A Simple and Fast Human Activity Recognition System Using Radio Frequency Energy Harvesting

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ABSTRACT

Recognizing indoor activities of an individual provides useful information in smart living, well-being monitoring, and fitness management. In this paper, we propose a simple and fast human activity recognition (HAR) system based on Radio Frequency energy harvesting (RFEH). The intuition is that the harvested voltage signals of different human activities exhibit distinctive patterns. Utilizing the data collected from four smartphones, the RFEH-based HAR system indicates over 91% accuracy of activity recognition across all devices. By combining the lightweight classifiers and making an ensemble classification, an overall accuracy of over 97% is achieved.

CCS CONCEPTS

• **Computer systems organization** → **Sensors and actuators**; **Embedded hardware**; • **Networks** → *Wireless local area networks*.

KEYWORDS

Wireless Network; Radio Frequency; Energy Harvesting; Human Activity; Recognition

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1 INTRODUCTION

Human Activity Recognition (HAR) has drawn considerable attention in the past two decades due to the growth of sensing technology. Detecting and learning a user's daily activities indoor can be very practical in many areas such as smart living [12], health surveillance [6, 9] and physical exercise monitoring/management [3, 18]. Previous works focused on using various sensors to detect human activities and required the user to carry a wearable device that is suffering from installation difficulties and high battery consumption [10]. Recently, Xu et al. [16] proposed to use wearable kinetic energy harvesting device to detect user's activities. Nevertheless, their systems like SEHS [11], KEH-Gait [16, 17] and CapSense [8] still need the user to be equipped with the device when he/she is performing activities. There are other non-intrusive HAR systems such as CARM [14] and E-eyes [13] that leveraged informative measurement like Channel State Information (CSI) for activity detection, whereas processing such huge amount of data will introduce high computational cost and time expense.

In this paper, we propose a simple and fast HAR system based on RF energy harvesting (RFEH) to detect five normal indoor activities. The RFEH-based HAR system needs to be put next to the Wi-Fi router while the user's phone is connecting to this Wi-Fi. Different physical movements of the user will cause difference in fluctuations of the amplitude and phase in the harvested RF energy from Wi-Fi signals [10]. with the obtained raw RF energy, the system further conducts data pre-processing and recognizes the activity type through several pre-trained classifiers. The empirical results indicate our system not only achieves high accuracy on human activity recognition but also saves computational cost compared with the aforementioned HAR works.

2 RFEH-BASED HAR SYSTEM

In this section, we first introduce the overview of RFEH-based HAR system and then present the harvested signals of several activity patterns.

2.1 System Overview

Figure 1 shows the structure of the RFEH-based HAR system. This system only requires the user to carry his/her WiFi-connected phone instead of wearing any intrusive devices. It uses the AC voltage signal harvested by the RF energy harvesting circuit (details will be included in the following section). The raw voltage signal will be processed by the data pre-processing module. A low-pass filter is applied to reduce the noise and the filtered signal is then fed into some pre-trained light-weight user activity classifiers. Finally, the classifiers output an ensemble result as the prediction of the most possible activity of the Wi-Fi user.

