MP-HAR: A Novel Motion-Powered Real-Time Human Activity Recognition System

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***Abstract*—With the rapid advance of the Internet of Things (IoT), more and more wearable devices are being developed for real-time monitoring. Most of these existing monitors are powered by chemical batteries. Replacing and disposing batteries for an exponentially increasing number of IoT nodes prohibitively results in labor-intensive maintenance. It is also environmentally unfriendly. Energy harvesting (EH), reclaiming the wasted ambient energy, is a promising technology for battery-free IoT. This article presents a novel motion-powered real-time human activity recognition (HAR) system called motion-powered HAR system (MP-HAR), where the harvester works as both an energy source and sensor. MP-HAR emphasizes low-power as well as low-cost characteristics, encompassing four necessary units: 1) energy transduction unit (ETU); 2) energy management unit (EMU); 3) energy user unit (EUU); and 4) edge computing unit (ECU). In particular, the unique intermittent operation based on the reconfigurable on/off threshold voltages given by the well-rounded energy-aware circuit has been discussed in detail. The balance between energy supply and information demand in MP-HAR has been achieved by using a handy design. Utilizing the unique correspondence between human arm swing frequency and harvested energy, the information flows with energy inside the system. By knowing the interval between transmitted packets, MP-HAR has realized HAR in real time. Moreover, an all-in-one prototype has been fabricated to validate the performance of the proposed system. Lab and field tests have demonstrated that MP-HAR can reliably recognize different human activities, such as standing, walking, jogging, and running. As a cyber-electro-mechanical codesign, MP-HAR has brought a promising solution for pervasive HAR and ubiquitous IoT.**

***Index Terms*—Battery-free Internet of Things (IoT) system, energy harvesting (EH), human activity recognition (HAR), simultaneously EH and sensing.**

I. Introduction

OVER the last decades, the thriving Internet of Things (IoT) has kept bridging the cyber and physical worlds. It features advanced monitoring, control, and management capabilities emphasizing low-power and low-cost demands [1], [2]. As experts predicted, IoT will encompass almost 30.9 billion wireless devices by 2025 [3]. Within this field, wearable IoT devices have gained considerable significance, with an expected market size of U.S.$ 265.4 billion by 2026 [4], for their pervasive use in multiple applications, including human activity recognition (HAR) [5], [6]. However, most wearable activity recognizers are powered by chemical batteries incompatible with long-term and large-scale IoT. As these nodes grow, replacing and disposing of batteries daily will become prohibitively labor-intensive and environmentally friendly [7]. Therefore, for the ubiquitous and everlasting deployment of massive IoT devices, battery-free solutions are required [8].

Energy harvesting (EH) technology, trying to reclaim wasted energy from the ambiance, is promising for self-powered IoT devices. In recent years, battery-free wearable activity recognizers are booming as solar photovoltaic (PV), radio frequency (RF), and kinetic energy-based EH technologies advance. For instance, SolAR [6], a solar-powered energy-positive human activity recognizer, identifies different human gestures locally via low-power machine learning methods. In addition, several RF-powered systems have been prototyped to demonstrate the feasibility of activity monitoring [9], [10]. However, due to the volatile light radiation and RF signals, solar and RF-powered devices might be unstable and subject to temporal and spatial constraints from time to time. For such cases, the kinetic energy harvesting (KEH)-based solution becomes relatively more reliable. A few KEH-based wearable IoT solutions have been developed and presented to prove that the energy generated by physical activity is sufficient to power sensors and enable HAR [11], [12], [13], [14], [15].

Traditional HAR relies on IMUs (Inertial Measurement Units) to periodically extract motion information from the human body. Yet, IMUs are usually incompatible with scenarios with constrained resources [16], despite the advanced electronics being ultralow-power [17]. Since the energy demand of the IMU may even exceed the harvested energy, considering both sensing needs and energy availability, i.e., the energy harvester acts as a power source as well as sensor, becomes significant for self-powered HAR [6], [8], [16], [18], [19], [20], [21], [22]. The state-of-the-art KEH-based HAR system is shown in Fig. 1(a). Most cutting-edge KEH-based HAR systems feed the collected sensor data into a recognizer, a trained model summarizing the characteristics of multiple activity samples. In addition, many systems have not truly satisfied the self-powered demand. The energy harvested from the KEH transducer is used to charge the battery to supplement the battery's lifetime.

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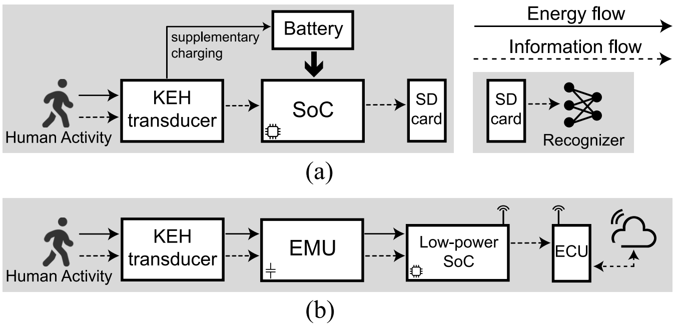


Fig. 1. Comparison of different HAR systems. (a) State-of-the-art KEH-based HAR system harvests energy and simultaneously performs the sensing function. Yet, the signal analysis is realized in a later separate stage. (b) Proposed motion-powered real-time HAR system, where the information flows along with the harvested energy.

Motivation: Due to the complicated source dynamics and intermittent load demand [23], most KEH-based self-powered IoT designs are still at the proof-of-concept or preliminary stage. The electric energy generated by kinetic energy harvesters usually needs additional power management, e.g., boosting the voltage for powering digital modules or better stored in the energy storage device [24]. Some existing KEH-based HAR systems separate the processes of data collection and analysis processes; therefore, they cannot realize real-time recognition, which is a vital demand for many IoT applications [20]. By taking the low-cost, self-powered, and real-time recognition demands into account toward a self-contained KEH-based HAR design, in this study, we propose a novel motion-powered HAR system (MP-HAR) based on the positive correlation among gait speed, arm swing frequency, generated energy, and transmitted packet count.

