Digital Twin of the Lung from Wearable Biosignals for Real-Time Respiratory Monitoring

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Abstract. Our work introduces a novel framework for generating a digital twin of the lung by leveraging diagnostic CT data and motion planning based on electrocardiogram (ECG) signals from wearable sensors. The simulation and real-time visualisation (3D+t) of lung motion is driven by automated predictions of respiratory signals. This dynamic framework provides an interface to visualise a patient's live breathing, enabling reliable, real-time monitoring of cardiorespiratory function. We evaluate our framework using two public datasets, BIDMC and CapnoBase, comprising 95 subjects with synchronised PPG, ECG, and reference respiratory signals. Central to our approach is a novel adaptive ECG-Derived Respiration (EDR) method, which serves as the input vector for kinetic simulation of the lung's digital twin. On the BIDMC dataset, our method achieves a Mean Adaptive Error (MAE) of 2.84 bpm with 98% accuracy within ±5 bpm. On the CapnoBase dataset (42 subjects), our method substantially reduces error to 3.54 bpm and improves accuracy to 79.3% within ±5 bpm. The results show significant improvements over spectral and decomposition-based baselines, including Welch Power Spectral Density (PSD) and Ensemble Empirical Mode Decomposition with Spectral Density Fusion (EEMD-SDF). These results demonstrate that ECG-based respiratory extraction provides robust and accurate motion signals that can drive real-time lung digital twin simulations. The framework supports reliable, wearable-driven respiratory monitoring and the simulation of cardiopulmonary behaviour. Our code is publicly available at https://github.com/Nikhil-Rao20/Digital_Twin.

Keywords: Digital Twin · Respiratory Rate · Wearable Sensors · ECG-Derived Respiration · Lung Monitoring

1 Introduction

Every breath we take carries important information about our health. Among the four primary vital signs, the respiratory rate (RR) has been largely over-

looked in routine clinical practice, even though it is the most sensitive indicator of physiological distress. Cretikos et al.[8] termed RR as *neglected vital sign* and mentioned that abnormal respiratory patterns are often the earliest warning before a patient's condition worsens quickly. Studies have shown that changes in breathing rate can predict cardiac arrest several hours before the actual arrest [9]. Yet, the continuous measurement of RR is still restricted to intensive care units, where it relies on dedicated machines such as capnography or impedance pneumography. For the millions of patients with chronic respiratory conditions living at home and over 8.3 billion people, there exists no practical way of continuously tracking how they breathe.

On the other side, the rise of consumer wearable devices has opened up new possibilities for bridging this gap. Modern smartwatches and fitness bands come equipped with photoplethysmography (PPG) and single-lead electrocardiogram (ECG) sensors, which are primarily designed for measuring heart rate and cardiac rhythm [4]. But the important thing here is that the breathing leaves a footprint on both of these cardiac signals. When we inhale, the heart rate slightly increases, and when we exhale it decreases, this naturally occurring phenomenon is known as respiratory sinus arrhythmia (RSA) [22] means that the ECG waveform carries precise respiration information within it. Similarly, the PPG waveform gets modulated by respiration through changes in blood volume, baseline wander and pulse timing [13].

In cardiology, patient-specific digital twins have already enabled personalised treatment planning [6, 17]. These cardiac digital twins demonstrated that when you combine patient data with physics based modelling, you can simulate and predict with good enough precision compared to traditional approaches. For the lung, Gonsard et al. [11] mentioned that while progress has been made in computational lung modelling, the field is still in its early stages compared to cardiology and Lam et al. [15] presented an approach for modelling the lung using developmental biology, but both rely on high-resolution imaging incompatible with real-time wearable operation. On the signal extraction side, Charlton et al. [3] provided a comprehensive review of algorithms for deriving breathing rate from PPG and ECG. For PPG, frequency-domain methods like Welch PSD and time-frequency approaches such as EEMD have been widely adopted [19]. For ECG, Moody and Mark [16] first showed that respiratory waveforms can be derived from R-R interval variations, with the Pan-Tompkins algorithm [18] serving as the backbone for QRS detection. Fusion strategies combining PPG and ECG estimates have also been explored [2]. However, most methods degrade with wearable-grade signals [7]. Moreover, these methods are focused only on estimating a scalar respiratory rate value, none of them have been designed to produce continuous respiratory motion signals that could create a dynamic 3D visualisation of lung breathing function.