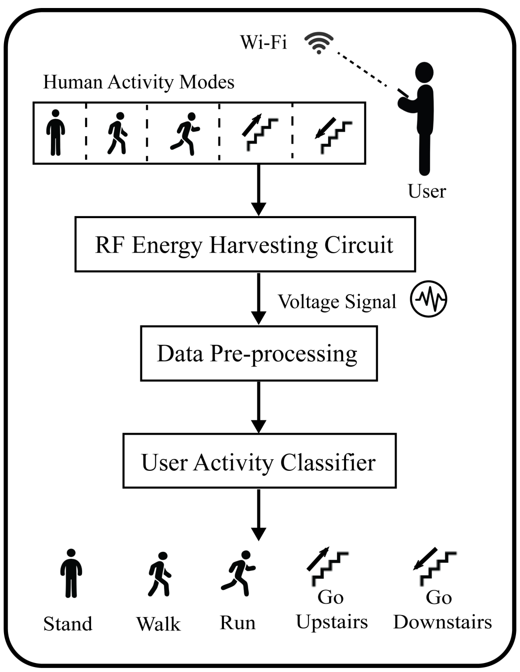

Figure 1: Overview of RFEH-based HAR system

2.2 Activity Patterns

We explore patterns of five different human activities from the RFEH voltage signals: Stand, Walk, Run, Go Upstairs and Go Downstairs. Figure 2 indicates the comparison of the harvested signals when the user performs various activities. We can observe that the signal shapes, vibrations, and amplitudes are very different among these activity patterns, implying that distinct features can be extracted from each harvested voltage signal.

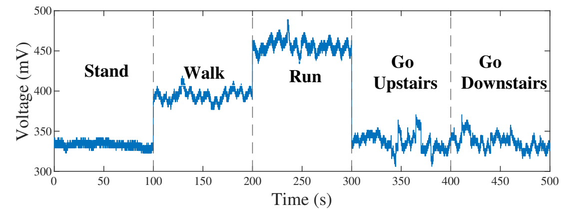

Figure 2: Harvested voltages signals from different user activities (each activity 100 seconds, iPhone 6S)

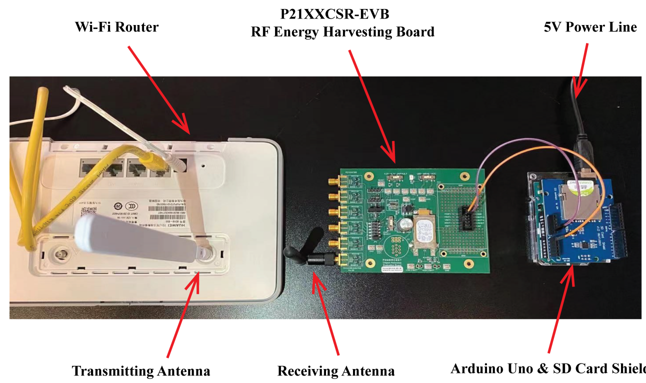

Figure 3: Hardware components: Wi-Fi router, RF energy harvesting circuit and data collection module

3 EXPERIMENT

In this section, we will illustrate the details of important components of the RFEH-based HAR system.

3.1 Hardware Platform

The hardware platform consists of three parts: (1) a single-antenna (Transmitting Antenna) Wi-Fi router that can generate 2.4 GHz RF signals to simulate a common indoor Wi-Fi access point; (2) an RF energy harvesting board from Powercast co. called P21XXCSR-EVB which can harvest energy from six different frequency bands. We use the 2.4 GHz frequency port by connecting an antenna (Receiving Antenna) to receive 2.4 GHz Wi-Fi signals; (3) a high-speed sampling module that contains an Arduino Uno and a 16 GB SD card. We set the sampling rate at 100 Hz for data sampling and all data has been collected and stored in the SD card. Figure 3 shows each part of the hardware platform that we made to conduct the experiments.

3.2 Data Collection and Feature Extraction

In the data collection process, we conducted the experiment in the circumstance as shown in Figure 4. The Wi-Fi router and our system were on a 3 m × 1 m table. The user was required to hold the phone (Wi-Fi connected) and performed three activities (Stand, Walk and Run) in a 6 m × 4 m room and other two activities (Go upstairs, Go downstairs) on the

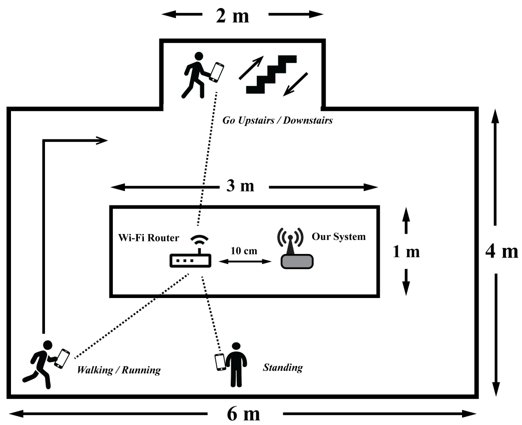

Figure 4: Experiment circumstance and setups

stairs with ten steps near the room. In the experiment, we set the sampling rate at 100 Hz and the distance between two antennas as 10 cm [1]. Here are the experimental details of different activity patterns.

