

HYGIEIA: A Wearable Metamaterial Patch for Calibration-free Carotid Hemodynamics Monitoring

CHENGHAN JIANG, Northwest University, China

SHIBO ZHANG, Northwest University, China

BOXUAN YANG, Northwest University, China

XIAOJING WANG, Northwest University, China

CHAO FENG, Northwest University, China

XINYI LI *, Northwest University, China

XIAOJIANG CHEN, Northwest University, China

Long-term, continuous cardiac monitoring is essential for early detection and risk prediction of cardiovascular diseases. Recently, electromagnetic-based monitoring methods have gained attention because they are not affected by skin tone or contact force compared to optical or pressure-based methods. While existing systems perform well, they typically rely on professional-grade RF transceivers or require subject-specific impedance tuning based on tissue composition, leading to high cost and per-user calibration that severely limit scalability in large-scale deployments. In this paper, we present HYGIEIA, a wearable, calibration-free, and low-cost electromagnetic patch that supports continuous, high-accuracy hemodynamic monitoring. HYGIEIA introduces an air-gap cavity sensing method that converts carotid-induced skin vibrations into resonant frequency shifts, effectively decoupling the hemodynamic measurement from individual differences. In addition, HYGIEIA combines spectral shaping with morphology-aware feature extraction to reconstruct fine-grained hemodynamic waveforms from noise and adaptively high-accuracy estimate hemodynamic indicators across heterogeneous users. We design and fabricate the HYGIEIA patch and readout hardware using commodity components at low cost, and validate the system through extensive experiments with 110 participants. HYGIEIA achieves 96.14% waveform similarity to medical-grade equipment and mean absolute errors below 0.04 s for time-based indicators on average, demonstrating high accuracy and robustness and continuous potential for practical monitoring.

CCS Concepts: • **Human-centered computing** → **Ubiquitous and mobile computing**.

ACM Reference Format:

Chenghan Jiang, Shibo Zhang, Boxuan Yang, Xiaojing Wang, Chao Feng, Xinyi Li, and Xiaojiang Chen. 2026. HYGIEIA: A Wearable Metamaterial Patch for Calibration-free Carotid Hemodynamics Monitoring. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* 10, 3, Article 114 (September 2026), 30 pages. <https://doi.org/10.1145/3832011>

*Corresponding author.

Authors' Contact Information: [Chenghan Jiang](#), Northwest University, Shaanxi Key Laboratory of Passive Internet of Things and Neural Computing, Xi'an, Shaanxi, China, jiangchenghan@stumail.nwu.edu.cn; [Shibo Zhang](#), Northwest University, Xi'an, Shaanxi, China, zhangshibo@stumail.nwu.edu.cn; [Boxuan Yang](#), Northwest University, Xi'an, Shaanxi, China, yangboxuan123@stumail.nwu.edu.cn; [Xiaojing Wang](#), Northwest University, Shaanxi International Joint Research Centre for the Battery-Free Internet of Things, Xi'an, Shaanxi, China, wxj@stumail.nwu.edu.cn; [Chao Feng](#), Northwest University, Xi'an Advanced Battery-Free Sensing and Computing Technology International Science and Technology Cooperation Base, Xi'an, Shaanxi, China, chaofeng@nwu.edu.cn; [Xinyi Li](#) (corresponding author), Northwest University, Xi'an Advanced Battery-Free Sensing and Computing Technology International Science and Technology Cooperation Base, Xi'an, Shaanxi, China, xinyili@nwu.edu.cn; [Xiaojiang Chen](#), Northwest University, Shaanxi International Joint Research Centre for the Battery-Free Internet of Things, Xi'an, Shaanxi, China, xjchen@nwu.edu.cn.



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ACM 2474-9567/2026/9-ART114

<https://doi.org/10.1145/3832011>

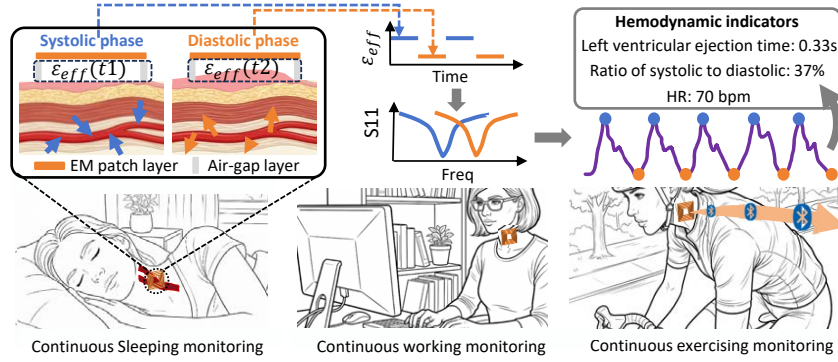


Fig. 1. The sensing principle and deployment scenarios of HYGIEIA in hemodynamic monitoring.

1 INTRODUCTION

Cardiovascular diseases (CVDs) are the world's leading cause of death, responsible for nearly 20 million annual fatalities [8]. Clinical studies indicate that CVDs often progress silently over many years but can deteriorate rapidly after symptom onset [48]. Consequently, long-term cardiac monitoring is essential for early detection and risk prediction. Hemodynamic parameters such as heart rate and cardiac output are critical biomarkers that indicate cardiac function, linking closely to CVD progression.

Non-invasive medical-grade techniques like Doppler ultrasound [60] and MRI [39] provide accurate hemodynamic measurements but are costly, require specialized resources, and are limited to discrete assessments, hindering continuous daily use. Wearable devices such as smartwatches offer a convenient alternative for continuous monitoring by detecting heartbeats at the wrist. However, their derived hemodynamic parameters, like left ventricular ejection time (LVET), and cardiac output (CO), are often biased and unstable. This is because peripheral arteries undergo divergent, sometimes opposite, pathophysiological changes compared to central arteries near the heart [66]. Local vascular regulation and pressure amplification substantially reshape the peripheral pulse waveform [15], obscuring the features needed to infer central hemodynamic indicators accurately.

Recently, monitoring the carotid artery—a central artery closely reflecting aortic hemodynamics—has emerged as a promising approach for accurate, continuous, and non-invasive assessment. Unlike photoplethysmography (PPG) sensors [35] and pressure-sensitive patches [32, 34], whose performance is sensitive to skin tone and contact pressure, electromagnetic (EM) carotid sensing detects hemodynamic waveforms via changes in the reflected EM field, rather than optical absorption or mechanical deformation. Consequently, EM-based sensing [16, 20] is far less affected by skin pigmentation and moderate contact force variations, enabling more comfortable and potentially long-term monitoring. Unfortunately, existing EM-based systems typically rely on professional-grade RF transceivers (e.g., vector network analyzers and bulky antennas), resulting in high cost and considerable deployment overhead. Moreover, prior designs often require tunable impedance networks for subject-specific impedance matching to achieve optimal performance [36, 43]. This need for individualized calibration further complicates system design and severely limits scalability in large-scale deployments.

In this paper, we present HYGIEIA¹, a wearable, calibration-free, and low-cost hemodynamic sensing system based on a home-made flexible metamaterial resonator patch. The overall idea is illustrated in Figure 1. We utilize a flexible resonator patch to capture the effective permittivity change caused by the hemodynamics. We achieve robust and continuous wearable potential to capture the hemodynamic waveform with high fidelity and extract detailed medical indicators, thanks to the ability of existing commercial capacitance-to-digital converters (CDC) to accurately extract resonant frequency shifts.

¹“Hygieia” is derived from a goddess in Greek mythology who embodied health.

To achieve HYGIEIA, we first need to solve the following significant and practical challenges:

Challenge 1: To build a sensing system that generalizes across users, a seemingly straightforward solution is to design a “one-size-fits-all” impedance-matching point. However, it is infeasible in practice. Variations in the thickness and composition of tissue layers (such as skin, fat, muscle, and vessel depth) substantially change the total load impedance seen by the patch, so the optimal matching condition differs from person to person. As a result, achieving a calibration-free solution without per-user tuning becomes a principal challenge for scaling HYGIEIA to large-scale deployments.

To address this challenge, HYGIEIA adopts a motion-based sensing approach rather than relying on precise impedance matching into heterogeneous tissue layers. Our key insight is that the changes in arterial volume during systolic contraction and diastolic relaxation will induce periodic vibrations on the skin surface. These periodic skin vibrations faithfully encode the underlying hemodynamic waveform. Thus, instead of driving energy deep into the vascular layer, HYGIEIA recovers hemodynamics by measuring minute motion at the skin. To make these small vibrations electromagnetically observable and less sensitive to tissue-layer variability, HYGIEIA introduces a thin air gap beneath the sensing patch, forming a cavity between the resonator and the skin. Carotid-driven skin motion modulates the thickness of this cavity, which in turn changes the effective permittivity around the resonator and induces measurable shifts in its resonant response. In this way, the sensing outcome depends primarily on the air–tissue interface motion, effectively decoupling the hemodynamic measurement from individual differences in deeper tissue composition.

Challenge 2: Patch designs need to achieve low-cost, comfort, and performance robustness. However, it is hard to achieve both the low-cost and comfort goals simultaneously. Specifically, while using a commercial CDC as the excitation source is a potential low-cost solution, the resonant frequency is typically very low (below 10 MHz). The lower the operating frequency of the patch, the larger its electrical dimensions, and this larger form factor poses a challenge to user comfort. Although some advanced fabrication techniques can improve electrical dimensions within a limited form factor, such as by spatially coiling, this incurs high manufacturing costs. Furthermore, since the electric field distribution is related to the sensing performance, users often introduce unavoidable positional errors during deployment. To prevent the performance reduction caused by unavoidable positional errors during deployment, it is necessary to ensure that the patch maintains a strong and uniform electric field distribution on the target sensing area.

To solve this challenge, first of all, select and optimize the basic structure guided by the electric field distribution and fabrication cost considerations, and limit the form factor to a wearable-level size. Secondly, we cleverly designed a “dual-loop” structure to achieve a strong and uniform electric field distribution. Thirdly, considering the operating frequency limitation when connected with the CDC chip. Using LC matching components, we offload the effort to lower the resonant frequency from the patch to the hardware circuit, solving the operation frequency limitation’s last-mile problem.

Challenge 3: Accurately deriving hemodynamic indices from the measured waveforms is challenging. First, carotid motion is inherently small (on the order of a 0.4 mm radius change) and may be further attenuated in diseased populations [68]. The resulting signals are easily masked by physiological and instrumental noise, which distorts the local temporal features that define these indices. Second, waveform shapes vary substantially with age, arterial stiffness, and individual physiology, so a single, globally tuned feature extraction method fails to work consistently across users.

To tackle this challenge, HYGIEIA combines spectral shaping with morphology-aware feature extraction. On the spectral side, we design a Multi-Narrowband Splicing Scheme (MNSS) that takes advantage of the fact that most cardiac content is concentrated around the heart-rate frequency and a few of its low-order harmonics. Instead of applying a broad passband, MNSS keeps a set of very narrow windows centered at these harmonics, which strongly reduces in-band noise while preserving the characteristic pulse shape. On the morphology side, we group the hemodynamic waveforms into a small set of representative types. Then, we design an adaptive and

tailored feature-detection method that locates cycle boundaries, systolic peaks, and diastolic notches of each type. This combination allows HYGIEIA to estimate hemodynamic indices robustly despite weak signals, noise, and inter-subject variability.

We develop the prototype of the HYGIEIA patch at a cost of 0.47 USD/piece and custom readout hardware. Using the medical-grade sensor HK-2000C as the ground-truth [4], HYGIEIA achieves above 96.14% waveform similarity. We evaluate the performance in 110 volunteers of diverse ages and genders, which demonstrates high accuracy with a mean absolute error (MAE) below 0.04 s for all time-domain indicators (LVET, SD, DD) across person diversity. HYGIEIA also achieves robustness under different scenarios. Furthermore, in a one-hour continuous monitoring comparison against HUAWEI Watch 5 and Apple Watch Series 9, HYGIEIA maintained an average error of heart rate below 2.6%. Additionally, User-experience studies reported an average comfort score of 9.02/10.

Contributions. The main contributions of HYGIEIA are: (i) We design a ready-to-use EM sensing solution, utilizing an air-gap to achieve generalized sensing across population diversity. This design effectively decouples the sensing mechanism from subject-specific tissue composition and impedance, enabling operation without per-user calibration. (ii) HYGIEIA introduces a physiology-guided signal processing pipeline that reconstructs fine-grained hemodynamic waveforms using a multi-narrowband splicing scheme and employs morphology-aware, derivative-based feature detectors to accurately estimate hemodynamic parameters. (iii) We fabricate the low-cost HYGIEIA patch with a hardware prototype and validate its effectiveness involving 110 volunteers in a wide range of practical impact factors.

2 RELATED WORK

Medical-grade monitoring. Long-term, continuous hemodynamic monitoring is fundamental for clinical cardiovascular assessment. Early methods primarily relied on invasive techniques such as pulmonary artery catheters (PACs) [46], which carry risks of discomfort and infection. Recent non-invasive alternatives—including MRI [39] and carotid Doppler ultrasound (CDU) [60] reduce such risks and provide accurate measurements. However, they remain costly, require specialized equipment and operators, and typically only offer discrete snapshot assessments, making them impractical for continuous daily monitoring.

Commercial wrist-based devices for monitoring. Many commercial devices, such as smartwatches and fitness bands, embed PPG sensors or ECG electrodes to monitor heart rate, respiration rate, and blood oxygen saturation from peripheral arteries at the wrist in daily life. Although these devices enable convenient long-term cardiac monitoring, wrist-based measurements fundamentally reflect peripheral rather than central hemodynamics. Due to pulse pressure amplification and local vascular regulation, peripheral arterial waveforms can diverge, and even behave oppositely, from those in central arteries near the heart [66]. As a result, peripheral sites are unreliable surrogates for key central hemodynamic indicators, limiting the ability of commercial wearables to assess central cardiovascular status.

Central-artery patches for hemodynamic monitoring. A number of recent works have explored wearable and flexible patches placed over central arteries, such as the carotid artery, to enable more accurate hemodynamic monitoring. Existing patches can be broadly classified into four categories: PPG-based, ultrasound-based, electromechanical-based, and electromagnetic (EM)-based systems: (1) Ultrasound-based solutions [67, 70] estimate hemodynamics by tracking changes in the vessel using the time-of-flight (TOF) of ultrasonic waves. However, their performance depends critically on the effectiveness of the acoustic coupling medium (typically gels or viscous liquids) between the transducer and the skin, which makes long-term monitoring unstable and uncomfortable [63]. (2) Electromechanical patches measure the mechanical strain or pressure at the skin surface, including piezoresistive [65], capacitive [34], and piezoelectric [32] designs. To achieve stable performance, these devices typically require carefully controlled contact pressure between the patch and the skin, making them highly

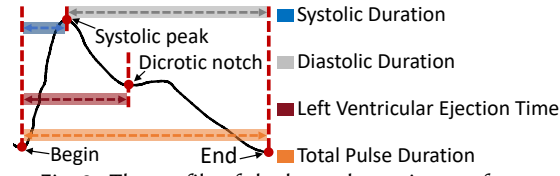


Fig. 2. The profile of the hemodynamic waveform.

sensitive to external force and posture changes. (3) Photoplethysmography (PPG) patches [35] are among the most prevalent due to the maturity of optical components and existing commercial devices. Nonetheless, PPG signals exhibit significant performance degradation on darker skin tones because increased optical absorption reduces the effective signal-to-noise ratio. (4) In contrast, EM-based carotid patches sense hemodynamics via changes in the reflected EM field rather than optical absorption or mechanical deformation, and have attracted growing interest in the research community. However, most existing systems rely on professional-grade or customized RF transceivers (e.g., vector network analyzers, professional antennas, and bulky readout hardware), resulting in high hardware cost, large form factors, and deployment burden [16, 20, 40]. In addition, prior EM-based designs often employ tunable impedance networks to satisfy subject-specific impedance-matching conditions for optimal monitoring performance [36, 43]. Such individualized calibration further complicates system design and severely limits scalability in large-scale deployments.

