SolAR: Energy Positive Human Activity Recognition using Solar Cells

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***Abstract*—The high power consumption of inertial activity sensors limits the battery lifetime of today's wearable devices. Recent studies promise to extend the lifetime of wearable devices by translating kinetic energy from human movements into electrical energy while using the harvesting signal to replace conventional activity sensors. However, in human-centric applications, the amount of harvested kinetic energy is not enough to power a real-time activity recognition algorithm and run the wearable device perpetually. In this paper, we propose Solar based human Activity Recognition (SolAR), which uses solar cells simultaneously as an activity sensor as well as an energy source. Our key observation is that the power available from a wrist-worn solar cell changes dynamically while a person moves, encoding information about the underlying activity. We collect empirical solar energy data to explore its activity sensing potential and implement the activity recognition pipeline on an ultra low-power micro-controller unit to evaluate the end-to-end power consumption of the system. Our analysis reveals that SolAR improves activity recognition accuracy by up to 8.3% and harvests more than one order of magnitude higher power compared to its kinetic counterpart. This enables SolAR to generate more energy than required for the entire activity recognition pipeline, which we term as *energy positive* activity recognition, achieving uninterrupted, autonomous, self-powered and real-time operation.**

***Index Terms*—Wearables, Solar, Kinetic, Energy Harvesting, Sensors, Human Activity Recognition, Energy Positive Sensing**

I. Introduction

With the advancement in technology, wearable Internet of Things (IoT) devices are becoming increasingly popular with an expected market size of US$ 51.62 billion by the year 2022 [1]. They have numerous applications in our daily lives including Human Activity Recognition (HAR), health and fitness monitoring [2], and transport route planning [3]. However, current wearable devices have limited lifetime due to the finite energy storage capacity of their batteries which impedes their pervasive deployment. A promising solution is to employ energy harvesters to convert ambient energy into electrical energy to power these wearable devices. Because the amount of harvested energy encodes information about the underlying physical processes, energy harvesters can be used as activity sensors to replace conventional power consuming sensors such as accelerometers and magnetometers [2]. For example, the harvesting signal from a wearable Kinetic Energy Harvesting (KEH) transducer changes according to the underlying human movements/vibrations and thus contains information about the activity [3], [4]. In addition to KEH transducers, solar cells are also used as a proxy for activity sensors [5], [6]. Ma et al. [5] employ solar cells for recognizing different types of hand gestures in a controlled environment under a lamp. Umetsu et al. [6] employ both solar and kinetic energy harvesters for room-level place recognition in a building. However, most previous works [4]–[6] operate KEH transducer and solar cells in an open circuit configuration, i.e. only as a sensor without extracting energy simultaneously.

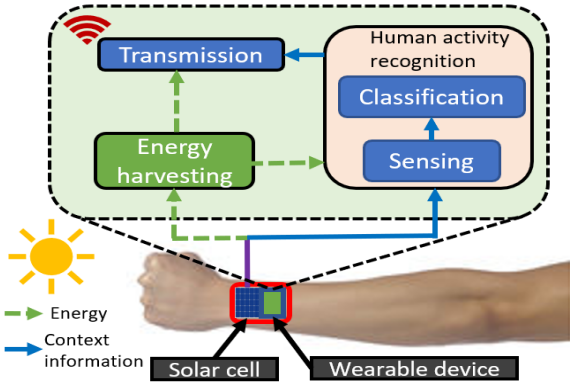


Fig. 1: Using solar cell for activity recognition as well as to power the sensor node, leading towards *energy positive HAR*

To address this issue, researchers [7], [8] employ KEH for simultaneous sensing and energy harvesting, showing that it can support energy positive signal acquisition, where the harvested energy exceeds the energy required for signal acquisition [7]. This enables applications where sensor data is logged on the device locally, and then manually transferred post deployment for offline processing and activity classification. However, real-time HAR with energy harvesting-based sensors, where users receive live feedback on their activities, requires that the harvested energy can power not only signal acquisition, but also classification, and transmission. Unfortunately, the harvested energy from a tiny, single, untuned KEH is not enough to power all components of a HAR system [7], [9]. Our objective in this paper is to enable *energy positive*

HAR, where the harvested energy exceeds the energy required for signal acquisition, classification, and activity transmission.

To this end, we propose Solar based human Activity Recognition (SolAR) which uses solar cells as a sensor for activity recognition as well as a source of energy. As the human activities interfere with the ambient light differently, the output signal from the wearable solar cell embeds a signature of the underlying activity. In addition, the harvested power from the solar cell can be sufficient to run the end-to-end HAR algorithm (including signal acquisition, classification and real-time wireless activity transmission) and thus enables *energy positive HAR* as depicted in Fig. 1. In order to evaluate SolAR, we collect Solar Energy Harvesting (SEH) data from 21 adult and healthy participants performing five common activities both indoors and outdoors. Using well-known machine learning algorithms, we discover that, compared to conventional KEH-based HAR systems [4], [10], the proposed SolAR system delivers an order of magnitude higher harvested power indoors, and up to $8.3\,\%$ higher HAR accuracy. In outdoor settings, SolAR offers comparable HAR accuracy and more than two orders of magnitude higher harvested power compared to KEH-based HAR. The significant increase in the harvested power enables real-time and *energy positive HAR*.

This paper makes the following main contributions:

- We propose SolAR, an *energy-positive HAR* mechanism which employs a wearable-sized solar cell to provide both activity information as well as energy simultaneously.
- We collect solar data from 21 participants in indoor as well as outdoor environments and implement a classification algorithm to infer the underlying activity. Our rigorous analysis reveals that SolAR provides up to $8.3\,\%$ higher HAR accuracy compared to KEH-based HAR.
- In order to measure the end-to-end power consumption, we implement the proposed classification pipeline on an ultra low-power Micro-controller Unit (MCU). We discover that SolAR offers *energy positive HAR* as the harvested power is higher than the power required to run the HAR algorithm on the wearable device, ensuring its autonomous, self-powered, real-time and perpetual operation without the need for any external energy source.