Stand The user stood in the middle of the room with 1.5 m away from the table for 720 seconds while holding the Wi-Fi connected smartphone.

Walk/Run The user stood for 120 seconds to get the initial static signals and then walked at approximately 1 m/s speed around the room for 600 seconds to collect the walking pattern data. Similarly, we asked the user to run for another 600 seconds at a speed of 3 m/s to gather running data.

Go Upstairs/Go Downstairs To collect data from Go Upstairs/Downstairs patterns, the user was required to hold a timer and go upstairs in 10 seconds and go downstairs in the following 10 seconds and repeated these action for 600 seconds (Also, set the first 120 seconds for collecting starting signals). Then we split the data based on each 10 seconds segment to make data sets of the Go Upstairs pattern and Go Downstairs pattern respectively.

After accomplishing the data collection, we applied a low-pass filter on the harvested signals to eliminate possible noise. Then, we calculated the average voltage in the first 120 seconds of each activity pattern and deducted this voltage in the 600 seconds activity data which can remove the interference from the different starting voltages. Next, we divided the processed 600 seconds signals into 2 seconds windows and for consecutive windows, we set the overlapping rate as 50%. Finally, we used these divided signal segments and corresponding labels to build the data corpus.

In this experiment, we collected data from four devices: iPhone 6S, iPhone 11, Huawei P9, and Samsung S10. Figure 5, 6, 7 show the harvested voltage signals (each activity 100 seconds) from the other three devices (iPhone 11, Huawei P9 and Samsung S10) respectively. We can know that even different devices can have various voltage signals when the user is doing the same activity, the signals of the five activity patterns are different. Then we used the same process to build four datasets that are shown in Table 1 (S: Stand, W: Walk, R: Run, GU: Go Upstairs, GD: Go Downstairs).

In the feature extraction process, we extracted features from the data of each window. Aforementioned works [5, 8] often extracted more than thirty features and designed an algorithm for feature selection. However, too many features may lead to an overfitting problem which makes the model specifically outperform on one dataset but show poor results on other datasets. Moreover, model complexity and time consumption will increase as more features are utilized. In fact, only a few important features are needed for the uncomplicated tasks such as detecting five human activities. Thus, we extracted fourteen common time-domain features [5] which are shown in the Table 2.

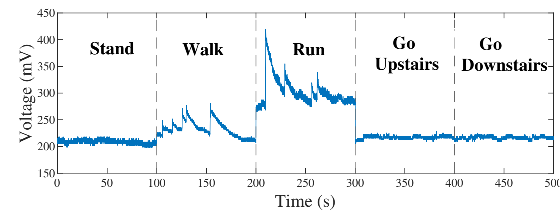

Figure 5: Harvested voltage signals of iPhone 11

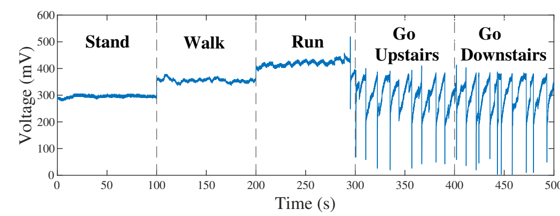

Figure 6: Harvested voltage signals of Huawei P9

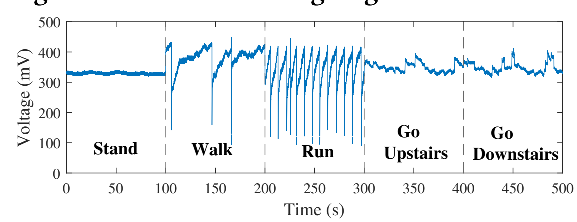

Figure 7: Harvested voltage signals of Samsung S10

Table 1: Summary of datasets from four devices (Numbers of collected data samples of five activities)