In contrast, our work introduces a vibration-sensing carotid patch that captures skin-surface motions originating from central arterial pulsations. This approach enables universal wearability by maintaining a stable air gap, eliminating subject-specific impedance matching. Moreover, we implement sensing using low-cost commercial chips, avoiding expensive RF hardware. We also develop an adaptive waveform algorithm to reliably extract fine-grained hemodynamic features across diverse subjects. Taken together, our system supports continuous, low-cost, and user-independent central hemodynamic monitoring.

3 BACKGROUND

This section explains how cardiac activity shapes the carotid artery hemodynamic waveform. As shown in Figure 2, during systole, the left ventricle ejects blood into the carotid arteries, increasing pressure and distending the arterial wall to form a steep systolic upstroke that peaks at the systolic peak. The subsequent diastolic phase begins as ejection ends, with pressure gradually falling to produce the descending limb. Aortic valve closure then induces a brief pressure drop and arterial recoil, manifested as the dicrotic notch. Following this notch, the waveform decays to its minimum before the next systolic upstroke, marking the cycle's end.

The carotid hemodynamic waveform encodes several features, including the systolic and diastolic phases, the dicrotic notch, and the cycle boundaries: (i) The time from the onset of the waveform to the systolic peak defines the *systolic duration* (SD), whereas the time from the systolic peak to the end of the waveform defines the *diastolic duration* (DD) [64]. A steeper ascending branch and shorter systolic duration generally indicate better ventricular contractility and arterial elasticity, and the ratio of systolic to diastolic duration has been used as an indicator of global ventricular function [18]. (ii) The *left ventricular ejection time* (LVET) is the interval from waveform onset to the dicrotic notch, and the *Ejection Duration Index* (EDx) [54] is defined as the ratio of LVET to the total cycle length. EDx approximates the time between aortic valve opening and closure and has long been used as a marker of left-ventricular systolic function and contractility [12]. In addition, the morphology and timing of the dicrotic notch are strongly associated with arterial stiffness, a known predictor of cardiovascular morbidity and mortality [9]. (iii) The interval from the start to the end of a single waveform cycle corresponds to the heart rate (HR) interval and is widely used to detect abnormal cardiac rhythms, such as atrial fibrillation.

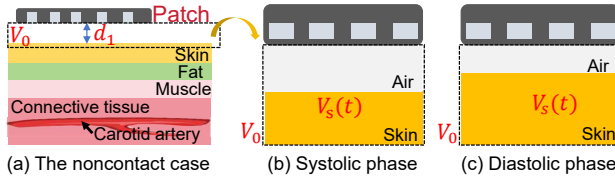


Fig. 3. Schematic diagram of internal changes in the cavity caused by skin vibration.

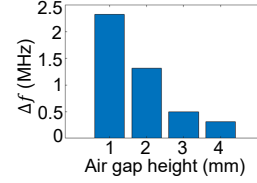


Fig. 4. The different air gap height result.

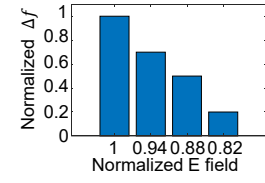


Fig. 5. The different E field intensity result.

4 SENSING PRINCIPLE AND PATCH DESIGN

In this section, we focus on introducing the calibration-free sensing solution of HYGIEIA in Section 4.1, and the details of patch design will be introduced in Section 4.2.

4.1 Air-Gap-Based EM Sensing of Carotid Hemodynamics

Electromagnetic (EM)-based hemodynamic monitoring infers cardiovascular dynamics from changes in a sensing patch's effective permittivity and reflection coefficient [20]. In conventional designs, the patch is placed directly against the skin, immersing its near field in biological tissue. This cross-material configuration, however, leads to substantial attenuation and scattering of the incident signal by the lossy, heterogeneous tissue. As a result, the patch response becomes highly subject-specific, necessitating tight impedance matching and frequent recalibration to maintain sensitivity. It is a barrier to real-world deployment across diverse users.

To achieve generalization for hemodynamic monitoring, HYGIEIA builds on two key observations. First, because air and tissue have markedly different permittivity, a significant fraction of the incident energy is reflected at the skin–air interface rather than propagating deep into the body. Second, pulsatile expansion and contraction of the carotid artery induce small but measurable vibrations of the skin. Therefore, unlike prior approaches [36, 43] that treat impedance mismatch and surface reflection as detrimental effects to be minimized, HYGIEIA deliberately exploits the reflected signal from the tissue surface as a carrier of these skin vibrations, and uses it to sense the hemodynamic waveform driven by the carotid artery.

To capture skin vibrations, a key design choice is inserting a thin space between the patch and the skin and forming a small air gap, which forms a finite-volume V_0 electromagnetic resonant cavity, as shown in Figure 3(a). In the cavity, the air gap can convert tiny carotid-driven skin motion into noticeable changes in the electromagnetic response of the patch. This is because air and biological tissue have markedly different permittivity (as shown in Table 1), small skin displacements that change the air-gap thickness alter how much of the near field traverses air versus tissue, and thus modulate the effective permittivity in the patch sensing area. Specifically, as illustrated in Figure 3(b) and Figure 3(c), we show the two phases of systole and diastole. During systole, the carotid artery expands and pushes the skin toward the patch, it will make the time-varying volume of skin $V_s(t)$ increase in the cavity and compresses the air gap so that the volume fraction of tissue $c_s(t) = \frac{V_s(t)}{V_0}$ in the sensing region increases while the volume fraction of air $c_{air}(t) = 1 - c_s(t)$ decreases. During diastole, the artery relaxes, the skin moves away, and the air gap re-expands, increasing $c_{air}(t)$ and reducing $c_s(t)$. This periodic change in the air–tissue volume ratio leads to a corresponding periodic modulation of the equivalent permittivity of the cavity. Here, the equivalent permittivity can be represented according to the Maxwell–Garnett approximation [6]:

$$\epsilon_{eff}^{V_0}(t) = \epsilon_{air} + 3V_s(t)\epsilon_{air} \frac{\epsilon_s - \epsilon_{air}}{V_0(\epsilon_s + 2\epsilon_{air}) - V_s(t)(\epsilon_s - \epsilon_{air})} \quad (1)$$

where ϵ_s and ϵ_{air} are the permittivity of tissue and air.

Table 1. The parameters of the carotid artery phantom.

Component	Thickness (mm)	Permittivity
Air	-	1
Skin	2	84
Fat	4	13.7
Muscel	3	72.6
Connective tissue	10	59.9
Blood	5	87

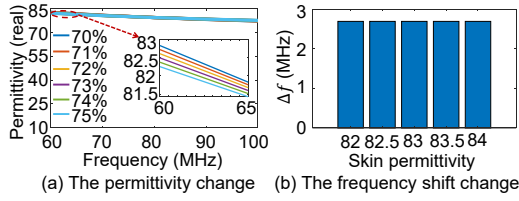


Fig. 6. The result of different skin permittivity and the caused frequency shift.

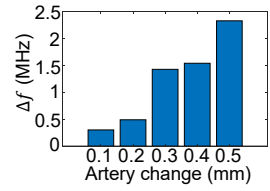


Fig. 7. The Overall performance.

The theory of resonant cavity perturbations [45] states that a permittivity change in material entering the cavity disturbs and then produces a new electromagnetic balance—an effect expressed as:

$$\Delta\omega \propto -\omega_0 \iiint_{V_0} \Delta\epsilon_{eff}^{V_0}(t) E^2(r) d^3r \quad (2)$$

where $E^2(r)$ is the electric field intensity confined in the cavity. ω_0 is the operating frequency and $\Delta\omega$ is the resonant frequency shift. Based on Eqn. 1 and Eqn. 2, the resonant frequency shift $\Delta\omega$ can be expressed as:

$$\Delta\omega = G(\epsilon_s, V_0, V_s(t), E(r), \epsilon_{air}, \omega_0) \quad (3)$$

where $G(\cdot)$ denotes a mapping function from the material and field parameters to the frequency shift. ϵ_{air} is a constant (in Tab. 1) and ω_0 is the baseline resonant frequency of the sensing patch. Therefore, for a given patch design and operating frequency, $\Delta\omega$ is primarily determined by the tissue permittivity ϵ_s , the baseline cavity volume V_0 , the time-varying skin-induced volume $V_s(t)$, and the local field distribution $E(r)$.

Here, we establish a phantom in High Frequency Simulation Software (HFSS) to verify how each parameter impacts the resonant frequency. Specifically, we simplify the 3D model of the carotid artery by regarding the carotid artery as a cuboid that is encapsulated in homogeneous connective tissue, which is distributed under skin, fat, and muscle. Based on the online tissue database [7], we set the average permittivity for each tissue in the interest frequency band. To simulate the vibration of carotid arteries caused by the cardiac motion, we vary the artery phantom height from 5 mm to 5.5 mm in 0.1 mm increments. With each step, the upper tissue layer moves upward to simulate tissue vibration. The prototype of the patch is detailed in Section 4.2.

(i) *The impact of V_0 .* We verify the impact of the different cavity volume V_0 , which is related to the height of the air gap we choose. Specifically, we set the air gap from 1 mm to 4 mm in steps of 1 mm and fix the artery phantom height changes from 5 mm to 5.5 mm. The result is shown in Figure 4, the total resonant frequency shift decreases from 2.32 MHz to 0.25 MHz as the height increases. This is because when the V_0 increases, the volume fraction of the perpetuated will decrease, so that the change of equivalent permittivity decreases. Therefore, we set the air gap as 1 mm to maintain the highest sensitivity. Such height of the air gap is easy to achieve in practice, and the details of the air gap prototype will be introduced in Section 6.1.

(ii) *The impact of E_r .* We verify the impact of different electric field intensities $E(r)$. Specifically, we change the normalized electric field intensity from 1 to 0.82 in steps of 0.06; the result is shown in Figure 5. The normalized frequency shift decreases as the electric field intensity decreases. Therefore, it is necessary to maintain a high electric field intensity on the target sensing area by designing the patch.

(iii) *The impact of ϵ_s .* The permittivity of skin ϵ_s shows differences due to the varying moisture contents across population diversity. Typically, the percentage of water in skin is in the range of 70% to 75% [3]. Therefore, we calculate the permittivity of skin in different percentages of water according to the Cole-Cole model and Maxwell-Garnett Model [38, 51]. The result is shown in Figure 6(a), it can be shown that the mixture's permittivity

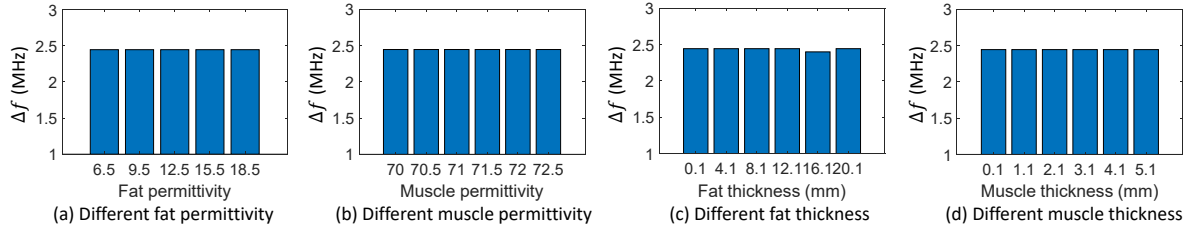


Fig. 8. The simulation of the different permittivity and thickness in person variety.

decreases from 82.83 to 82.25 as the percentage of water increases. To verify how the larger change of skin's permittivity reflects in the total frequency shift, we expand the range of values of ϵ_s from 82 to 84 in steps of 0.5. The results are shown in Figure 6(b), it can be found that the frequency shift still remains almost unchanged.

(iv) *The impact of $V_s(t)$.* The time-varying skin-induced volume $V_s(t)$ is related to the hemodynamic details. Therefore, we verify different changes of $V_s(t)$ by changing the height of the carotid artery phantom. Specifically, we change the difference from 0.1 mm to 0.5 mm in steps of 0.1 mm. The result is shown in Figure 7, the frequency shift increases from 0.3 MHz to 2.32 MHz. Consequently, it demonstrates that tiny vibration will lead to a resonant frequency, which can reflect the details and fine-grained hemodynamic waveform patterns.

(iv) *The impact of diverse physiological conditions.* To verify the performance of the method we proposed under diverse physiological conditions, we verify the frequency shift in the different permittivity and thickness of muscle and fat in HFSS. Specifically, the permittivity of muscle is related to the percentage of fat infiltration. We obtain the permittivity under average infiltration (13.7) and no infiltration (6.5) from the TISSUE PROPERTIES online [7]. So we change the permittivity of fat from 6.5 to 18.5 in steps of 3. Such a huge range can fully cover the whole potential permittivity under different infiltration conditions. For the permittivity of muscle, the value is related to the percentage of glucose, because it stores the most glucose in the human body. Therefore, we change the concentrations of glucose from 0 mg/dL to 500 mg/dL. When the concentration of glucose is up to 500 mg/dL, it is considered extremely dangerous and requires emergency care. Therefore, such a value range can cover the whole range of different levels. We calculate the complex permittivity of muscle under different glucose levels [43], and the range is from 70 to 72.5. We change the permittivity in steps of 0.5. In addition, based on the statistical results of previous studies on multiple population groups [44, 61], we change the thickness of fat and muscle from 0.1 mm to 5.1 mm in steps of 1 mm, and from 0.1 mm to 20.1 in steps of 4 mm, respectively. In each simulation run, only one of the aforementioned variables was altered at a time, while the magnitude of vascular pulsation was held constant at 0.5 mm. The results are shown in Figure 8. We observe that the resonant frequency shift has almost no change, regardless of the thickness and permittivity change. This is due to the dielectric discontinuity at the air-to-skin interface (i.e., impedance mismatch), the majority of electromagnetic waves are reflected and fail to penetrate deep into the tissue. Consequently, changes in the permittivity and the thickness of the underlying tissues (fat and muscle) have a tiny effect on the overall resonant response. This demonstrates that the proposed system is dependent solely on the magnitude of surface skin vibration and remains virtually unaffected by other physiological factors. It is worth noting that the pathological vascular conditions are not included in the simulation. We have discussed it in Section 8.

Based on the foregoing analysis, we draw three main conclusions: (i) The resonant frequency shift demonstrates clear potential for monitoring hemodynamic waveforms. (ii) Despite population-specific variation, skin permittivity has negligible influence on our design's resonant frequency, enabling generalized sensing across subjects. (iii) The direct link of electric field intensity to sensing performance guides subsequent patch design.

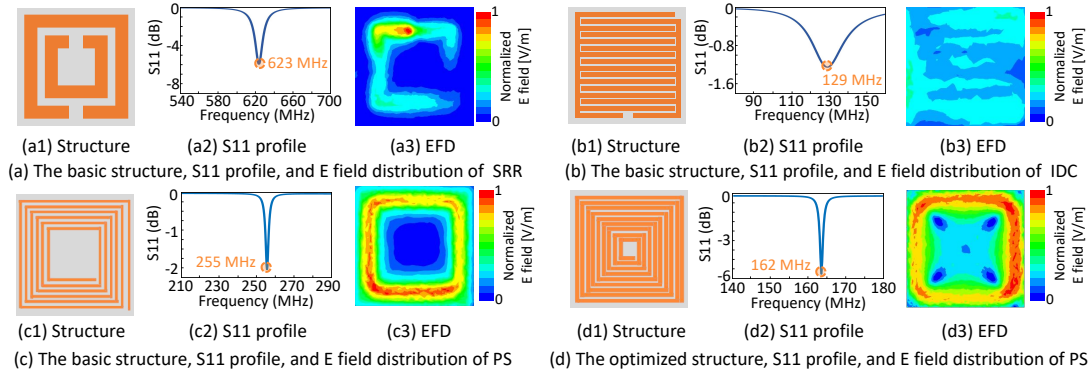


Fig. 9. The layout and the result of the established phantom.

4.2 Patch Design

In this section, we introduce the hardware design of HYGIEIA, including the patch and activation source design.

4.2.1 Design Goals. To realize the vision of long-term, low-cost, and high-accuracy hemodynamic monitoring, HYGIEIA targets the following three objectives:

Goal 1: To enable wearable daily monitoring, the sensor patch needs to eliminate reliance on bulky, professional instruments. Although commercial capacitance-to-digital converters (CDC) provide a potential path to achieve the patch activation, they typically operate at a low maximum frequency (ie, FDC2214 only serves a 10 MHz maximum operating frequency). This presents a fundamental design conflict: the operating frequency of an antenna is closely related to its electrical size, and the wavelength at 10 MHz is approximately 30 meters, which is directly at odds with the miniaturized dimensions required for a wearable device.