The block diagram of the proposed real-time HAR system is shown in Fig. 1(b). Instead of regarding all parts except the load and sensor as a stable power source, MP-HAR utilizes the relationship between human activities and limb swing frequency. It captures the motion information from the harvester. Thanks to an energy transduction unit (ETU), a dedicatedly designed KEH transducer, and a self-contained energy management unit (EMU), MP-HAR can efficiently convert energy without a boost circuit, keeping the low-power feature while achieving low cost. Furthermore, a customized low-power SoC (system on chip) serves as an energy user unit (EUU), realizing real-time IoT communication with a high-performance edge computing unit (ECU), which can also connect to the cloud platform for more applications. Different activities produce specific frequencies of limb swinging, determining the capacitor charging rates and ultimately affecting the corresponding intervals between the delivered Bluetooth low-energy (BLE) beacon packets. Lab experiments prove that the energy generated from each swing motion is relatively stable, reinforcing the reliability of MP-HAR. The mechanical, electrical, and cyber parts are inextricably linked. Thus, by knowing the signal intervals, MP-HAR can recognize various activities, such as standing, walking, jogging, and running. Moreover, a compact prototype has been assembled for better experimental validation.

The proposed MP-HAR has three significant features.

1) MP-HAR is a real-time, self-contained, and self-powered HAR system based on KEH, where the harvester works as both an energy source and a sensor. It brings a promising solution for pervasive HAR.
2) An all-in-one compact prototype, which is well-designed for wearing and testing, has been fabricated. It proves the feasibility and validates the performance of the proposed system.
3) As a cyber-electro-mechanical co-design, MP-HAR encompasses ETU, EMU, EUU, and ECU, which proves a comprehensive KEH-IoT architecture. MP-HAR achieves low-cost and low-power characteristics due to the customized ETU and EMU. It provides valuable guidance for designing and developing future perpetual IoT systems.

The remainder of this article is organized as follows. Section II discusses the related work on HAR and battery-free IoT systems. Section III overviews the proposed system. Section IV presents the principle of MP-HAR, where the energy and information flow and the unique intermittent operation are discussed in detail. Section V introduces the all-in-one prototype and multiple experimental evaluations have been conducted. Finally, the conclusion and future work are given in Section VI.

II. Related Work

A. HAR

With the pretrained model, HAR systems can detect specific activities, such as standing, walking, and running, by knowing the sensory data of these actions [2], [25], [26], [27], [28]. In response to the aging population and disability trends, HAR is becoming crucial for supplying close monitoring in real-time to many elderly and patient groups suffering from mobility impairments [29], [30].

Typical HAR technologies realize data acquisition through IMUs, such as accelerometers, gyroscopes, and magnetometers [18], [31], [32]. However, while providing accurate sensing, these activity sensors consume considerate energy for their high-frequency data sampling [33].

Therefore, for power consumption reduction and sense from a single element, leveraging an energy harvester instead of IMU to sense the ambiance has been a research focus recently [21], [34], [35]. For instance, SolarGest [36], a system for gesture recognition, uses solar cells for ambient sensing under a fixed lamp. Khalifa et al. [19] proposed a novel HAR method called HARKE, which collects data by a kinetic energy harvester and achieves basic activity recognition with advanced machine learning methods. The result shows that the accuracy of HARKE ranges from 80% to 95%, while the system power consumption is reduced by 79% compared with the IMU-based methods. Moreover, in [28], a secret key generation system based on piezoelectric sensors is implemented. To further attain low-power operation, simultaneously employing an energy harvester as a source of energy and information has attracted growing attention, which can compensate for the battery consumption [22].

However, the replace-required batteries truly limit the pervasive HAR, though other optimizing methods for extending the lives of batteries have been proposed, such as sensor reduction [37], adaptive sampling mechanisms [38], and low-power system design [39]. Battery-free HAR has become an urgent requirement, which is also the highlight of this article. To date, most self-powered HARs are powered by solar energy or RF energy. For example, Li et al. [40] utilized photodiode arrays to power the proposed gesture recognition system. In another study [41], WISPCam is an RF-powered camera, where the RF wave transfers the picture signal as well.

KEH, converting kinetic energy into electrical energy, is said to be a feasible method to power wearable devices [42]. Given the instability of light radiation and RF signals, the significance of KEH-based HAR has gradually caught more attention due to its unique mechanical characteristics. A wide assortment of KEH models have already been studied in depth [12], [13], [43], [44], [45], [46]. Nevertheless, most of the previous research emphasizes optimizing the parameters of proposed models, which means the results are only theoretical. There is a gap between the proof-of-concept and real-world applications.

Among all related studies, only a few systematic designs based on KEH have emerged as valuable references for KEH-based HAR. ViPSN-pluck [8] can be considered a self-powered motion detector and a holistic system for transient-motion-powered IoT applications. It emphasizes the potential energy precharging process. Furthermore, Sandhu et al. [47] presented an energy-positive scheme that simultaneously considers KEH as a source of energy and information. Yet, these researches were not specifically designed for wearable devices.

B. Battery-Free IoT Systems

Batteries, in some way, did constrain the ubiquitous implementation of massive wireless devices, which gives the opportunity and expectation for battery-free IoT terminals to operate and harvest ambient energy autonomously. EH, converting the available energy captured from the ambiance into electrical energy, is an emerging technology enabling self-maintained IoT devices. Given the unstable nature of most environmental micro-energy, in recent years, how to better integrate different parts, such as EH, sensing, computing, and communicating, into a battery-free IoT system has attracted interest from IoT academia and industry [23].

The energy sources of state-of-the-art self-powered equipment encompass solar, RF, kinetic energy, etc. [48]. Great progress has been made in the field of solar and RF-based IoT. For instance, in [49], a low-resolution camera is developed to harvest energy from ambient light and transmit data to the hub based on back-scatter communication. The low-cost hub runs a deep learning model. It can achieve human occupancy detection. Achieving a similar function, Giordano et al. [48] presented a LoRa-based solar-powered smart camera. On the other hand, Gemini [50], a battery-less power meter, powers itself using a current transformer. Besides utilizing solar and RF technology, some KEH-based devices were also developed [47], [51].

A general EH-IoT system consists of five parts [24]: 1) ETU; 2) Input power management unit (PMU); 3) Energy storage unit (ESU); 4) Output PMU; and 5) Load. Such complex and closely connected parts predestine the interdisciplinary characteristic of battery-free IoT systems. However, most studies have considered the real-time communication of IoT while simplifying the mechanics and circuit. Or, they have focused on the dynamics of mechanics and circuits while ignoring the IoT elements. Some EH-based products, such as EnOcean [52], EnSole [53], and PowerWatch [54], have already appeared on the market, but their stability, practicality, and compactness still have a large room to improve. For battery-free IoT, it is necessary to carry out more holistic research among mechanical, electrical, and cyber parts.

A battery-free sensing and transmitting platform called WISP was proposed in [55]. As a pioneering RF-powered IoT system, WISP facilitates multiple derivatives, e.g., WISPCam [41], and the prosperity of RF-based IoT. Besides, ViPSN [23], the first open-source development platform specified for vibration-powered IoT devices, comprehensively considers the specific research and development demands of vibration energy harvesting (VEH)-based IoT systems. Moreover, Hester and Sorber [56] presented an all-rounded IoT system called Flicker, which supports solar, RF, VEH sources, and a wide assortment of peripherals.

