IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received April 12, 2019, accepted May 16, 2019, date of publication May 23, 2019, date of current version June 4, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2918555

Energy Harvesting-Based Smart Transportation Mode Detection System via Attention-Based LSTM

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This work was supported in part by the National Science Foundation of China under Grant U1713212, Grant 61572330, Grant 61836005, Grant 61702341, Grant 61602319, Grant 61806130, in part by the Natural Science Foundation of Guangdong Province under Grant 2017A030313357, in part by the Technology Planning Project of Shenzhen City under Grant JCYJ20170302143118519, Grant GGFW2018021118145859, and Grant JSGG20180507182904693, and in part by the China Postdoctoral Science Foundation under Grant 2018M643182.

ABSTRACT Detecting the transportation mode of an individual's everyday travel provides useful information in urban design, real-time journey planning, and activity monitoring. In existing systems, the accelerometer and GPS are predominant signal sources which quickly drain the limited battery life of the wearable devices. In this paper, we present an alternative approach for fine-grained transportation mode detection using kinetic energy harvester (KEH). We demonstrate the feasibility of using the output signal from the KEH device as the information source to achieve transportation mode detection. The proposed system is motivated by the fact that different transportation modalities produce distinctive motion patterns which are expected to leave distinctive patterns for context detection. To achieve fine-grained transportation mode detection, we design a transportation detection framework based on attention-based Long Short Term Memory (LSTM). We evaluate our approach using 38.6 hours of transportation data, which is collected from a total of six volunteers in three months' time using our prototype. The evaluation results show that our approach is able to reach an overall accuracy of over 97% to detect fine-grained transportation modalities. In addition, our measurements show that the power consumption of the sampling KEH signal is only 460uW which significantly outperforms the existing transportation mode detection systems.

INDEX TERMS Transportation detection, energy harvesting, accelerometer, deep learning.

I. INTRODUCTION

With the prevalence of wearable devices such as smart watches and fitness bands, physical activity recognition using wearable sensing units has attracted lots of attention from both academic and industry which brings many context-aware applications. Examples such as Google Now which tracks user's activity to provide better localization services, and augmented reality applications like PokeFit[1] that utilizes continuously user activity monitoring to ensure better user experience. Transportation mode detection is a special case of context-awareness where wearable devices are able to understand user's traveling mode intelligently. The information of individual's traveling pattern is extremely useful in many research and application fields. For instance, in urban sensing and planning [1], the profiling of a large group of user's daily routine and traveling modes can help urban planners to gain insight of people's everyday movement patterns and propose better urban planning. In addition, information of individual transportation dynamics can be used to provide individual-oriented service, such as location-based service [2], everyday traveling route planning [3].

However, profiling of an individual's transportation habit usually involves long-term continuous sensing, which arises a critical issue on the limited battery life of today's wearable devices. The problem becomes more severe given the fact that existing transportation detection systems are largely rely on energy-hungry sensors, such as GPS [4] or Wi-Fi/Cellular signal [5]. Another predominantly used sensor is

The associate editor coordinating the review of this manuscript and approving it for publication was John Tadrous.

[1]PokeFit: http://pokefit-app.com/

accelerometer [6], [7], though the power consumption of accelerometer is relatively low (typically in the order of a few milliwatts), long-term continuous monitoring still drains battery life quickly. Although, the power consumption incurred by accelerometer may be not a big issue for mobile devices with large batteries such as smart phones, for other wearables like wristband and smart watches, the critical aspect of battery life remains pretty much unchanged. Since for most wearable devices, they can hardly take advantage from large size batteries due to the requirement of small form factor and light weight. For instance, the maximum battery-life reported for Apple Watch is approximately 8 hours with sensors enabled, and further reduced to 5 hours if the built-in GPS is activated.[2]

To address the limited battery life of wearable devices, a current trend in the literature is to investigate kinetic energy harvesting (KEH) solutions to power the wearables [8], [9]. KEH is the process of converting energy released from human or machine motions into usable electrical energy to power the wearable devices so that devices can function continuously without battery recharge. Recent efforts in academic such as the backpack-based and insole-like energy harvester proposed in [10] is able to power wearable electronics, similar work like the piezoelectric energy harvester-based pedometer system proposed in [11], as well as the work proposed in [12] where the power generated by the insole energy harvester are used to power accelerometer and wireless radio. Examples of current advancements in the industry, such as AMPY[3] has released the world's first wearable motion-charger which can transform the kinetic energy from user's motion into battery power, and SOLEPOWER[4] have developed smart boots that use user's steps to power embedded sensors.

Unfortunately, though we have witnessed and believe energy harvesting based solutions will be used to augment or substitute batteries in the near future, KEH is still at its early stage of development in practice. The fundamental problem in using KEH to power wearable devices and achieve long-term transportation mode detection is that the amount of energy that can be practically harvested from human motions can hardly meet the energy requirement of the system. For example, the average power consumption of the accelerometer-based transportation mode detection system [6] is 85 mW, in which 21 mW results from accelerometer sampling. The result becomes even worse if GPS signal is used, as a typical GPS-based system [4] could consume up to 240 mW. On the contrary, the harvested power from human motion is in the order of microwatts [8], [9], especially in the case where people may be stationary in most of the time (i.e., stationary and sitting/standing in the moving vehicles).

To address the energy consumption issue, in this paper, we investigate the feasibility of using the output voltage generated by the KEH as the signal source to achieve energy-efficient transportation context detection. The proposed idea is based on the intuition that the vibrations experienced by the passenger during motoring of different transportation modes are different. Thus, voltage generated by the energy harvester should contain distinctive features to classify different transportation modes. Although the proposed idea looks promising, it is nontrivial to achieve high system performance. Unlike accelerometer which is able to capture acceleration signal in 3 different axes, KEH signal is single axis. As a result, KEH-based context detection systems usually suffer from accuracy lost [13]–[15].