Goal 2: To enable large-scale adoption, the design needs to maintain low production costs and avoid dependence on expensive novel materials or complex micro-fabrication processes to ensure both affordability.

Goal 3: As analyzed above in Eqn. 2, the sensing performance is sensitive to the electric field intensity. To achieve sensitive and robust sensing, the patch must provide a stronger and more uniform field distribution.

4.2.2 Patch Design Details. Here, we focus on three classic low-cost metamaterial resonant structures: the split-ring resonator (SRR), the interdigitated capacitor (IDC), and the planar spiral (PS), as shown in Figure 9(a1, b1, and c1). Their compact yet long electrical length and flexible-electronics compatibility support large-scale fabrication [28, 30, 50].

For each structure, we use HFSS to simulate its resonant frequency and near-field distribution. Since HYGIEIA senses carotid-induced motion through the field coupling across a thin air gap and into the underlying tissue, we analyze the vertical electric field component within a 1 mm region below the patch, which corresponds to the intended sensing gap. The simulation results are shown in Figure 9(a, b, c). First, the SRR exhibits a resonant frequency significantly higher than that of the IDC and PS structures with the same lateral size. This is because both the IDC and PS introduce a longer effective current path through bending and coiling, which increases the effective inductance and lowers the resonant frequency. Second, compared to the IDC, the PS structure generates a stronger, more concentrated vertical field in the sensing region because the IDC's field is largely confined laterally between fingers, yielding a weaker vertical component below. In our prototype design, we choose the planar spiral sensing element for its dual advantages: a low resonant frequency under a compact footprint and a strong vertical electric field in the 1 mm sensing region.

Our focus now shifts to optimizing the PS patch to lower its operating frequency. The detailed layout is shown in Figure 10. First, selecting a flexible substrate is essential for wearability. While materials like TPU and PI are

common choices, ensuring a stable, conformal interface with skin is critical; any movement can compromise long-term monitoring robustness. We therefore prioritize the substrate's stretchability and softness. Compared to TPU and PI, PDMS exhibits a significantly lower Young's modulus (by three and six orders of magnitude, respectively) [25], making it the optimal substrate for achieving both wearable and stable conformal integration.

Secondly, we need to identify the key parameters that impact the resonant frequency. The resonant frequency f_c is set by the equivalent inductance L and capacitance C , which can be calculated as $f_c = \frac{1}{2\pi\sqrt{LC}}$. Hence, we analyze the parameters that affect its capacitance and inductance to reflect the impact on the resonant frequency. Specifically, the inductance of the PS structure can be calculated by the Modified Wheeler Formula as:

$$L = R_1\mu_0 \frac{N^2(d_{out} + d_{in})}{2(1 + R_2\rho)}, \quad (4)$$

where N is the number of spiral turns, and R_1 and R_2 are geometry-dependent constants, with values of 2.34 and 2.75 for a square PS layout, respectively [41]. μ_0 is the vacuum permeability. d_{out} and d_{in} are the outer and inner diameters of the spiral, respectively. $\rho = \frac{d_{out}-d_{in}}{d_{out}+d_{in}}$ is the fill ratio. For ease of analysis, we rewrite d_{in} as:

$$d_{in} = d_{out} - 2N(W_s + W_l) + 2W_s, \quad (5)$$

where W_s and W_l are the interval and width of the spiral, respectively. Combining Eqn. 4 and Eqn. 5, the value of inductance L can be expressed as:

$$L = H(R_1, R_2, \mu_0, N, d_{out}, W_s, W_l) \quad (6)$$

where $H(\cdot)$ is the mapping function from a series of parameters to the inductance L . R_1 , R_2 and μ_0 are the constant as mentioned above. Therefore, L is primarily determined by the number of turns N , the outer diameter d_{out} , the interval W_s , and the line width W_l .

In addition, the capacitance value of the planar spiral can be represented as [24]:

$$C_p = \left(\frac{1}{2}\epsilon_0\epsilon_a \frac{K(k'_1)}{K(k_1)} + \epsilon_0\epsilon_a \frac{h_l}{W_s} + \frac{1}{2}\epsilon_0\epsilon_p \frac{K(k'_2)}{K(k_2)} \right) \frac{(l - 4d_{out})}{N} \quad (7)$$

where ϵ_0 , ϵ_a , and ϵ_p are the dielectric constants of vacuum, air, and PDMS substrate. h_l is the thickness of the copper. $l = 2d_{out}N(1 + d_{in}/d_{out})$ is the total spiral length. Where the function $K(\cdot)$ is the complete elliptic integral of the first kind, which is defined as: $K(x) = \int_0^{\frac{\pi}{2}} \frac{d\varphi}{\sqrt{1-x^2\sin^2\varphi}}$. k_1, k'_1, k_2 and k'_2 can respectively calculate as

$$k_1 = \frac{w_s}{w_s + w_l}, k'_1 = \sqrt{1 - k_1^2}, k_2 = \frac{\tanh(\frac{\pi w_s}{4h_b})}{\tanh(\frac{\pi(W_s + 2W_l)}{4h_b})}, \text{ where } h_b \text{ is the thickness of substrate, and } k'_2 = \sqrt{1 - k_2^2}.$$

To assist understanding, we can rewrite Eqn. 7 according to a mapping function $Q(\cdot)$ as:

$$C = Q(\epsilon_0, \epsilon_a, \epsilon_p, N, d_{out}, W_s, W_l, h_b, h_l) \quad (8)$$

ignoring the constants $(\epsilon_0, \epsilon_a, \epsilon_p)$, the capacitance C is related to d_{out} , N , W_s , W_l , h_b , and h_l . Totally, based on Eqn. 6 and Eqn. 8, the total frequency f_c is highly correlated with the independent variables $N, h_b, h_l, W_l, W_s, d_{out}$.

To investigate how these factors affect the f_c , we perform comprehensive simulations using HFSS. Specifically:

(i) *The outer diameter d_{out} .* Figure 11(a) shows that f_c decreases from 280.7 MHz to 226.3 MHz as d_{out} increases from 24 mm to 30 mm. Hence, selecting a larger d_{out} is an effective approach to decrease the operating frequency. However, it is significant to consider the deployment in practice. To avoid compromising user comfort with an overly large patch, existing carotid hemodynamic monitors [37] set the effective sensing width to about 3 cm to maintain performance. Therefore, in our prototype, we conservatively select 3 cm as the outer diameter.

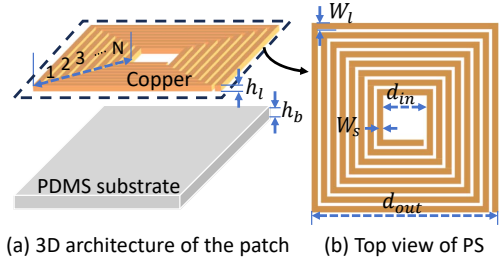


Fig. 10. The details of the PS structure.

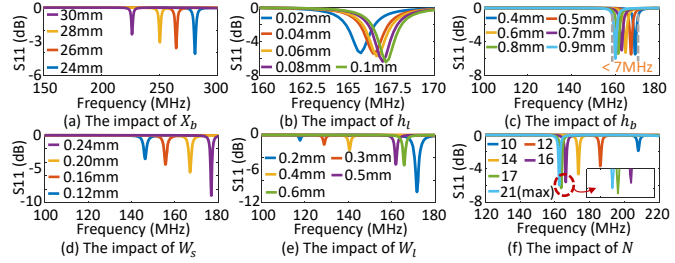


Fig. 11. The results of different parameters.

(ii) *The thickness of copper h_l .* To verify how the copper thickness impacts the resonant frequency, we change the thickness h_l from 0.02 mm to 0.1 mm in steps of 0.02 mm. The result illustrates in Figure 11(b), shows that the resonant frequency increases gradually from 165.8 MHz to 167.2 MHz as h_l increases. Therefore, in order to keep the operating frequency at a low level, we select 0.02 mm as the thickness of copper. We use a commercially available 0.02 mm copper foil, which is easy to fabricate at this thickness and at low cost.

(iii) *The thickness of substrate h_b .* We evaluate the impact of substrate thickness by varying h_b from 0.4 mm to 0.9 mm. As shown in Figure 11(c), increasing the thickness lowers the resonant frequency, with a total shift of less than 7 MHz across this range. However, a thicker substrate increases the overall distance from the metal spiral to the sensing region (i.e., substrate plus air gap), which enhances attenuation of the electromagnetic signal and reduces electric field strength at the target, thereby degrading sensing sensitivity. To balance resonant frequency with signal sensitivity, a substrate thickness of 0.5 mm was selected as the optimal choice.

(iv) *The interval width W_s of the spiral.* Different intervals impact the operating frequency. We increase the W_s from 0.12 mm to 0.24 mm in steps of 0.4 mm, and the result of operating frequency is shown in Figure 11(d). We observe that the operating frequency decreases as the interval width W_s decreases. Therefore, we should have chosen to make W_s as small as possible in order to reduce the operating frequency. While smaller line spacing makes peeling more difficult, we chose 0.2 mm to enable smooth, instrument-free removal from the patch.

(v) *The line width W_l of the spiral.* To verify the impact of different line widths W_l , we evaluate the frequency change in different W_l (from 0.2 mm to 0.6 mm in steps of 0.1 mm). The result is shown in Figure 11(e), we see that as the line width decreases, the operating frequency decreases. Because the high thermal conductivity of copper foil causes heat to accumulate during laser engraving, a narrower line width leads to higher temperatures per unit area. Copper lines with narrow widths pose a risk of scorching or breakage, thus affecting the yield rate of patch fabrication. Therefore, considering the yield rate during production, we set the linewidth to 0.5 mm.

(vi) *The number of spiral turns N .* Figure 11(f) shows that increasing the number of spiral turns lowers the resonant frequency. Adding turns lengthens the current path and strengthens inter-turn coupling, which increases both the equivalent inductance and capacitance, leading to a lower frequency. In addition, the number of turns can not increase without limitation; the maximum turns is related to the w_s , w_l , and d_{out} based on Eqn. 5. Therefore, we set N to the maximum value of 21 in our system.

Table 2 summarizes the optimized patch configuration. As shown in Figure 9(d2), despite lowering the resonant frequency through parametric tuning, the optimized PS structure still does not meet the CDC's low-frequency requirement. Under the dual constraints of wearable size and fabrication cost, the parameter space for further reducing the frequency of the basic PS geometry is exhausted.

Furthermore, Fig. 9(d3) reveals that the horizontal electric-field distribution is uneven. According to Eqn. 2, sensing sensitivity in the frequency domain depends strongly on the local electric-field intensity $|\vec{E}_0|$. A non-uniform field creates position-dependent sensitivity, degrading the measurable frequency shift if misalignment

Table 2. The parameters of optimized PS structure.

Para	Value	Para	Value	Para	Value
d_{out}	30 mm	W_l	0.5 mm	h_l	0.02 mm
W_s	0.2 mm	N	21	h_b	0.5 mm

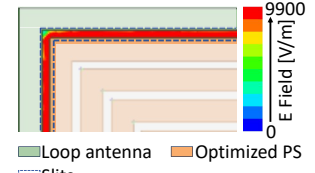
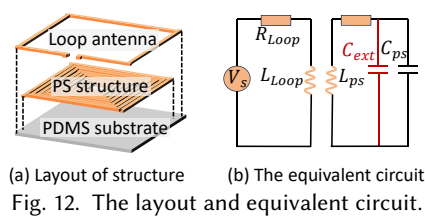


Fig. 13. Electric field distribution in slits.

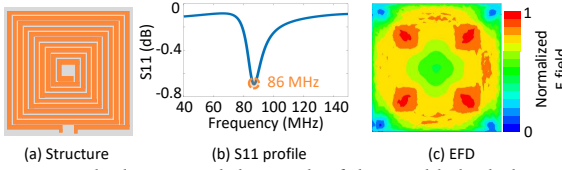


Fig. 14. The layout and the result of the established phantom.

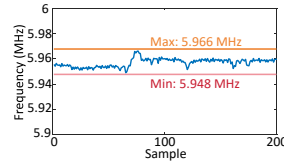


Fig. 15. The result combined LC network.

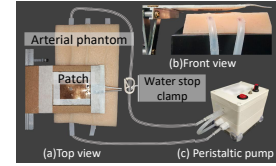


Fig. 16. The layout of the established phantom.

shifts the artery from the hotspot. Therefore, the next step focuses on homogenizing the field and lowering the operating frequency to meet the CDC specification.

4.2.3 Further Frequency Reduction and Field Shaping. The parametric optimization of the basic planar spiral (PS) structure is fundamentally limited by wearable-level size, manufacturability, and cost constraints, preventing it from reaching the CDC's target frequency range and from providing a more uniform electric field distribution.

To overcome this bottleneck, an interesting phenomenon in wireless power transfer (WPT) systems inspires us: the resonant frequency of a coil decreases as it is brought closer to the read antenna, due to the introduction of a significant parasitic capacitance between them [21]. Therefore, we introduce a coplanar loop microstrip antenna surrounding the pre-optimized PS structure, as shown in Figure 12(a). The intention is to deliberately create a controlled parasitic capacitance between the loop and the PS structure to further lower the system's resonant frequency. Specifically, the equivalent circuit of this combined structure is shown in Figure 12(b), where R_{Loop} and L_{Loop} represent the resistance and inductance of the loop antenna, respectively. C_{PS} is the capacitance of the optimized PS structure, and C_{ext} models the extra coupling capacitance. At this time, C_{ext} effectively adds in parallel to C_{PS} , and the totally operating frequency can be formulated as [21]: $f_c = \frac{1}{2\pi\sqrt{L_{PS}(C_{PS}+C_{ext})}}$. We can find that the operating frequency f_c will be decreased due to the equivalent capacitance increase.

We conduct the simulation to verify the existence of the C_{ext} . Specifically, we fix the pre-optimized PS structure, equip a loop antenna that keeps a gap of 0.2 mm away from the PS structure, and set the line width to 0.5 mm, as shown in Figure 14(a). We evaluate the electric field distribution in the gap area, and we can observe that the strong electric field is concentrated in the slot between the loop and the PS, as shown in Figure 13. It implies that the extra capacitance C_{ext} exists in the structure. Then, we verify the operating frequency of the PS equipped with the loop antenna; the operating frequency decreases from 162 MHz to 86 MHz compared with the optimized PS structure without a loop antenna. Meanwhile, a key observation is as follows:

Observation: Compared with the electric field distribution on the target sensing area (bottom of the patch at 1 mm) of the original optimized PS structure as shown in (Figure 14(c)), PS structure equipped with a loop antenna shows a more uniform electric field distribution on the target sensing area. The loop antenna acts as

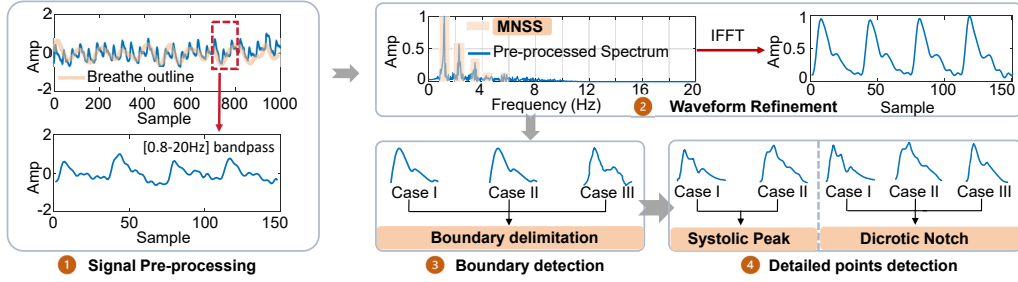


Fig. 17. The framework of the software design.

a boundary that reflects and confines field lines, thereby improving field strength and uniformity for sensing, according to the principle in [29].