Instead of adopting off-the-shelf commercialized models in PMU, MP-HAR adopts a novel low-cost, well-rounded EMU, while no boost circuit is needed. Table I lists the comparison of this proposed MP-HAR design with other existing representative works in the literature. To the best of the authors' knowledge, a wearable and motion-powered real-time HAR solution remains unexplored in the field of KEH-based HAR. The compact, low-cost, and low-power cyber-electro-mechanical co-design provides a valuable reference for other KEH-based IoT system designs.

III. System Overview

Fig. 2 shows the architecture of the proposed motion-powered HAR system. It encapsulates three hardware units: 1) ETU; 2) EMU; 3) EUU; and 4) one software computing unit (ECU). The hardware units bridge the real-world human body movement and the intermittent radio transmission from the SoC. ECU analyzes the received signals and then achieves HAR in real time.

A. ETU

As shown in Fig. 2(a), when the human arm swings, the kinetic energy is captured by the mass in the ETU. Subsequently, the soft beam is driven to bend. Finally, the iron bar realizes a relative position change, which causes the magnetic field direction to swap, producing electricity on the copper coil. Therefore, the captured inertial energy is converted into useful electrical energy through the ETU. During the periodic swinging, the energy and information simultaneously flow to the next unit, EMU, for power management and sensing.

TABLE I
COMPARISON AMONG EXISTING TECHNOLOGIES AND THIS WORK

Literature	Battery-free	KEH	Harvester as sensor	Real-time	Boost-less	Prototyped	Wearable
MARS [26]	-	-	-	-	-	-	√
WISPCam [41]	√	-	-	√	√	√	-
SolAR [6]	√	-	√	√	-	√	√
Marco et al. [48]	√	-	-	-	√	√	-
Cai et al. [11]	√	√	-	√	-	√	√
Ben et al. [12]	√	√	-	√	-	-	√
Gorlatova et al. [46]	√	√	-	√	-	-	√
SolarGest [36]	-	-	√	-	-	√	-
HARKE [19]	-	√	√	-	√	√	√
Manjarrés et al. [21]	-	√	√	-	√	-	√
SEHS [22]	-	√	√	-	√	√	√
Li et al. [40]	√	-	√	√	-	√	√
ViPSN-pluck [8]	√	√	√	√	√	√	-
Sandhu et al. [47]	√	√	√	-	-	√	-
This work	√	√	√	√	√	√	√

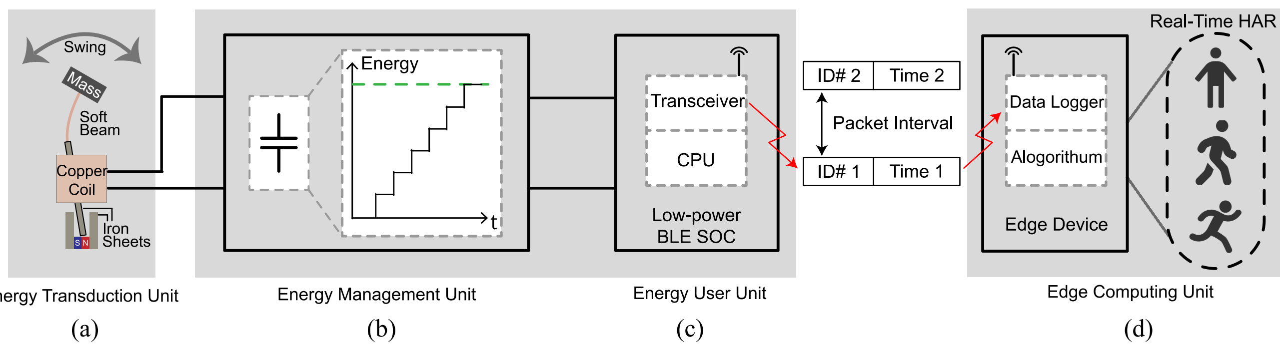


Fig. 2. Architecture of MP-HAR, encompassing four necessary units: (a) ETU, (b) EMU, (c) EUU, and (d) ECU.

B. EMU

Since the energy generated from the ambiance is still insufficient for supporting the stable operation of SoC, the capacitor inside the EMU first stores the converted energy from the ETU. While embedded with the under-voltage lockout (UVLO) function, EMU can sense the voltage of the capacitor and turn on the load when the stored energy is sufficient. Hence, when the voltage of the capacitor is higher than the threshold voltage, the EUU is turned on, as depicted in Fig. 2(b). It utilizes the harvested energy to process the associated information.

C. EUU

A low-power BLE SoC-based minimum system with a transceiver and CPU is developed as the EUU, as Fig. 2(c) shows. It starts running when the EMU acknowledges that the energy reaches the threshold. It ensures stable operation. Given the awareness of intermittent operation, the software program is set to allow the EUU only to run the necessary initialization and radio functions. Subsequently, when EMU senses that the energy consumption has reached a certain level, EUU is cut off and remains in hibernation until the next running cycle. The unique intermittent operation process is comprehensively discussed in Section IV.

D. ECU

Low-power edge computing units are edge nodes distributed in various battery-free IoT scenarios using edge devices, such as phones and micro-controllers (MCUs) with lower power consumption. They reduce the pressure on the cloud platform, shorten the data response delay, and improve the privacy and security of data transmission. A mobile app from a cell phone is developed as an ECU in this study, which listens for packets from MP-HAR, as shown in Fig. 2(d). Upon packet reception, ECU records the arrival time of every data. Since the intervals between packets are closely related to human activities, after inserting a customized algorithm, the real-time HAR can be carried out by ECU by knowing the intervals of signals. In addition, the data results can be visualized locally or sent to the cloud for centralized storage and analysis. Due to each beacon packet's unique ID, multiple MP-HARs can work simultaneously. Moreover, the same functions can be achieved by MCUs, e.g., ESP32 by Espressif Systems Inc., RaspberryPi, and FPGA, depending on the demands of users.

