee *et al.*, "Respiratory rate detection algorithms by photoplethysmography signal processing," in *Conf Proc Eng Med Biol Soc.* IEEE, 2008, pp. 1140–3.

[113] J. Lee and K. H. Chon, "Respiratory rate extraction via an autoregressive model using the optimal parameter search criterion," *Annals of Biomedical Engineering*, vol. 38, no. 10, pp. 3218–25, 2010.

[114] J. Lee and K. H. Chon, "Time-varying autoregressive model-based multiple modes particle filtering algorithm for respiratory rate extraction from pulse oximeter," *IEEE Transactions on Biomedical Engineering*, vol. 58, no. 3, pp. 790–4, 2011.

[115] J. Lee and K. H. Chon, "An autoregressive model-based particle filtering algorithms for extraction of respiratory rates as high as 90 breaths per minute from pulse oximeter," *IEEE Transactions on Biomedical Engineering*, vol. 57, no. 9, pp. 2158–67, 2010.

[116] J. Lee, J. P. Florian, and K. H. Chon, "Respiratory rate extraction from pulse oximeter and electrocardiographic recordings," *Physiological Measurement*, vol. 32, no. 11, pp. 1763–73, 2011.

[117] M. Leier, G. Jervan, and W. Stork, "Respiration signal extraction from photoplethysmogram using pulse wave amplitude variation," in *Proc ICC*. IEEE, 2014, pp. 3535–40.

[118] P. Leonard *et al.*, "Standard pulse oximeters can be used to monitor respiratory rate," *Emergency Medicine Journal*, vol. 20, no. 6, pp. 524–5, 2003.

[119] P. a. Leonard *et al.*, "An automated algorithm for determining respiratory rate by photoplethysmogram in children," *Acta Paediatrica*, vol. 95, no. 9, pp. 1124–8, 2006.

[120] P. a. Leonard *et al.*, "A fully automated algorithm for the determination of respiratory rate from the photoplethysmogram," *Journal of Clinical Monitoring and Computing*, vol. 20, no. 1, pp. 33–6, 2006.

[121] P. Leonard *et al.*, "An algorithm for the detection of individual breaths from the pulse oximeter waveform," *Journal of Clinical Monitoring and Computing*, vol. 18, no. 5-6, pp. 309–12, 2004.

[122] N. N. Lepine *et al.*, "Robust respiration rate estimation using adaptive Kalman filtering with textile ECG sensor and accelerometer," in *Conf Proc Eng Med Biol Soc.*, 2016, pp. 3797–800.

[123] D. Li, H. Zhao, and S. Dou, "A new signal decomposition to estimate breathing rate and heart rate from photoplethysmography signal," *Biomedical Signal Processing and Control*, vol. 19, pp. 89–95, 2015.

[124] S. L. Lin, C. K. Chen, and C. S. Chien, "Implementation and validation of ECG-derived respiration with QRS characteristics," *Applied Mechanics and Materials*, vol. 479-80, pp. 457–62, 2013.

[125] Y.-D. Lin, Y.-H. Chien, and Y.-S. Chen, "Wavelet-based embedded algorithm for respiratory rate estimation from PPG signal," *Biomedical Signal Processing and Control*, vol. 36, pp. 138–45, 2017.

[126] L. G. Lindberg, H. Ugnell, and P. Å. Öberg, "Monitoring of respiratory and heart rates using a fibre-optic sensor," *Medical & Biological Engineering & Computing*, vol. 30, no. 5, pp. 533–7, 1992.

[127] G. Liu *et al.*, "Automatic detection of respiratory rate from electrocardiogram, respiration induced plethysmography and 3D acceleration signals," *Journal of Central South University*, pp. 2423–31, 2013.

[128] K. V. Madhav, E. H. Krishna, and K. A. Reddy, "Extraction of surrogate respiratory activity from pulse oximeter signals using SSA," in *Conf Proc ICEEOT.*, 2016, pp. 1717–1721.

[129] K. V. Madhav, E. H. Krishna, and K. A. Reddy, "Extraction of respiratory activity from pulse oximeter's PPG signals using MSICA," in *Conf Proc WiSPNET.*, 2016, pp. 823–7.