System Integration with Commercial Readout Circuit. After the structural optimizations, the electric field distribution becomes strong and uniform. Although the resonant frequency of the patch reduces in a large range, it still falls outside the optimal operating range of low-cost, commercial CDCs, such as the FDC2214. In addition, the fabrication and cost limit us from further reducing the operating frequency by patch design.

To solve this issue, our key idea is to bridge this final frequency gap, assisted by the outer external Interface, rather than the patch itself. Specifically, we totally combine the patch and an extra external LC matching network into the readout circuit inspired by the maximum RF frequency limitation method [69] in commercial CDC. This approach allows us to fine-tune the system's overall resonant frequency by setting the capacitance and inductance values of the LC network. Besides, since the patch does not change anymore, it implies that the patch can still maintain the compact form factor, low-cost fabrication, and uniform electric field distribution. Specifically, following the FDC2214 design [23], the operating resonant frequency should remain below 10 MHz. The resonant frequency is given by $f = \frac{1}{2\pi\sqrt{L_0(C_0+C_p)}}$, where L_0 and C_0 denote the external inductor and capacitor, respectively, and C_p denotes the intrinsic capacitance of the sensing patch. We select $C_0 = 33$ pF and $L_0 = 18$ μ H, which generate an unloaded resonant frequency of approximately 6.5 MHz. When the patch is attached to different users, the patch and skin interface introduces an additional capacitance in parallel with the resonant system, further reducing the resonant frequency. Therefore, the system remains safely below the 10 MHz operating limit after integration with the patch and the user body, without requiring extra tuning for patch- or user-dependent variations.

To verify the total frequency, we fabricate the patch using the process shown in Appendix A. The prototype of the patch is shown in Figure 26 (a), which is flexible and waterproof. We connect the optimized patch to the hardware equipped with the LC network (the layout of the hardware is shown in Figure 26 (b)). The total frequency is shown in Figure 15, and we see it satisfies the maximum frequency of commercial CDC. Then, we verify the in-vitro sensing performance for HYGIEIA. Specifically, we construct an arterial flow phantom (Figure 16). We fix the distance from the patch to the phantom surface at 1 mm. A peristaltic pump simulates pulsatile blood flow, while a vascular clamp introduces reflections to mimic arterial compliance. The unprocessed signal captured from HYGIEIA under these simulated physiological conditions is presented in Figure 18(a). The patch clearly captures every hemodynamic-induced vessel pulsation, verifying our design.

5 OBTAIN HEMODYNAMIC INDICATORS

In this section, we present a generic pipeline for extracting physiological details from the raw hemodynamic waveforms. As shown in Figure 17, the signal processing chain consists of three main stages. First, a second-order Butterworth bandpass filter is applied to remove low-frequency components (DC drift and respiration) and high-frequency hardware noise. Second, to suppress in-band noise while preserving the waveform morphology,

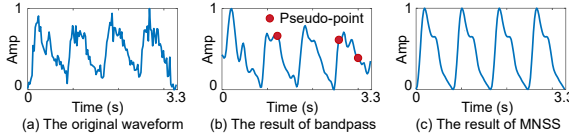


Fig. 18. The results of different filter methods.

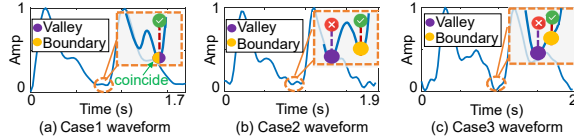


Fig. 19. Three cases in the segment boundary.

we design a multi-narrowband splicing scheme (MNSS) that reconstructs a clean waveform from the filtered signal. Finally, we developed a generalized feature detection method to obtain precise hemodynamic indicators across diverse user waveforms by localizing cycle boundaries, systolic peaks, and the diastolic notch.

5.1 Hemodynamic Waveform Reconstruction

In this section, we concentrate on how to refine the hemodynamic waveforms out of the multiple noise.

Signal pre-processing. We first apply a second-order Butterworth bandpass filter from 0.8 Hz to 20 Hz because this band retains the physiological waveform. Frequencies below 0.8 Hz are typically unrelated to carotid hemodynamic and are dominated by DC drift and respiration [22], whereas the relevant hemodynamic content lies mainly below 20 Hz [11]. However, bandpass filtering alone cannot remove noise that overlaps with the band of interest. As shown in Figure 18(b), the filtered signal still contains in-band noise that distorts the hemodynamic waveform, especially in its fine-grained details. These residual artifacts can severely degrade the accuracy of hemodynamic indicators that are sensitive to waveform shape.

Multi-narrowband splicing scheme (MNSS). To further suppress the remaining artifacts, we separate physiologically relevant components from irrelevant components within the passband. However, identifying artifact frequencies is difficult because their spectral content is highly uncertain and time-varying, making them hard to pinpoint and selectively filter. Fortunately, clinical pulse-wave analysis shows that most cardiac information is concentrated near the fundamental frequency (i.e., heart rate) and a few low-order integer harmonics (e.g., components related to the diastolic notch and reflected waves) [13]. Therefore, HYGIEIA focuses on extracting the fundamental and its harmonics from the interesting band.

A straightforward approach is to retain discrete spectral lines at the fundamental and integer harmonics. However, real pulse waves are quasi-periodic due to heart-rate variability, which introduces cycle-to-cycle jitter, harmonic drift, and spectral broadening. As a result, reconstructing the waveform from fixed spectral lines is unreliable and fails to accurately recover hemodynamics.

To address this issue, we propose a multi-narrowband splicing scheme (MNSS). Instead of sampling the spectrum at isolated harmonic lines, MNSS preserves ultra-narrow bandpass slices centered at the fundamental and its harmonics. These slices are wide enough to capture harmonic drift caused by quasi-periodicity, yet narrow enough to limit the noise bandwidth, thus balancing drift coverage and signal-to-noise ratio (SNR) while preserving hemodynamics. Specifically, we first estimate the fundamental frequency f_0 , which corresponds to the heart rate [53], by locating the dominant spectral peak within 0.8–2 Hz:

$$f_0 = \arg \max_{f \in [0.8, 2]} |X(f)|. \quad (9)$$

where $X(f)$ is the frequency spectrum of the waveforms after pre-processing. We then determine the harmonics components $f_k = kf_0$ for $k = 1, \dots, K$ in $X(f)$. Around each harmonic, MNSS uses an ultra-narrow bandpass in width of B to preserve a sub-spectrum. In our system, the bandwidth B is set to 0.5 Hz. This value was selected via a sweep over candidate B that balances drift coverage and SNR (see Section 7.4 for more details). The ultra-narrow bandpass filter can be represented as:

$$H_k(f) = \begin{cases} 1, & \text{for } |f - f_k| \leq \frac{B}{2} \\ 0, & \text{Otherwise} \end{cases} \quad (10)$$

Each selected sub-spectrum is $\hat{X}_k(f) = X(f)H_k(f)$. Then, we splice all sub-spectra to yield the final spectrum, which can be represented as: $X'(f) = \sum_{k=1}^K \hat{X}_k(f)$. After obtaining the reconstructed spectrum $X'(f)$, we turn the waveform to the time domain via inverse transform, which can be formulated as:

$$y_r(n) = \mathcal{F}^{-1} \{X'(f)\} \quad (11)$$

where n is the sample index of the received waveform.

To evaluate the performance of MNSS, we apply MNSS to the waveform after pre-processing. The result is shown in Figure 18(c), it can be observed that MNSS can effectively filter out artifacts within the band and preserve waveform details that are related to hemodynamics.

5.2 Details of Feature Extraction from Hemodynamic Waveform

In this section, we introduce how to extract the detailed hemodynamic information, such as the cycle boundary, systolic peaks, and dicrotic notch.

5.2.1 Segment the Boundary of the Hemodynamic Waveform. After reconstructing the hemodynamic waveform, we aim to identify the cycle boundary of the waveform, which is essential for extracting the cycle-resolved hemodynamic indicators, like heart rate (HR) and ejection duration index (EDx).

Existing methods typically regard the lowest valley between the two systolic peaks as the cycle boundary, and detect the valley by exploiting valley detection or self-correlation-based matching [47]. Unfortunately, our dataset of 110 participants shows that the lowest valley can not serve as a universal segmentation criterion, as cycle boundaries exhibit three distinct morphological patterns. Specifically:

(i) Case 1: As shown in Figure 19(a), after the diastolic phase ends, arterial pressure reaches its lowest value as blood returns to the heart. When a new cardiac cycle begins, the heart ejects blood into the arteries, and the pressure rises rapidly, forming the systolic upstroke. In this pattern, the cycle boundary is well defined as the lowest valley between two adjacent cycles, overlapping with the onset of the rapidly rising edge.

(ii) Case 2: The second case corresponds to a waveform commonly observed in subjects with arteriosclerosis (Figure 19(b)). A small secondary wavelet appears near the end of the cycle, introduced by reduced vascular elasticity and the resulting pressure surge when reflected waves return during late diastole. In this situation, the cycle boundary is no longer the lowest valley, but instead the onset of the rapidly rising edge.

(iii) Case 3: The third case is a special situation of Case 2 (Figure 19(c)). Here, the pressure increase caused by the returning reflected wave persists until the next cycle begins, so the new systolic upstroke starts from an already elevated pressure level. In this waveform, the boundary of the cycle is still not the lowest valley, but becomes the point where the slope of the rising edge changes.

We therefore propose the Adaptive Period Segmentation Algorithm (APSA), a detection method capable of adaptively distinguishing cycle boundaries to achieve high-accuracy segmentation across heterogeneous waveform patterns. The design of APSA is driven by the following key observations:

Observation 1: Across all three waveform cases, as shown in Figure 20, we observe two characteristic points consistently existing within each of the two adjacent valleys (marked in yellow). Specifically, the first point is the fastest rising point in the systolic branch, which corresponds to the maximum peaks in the derivative waveform (marked in orange). We define it as the anchor. The second point is the first local valley point on the left of the anchor. We define it as the zero-crossing (marked in green).

Observation 2: The cycle boundary can be determined by examining the monotonic behavior of the waveform segment between the zero-crossing and the anchor. Specifically, if the waveform rises monotonically in this

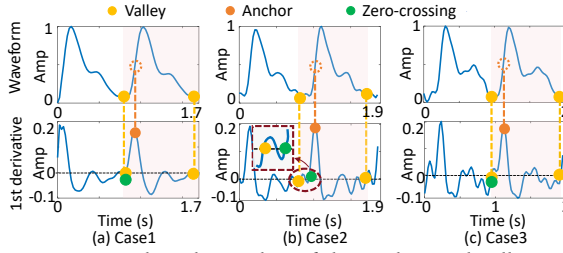


Fig. 20. The relationship of the anchor and valley.

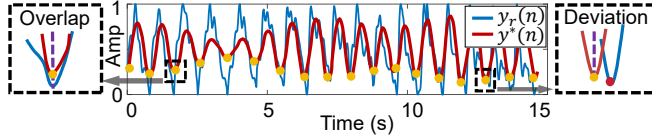
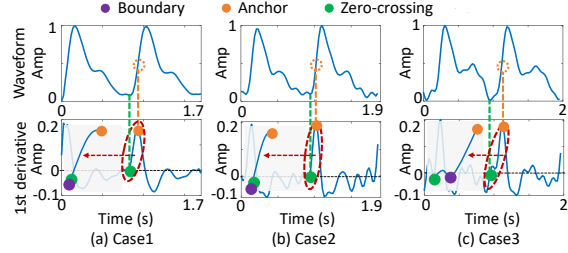
Fig. 22. The relationship between the $y^*(n)$ and $y_r(n)$.

Fig. 21. The monotonic of different cases.

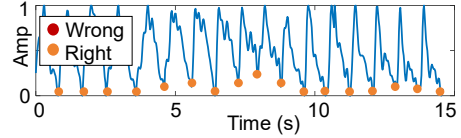


Fig. 23. The results of real valley detection.

interval, the zero-crossing is taken as the cycle boundary, as shown in Figure 21(a) and (b). In contrast, in Figure 21(c), the segment is not monotonic. Here, a new cardiac contraction begins before diastole completes; the resulting pressure surge alters the rate of increase, generating an extra deflection and a local trough between the zero-crossing and anchor point. In this scenario, we can define the local trough as the hemodynamic cycle boundary.

Based on the two observations above, our strategy is to first identify valley points and then use them to localize the anchor and zero-crossing points. We then examine the monotonicity of the waveform between the zero-crossing and the anchor to discriminatively determine the cycle boundary under different waveform cases.

However, reliably detecting valley points is non-trivial. Fine-grained morphological features in hemodynamic waveforms — such as the dicrotic notch — can create additional local minima (i.e., interference) that are easily misclassified as valleys. Simple heuristics attempt to solve the issue, such as setting an adaptive amplitude threshold. But it faces the calibration across population diversity due to the inter-individual variations in vascular pressure, which increases the burden of detection in practice. To tackle this challenge, APSA includes the following steps.

Valley detection. To eliminate interference caused by fine-grained hemodynamic features, we first extract the fundamental (heart-rate related) components $y^*(n)$ from $y_r(n)$, preserving only the dominant cyclical heartbeat information while excluding finer morphological details that cause valley detection errors. Since the waveform $y^*(n)$ at this time is a quasi-sine wave, we can easily capture the valley C_v^{i*} in the i^{th} cycle of such a smooth waveform, as shown in Figure 22. However, due to the loss of high-frequency harmonic information compared to the original waveform $y_r(n)$, which leads to the slight shift between C_v^{i*} and the ground-truth valley C_v^i .

To compensate for this offset, since the ground-truth valley C_v^i is highly correlated with the cardiac cycle, and the fundamental frequency component f_0 reflects the frequency of that cardiac cycle (i.e., heart rate), the offset range of the real valley is naturally constrained to a certain proportional neighborhood of the cycle duration, using the cycle length corresponding to f_0 as a reference. Based on this, we propose a dynamic thresholding method that adapts to the fundamental frequency cycle to accurately locate the true trough within this neighborhood. This method can be expressed as:

$$C_v^i = \underset{n \in [C_v^{i*} - \xi, C_v^{i*} + \xi]}{\operatorname{argmin}} y_r(n). \quad (12)$$

where ξ is a sample-level threshold, which can be calculated as:

$$\xi = \text{floor}(cf_s/f_0) \quad (13)$$

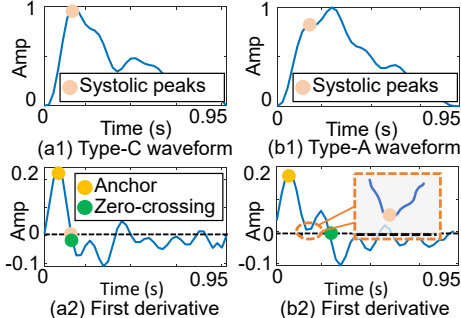


Fig. 24. The two different systolic cases.

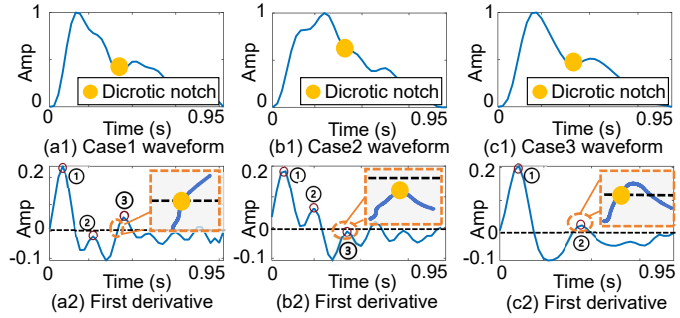


Fig. 25. The three different dicrotic notch cases.

we set the percentage value $c = 30\%$ in our system (the choice is evaluated in Section 7.1), and f_s is the sampling rate of the waveform. The valley detection results are shown in Figure 23, and we can see the valley C_v^i can be detected correctly.

Discriminative Boundary Detection. After locating the valley C_v^i , the anchor C_a^i can be captured as:

$$C_a^i = \underset{n \in [C_v^{i-1}, C_v^i]}{\operatorname{argmax}} y'_r(n) \quad (14)$$

the first zero-crossing C_z^i on the left of the anchor C_a^i is located by finding where its first derivative equals zero.