Device	S	W	R	GU	GD	Total
iPhone 6S	719	498	607	299	299	2422
iPhone 11	439	899	899	199	199	2635
Huawei P9	679	679	679	199	199	2435
Samsung S10	439	699	699	299	299	2435

Table 2: Time-domain feature set. The following 14 features are calculated from a 2 seconds window

Feature	Description
Mean	The average value of voltage samples.
Standard Deviation	The amount of variation or dispersion of voltage samples.
Maximum	The maximum value of voltage samples.
Minimum	The minimum value of voltage samples.
Range	The difference between maximum and minimum.
Root Mean Square	Measures the effective energy of. a voltage signal segment
Absolute Mean	The average of absolute voltage values.
Coefficient of Variation	The ratio of Standard Deviation and Mean.
Skewness	Measures the asymmetry of voltage signal distribution.
Kurtosis	Measures the peakedness of voltage signal distribution.
1st Quartile (Q1) Median 3rd Quartile (Q3)	The first, second (median), third quartiles. Measures the overall distribution.
Inter Quartile Range	The difference of Q3 and Q1. It also indicates dispersions.

3.3 Activity Classifiers

We select four fast, light-weight supervised machine learning classifiers to evaluate the recognition performance of our system: (1) CART [2] Decision Tree with *entropy* criterion; (2) Linear Support Vector Classifier (LinearSVC) with L2-norm penalization; (3) Support Vector Machine (SVM) with RBF kernel; (4) Random Forest with 100 trees and the upper bound of forest depth is 15. We exploit the Python *sklearn* library to build these classifiers. Meanwhile, *Grid Search* and *Random Search* are used for hyperparameter tuning.

For each dataset, 80% data are utilized for training the four classifiers with 10-fold cross-validation [4] and we use the other 20% data to evaluate the model performance.

4 EVALUATION

In this section, we evaluate the system performance on the four datasets. In addition, we analyze the incorrect recognition cases and explore the limitations of our system.

4.1 Results

We evaluate the performance of our system by applying the four light-weight classifiers and calculating their accuracies on the collected datasets respectively. Table 3 shows the classification accuracy results. We discover that our system achieves over 98% recognition accuracy of each classifier on the Huawei P9 dataset. Besides, it can achieve over 91%, 96%, and 93% accuracies on the other three datasets (iPhone 6S, iPhone 11, and Samsung S10).

Table 3: Accuracy (%) of classifiers on four datasets

Classifier	iPhone 6S	iPhone 11	Huawei P9	Samsung S10
Decision Tree	99.18	98.48	98.97	98.15
LinearSVC	91.75	96.77	98.36	93.63
SVM (RBF)	94.02	98.10	99.18	97.33
Random Forest	99.18	97.91	99.79	97.74

Furthermore, Table 3 indicates that classifiers like Decision Tree and Random Forest perform better than LinearSVC and SVM with RBF kernel. Even though the accuracy of all classification results is high (overall > 91.75%), we still find errors in the activity recognition and the analysis will be discussed in the following section.

4.2 Error Analysis

To understand and explore the errors, we investigate the confusion matrices of two cases: **a.** LinearSVC classifier on iPhone 6S dataset. **b.** SVM (RBF) classifier on iPhone 6S dataset. We examine the correctly recognized activities by presenting the True Positive Rate (TPR) values of each activity in the classification.

Table 4 and Table 5 show the confusion matrices of the two cases (Stand: S, Walk: W, Run: R, Go Upstairs: GU, Go Downstairs: GD). For case **a**, activity patterns such as W and R are recognized with very high accuracy (98% and 100%) while the other three activities S, GU, and GD have relatively lower accuracies (86%, 83%, and 85%). For case **b**, S, W, and R indicate excellent classification results (all > 95%) but the performance of GU and GD are still poor (only 77% and 78%). The TPR values of GU and GD are lower than S, W, and R which reveals these two activities are quite similar and can lead to confusion [5]. It also matches the harvested voltage signals that are shown in Figure 2 and Figure 5- 7. The signal shapes are quite different of activities Stand, Walk and Run. Nevertheless, the signal shape of Go Upstairs is close to the Go Downstairs.