In this paper, we address this challenge by conducting a detailed feature selection study and designing a Recurrent Neural Network (RNN)-based classification framework. To the best of our knowledge, this is the first work that detects transportation modes by exploiting harvested voltage from the KEH wearable devices as the signal source. The main contributions of this paper are as follows:

- We propose a novel transportation detection system, which uses only KEH voltage signal as the source information to achieve fine-grained transportation mode detection.
- We build a prototype based on piezoelectric energy harvester (PEH). Using the prototype, we evaluate the proposed system using 38.6 hours of transportation data collected from 6 volunteers. Results show that the proposed system can reach $> 97\%$ classification accuracy.
- We design a RNN based framework to classify different vehicle modes. Evaluation results show our approach improves recognition accuracy by over 16% compared to traditional classification algorithms such as SVM, KNN and Naive Bayes.
- Finally, using measurements, we demonstrate that the power consumption of sampling KEH signal is only 480uW which significantly outperforms existing transportation mode detection systems which uses GPS, WiFi/Cellular, accelerometer and barometer.

The rest of the paper is structured as follows. We discuss related work in Section II. Then, we provide an overview of the proposed system in Section III and present the design details in Section IV. Section V introduces prototype design and data collection. Section VI presents the evaluation results. Finally, we conclude our work in Section VIII.

II. RELATED WORK

A. TRANSPORTATION MODE DETECTION USING WEARABLE SENSORS

Based on the types of sensors used, previous studies can be broadly grouped into four categories: GPS, Wi-Fi/Cellular, accelerometer, and barometer based systems.

1) GPS

GPS is a powerful sensor for activity detection because it can provide useful information including the location and the speed of movements. Zheng *et al.* [16] use solely GPS to detect the modes walking/driving/bike. However, GPS-based solution only works well for coarse grained transportation

[2]Apple Watch: http://www.apple.com/au/watch/battery.html
[3]AMPY Move: http://www.getampy.com/ampy-move.html
[4]SOLEPOWER: http://www.solepowertech.com/

mode detection, it performs poorly when classification of travel modes involve similar speed, such as running, biking and slow motorized motions. It is possible to use a combination of sensors to provide more detailed information about the user's activities. For instance, Reddy *et al.* [4] use GPS in conjunction with accelerometer to infer user's movements such as idel/walking/bike/vehicle. Stenneth *et al.* [17] proposed the use of smartphone GPS sensor together with the knowledge of underlying transportation network to achieve transportation mode detection. The main limitation of GPS-based system is the high power usage. Additionally, it cannot be used in indoor and underground environments.

2) Wi-Fi/CELLULAR

The variations in the radio signal can also be explored to infer user's movements. Sohn *et al.* [5] identified activities of walking, driving, and staying at the same place (dwelling) by using the GSM traces only. Anderson and Muller [18] used fluctuations in GSM cell tower observations to estimate whether a user is still, walking or in motorized transport. In [19], Wi-Fi signals were used to infer whether the user is moving or stationary. Similarly, in [20], a hybrid approach utilizing both Wi-Fi and GSM signals were used to detect the transportation mode.

3) ACCELEROMETER

According to a recent survey [21], accelerometer is the predominant sensor used for detecting transportation modes. Exisitng works such as that proposed by Randell *et al.* [22] uses a single accelerometer to detect stationary, walking and running activities. Miluzzo *et al.* [23] use the three-axis accelerometer on Nokia N95 mobile phone to infer the different classes of walking motions (e.g., walking, in conversation, at the gym). For accelerometer-based system, a large number of features should be extracted and selected carefully [6]. Different from Wi-Fi and Cellular, accelerometer is able to achieve fine-grained transportation mode detection. Although the power consumption of accelerometer is low, continuously detection still consumes large amount of energy thus reducing battery life [7].

4) BAROMETER

In a recent study, Kartik *et al.* [24] proposed to detect transportation mode using mobile phone barometer. The main advantage of barometer is the position-independent characteristic, as it measures the variation of air pressure during movement instead of acceleration changes. However, the barometer can only be used for coarse-grained transportation detection as it is not sensitive to speed and height changes [24].

B. USING KEH AS LOW POWER MOTION SENSOR

Kinetic energy harvesting is the process of generating electrical energy from ambient vibration sources. The most widely used energy conversion techniques are the piezoelectric, electromagnetic, and electrostatic. Among them, piezoelectric energy harvesting (PEH) has been widely shown the greatest potential to achieve better performance (higher voltage and power density levels) in harvesting energy [25]. Recent efforts in the literature are applying PEH as a low power vibration sensor to replace conventional motion sensors, such as activity recognition [26], health monitoring [27], gait-based user authentication [14], and sports training [28]. The prototype designed in this paper is based on piezoelectric technique.

TABLE 1. Comparison of existing work and KEH.

Sensors	Power Consumption	Limitations
GPS	240mW	Susceptible to obstructions Unavailable indoor/underground High power consumption
WiFi/Cellular	230mW	Susceptible to access points and cellular towers density
Accelerometer	85mW	Direction dependent Continuously sampling reduces battery life
Barometer	88mW	Only achieve coarse grained classification
KEH	480uW (sampling only)	Ultra low power Direction independent Usable everywhere Fine grained classification

Table 1 summaries the power consumption and limitations of previous sensor-based transportation mode detection systems, and the corresponding advantages of the proposed KEH-based system. The system power consumption listed in the table are derived from the measurement results reported in [4], [6], [24]. The power consumption of the KEH-based system is based on our measurements in Section VII.