Therefore, based on Observation 2, the boundary of different cases can be detected reliably according to the monotonicity between the $[C_z^i, C_a^i]$ period. If monotonicity exists within a certain interval $[C_z^i, C_a^i]$, the boundary C_b^i is the zero-crossing C_z^i . Otherwise, C_b^i is the trough point within the period, which can be detected by:

$$C_b^i = \begin{cases} \max\{n \in [C_v^{i-1}, C_a^i] | y'(n) = 0\}, & \text{if } [C_z^i, C_a^i] \text{ exists monotonicity} \\ \max\{n \in [C_z^i, C_a^i] | y'(n+1) > y'(n)\}, & \text{Otherwise} \end{cases} \quad (15)$$

5.2.2 Extract the Systolic Peaks and Dicrotic Notch Point of the Hemodynamic Waveform. In this section, we detect the systolic peak and dicrotic notch, which are required to derive hemodynamic indicators, such as systolic duration (SD) and left ventricular ejection time (LVET).

Systolic peak detection. The prior solution focuses on detecting the peaks in each cycle as the systolic peak [64]. Although it performs well in *Type-C* in cardiovascular medicine [27, 52], it fails to distinguish *Type-A* waveforms since the systolic peak is not the highest point within a waveform cycle, as shown in Figure 24(a1,b1).

To reliably detect systolic peaks across different waveform types, we observe that they can be determined by examining the monotonic behavior of the waveform segment between the anchor point C_a^i and the first zero-crossing C_{rz}^i to its right. If the waveform rises monotonically over this interval, the zero-crossing C_{rz}^i is taken as the systolic peak, as in *Type-C* (Figure 24(a)). In contrast, in *Type-A* waveforms (Figure 24(b)), the segment between C_a^i and C_{rz}^i is not monotonic. After the true systolic peak, the waveform continues to rise but with a reduced slope, causing the first derivative to exhibit an additional local maximum within this interval. In this case, we locate the systolic peak at this local maximum of the derivative rather than at the zero-crossing. Specifically:

$$C_s^i = \begin{cases} \min\{n \in [C_a^i, C_{rz}^i] | y'(n) = 0\}, & \text{if } [C_a^i, C_{rz}^i] \text{ exists monotonicity} \\ \min\{n \in [C_a^i, C_{rz}^i] | y'(n+1) > y'(n)\}, & \text{Otherwise} \end{cases} \quad (16)$$

Dicrotic notch detection. Traditional methods typically rely on detecting the first zero-crossing after the secondary inflection as the dicrotic notch [31], or the first zero-crossing after the systolic peaks [14]. However, the morphology and distribution of the three different types of dicrotic notches indicate that the existing solution, which relies on single fixed rules, is not universally applicable:

(i) Case 1: The waveform pattern is shown in Figure 25(a1), where the dicrotic notch appears as the valley preceding a minor secondary peak. In the first derivative of the waveform (Figure 25(a2)), the dicrotic notch corresponds to the first zero-crossing point to the left of the third peak (marked in yellow).

(ii) Case 2: With elevated vascular stiffness [49], the segment following the dicrotic notch shows no upward trend but rather a slower descent, as shown in Figure 25(b1). This phenomenon leads to the notch point coinciding with the third peak in the first derivative waveform, as shown in Figure 25(b2).

(iii) Case 3: As shown in Figure 25(c1), the waveform does not exist the reflect wave after the systolic peak. In cardiovascular medicine, this waveform case is defined as *Type-B* [19]. It implies that the dicrotic notch's location changes completely, as shown in Figure 25(c2), we can observe that the dicrotic notch's relative position transfers from the third peak to the second peak compared with Case 1.

To accurately detect the dicrotic notch under varying conditions, we propose an algorithm that adaptively identifies waveform cases for dicrotic notch detection. Our solution is driven by the following observation.

Observation 1: The dicrotic notch appearance is related to the closure of the left ventricle. The duration of left ventricular openness (from the onset of the waveform to the dicrotic notch) typically accounts for less than 50% of the entire cardiac cycle [42]. Therefore, if a reflected wave exists, the first derivative of the waveform will form three peaks during the duration of left ventricular openness (less than 50% of the cardiac cycle) as shown in Figure 25(a2,b2), caused by the rapid rise, the reflected wave, and the dicrotic notch. Conversely, if a reflected wave is absent, only two peaks are present within this time frame (caused by the rapid rise and the dicrotic notch) as shown in Figure 25(c2). Therefore, once we determine the number of peaks in the first 50% duration of the waveform's first derivative, we can filter whether the waveform belongs to Case 3. Furthermore, by comparing Case 1 and Case 2, we can easily distinguish which waveform belongs to which according to the sign of the third peak. If it is positive, the waveform belongs to Case 1. Otherwise, it belongs to Case 2.

Observation 2: Once the case of the waveform is identified, the dicrotic notch can be captured as the first zero-crossing on the left of the second peak for Case 3, as shown in Figure 25(c2). In contrast, if Case 1 occurs, the dicrotic notch is the first zero-crossing on the left of the third peak, as shown in Figure 25(a2). Otherwise, for Case 2, Figure 25(b2) shows the dicrotic notch can be regarded as the third peak on the waveform's first derivative.

Based on the two observations above, our strategy is to first classify the waveform case by analyzing the number and locations of peaks in the first derivative over the early portion (ie, within the $[C_b^{i-1} + 1, \frac{C_b^i}{2}]$, C_b^i is the boundary of i^{th} cycle) of each cycle. We then focus on detecting the dicrotic notch accordingly. Specifically, in the first derivative waveform of the i^{th} cycle, each local peak corresponds morphologically to an inflection point where the waveform rises and then falls. Therefore, we capture inflection points by analyzing the point-wise difference waveform $d^i(n)$, which reflects rising/ falling trends and is defined as:

$$d^i(n) = y'(n+1) - y'(n), n \in [C_b^{i-1} + 1, \frac{C_b^i}{2}] \quad (17)$$

If the $d^i(n)$ is negative, and the $d^i(n-1)$ is positive, it implies that the index n is a local peak. To statistic the total peak number, we introduce $N_p = \sum_{n=2}^{N-1} (I(n))$, where $I(\cdot)$ is an indicator function. If n is a local peak, $I(n) = 1$. Otherwise, $I(n) = 0$. In addition, we can capture the k^{th} peak location by:

$$n_k^i = \min \left\{ n : \sum_{n=2}^{N-1} I(n) = k, k \leq N_p \right\} \quad (18)$$

Now, if N_p is equal to 2, we can identify that the waveform belongs to Case 3. Besides, if N_p is equal to 3, and the value of the third peak $y'(n_3^i)$ is positive, the waveform belongs to Case 1. Otherwise, it belongs to Case 2.

After identifying the waveform category adaptively, the dicrotic notch C_{dic}^i is detected as follows:

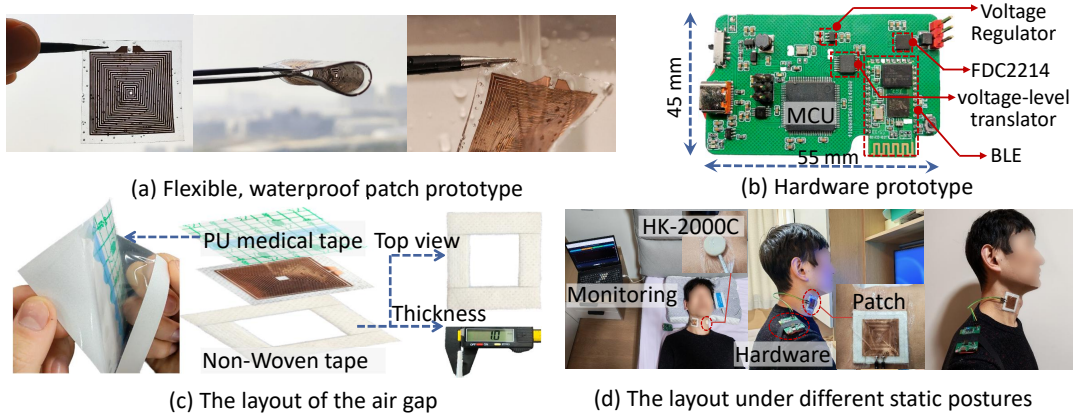


Fig. 26. Prototype and layout of the system.

$$c_{dic}^i = \begin{cases} \max\{n \in [c_b^{i-1}, n_2^i] \mid y'(n) = 0\}, & \text{if } N_p = 2 \\ \max\{n \in [c_b^{i-1}, n_3^i] \mid y'(n) = 0\}, & \text{if } N_p = 3 \mid y'(n_3^i) > 0 \\ \max\{n \in [c_b^{i-1}, n_3^i] \mid y'(n+1) < y'(n)\}, & \text{if } N_p = 3 \mid y'(n_3^i) < 0 \end{cases} \quad (19)$$

Totally, we can accurately extract the fine-grained morphological characteristics of hemodynamic waveform across the diversity of patterns, which assists in the precise extraction of indicators.

6 IMPLEMENTATION

6.1 HYGIEIA Prototype

The prototype of the patch. The prototype production process is introduced in Appendix A. The prototype is shown in Figure 26(a). It exhibits significant flexibility, facilitating folding. Furthermore, the PDMS encapsulation grants the patch the critical property of being washable, enhancing its practicality for long-term wearable use.

Hardware controller implementation. The hardware layout is shown in Figure 26(b), which comprises a high-performance MCU (ATMEGA2560-16AU), a capacitance-to-digital converter (FDC2214) to detect frequency shift of the system, and a Bluetooth module (HC-05) for wireless data transmission. Furthermore, a bidirectional voltage-level translator (TXS0104EPWR) ensures signal compatibility, and a step-down regulator (RT9013-33GB) provides stable power. Under a supply voltage of 3.7 V, the power consumption of each of the above components is as follows: 22.2 mA, 2.1 mA, 10 mA, 50 mA, and 0.05 mA. The power consumption of HYGIEIA's hardware is about 84.35 mA. In our system, the prototype is powered by a rechargeable 2000 mAh lithium battery commonly used in consumer electronics and medical devices [1], which can support up to 23.7 hours of continuous operation. In another way, we can use a smaller and lighter button battery, such as the PKCELL CR3032 with 500 mAh, to enable 6 hours of continuous monitoring. The hardware cost of HYGIEIA is approximately 19 USD.

Practical Consideration. As mentioned in Section 4.1, HYGIEIA relies on an air gap for sensing. Considering stability and user comfort, we use medical-grade non-woven fabric tape to create a 1 mm thickness support around the bottom edges of the patch to provide a stable air gap, as shown in Figure 26(c). Additionally, to ensure the patch does not shift during slight user movements, we applied medical-grade transparent waterproof PU tape to the top of the patch. This allows the patch to remain relatively stationary on the user's carotid.

Data Collection. We recruit a total of 110 volunteers (52 males, 58 females) with different ages (8–62 years old), weights, and heights (BMI ranges from 17.3 to 31.2). The ground truth is obtained by the HK-2000C pulse sensor [4]. The volunteer is advised to keep quiet to avoid extra interference. The related experiment layout is

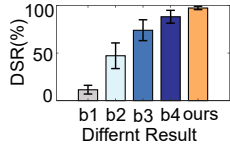


Fig. 27. Verification of the periodic segmentation algorithm.

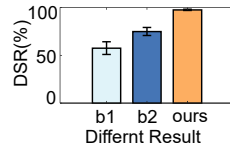


Fig. 28. Verification of the systolic peak detection algorithm.

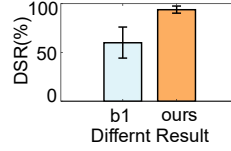


Fig. 29. Verification of the dicrotic notch detection.

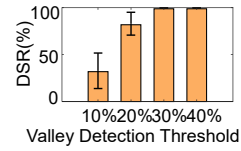


Fig. 30. Verification of the choice of percentage value in APSA.

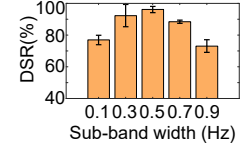


Fig. 31. Verification of the choice of sub-band in MNSS.

shown in Figure 26(d). Each volunteer collects data both in the patch and in the ground truth. Everyone is asked to fill out a Questionnaire for the UX study. This research protocol has been approved by our IRB.

Metric. In order to verify the performance of HYGIEIA in different aspects. We evaluate it in different metrics as follows: (i) *similarity in waveform*: We use three common metrics to evaluate the similarity of waveform between ground-truth and HYGIEIA, which are Pearson correlation coefficient, Cosine Similarity, and Cross-Correlation. (ii) *Detect success rate (DSR)*: We use the detect success rate to verify the algorithm with baselines. It reflects the proportion of the number of periods N_{succ} in which the relevant points were correctly detected in the N_{all} periods. A higher result indicates a more effective algorithm. It is calculated as: $DSR = \frac{N_{succ}}{N_{all}}$. (iii) *Mean Absolute Error (MAE)*: We use six strict indicators to evaluate HYGIEIA's overall performance, including three time-based indicators (LVET, SD, DD); two ratio-based indicators (EDx, S/D); and HR. For each of the indicators, we calculate the MAE between our estimate and the ground truth, the mean absolute difference between the estimated value (denoted by V^E) and the ground truth (denoted by V^T). It can be defined as: $MAE = \frac{1}{N} \sum_{i=1}^N |V_i^E - V_i^T|$

7 EVALUATION

7.1 Micro-Benchmark

Verification of Cycle Segmentation Algorithm. We compare it against three baselines using data from 10 participants to evaluate the cycle-boundary detection algorithm. Baseline 1 (B1) exploits the self-correlation, Baseline 2 (B2) applies valley detection directly; Baseline 3 (B3) uses the real valley points as boundaries (Sec. 5.2.1); Baseline 4 (B4) takes the first zero-crossing point left of the anchor point as the boundary. As shown in Figure 27. The average DSR for the boundaries is 11.5%, 47.3%, 74.1%, 88.3%, and 97.5%. B1 and B2 perform worst, failing to segment Case 2 and 3 correctly and even introducing errors in Case 1; in contrast, B3 and B4 maintain high accuracy for Cases 1 and 2 but fail on Case 3. In contrast, our algorithm correctly identifies boundaries across all three waveform types, demonstrating its robustness and effectiveness.

Verification of Systolic Peak Detection. We evaluate our systolic peak detection algorithm against the Baseline 1 (B1), which directly detects all local peaks; Baseline 2 (B2) locates the first zero-crossing point to the right of the anchor point. As shown in Figure 28, the average Detection success rate (DSR) are 57.6%, 75.1%, and 97.7%. B1 often identifies multiple local peaks per cycle, lacking robustness; B2 performs well for Type-C but fails for Type-A waveforms, as detailed in Section 5.2.2. In contrast, our algorithm is robust and effective, correctly identifying boundaries across all three waveform types.

Verification of Dicrotic Notch Detection. We evaluate our dicrotic notch detection algorithm against a zero-crossing detection baseline (B1) [31]. As shown in Figure 29, our method achieves an average accuracy of 93.9%, outperforming B1. This is because B1 only works reliably on normal waveforms (Figure 25(a1)), whereas our divide-and-conquer approach correctly identifies all waveform cases.

Validation of the percentage c in the threshold in APSA. According to Eqn. 14, the choice of the time percentage c directly influences the search range for detecting the real valley. We evaluate from 10% to 40% in 10% increments. As shown in Figure 30, the DSR for valley detection improves with c and stabilizes at 30%, where the search neighborhood reliably contains the true troughs. Therefore, we select this value for implementation.

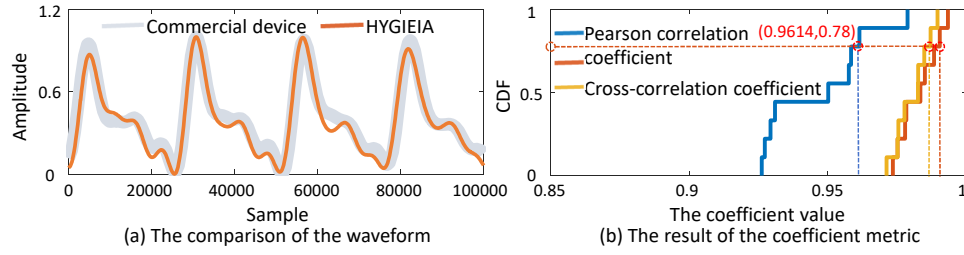


Fig. 32. The results of the waveform similarity.