IV. PRINCIPLE OF MP-HAR

A. Toggling States

To better capture the kinetic energy from arm swing, ETU is designed as an inertia-driven electromagnetic energy harvester, consisting of an all-in-one swinging soft beam and an electromagnetic energy harvester. A toggle iron bar and a pair of masses are installed on both sides of the soft beam. A magnet, two iron bars, and a copper coil form the harvester with a frame for support, as illustrated in Fig. 3(a). Due to the special design of the frame, the soft beam is clamped on both sides in

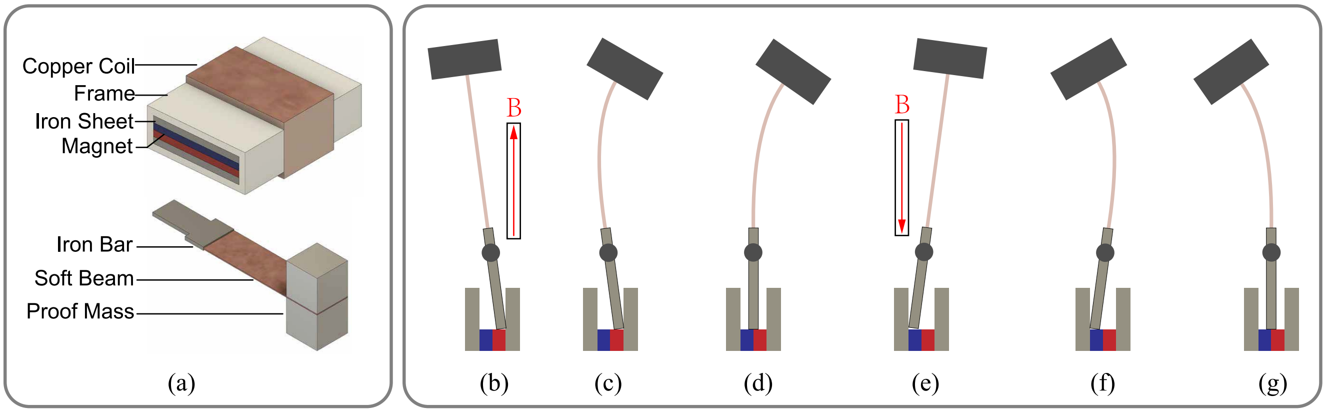


Fig. 3. Structure and operation phases of ETU. (a) 3-D model of the adopted KEH transducer. (b)–(g) Six phases of ETU in an arm swing cycle.

one position so that it can be considered a recursive rotation around a shaft during toggling.

During one cycle of back-and-forth arm swing, the ETU passes through six key states, as shown in Fig. 3(b)–(g). At the initial point, as shown in Fig. 3(b), the iron sheet sucks the toggle iron bar. The whole soft beam is fixed by magnetic force and shaft. Since the relatively large rigidity of the soft beam, the deformation caused by the mass at the initial point is ignored. Fig. 3(c) denotes the critical point, which shows that the mass has captured certain inertial energy from the arm swing. At this point, the bending soft beam reaches the maximum deformation. When the restoring force of the bending beam becomes bigger than the magnetic force, the beam is rapidly released, then the soft beam comes to the moving point, as shown in Fig. 3(d). At this point, the iron piece is rotating around the shaft. Subsequently, the harvester reaches the end state of one swing, which is also the initial point of the next opposite swing, as Fig. 3(e) shows. Therefore, the states from (b) to (e) in Fig. 3 prove a complete cycle of one swing motion, and the magnetic field flowing through the iron piece is reversed during this period, producing electricity through a coil. With the same principle, the states from (e) to (g) and back to (b) in Fig. 3 are a complete cycle of the opposite swing motion, where (f) and (g) correspond to (c) and (d), respectively.

A round of back-and-forth swing of the arm generates two voltage pulses, matching low-frequency human motion excitation without frequency up-conversion. It means the generated energy flows along with the information on swinging speed. This unique characteristic of the electromagnetic transducer is the significant principle of MP-HAR that senses the arm swing without using an IMU, i.e., simultaneously utilizing an electromagnetic energy harvester as a sensor and power source.

B. Energy Dynamics of ETU

The energy picture during one swinging cycle is illustrated in Fig. 4. There exist four regions corresponding to four types of energy in the process: 1) mechanical potential energy (in red); 2) mechanical kinetic energy (in orange); 3) thermal energy (in cyan); and 4) electrical energy (in purple).

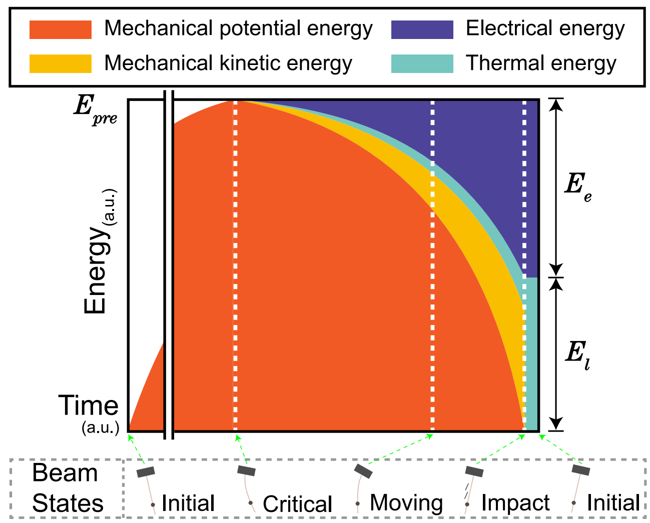


Fig. 4. Energy picture of ETU in an arm swing cycle.

The energy transformations under a single swing can be summarized as four special timing points, which are also shown in Fig. 4.

1) Initial Point: At the beginning, the harvester is attracted to one side by the magnetic force. The deformation of the soft beam can be seen as zero due to the relative stationary state of the arm. Hence, the energy sum of the ETU stays zero at this point.

2) Critical Point: As the arm begins swinging, the kinetic energy of the arm is captured by the mass and converted into mechanical potential energy stored in the deformed beam, which can be called potential energy precharging. Since this process is relatively long, most of the time in between is omitted in the energy picture with two vertical lines. When the magnetic force barely balances the restoring force of the bending beam, ETU comes to the critical point, where the deformation of the beam reaches a maximum, i.e., the precharged potential energy comes to the maximum point. The precharged energy at this time is denoted as E_{pre}, which proves the whole energy ETU scavenged during a single swing motion.

3) Moving Point: The beam is rapidly released after the critical point. During this very short moment, the precharged potential energy is divided and converted into kinetic energy, thermal energy due to mechanical damping, or useful electrical energy through the electromagnetic transducer.

4) Impact Point: When the all-in-one soft beam hits the opposite iron sheet, the accumulated kinetic energy instantly drops from its maximum value to zero. In the meantime, all the kinetic energy is transformed into thermal energy, i.e., the thermal energy reaches the maximum value, called the loss energy E_l, while the useful electrical energy E_e stays stable. After the impact, the whole mechanical characteristic and energy dynamics of ETU return to the initial point, and only the position of the all-in-one soft beam becomes the opposite. The harvested energy E_e is transferred and stored in the next unit, EMU.