C. STUDIES ON KEH

The first idea of using energy harvesting as a sensing technology was proposed in [13], [26], where the authors investigated the feasibility of using the voltage signal of energy harvester for daily activity classification. Their results showed that the proposed system can achieve 83% classification accuracy. Since then, a number of work have been done to explore the feasibility of using harvested energy to monitor human activity. For instance, the authors of [27] carried out the first study of estimating calorie expenditure of different daily activities from output voltage of piezoelectric energy harvester. Their results show that KEH is a promising technology to replace accelerometer. In another recent work, the authors of [14] proposed an authentication system which uses energy harvesting signal to authenticate the user based on gait analysis. Their main claim is that the proposed system can save significant energy by using energy harvester to replace accelerometer. Indeed, their evaluation results show their system can save up to 78% energy compared to traditional gait recognition system. In this paper, we propose to detect user's transportation mode by utilizing the voltage signal generated by the kinetic energy harvester. By doing so, the proposed system is able to reduce the power consumption of the transportation mode classification in the wearable device by not using any energy-hungry sensors like accelerometer and GPS.

D. DEEP LEARNING

Deep learning has achieved great success over the past several years for the excellent ability on high-level feature

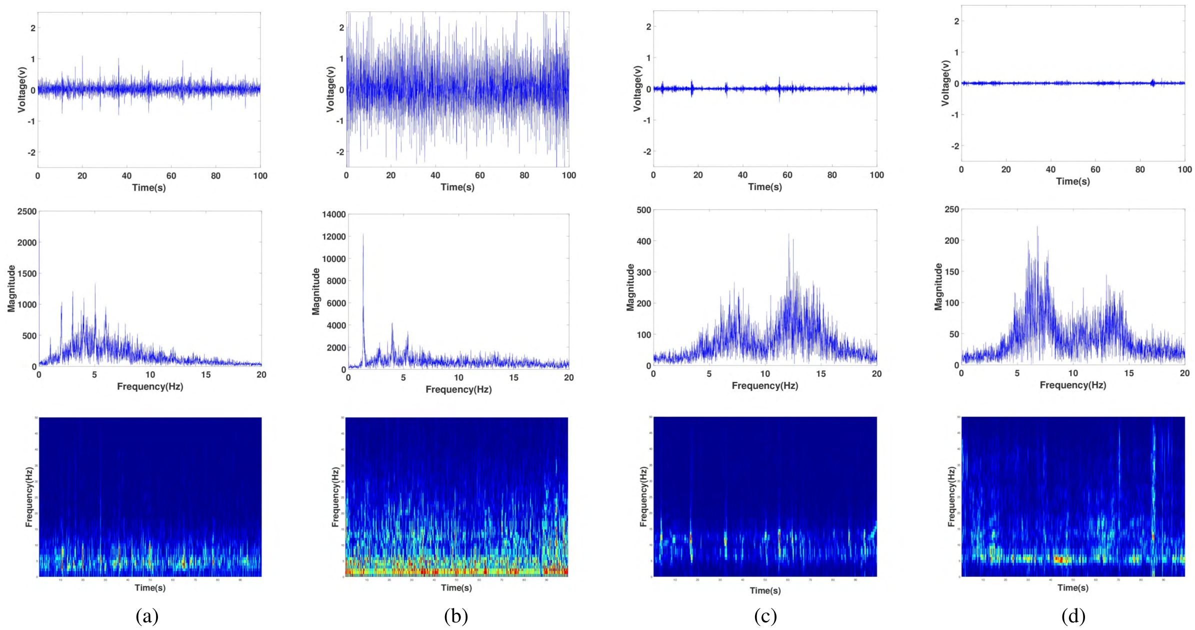

FIGURE 1. A comparison of the voltage signal from different transportation modalities. Figures in the first row plots the voltage signal in the time domain; figures in the second row indicate the frequency domain features; figures in the last row show the corresponding spectrogram. (a) Walking. (b) Running. (c) Car. (d) Train.

learning and representative information discovering. Specifically, deep learning has been widely used in a number of areas, such as computer version [29], activity recognition [30], sensory signal classification [31], and brain computer interface [32]. Wen *et al.* [29] propose a new supervision signal, called center loss, for face recognition task. The proposed center loss function is demonstrated to enhance the discriminative power of the deeply learned features. Measurement Unit signals. Zhang *et al.* [31] combine deep learning and reinforcement learning to deal with multimodal sensory data (e.g., RFID, acceleration) and extract the latent information for better classification. Recently, deep learning involves in the brain signal mining in brain computer interface (BCI). Zhang *et al.* [32] propose an attention-based Encoder-Decoder RNNs (Recurrent Neural Networks) structure in order to improve the robustness and adaptability of the brainwave based identification system.

There are also several works that apply deep learning techniques in embedded devices. Lane and Georgiev [33] propose low-power Deep Neural Network (DNN) model for mobile sensing. CPU and DSP in one mobile device are exploited for activity recognition. Lane *et al.* [33] also design a DNN model for audio sensing in mobile phone by using dataset from 168 places for the training purpose. A framework DeepX is further proposed for software accelerating on mobile devices [34]. In this work, we apply an attention-based LSTM network to achieve accurate transport mode detection.

III. SYSTEM OVERVIEW

In this section, we introduce the intuition of proposed KEH-based transportation mode detection, and the system architecture.

A. INTUITION BEHIND THE PROPOSED SYSTEM

The intuition behind the proposed system is that different transportation modes produce distinct vibrations caused by speed, roads, height and different motor types. The KEH is sensitive enough to capture such dynamics when the user or vehicle is moving. As an example, Figure 1 compares the voltage signal generated by the KEH from different transportation modalities in the time domain, frequency domain, and spectrogram. We can see that different transportation modes exhibit distinguishable time domain and frequency domain features. Intuitively, running produces larger voltage as it is a more vibrant activity than walking. In comparison, the generated voltage signal when the user is traveling by a vehicle like car and train is much moderate, since the user is in stationary mode when they take vehicles. This figure demonstrates the feasibility of using voltage signal generated by the KEH device to classify different transportation modes.