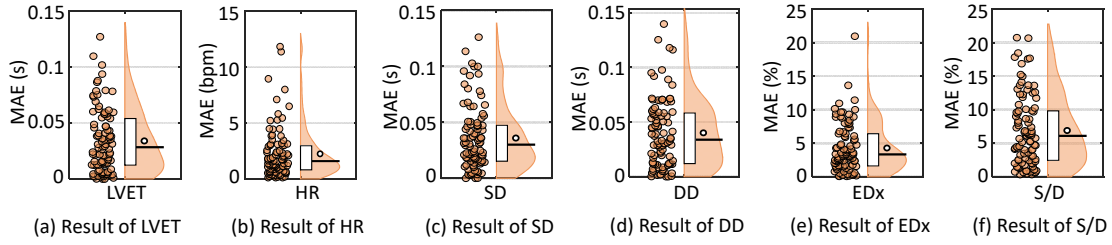


Fig. 33. The overall performance under population diversity.

Validation of the Sub-band Width B in MNSS. According to Eqn. 10, the sub-band filter performance depends on the chosen bandwidth. We therefore evaluate from 0.1 Hz to 0.9 Hz in steps of 0.2 Hz, using DSR of the dicrotic notch as the performance metric. As shown in Figure 31, the mid-range bandwidth values yield higher DSR. This is because a too-narrow bandwidth tends to lose fine morphological details such as the dicrotic notch, while a too-wide bandwidth expands the passband beyond the relevant harmonic components and introduces more extra noise. We select a 0.5 Hz bandwidth to balance detail preservation and noise suppression.

7.2 Waveform Similarity Compared with Ground Truth

To evaluate waveform quality, HYGIEIA's output (right carotid artery) is compared with ground truth from a commercial sensor on the left carotid artery while volunteers lie supine. Both signals are processed through the same pipeline; interpolation aligns data lengths due to different sampling rates for detailed comparison. As shown in Figure 32(a), the waveforms closely match. Cumulative distributions of three similarity metrics (Figure 32(b)) indicate that approximately 78% of the data distribution achieves above 96.14% similarity for all metrics. Validating the accuracy, stability, and robustness of HYGIEIA for continuous arterial waveform monitoring.

7.3 Overall Performance under Person Diversity

We evaluate the overall performance of the system using data from 110 volunteers, with 97 subjects providing valid samples after quality screening. As shown in Figure 33, the average MAE for HR is around 2.3 bpm. Moreover, the MAE for SD, DD, and LVET are all below 0.04 s, demonstrating high accuracy in locating systolic peaks and the dicrotic notch. The derived indices S/D and EDx also show low errors, with average MAE are below 7.1% and 4.3%, respectively. A small number of recordings exhibit slightly larger deviations from the mean, likely due to inherent physiological variations during measurement. Nevertheless, the high consistency observed across the vast majority of samples underscores the reliability and practical applicability of the system in real-world scenarios. Overall, these results validate the robustness and accuracy of HYGIEIA across different individuals.

Subgroup performance. To further examine the calibration-free generalization of HYGIEIA across heterogeneous users, we analyze its performance on different subgroups, including age, gender, and BMI. Specifically, we divide the age subgroup into younger than 20 years old, older than 60 years old, and mid-age. For the BMI subgroup,

Table 3. The result of subgroup analysis.

Indicators error	Gender				Age						BMI					
	Male		Female		Age < 20		Mid age		Age > 60		BMI < 18.5		Normal		BMI > 24.9	
	Mean	PSD	Mean	PSD	Mean	PSD	Mean	PSD	Mean	PSD	Mean	PSD	Mean	PSD	Mean	PSD
LVET (s)	0.033	0.027	0.033	0.028	0.023	0.019	0.034	0.028	0.037	0.023	0.025	0.016	0.032	0.028	0.046	0.029
HR (bpm)	2.04	2.08	2.49	2.40	3.20	2.51	2.17	2.22	2.83	2.24	3.23	1.98	2.17	2.28	2.49	2.28
SD (s)	0.033	0.025	0.040	0.031	0.027	0.02	0.038	0.030	0.027	0.014	0.042	0.021	0.036	0.029	0.041	0.035
DD (s)	0.036	0.028	0.041	0.031	0.049	0.049	0.038	0.027	0.020	0.013	0.058	0.037	0.036	0.029	0.046	0.020
EDx (%)	3.94	3.28	4.34	3.60	2.65	2.14	4.35	3.57	4.08	2.94	4.03	2.14	4.05	3.60	5.54	3.04
S/D (%)	6.02	4.92	7.91	5.64	5.54	4.38	7.34	5.56	5.25	2.75	8.53	3.67	6.85	5.39	7.87	6.87

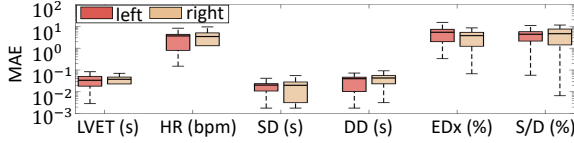


Fig. 34. The result of different sides.

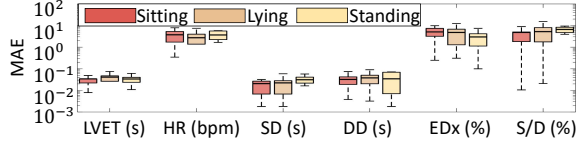


Fig. 35. The result of different static postures.

we divide into three subgroups: overweight (BMI>24.9), underweight (BMI<18.5), and normal [2]. The total number in each subgroup is 55 and 42 for females and males. The number of each age subgroup is 10, 3, and 84. The number of underweight, normal, and overweight is 9, 80, and 8. For each subgroup, we calculate the mean absolute error (MAE) of the estimated physiological indicators. For each group, we calculate the average of MAE and the Population Standard Deviation (PSD) of MAE to reflect the variability. The results are summarized in Table 3. Overall, HYGIEIA achieves consistently good performance across different age, gender, and BMI groups, demonstrating its robustness to inter-user variations. For the gender subgroup, the MAE of male participants is slightly lower than that of female participants across all indicators. This is because males generally have larger hearts and greater blood ejection volume, which can produce stronger pulse-induced vessel vibrations [58]. For the BMI subgroup, the overweight group shows slightly higher errors than the normal weight group. One possible reason is that the blood vessels of overweight participants are farther from the skin surface, leading to higher attenuation of pulse-induced vibrations before being captured by the patch.

7.4 The Impact of Various Factors

Impact of different attachment sides. To assess bilateral compatibility, we deploy sensor patches on both left and right carotid arteries of volunteers, collecting five independent datasets per side alongside reference measurements from a commercial device. Performance results in Figure 34 show that the MAEs for time-related indicators on the left/right sides are: LVET = 0.034 s / 0.038 s; SD = 0.020 s / 0.020 s; DD = 0.040 s / 0.043 s. For ratio-based indicators, MAEs are EDx = 5.33% / 3.74% and S/D = 4.32% / 4.60%. Heart-rate MAEs are 3.63 bpm (left) and 3.41 bpm (right). The overall differences between sides are subtle, indicating that HYGIEIA provides reliable bilateral detection and allows users to freely choose the monitoring side without compromising accuracy.

Impact of different user postures. We evaluate HYGIEIA's performance across three stationary postures: sitting, lying, and standing. Results are shown in Figure 35. For time-based parameters (LVET, SD, DD), the average range (min/max) of MAE for different postures is 0.034 s / 0.041 s, 0.021 s / 0.031 s, and 0.032 s / 0.038 s. For ratio-based indicators (EDx and S/D), they are 2.97% / 5.08%, 4.79% / 6.65%. Besides, the HR can maintain below 3.74 bpm in all three different postures. The results show HYGIEIA's robust performance across postures.

Impact of different sample rates. We evaluate HYGIEIA's performance at different sampling rates. We change the sample rate from the minimum 43 Sa/s to 229 Sa/s by modifying the internal registers of FDC2214 CDC. The average MAE of all six indicators is shown in Table 4. We observe that the MAE varies slightly at different sample rates. These fluctuations may be due to the influence of noise. For the carotid artery hemodynamic waveform, the frequency band of the signal is within 20 Hz. Therefore, it supports us in selecting the lowest sample rate

Table 4. The performance under different sample rates.

Sample rate (Sa/s)	Indicators					
	LVET (s)	HR (bpm)	SD (s)	DD (s)	EDx (%)	S/D (%)
43	0.020	3.04	0.024	0.044	2.55	3.96
86	0.023	5.45	0.033	0.071	3.45	5.01
136	0.027	4.50	0.040	0.052	3.41	5.63
229	0.050	6.30	0.046	0.091	7.70	8.04

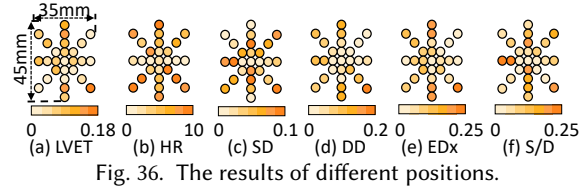


Fig. 36. The results of different positions.

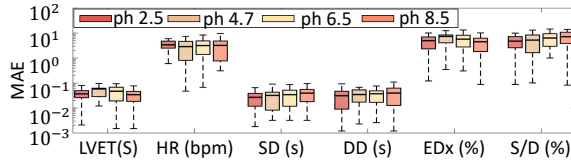


Fig. 37. The result of PH.

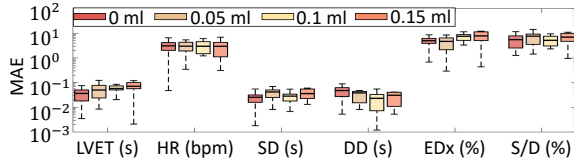


Fig. 38. The result of sweat volume.

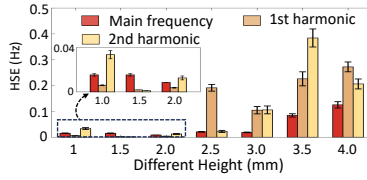
(43 Sa/s) for FDC2214 to collect the signal because it satisfies the Nyquist–Shannon sampling theorem, which is sufficient to capture the details of the hemodynamic waveform without distortion.

Impact of patch position. To verify the tolerance of HYGIEIA during deployment, we find the location of the strongest pulse on the right carotid artery as a baseline. Then we align the patch's center with the reference point. We then move the patch in increments of 5 mm and totally 27 points covered within $45\text{mm} \times 35\text{mm}$. The result is shown in Figure 36. Firstly, we evaluate the internal area within a $15\text{mm} \times 15\text{mm}$ range around the baseline position, the average MAE of the system are: 0.038 s, 2.43 bpm, 0.037 s, 0.035 s, 5.59% and 5.99%. After multiple practical verifications, we prove that users can easily position the patch within this deployment range. Furthermore, we verify the total areas, and the MAE is 0.060 s, 4.76 bpm, 0.050 s, 0.067 s, 10.37%, and 8.77% on average. We observe that as the area becomes larger, the accuracy reduces. This is because as the distance between the patch deployment location and the carotid artery increases, the vibration sensed by the HYGIEIA becomes weaker, leading to a larger error in extracting fine-grained parameters. The results show that the system can tolerate errors introduced by routine deployment, which provides deployment robustness for daily monitoring.

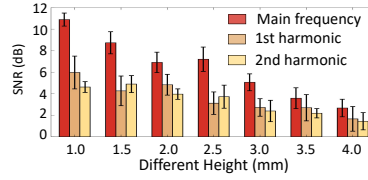
Impact of different sweat pH values. We evaluate the performance under varying sweat pH conditions. Specifically, four different pH levels of artificial sweat (2.5, 4.7, 6.5, and 8.5) are applied in carotid skin equally. The results in Figure 37 shows that under four pH conditions, for EDX and S/D, the MAE ranges from 4.48% to 7.32% on average for different pH levels. The MAE of HR is maintained below 3.38 bpm. The results show HYGIEIA's robustness across sweat pH levels, indicating suitability for use in diverse physiological conditions.

Impact of different degrees of sweat. Specifically, artificial sweat with a pH value of 6.5 is applied below the patch attachment area from 0 ml to 0.15 ml in steps of 0.05 ml. As shown in Figure 38, the comparative analysis of six indicators demonstrates that the MAE in time-based indicators (LVET, SD, DD) is between 0.023 s and 0.071 s; the MAE in ratio-based (EDX, S/D) is between 4.71% and 7.69%; in terms of heart rate (HR), the MAR is less than 3.09 bpm under all sweat degrees. HYGIEIA maintains stable measurement accuracy under different sweat levels, demonstrating its good robustness in practical applications with varying sweating intensities.

The tolerance of the air gap height. To evaluate the robustness of HYGIEIA to variations in air-gap height, we varied the gap from 1 mm to 4 mm in 0.5 mm increments. We use two indicators to evaluate the quality of the captured signal: signal-to-noise ratio $SNR_i = 10 \log_{10}(A_{f_i}/A_n)$, where A_{f_i} is the spectral amplitude of the i^{th} hemodynamic-related harmonic component and A_n is the background noise amplitude; and harmonic spectrum error $HSE_i = |f_i - f_i^g|$, where f_i^g is the ground-truth harmonic frequency. The higher the SNR_i value is, the higher the quality of the captured signal is. On the contrary, since the indicators we extract are highly related to the time dimension, the larger the HSE_i is, the larger the error introduced. In this experiment, we computed both metrics for the main frequency, the first harmonic, and the second harmonic. As shown in Figure 39 (a), the SNR



(a) The result of HSE



(b) The result of SNR

Fig. 39. The result of different air gap heights.

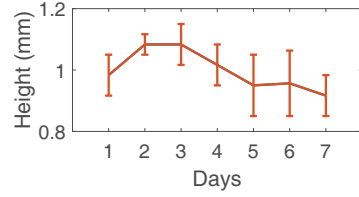


Fig. 40. Air gap height under 7 days.

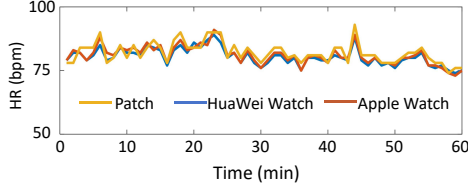


Fig. 41. The result of a one-hour continuous study.

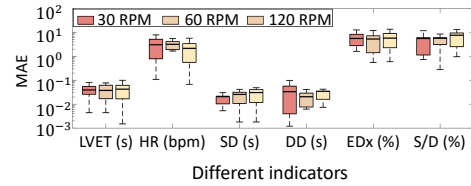
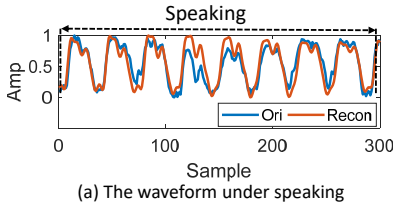
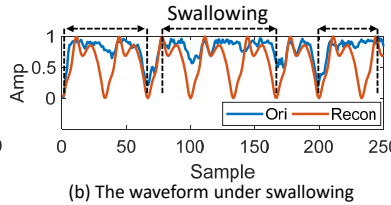


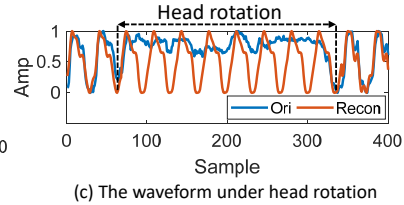
Fig. 42. The monitor feasibility of the mobile scenario.



(a) The waveform under speaking



(b) The waveform under swallowing



(c) The waveform under head rotation

Fig. 43. The performance under different activities.

attenuates as the air gap increases, which is due to the resonant frequency shift becoming smaller. Despite this, as shown in Figure 39 (b), we observe that within a range of 2 mm, HSE_i for each frequency component can be relatively stably maintained at a low level. When the height of the air gap is larger than 2 mm, the HSE_i starts to rise sharply. Therefore, to achieve a strict error limit, we regard the performance tolerance of HYGIEIA as 2 mm.

