

A Flexible Wearable Platform with On-Device TinyML for Context-Aware Bio-Signal Monitoring

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Summary: This paper presents a flexible, standalone wearable platform for context-aware bio-signal monitoring for emergency scenarios; and introduced heart rate detection as the proof-of-concept. On-device TinyML model running on a resource-constrained microprocessing unit to distinguishing motion states was realized using synchronized photoplethysmography and inertial measurement unit data. This low-power context awareness forms the critical foundation for active noise-filtering to ensure robust, immediate physiological alerts for first responders and elder care without external networks.

Keywords: Flexible sensors, heart rate monitoring, motion artifacts, photoplethysmography, TinyML, wearable sensors.

Background, Motivation and Objective

Continuous monitoring of physiological signals is critical for early-warning health systems and emergency first response [1]. While commercial wearable devices (e.g., smartwatches) are widely available, they are primarily engineered for long-term lifestyle and exercise habit tracking, relying heavily on continuous cloud data accumulation and smartphone pairing [2]. In specific emergency situations such as running exercise in remote area or natural disasters, this dependence on external web infrastructure introduces unacceptable latency and vulnerability. There is a distinct need for a standalone and one-shot alarming system that provides immediate, reliable physiological feedback directly on the edge. To address this gap, we designed and are currently prototyping a flexible, wearable platform addressing that specific niche.

Research strategy

A primary challenge in ambulatory photoplethysmography (PPG) is signal corruption from motion artifacts [3]. Rather than transmitting raw data to the cloud for processing, the objective is to achieve an intelligent understanding of the user's situation entirely on-device using minimal computational power. As illustrated in Fig. 1, achieving robust heart rate (HR) extraction during dynamic movement and triggering timely alert requires a multi-stage approach. The necessary first step is accurate context awareness via motion state detection. By synchronizing the PPG sensor with an inertial measurement unit (IMU) and deploying a tiny machine learning (TinyML) classification model, the device successfully distinguishes between stationary and in-motion states. The second phase is to use this context awareness to trigger active, on-device filtering algorithms, extracting relevant HR data from highly disturbed signals. The third phase concerns the decision to ensure a fully autonomous, reliable alert transmission for caregivers. Here, we report on the implementation of the first phase.

Experimental

The wearable platform integrates sensing, processing, and feedback mechanisms on a flexible printed circuit board (FPCB) mounted on a polydimethylsiloxane (PDMS) substrate. The sensing elements comprise an optical module (Osram, SFH7072) for capturing the PPG and IMU (LSM6DS3) signals. These components are driven by a microprocessing unit (MCU, Seeed Studio, XIAO nRF52840), which handles data acquisition, manages multimodal feedbacks with

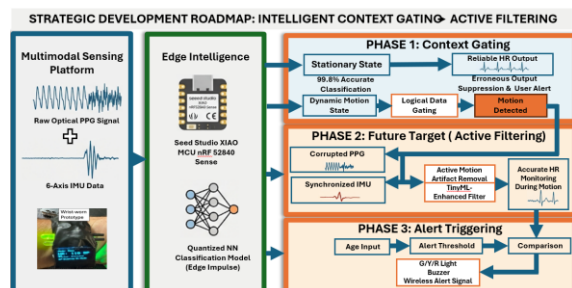


Figure 1: Strategic development roadmap of the context-aware wearable platform. Phase 1 : the on-device TinyML gating mechanism for classifying stationary versus dynamic motion. Phase 2 : active signal filtering for continuous, reliable monitoring during dynamic movement. Phase 3 : alert triggering based on bio-signal.

a LED, a piezoelectric buzzer, and an OLED display with the TinyML classification model on the edge (Fig.2).