B. SYSTEM ARCHITECTURE

Figure 2 gives a high-level overview of the KEH-based transportation mode detection system. The whole system consists of two parts: a wearable device and a remote server. The wearable device is embedded with a KEH and will be carried by the user in daily life. The wearable device collects the output voltage signal of the energy harvester and sends the voltage samples to the server where data processing and context detection algorithm are running.

Instead of relying on any accelerometer or GPS signal, the wearable device exploits the AC voltage generated from the KEH to achieve transportation mode detection. In the server, our system process the signal as follows. First, the raw voltage signal from the KEH device is going through the

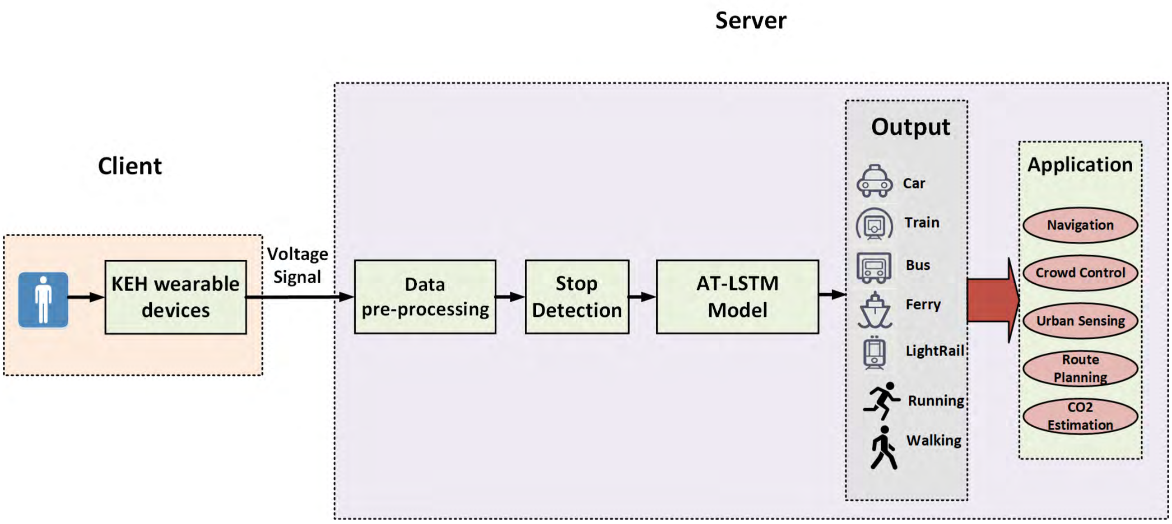

FIGURE 2. Overview of KEH-based transportation mode detection.

data pre-processing which applies a low-pass filter to eliminate possible noise. In addition, during data pre-processing, we have designed a stop-detection algorithm to detect and filter the stop/pause segments out from the voltage signal profile. Then, the processed signal is feed into the RNN classification module to determine the exact motion which the person is performing. The transportation activities considered in this paper include seven normal daily transportation modes: bus, train, car, ferry, light rail, running and walking.

IV. SYSTEM DESIGN

A. SIGNAL PRE-PROCESSING

The real time data from an energy harvester contains much noise that needs to be filtered out before using it for transportation mode detection. Thus a moving average filter of order 3 is applied for noise removal. After noise reduction, continuous voltage data is segmented into T seconds sliding windows with 50% overlap. The window size T is chosen to balance between classification accuracy and latency as evaluated in Section VI-A.1. The overlap in sliding window is used to capture changes or transitions around the window limits. In the following, we use voltage signal in the windows to detect transportation mode.

B. STOP DETECTION AND REMOVAL

During traveling, a vehicle has to make some stop/pauses due to traffic congestion, traffic light, or arriving at the bus stop. Similarly, for pedestrian traveling, people may also have some stationary periods. The stop detection is usually regarded as one of most fundamental context in motion tracking, which provides the binary information of the user's motion state (i.e., moving or stationary). By tracking the number of stops, such information can be greatly useful for a variety of positioning and navigation systems [35].

For accelerometer-based system, the stop of the vehicle is detected by comparing the average acceleration magnitude

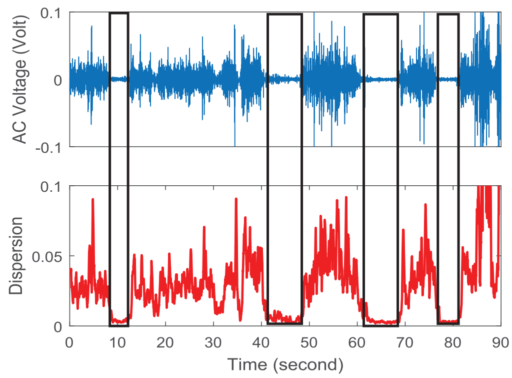

FIGURE 3. Example of stop detection.

within a certain time window to a pre-defined threshold, or by using a probabilistic model of the acceleration magnitude to determine the status of the vehicle. Similar to the accelerometer-based stop detection algorithms, the idea underlying in the detection of the stop/pause periods is based on the fact that the AC voltage signal from the KEH device is fluctuating while traveling, whereas it is very stable during the stop/pause periods. Based on this observation, we apply a thresholding algorithm to identify the stop periods from the AC voltage signal. For a given voltage sample s_t generated at time t, we calculate the standard deviation of the previous k samples that observed before s_t. The value of k equals to the sampling frequency used during the data sampling. If the stand deviation is smaller than a predefined threshold, we consider it as a voltage sample generated in the stationary period, and filtered it out from the signal trace.