Impact of air gap collapse. HYGIEIA uses medical-grade non-woven fabric tape to create a 1 mm-thick support layer around the bottom edges of the patch to provide a stable air gap. To verify the impact of potential loss of adhesion or pressure collapse of medical nonwoven fabric during long-term deployment, we deploy the patch on the bionic skin phantom and measure the air gap height over 7 days. The results are shown in Figure 40. We can see that the height variation is less than 0.4 mm, which is within the tolerance range of the system, i.e., 2 mm (See more details in the tolerance of the air gap height in Section 7.3). In the future, we can use more robust air gap designs, such as integrated 3D-printed flexible microstructures [26], or form-stable air gap layers [33] to enhance long-term air gap height reliability.

7.5 Case Study

In this section, we will show the monitor feasibility of HYGIEIA, including the continuous monitoring, dynamic scenario monitoring, and two typical pathological models (acute occlusion and carotid artery stenosis).

One-hour continuous study. We validate HYGIEIA in continuous sensing. Specifically, the user attaches a HYGIEIA patch and keeps a lie position. To compare with commercial devices, the user wears a HUAWEI Watch 5 and an Apple Watch Series 9 on the left and right wrists to record heart rate. The result is shown in Figure 41. The average MAEs of HYGIEIA are only 1.7 bpm and 2.1 bpm compared with two devices, and the total percentage of error is lower than 2.6% on average. It shows the effectiveness of HYGIEIA in continuous hemodynamic monitoring.

Dynamic scenario study. To verify the HYGIEIA performance in dynamic scenarios, we conduct experiments on a low-magnetic-resistance indoor cycling. Specifically, we verify the results at different cadences, ranging

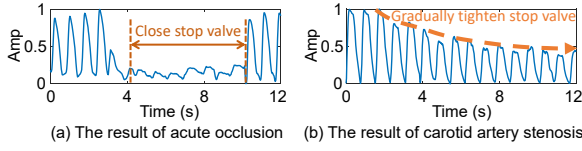


Fig. 44. The result under acute occlusion of the carotid artery simulation.

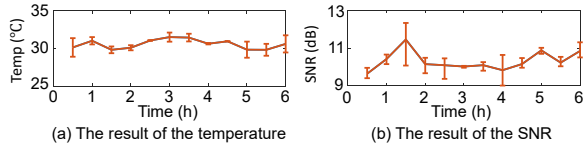


Fig. 45. The result of the hardware performance under continuous six-hour operation.

from 30 RPM to 120 RPM, and the accuracy of the extracted metrics. The experimental results are shown in Figure 42. For time-related metrics, the average MAE results at different RPM are around 0.04 s, 0.03 s, and 0.03 s. For heart rate, the average error at different cadences is less than 3.36 bpm. Furthermore, the error ranges for proportionality-related metrics (EDx, S/D) at different RPM are 5.60% to 6.79% and 6.03% to 7.63%, respectively. Therefore, maintains effective and robust monitoring capabilities under localized limb movements (such as cycling).

Monitoring under daily activities. To verify the effectiveness of HYGIEIA under daily activities, such as swallowing, speaking, and head rotation, the user performs swallowing activities three times, reads personal information one time, and slowly turns the head from left to right. From Figure 43(a), we can see that the high-frequency but small vibration in speaking has less impact on the original waveform. In contrast, from Figure 43 (b,c), the large muscle motion artifacts around the carotid caused by swallowing and head rotation can submerge the hemodynamic details in the original waveform. However, HYGIEIA can work well for all cases. This is because HYGIEIA can filter noise and preserve the hemodynamically relevant components by using the MNSS method. Overall, these results demonstrate that HYGIEIA can achieve robustness under daily activities.

Typical pathological models study. (1) *Acute ischemic stroke (AIS)*: To assess the system's ability to monitor AIS, we employ an in vitro model that simulates arterial occlusion by clamping the vessel (Figure 16). The results (Figure 44(a)) show a significant reduction in waveform amplitude during occlusion, as blocked blood flow prevents new cardiac cycles from propagating. This confirms the feasibility of detecting AIS with our system. (2) *Carotid artery stenosis*: We further evaluated HYGIEIA under graded stenosis by progressively closing the clamp. As shown in Figure 44(b), waveform amplitude decreases with increasing stenosis severity, demonstrating the system's effectiveness in monitoring the degree of change in stenosis.

7.6 Comprehensive Prototype Evaluation

The thermal behavior and stability analysis. We evaluate the thermal behavior and the system performance of HYGIEIA. Specifically, we attach HYGIEIA to an in-vitro phantom and operate it for 6 hours. We record the signal-to-noise ratio (SNR) and the average temperature of six representative points on the PCB, including major components and the battery, every 0.5 hours. As shown in Figure 45, the maximum measured temperature is 27.97°C, well below the 43°C limit required by the IEC 60601 standard for medical electrical equipment [5]. Meanwhile, the SNR remains stable throughout the 6-hour test, with the minimum value above 9 dB. These results demonstrate that HYGIEIA can support continuous operation with stable signal quality and safe thermal behavior.

Real-time monitoring analysis. We evaluated the end-to-end overhead of HYGIEIA, including data transmission, processing latency, and memory usage. All processing steps are executed on a PC equipped with a 12th Gen Intel(R) Core(TM) i5-12500H (2.50 GHz). A MATLAB stopwatch timer is used to measure the execution time of each software module. Each analysis window contains 1000 samples, corresponding to 23.5 s of data collection and a 22 KB file. Bluetooth transmission takes about 90 ms. As summarized in Table 5, the end-to-end latency is 397.18 ms with only 39.4 KB memory usage. These results show that HYGIEIA can be used for real-time continuous monitoring on mobile platforms.

Table 5. The computational overhead of the software. DT, RD, WR, IE stand for the data transmission, reading data, waveform reconstruction (MNSS), and indicator extraction, respectively.

Component	DT	RD	WR	IE	Total
Latency (ms)	90	51.06	178.45	79.67	397.18
Memory (KB)	–	22.0	11.2	6.2	39.4

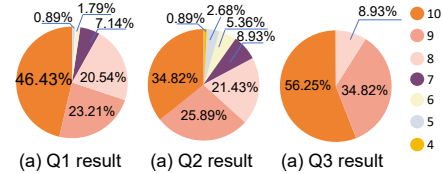


Fig. 46. The user acceptance result.

The acceptance validation. In our satisfaction survey, we set three questions: (Q1) *How comfortable do you think the patch is?* (Q2) *How comfortable do you think commercial equipment is?* (Q3) *Would you be willing to use this for home monitoring?* All questions are scored, with the highest score being 10 points. The results are shown in Figure 46, the average scores for the three questions are 9.03, 8.64, and 9.94. Besides, it can be found that the acceptance for HYGIEIA is higher than that of the commercial device. This is because the commercial device has to add extra strength to make the patch attach to the skin closely, which will bring discomfort.

8 DISCUSSION AND FUTURE WORK

In this section, we aim to discuss the limitations of HYGIEIA and future work.

Justification of cross-side ground-truth acquisition. In our evaluation, we use contralateral carotid measurements as the ground truth to ensure consistency of indicators during continuous monitoring. In other situations, the left and right carotid waveforms are not strictly identical, which may arise from anatomical branching asymmetry, posture changes, or unilateral vascular conditions, such as stenosis or plaque. Therefore, in future evaluations, especially for users with potential unilateral vascular abnormalities, we will incorporate same-side or proximal reference measurements to further validate the system performance. Contralateral or nearby measurements have been widely adopted in continuous physiological monitoring studies [17, 32, 55].

Monitoring under pathological vascular conditions. For pathological conditions, the pulsation magnitude may differ from that of normal individuals. We use far-field simulations to demonstrate the robustness across the different individual factors in Section 4.1. But the simulation assumes a fixed vascular pulsation magnitude and does not fully cover cases with altered vascular stiffness, plaque, or weak pulsation amplitude. Therefore, it is hard to extend the advantages of calibration-free procedures to pathological patients currently. We have shown the feasibility in vitro phantom of pathological vascular conditions in Section 7.4. We will focus on addressing the challenges when applying the HYGIEIA to pathological vascular conditions in future work.

Comparison with the non-contact RF technologies. Non-contact RF sensing technologies have shown high performance in vital signal monitoring [17, 64]. Their short wavelengths and large bandwidth enable the capture of subtle physiological motions. However, these systems are often sensitive to the surrounding RF environment, user posture, and body movement. In contrast, as a wearable device, HYGIEIA can flexibly conform to the user's carotid artery sites, thus exhibiting greater robustness to the user's position and body movements. In addition, compared with commercial mmWave and UWB devices that cost hundreds of dollars, the prototype of HYGIEIA is only around $3.4 \times 3.4 \text{ cm}^2$ flexible patch and costs about 19 USD. This makes HYGIEIA more suitable for robust wearable monitoring in daily scenarios.

Monitoring under vigorous movement scenarios. One potential approach is to use deep learning networks to separate the hemodynamics information from motion artifacts [10]. Or, leveraging the extra reference sensor [56, 62] to record the influence of activities and remove the movement artifacts. This will be one of our future works.

Pressure-related indicators monitoring. Another important class of hemodynamic parameters is those related to pressure waveform amplitude, such as the Augmentation Index (AIx) and Blood Pressure (BP). Monitoring these indicators requires accurate pressure changes, which necessitate mapping pressure to the resonant frequency shift of the patch. One potential way to extract this mapping is to establish curve fitting by quantifying the

frequency shift under different pressure baselines, and another is to use deep learning networks to extract the relationship between the current waveform and the pressure curve. Currently, our focus is on extracting accurate time-related indicators; we will put the pressure-related indicators extraction in future work.

Integration with Deep Neural Networks. Deep learning has been widely adopted for physiological signal analysis, focusing on tasks such as waveform enhancement and direct mapping from waveforms to clinical indicators. These models learn fine-grained morphological patterns based on underlying physiological principles. Our approach complements such deep-learning pipelines: by supplying cleaner, higher-fidelity waveform data, our system provides an optimized input foundation for downstream neural networks. In turn, deep learning can further improve the robustness of indicator extraction and extend the system's utility to broader applications—including pathology screening and personalized cardiovascular risk assessment.

Low-power monitoring. How to reduce the power consumption of wearable sensing for supporting long-time continuous monitoring is a currently active research field [59, 71]. Furthermore, some novel energy harvesting technologies can also provide the potential for continuous monitoring, such as a freestanding triboelectric nanogenerator (FTENG) [57], which converts the mechanical energy created by human motion into electrical energy, helping wearable systems achieve battery-free operation. We will look into integrating some of the recent advances in this line of research into HYGIEIA and evaluate the performance of the resulting system in the future.

9 CONCLUSION

We present HYGIEIA, the first ready-to-use, wearable, and flexible carotid artery hemodynamic monitoring system that practically exploits electromagnetic waves. We implement HYGIEIA with low-cost fabrication/hardware and an adaptive software pipeline to extract fine-grained hemodynamic indicators across diverse populations, conducting extensive performance experiments. Compared to commercial devices, HYGIEIA offers greater inclusivity and robustness across diverse, including dynamic scenarios.

Acknowledgments

This work was supported by the Funds for International Cooperation and Exchange of the National Natural Science Foundation of China (Grant No. W2511073), the National Science Foundation for Young Scientists of China (Grant No. 62402269), Shaanxi Science and Technology Innovation Team Program under Grant 2024RSCXTD05.

References

- [1] [n. d.]. 2000mAh LiPo Battery. <https://www.ufinebattery.com/products/3-7-v-2000mah-lithium-ion-battery-103450/>.
- [2] [n. d.]. BMI standard. <https://www.cancer.org/cancer/risk-prevention/diet-physical-activity/body-weight-and-cancer-risk/body-mass-index-bmi-calculator.html>.
- [3] [n. d.]. De Felipe dermatology clinic. <https://london.defelipe.com/2024/11/14/what-happens-to-my-skin-if-i-dont-drink-water/>.
- [4] [n. d.]. HK-2000C sensor. <http://www.hfhuake.com/chanpinzhanshi/yiliaochuanganganqi/yadianshimaibochua/2014/1230/17.html>.
- [5] [n. d.]. IEC 60601-1. <https://medicaladaptertech.com/medical-industry-news/iec-60601-1-thermal-limits-otp-prevents-thermal-runaway/>.
- [6] [n. d.]. Maxwell Garnett equation. https://en.wikipedia.org/wiki/Effective_medium_approximations.
- [7] [n. d.]. Tissue Database. <https://itis.swiss/virtual-population/tissue-properties/database/tissue-frequency-chart/>.
- [8] [n. d.]. World Health Organization. Cardiovascular diseases (CVDs) fact sheet. [https://www.who.int/news-room/fact-sheets/detail/cardiovascular-diseases-\(cvds\)](https://www.who.int/news-room/fact-sheets/detail/cardiovascular-diseases-(cvds)).
- [9] Abdelrahman Abushouk, Tikal Kansara, Omar Abdelfattah, Osamah Badwan, Essa Hariri, Pulkit Chaudhury, and Samir R Kapadia. 2023. The dicrotic notch: Mechanisms, characteristics, and clinical correlations. *Current Cardiology Reports* 25, 8 (2023), 807–816.
- [10] Amir Hosein Afandizadeh Zargari, Seyed Amir Hossein Aqajari, et al. 2023. An accurate non-accelerometer-based PPG motion artifact removal technique using CycleGAN. *ACM Transactions on Computing for Healthcare* 4, 1 (2023), 1–14.
- [11] Jordi Alastruey, Peter H Charlton, Vasiliki Bikia, Birute Paliakaite, Bernhard Hametner, Rosa Maria Bruno, Marijn P Mulder, Samuel Vennin, Senol Piskin, Ashraf W Khir, et al. 2023. Arterial pulse wave modeling and analysis for vascular-age studies: a review from VascAgeNet. *American Journal of Physiology-Heart and Circulatory Physiology* 325, 1 (2023), H1–H29.

