A Feasibility Study on Battery-less Travel Context Estimation Using Ambient Backscatter

Toru Maeda, Akira Uchiyama, Teruo Higashino
Graduate School of Information Science and Technology, Osaka University
{t-maeda, uchiyama, higashino}@ist.osaka-u.ac.jp

***Abstract*—Wearable devices are spreading for various applications. However, many users quit using them partly because of the maintenance cost for charging or replacing batteries. To overcome the problem, some manufactures have applied energy harvesting to wearable devices. Nevertheless, the performance of such devices is still limited due to the limited amount of harvested energy. In this paper, we investigate a novel design of cooperative wearable devices to enhance its performance in terms of reliability and accuracy. Our key idea is applying ambient backscatter to battery-less (i.e. energy harvest) wearable devices for wireless communication among them. Ambient backscatter is an emerging technology which achieves ultra-low power wireless communication. We focus on travel context estimation as a target application and design a framework by combining battery-less wearable devices and ambient backscatter. Since the energy of the battery-less devices is still limited, the framework should be energy efficient. We carefully design the division of tasks considering the classification algorithm. The experimental results show our frame work achieves 92% accuracy while the energy consumption is up to 52.94 μW, which is sufficient to work with the energy harvesting.**

***Index Terms*—activity recognition, battery-less devices, ambient backscatter, decision tree**

I. INTRODUCTION

With the emerging growth of Internet of Things (IoT) technologies, wearable devices are rapidly spreading to our daily life for various applications such as healthcare, fitness tracking, elderly care, etc. However, many users stop using them partly because of the maintenance cost for charging them or replacing their batteries [1]. Many manufactures and researchers have been working to overcome the problem by combining various technologies such as energy harvesting and low power operations. Nevertheless, the performance of such devices is still limited because the amount of harvested energy is tiny. This is critical for some tasks such as activity recognition which essentially require continuous sensing.

To tackle with the problem, we investigate a novel design of cooperative battery-less wearable devices to enhance its performance in terms of reliability, accuracy, and so on. The key idea is to utilize ultra-low power wireless communication called ambient backscatter [2] for cooperation among the devices. Ambient backscatter communication has been attracting great attention because it achieves ultra-low power wireless communication (μW level) by leveraging ambient Radio Frequency (RF) such as TV. It generates 0/1 bits by switching the antenna impedance between reflective and absorptive, which is easily achieved by a transistor switch with ultra-low power. Our aim is to enhance the performance of battery-less wearable devices by dividing tasks such as sensing and processing.

In this paper, we focus on travel context estimation such as walking, bus, and train as a target application and design a framework based on the combination of battery-less wearable devices and ambient backscatter to enhance the accuracy and robustness. Although some researchers make effort to save energy of activity recognition (e.g. decrease sampling rate [3], use low-power sensors [4], etc.), they assume the battery has sufficient energy. Ref. [5] combines battery-less devices attached on shoes and ambient backscatter to count the number of steps. However, to the best of our knowledge, the feasibility and the performance of the travel context estimation by the battery-less devices are not investigated yet.

The performance of the battery-less device depends on the amount of harvestable energy and the energy consumption for the tasks such as sensor data acquisition, data processing, and backscatter communication. Although the harvested energy varies depending on the environment, the energy consumption depends on the operation of the device. Therefore, we design the framework for travel context estimation and evaluate its performance and energy consumption. For the travel context estimation, we need a low-power design since the battery-less device operates by harvested energy. We select a classifier based on Decision Tree (DT) which is lightweight in terms of computation. To show the feasibility and the effectiveness of our design, we also implement the classifier on the micro-controller. The experimental results indicate the classifier achieves up to 92% accuracy while the energy consumption is less than 52.94 μW, which is sufficient to work with the small amount of harvested energy.

In summary, our contributions are three-fold:

- We carefully design a framework for travel context estimation by cooperation of battery-less devices.
- We present a method to reduce the traffic focusing on the characteristic of Decision Tree.
- We show its feasiblity and effectiveness through real experiment incuding prototype implementation.

II. RELATED WORK

A. Activity Recognition

Human Activity Recognition (HAR) has been widely studied in ubiquitous and pervasive computing communities. The

978-1-5386-9151-9/19/$31.00 ©2019 IEEE

majority of HAR methods use accelerometers while some works additionally use various sensors such as a gyroscope and a magnetometer.