II. Related Work and Motivation

A. Previous HAR mechanisms

Previous HAR techniques rely mainly on conventional activity sensors [11] such as accelerometers and magnetometers which consume significant energy and require an external energy source for their perpetual operation [2]. In order to allow uninterrupted operation and to reduce the energy consumption of IoT sensor nodes, recently, KEH transducers are also being used as activity sensors for HAR. Khalifa et al. [4] show that KEH-based sensing can offer reasonable HAR accuracy with significantly reduced energy consumption compared to conventional activity sensors. Kalantarian et al. [12] design a KEH-based necklace for monitoring food intake and eating habits. Lan et al. [13] use a capacitor to store the harvested energy from KEH and then use the capacitor voltage signal for HAR. This reduces the energy consumption due to the reduced sampling rate for acquiring the slowly varying capacitor voltage. Instead of using a single KEH transducer, Ma el al. [8] employ two transducers in a shoe to identify the underlying human activities. They use both transducers for HAR as well as for extracting energy (stored in the capacitors), but do not consider the effect of a realistic, dynamic load. Sandhu et al. [7], instead, use a KEH transducer as an activity sensor and source of energy simultaneously to power a dynamic load. They show that KEH offers energy positive signal acquisition, which means that the harvested energy is higher than the energy required for acquiring the activity signal. However, in human-centric applications, the limited harvested energy from a KEH transducer may not be sufficient to run all tasks on the sensor node, including signal acquisition, classification and transmission without the need for any external energy source [7]. This limits its application to scenarios with offline, cloud-based classification. Therefore, there is still a significant need for alternative HAR mechanisms that can ensure the autonomous and perpetual operation of sensor nodes for running the HAR algorithm leading towards a truly pervasive energy harvesting-based IoT.

TABLE I: Properties of SEH and KEH [14], [15]

Property	Photovoltaic	Piezoelectric
Power density [μW/cm^2]	$10\,\mu$W to $15\,$mW	upto $330\,\mu$W
Conversion efficiency	up to 40%	up to 30%
Robustness	High	Low

Previous studies illustrate that ambient light also contains information about the human context and, for example, can be used to analyse human eating habits [16] when combined with other sensory data. The authors in [17] deploy light sensors on the floor and use the output signals to detect human gestures. Zhang et al. [18] develop a photodiode array and use it in various applications including detection of door opening/closing, liquid level detection, step count and touch detection, etc. Instead of using conventional light sensors, the authors of [5] employ solar cells to recognise various hand gestures under a fixed lamp. Furthermore, Li et al. [19] use arrays of photodiodes for finger gesture recognition and employ the harvested energy to power the gesture recognition module. However, they perform gestures by touching the arrays of photodiodes and thus their system may not recognise finger gestures performed in the vicinity of (without touching) the photodiode array. In another study [6], a combination of solar and kinetic energy harvesters (placed on the human chest) is used for room-level place recognition in buildings. These works employ SEH either in a controlled environment [5] (indoor only) or in a combination with KEH transducers [6]. Furthermore, they (except [19]) employ SEH merely as an activity sensor without harvesting energy to power a dynamic load. Moreover, to the best of our knowledge, the potential of using solar cells to detect human physical activities (indoors and outdoors) in HAR applications remains unexplored.

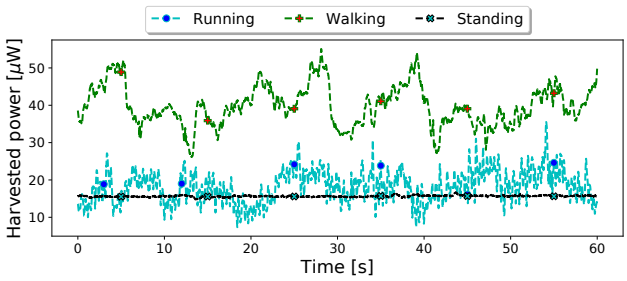


Fig. 2: Solar harvested power during various human activities

B. Motivation

Solar (or photovoltaic) cells are the most common and economical source of energy used to power IoT sensor nodes [20]. A solar cell consists of a semiconductor material and generates an electric current (photocurrent) in response to the ambient light energy falling on its surface [21]. Due to the wide availability and ease of implementation in indoor and outdoor environments, they are used in a variety of applications including handheld calculators, garden lights [5] and wearable devices. Table I [15] shows that visible light offers higher power density compared to kinetic energy. The table also shows that SEH possesses significant advantages in terms of conversion efficiency and robustness compared to its counterpart of motion/kinetic energy. High conversion efficiency means that a certain harvesting technique can extract a higher proportion of energy from the source, whereas robustness means that the system is sufficiently reliable, requires limited maintenance and offers a consistent response each time it is exposed to a similar environment.

The harvested energy from a solar cell varies according to the intensity of incident light and orientation of the solar surface relative to the light source [5]. When worn on the human body, the harvested energy changes during various human activities thanks to the different type of mobility relative to the source(s) of light as well as shadowing, which contains a unique signature of the underlying activity. Fig. 2 plots the generated power from a wrist-wearable small-sized solar cell during three common indoor human activities: running, walking, and standing. As various human activities interfere with the ambient light differently – resulting in distinct harvesting patterns, we can use the harvesting signal as a sensing signal in order to classify the current activity. Thus, solar cells offer an attractive combination of activity information and harvested energy for realizing pervasive energy harvesting-based HAR.