While digital twin technology has achieved impressive results in cardiac modelling, its extension to lung driven by wearable biosignals remains an unresolved problem. The existing respiratory digital twin efforts are either too complex for real time operation or too simplistic. To our knowledge, there is currently no

framework that connects the signal level extraction of respiratory patterns from a wearable ECG sensor to a dynamic, patient specific 3D lung model which can breathe in synchrony with the patient. This is the core gap that motivated this work, in this work we bridge wearable respiratory signal extraction with organ-level digital twin simulation. The aim of this study is to develop a real-time digital twin framework of the lung that is driven by respiratory signals extracted from wearable ECG sensors, enabling dynamic 3D visualisation of patient-specific breathing. In this context, we make two major contributions:

1. The ECG-derived respiration (EDR) method, used for efficient extraction of respiratory signals from the wearable devices, with optimized biquad band-pass filter also comparing with conventional butterworth based EDR approaches and other PPG based baselines on two public benchmark datasets, BIDMC (53 patients) and CapnoBase (42 patients).
2. 3D synchronous breathing lung, we present the first of it's kind framework that translates wearable extracted respiratory signals into real time 3D lung mesh animations, creating a functional lung digital twin for continuous monitoring.

2 Methodology

Our framework follows a three-stage pipeline: (i) extraction of a continuous respiratory waveform from wearable ECG data using our proposed adaptive EDR method, (ii) estimation of the respiratory rate from the extracted signal, and (iii) conversion of the respiratory waveform into a dynamic 3D lung mesh animation that forms the digital twin. An overview of the complete pipeline is shown in Fig. 1. In the following subsections, we describe the datasets used for validation, our proposed EDR method, the baseline approaches we compare against, and the digital twin rendering pipeline.

2.1 Datasets

We validate our framework on two publicly available benchmark datasets that are widely used in respiratory rate estimation research both hosted on PhysioNet [10][4]. BIDMC Dataset[5] [19] was collected from 53 critically ill patients in the intensive care unit of Beth Israel Deaconess Medical Center, Boston. Each recording is approximately 8 minutes long and sampled at 125 Hz, containing synchronised PPG (PLETH), ECG (Lead II) and impedance-based respiration signals. The ground truth respiratory signal was derived from manual breath annotations made independently by two expert annotators and the final reference was taken as the mean of both annotations.

[4] Both datasets are publicly available and de-identified. Therefore, no additional ethical approval was required.

[5] Link to BIDMC Dataset: https://physionet.org/content/bidmc/1.0.0/

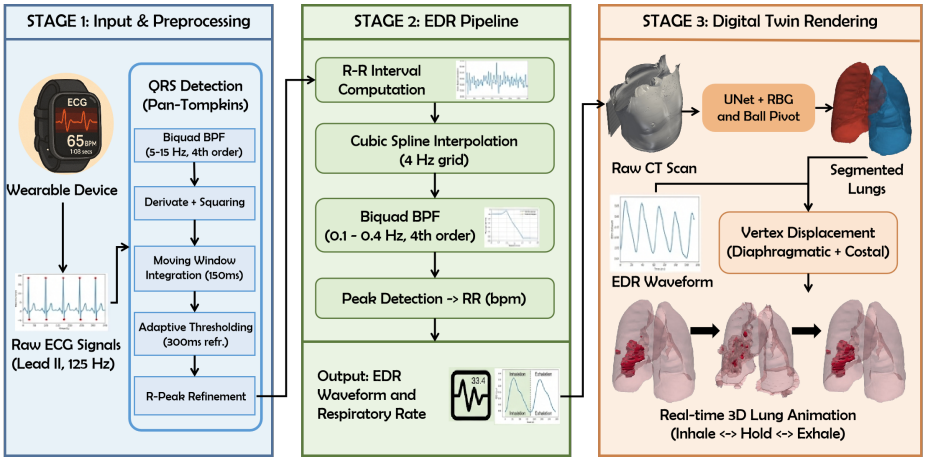


Fig. 1: Overview of the proposed framework. **Stage 1**: A wearable ECG signal is preprocessed and QRS complexes are detected using the Pan-Tompkins algorithm. **Stage 2**: R-R intervals are computed, resampled via cubic spline interpolation, and bandpass filtered with our optimised biquad filter (0.1–0.4 Hz) to produce the EDR waveform and respiratory rate estimate. **Stage 3**: The continuous EDR signal drives vertex displacements on a CT-derived lung mesh, producing a real-time-capable 3D lung animation that breathes in synchrony with the patient.

The CapnoBase dataset[6] [14] contains recordings from 42 subjects undergoing elective surgical procedures under general anaesthesia, sampled at 300 Hz. This contains synchronised PPG, ECG and capnography (end-tidal CO_2) signals. The ground truth was derived from the capnography waveform. Together, these two datasets provide a diverse evaluation for a total of 95 subjects across two different clinical populations, two different sampling rates and two different ground truth modalities.