Table 4: The confusion matrix of LinearSVC classifier on the iPhone 6S dataset (Case a)

		Predicted activity					
		S	W	R	GU	GD	TPR
True activity	S	125	16	0	0	5	0.86
	W	1	86	1	0	0	0.98
	R	0	0	145	0	0	1.00
	GU	1	4	0	43	4	0.83
	GD	0	0	0	8	46	0.85

Table 5: The confusion matrix of SVM (RBF) classifier on the iPhone 6S dataset (Case b)

		Predicted activity					
		S	W	R	GU	GD	TPR
True activity	S	145	1	0	0	0	0.99
	W	3	84	1	0	0	0.95
	R	0	0	145	0	0	1.00
	GU	7	0	0	40	5	0.77
	GD	2	0	0	10	40	0.78

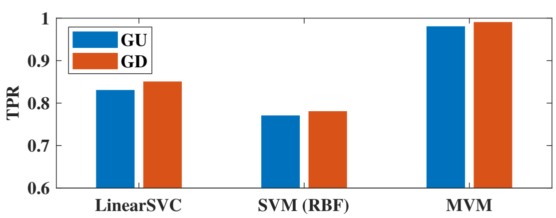

Figure 8: The TPR values of GU, GD from single classifier and MVM ensemble method (iPhone 6S) .

Table 6: Accuracy (%) of using ensemble method classification (MVM) on four datasets

Method	iPhone 6S	iPhone 11	Huawei P9	Samsung S10
MVM	99.18	98.10	98.36	97.74

Hence, to reduce the confusion between similar human activities, we propose an ensemble output method instead of giving a result from the classifiers directly. We consider using the Majority Voting Method (MVM) [7] since we want to save computational cost and make a system that is easy to understand and operate. The MVM will combine the predictions from the four classifiers and output the recognition result that receives more than half of the votes (over two classifiers). Figure 8 shows the TPR values of GU and GD have been enhanced a lot after utilizing the ensemble method (GU: 0.98, GD: 0.99). Then we calculate accuracies of ensemble method classification on four datasets which are shown in Table 6.

4.3 Limitations

The empirical results have demonstrated that the superior performance of the RFEH-based HAR system. However, we still find some limitations of our system and provide suggestions and directions for further exploration.

Complicated human activities In the data collection part, we only collected five common human activities. Nevertheless, human activities have a wide degree of versatility and some other works are exploring these complex activities by using fine-grained measurement like Channel State Information (CSI) [10]. For example, Zhang et al. [18] proposed a model that can detect exercising activities such as Push-up, Sit-up, and Walk-out. Moreover, Wang et al. [15] presented a system that can profile a variety of walk activities (From bedroom to kitchen, outside to bedroom, etc.) and determine if the user is cooking. So much more features are needed to be extracted from the harvested signals for deeper recognition in future work.

Interference Many wireless sensing systems (e.g. activity detection, gesture recognition, and indoor localization) are heavily impacted by the experimental environment [10]. We conducted our experiment in an empty room with only one Wi-Fi router so that the interference from the environment can be ignored, yet the interference from other Wi-Fi sources is inevitable in real situations. Thus, much more data should be collected from diverse situations for analyzing the possible noise influence. Additionally, selecting a proper filter to reduce noise is another significant issue in order to build a robust system.

5 CONCLUSION

In this paper, we introduce a novel, intelligible HAR system using RF energy harvesting. The experimental results have shown that our system can achieve over 91.7% accuracy on the detection of five daily human activities across different devices. We utilize fewer time-domain features compared with previous works and also apply an ensemble method of lightweight classifiers which improve the overall recognition accuracy over 97.7%. The current work illustrate that the system can accurately detect basic activities, which inspires us to investigate the possibility of extending our system to more sophisticated activities in the future.

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