III. SolAR: A Novel Human Activity Recognition System

This section describes the architecture of our proposed SolAR system whereas the implementation specific details are provided in Section IV. We employ a wearable solar cell as an activity sensor for HAR as well as an energy source to power the system load for the autonomous and perpetual operation of wearable IoT devices. Fig. 3 depicts the architecture of the SolAR model, showing both the energy and data flows. We use a DC-DC boost converter with maximum

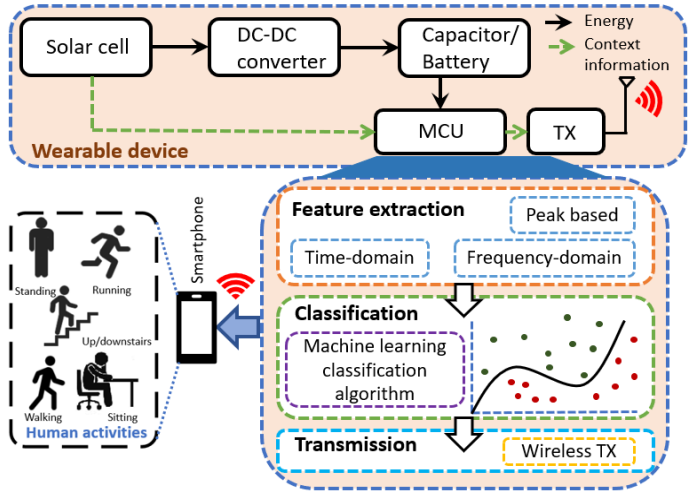


Fig. 3: Proposed SolAR model using the solar cell as an activity sensor as well as an energy source simultaneously

power point tracking to optimize harvested energy [22] and to decouple the harvesting signal from the energy storage and load behaviour [7]. The harvested energy is stored in an energy storage (a capacitor/battery) and is finally used to power the system. The information about the underlying activity is only encoded in the harvesting current, because the DC-DC boost converter regulates the voltage of the solar cell to a constant, optimized value [7]. We use an MCU to sample and process this current signal and to infer the underlying activity as shown in Fig. 3. Firstly, various time and frequency domain features are extracted from the acquired SEH signal [4], [7]. Then, extracted features are used as input to a classifier to detect the underlying activity. Finally, the result of the inferred activity is transmitted to a receiver (e.g., a smartphone) where it is exploited, e.g., by health or fitness applications. Note that, in contrast to [7] which samples the KEH signal locally and streams the raw data to a server, SolAR implements signal acquisition, feature extraction, classification and activity transmission on the wearable device powered only by the harvested energy from the wearable solar cell. Implementing the complete HAR pipeline on the sensor node not only reduces the power consumption [23], [24], but also improves application latency and privacy [25], [26]. Omitting conventional activity sensors, rectification circuits (required for KEH) and external energy sources, SolAR minimizes the cost, complexity, form factor, and environmental impact of the wearable IoT system. This finally realises the vision of *energy positive HAR* in which end-to-end HAR is performed in real-time on the wearable devices using only harvested energy.

IV. Measurement Setup, Data Collection and Implementation of the Proposed Model

This section explains the measurement setup, the data collection procedure as well as the data traces and implementation process of SolAR.

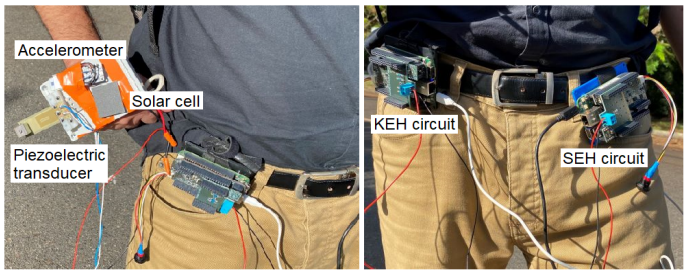


Fig. 4: Experimental setup for data collection using SEH and KEH transducers during various human activities

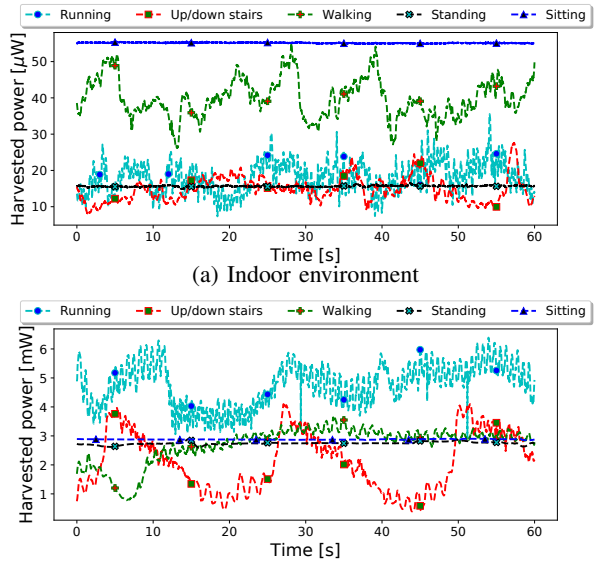
A. Measurement setup

We use the tool from [27] to sample the solar current from an off-the-shelf IXYS SLMD121H10L solar module during five human activities. The solar cell measures $4.2\,\mathrm{cm} \times 3.5\,\mathrm{cm}$ and weighs $4.5\,\mathrm{g}$, which is suitable for wearable devices and smart watches [28]. As a baseline, we simultaneously record the harvesting current from a $7.1\,\mathrm{cm} \times 2.54\,\mathrm{cm}$ MIDÉ technology S230-J1FR-1808XB two-layered piezoelectric bending transducer. We use a tip mass of $24.62\,\mathrm{g}\pm0.5\%$ to tune the resonance frequency of the KEH transducer to the low frequency vibrations typically observed in human-centric applications [4], resulting in a total mass of $30.46\,\mathrm{g}$. Both energy harvesting signals are sampled with an 18-bit Analog-to-Digital Converter (ADC) at $100\,\mathrm{kHz}$. Finally, we also record acceleration data from an InvenSense MPU9250 3-axis accelerometer with a 12-bit ADC at $100\,\mathrm{Hz}$. Before processing, the energy harvesting signals are down-sampled to the corresponding target frequency (see Sec. V-D). The solar cell, the piezoelectric transducer and the accelerometer are mounted on the wrist of the participants as shown in Fig. 4. Whereas, the recording devices are placed on the waist of the participants as depicted in Fig. 4.