[130] K. V. Madhav *et al.*, "A model based method for deriving respiratory activity from photoplethysmographic signals," in *Conf Proc ISSPA*. IEEE, 2010, pp. 312–5.

[131] K. V. Madhav *et al.*, "Use of multi scale PCA for extraction of respiratory activity from photoplethysmographic signals," in *Conf Proc Instrumentation and Measurement Technology*. IEEE, 2012, pp. 1784–7.

[132] K. V. Madhav *et al.*, "Extraction of respiratory activity from ECG and PPG signals using vector autoregressive model," in *Proc Int Symp Medical Measurements and Applications*. IEEE, 2012, pp. 1–4.

[133] K. V. Madhav *et al.*, "Extraction of respiration rate from ECG and BP signals using order reduced-modified covariance AR technique," in *Proc CISP.*, vol. 9. IEEE, 2010, pp. 4059–63.

[134] K. V. Madhav *et al.*, "Robust extraction of respiratory activity from PPG signals using modified MSPCA," *IEEE Transactions on Instrumentation and Measurement*, vol. 62, no. 5, pp. 1094–106, 2013.

[135] K. V. Madhav *et al.*, "Estimation of respiration rate from ECG, BP and PPG signals using empirical mode decomposition," in *Conf Proc Instrumentation and Measurement Technology*. IEEE, 2011.

[136] K. V. Madhav *et al.*, "Extraction of respiratory activity from PPG and BP signals using Principal Component Analysis," in *Conf Proc Communications and Signal Processing*. IEEE, 2011, pp. 452–6.

[137] K. V. Madhav *et al.*, "A robust signal processing method for extraction of respiratory activity from artifact corrupted PPG signal," in *Proc RAICS*. IEEE, 2011, pp. 451–6.

[138] K. V. Madhav *et al.*, "Estimation of respiratory rate from principal components of photoplethysmographic signals," in *Conf Proc IECBES*. IEEE, 2010, pp. 311–4.

[139] S. Mann and R. Orglmeister, "ECG, PPG and ABP sensor fusion for a PCA-based respiratory activity estimation," *Biomedizinische Technik*, vol. 57, no. Suppl. 1, pp. 232–5, 2012.

[140] C. Mason and L. Tarassenko, "Quantitative assessment of respiratory derivation algorithms," in *Conf Proc Eng Med Biol Soc.* IEEE, 2001, pp. 1998–2001.

[141] B. Mazzanti, C. Lamberti, and J. de Bie, "Validation of an ECG-derived respiration monitoring method," in *Conf Proc CinC*. IEEE, 2003, pp. 613–6.

[142] O. Meste, G. Blain, and S. Bermon, "Analysis of the respiratory and cardiac systems coupling in pyramidal exercise using a time-varying model," in *Conf Proc CinC*. IEEE, 2002, pp. 429–32.

[143] M. Mestek *et al.*, "Accuracy of continuous noninvasive respiratory rate derived from pulse oximetry in chronic obstructive pulmonary disease patients," *Chest*, vol. 142, no. 4, 2012.

[144] M. Mestek *et al.*, "Accuracy of continuous noninvasive respiratory rate derived from pulse oximetry in congestive heart failure patients," *Chest*, vol. 142, no. 4, p. 113A, 2012.

[145] M. Mestek *et al.*, "Accuracy of continuous non-invasive respiratory rate derived from pulse oximetry in the post-anesthesia care unit," in *Anesthesiology Annual Meeting*. American Society of Anesthesiologists, 2012.

[146] L. Mirmohamadsadeghi *et al.*, "Real-time respiratory rate estimation using imaging photoplethysmography inter-beat intervals," in *Conf Proc CinC.*, 2016, pp. 861–864.

[147] L. Mirmohamadsadeghi and J.-M. Vesin, "Real-time multi-signal frequency tracking with a bank of notch filters to estimate the respiratory rate from the ECG," *Physiological Measurement*, vol. 37, no. 9, pp. 1573–87, 2016.

[148] L. Mirmohamadsadeghi and J.-m. Vesin, "Estimating the real-time respiratory rate from the ECG with a bank of notch filters," in *Conf Proc CinC*. IEEE, 2015, pp. 581–4.

