Smartphone-Based Real-Time Respiration Tracking with Dual-Sided Inkjet-Printed Wearable Electrodes

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***Abstract*—This paper introduces a novel wearable solution for continuous respiratory monitoring through electrocardiogram-derived respiration (EDR) using custom-designed, dual-sided grid-patterned inkjet-printed (IJP) flexible dry electrodes and real-time smartphone-based analysis. The proposed electrode design reduces silver ink usage while maintaining signal quality and wearer comfort. We first compared ECG signal quality across gel, one-sided, and two-sided grid-patterned electrodes. Our mobile application, CardioHelp, processes ECG signals in real time to extract respiratory waveforms and continuously updates the respiration rate. EDR performance was validated against a commercial respiration belt across four activity conditions in five healthy adults. Bland–Altman and statistical analyses revealed minimal bias (mean difference $<$0.5 bpm), MAE$\leq$0.36 bpm, and RMSE$\leq$0.38 bpm. These results confirm robust and reliable performance. This integrated solution provides an affordable and practical approach to continuous cardiorespiratory monitoring in everyday life.**

***Index Terms*—ECG-derived respiration (EDR), Inkjet Printing (IJP), Mobile Health, Respiratory Monitoring, Wearable Sensors**

I. Introduction

Respiratory rate (RR) is a fundamental vital sign closely monitored in clinical practice. Abnormal breathing rates can signal health issues like pneumonia or metabolic acidosis, and a persistently high RR may warn of serious events like cardiac arrest [1]. Beyond acute care, continuous respiration monitoring is valuable for managing chronic and everyday health conditions. However, maintaining continuous RR surveillance in everyday environments remains challenging due to the limitations of current monitoring methods. Many conventional approaches are impractical for long-term use, and they often prove susceptible to motion or adherence issues during daily activities. Even wearable alternatives like respiratory belts or inertial sensors suffer from reduced accuracy and significant motion artifacts when compared to clinical standards [2].

Recent work has investigated both contactless and contact-based approaches for continuous respiration monitoring. Contactless methods such as camera vision, radar, or thermal sensing require controlled environments or specialized hardware and have not yet seen widespread clinical use due to accuracy and practicality concerns [3]. Contact-based techniques, such as nasal cannulas and spirometers, offer reliable measurements but remain cumbersome for daily long-term wear [4]. ECG-derived respiration (EDR) has emerged as a promising alternative. EDR algorithms use subtle breathing-related changes in the ECG waveform caused by chest movement and heart axis shifts to estimate breathing without dedicated respiratory sensors [5]. While EDR addresses the sensor modality challenge, the physical interface of the electrodes themselves poses another practical consideration for long-term monitoring. Traditional gel ECG electrodes require adhesive and conductive gel, which dry out and irritate the skin over time, making them unsuitable for prolonged use. To overcome these issues, researchers have developed various dry electrode technologies. In particular, flexible printed electrodes offer a comfortable, reusable option for wearable ECGs [6].

In parallel with innovations in sensors, recent advances in mobile computing have opened new opportunities for real-time health monitoring on wearable and personal devices. Modern smartphones now possess substantial processing power and connectivity, enabling complex physiological signal analysis directly on the device [7]. This on-device processing enhances data privacy, reduces latency, and eliminates the need for continuous cloud connectivity. Building on our previous validation of heart rate detection from wearable ECG signals on smartphones [8], we have developed a novel wearable respiratory monitoring system that combines inkjet-printed flexible dry electrodes with a mobile edge analytics platform.

Our system uses custom-designed, grid-patterned electrodes that significantly reduce material use while maintaining high signal quality and maximizing wearer comfort for extended monitoring. These electrodes utilize a two-sided printing process with a through-hole connection, which provides a robust electrical contact while separating all wiring and attachment components from the skin-facing surface for improved comfort. The wearable continuously acquires ECG signals, which are transmitted wirelessly to a custom mobile application. Within the app, real-time algorithms extract EDR waveforms and update the respiratory rate. Unlike traditional methods that rely on separate respiratory sensors or bulky hardware, our solution enables robust and comfortable cardiorespiratory monitoring with printed electrodes, a custom wearable device, and smartphone processing. By integrating flexible printed electronics, advanced biosignal processing, and mobile health technology, this system provides a platform for continuous physiological monitoring in daily life.