B. Data collection

We collect SEH, KEH and accelerometer data from five common human[1] activities, i.e., sitting (while putting hands on the table), standing, walking, running and going up/downstairs. In order to be able to explore the performance of SolAR under different light conditions, we conduct two separate sets of experiments: the first set of experiments is conducted indoors in a mostly carpeted room of size $9m \times 22.5m$ with 13 healthy adults (age: 34±9.2 years, mass: 78.4±12.5 kg), and the second set of experiments is conducted outdoors with 8 healthy adults (age: 32.4±4.4 years, mass: 79.7±8.8 kg). In order to collect a representative SEH dataset which reflects diverse lighting intensity conditions that can be observed at different locations, we conduct the experiments on different days with different weather conditions (i.e., sunny, cloudy and partially cloudy) and at different times (i.e., morning, noon and evening). The participants are asked to perform each of the five activities for three minutes with a break of one minute after each activity. The participants are advised to perform the activities according to their daily routine and as naturally as possible. In total, we collect 390 minutes of data from five human activities and 21 participants.

[1]Ethical approval has been granted from CSIRO [106/19] for carrying out this experiment.



(a) Indoor environment

(b) Outdoor environment

Fig. 5: A wrist-wearable solar cell generates distinct pattern of harvested power during various human activities in (a) indoor and (b) outdoor environments

C. Solar cell as a novel human activity sensor

We present the sample data traces collected from a wrist-wearable solar cell during various human activities in indoor as well outdoor environments in Fig. 5(a) and Fig. 5(b) respectively. The figure depicts that the harvested power from SEH during various human activities is significantly higher outdoors compared to indoors thanks to the higher power density of the sunlight compared to artificial indoor light. Fig. 5 also shows that the harvested power during sitting is higher than standing due to the direct incidence of light on the solar cell, for example, when placing the hands on the table in a sitting position. In addition, dynamic activities such as walking, running and up/downstairs cause a dynamically changing orientation of the wrist-wearable solar cell relative to the light source, which results in a distinct pattern of harvested power. During walking, for example, the human body produces distinct shadowing effect on the moving wrist-worn solar cell, generating unique pattern of the harvested power. We also observe that indoor environment has multiple sources of light which may complement each other whereas outdoor environment contains only one source of light i.e., sun. In addition, outdoors there are more obstacles (such as trees and buildings) between the single light source and the solar cell, which result in more shadowing compared to the indoor environment. Therefore, although the harvested energy outdoors is higher than indoors, we expect higher activity detection accuracy indoors due to multiple light sources which complement each other and reduce shadowing effects.

TABLE II: Selected features from the SEH signal

Signal	Features
SEH-indoor	Peak-to-peak value, Coefficient-of-variation, Absolute area, Max. distance between peaks, 1st Quartile, 2nd Quartile, Frequency domain entropy, Median, Spectral peak, Min. value, Mean distance between peaks, Range, Max. value, Root-mean-square value, Absolute mean, Dominant frequency ratio, Kurtosis.
SEH-outdoor	Peak-to-peak value, Coefficient-of-variation, Absolute area, Max. distance between peaks, 1st Quartile, 2nd Quartile, Frequency domain entropy, Median, Spectral peak, Min. value, Mean distance between peaks, Range, Max. value, Min. peaks, Standard deviation, Median absolute deviation, Frequency domain energy, Mean, 3rd Quartile, Max. peak, Autocorrelation.

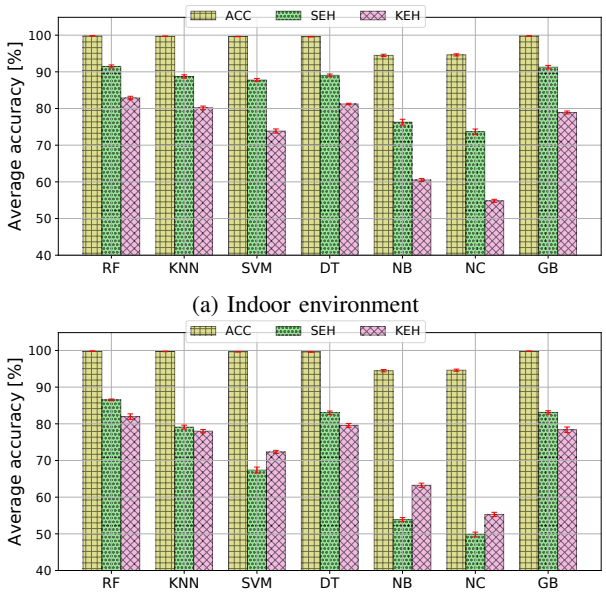
D. Implementation of SolAR

Below, we describe the implementation of SolAR in detail.

1) Pre-processing: The collected energy harvesting data from SEH contains stop periods (after each activity) which are removed from the data. Then, we segment the collected energy harvesting data into equal sized windows of 2 s [29] which is a typical time required to cover one stride length during walking [30], [31]. In order to retain the context information at both edges of windows and to enhance the data points, we overlap [4] the consecutive windows before feature extraction. Analysing the effect of varying degree of window overlap on the HAR accuracy, we observe that activity recognition accuracy increases with the increase in window overlapping degree. However, increasing the overlap also increases cost in terms of complexity and energy consumption, which is particularly relevant under a limited energy budget. Therefore, in line with previous works [4], [7], we choose a window overlap of 50 % as a trade-off between HAR accuracy and energy consumption.

2) Feature extraction: We extract various time and frequency domain features [4], [7], [11] from the energy harvesting data as presented in Table II. In addition to time and frequency-domain features, we consider various peak-based features, such as peak-to-peak value, maximum distance between peaks, mean distance between peaks, maximum peak value, etc. These peak-based features have proven to be useful to improve human context detection from KEH signals [4]. In order to discover the minimum set of features that offers highest HAR accuracy, we employ various supervised and unsupervised feature selection algorithms such as mutual information [32], principal component analysis [33], univariate [34], and correlation based feature selection [35]. After extensive analysis, we find that the mutual information based feature selection scheme achieves the highest HAR accuracy with the lowest number of features. The resulting, reduced feature set contains 17 and 21 features for SEH (as shown in Table II), and 25 and 13 features for KEH, in indoor and outdoor environments respectively.