[149] L. Mirmohamadsadeghi and J.-M. Vesin, "Respiratory rate estimation from the ECG using an instantaneous frequency tracking algorithm," *Biomedical Signal Processing and Control*, vol. 14, pp. 66–72, 2014.

[150] M. Momot *et al.*, "Estimation of respiratory rate based on ECG signal using regression coefficients and spectral analysis," in *Proc. 14th Int Conf Biomed Eng*, Kaunas, Lithuania, 2010, pp. 49–52.

[151] M. A. Motin, C. Karmakar, and M. Palaniswami, "Ensemble empirical mode decomposition with principal component analysis: a novel approach for extracting respiratory rate and heart rate from photoplethysmographic signal," *IEEE Journal of Biomedical and Health Informatics [in press]*, 2017.

[152] M. A. Motin *et al.*, "An EEMD-PCA approach to extract heart rate, respiratory rate and respiratory activity from PPG signal," in *Conf Proc Eng Med Biol Soc*. IEEE, 2016, pp. 3817–20.

[153] K. Nakajima, T. Tamura, and H. Miike, "Monitoring of heart and respiratory rates by photoplethysmography using a digital filtering technique," *Medical Engineering & Physics*, vol. 18, no. 5, pp. 365–72, 1996.

[154] K. Nakajima *et al.*, "Photoplethysmographic measurement of heart and respiratory rates using digital filters," in *Conf Proc Eng Med Biol Soc.*, vol. 18, no. 5. IEEE, 1993, pp. 1006–7.

[155] A. Nayan, N. Risman, and R. Jaafar, "Breathing rate estimation from a single-lead electrocardiogram acquisition system," *International Journal of Applied Engineering Research*, vol. 10, no. 17, pp. 38 154–8, 2015.

[156] N. A. Nayan, N. S. Risman, and R. Jaafar, "A portable respiratory rate estimation system with a passive single-lead electrocardiogram acquisition module," *Technology and Health Care*, vol. 24, pp. 591–7, 2016.

[157] S. Nemati, A. Malhotra, and G. D. Clifford, "Data fusion for improved respiration rate estimation," *EURASIP Journal on Advances in Signal Processing*, vol. 2010, p. 926305, 2010.

[158] L. Nilsson, A. Johansson, and S. Kalman, "Monitoring of respiratory rate in postoperative care using a new photoplethysmographic technique," *Journal of Clinical Monitoring and Computing*, vol. 16, no. 4, pp. 309–15, 2000.

[159] M. Noriega *et al.*, "Respiratory rate estimation from multilead directions, based on ECG delineation," in *Conf Proc Eng Med Biol Soc.* IEEE, 2016, pp. 3813–6.

[160] M. Noriega *et al.*, "Instantaneous respiratory rate estimation from multilead ECG delineation using VCG directions on fiducial points," in *Conf Proc CinC.*, 2016, pp. 397–400.

[161] E. Olsson *et al.*, "Photoplethysmography for simultaneous recording of heart and respiratory rates in newborn infants," *Medical and Biological Engineering and Computing*, vol. 34, no. Suppl 1, p. 277, 1996.

[162] M. Orini *et al.*, "Estimation of spontaneous respiratory rate from photoplethysmography by cross time-frequency analysis," in *Conf Proc CinC*. Hangzhou: IEEE, 2011, pp. 661–4.

[163] C. Orphanidou *et al.*, "Data fusion for estimating respiratory rate from a single-lead ECG," *Biomedical Signal Processing and Control*, vol. 8, no. 1, pp. 98–105, 2013.

[164] C. Orphanidou, "Derivation of respiration rate from ambulatory ECG and PPG using Ensemble Empirical Mode Decomposition: Comparison and fusion," *Computers in Biology and Medicine*, vol. 81, pp. 45–54, feb 2017.

[165] C. Orphanidou *et al.*, "Spectral fusion for estimating respiratory rate from the ECG," in *Conf Proc ITAB*. IEEE, 2009, pp. 1–4.

[166] R. Paamand *et al.*, "Reliable monitoring of respiration rate with reflectance-mode photoplethysmography," *Clinical Neurophysiology*, vol. 125, no. 2014, pp. S177–S178, 2014.