II. Overall Architecture and Methods

Figure 1 illustrates the architecture of our wearable system for real-time ECG-derived respiration (EDR) monitoring. The wearable uses custom inkjet-printed (IJP) dry ECG electrodes. ECG signals captured from these electrodes contain subtle amplitude modulations induced by respiratory movements. This enables the accurate extraction of respiration without additional sensors. ECG signals are acquired and digitized by an nRF52840 microcontroller (SparkFun Electronics, USA) and streamed to a smartphone via Bluetooth Low Energy (BLE 5.3) for on-device processing in the CardioHelp app. The app continuously estimates heart rate, cardiac status, and respiratory rate, and displays live waveforms and metrics. Data are stored locally and synchronized securely to the cloud for remote review and long-term trend analysis. Our custom device operates at low power, drawing 5.9 mA during continuous acquisition and streaming, with an internal rechargeable lithium-polymer battery providing ∼60 hours of operation on a single charge. BLE pairing is authenticated and encrypted, and cloud synchronization uses transport-layer encryption. Most processing occurs on-device to minimize transmitted data. This wearable-app workflow supports accurate, comfortable, and continuous respiratory monitoring in real-world settings.

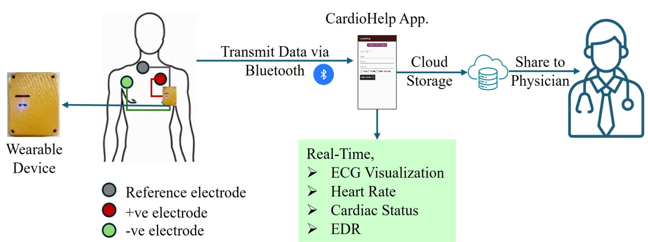

Fig. 1. Overall architecture of the real-time health monitoring and diagnosis system.

A. Sensor Design

The sensor components of our wearable system are custom-engineered to optimize comfort, signal integrity, durability, and manufacturing efficiency. The electrodes were fabricated using Metalon® JS-A191 silver (Ag) nanoparticle ink (Novacentrix Inc., TX, USA), printed onto flexible polyimide substrates with a Dimatix Materials Printer (DMP-2850, FujiFilm Inc., USA). Our ECG electrode design (Figure 2) employs a distinctive grid pattern that reduces silver ink usage by approximately 36.6% compared to traditional solid electrodes, without compromising conductivity or signal reliability. The electrode layout was created using the Inkscape software tool, exported as a PNG file, and converted to a monochrome bitmap (BMP) for import into the Dimatix Drop Manager software, which controls droplet placement and printing during fabrication.

Each electrode uses a 20 mm circular sensing area. This size balances low skin–electrode impedance, wearer comfort, and stable adhesion across chest placements. A 2 mm peripheral ring provides mechanical robustness and supports uniform current distribution. The 1 mm grid traces maintain effective contact through many micro-contacts while using substantially less silver ink. A small through-hole allows silver ink to flow to the inner surface. The trace and contact pad are printed on the reverse side, so additional ink passes through the hole and connects both sides. This enables strong electrical contact between the two surfaces without extra steps. Lead wires are bonded on the reverse side with silver epoxy (MG Chemicals 8331D-14G), which keeps the skin interface smooth and free of adhesives. This dual-sided design not only improves comfort but also ensures stable, high-quality ECG signal acquisition.