In travel context estimation, Ref. [6] shows that the fusion of GPS and an accelerometer improves the accuracy. When an accelerometer is used at sampling rate of 10Hz with GPS, the accuracy improves by 27% compared to an accelerometer only [7], [8]. However, GPS greatly increases the energy consumption, which is not suitable for energy harvesting devices. On the other hand, Ref. [4] proposes a novel concept using a barometer for low power travel context estimation. The only disadvantage is the target travel contexts are limited to those with significant changes in atmospheric pressure such as idle, walking, and vehicle.

To reduce the energy consumption of HAR, Ref. [9] investigates the trade-off between the accuracy along with the sampling rate and the energy consumption. Although they show the high accuracy is still achievable even at the low sampling rate, they still rely on the battery, which is different from our design principle.

B. Backscatter Communication

Since the concept of ambient backscatter [2] was proposed, many researchers have proposed various backscatter communication techniques. Originally, Ref. [2] has shown that the transmission rate of ambient backscatter is 1 kbps over distances of 76 cm. To further enhance the capability of ambient backscatter, Parks et al [10] extended transmission distances more than 24 m even through walls by applying a coding mechanism called μcode, which is suitable for analog (ultra-low power) hardware implementation. Passive Wi-Fi [11] achieves a communication distance of 100 feet at a rate of 1Mbps to 11Mbps by controlling RF transmitted by the base station.

By using these technologies, we can realize cooperation of battery-less sensors. In this paper, since we assume the travel context estimation, we use ambient backscatter [2] which can be used in various outdoor environments.

C. Battery-less Sensing

Battery-less sensing operated by energy harvesting is one of the challenging topics where many researchers have been working. For long-term periodic reports of sensing data, Ref. [12] presents various sensors that generate power by surrounding heat source or temperature change. Also, an energy harvesting pedometer is proposed in Ref. [5] which divides the sensing task and the Bluetooth transmission task between the energy harvesting devices attached to the left and the right feet by leveraging ambient backscatter. The above works achieve battery-less sensing with energy harvesting by limiting its capability to some simple targets such as periodic reporting of sensor data and step counting. On the contrary, Ref. [13] proposes pervasive self-powered HAR by using energy harvesting which directly estimates activities from the amount of harvested energy. However, the result indicates that a hybrid approach of an accelerometer and the energy harvester is important for accuracy.

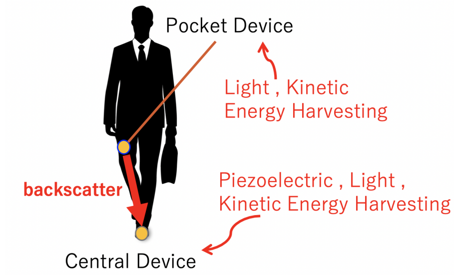


Fig. 1. An example scenario.

Compared to the previous works, our goal is to investigate a novel concept of cooperative battery-less wearable devices in order to enhance HAR performance. In this paper, we focus on travel context estimation and present its design through prototype implementation.

III. SYSTEM DESIGN

A. Overview

Fig.1 illustrates our example scenario. The user wears battery-less devices on multiple parts such as a shoe and a wrist. We use accelerometers of multiple body parts and a barometer for travel context estimation. This is because the accelerometer can provide useful information in terms of various HAR and the barometer is typically low power due to its lower sampling rate compared to the other sensors. Each device processes its sensor data and transmits the result to a central device by ambient backscatter. The central device estimates the travel contexts by combining the sensor data from multiple devices. In this paper, we define the target travel contexts as {*Walking, Idle, Going up stairs, Going down stairs, Bus, Train*} based on our subjects' travel contexts in their daily commute.

In the following sections, we describe the travel context estimation designed for the above cooperative battery-less devices considering the energy consumption followed by the prototype design.