[167] C. Park and B. Lee, "Real-time estimation of respiratory rate from a photoplethysmogram using an adaptive lattice notch filter," *Biomedical Engineering Online*, vol. 13, p. 170, 2014.

[168] S.-B. Park *et al.*, "An improved algorithm for respiration signal extraction from electrocardiogram measured by conductive textile electrodes using instantaneous frequency estimation," *Medical & Biological Engineering & Computing*, vol. 46, no. 2, pp. 147–58, 2008.

[169] R. Pehrson and A. Bulhak, "Respiration rate derived from ECG in dogs," *Journal of Pharmacological and Toxicological Methods*, vol. 66, no. 2, p. 183, 2012.

[170] M. D. Peláez-Coca *et al.*, "Cross time-frequency analysis for combining information of several sources: Application to estimation of spontaneous respiratory rate from photoplethysmography," *Computational and Mathematical Methods in Medicine*, vol. 2013, p. 631978, 2013.

[171] M. A. F. Pimentel *et al.*, "Probabilistic estimation of respiratory rate using Gaussian processes," in *Conf Proc Eng Med Biol Soc*. IEEE, 2013, pp. 2902–5.

[172] B. Prathyusha, T. Rao, and D. Asha, "Extraction of respiratory rate from PPG signals using PCA and EMD," *International Journal of Research in Engineering and Technology*, vol. 1, no. 2, pp. 164–84, 2012.

[173] K. Rajkumar and K. Ramya, "Respiration rate diagnosis using single lead ECG in real time," *Global Journal of Medical Research*, vol. 13, no. 1, pp. 7–11, 2013.

[174] R. Ruangsuwana, G. Velikic, and M. Bocko, "Methods to extract respiration information from ECG signals," in *Conf Proc ICASSP*. IEEE, 2010, pp. 570–3.

[175] M. Sakai *et al.*, "Development of lead system for ECG-derived respiration aimed at detection of obstructive sleep apnea syndrome," in *Conf Proc SITIS*. IEEE, 2013, pp. 971–5.

[176] J. Salinger *et al.*, "Measurement of breathing frequency from ECG in the examination of autonomous nervous system activities: suggested methods and their verification," *Acta Univ. Palacki. Olomuc.*, vol. 35, no. 2, pp. 95–103, 2005.

[177] S. Sarkar, S. Bhattacherjee, and S. Pal, "Extraction of respiration signal from ECG for respiratory rate estimation," in *Michael Faraday IET International Summit 2015*. Kolkata: Institution of Engineering and Technology, 2015, pp. 336–40.

[178] A. Schäfer and K. W. Kratky, "Estimation of breathing rate from respiratory sinus arrhythmia: comparison of various methods," *Annals of Biomedical Engineering*, vol. 36, no. 3, pp. 476–85, 2008.

[179] M. Schmidt *et al.*, "ECG derived respiration: comparison of time-domain approaches and application to altered breathing patterns of patients with schizophrenia," *Physiological Measurement*, vol. 38, no. 4, pp. 601–15, apr 2017.

[180] N. Selvaraj and K. H. Chon, "Algorithms for real-time detection of motion artifacts and accurate estimation of respiratory rates using pulse oximeter."

[181] R. Sethi *et al.*, "Comparison of respiration rate derived from pulse oximetry and transthoracic impedance," *European Journal of Anaesthesiology*, vol. 31, pp. 30–1, 2014.

[182] S. A. Shah *et al.*, "Continuous measurement of respiration rate using the photoplethysmogram and the electrocardiogram," in *Proc UK & RI Postgraduate Conference in Biomedical Engineering and Medical Physics.*, 2009, pp. 11–2.

[183] S. A. Shah *et al.*, "Respiratory rate estimation during triage of children in hospitals," *Journal of Medical Engineering & Technology*, vol. 39, no. 8, pp. 514–24, 2015.

[184] H. Sharma, K. Sharma, and O. L. Bhagat, "Respiratory rate extraction from single-lead ECG using homomorphic filtering," *Computers in Biology and Medicine*, vol. 59, pp. 80–6, 2015.