Therefore, every swing motion involves an energy precharging process, which ensures the lower bound of the E_e and the stability of the whole self-powered system. Such a feature, precharging before electromechanical transduction, is unique in this wearable electromagnetic energy harvester design. When using a parameter η to define the efficiency of electromechanical energy conversion, the harvested electrical energy can be expressed as $E_e = \eta\, E_{pre}$. In addition, the precharged potential energy can be handily adjusted by tuning the length of the beam and the magnetic force, etc.

C. Low-Cost Well-Rounded EMU

As we know, EMU is of significance to every battery-free KEH-based IoT system. Since the kinetic energy from the ambiance is still insufficient for the continuous operation of IoT devices. Let alone its fluctuating feature. Intermittent operation is proven to be the better executing mode for KEH-based IoT systems [57]. In this case, an EMU is required to manage the energy and realize the intermittency in computing. There are four demands for a superior EMU.

1) UVLO: The EMU should be aware of the stored energy and provide two threshold voltages, V_{start} and V_{close}. When the voltage of the stored energy reaches V_{start}, the IoT device is turned on for one round operation (sensing, computing, and transmitting). As the voltage of the capacitor comes lower than V_{close}, the IoT device would be rapidly turned off or set to sleep mode and wait for the next round of operation. Such a function ensures the stable executing process of the load devices.

2) Low-Power Operation: During the energy build-up process, the current flowing through the EMU should be extremely low, enabling the highly efficient use of the energy. Besides, using the analog-to-digital converter (ADC) integrated with an SoC for UVLO [58], which has high-power consumption, is not recommended.

3) Low Cost: Instead of depending on the commercial power management chip, it has a lower cost and is compact to utilize the discrete-based circuit. In addition, the fewer components used for different functions in the circuit, the better.

4) Handy Configuration: The threshold voltage of the general UVLO function is fixed, which makes the EMU extremely inflexible and only suitable for certain applications. Reconfigurable threshold voltage enables the whole system to approach the supply–demand balancing, i.e., matching the required energy to the known consuming energy by adjusting the threshold voltage.

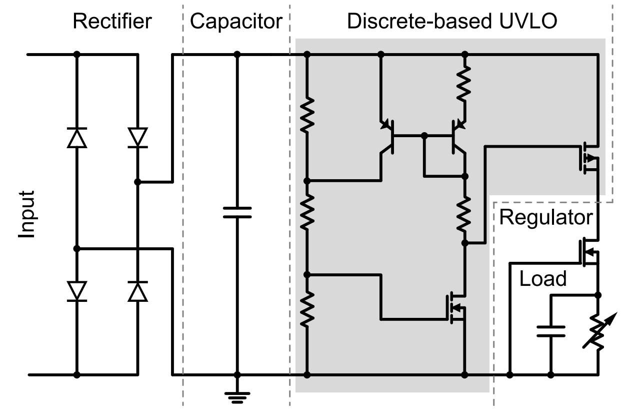


Fig. 5. Self-contained energy-aware circuit designed for energy management.

Inside MP-HAR, a comprehensive board-level energy-aware circuit, incorporating rectification, energy storage, and voltage regulation functions, is designed and utilized for reliable performance [59], as Fig. 5 shows. Embedded with the low-power analog UVLO circuit, EMU can flexibly change the on/off threshold voltages by adjusting the resistor network, which is more advanced than LTC3588, a widely used commercial chip. The nano-level of the static power consumption and the minimal number of required components empower MP-HAR with ultralow power and low-cost characteristics. Moreover, this circuit offers a comparably stable regulated output voltage to power the IoT devices while requiring no additional quiescent current by skillfully using a depletion-mode MOSFET [59].

The drain current of the gate-grounded depletion MOSFET is calculated as follows:

$$I_d = K_p \frac{W}{L}(-V_o - V_{th})^2 \tag{1}$$

where K_p, W, L, V_o, and V_{th} are the transconductance, width, length, output voltage, and the threshold voltage of the depletion-mode N-channel MOSFET, respectively. Therefore, after a simple transformation, this equation can be written as follows:

$$V_o = -\sqrt{\frac{I_d L}{K_p W}} - V_{th}. \tag{2}$$

The converted energy from the ETU is rectified and stored inside the EMU. When the voltage of the capacitor becomes higher than V_{start}, the energy would be regulated to provide a constant voltage output to the EUU.

D. Intermittent Operation

As mentioned above, EH-based IoT devices mostly work intermittently. Fig. 6(a) demonstrates the typical energy picture for a self-powered IoT system during the normal intermittent working cycle. There are two basic phases: 1) charging and 2) computing and transmitting. In the beginning, the stored energy is close to the off threshold. As the energy keeps flowing into the storage capacitor, the stored energy accumulates.

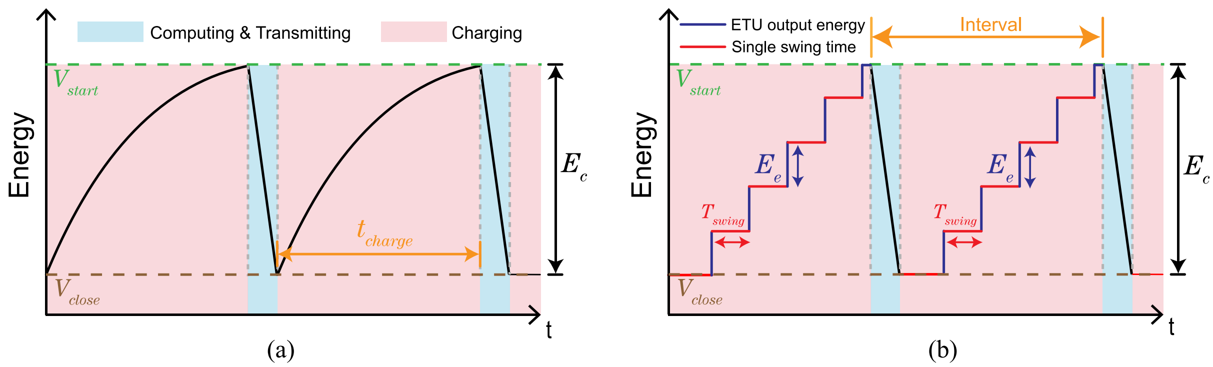


Fig. 6. Energy picture of the system during intermittent operation mode. (a) Typical intermittent working process of a battery-free IoT system. (b) Unique intermittent working process of the proposed system. The inversely proportional relationship between the swinging frequency and packet interval can be implicitly derived from the energy picture. The balance between supply and demand is achieved by setting an on/off threshold with minimal energy consumption of the SoC as a reference, i.e., E_c in the figure.