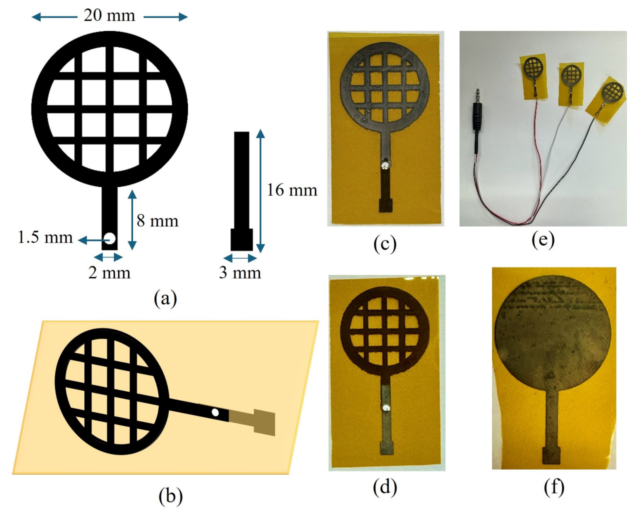

Fig. 2. Schematic and fabrication of inkjet-printed (IJP) grid electrodes. **(a)** Design schematic with key dimensions; **(b)** Illustration of electrode placement on flexible substrate; **(c)** Skin-facing side and **(d)** reverse side of the grid-patterned electrode, highlighting the through-hole connection; **(e)** Fully assembled electrodes with lead wires attached via silver epoxy; **(f)** Circular IJP electrode with one-sided printing (20 mm diameter), shown for comparison.

B. Mobile Application

The CardioHelp mobile application functions as the core platform for real-time EDR monitoring. ECG data is transmitted wirelessly from the wearable device and processed continuously within the application. The app follows a structured algorithm (Algorithm 1) to reliably extract respiratory information from ECG signals, updating the respiratory rate (RR) every 30 seconds based on overlapping one-minute ECG segments. Specifically, the application collects ECG data in 30-second windows and identifies the positions and amplitudes of the R-peaks. When a sufficient number of R-peaks are detected within the 30-second segment, cubic spline interpolation is performed to generate a continuous respiratory waveform from these discrete points. This interpolated waveform is then smoothed using a moving average filter to minimize noise and artifacts. Next, the algorithm identifies respiratory peaks within the smoothed waveform. The respiration rate displayed by the app is calculated from respiratory peaks detected in overlapping one-minute intervals, with updates occurring every 30 seconds. All calculated parameters, including respiratory waveforms and RR values, are securely stored locally and synced to cloud storage for remote clinician access, trend analysis, and historical record-keeping.

Algorithm 1 Real-Time ECG-Derived Respiration Processing

Input: ECG data segments (30 seconds each)
Detect ECG R-peaks positions (x) and amplitudes (y) within each 30-second segment
if sufficient number of R-peaks detected **then**
  Perform cubic spline interpolation on (x, y) points.
  Generate dense interpolated signal for smooth waveform representation.
  Apply a moving average filter to smooth the signal.
  Perform peak detection on the smoothed respiratory waveform:
    Identify each local maximum.
    Ensure a minimum gap between consecutive peaks to avoid false positives.
  For each new 30-second segment, combine detected peaks with the previous segment to create an overlapping 1-minute window.
  Compute RR by counting peaks within each overlapping 1-minute window.
  Update and display real-time RR in the mobile app.
  Store RR values and waveforms locally and sync to cloud storage for clinician access and trend analysis.
else
  Discard segment and wait for next data window.
end if
Output: Real-time respiration rate (RR) and secure data storage.

III. Experimental Protocol

A. Electrode Performance Comparison

To evaluate ECG electrode performance, we first collected data from four healthy adult subjects. Each subject underwent three consecutive 20-minute recording sessions in a seated resting position. The electrodes tested were: (1) commercial sticky gel electrodes (3M™ Red Dot™ Foam Monitoring Electrode 2560, 4 cm × 3.5 cm), (2) circular IJP electrodes (one-sided printing), and (3) grid-pattern IJP electrodes (two-sided printing, through-hole connection). The order of electrode use was randomized, with a brief break between sessions to allow for electrode changes. ECG data were acquired using our custom wearable device and later analyzed for signal-to-noise ratio (SNR), kurtosis, and skewness.