[185] A. Shayei, S. P. Ehsani, and M. Shabany, "Efficient implementation of real-time ECG derived respiration system using cubic spline interpolation," in *Proc ISCAS.*, 2013, pp. 1083–6.

[186] K. H. Shelley *et al.*, "The use of joint time frequency analysis to quantify the effect of ventilation on the pulse oximeter waveform," *Journal of Clinical Monitoring and Computing*, vol. 20, no. 2, pp. 81–7, 2006.

[187] E. F. Sierra-Alonso, L. M. Sep, and R. Bail, "Estimating respiratory frequency from HRV during treadmill exercise testing," in *Conf Proc CinC*. IEEE, 2013, pp. 121–4.

[188] R. Singhathip *et al.*, "Extracting respiration rate from ECG raw signals," *Biomedical Engineering: Applications, Basis and Communications*, vol. 22, no. 04, pp. 307–314, 2010.

[189] D. Sinnecker *et al.*, "Assessment of mean respiratory rate from ECG recordings for risk stratification after myocardial infarction," *Journal of Electrocardiology*, vol. 47, no. 5, pp. 700–4, 2014.

[190] A. Sobron, I. Romero, and T. Lopetegi, "Evaluation of methods for estimation of respiratory frequency from the ECG," in *Conf Proc CinC*. IEEE, 2010, pp. 513–6.

[191] L. Sohrt-Petersen, "Evaluation of algorithms for ECG derived respiration in the context of heart rate variability studies," Master's Thesis, Aalborg University, 2013.

[192] K. T. Sweeney *et al.*, "Employing ensemble empirical mode decomposition for artifact removal: extracting accurate respiration rates from ECG data during ambulatory activity," in *Conf Proc Eng Med Biol Soc.* IEEE, 2013, pp. 977–80.

[193] J. Thayer *et al.*, "Estimating respiratory frequency from autoregressive spectral analysis of heart period," *IEEE Engineering in Medicine and Biology Magazine*, vol. 21, no. 4, pp. 41–5, 2002.

[194] H. R. W. Touw *et al.*, "Photoplethysmography respiratory rate monitoring in patients receiving procedural sedation and analgesia for upper gastrointestinal endoscopy," *Journal of Clinical Monitoring and Computing [in press]*, 2016.

[195] H. Ugnell, L.-G. Lindberg, and P. Oberg, "Monitoring Of heart- and respiration rates using a fiber optic sensor," in *Conf Proc Eng Med Biol Soc.*, vol. 13. IEEE, 1991, pp. 1566–7.

[196] M. Varanini *et al.*, "Adaptive filtering of ECG signal for deriving respiratory activity," in *Conf Proc CinC*. Chicago, IL: IEEE, 1991, pp. 621–4.

[197] M. Vegfors *et al.*, "Experimental evaluation of two new sensors for respiratory rate monitoring," *Physiological Measurement*, vol. 14, no. 2, pp. 171–81, 1993.

[198] N. Vinh *et al.*, "Comparison of two methods for demodulation of pulse signals - application in case of central sleep apnea," *Journal of Science and Technology*, vol. 49, no. 1, 2011.

[199] C. Wang, Z. Li, and X. Wei, "Monitoring heart and respiratory rates at radial artery based on PPG," *Optik - International Journal for Light and Electron Optics*, vol. 124, no. 19, pp. 3954–6, 2013.

[200] E. H. Weiss *et al.*, "An optimized method for the estimation of the respiratory rate from electrocardiographic signals: implications for estimating minute ventilation," *American Journal of Physiology. Heart and Circulatory Physiology*, vol. 307, no. 3, pp. H437–47, 2014.

[201] S. M. Wendelken *et al.*, "Monitoring respiration rate in PACU patients using the plethysmogram from a pulse oximeter," in *Conf Proc Soc Technology in Anesthesia.*, vol. 3, no. 4, 2005, p. 89.

[202] D. Wertheim *et al.*, "Extracting respiratory data from pulse oximeter plethysmogram traces in newborn infants," *Archives of Disease in Childhood. Fetal and Neonatal Edition*, vol. 94, no. 4, pp. F301–3, 2009.