It is the charging period when the IoT device is turned off. Generally speaking, the charging time is much longer than the discharging time. When the energy reaches the turn-on threshold, the IoT device is turned on to execute tasks like computing and transmitting. The energy consumption of the IoT device can be measured and denoted as E_c. As the load completes the scheduled tasks, the stored energy drops quickly and reaches the off threshold. Repeatedly, the IoT device would be turned off and wait until the energy is sufficient.

Owing to the cooperation of the ETU, EMU, and EUU of MP-HAR, the unique energy flow among them allows the IoT device to work intermittently. The energy picture of MP-HAR is shown in Fig. 6 (b). During the charging process, the energy, E_e, generated by ETU as the human arm swings is stored in the capacitor of EMU. Assuming that the frequency of arm swing is relatively constant when a person maintains a particular gait activity, the time of each one-way swing is $T_{\text{swing}} = 1/(2f)$, where f is the swinging frequency. Therefore, the charging process of MP-HAR appears to be a stairway made of many steps due to the special mechanical characteristics of the ETU. For each step, the height is the energy E_e from the ETU, and the width is the period T_{swing}.

After measuring the total energy consumed by the EUU for one round of necessary operation, we can derive the minimal energy required for each interval, i.e., E_c. According to the energy formula

$$E_c = \frac{1}{2}C\left(V_{\text{start}}^2 - V_{\text{close}}^2\right) \tag{3}$$

the harvested energy in each round can be set as small as possible by taking E_c as a reference and handily adjusting the on/off threshold voltages of the EMU. This balance of supply and demand by matching the required energy with the supplied energy is critical for battery-free IoT systems.

While storing the energy that comes from ETU, the accompanying human swing information is simultaneously sensed by EMU. When the arm swing reaches a certain number of times, the harvested energy would be recognized as sufficiently large to kick off a round of communication. Subsequently, the EUU is turned on to transmit wireless packets. The number of arm swings in one round of wireless communication is approximately rounded up as follows:

$$n = \left\lceil \frac{E_c}{E_e} \right\rceil. \tag{4}$$

Therefore, the interval between two adjacent wireless transmitted packets reflects the frequency of the arm swing motion. The packet interval can be approximately formulated as follows:

$$\text{Packet interval} = n \cdot T_{\text{swing}} + t_c \approx \left\lceil \frac{E_c}{E_e} \right\rceil \frac{1}{2f} \tag{5}$$

where t_c is the computing and transmitting time of the SoC. It can be taken as a constant time interval. Since t_c is a relatively short interval compared with the charging time, its percentage within a packet interval can be neglected. E_e is relatively stable against the swinging frequency changes, owing to the special design of the transducer. Therefore, E_e can also be regarded as a constant. The time interval between packets is inversely proportional to the frequency of arm swing. According to the relation between swing frequencies and different human activities, the specific type of human activity can be identified by counting the interval between wireless packets.

E. Mechanisms to Enhance Recognition

Two mechanisms are implemented in the software codes on either the transmitter or receiver sides to enhance the success rate and correctness of activity recognition.

1) In the transmitter, the cyber-electro-mechanical prototype is specifically co-designed to send two packets at a time based on the balance between supply and demand. Such a mechanism reduces packet loss rate and enhances the quality of communication.
2) In the receiver, the app would start recognizing activities or make a rerecognition only when two intervals with a similar duration are recorded. In other words, only a periodic wrist movement can initiate the recognition process, while only a stabilized periodic wrist movement after a pace change confirms the activity transition.

Besides these two mechanisms, to recognize the standing still state, we set an idling time of 12 seconds as the threshold. Due to MP-HAR's mechanical structure, slight wrist movements

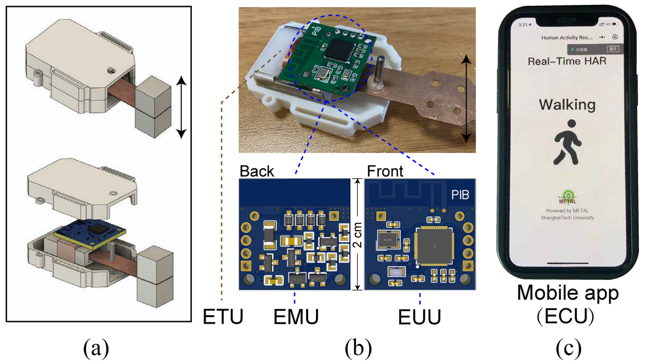


Fig. 7. All-in-one prototype of MP-HAR. ETU, EMU, and EUU form the hardware part of MP-HAR, where EMU and EUU are integrated on a $2{\times}2$ cm^2 PCB, which can be easily assembled with ETU. (a) Prototype and its exploded view. (b) Three hardware units. (c) Edge computing unit.

TABLE II
MP-HAR SPECIFICATIONS

Unit	Component	Specification	
ETU	Iron piece	Size	$7{\times}18{\times}1$ mm^3
	Soft beam	Material	Copper
		Size	$10{\times}38{\times}0.3$ mm^3
	Proof mass	Weight	24g
	Copper coil	680 turns	
	Shell	Material	PLA
	Iron sheet	Size	$16{\times}6.6{\times}1.2$ mm^3
	Magnet	180 mT	
EMU	Energy-aware circuit [59]	Resistance	1, 18, 31, 20, 0.1 MΩ
		Capacitance	100, 1 μF
EUU	SoC	nRF52832	
	Software	nRF5 SDK V17.1	
ECU	Mobile app	WeChat Mini Program	

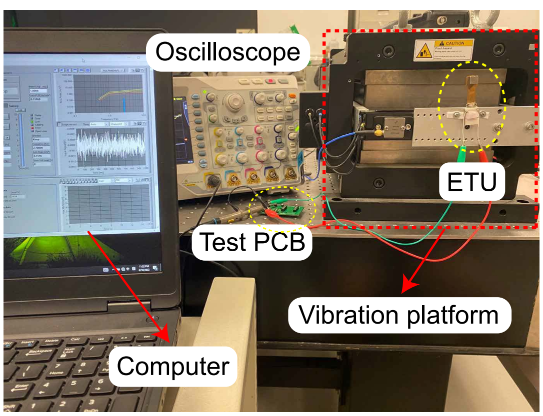


Fig. 8. Experimental setup for evaluating the harvested energy from ETU.

at standing cannot trigger the device to generate electricity; therefore, no packet is sent. In the case of occasional large wrist movements in the standing state, the double-period confirmation mechanism also takes effect. It helps filter irregular movement and avoid misrecognition.