B. Travel Context Estimation

1) Preprocessing: We apply both high-pass and low-pass filters to the acceleration. The high-pass filter removes the influence of gravity and captures vibrations specific to trains and buses while the low-pass filter keeps the direction of gravity and mitigates the noise. Also, by applying a low-pass filter to the barometer readings, we remove the barometer noise. The high-pass filtered value $x_h(t)$ at time t is defined as

$$x_h(t) = x(t) - x_l(t), \tag{1}$$

where $x(t)$ is the sensor reading at time t and $x_l(t)$ is the low-pass filtered value at time t. $x_l(t)$ is given as

$$x_l(t) = \alpha \cdot x_l(t-1) + (1-\alpha) \cdot x(t) \tag{2}$$

TABLE I
FEATURE CANDIDATES

Feature	formula
average	$\overline{x} = \frac{1}{N}\sum_{i=1}^{N} x_i$
dispersion	$\sigma_x^2 = \frac{1}{N}\sum_{i=1}^{N}(x_i - \overline{x})^2$
skewness	$\alpha_x = \frac{1}{N}\sum_{i=1}^{N}(\frac{x_i - \overline{x}}{\sigma_x})^3$
kurtosis	$\beta_x = \frac{1}{N}\sum_{i=1}^{N}(\frac{x_i - \overline{x}}{\sigma_x})^4$
signal power	$\overline{x^2} = \frac{1}{N}\sum_{i=1}^{N} x_i^2$
covariance	$\sigma_{xy}^2 = \frac{1}{N}\sum_{i=1}^{N}(x_i - \overline{x})(y_i - \overline{y})$
root mean square	$\gamma_{xyz} = \sqrt{\overline{x}^2 + \overline{y}^2 + \overline{z}^2}$

where α is the weight, which is empirically set to 0.9 in this work.

2) Feature Extraction: We extract features from the filtered acceleration and pressure by a sliding window of width W. In this paper, we set the $W = 4s$ and the overlap rate of the window to 50%. We carefully design the feature candidates for low energy consumption as shown in Table I. For the acceleration, we select the mean, variance, skewness, kurtosis, and signal power for each of the three axes, the covariances of xy, yz, and zx, and the root mean square of the three axes. We use the both of low/high-pass filtered acceleration to extract the above features. We note that we do not use the feature in the frequency domain since the Fourier transform incurs a high computation cost. The pressure is mainly used for the travel contexts which lead to elevation change such as stairs. We select the change of the pressure in 10 seconds as the pressure feature. We note that the length of the feature vector depends on the combination of battery-less devices. For each device, we obtain 38 features from its accelerometer. Therefore, for example, if we use two devices, the feature vector length is 77 consisting of two sets of 38 acceleration-based features and one barometer-based feature. We investigate the effect of the combination of the devices as well as feature selection in Section IV-C.

3) Classification by Decision Tree: In HAR, various machine learning algorithms are used to build classifiers such as Support Vector Machine, Random Forest, and Deep Learning. However, the computation cost of these methods is relatively high if we implement their classifiers on a low-power micro-controller. Therefore, we use Decision Tree (DT) for the classifier since it consists of if-then clauses, leading to the low computation cost and simple implementation.

4) Context Correction Algorithm: The output of the classifier may be wrong due to remaining noise or temporal change of sensor readings. To mitigate such effects, we leverage the knowledge on the natural travel behavior that the travel context does not change frequently. Since the classifier outputs the estimated context every time window, we take the majority of the M consecutive windows to obtain the final estimated travel context.

C. Prototype Design for Energy Consumption Measurement

To evaluate the energy consumption of the battery-less devices, we design a prototype consisting of an accelerometer, a barometer, and a micro-controller. We use MSP430FR5969[1] as the low-power micro-controller. The MSP430FR5969 has a 16-Bit RISC architecture up to 16MHz Clock and optimized ultra-low-power modes. The energy consumption in the active mode is $100\mu W/MHz$. A deep sleep mode is also available, which consumes less than 1 μA. The micro-controller operates at 1 MHz clock in the active mode while it waits for interruptions from the sensors in the deep sleep mode.

For the accelerometer, we use ADXL362[2] which can store 170 samples each for 3-axis acceleration in the buffer. For the Barometer, we use DPS310[3] that has a 32-sample FIFO buffer and the temperature sensor for calibration.

To evaluate the energy consumption of ambient backscatter, we reproduce the same operations of the micro-controller during transmission and reception of the backscatter communication. Ambient backscatter uses FM0 coding [14]. FM0 coding has a symbol transition at the beginning of each bit period, meaning a transition of every mid-bit for '1' and no transition for '0'. The Tx operation is reproduced by switching the output of the micro-controller pin according to the transmission rate. The Rx operation is reproduced by checking the input value of the micro-controller pin according to the same rate.