B. Evaluation of EDR Performance Across Activities

To provide a systematic device-level comparison, we benchmarked our EDR system against a commercial reference, the Go Direct® Respiration Belt (Vernier Software & Technology, USA). We conducted controlled experiments with five healthy adults (ages 25–35 years) under four activity conditions. Each participant wore our chest-mounted device with grid IJP electrodes and the respiration belt. The protocol comprised: (1) sitting quietly, (2) walking at 2 mph, (3) running at 3 mph, and (4) stationary cycling at 6–7 mph; each activity lasted five minutes and was followed by a five-minute rest. All signals were time-stamped for synchronization. The study was approved by the Institutional Review Board (IRB2020-783), and all participants provided written informed consent. The experimental setup and protocols are shown in Figure 3.

Fig. 3. Experimental protocol and data collection setup. (a) Real-time CardioHelp app visualization; (b) Sitting with the custom wearable device, ECG electrodes, and reference respiration belt; (c) Walking at 2 mph and (d) running at 3 mph on a treadmill; (e) Stationary cycling at 6-7 mph.

IV. Experimental Results

We first evaluated three electrode types using data from four subjects (Table I). Gel electrodes showed slightly higher SNR (29.2 dB) than Grid IJP (28.4 dB) and IJP Circular (27.7 dB). However, the Grid IJP had the highest kurtosis (7.3) and low skewness (0.21), indicating sharp, symmetric R-peaks and preserved ECG morphology. These results suggest that the more comfortable two-sided grid design maintains signal quality comparable to gel electrodes.

TABLE I
Performance Analysis of ECG Signals with Different Electrodes (Averaged over Four Subjects, 20 min per Electrode)

Electrode Type	SNR (dB)	Kurtosis	Skewness
Gel	29.2	7.1	0.15
IJP Circular (one-sided)	27.7	6.8	0.27
Grid IJP (two-sided, through-hole)	28.4	7.3	0.21

Next, the performance of our proposed EDR system was validated across four distinct physical activities using data from five healthy subjects. Figure 4 shows representative respiratory waveforms during treadmill running at 3 mph for one subject. The figure demonstrates excellent alignment between the EDR and the reference belt signals. This confirms robust respiration extraction even under dynamic conditions. The upper panel clearly illustrates the ECG waveform and its envelope, which are used for respiration estimation.

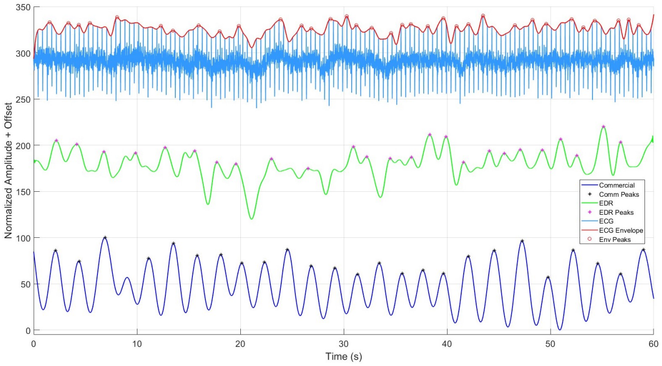

Fig. 4. EDR and belt waveforms for one subject during 3 mph running.

TABLE II
RESPIRATION RATE (BPM) FROM EDR (E) AND RESPIRATION BELT (B) ACROSS SUBJECTS AND EXPERIMENTAL CONDITIONS (5-MIN AVG).