As an example, Figure 3 shows a trace of the voltage signal recored during a car trip. The upper plots show a time series of the AC voltage signal generated by our KEH prototype during traveling by car. The lower graph indicates the stand deviation of the corresponding voltage signal. We can clearly observe that there exists several periodic slots in which the

TABLE 2. List of features and RMI.

Statistical Features	RMI			RMI	
Length	2.7%		1 and 3 Quartile	10.6%	✓
Min	15.4%	✓	Skewness	4.6%	
Mean	1.4%		Kurtosis	7.2%	
Median	0.7%		Absolute area	14.7%	✓
Max	14.9%	✓	Mean of peaks	16.4%	✓
STD	14.3%	✓	Mean of distance between peaks	14.8%	✓
RMS	3.4%		Max distance between peaks	13.4%	✓
Mean of absolute value	13%	✓	Max of peaks	16.3%	✓
Number of samples higher than threshold 1,2,3	19.4%	✓	Peak to peak	12.4%	✓
spectral entropy	9.4%		Peak to peak difference	10.7%	
Spectrum peak position	17.9%	✓	**Frequency domain features**		
FFT coefficients (1-50Hz)	15.3%	✓	2 Dominant frequencies	16.8%	✓
Time domain features			Dominant frequency ratio	12.4%	✓
Range	2.5%		Mean of power spectrum	4.5%	
Mean of absolute deviation	6.4%		Total energy of spectrum	8.9%	✓
Number of datapoint cross mean	3.2%		Min of power spectrum	3.6%	
Coefficient variation	1.6%		Max of power spectrum	2.7%	
Interquartile range	7.4%	✓			

values of the voltage signal are much smaller and more stable than those of the other periods. These slots correspond to the stop periods of the vehicle. Intuitively, this is because during the stop/pause of the vehicle, the vibration applies to the KEH device is quite small and stable, and as a result, these features are reflected on the voltage signal.

C. FEATURE SELECTION

Feature selection is crucial for a classification system for two reasons: (a) it can help us select the best features when the whole feature set is high-dimensional and (b) it is able to gain better insights into why this feature works. Therefore, in this section we will first describe different types of features, explain the reason behind each choice. Then we will determine the quality of features according to the information they reveal about the transportation mode. It is worth mentioning that although feature selection is usually unnecessary in deep neural network, we find that using raw KEH signal as input does not produce high prediction accuracy. Instead, the system can achieve high accuracy by extracting features to represent the raw signal.

D. FEATURE TYPES

After stop detection and removal, we extract a set of features from each window. The features used in this paper can be broadly classified into two types: window-based features and peak-based features. Below we detail each feature set and describe their function in the system. A complete list of features are summarized in Table 2.

1) WINDOW-BASED FEATURES

From each window, we extract 27 window-based features from voltage data. The features we extract include statistical features (e.g., min, variance and kurtosis), time-domain features (e.g., range, number of datapoint cross mean) and frequency-domain features (e.g., spectral entropy and FFT coefficients). The features considered in our study were chosen based on the analysis by [6]. The window-based features are able to effectively capture the general characteristics of different vehicles.

2) PEAK-BASED FEATURES

While the window-based features can effectively capture the overall patterns of different vehicles, they do not represent the information of movements with lower frequencies, such as acceleration and breaking periods of motorised vehicles. These changes are reflected as peaks and troughs in the voltage data. To represent these key periods of vehicular movement, we extract a set of peak-based features such as mean of peaks, peak to peak difference.

E. FEATURE SELECTION PROCESS

There are a number of techniques that can be used to determine feature quality and select features, such as information gain [36] and ReliefF algorithm [37]. In the proposed system, we choose to use the mutual information (MI) to determine the quality of features because they can measure the amount of information about the transportation mode revealed by each feature. In order to measure the mutual information relative to the entire amount of uncertainty, we use the relative mutual information (RMI) which measures the percentage of entropy that is removed from the transportation mode when a feature is known. The RMI is calculated as follows:

$$RMI(id, F) = \frac{H(id) - H(id|F)}{H(id)} \tag{1}$$

where $H(F)$ is the entropy of F, and $H(id|F)$ is the entropy of id conditioned on F. A high RMI indicates that the feature is distinctive on its own, but it is crucial to consider the correlation between features as well when choosing a feature set. For example, several features that are not particularly distinctive on their own may be more useful when combined.

Table 2 lists the RMI of each features. In order to determine the optimal feature set, we apply the Minimum Redundancy Maximum Relevance (mRMR) algorithm [38]. This algorithm selects those features that share a high amount of information with the classification results (i.e., transportation mode) while showing low redundancy with other features in the set. In order to achieve a good trade-off between classification speed and accuracy, we choose the best features as computed by mRMR algorithm. The list of those features can be seen in Table 2.

F. ATTENTION BASED LSTM CLASSIFICATION

LSTM is a Recurrent Neuron Network (RNN) based neural network [39], [40]. LSTM networks are well-suited to classifying, processing and making predictions based on time series data, since there can be lags of unknown duration between important events in a time series. However, the standard LSTM cannot detect which is the important part for fine-grained transportation mode classification. To overcome this limitation, we design an attention mechanism that can capture the key part of the samples in response to a given transportation mode.