2.2 Proposed Method: ECG-Derived Respiration (EDR)

We propose ECG-Derived Respiration (EDR) which derives the respiratory signal directly from the ECG waveform by leveraging respiratory sinus arrhythmia (RSA) [22, 20]. The key idea is that by tracking the beat-to-beat variability in the R-R intervals of the ECG, we can reconstruct a continuous respiratory waveform that is sufficiently accurate to drive a real-time lung digital twin. The first stage uses the Pan-Tompkins algorithm [18] for robust detection of QRS. The ECG signal is passed through a bandpass filter (5–15 Hz) to enhance QRS morphology, followed by a 5-point derivative filter and signal squaring to amplify the QRS components while suppressing P and T waves. A moving window

[6] Link to CapnoBase Dataset: https://ppg-beats.readthedocs.io/en/latest/datasets/capnobase/

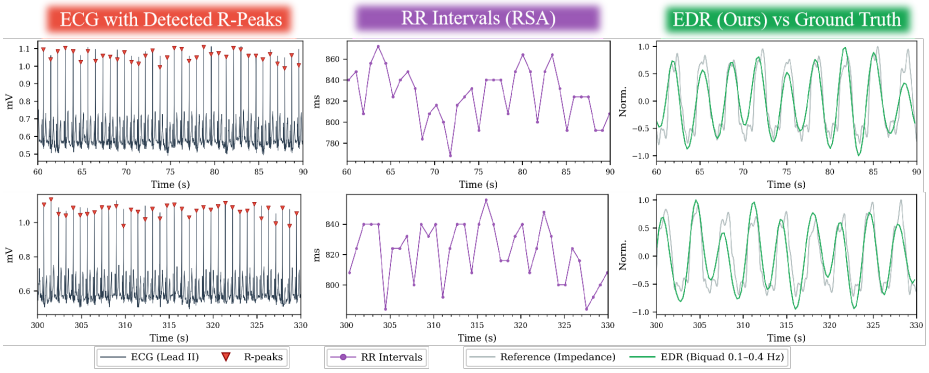


Fig. 2: Qualitative results of our proposed EDR method on BIDMC subject bidmc36 across two time windows (60–90 s and 300–330 s). (a) Raw ECG (Lead II) with detected R-peaks (red triangles). (b) Beat-to-beat R-R intervals showing respiratory sinus arrhythmia. (c) Extracted EDR waveform (green) overlaid with the impedance-based reference respiration signal (grey), demonstrating strong morphological correspondence.

integration (150 ms) smooths the detection signal. Adaptive thresholding with a 300 ms refractory period prevents double detection. The precise R-peak locations are then refined by searching for local maxima in the bandpass-filtered ECG within ±50 ms of each detected QRS onset. From the detected R-peaks, we compute beat-to-beat R-R intervals, which naturally fluctuate with respiration due to RSA. These irregularly sampled intervals are then resampled onto a uniform 4 Hz time grid using cubic spline interpolation, producing a continuous EDR waveform. The interpolated EDR signal is filtered using a 4th-order biquad bandpass filter (cascaded second-order sections) with cutoffs of 0.1–0.4 Hz (6–24 bpm). The biquad (SOS) implementation ensures numerical stability at these low frequencies, and the tighter 0.4 Hz upper cutoff suppresses noise that dominates the 0.4–0.5 Hz range in most subjects (please refer to the 'ablation' in Section 3.3). The respiratory rate is then estimated from inter-peak intervals in the filtered signal.

2.3 Baseline Methods and Evaluation Metrics

We compare against three baselines: (1) Welch PSD (PPG) [21], which estimates the respiratory rate from the peak frequency of the PPG power spectrum within 0.1–0.5 Hz using 30-second Hanning-windowed segments with 50% overlap; (2) Fusion: Welch + EEMD-SDF (PPG) [12, 5], which fuses the Welch estimate with an EEMD-based decomposition (100 ensemble trials) via a signal quality index; and (3) Butterworth EDR (ECG), which applies the same R-R interval pipeline as our method but with a conventional 2nd-order Butterworth filter at 0.1–0.5 Hz, serving as the direct ablation baseline that isolates the effect

of our biquad filter design. All methods are evaluated on 30-second windows with 50% overlap using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the percentage of windows within ±2 bpm and ±5 bpm of the reference respiratory rate.