[203] D. Wertheim *et al.*, "Monitoring respiration in wheezy preschool children by pulse oximetry plethysmogram analysis," *Medical & Biological Engineering & Computing*, vol. 51, no. 9, pp. 965–70, 2013.

[204] D. Widjaja *et al.*, "ECG-derived respiration: comparison and new measures for respiratory variability," in *Conf Proc CinC*. IEEE, 2010, pp. 149–52.

[205] B. F. Womack, "The analysis of respiratory sinus arrhythmia using spectral analysis and digital filtering," *IEEE Transactions on Biomedical Engineering*, vol. BME-18, no. 6, pp. 399–409, 1971.

[206] D. Wu, M. Y. M. Wong, and Y.-t. Zhang, "The accuracy of respiratory rate estimation using electrocardiography and photoplethysmography," in *Conf Proc ITAB*. IEEE, 2010.

[207] D. Wu *et al.*, "Automatic estimation of respiratory rate from pulse transit time in normal subjects at rest," in *Conf Proc Eng Med Biol Soc BHI.*, vol. 25. IEEE, 2012, pp. 779–81.

[208] B. Yang and K. H. Chon, "A novel approach to monitor nonstationary dynamics in physiological signals: application to blood pressure, pulse oximeter, and respiratory data," *Annals of Biomedical Engineering*, vol. 38, no. 11, pp. 3478–88, 2010.

[209] W. Yi and K. Park, "Derivation of respiration from ECG measured without subject's awareness using wavelet transform," in *Conf Proc Eng Med Biol Soc.* IEEE, 2002, pp. 130–1.

[210] C. Yi-Hsin, W. Hau-Tieng, and H. Shu-Shya, "ECG-derived respiration and instantaneous frequency based on the synchrosqueezing transform: application to patients with atrial fibrillation," *arXiv preprint*, 2011.

[211] Y. Yoshida, K. Yokoyama, and N. Ishii, "Real-time continuous estimation of respiratory frequency during sleep based on heart rate time series," in *Conf Proc Eng Med Biol Soc.* IEEE, 2007, pp. 648–51.

[212] T. Yoshimura *et al.*, "An ECG electrode-mounted heart rate, respiratory rhythm, posture and behavior recording system." in *Conf Proc Eng Med Biol Soc.* IEEE, 2004, pp. 2373–4.

[213] R. Yousefi and M. Nourani, "Separating arterial and venous-related components of photoplethysmographic signals for accurate extraction of oxygen saturation and respiratory rate," *IEEE Journal of Biomedical and Health Informatics*, vol. 19, no. 3, pp. 848–57, 2015.

[214] N. A. Zainudin *et al.*, "Respiratory rate of photoplethysmogram signal from anaesthetic patients," in *Conf Proc ISCAIE.* IEEE, 2015, pp. 171–4.

[215] X. Zhang and Q. Ding, "Fast respiratory rate estimation from PPG signal using sparse signal reconstruction based on orthogonal matching pursuit," in *2016 50th Asilomar Conference on Signals, Systems and Computers*. IEEE, 2016, pp. 1631–5.

[216] X. Zhang and Q. Ding, "Respiratory rate estimation from the photoplethysmogram via joint sparse signal reconstruction and spectra fusion," *Biomedical Signal Processing and Control*, vol. 35, pp. 1–7, 2017.

[217] X. Zhang and Q. Ding, "Respiratory rate monitoring from the photoplethysmogram via sparse signal reconstruction," *Physiological Measurement*, vol. 37, no. 7, pp. 1105–19, 2016.

[218] L. Zhao, S. Reisman, and T. Findley, "Derivation of respiration from electrocardiogram during heart rate variability studies," in *Conf Proc CinC*. IEEE Comput. Soc. Press, 1994, pp. 53–6.

[219] L. Zhao, S. Reisman, and T. Findley, "Respiration derived from the electrocardiogram during heart rate variability studies," in *Conf Proc Eng Med Biol Soc.* IEEE, 1994, pp. 123–4.

[220] T. Zhu *et al.*, "Bayesian fusion of algorithms for the robust estimation of respiratory rate from the photoplethysmogram," in *Conf Proc Eng Med Biol Soc.* IEEE, 2015, pp. 6138–41.