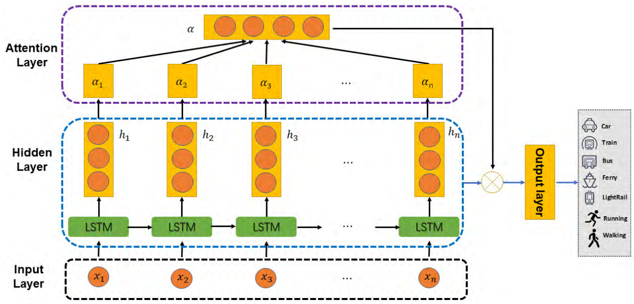

FIGURE 4. The architecture of attention-based LSTM.

Figure 4 shows the architecture of the AT-LSTM model. As discussed earlier in Section IV-E, we extract a number of features from a segment of KEH voltage data such as statistical features and frequency-domain features. Suppose we have extracted n features from each segments: $\{x_1, x_2, \cdots, x_n\}$. In the input layer, the features are fed into LSTM network to obtain hidden state $\{h_1, h_2, \cdots, h_n\}$. Then all the ouput of LSTM networks are fed into the attention layer. If we assume the feature importance vector is u_t, the normalized weights α_t can be obtained as follows.

$$u_t = \tanh(Wh_t + b) \tag{2}$$

$$\alpha_t = \frac{exp(u_t^T u)}{\sum_t exp(u_t^T u)} \tag{3}$$

where W, b and u are parameters during training. Followed by that, we calculate the weighted sum of each hidden state h_t with its corresponding weight α_t: $v = \sum_t \alpha_t h_t$. Finally, we input vector v to the output layer with softmax activation to obtain the probabilities of each class. The class with the highest probability is the current transportation mode.

In the AT-LSTM network, we use the following loss function:

$$loss = -\sum_i \sum_j y_i^j log\hat{y}_i^j + \lambda \, \|\theta\|^2 \tag{4}$$

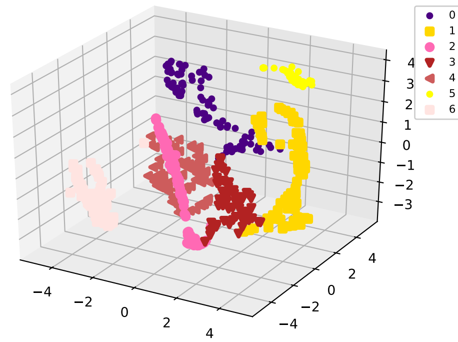

FIGURE 5. t-SNE projection of different transportation modes (0-Walking; 1-Running; 2-Car; 3-Bus; 4-Light rail; 5-Train; 6-Ferry).

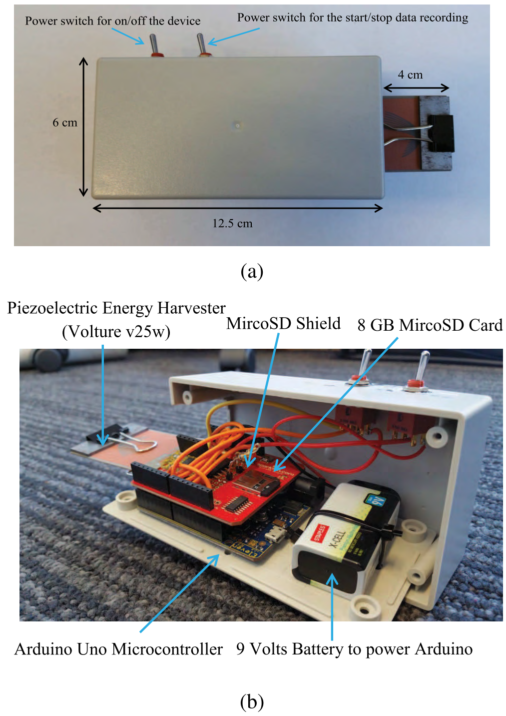

FIGURE 6. Custom-made VEH data recorder. (a) VEH data recorder.

where i is the index of the i-th segment, j is the index of the j-th class. θ is the parameter set, λ is the L_2-Regularization term. The AT-LSTM model is trained on the collected data with the goal of minimizing the cross-entropy between the predicted distribution $\hat{y}$ and ground truth distribution y using gradient descent. With repeated training and repair, the loss will reach a state of convergence, and the training has been completed. Figure 5 shows the T-distributed Stochastic Neighbor Embedding (t-SNE) projection of all transportation modes after training. We can see that the AT-LSTM model can effectively distinguish different transportation modes.

V. HARDWARE PLATFORM AND DATA COLLECTION

A. PROTOTYPE

We built a PEH prototype to collect PEH voltage signals generated from different transportation modes. Figure 6 shows the design of our prototype. We use the piezoelectric

TABLE 3. Summary of collected data.

Subjects	Walking	Running	Car	Bus	Train	Ferry	Light rail	Total
6	12 traces	10 traces	20 traces	27 traces	26 traces	16 traces	8 traces	119 traces
	5.6 hours	4.8hours	2.4 hours	8.6 hours	8.5 hours	4.5 hours	4.2 hours	38.6 hours

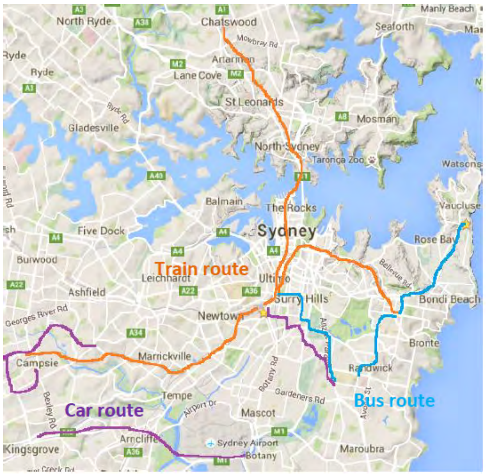

FIGURE 7. Sample traces in Sydney.

transducer from MIDÈ as the vibration energy harvester which is mounted on the Arduino UNO board. The Arduino Uno board is an open source development platform based on the ATmega328P micro-controller (MCU). We do not physically store the energy generated by the PEH on our device, but the output AC voltage from the harvester is sampled by the MCU via its onboard 10-bit analog-to-digital converter (ADC) at 100Hz and the sampled AC voltage data are stored in a microSD card for further analysis. The whole system is powered by an external 9V battery. The Arduino measures voltage between 0 and 5 volts and provides 10 bits of resolution (i.e., 1024 different values). Besides, our prototype also includes a 3-axis accelerometer to record the acceleration signals simultaneously which allows us to compare the performance of accelerometer signal and KEH signal.