V. PROTOTYPE AND EVALUATION

MP-HAR is designed based on the inversely proportional relationship between the wireless packet interval and the frequency of arm swing. For thoroughly validating the feasibility and performance of MP-HAR, an all-in-one prototype is fabricated based on the proposed system, as shown in Fig. 7. The specifications of MP-HAR are listed in Table II. The EMU

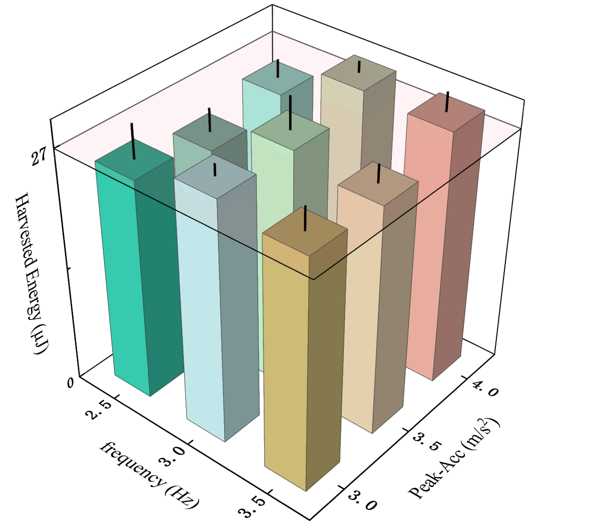


Fig. 9. Harvested energy at the vibration frequency ranging from 2.5 to 3.5 Hz for peak accelerations ranging from 3 to 4 m/s^2. The results prove the relatively stable amount of harvested energy E_e.

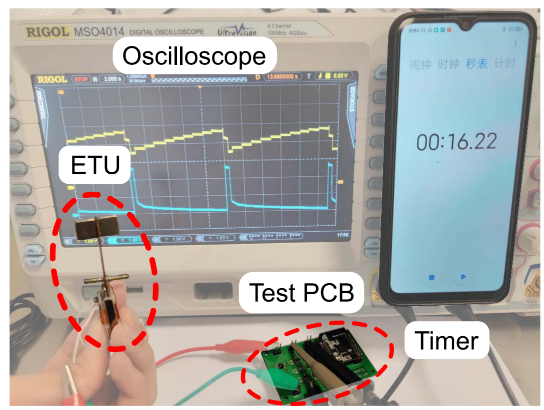


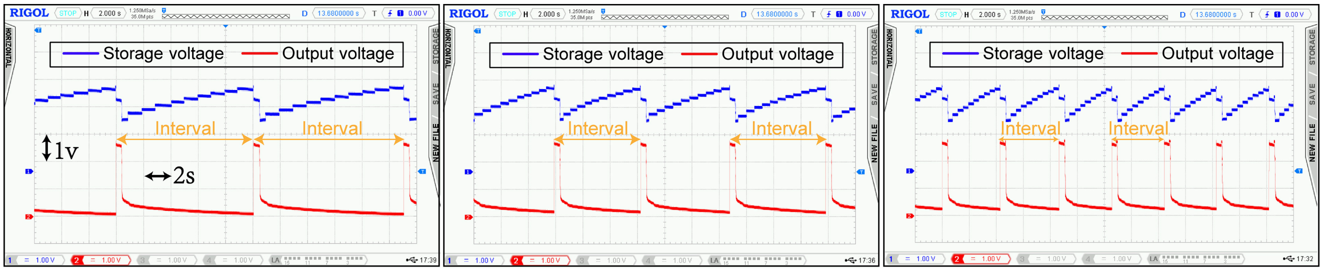
Fig. 10. Experimental setup for testing the operation and feasibility of MP-HAR.

and EUU are integrated into a $2{\times}2$ cm^2 printed circuit board (PCB), which can be handily assembled with the prototyped ETU. The shell is manufactured using a 3-D printer. When the prototype is worn on the wrist, the gait information of the human body can be transmitted to the nearby ECU via wireless signal packets.

In the laboratory environment, we first evaluate the energy ETU generates in different arm swing frequencies and accelerations. Subsequently, a prototyped ETU and PCB are tested to validate the feasibility of MP-HAR. Finally, an all-in-one prototype is used to comprehensively evaluate the field performance.

A. Energy Evaluation Under Periodic Movements

To evaluate the relationship between the harvested energy E_e and different human gait patterns, we conducted multiple lab experiments. Fig. 8 shows the experimental setup. The prototyped ETU is installed on the vibration platform, controlled by a computer-based controller. The computer gives various excitation of sinusoidal signals for simulating the arm swings.



(a) (b) (c)

Fig. 11. Results of the operation test. (a)–(c) Waveform showing the voltage of the storage capacitor and SoC when the hand swing frequency is at 0.5, 1, and 1.5 Hz, respectively.

As the vibration platform oscillates at a certain frequency and acceleration, the energy generated by the ETU would flow and be stored in the capacitor of the test PCB. In the meantime, the voltage of the capacitor is read on the oscilloscope. Using the formula, $E = CV^2/2$, the harvested energy can be derived.

As a result, the harvested energy stands relatively stable even at the high-frequency range from 2.5 to 3.5 Hz for peak accelerations ranging from 3 to 4 m/s^2, as shown in Fig. 9. The average energy is calculated to be 27 μJ, which is the same at a relatively low frequency. Therefore, the energy generated by each arm swing is relatively stable regardless of the gait. It validates the robustness of the proposed MP-HAR in energy generation.

B. Validation of MP-HAR Operation

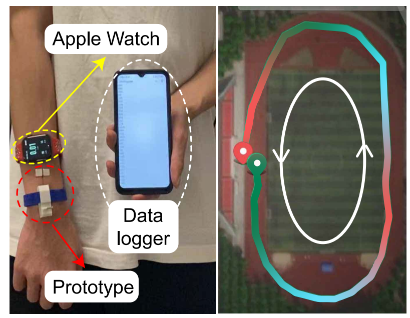
A lab test on the operation of the whole system is carried out to evaluate the feasibility of MP-HAR. Fig. 10 shows the experimental setup. By looking at the timer, the hand swings the prototyped ETU at a specific frequency for simulating the arm swing. The energy from each swing action flows to the prototyped electronic system, which integrates the energy-aware circuit and SoC. The oscilloscope records the storage voltage and output voltage of the EMU.

Fig. 11(a)–(c) show the waveform under the hand swing frequencies of 0.5, 1, and 1.5 Hz, respectively. The on and off threshold voltages of MP-HAR are set to 3.1 and 2 V, respectively, while the regulated output voltage is set to 2.8 V. From the waveform, we can see the system is working intermittently as originally designed. To make a tradeoff between energy consumption and system robustness, the software code of the EUU is optimized to initialize and broadcast two BLE beacon packets in one round. The time and energy consumed by EUU in one round are demonstrated to be constant. In addition, the harvested energy from each swing motion can be implicitly seen as relatively stable. As a result, the operation interval becomes shorter when the swing frequency gets higher. Human activity can be deduced in real-time by counting the interval between received wireless packets. In other words, the feasibility of the proposed system is validated.