3) Activity classification and transmission: Prior to the implementation of classification algorithms, we employ Borderline-Synthetic Minority Oversampling Technique (SMOTE) [36] to handle imbalanced data from various human activities. Then, we apply seven well-known supervised machine learning classification algorithms including Random Forest (RF), K-Nearest Neighbor (KNN), Support Vector Machine (SVM), Decision Tree (DT), Naive Bayes (NB), Nearest Centroid (NC) and Gradient Boosting (GB) on the energy harvesting datasets. The classification algorithms are trained offline and the trained model is then imported on the embedded device for activity recognition from the real-time SEH signals. After implementing the classification algorithm, the inferred activity is transmitted using the Bluetooth Low Energy (BLE) wireless communication protocol. Thus, the proposed work not only acquires the activity signals [7] but also implements the classification algorithm on the node using the harvested energy without the need of any external energy source.



(a) Indoor environment

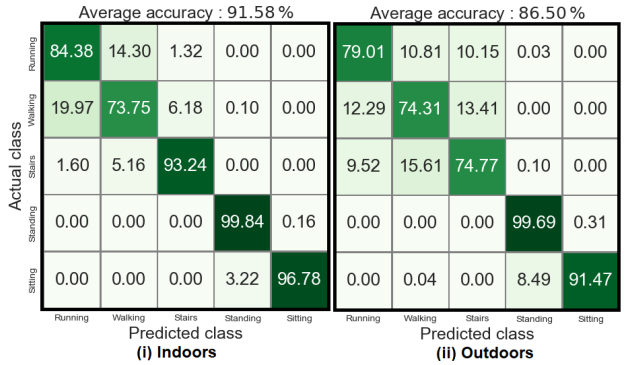
(b) Outdoor environment

Fig. 6: HAR accuracy of 3-axis accelerometer (ACC), SEH and KEH signals in (a) indoor and (b) outdoor environments using various classification algorithms (window size = 2 s)

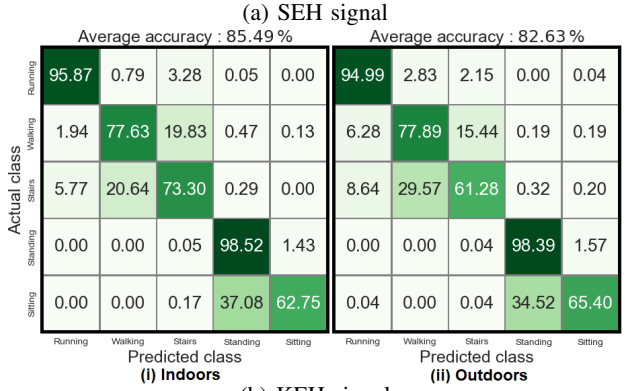
In order to enable comparability of our results to the state-of-the-art [3], [5], all the results in this paper are obtained using 10-fold Cross Validation (CV) (except Section V-E which presents results using leave-one-user-out CV to analyse the robustness of our system with user variance), and are presented with 95% confidence level. In order to ensure robust performance of the classifier, the folds are selected randomly from the available data. Prior to invoking the classification algorithms, we augment the data from various human activities and normalise the features with zero mean and standard deviation of one. Unless stated otherwise, the results are obtained using activity signals sampled at 100 Hz.

V. Performance Evaluation

SolAR relies on ambient light to generate energy and uses the solar harvesting current signal for HAR. Since the ambient light differs significantly between indoor and outdoor environments, we initially evaluate the performance of SolAR using



(a) SEH signal



(b) KEH signal

Fig. 7: Confusion matrices for HAR using (a) SEH and (b) KEH signals in indoors and outdoors (window size = 2 s)

SEH data from indoor and outdoor experiments separately, with an extensive comparison to accelerometer and KEH-based HAR. We present classification results of well-known classifiers, analyse variability of human activities as well as the effect of varying window sizes and sampling frequency on the activity recognition accuracy. Then, we examine the robustness of SolAR against new/unseen users. Finally, we evaluate the performance of SolAR using the combined data from both indoor and outdoor experiments.

A. Classification accuracy

Fig. 6 depicts the HAR accuracy offered by SEH, KEH and 3-axis accelerometer signals using various classification algorithms in indoor (Fig. 6(a)) and outdoor (Fig. 6(b)) environments. We find that, among all the classification algorithms, the RF classifier offers highest HAR accuracy for all types of signals. Therefore, in the rest of the paper, all results are obtained using the RF classification algorithm. Furthermore, among the activity signals, the accelerometer signal offers highest HAR accuracy due to the rich context information embedded in its 3-axis signal. Fig. 6 shows that among the two energy harvesting signals, SEH indoor and outdoor offers higher HAR accuracy than KEH thanks to the higher signal amplitude and unique harvested energy pattern during various human activities. In addition, SEH indoor offers higher HAR accuracy than SEH outdoor due to the uniform light availability, less shadowing and more light sources which complement each other. In other words, the diversity of light sources indoors edges its performance closer to the 3-axis

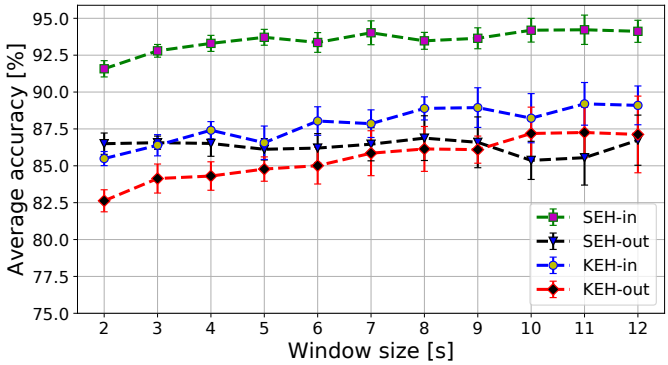


Fig. 8: HAR accuracy using SEH and KEH signals with increasing window sizes in indoor and outdoor environments

accelerometer, which captures three orthogonal signals for activity classification. Thus, SEH-based HAR outperforms conventional KEH-based HAR systems [4], [13] in terms of activity recognition accuracy.