B. DATA COLLECTION

Our evaluation is based on 38.6 hours of traces collected in anonymous city by 6 volunteers in 3 months' time. Volunteers were asked to carry the prototype with them during their daily transportation. No special instructions were given about how to carry the device, and none of the journeys were decided in advance. The ground truth is obtained by pressing buttons on the prototype. The everyday data covers a wide range of transportation behaviors within our target city: a total of 119 traces were collected during various times and traffic conditions. Table 3 provides a summary of the traces collected from each volunteer. There are more than 10 hours pedestrian activity (e.g., walking and running) and 28 hours of vehicle activity. In particular, we collect 16 traces from ferry activity which has not been investigated in previous studies. In total, there are 119 traces and 38.6 hours of data. Unlike the data collection methodology in previous studies [6], [24], we are not able to collect traces from multiple countries due to the limited number of prototypes.

VI. EVALUATION

A. GOALS, METRICS AND METHODOLOGY

In this section, we evaluate the performance of the proposed system based on the collected dataset. The goals of the evaluation are threefold: 1) evaluate the performance of the proposed system in transportation mode detection; 2) compare the proposed system with accelerometer-based system; 3) compare the proposed classification framework with traditional classification algorithms.

For fair comparison, we perform the same signal processing, feature selection and classification method on acceleration data. The only difference is the feature vector is obtained by concatenating features extracted along three axes in one window together. This is because acceleration signal is sensitive to direction and different volunteers may carry prototype in different ways.

In the evaluation, we compare our classification framework with Support Vector Machine (SVM), K-Nearest Neighbor (KNN), and Naive Bayes (NB) which are popular machine learning algorithms in activity classification. The parameters in SVM, KNN and NB are well tuned to give highest accuracy. For KNN classifier we set the number of nearest neighbors as 10. For SVM classifier, we choose linear kernel function, and the soft margin constant is 8. We choose normal Gaussian distribution for NB. For each classifier, we perform 10-fold cross-validation on the collected dataset.

In this paper, we focus on the following four evaluation metrics: *accuracy*, *precision*, *recall* and *F1-score*. We plot the results of the average values and 95% confidence level obtained from 10 folds cross-validation.

1) KEH-BASED V.S. ACCELEROMETER-BASED

In this section, we investigate how is the performance of the proposed KEH-based system against the conventional accelerometer-based system.

We vary T from $1s$ to $5s$ and plot the results in Figure 8. First, we can see that the accuracy of both methods increases as T increases. This is because with larger T, we can obtain more information for classification. However, there is a big gap between these two systems when $T = 1$. There are two reasons. First, accelerometer has 3 axes, thus it can take advantage and capture more useful information from 3 directions. However, KEH-based system suffers from information loss due to its single axis characteristic. Second, accelerometer is designed to detect minor vibrations whereas KEH signal contains much noise since it is not designed for precise

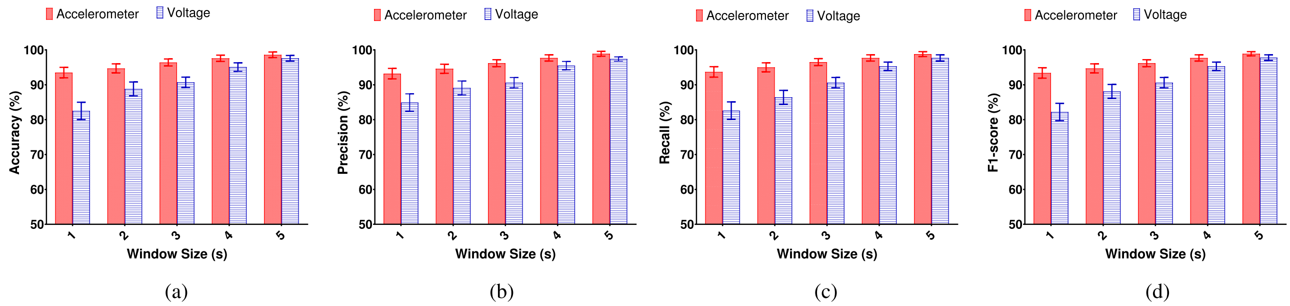

FIGURE 8. Comparison with accelerometer. (a) Accuracy. (b) Precision. (c) Recall. (d) F1-score.