[221] D. Widjaja *et al.*, "Application of kernel principal component analysis for single-lead-ECG-derived respiration," *IEEE Transactions on Biomedical Engineering*, vol. 59, no. 4, pp. 1169–76, 2012.

[222] R. D. Berger *et al.*, "An efficient algorithm for spectral analysis of heart rate variability," *IEEE Transactions on Biomedical Engineering*, vol. 33, no. 9, pp. 900–4, 1986.

[223] R. Bailón *et al.*, "The integral pulse frequency modulation model with time-varying threshold: application to heart rate variability analysis during exercise stress testing." *IEEE Transactions on Biomedical Engineering*, vol. 58, no. 3, pp. 642–52, 2011.

[224] S. Fleming *et al.*, "Normal ranges of heart rate and respiratory rate in children from birth to 18 years of age: a systematic review of observational studies," *Lancet*, vol. 377, no. 9770, pp. 1011–8, 2011.

[225] C. Orphanidou *et al.*, "Signal-quality indices for the electrocardiogram and photoplethysmogram: derivation and applications to wireless monitoring," *IEEE Journal of Biomedical and Health Informatics*, vol. 19, no. 3, pp. 832–8, 2015.

[226] D. Birrenkott *et al.*, "A robust fusion model for estimating respiratory rate from photoplethysmography and electrocardiography," *submitted for publication*.

[227] F. Yasuma and J. I. Hayano, "Respiratory Sinus Arrhythmia: Why Does the Heartbeat Synchronize with Respiratory Rhythm?" *Chest*, vol. 125, no. 2, pp. 683–690, 2004.

[228] M. Saeed *et al.*, "Multiparameter Intelligent Monitoring in Intensive Care II: a public-access intensive care unit database," *Critical Care Medicine*, vol. 39, no. 5, pp. 952–60, 2011.

[229] J. Welch *et al.*, "The Massachusetts General Hospital-Marquette Foundation Hemodynamic and Electrocardiographic Database – Comprehensive collection of critical care waveforms," *Journal of Clinical Monitoring*, vol. 7, no. 1, pp. 96–7, 1991.

[230] G. Moody and R. Mark, "A database to support development and evaluation of intelligent intensive care monitoring," in *Proc CinC*. IEEE, 1996, pp. 657–60.

[231] N. Iyengar *et al.*, "Age-related alterations in the fractal scaling of cardiac interbeat interval dynamics," *The American Journal of Physiology*, vol. 271, no. 4 Pt 2, pp. R1078–84, 1996.

[232] A. L. Goldberger *et al.*, "PhysioBank, PhysioToolkit, and PhysioNet: components of a new research resource for complex physiologic signals," *Circulation*, vol. 101, no. 23, pp. E215–20, 2000.

[233] M. A. García-gonzález *et al.*, "A comparison of heartbeat detectors for the seismocardiogram," in *Proc CinC*. IEEE, 2013, pp. 461–4.

[234] F. Pinciroli *et al.*, "A respiration-related EKG database," in *Proc CinC*. IEEE, 1988, pp. 477–80.

[235] Y. Ichimaru and G. B. Moody, "Development of the polysomnographic database on CD-ROM," *Psychiatry and Clinical Neurosciences*, vol. 53, no. 2, pp. 175–7, 1999.

[236] T. Penzel *et al.*, "The apnea-ECG database," in *Proc CinC*. IEEE, 2000, pp. 255–8.

[237] Portland State University Biomedical Signal Processing Lab, "Traumatic brain injury data."

[238] P. D. Larsen *et al.*, "Spectral analysis of AC and DC components of the pulse photoplethysmograph at rest and during induction of anaesthesia," *International Journal of Clinical Monitoring and Computing*, vol. 14, no. 2, pp. 89–95, 1997.

[239] L. Nilsson *et al.*, "Combined photoplethysmographic monitoring of respiration rate and pulse: a comparison between different measurement sites in spontaneously breathing subjects," *Acta Anaesthesiologica Scandinavica*, vol. 51, no. 9, pp. 1250–7, 2007.