B. Variability analysis of human activities

In order to analyse the classification results for individual human activities and to explore their variability, we show the confusion matrices using SEH and KEH signals (using the RF algorithm) in indoor as well as outdoor environments in Fig. 7. The figure shows that SEH offers higher recognition accuracy for static activities i.e., standing and sitting. The incident angle of the ambient light changes with the orientation of the solar cell, generating a significantly different amount and pattern of energy during static positions, which can be used to identify the underlying human activities. KEH, instead, generates a negligible amount of energy during static positions, which may not have significantly different patterns and thus offers lower HAR accuracy. Furthermore, SEH provides higher recognition accuracy during up/downstairs activity due to a different distribution of light compared to other activities. In contrast, using KEH, up/downstairs activity is confused with walking due to similar arm movement which generates an identical signal from the KEH transducer. Finally, KEH provides higher recognition accuracy for dynamic activities including walking and running, due to the motion-specific harvesting signal and significantly different type of mobility compared to other activities. On the other hand, due to the similar distribution of light sources, the harvesting signal pattern from SEH may have a certain degree of similarity during dynamic activities and thus offers lower HAR accuracy compared to the KEH signal.

C. Varying window sizes

Next, we explore the impact of larger window sizes on the activity recognition accuracy. Fig. 8 shows the activity recognition accuracy using various window sizes from 2 s to 12 s for SEH and KEH signals (using RF algorithm) in indoor as well as outdoor environments. We find that indoor SEH offers relatively stable HAR accuracy with a slight increase of about 2.8% when increasing the window size from 2 s to 12 s.

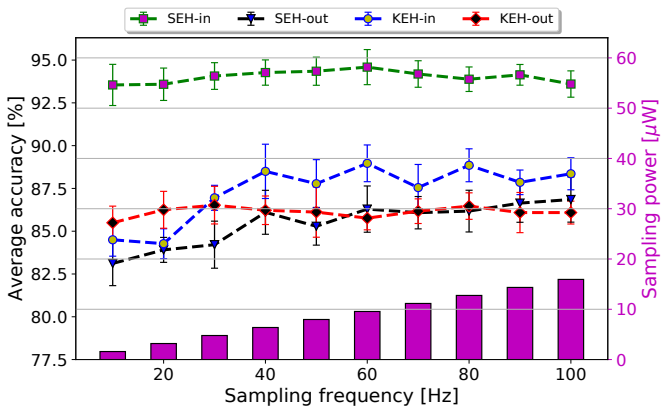


Fig. 9: Average HAR accuracy and required power with varying sampling frequencies of SEH and KEH signals in indoor and outdoor environments (window size = 8 s)

The outdoor SEH signal instead is less sensitive to the increase in window size and offers constant HAR accuracy from 2 s to 9 s and for 12 s. The HAR accuracy of KEH signals (indoors and outdoors), on the other hand, increases by about 6% with an increase of the window size from 2 s to 12 s.

However, increasing the window size also results in increased latency, computational complexity and memory requirements. Therefore, the window size should be selected keeping in mind the required HAR accuracy, responsiveness of the system as well as the processing complexity due to the miniaturized and resource constrained target (wearable) device. Based on the previous discussion, we observe in Fig. 8 that 8 s is the minimum size of the window that offers best results in terms of HAR accuracy for all types of signals. Therefore, the remainder of the results in this paper are presented using a window size of 8 s.

D. Varying signal sampling frequency

Fig. 9 shows the HAR performance over varying sampling frequencies ranging from 10 Hz to 100 Hz (using RF algorithm). The figure shows that the SEH signal indoors offers stable HAR accuracy which does not exhibit a perceptible change when sampling rate is increased from 10 Hz to 100 Hz. In contrast, the SEH signal outdoors offers a small increase of about 3.7% in HAR accuracy with the increase in sampling rate from 10 Hz to 100 Hz. The HAR accuracy of indoor KEH signal increases by about 3.8% at a sampling frequency of 100 Hz compared to 10 Hz. The KEH signal outdoors is not sensitive to the increase in sampling frequency and provides relatively stable HAR accuracy at all sampling frequencies.

TABLE III: Average HAR accuracy from the robustness experiment

Type of signal	10-fold CV	Leave-one-user-out CV
SEH-indoor	93.47	84.62
SEH-outdoor	86.87	61.69
KEH-indoor	88.89	83.25
KEH-outdoor	86.14	66.43
Accelerometer	99.3	92.27

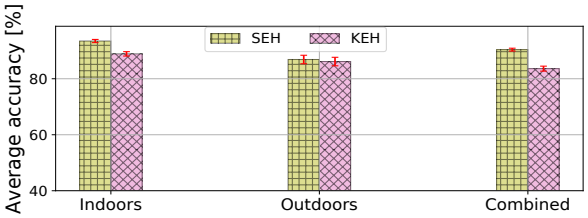


Fig. 10: HAR accuracy using separate as well as combined data from indoor and outdoor environments (window size=8 s)

The improvement in HAR accuracy at higher sampling rates stems from the higher resolution of the signal and its ability to capture more fine grained details of the activity pattern. However, as depicted in Fig. 9, the energy consumption increases with the increase in sampling frequency due to the acquisition of more samples in a fixed time interval. Therefore, depending on the type of application and the amount of harvested energy, the SEH sampling rate can be chosen as low as 10 Hz to minimize the energy consumption, while still offering activity recognition accuracy of above 93% and 83% in indoor and outdoor environments, respectively.

E. Robustness to user variance

In this subsection, we analyse the robustness of SolAR system against new/unseen users. To this end, we perform leave-one-user-out CV on the collected data (using RF algorithm) and present the averaged results in Table III. The table shows that SEH indoor, accelerometer and KEH indoor signals are least sensitive to the variation in the user and offer 5-9% decreased HAR accuracy for new and unseen users. On the other hand, SEH and KEH signals outdoors are significantly affected by the user variance and offer decreased HAR accuracy by 19-25% for new users due to the significant variation in the activity pattern. However, the SEH transducer still offers more than 84% HAR accuracy in indoor environments for new and unseen users, which shows its applicability in practical and real-world scenarios. We expect that a larger training sample will further reduce this sensitivity.