In our classifier implementation, we significantly reduce the traffic amount exchanged among multiple devices by focusing on the characteristic of DT. Since a node of DT is a simple comparison of a single feature, each device extracts the features and computes the result (true or false) of each node which is related to the sensor readings of the device. Then, each node transmits the results along with their node IDs. The bit length of the node ID depends on the depth k of the decision tree defined as $k - 1$. The central device receives all the results from the other devices to classify the travel contexts.

IV. EXPERIMENT

A. Settings

To evaluate the performance of the travel context estimation, we asked three male subjects to collect acceleration and atmospheric pressure in various travel contexts. We collected 35 mins idle, 40 mins walking, 10 mins going up/down stairs each, 30 mins bus, and 40 mins train travel context data from each subject. We note that contexts are labeled as train only

[1]http://www.ti.com/product/MSP430FR5969

[2]https://www.analog.com/en/products/adxl362.html

[3]https://www.infineon.com/cms/en/product/sensor/barometric-pressure-sensor-for-consumer-applications/dps310/

TABLE II
SENSORS FOR DATA COLLECTION.

Attached Part	Sensor
shoes, bag	ATR-Promotions TSND121
trousers pocket	LG Nexus5
left arm	Microsoft Band2

Fig. 2. Sensor placement.

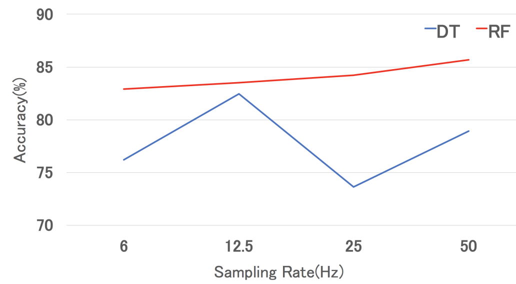


Fig. 3. Effect of sampling rate on the accuracy.

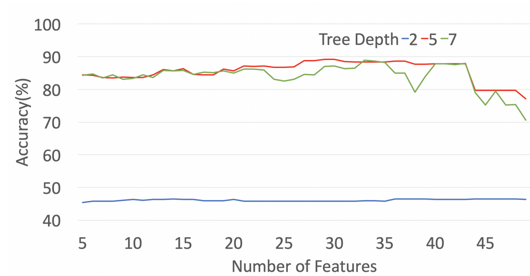


Fig. 4. Accuracy for different tree depth and features

when trains are moving since there is no significant sensor readings during stops at stations.

For data collection, we used sensors listed in Table II. Each subject placed the sensors as shown in Fig.2. The sampling rate of acceleration on the wrist is 62 Hz due to the device constraint while it is 100 Hz for the other parts. The sampling rate of atmospheric pressure is 10 Hz. We re-sampled the original data to simulate lower sampling rates. We simulated 6, 12.5, 25, and 50 Hz for the acceleration and 1 Hz for the pressure.

We conducted leave-one-subject-out cross-validation where the two of the subjects' data are used for the training while the other is used for the testing. To eliminate the bias due to the sample imbalance, we used SMOTE [15] for oversampling.

B. *Effect of Sampling Rate*

Fig.3 shows the context estimation accuracy of the different sampling rate. For comparison, the figure also shows the result of Random Forests (RF). We set the depth of the DT and RF trees to 6 and the number of RF trees to 100. We note that similar trends are observed in other metrics such as the F1-score.

From the result, we see DT achieves the highest accuracy for the sampling rate of 12.5 Hz. The accuracy of RF increased with the increase of the sampling rate although we do not observe the similar trend in DT. This is because RF is more robust to fluctuation of sensor readings by using the results of multiple decision trees with randomness. Nevertheless, DT can achieve the comparable accuracy in the appropriate setting.