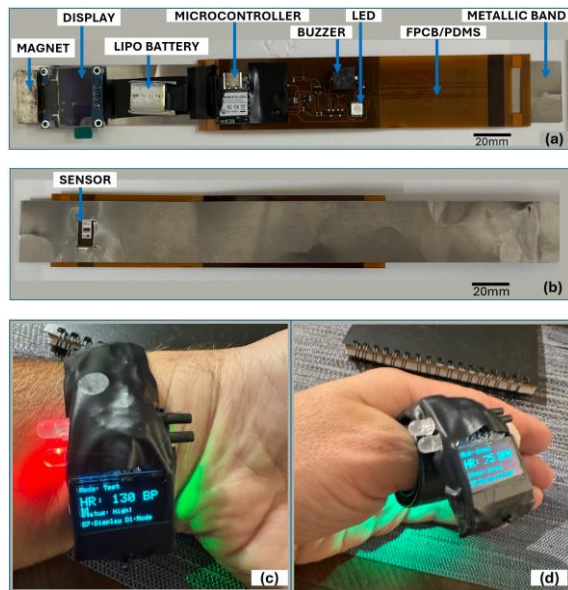


Figure 2: The (a) front and (b) back side of the proposed platform with corresponding components mounted before packaged for prototyping with (c) wrist-worn configuration (d) thumb-worn configuration.

To enable real-time motion classification, a neural network was trained utilizing the edge impulse platform. IMU data streams across dynamic (walking) and static (seating) activity states were collected. A signal processing pipeline employing spectral analysis extracted essential frequency features, training a compact neural network that achieved a validation accuracy of 99.8%. The resulting model was quantized and deployed directly into the device firmware as a self-contained library for continuous, low-power inference.

Results and Conclusion

System validation showed a precise correlation between the classified motion context and PPG signal integrity. Validation against a commercial smartwatch benchmark during these periods yielded a high correlation (linear coefficient of determination of 0.9291, Fig. 3(a)). During static periods, the IMU registered minimal activity, yielding a clean, periodic PPG signal for reliable HR extraction (Fig. 3(b) and 3(d)). On contrary, dynamic states generated large, high-frequency IMU transients that directly corrupted the PPG waveform (Fig. 3(c) and 3(e)). Operating entirely on-device, the TinyML model successfully recognized these dynamic transients in real-time. This validates the claimed context-aware, low-power gating mechanism in Phase 1 of our strategy (Fig. 1). Leveraging this accurate edge-classification framework, we are working on the

integration of active filtering algorithms to extract valid HR waveforms during dynamic motion (Phase 2), and a fully autonomous, context-aware emergency alert platform (Phase 3).

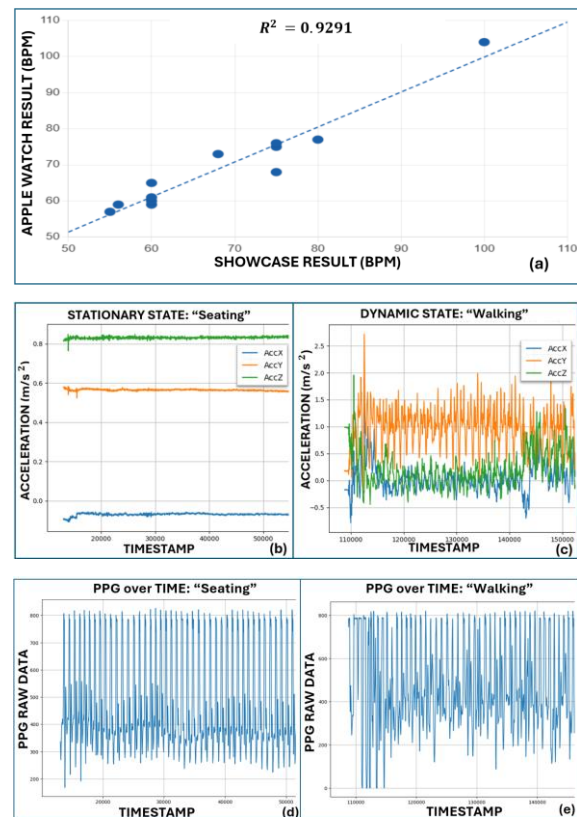


Figure 3: System validation and motion classification. (a) HR correlation between the proposed prototype and an Apple Watch. (b) Baseline IMU data and (d) the resulting stable HR profile during the static "seating" state. (c) High-frequency IMU transients and (e) the corresponding corrupted HR profile during the dynamic "walking" state, demonstrating the necessity of the on-device TinyML gating.

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