2.4 Digital Twin Rendering

The final stage translates the extracted EDR waveform into a dynamic 3D lung visualisation. A reference lung mesh is obtained from a diagnostic CT scan and segmented into left and right lung volumes [1]. The mesh vertices help us change the shape of the lung, and are moved in direction that mimic how a real lung actually moves when you breathe, primarily diaphragmatic (inferior-superior) and costal (anterior-posterior), with displacement amplitude is controlled by the normalised EDR signal. The lung mesh expands during inhalation (positive EDR) and contracts during exhalation (negative EDR), producing a dynamic animation that breathes in synchrony with the patient. A unified deep learning framework for automated 3D lung segmentation from our previous work achieved a Dice score of 0.74, outperforming INF-Net, Semi-INFNet, and nCoVSegNet, along with reconstruction using U-Net with RBF and Ball Pivoting algorithm for mesh refinment from CT scans, to accelerate and enhance clinical diagnosis of specific pulmonary conditions[1]. Color-coded visualization produces high-fidelity 3D models, enabling quantitative assessment and preoperative planning as shown in Fig.3.

Table 1: Respiratory rate estimation on the BIDMC dataset (53 subjects). Baselines are Welch PSD, PPG Fusion, and EDR Butterworth. Our proposed method (EDR Biquad) and integrated fallback configuration in **bold**.

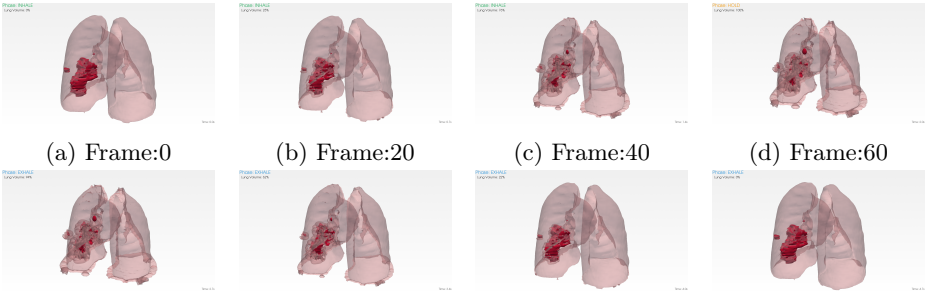
Metric	**Welch PSD**	**PPG Fusion**	**EDR Butter.**	**EDR Biquad (Ours)**	**Integrated (Ours)**
Subjects processed	53/53	53/53	52/53	45/53	**52/53**
Analysis windows	1,590	1,590	1,559	1,349	**1,559**
MAE (bpm)	3.21	3.25	3.90	**2.80**	**2.84**
RMSE (bpm)	3.96	4.21	5.26	**4.12**	**4.15**
Within ±2 bpm (%)	36.2	38.4	37.5	**48.8**	**48.2**
Within ±5 bpm (%)	79.1	79.5	68.4	**84.0**	**83.6**

3 Experiments and Results

Table 1 and Table 2 summarises the results on the BIDMC and CapnoBase datasets respectively. On BIDMC, both PPG baselines performed similarly (MAE $\approx$ 3.2 bpm), while the Butterworth EDR baseline gave the worst result at 3.90 bpm. Our proposed biquad EDR achieved the best MAE of **2.80 bpm** with **84.0%** of windows within ±5 bpm, a 28% reduction over the Butterworth

Table 2: Respiratory rate estimation on the CapnoBase dataset (42 subjects). Our proposed method (EDR Biquad) in **bold**.

Metric	**Welch PSD**	**EDR Butter.**	**EDR Biquad (Ours)**
Subjects processed	42/42	42/42	42/42
MAE (bpm)	6.95	3.62	**3.54**
RMSE (bpm)	10.17	6.97	**5.84**
Within ±2 bpm (%)	21.5	63.5	**67.2**
Within ±5 bpm (%)	57.1	78.3	**79.3**



(a) Frame:0 (b) Frame:20 (c) Frame:40 (d) Frame:60

(e) Frame:80 (f) Frame:100 (g) Frame:120 (h) Frame:140

Fig. 3: Sequential frames from the lung digital twin animation driven by the extracted EDR waveform. Frames (a)–(d) show the inhalation phase with progressive lung expansion, and frames (e)–(h) show the exhalation phase with lung contraction. The red spot shows the Carcinoma tissues of Lung obtained by deep learning based segmentation of Lung CT images from Medical-Decathlon Dataset[1].

baseline. It is required to observe that 8 subjects with respiratory rates above 24 bpm fall outside our optimised passband, reducing the coverage. To handle this, we implemented a fallback strategy where the biquad EDR is the primary method but switches to Butterworth EDR for subjects where biquad produces insufficient valid windows. This integrated approach covers 52/53 subjects on BIDMC with only a marginal increase in MAE to 2.84 bpm and -0.6% and -0.4% percentage decrease in ±2 bpm and ±5 bpm.