Subj	Sitting		Walk		Run		Cycle	
	E	B	E	B	E	B	E	B
1	17.6	17.2	18.9	19.5	22.7	23.0	27.9	27.5
2	19.2	19.5	20.5	20.2	22.6	22.3	26.5	26.8
3	17.0	16.8	21.4	21.7	21.8	22.1	29.6	29.3
4	20.1	19.8	23.2	23.5	26.3	25.9	30.2	30.5
5	18.2	18.5	20.1	19.8	24.0	24.5	28.5	28.2

Respiration rates averaged over each 5-minute session for all subjects are presented in Table II. Across sitting, walking, running, and cycling, the EDR rates closely matched those from the respiration belt, with minimal deviations even during vigorous activity. Although the table reports 5-minute averages, RR is recomputed every 30 s from overlapping 60 s windows (9 estimates per 5-minute), so each value summarizes time-resolved measurements rather than a single snapshot.

TABLE III
AGGREGATED ACCURACY OF RESPIRATORY RATE ESTIMATION FROM EDR ACROSS ALL SUBJECTS. E = EDR, B = BELT.

Condition	Resp. rate (mean±SD)		MAE	RMSE	p-value
	E	B	(bpm)	(bpm)	(t-test)
Sitting	18.42±1.24	18.36±1.34	0.30	0.31	0.71
Walking	20.82±1.61	20.94±1.66	0.36	0.38	0.54
Running	23.48±1.76	23.56±1.61	0.36	0.37	0.68
Cycling	28.54±1.45	28.46±1.47	0.32	0.32	0.64

Table III summarizes the aggregated accuracy metrics for respiratory rate estimation. Mean respiratory rates from EDR and the reference belt showed minimal absolute errors (MAE$\leq$0.36 bpm) and low root mean square errors (RMSE$\leq$0.38 bpm) for all activities. Paired t-test analysis revealed no significant differences ($p>0.05$), which confirms the reliable performance of the EDR approach across both static and dynamic conditions.

Finally, Bland-Altman plots (Figure 5) confirmed strong agreement between EDR and belt-derived respiration rates, with differences near zero and most points falling within the 95% limits of agreement. The near-zero bias and narrow 95% limits indicate consistency over time. These results collectively demonstrate accurate and reliable respiratory monitoring across diverse activities.

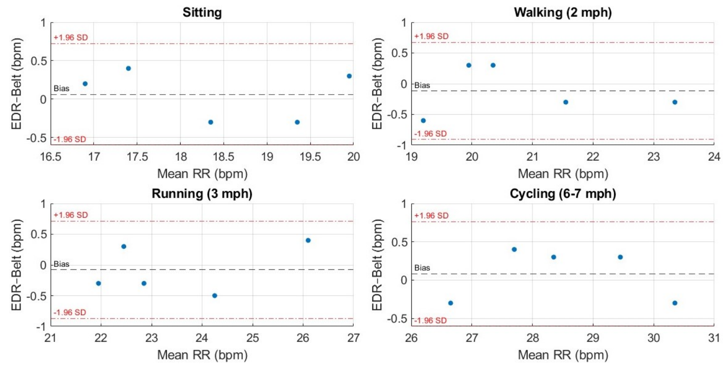

Fig. 5. Bland–Altman plots illustrating the agreement between EDR-derived and belt-measured respiration rates across all activity conditions. The central dashed line shows mean bias, and the red dash-dot lines indicate the 95% limits of agreement (mean bias ±1.96 standard deviations).

V. CONCLUSION

This work presented a wearable system for continuous respiratory monitoring that integrates ECG-derived respiration, innovative dual-sided inkjet-printed flexible electrodes, and a real-time mobile app. In future studies, we plan to validate our approach with larger and more diverse populations, including individuals with respiratory conditions, and to add artificial intelligence-based analytics for early detection of breathing abnormalities. Our results show that the system delivers accurate and robust respiratory rate tracking during a range of daily activities, offers comfort and stable signal quality, and performs comparably to traditional commercial electrodes while using less material. These strengths make our approach a promising solution for practical and unobtrusive respiratory monitoring in both clinical practice and everyday life.

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