- [12] Alia S Alhakak, John R Teerlink, Joann Lindenfeld, Michael Böhm, Giuseppe MC Rosano, and Tor Biering-Sørensen. 2021. The significance of left ventricular ejection time in heart failure with reduced ejection fraction. *European journal of heart failure* 23, 4 (2021), 541–551.
- [13] Aymen Alian, Kirk Shelley, and Hau-Tieng Wu. 2023. Amplitude and phase measurements from harmonic analysis may lead to new physiologic insights: lower body negative pressure photoplethysmographic waveforms as an example. *Journal of Clinical Monitoring and Computing* 37, 1 (2023), 127–137.
- [14] VG Almeida, P Santos, Edite Figueiras, Elisabeth Borges, Tânia Pereira, J Cardoso, C Correia, and Helena Catarina Pereira. 2011. Hemodynamic features extraction from a new arterial pressure waveform probe. In *International Conference on Bio-inspired Systems and Signal Processing*, Vol. 2. SCITEPRESS, 195–200.
- [15] Matthew K Armstrong, Martin G Schultz, Dean S Picone, J Andrew Black, Nathan Dwyer, et al. 2019. Brachial and radial systolic blood pressure are not the same: evidence to support the Popeye phenomenon. *Hypertension* 73, 5 (2019), 1036–1041.
- [16] Dilpreet Buxi, Evelien Hermeling, Marco Mercuri, Fabian Beutel, Roberto Garcia van der Westen, Tom Torfs, Jean-Michel Redoute, and Mehmet Rasit Yuce. 2017. Systolic time interval estimation using continuous wave radar with on-body antennas. *IEEE journal of biomedical and health informatics* 22, 1 (2017), 129–139.
- [17] Yetong Cao, Shujie Zhang, Fan Li, Zhe Chen, and Jun Luo. 2024. hBP-Fi: Contactless Blood Pressure Monitoring via Deep-Analyzed Hemodynamics. In *IEEE INFOCOM 2024-IEEE Conference on Computer Communications*. IEEE, 1211–1220.
- [18] Lifang Cheng, Kangla Liao, Yingying Wang, Fajin Lv, Xingming Guo, Yineng Zheng, and Jian Qin. 2021. Study of the correlation between the ratio of diastolic to systolic durations and echocardiography measurements and its application to the classification of heart failure phenotypes. *International Journal of General Medicine* (2021), 5493–5503.
- [19] Mirko De Melis, Umberto Morbiducci, Ernst R Rietzschel, Marc De Buyzere, Ahmad Qasem, Luc Van Bortel, Tom Claessens, Franco M Montevocchi, Albert Avolio, and Patrick Segers. 2009. Blood pressure waveform analysis by means of wavelet transform. *Medical & biological engineering & computing* 47, 2 (2009), 165–173.
- [20] Mona K El Abbasi, Mervat Madi, Herbert F Jelinek, and Karim Y Kabalan. 2022. Wearable blood pressure sensing based on transmission coefficient scattering for microstrip patch antennas. *Sensors* 22, 11 (2022), 3996.
- [21] Mahmoud Elgeziry et al. 2022. Design guidelines for sensors based on spiral resonators. *Sensors* 22, 5 (2022), 2071.
- [22] Yasmin Elshahar, Kaddour Bouazza-Marouf, David Kerr, Atul Gaur, Vipul Kaushik, and Sijung Hu. 2018. Breathing pattern interpretation as an alternative and effective voice communication solution. *Biosensors* 8, 2 (2018), 48.
- [23] FDC2214 FDC2212 and FDC2112. 2015. FDC2x1x EMI-Resistant 28-Bit, 12-Bit Capacitance-to-Digital Converter for Proximity and Level Sensing Applications.
- [24] Spartak S Gevorgian, Torsten Martinsson, Peter LJ Linner, and Erik L Kollberg. 2002. CAD models for multilayered substrate interdigital capacitors. *IEEE Transactions on microwave theory and techniques* 44, 6 (2002), 896–904.
- [25] Muhammad Hassan, Ghulam Abbas, Ning Li, Annum Afzal, Zeeshan Haider, Saad Ahmed, Xiuru Xu, Caofeng Pan, and Zhengchun Peng. 2022. Significance of flexible substrates for wearable and implantable devices: recent advances and perspectives. *Advanced Materials Technologies* 7, 3 (2022), 2100773.
- [26] David W Holmes, Dilpreet Singh, Riki Lamont, Ryan Daley, David P Forrestal, Peter Slattery, Edmund Pickering, Naomi C Paxton, Sean K Powell, and Maria A Woodruff. 2022. Mechanical behaviour of flexible 3D printed gyroid structures as a tuneable replacement for soft padding foam. *Additive Manufacturing* 50 (2022), 102555.
- [27] Kentaro Iizuka, Hidehiro Takekawa, Akio Iwasaki, Haruki Igarashi, Keisuke Suzuki, Saro Kobayashi, Daisuke Tsukui, and Koichi Hirata. 2020. Suitable methods of measuring acceleration time in the diagnosis of internal carotid artery stenosis. *Journal of Medical Ultrasonics* 47, 2 (2020), 327–333.
- [28] Srinivasulu Kanaparthi, Santu Kayal, and Shiv Govind Singh. 2019. Simple and facile microfabrication of a flexible interdigitated capacitor for sensing applications. *Flexible and Printed Electronics* 4, 1 (2019), 015005.
- [29] Abhishek Kandwal, Tobore Igbe, Jingzhen Li, Yuhang Liu, Sinan Li, et al. 2020. Highly sensitive closed loop enclosed split ring biosensor with high field confinement for aqueous and blood-glucose measurements. 10, 1 (2020), 4081.
- [30] Abhishek Kandwal, Louis Wy Liu, Tobore Igbe, Jingzhen Li, Yuhang Liu, Ranjan Das, Binod K Kanaujia, Lei Wang, and Zedong Nie. 2021. A novel method of using bifilar spiral resonator for designing thin robust flexible glucose sensors. *IEEE Transactions on Instrumentation and Measurement* 70 (2021), 1–10.
- [31] Bing Nan Li, Ming Chui Dong, and Mang I Vai. 2010. On an automatic delineator for arterial blood pressure waveforms. *Biomedical Signal Processing and Control* 5, 1 (2010), 76–81.
- [32] Jian Li, Huiling Jia, Jingkun Zhou, et al. 2023. Thin, soft, wearable system for continuous wireless monitoring of artery blood pressure. *Nature communications* 14, 1 (2023), 5009.
- [33] Wei Li, Xin Jin, Yide Zheng, Xudong Chang, Wenyu Wang, Tong Lin, Fan Zheng, Obiora Onyilagha, and Zhengtao Zhu. 2020. A porous and air gap elastomeric dielectric layer for wearable capacitive pressure sensor with high sensitivity and a wide detection range. *Journal of Materials Chemistry C* 8, 33 (2020), 11468–11476.
- [34] Xin Li, Quan Liang, Huifang Liu, Luyao Zhao, Chuanming Sun, and Chunye Hou. 2025. High-Sensitivity MXene/MWCNTs/PDMS Flexible Capacitive Sensor for Wearable Health Monitoring. *Advanced Materials Technologies* 10, 18 (2025), e00677.

- [35] Zirui Lou, Jun Tao, Binbin Wei, Xinyu Jiang, Simin Cheng, Zehao Wang, Chao Qin, Rong Liang, Haotian Guo, Liping Zhu, et al. 2023. Near-Infrared Organic Photodetectors toward Skin-Integrated Photoplethysmography-Electrocardiography Multimodal Sensing System. *Advanced Science* 10, 36 (2023), 2304174.
- [36] Ruichun Ma and Wenjun Hu. 2024. RF-Mediator: Tuning Medium Interfaces with Flexible Metasurfaces. In *Proceedings of the 30th Annual International Conference on Mobile Computing and Networking*. 155–169.
- [37] Kuldeep Mahato, Tamoghna Saha, Shichao Ding, Samar S Sandhu, An-Yi Chang, and Joseph Wang. 2024. Hybrid multimodal wearable sensors for comprehensive health monitoring. *Nature Electronics* 7, 9 (2024), 735–750.
- [38] Thomas Meissner and Frank J Wentz. 2004. The complex dielectric constant of pure and sea water from microwave satellite observations. *IEEE Transactions on Geoscience and remote Sensing* 42, 9 (2004), 1836–1849.
- [39] Jaques S Milner, Jennifer A Moore, et al. 1998. Hemodynamics of human carotid artery bifurcations: computational studies with models reconstructed from magnetic resonance imaging of normal subjects. *Journal of vascular surgery* 28, 1 (1998), 143–156.
- [40] Noor Mohammed, Kim Cluff, Jacob Griffith, and Ben Loflin. 2019. A noninvasive, electromagnetic, epidermal sensing device for hemodynamics monitoring. *IEEE transactions on biomedical circuits and systems* 13, 6 (2019), 1393–1404.
- [41] Sunderarajan S Mohan, Maria del Mar Hershenson, Stephen P Boyd, and Thomas H Lee. 2002. Simple accurate expressions for planar spiral inductances. *IEEE Journal of solid-state circuits* 34, 10 (2002), 1419–1424.
- [42] Srivani Padma, Sharath Umesh, Talabattula Srinivas, and Sundararajan Asokan. 2017. Carotid arterial pulse waveform measurements using fiber Bragg grating pulse probe. *IEEE Journal of Biomedical and Health Informatics* 22, 5 (2017), 1415–1420.
- [43] Hao Pan, Yezhou Wang, Jiting Liu, Ruichun Ma, Lili Qiu, Yi-Chao Chen, Guangtao Xue, and Ju Ren. 2025. CGMM: Non-invasive continuous glucose monitoring in Wearables using metasurfaces. In *Proceedings of the 31th Annual International Conference on Mobile Computing and Networking*. 1–16.
- [44] Carmelo Pirri, Caterina Fede, Chenglei Fan, Diego Guidolin, Veronica Macchi, Raffaele De Caro, and Carla Stecco. 2021. Ultrasound imaging of head/neck muscles and their fasciae: an observational study. *Frontiers in Rehabilitation Sciences* 2 (2021), 743553.
- [45] David M Pozar. 2021. *Microwave engineering: theory and techniques*. John Wiley & sons.
- [46] Aniket S Rali, Amy Butcher, Ryan J Tedford, Shashank S Sinha, Pakinam Mekki, Harriette GC Van Spall, and Andrew J Sauer. 2022. Contemporary review of hemodynamic monitoring in the critical care setting. *US Cardiology Review* 16 (2022), e12.
- [47] D Rangaprakash and D Narayana Dutt. 2015. Study of wrist pulse signals using time domain spatial features. *Computers & Electrical Engineering* 45 (2015), 100–107.
- [48] Anum Saeed, Oscar Lopez, Ann Cohen, and Steven E Reis. 2023. Cardiovascular disease and Alzheimer’s disease: the heart–brain axis. *Journal of the American Heart Association* 12, 21 (2023), e030780.
- [49] Mahya Saffarpour, Debraj Basu, Fatemeh Radaei, Kourosh Vali, Jason Y Adams, Chen-Nee Chuah, and Soheil Ghiasi. 2023. Physiowise: a physics-aware approach to dicrotic notch identification. *ACM transactions on computing for healthcare* 4, 2 (2023), 1–17.
- [50] Ahmed Salim, Aqeel Hussain Naqvi, Eiyong Park, Anh Duc Pham, and Sungjoon Lim. 2019. Inkjet printed kirigami inspired split ring resonator for disposable, low cost strain sensor applications. *Smart Materials and Structures* 29, 1 (2019), 015016.
- [51] Kensuke Sasaki, Kanako Wake, and Soichi Watanabe. 2014. Development of best fit Cole-Cole parameters for measurement data from biological tissues and organs between 1 MHz and 20 GHz. *Radio science* 49, 7 (2014), 459–472.
- [52] Patrick Segers, Ernst Rietzschel, Steven Heireman, Marc De Buyzere, Thierry Gillebert, Pascal Verdonck, and Luc Van Bortel. 2005. Carotid tonometry versus synthesized aorta pressure waves for the estimation of central systolic blood pressure and augmentation index. *American journal of hypertension* 18, 9 (2005), 1168–1173.
- [53] Hongming Shen, Chen Xu, Yongjie Yang, Ling Sun, Zhitian Cai, Lin Bai, Edward Clancy, and Xinming Huang. 2018. Respiration and heartbeat rates measurement based on autocorrelation using IR-UWB radar. *IEEE transactions on circuits and systems II: express briefs* 65, 10 (2018), 1470–1474.
- [54] Chaoyang Shi, Han Zhang, Xiaolong Ni, and Kaifeng Wang. 2023. An FBG-based sensor with both wearable and handheld forms for carotid arterial pulse waveform measurement. *IEEE Transactions on Instrumentation and Measurement* 72 (2023), 1–10.
- [55] Zhenguo Shi, Tao Gu, Yu Zhang, and Xi Zhang. 2022. mmbp: Contact-free millimetre-wave radar based approach to blood pressure measurement. In *Proceedings of the 20th ACM Conference on Embedded Networked Sensor Systems*. 667–681.
- [56] Masudur R Siddiquee, J Sebastian Marquez, Roozbeh Atri, Rodrigo Ramon, Robin Perry Mayrand, and Ou Bai. 2018. Movement artefact removal from NIRS signal using multi-channel IMU data. *Biomedical engineering online* 17, 1 (2018), 120.
- [57] Yu Song, Jihong Min, You Yu, Haobin Wang, Yiran Yang, Haixia Zhang, and Wei Gao. 2020. Wireless battery-free wearable sweat sensor powered by human motion. *Science advances* 6, 40 (2020), eaay9842.
- [58] Sarah R St. Pierre, Mathias Peirlinck, and Ellen Kuhl. 2022. Sex matters: a comprehensive comparison of female and male hearts. *Frontiers in physiology* 13 (2022), 831179.
- [59] Lisa T Su. 2013. Architecting the future through heterogeneous computing. In *2013 IEEE International Solid-State Circuits Conference Digest of Technical Papers*. IEEE, 8–11.
- [60] Irene Suriani, Joris van Houte, Esmée C de Boer, Luuk van Knippenberg, et al. 2023. Carotid Doppler ultrasound for non-invasive haemodynamic monitoring: a narrative review. *Physiological Measurement* 43, 10 (2023), 10TR01.

- [61] Erwin Tafeit, Joachim Greilberger, Gerhard Cvirn, Rainer Walther Lipp, Wolfgang Johann Schnedl, Toivo Jürimäe, Jaak Jürimäe, and Sandra Johanna Wallner-Liebmann. 2009. Estimating DXA total body fat percentage by lipometer subcutaneous adipose tissue thicknesses. *Collegium antropologicum* 33, 2 (2009), 391–396.
- [62] Jianxun Wang, Marc Foster, et al. 2022. Motion-resilient ECG signal reconstruction from a wearable IMU through attention mechanism and contrastive learning. In *Proceedings of the Ninth International Conference on Animal-Computer Interaction*. 1–11.
- [63] Muyao Wang, Lu Jia, Li, et al. 2025. Wearable Ultrasound Devices for Biomedical Applications. *FlexTech* 1, 1 (2025), 35–43.
- [64] Zhi Wang, Beihong Jin, Yuhui Chen, Fusang Zhang, Siheng Li, Junqi Ma, Tao Gong, and Yu Fu. 2025. RF-AE: Single-site Arterial Elasticity Estimation Using UWB Signals. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 9, 2 (2025), 1–26.
- [65] Haicheng Yao, Weidong Yang, Wen Cheng, Yu Jun Tan, Hian Hian See, Si Li, Hashina Parveen Anwar Ali, Brian ZH Lim, Zhuangjian Liu, and Benjamin CK Tee. 2020. Near-hysteresis-free soft tactile electronic skins for wearables and reliable machine learning. *Proceedings of the National Academy of Sciences* 117, 41 (2020), 25352–25359.
- [66] Shikai Yu and Carmel M McEniery. 2020. Central versus peripheral artery stiffening and cardiovascular risk. *Arteriosclerosis, Thrombosis, and Vascular Biology* 40, 5 (2020), 1028–1033.
- [67] Jiawei Yuan, Zhikang Li, Yihe Zhao, Ruiyan Luo, Shaohui Qin, Jie Li, et al. 2025. Skin-adaptive focused flexible micromachined ultrasound transducers for wearable cardiovascular health monitoring. *Science Advances* 11, 37 (2025), eadw7632.
- [68] Guillaume Zahnd, Loïc Bousset, Adrien Marion, Marion Durand, Philippe Moulin, André Sérusclat, and Didier Vray. 2011. Measurement of two-dimensional movement parameters of the carotid artery wall for early detection of arteriosclerosis: a preliminary clinical study. *Ultrasound in medicine & biology* 37, 9 (2011), 1421–1429.
- [69] Lingxi Zeng, Gen Li, Jiajie Xu, Rui Zhu, Mingyan Li, Shengtong Yin, et al. 2023. A wearable device for dynamic monitoring of cerebral blood flow based on electromagnetic coupling sensing. *IEEE Sensors Journal* 23, 23 (2023), 29571–29584.
- [70] Sai Zhou, Geonho Park, Katherine Longardner, Muyang Lin, Baiyan Qi, Xinyi Yang, et al. 2025. Clinical validation of a wearable ultrasound sensor of blood pressure. *Nature biomedical engineering* 9, 6 (2025), 865–881.
- [71] Josip Zidar, Tomislav Matić, Ivan Aleksi, and Željko Hocenski. 2024. Dynamic voltage and frequency scaling as a method for reducing energy consumption in ultra-low-power embedded systems. *Electronics* 13, 5 (2024), 826.

APPENDIX

A The Production Process of a Patch

As shown in Figure 47, we first mix commercial PDMS and curing agent in a ratio of 10:1, stir thoroughly, and let it stand until there are no bubbles in the mixture. The second step is to pour the mixture into a clean mold and rotate it evenly using a centrifuge. Next, lay copper foil on the PDMS and heat and cure it in a dryer at 80°C for 15 minutes. After that, use a laser engraver to engrave the patch structure pattern, and carefully remove the excess copper wire. To achieve waterproofness, apply a top layer of PDMS solution to the patch. Finally, heat and cure it again and demold it.

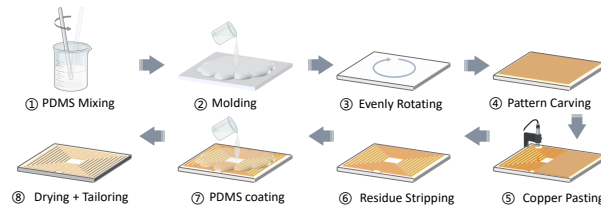


Fig. 47. Workflow of patch fabrication.