C. *Selection of Features and Tree Depth*

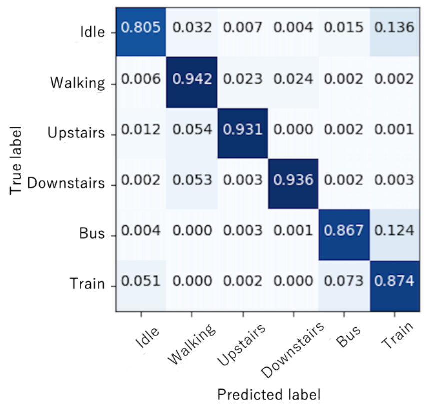
We used the feature importance obtained during the learning phase of RF for feature selection. We sorted the feature candidates according to the importance and used top-N features. We also changed the depth of the tree. Fig.4 shows the accuracy for the different numbers of features and tree depth. Fig.4 shows that the accuracy is 89.3% for the tree depth of 5 and 30 features, which is almost the same as the 89.5% for the tree depth of 8 and 29 features. The 30 features include the dispersion and signal power after high/low-pass filtering from multiple devices. In particular, many features from shoes have high importance since the vibration of trains and buses is clearly captured. The importance of many features of the bag and pocket was also high although that of the wrist device was relatively low. This is because the wrist device captures various hand motions, which is difficult to estimate the travel contexts. From the above result, we use the tree depth of 5 in the following evaluation.

D. *Selection of Device Combination*

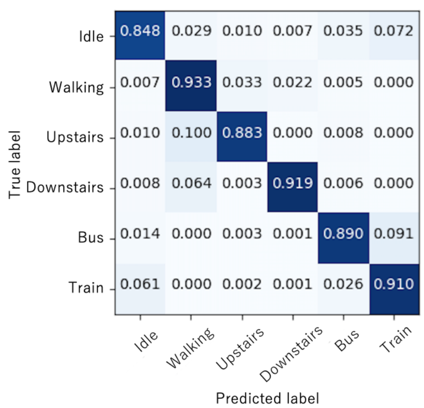
Table III shows the accuracy of the different combinations of the devices. It is clear that either of the shoes solely achieves good accuracy. We also see slight improvement by the device combinations. To see the result in detail, we show the confusion matrices of the right shoe and the combination of the right shoe and the pocket in Fig.5. The improvement by the combination is only 1.8%, however, we see the accuracy of some classes (i.e. idle, bus, and train) increases 2 to 4%. This result implies that the combination of multiple devices can improve the robustness of the travel context estimation. We note that the accuracy strongly depends on the data set. For example, if some users experience train travels frequently, the improvement by the combination becomes greater. From the result, we use the combination of the right shoe and the pocket in the following evaluation.

TABLE III
COMBINATIONS OF DEVICES.

Attatched Part	Accuracy
Right Shoe	86.967%
Left Shoe	84.155%
Pocket	85.5%
Bag	75.730%
Wrist	67.348%
Left Shoe & pocket	88.505%
Right Shoe & pocket	88.799%
All Sensors	89.294%



(a) Right shoe



(b) Right shoe and pocket

Fig. 5. Confusion matrices of right shoe and pocket.

E. Effect of Context Correction

In order to confirm the effect of the context correction algorithm described in Section III-B4, we changed the number M of windows for the majority voting. From the result shown in Fig.6, we see the accuracy slightly increases as the number of windows increases, reaching up to 92.4% at five windows compared to 88.8% without the correction (i.e. zero window). Therefore, we confirmed the context correction is helpful to improve the accuracy although the impact is not large.

F. Energy Consumption

We measure energy consumption by using the prototype, assuming the combination of the right shoe and the pocket. In

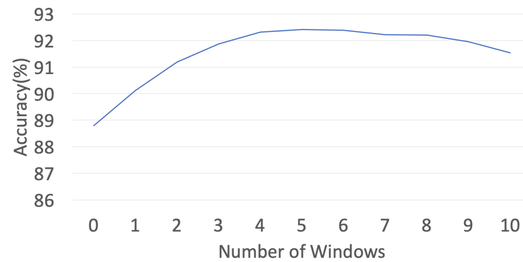


Fig. 6. Effect of context correction.

TABLE IV
TRANSMITTER ENERGY CONSUMPTION.

Component(Input Voltage)	Average Power Consumption
Micro-controller(2.0V)	29.4μW
Accelerometer(2.0V)	3.0μW
Analog components [2]	0.25μW
Total	32.65μW

the design of the battery-less devices, we also need to consider energy harvesting. Since we can expect sufficient amount of harvested energy by the movement of users, we assume the right shoe device as the central device. The pocket device also harvests energy from the vibration. Photodiodes are also used to harvest energy from lights during travel contexts without user movement such as idle, bus, and train.