C. Field Test

After the experiments in the lab to investigate the robustness and feasibility of MP-HAR, multiple field tests are conducted to validate the stability and performance in real scenarios. The testing subject wears the all-in-one compact prototype and an Apple Watch on one wrist, while the other hand holds a mobile phone running a customized app for data logging, as shown in Fig. 12(a). The sports ground, shown in Fig. 12(b), is selected as the experiment site since it has relatively accurate distance scales. The Apple Watch records the message of the actual gait states, such as steps, time, and pace, enhancing the experimental reliability. The data logger shows the intervals between received packets from the prototype. The previous studies showed a strong relationship among pace, stride frequency, and gait conditions [60]. Wrist swings usually at the same frequency as the stride, which is inversely proportional to pace. Thus, we focus on the relationship between pace and packet interval.

The data set collected when the subject performs different gaits, i.e., walking, jogging, and running, is shown in Fig. 13. The subject randomly switched different gait states within one



(a) (b)

Fig. 12. Experimental setup for field testing. (a) While wearing the prototype and Apple Watch simultaneously, multiple experiments have been conducted in the playground using a customized mobile app for data logging. (b) Experiment site. Different colors denote different activities.

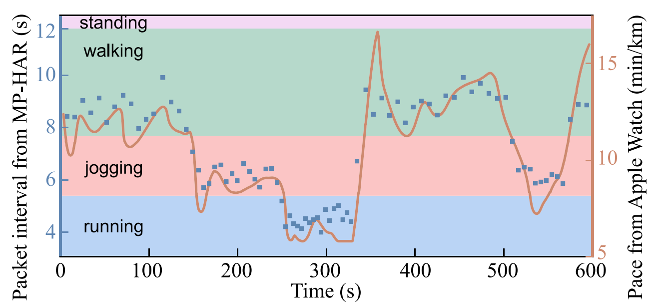


Fig. 13. Data set recorded when a subject does different activities in 1 km.

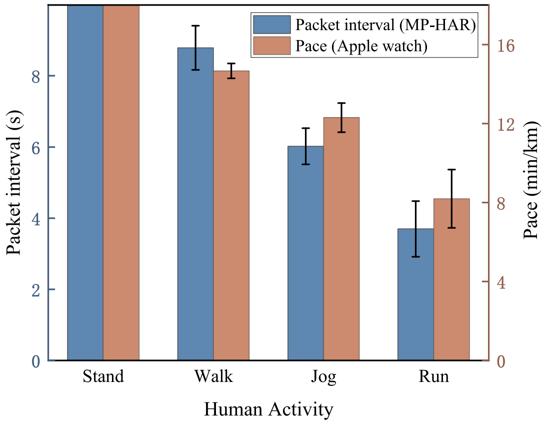


Fig. 14. Performance of MP-HAR during several real-world human activities. The paces obtained from the intelligent watch prove the actual activities. As a result, according to the packet intervals, we manage to differentiate the frequency of different activities and realize real-time HAR.

kilometer to verify the positive relationship between packet interval and pace in the field test. For each gait, the testing subject tried to maintain a constant pace. However, the Apple Watch cannot accurately fit the matching speed at the gait transition points. Overshoots are found at the beginning of almost all pace transitions. It might be due to the overestimation by the algorithm in the Apple Watch. Except for these small discrepancies, the results from both measurements match each other quite well. The interval data from the MP-HAR can be well clustered into three classes, representing three gaits.

Besides the aforementioned varying gaits continuous field test, we have carried out more than 100 sets of tests on the sports ground with constant gait in walking, jogging, and running at different distances (50, 100, 200, or 400 m) to better calibrate the relation between the packet interval from the proposed device and the pace data from the Apple Watch. The results are shown in Fig. 14. The figure shows the positive correlation between paces and packet intervals under the activities of standing, walking, jogging, and running. A mobile app can differentiate these four kinds of human activities in real-time by simply setting some threshold values.

In all the experiments and field tests, we found no data loss within a distance of 15 m around the data logger. Besides a mobile phone used as a receiver, other low-cost terminals, such as MCU, FPGA, or Raspberry Pi, can also be used. The receiver has no downtime problem during the experiment due to the stable power supply. The proposed system is generally validated for carrying out real-time HAR in the field test.

VI. Conclusion and Future Work

This article introduced MP-HAR, a new real-time, low-cost HAR system based on KEH, which encapsulates four well-designed parts: 1) ETU; 2) EMU; 3) EUU; and 4) ECU. Inside MP-HAR, the unique energy and information flow among the hardware units bring MP-HAR the capacity of simultaneously EH and sensing from the ambiance. In other words, the proposed system can be a self-powered HAR system without using an IMU. In the normal intermittent operation, by knowing the minimal power consumption of one round of computational tasks, we have set the on/off thresholds of the energy-aware circuit to realize a balance between supply and demand. For comprehensively evaluating the proposed system, an all-in-one prototype has been fabricated. Lab tests proved the relatively stable harvested energy and the inversely proportional relationship between arm swinging frequency and packet interval. Field tests validated that MP-HAR can reliably identify the human motions of standing, walking, jogging, and running by knowing the differentiable packet intervals. The proposed cyber-electro-mechanically synergetic design provided a promising application prospect for wearable devices with critical cost and power requirements while setting a good engineering example of pervasive HAR and low-cost battery-free IoT systems.

Besides only one device on the subject's wrist, more devices can be worn in other places of the human body to extract more information about the movement. Moreover, MP-HAR might be applied to humans, pets, or livestock to monitor their movements. When largely deployed, the performance for recognizing multiple units can be further improved by using AI techniques [61]. The battery-free monitoring solution of MP-HAR provides a promising prospect for pervasive sensing and ubiquitous IoT.

In future work, we will continue to better analyze and optimize the mechanical design and circuit. More sophisticated and suitable communication protocols and recognition algorithms will be developed to enhance communication reliability and recognition correctness further. In addition, using cutting-edge federal learning, on-device learning, and tiny machine learning (TinyML) techniques for the whole end-edge-cloud orchestrated HAR network is also worth exploring.

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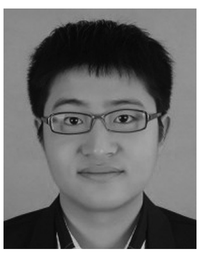

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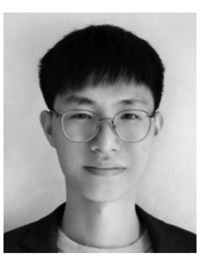

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