[240] K. H. Shelley *et al.*, "What is the best site for measuring the effect of ventilation on the pulse oximeter waveform?" *Anesthesia and Analgesia*, vol. 103, no. 2, pp. 372–7, 2006.

[241] H. Ugnell, "The respiratory synchronous photoplethysmographic signal. Its dependence on tight wavelength and sample volume." in *Conf Proc Eng Med Biol Soc.*, 1996, pp. 275–276.
[242] M. Klum *et al.*, "Minimally spaced electrode positions for multifunctional chest sensors: ECG and respiratory signal estimation," *Current Directions in Biomedical Engineering*, vol. 2, no. 1, pp. 695–699, 2016.
[243] N. Selvaraj, "Long-term remote monitoring of vital signs using a wireless patch sensor," in *Conf Proc HIC*. IEEE, 2014, pp. 83–6.
[244] C. O'Brien and C. Heneghan, "A comparison of algorithms for estimation of a respiratory signal from the surface electrocardiogram," *Computers in Biology and Medicine*, vol. 37, no. 3, pp. 305–14, mar 2007.
[245] T. Yilmaz, R. Foster, and Y. Hao, "Detecting vital signs with wearable wireless sensors," *Sensors*, vol. 10, no. 12, pp. 10 837–62, 2010.
[246] M. Młyńczak and G. Cybulski, "Impedance pneumography: is it possible?" in *Photonics Applications in Astronomy, Communications, Industry, and High-Energy Physics Experiments 2012*, R. S. Romaniuk, Ed., vol. 8454, 2012, p. 84541T.
[247] B. G. Goudra, "Comparison of Acoustic Respiration Rate, Impedance Pneumography and Capnometry Monitors for Respiration Rate Accuracy and Apnea Detection during GI Endoscopy Anesthesia," *Open Journal of Anesthesiology*, vol. 3, pp. 74–9, 2013.
[248] C. Orphanidou *et al.*, "Telemetry-based vital sign monitoring for ambulatory hospital patients," in *Conf Proc Eng Med Biol Soc.* IEEE, 2009, pp. 4650–3.
[249] S. Lapi *et al.*, "Respiratory rate assessments using a dual-accelerometer device," *Respiratory Physiology and Neurobiology*, vol. 191, no. 1, pp. 60–6, 2014.
[250] M. Cvach, "Monitor alarm fatigue: an integrative review," *Biomedical Instrumentation & Technology*, vol. 46, no. 4, pp. 268–77, 2012.
[251] V. Nangalia, D. R. Prytherch, and G. B. Smith, "Health technology assessment review: remote monitoring of vital signs – current status and future challenges," *Critical Care*, vol. 14, no. 5, p. 233, 2010.
[252] S. A. Shah *et al.*, "Exacerbations in chronic obstructive pulmonary disease: identification and prediction using a digital health system," *Journal of Medical Internet Research*, vol. 19, no. 3, p. e69, 2017.
[253] F. Zhao *et al.*, "Remote measurements of heart and respiration rates for telemedicine." *PloS one*, vol. 8, no. 10, p. e71384, jan 2013.
[254] T. Bonnici *et al.*, "Testing of Wearable Monitors in a Real-World Hospital Environment: What Lessons Can Be Learnt?" in *Conf Proc 9th Wearable and Implantable BSNs.* IEEE, 2012, pp. 79–84.
[255] M. V. Pitzalis *et al.*, "Respiratory systolic pressure variability during atrial fibrillation and sinus rhythm," *Hypertension*, vol. 34, no. 5, pp. 1060–1065, 1999.
[256] M. Dommasch *et al.*, "Nocturnal respiratory rate predicts non-sudden cardiac death in survivors of acute myocardial infarction," *Journal of the American College of Cardiology*, vol. 63, no. 22, pp. 2432–3, 2014.

Peter H. Charlton received the M.Eng. degree in Engineering Science from the University of Oxford, UK, in 2010. In 2017 he received the Ph.D. degree in Bioinformatics from King's College London, UK. His thesis focused on continuous BR monitoring to detect clinical deterioration using wearable sensors. He is an investigator on two National Clinical Trials investigating the performance and clinical utility of BR algorithms. His current research focuses on assessment of arterial stiffness through pulse wave analysis.