First, in order to measure the energy consumption at the transmitter, we reproduced the operations of the pocket device. The sampling rate of the accelerometer was set to 12.5 Hz. When the accelerometer's FIFO buffer becomes full (every 13.6 secs.), the micro-controller wakes up by interruption, computes the results of DT nodes, and transmits them. The measurement result of energy consumption at the pocket device is shown in Table IV. Since the analog component is not implemented on the prototype, we use its energy consumption shown in Ref. [2]. The result indicates the energy consumption of the micro-controller is the largest (29.4μW) because it conducts various operations such as feature extraction, computation, and data transmission.

Also, the energy consumption of the receiver (i.e. central device) is shown in Table V. The receiver computes the output of DT by combining the received data and its own sensor data (pressure and acceleration) The energy consumption of the receiver is 52.94μW as shown in Table V, which is greater than the transmitter. This is because of the computation cost of the DT output and the additional sensor.

To see the feasibility of our concept, we need to compare the energy consumption with the harvested amount of energy. For this purpose, typical amount of harvested energy in different harvesters is shown in Table VI. Piezoelectric materials generate energy up to 1mW during walking by attaching them into shoe insoles [16], [17]. Ref. [18] reports vibration during walking and running can produce 100-800 μW while it becomes 5 μW at idle time. Therefore, we can expect sufficient amount of harvested energy during movement. On the other

TABLE V
RECEIVER ENERGY CONSUMPTION.

Component(Input Voltage)	Average Power Consumption
Micro-controller(2.0V)	43.8μW
Accelerometer(2.0V)	3.0μW
Barometer(2.0V)	5.6μW
Analog components [2]	0.54μW
Total	52.94μW

TABLE VI
REPORTED AMOUNT OF HARVESTED ENERGY

Energy Harvesting Type	Harvested Energy Amount
Piezoelectric materials [16], [17]	$1m$W
Motion(Kinetic) Energy [18]	40–800μW
RF Energy [19]	1–100μW
Solar Cell [20]	15–20μW(1cm^2,500lux)

hand, for stationary scenarios, we may rely on other sources such as light and radio frequency (RF). Another option is to store the energy in a super capacitor during movement and use the stored energy later. According to Ref. [19], 100 μW is harvested at 6.3 km away from Tokyo Tower by RF. Photodiodes of 1 cm^2 produce 20 μW for a typical office environment (500 lux) [20], meaning photodiodes of 4 cm^2 are sufficient to operate our battery-less device.

From the above results and discussion, we confirmed the feasibility of the cooperative battery-less devices.

V. CONCLUSION

In this paper, we investigated the feasibility of cooperative battery-less wearable devices through the prototype implementation to enhance their performance. We also showed the effectiveness of device cooperation for travel context estimation through the experiment.

Currently, we are planning to investigate other applications where device cooperation is more effective. Also, we will combine the energy harvester to show the feasibility through real experiments. The implementation of the ambient backscatter is another part of our future work.

REFERENCES

[1] H. Lee and Y. Lee, "A look at wearable abandonment," in *2017 18th IEEE International Conference on Mobile Data Management (MDM)*, May 2017, pp. 392–393.

[2] V. Liu, A. Parks, V. Talla, D. Gollakota, Shyamnath andWetherall, and J. R. Smith, "Ambient backscatter: Wireless communication out of thin air," *SIGCOMM Computer Communication Review*, vol. 43, no. 4, pp. 39–50, 2013.

[3] X. Qi, M. Keally, G. Zhou, Y. Li, and Z. Ren, "Adasense: Adapting sampling rates for activity recognition in body sensor networks," in *Real-Time and Embedded Technology and Applications Symposium (RTAS), 2013 IEEE 19th*. IEEE, 2013, pp. 163–172.

[4] K. Sankaran, M. Zhu, X. F. Guo, A. L. Ananda, M. C. Chan, and L.-S. Peh, "Using mobile phone barometer for low-power transportation context detection," in *Proceedings of the 12th ACM Conference on Embedded Network Sensor Systems(SenSys '14)*, 2014, pp. 191–205.