F. Environment-agnostic analysis

Instead of training the classification model separately in indoor and outdoor environments, we combine the energy harvesting data from both environments in an environment-agnostic scenario. We train the classification algorithm using all features listed in Table II and plot the classification results (using RF algorithm) from individual as well as combined datasets in Fig. 10. The figure shows that SolAR can recognise human activities in an environment-agnostic scenario with a 7% higher accuracy than conventional KEH-based HAR. Furthermore, the performance of SolAR in the environment-agnostic scenario is higher than that of the outdoor environment, and it is close to the performance in the indoor environment. This demonstrates the general applicability of our proposed approach in different environments.

TABLE IV: Average harvested power during various activities

Human activity	Harvested Power [μW] Outdoor Kinetic	Outdoor Solar	Indoor Kinetic	Indoor Solar
Running	11.7	3800	6.5	29.7
Walking	3.16	2800	2.4	29.6
Using stairs	3.57	2100	2.8	13
Standing	0.49	840	0.45	26
Sitting	0.47	1900	0.21	54.7
Average power	**3.88**	**2288**	**2.47**	**30**
Power density [μW/cm^2]	**0.218**	**163.429**	**0.139**	**2.143**

VI. Energy Positive HAR

In this section, we analyse the harvested power from SEH and KEH transducers during various human activities as well as the required power for running SolAR on a wearable device.

A. SolAR harvested power

We calculate the average harvested power from the collected SEH and KEH data during various human activities and present the results in Table IV. The last row of Table IV describes the power density, i.e., the harvested power per area. We find that, on average, SEH generates more than one order of magnitude higher power indoors, and more than two orders of magnitude higher power outdoors compared to KEH due to the higher power density of visible light as well as higher conversion efficiency of solar cells [15]. The results also show that harvested power from SEH is less dependant on the physical human movements as compared to KEH; there is a minimum power level that can be harvested from SEH even during static activities such as standing and sitting. KEH, on the other hand, harvests only a small amount of power (i.e., 0.21 μW-0.49 μW) during these static activities due to lower movements of the human body. The harvested power outdoors is higher than indoors for both SEH and KEH. For SEH, this is because natural sunlight has a higher power density compared to the artificial indoor lights. For KEH, we suspect a combination of two effects: (1) walking on a paved surface generates a higher degree of vibrations than walking on a carpeted floor indoors [37] and, (2) people tend to move faster outdoors which results in higher vibrations and, as a result, higher KEH power.

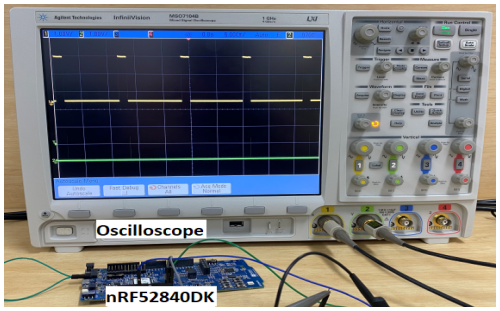


Fig. 11: Experimental setup for measuring the power consumption in implementing the HAR model

TABLE V: Average required power to implement the end-to-end HAR algorithm on the sensor node using SEH signal in an indoor environment (window size = 8 s)

Task	Power [mW]	Time [μs]	Avg. power [μW]
Sampling (@10 Hz)	8.6	2752	1.59
Feature extraction	6.6	1985	1.64
Classification	6.6	74	0.06
Data transmission	11.2	491	0.12
Sleep mode	0.0045	7.995×10^6	4.5
Total	**33.004**	**8×10^6**	**7.92**

B. SolAR power consumption

We implement the SEH- and KEH-based HAR models on an ultra low power Nordic Semiconductor nRF52840 wireless MCU (shown in Fig. 11) to measure and compare the power consumption of the individual tasks, i.e., sampling, feature extraction, classification and transmission. Based on the results from Section V, we choose a window size of 8 s, a sampling frequency of 10 Hz and the RF classification algorithm. The result of the classification is transmitted as a BLE packet (after every 8 s), consisting of 6 bytes header, 3 bytes checksum and 1 byte payload, encoding the result of the classification. To measure the current, we place a 10 Ω shunt resistor in series with the 2 V supply voltage and measure the voltage drop with an Agilent Technologies MSO4104B oscilloscope as depicted in Fig. 11. The firmware is configured to set a dedicated General Purpose Input/Output (GPIO) pin high while executing a task. By simultaneously recording the current and GPIO pins, we can precisely measure the execution time and power consumption of each task.

Table V shows the average, per-task power requirements of running SolAR with the indoor feature set. Sampling takes 1.594 μW, including 0.294 μW for the ADC and 1.3 μW for converting the ADC data into floating point values. Feature extraction and classification take 1.637 μW and 0.061 μW, respectively. Transmitting the result over the wireless channel takes 0.125 μW, including 0.067 μW to power up the high frequency clock and 0.058 μW for transmitting the packet. For 99.93 % of the time, the MCU remains in deep sleep mode consuming only 4.5 μW. Thus, the total average power

TABLE VI: Required power to implement the embedded machine learning HAR (window size = 8 s)

Signal	No. of features	Required Power [μW] Feature ext.	Classification	**Total**
SEH-indoor	17	1.637	0.061	**1.698**
SEH-outdoor	21	2.236	0.073	**2.309**
KEH-indoor	25	2.557	0.078	**2.635**
KEH-outdoor	13	1.567	0.072	**1.639**

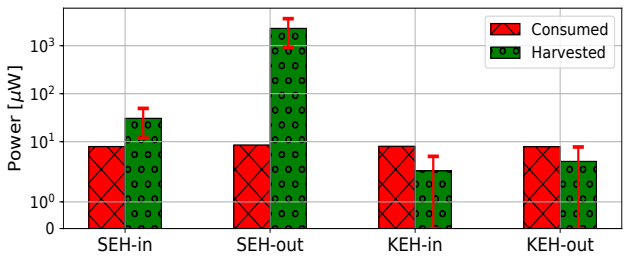


Fig. 12: Average harvested and consumed power in implementing end-to-end HAR model using SEH and KEH signals indoors and outdoors

consumption of our implementation is 7.92 µW. Table VI compares the power requirements of SEH- and KEH-based HAR with the indoor and outdoor feature sets, respectively. We find that, because SEH- and KEH-based HAR have different features, they have a different power consumption. Interestingly, the average power for the classifier (0.061 µW to 0.078 µW) is more than one order of magnitude lower than the power required in feature extraction across the board.