On CapnoBase, the PPG-based Welch PSD showed significantly degraded performance (MAE = 6.95 bpm), likely because anaesthetised patients under mechanical ventilation exhibit different PPG characteristics. Our method achieved **3.54 bpm** MAE with 79.3% within ±5 bpm across all 42 subjects, and no fallback was needed since all subjects were covered. Across both datasets combined, the framework achieves 94 out of 95 subjects (98.9% coverage) with a weighted MAE of approximately 2.92 bpm. Fig. 2 shows qualitative results on a representative BIDMC subject (bidmc36), and Fig. 3 shows frames from the lung digital twin animation driven by the extracted EDR waveform.

3.1 Ablation Study: Filter Parameter Optimisation

Table 3 presents the systematic parameter sweep we conducted on the BIDMC dataset, varying filter orders, QRS bandpass frequencies, and respiratory bandpass boundaries. Starting from the Butterworth baseline (MAE = 3.90 bpm), most configurations that simply increased filter order or changed the QRS band actually worsened the MAE (increases of +1.0 to +1.7 bpm). The critical parameter turned out to be the upper cutoff of the respiratory bandpass, narrowing it from 0.5 Hz to 0.4 Hz produced the 28% reduction in MAE, while widening to 0.6 Hz caused severe degradation to 7.95 bpm. We also tested combined parameter changes (e.g., higher filter order with shifted QRS band), but none of them matched the improvement from adjusting the respiratory cutoff alone. This confirms that the 0.4–0.5 Hz range is dominated by noise rather than respiratory content for most subjects.

Table 3: Ablation study on EDR filter parameters (BIDMC dataset). ΔMAE is relative to the Butterworth baseline (3.90 bpm). The optimal configuration is highlighted in **bold**.

Configuration	**Subj.**	**MAE**	**±2 bpm**	**±5 bpm**	**ΔMAE**
Filter Order (QRS: 5–15 Hz, Resp: 0.1–0.5 Hz)					
QRS=2, Resp=2	46	5.24	26.7%	56.7%	+1.33
QRS=2, Resp=4	46	5.47	23.3%	53.2%	+1.57
QRS=2, Resp=6	46	5.64	23.0%	51.6%	+1.74
QRS=4, Resp=4	45	5.27	23.5%	55.2%	+1.36
QRS Bandpass (Order=4, Resp: 0.1–0.5 Hz)					
8–20 Hz (Narrow)	48	5.49	22.8%	51.3%	+1.58
3–12 Hz (Low)	42	4.90	26.3%	58.6%	+1.00
Respiratory Bandpass (Order=4, QRS: 5–15 Hz)					
0.08–0.5 Hz (Wider)	45	5.25	23.3%	55.3%	+1.35
0.1–0.4 Hz (Optimal)	**45**	**2.80**	**48.8%**	**84.0%**	**−1.10**
0.12–0.6 Hz (Extended)	45	7.95	11.3%	30.0%	+4.04
Combined Parameter Optimisation					
QRS=6, Resp=6, 5–15/0.1–0.5 Hz	45	5.41	22.8%	52.9%	+1.51
QRS=4, 3–12 Hz, Resp=4, 0.08–0.5 Hz	48	5.40	24.1%	52.2%	+1.49

4 Conclusion

We presented a framework that connects a single wearable ECG lead to a real-time-capable 3D lung digital twin through an adaptive EDR pipeline, achieving a MAE of 2.84 bpm on BIDMC and 3.54 bpm on CapnoBase with 98.9% subject coverage, where simply narrowing the respiratory bandpass to 0.1–0.4 Hz produced a 28% error reduction, challenging the commonly assumed 0.5 Hz cutoff.

Lung digital twins have so far relied on expensive imaging that are incompatible with continuous monitoring, but in this work we showed that a single ECG lead is sufficient to drive 3D lung breathing representation, bringing respiratory digital twin closer to practical deployment for patients suffering with conditions like COPD at home. A key limitation is the lack of synchronized ECG and 4D CT data for quantitative validation of lung motion. Future work will focus on validating the EDR pipeline under diverse physiological conditions and coupling it with cardiac digital twin frameworks to enable a unified cardiopulmonary digital twin from a single wearable device.

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Disclosure of Interests

The authors have no competing interests to declare that are relevant to the content of this article.

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