[5] Q. Huang, Y. Mei, W. Wang, and Q. Zhang, "Battery-free sensing platform for wearable devices: The synergy between two feet," in *Proceedings of The 35th Annual IEEE International Conference on Computer Communications(INFOCOM 2016)*, 2016, pp. 1–9.

[6] C. Zhu and W. Sheng, "Realtime recognition of complex human daily activities using human motion and location data," *IEEE Transactions on Biomedical Engineering*, vol. 59, no. 9, pp. 2422–2430, 2012.

[7] S. Reddy, M. Mun, J. Burke, D. Estrin, M. Hansen, and M. Srivastava, "Using mobile phones to determine transportation modes," *ACM Transactions on Sensor Networks.*, vol. 6, no. 2, pp. 13:1–13:27, 2010.

[8] J. Ryder, B. Longstaff, S. Reddy, and D. Estrin, "Ambulation: A tool for monitoring mobility patterns over time using mobile phones," in *Proceedings of the 2009 International Conference on Computational Science and Engineering(CSE'09)*, vol. 4, 2009, pp. 927–931.

[9] Y. Nakajima, K. Murao, T. Terada, and M. Tsukamoto, "A method for energy saving on context-aware system by sampling control and data complement," in *Wearable Computers (ISWC), 2010 International Symposium on*. IEEE, 2010, pp. 1–4.

[10] A. N. Parks, A. Liu, S. Gollakota, and J. R. Smith, "Turbocharging ambient backscatter communication," in *Proceedings of the 2014 ACM Conference on SIGCOMM(SIGCOMM '14)*, 2014, pp. 619–630.

[11] B. Kellogg, V. Talla, S. Gollakota, and J. R. Smith, "Passive wi-fi: Bringing low power to wi-fi transmissions," in *Proceedings of the 13th Usenix Conference on Networked Systems Design and Implementation(NSDI'16)*, 2016, pp. 151–164.

[12] C. Zhao, S. Yisrael, J. R. Smith, and S. N. Patel, "Powering wireless sensor nodes with ambient temperature changes," in *Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing(UbiComp '14)*, 2014, pp. 383–387.

[13] S. Khalifa, M. Hassan, and A. Seneviratne, "Pervasive self-powered human activity recognition without the accelerometer," in *2015 IEEE International Conference on Pervasive Computing and Communications (PerCom)*. IEEE, 2015, pp. 79–86.

[14] Y. Liu, C. Huang, H. Min, G. Li, and Y. Han, "Digital correlation demodulator design for rfid reader receiver," in *Proceedings of the Wireless Communications and Networking Conference (WCNC 2007)*, 2007, pp. 1664–1668.

[15] N. V. Chawla, K. W. Bowyer, L. O. Hall, and W. P. Kegelmeyer, "Smote: Synthetic minority over-sampling technique," *Journal of artificial intelligence research*, vol. 16, pp. 321–357, 2002.

[16] J. Zhao and Z. You, "A shoe-embedded piezoelectric energy harvester for wearable sensors," *Sensors*, vol. 14, no. 7, pp. 12 497–12 510, 2014.

[17] D. Han and V. Kaajakari, "Microstructured polymer for shoe power generation," in *Proceedings of the 15th International Conference on Solid-State Sensors, Actuators and Microsystems(Transducers 2009)*, 2009, pp. 1393–1396.

[18] M. Gorlatova, J. Sarik, G. Grebla, M. Cong, I. Kymissis, and G. Zussman, "Movers and shakers: Kinetic energy harvesting for the internet of things," in *Proceedings of the 2014 ACM International Conference on Measurement and Modeling of Computer Systems(SIGMETRICS '14)*, 2014, pp. 407–419.

[19] R. Shigeta, T. Sasaki, D. M. Quan, Y. Kawahara, R. J. Vyas, M. M. Tentzeris, and T. Asami, "Ambient rf energy harvesting sensor device with capacitor-leakage-aware duty cycle control," *IEEE Sensors Journal*, vol. 13, no. 8, pp. 2973–2983, 2013.

[20] F. De Rossi, T. Pontecorvo, and T. M. Brown, "Characterization of photovoltaic devices for indoor light harvesting and customization of flexible dye solar cells to deliver superior efficiency under artificial lighting," *Applied Energy*, vol. 156, pp. 413–422, 2015.