C. Energy positive HAR

In this subsection, we examine if SolAR achieves energy positive HAR by comparing the harvested power to the required power to run SolAR on the wearable device. To this end, we define the HAR power ratio (P^r_{har}), similar to the signal acquisition power ratio in [7]:

$$P^r_{har} = \frac{Harvested\_power}{HAR\_power} \tag{1}$$

When the harvested power from a wearable-sized transducer is less than the power required for running the HAR model ($P^r_{har} < 1$), the system is *energy negative*. On the other hand, if the harvested power is greater than the power required for running the HAR model ($P^r_{har} > 1$), the system is *energy positive*. Fig. 12 compares the harvested power from SEH and KEH with the corresponding power to run the HAR model averaged over all activities. The average SEH power is higher than the power required to run the HAR model on the sensor node both indoors and outdoors. Thus, SolAR is *energy positive* and enables autonomous and perpetual operation of the sensor node without the need of any external energy source. Although the KEH transducer that we used in our experiments is larger and heavier than the solar cell (18.03 cm^2, 30.46 g vs. 14.7 cm^2, 4.5 g), the average KEH power is not sufficient to run the HAR model on the node and thus provides *energy negative HAR*.

Fig. 13 plots the HAR accuracy and HAR power ratio of individual activities for SEH- and KEH-based HAR indoors and outdoors. We find that SolAR offers higher HAR accuracy and is *energy positive* across all activities indoors and outdoors. KEH-based HAR instead is mostly energy negative due to significantly lower harvested power (see Table IV). The only exception, where KEH also delivers sufficient power for end-to-end HAR is the *running* activity outdoors. Note that

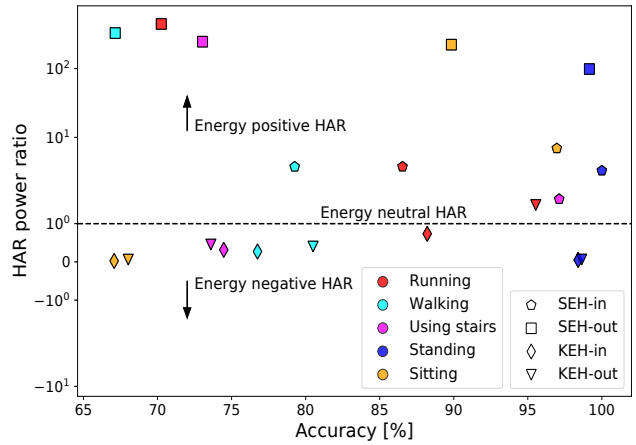


Fig. 13: HAR accuracy vs HAR power ratio for various human activities using a small-sized and lightweight SEH (14.7 cm^2, 4.5 g) compared to the KEH transducer (18.03 cm^2, 30.46 g)

a custom-designed energy harvesting circuit with a perfectly tuned KEH transducer may deliver higher power [38] than observed in this study. While this could potentially result in energy positive HAR for some dynamic activities, it is impractical to tune the KEH transducer to specific scenarios. Furthermore, KEH transducers are fundamentally unable to deliver energy during mostly static activities. Because humans generally spend a great proportion of their time performing such activities, the average harvested energy from KEH transducers may not be sufficient to ensure the perpetual operation of the wearable devices. Thus, SEH offers clear advantages over KEH in terms of higher harvested energy, higher HAR accuracy, as well as the fact that it does not require hardware customization for different application scenarios.

In contrast to the previous work [7] that achieves energy positive sensing only for signal acquisition using KEH, SolAR ensures end-to-end *energy positive HAR*. We find that SEH harvests 22.08 µW and 2.28 mW higher power than required for running the end-to-end HAR model indoors and outdoors respectively, as shown in Tables IV and V. This means that the size of the solar cell can be reduced significantly or additional harvested power can be used to run other body sensors which ensures real-time, continuous and perpetual monitoring of human health, fitness and activity without the need of any external depletable energy source leading towards truly pervasive IoT. Moreover, in order to achieve a better trade-off between energy and HAR accuracy, a scheduling technique [39], [40] can be devised which makes the best use of the accelerometer, SEH and KEH signals for activity recognition depending on the energy budget.

VII. Conclusion and Future Work

In order to run wearable IoT devices perpetually, recently, KEH transducers have been used as activity sensors as well as source of energy simultaneously. However, the harvested energy from human movements using miniaturized KEH transducers is not enough to run the wearable devices perpetually.

In this paper, we propose SolAR, a novel HAR mechanism which employs solar cells for recognizing human activities as well as to power the wearable device. As the human activities interfere with the ambient light differently, the harvesting signal from the wearable solar cell contains information about the underlying activities. In order to explore the sensing potential of solar cells, we collect SEH data from 21 participants performing five common human activities in indoor as well as outdoor environments. After rigorous analysis, we find that SolAR offers up to $8.3\,\%$ higher HAR accuracy compared to the previous KEH-based HAR mechanisms. In addition, the harvested power from wearable-sized solar cells is higher than required for running the end-to-end HAR model on the sensor node and thus ensures *energy positive HAR*.

It is worth mentioning that as SolAR requires a light source for its operations, it may confront difficulties in recognising the activities in dark environments (such as at night). Consequently, our proposed system may face challenges such as lower harvested energy, decreased sensing accuracy and higher latency in activity transmission with significantly varying ambient lighting conditions. However, these challenges can be overcome by employing multi-source energy harvesters (such as kinetic, thermal, RF) that provide energy and context information concurrently. Furthermore, although we collected SEH data on different days with distinct lighting conditions, more detailed data can be collected from various scenarios (e.g., different buildings with varying (indoor) light conditions and different (outdoor) locations) in the future to thoroughly investigate the performance of our system. Finally, the prototype that we used to evaluate our proposed algorithm is an off-the-shelf evaluation board that does not have the required harvesting and sensing circuitry and that building a fully functional, low powered device implementing SolAR online remains a challenge for future work.

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