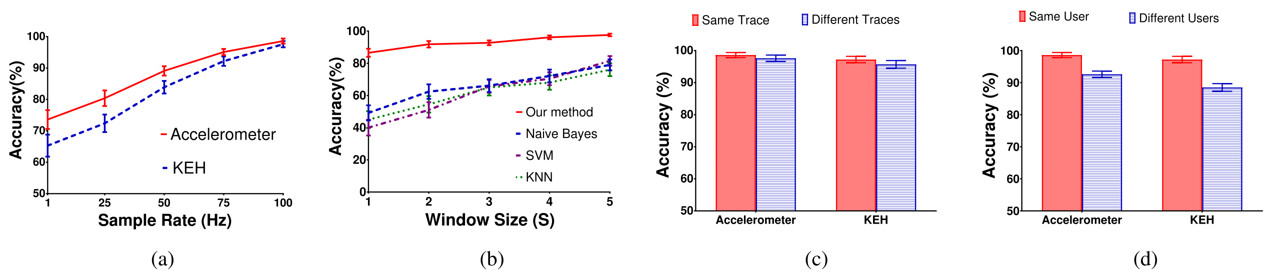

FIGURE 9. Evaluation results. (a) Impact of sample rate. (b) Comparison with other classifiers. (c) Robustness to trace variance. (d) Robustness to user variance.

vibration detection. Nevertheless, we can see that the gap between accelerometer-based method and KEH-based method diminishes as T increases. When $T = 5$, the difference of accuracy, precision, recall and F1-score are only 1.2%, 1.7%, 1.1%, and 0.9% respectively. The results suggest that the KEH-based approach can achieve comparable accuracy compared to accelerometer-based system when we collect more data. It is worth mentioning that piezoelectric-based accelerometer has been developed in the past few years. Our future research will focus on studying the accuracy and energy consumption of this new type of accelerometer.

2) RECOGNITION ACCURACY V.S. SAMPLING RATE

In this subsection, we examine the impact of sampling rate on the recognition accuracy for both accelerometer-based and KEH-based system. We down-sample both the KEH and acceleration data from 100Hz to 1Hz, and then apply the same feature extraction and classification algorithms on the down-sampled data. Figure 9(a) exhibits the system accuracy with different sampling rates. We can see that the accuracy increases with the sampling rate for both KEH and accelerometer-based systems. The gap between these two systems also reduces with the increment of sample rate.

3) COMPARISON WITH OTHER CLASSIFICATION METHODS

Next, we compare the accuracy of the proposed deep learning classification framework to traditional classification algorithms. Again, we use the same features and vary T from $1s$ to $5s$. From the results in Figure 9(b), we can see that our approach is up to 16% more accurate than the second best method. There are two reasons for the improvement.

TABLE 4. Confusion matrix.

	Bus	Car	Ferry	Light rail	Train	Walk	Run
Bus	96.5%	1.2%	0.8%	0.5%	0.5%	0.2%	0.3%
Car	0.9%	95.5%	0.85%	1%	1.05%	0.41%	0.29%
Ferry	0.25%	0.14%	98.5%	0.5%	0.26%	0.15%	0.2%
Light rail	1%	0.23%	0.21%	97.8%	0.46%	0.18%	0.12%
Train	0.25%	0.5%	0.2%	0.15%	98.5%	0.1%	0.3%
Walk	0.4%	0.6%	1.1%	0.7%	0.2%	95.8%	1.2%
Run	0.5%	0.3%	0.4%	1.1%	0.3%	0.6%	96.8%

First, we conduct a detailed feature selection study and choose a feature subset that can best represent the difference of different transportation modes. Second, the AT-LSTM approach has proven to show better performance than other machine learning methods in time series data classification. As an example, Table 4 shows the confusion matrix of the proposed system with $T = 5s$. We can see that it can reach high recognition accuracy and the average accuracy achieved is 97.05%.

B. SYSTEM ROBUSTNESS

In this subsection, we evaluate the robustness of the proposed system against two major variations: the variance resulting from different traveling traces and the variance due to user difference.

1) ROBUSTNESS TO TRACE VARIANCE

To demonstrate the capability of our approach to classify transportation mode on new traces, we carry out leave-one-trace-out cross validation. The results of this evaluation are shown in Figure 9(c). As expected, the recognition accuracy decreases when we use different traces for training and testing. However, the accuracy of the accelerometer-based system and KEH-based system only drop by 0.9% and 1.5%, respectively. The results demonstrate the robustness of our system to new traces.

2) ROBUSTNESS TO USER VARIANCE

To evaluate the robustness of our approach against different users, we carry out leave-one-user-out cross validation. From the results in Figure 9(d), we notice that the user variance has noticeable impact on the recognition accuracy. The accuracy of the accelerometer-based system and KEH-based system drops by 6.4% and 8.7%, respectively. This is because different users tend to carry the device in different ways during the data collection. For example, some users hold the prototype in the hand while others may put it in the backpack. As a result, variations in user characteristics have a more significant influence on the results than variations in traces.

VII. ENERGY CONSUMPTION PROFILE

We first investigate how much energy can be harvested from different transportation modes. Table 5 shows the average amount of energy that can be harvested from each transportation mode. We can see that it can hardly meet the energy consumption requirement of common sensors like accelerometer whose energy consumption is in the order of mW [14]. The results are intuitive as the harvested energy is directly related to the motion vibrations of different activities. Running ranks first because it produces the largest movement. The harvested energy of vehicles is similar because they produce similar vibrations.

TABLE 5. Harvested power.

	Bus	Car	Ferry	Light rail	Train	Walking	Running
Power(μW)	9.6	8.4	6.3	5.5	3.4	16	50

The energy consumption of our system consists of three parts: sensor sampling, memory reading/writing, and data transmission. According to previous study [14], [41], memory reading/writing consumes significant less energy compared to the other two parts. Therefore, we only consider the energy consumption of sensor sampling and data transmission in our evaluation.

In order to capture both the average current and the time, the Agilent DSO3202A oscilloscope is used in the experiment. We connect the prototype with a 10Ω resistor in series and power it using a 9V battery. The oscilloscope probe is then connected across the resistor to measure the current going through. Figure 10 shows the details of KEH voltage sampling. We can see that at the beginning of each sampling event, the MCU is waked up by the software interrupt from the power-saving deep-sleep mode, and it boots ADC to sample before going back to sleep. The details of power consumption and time duration for voltage sampling event are shown in Table 6. We find that sampling the voltage takes only 0.6ms and consumes 480μW. This is significantly lower

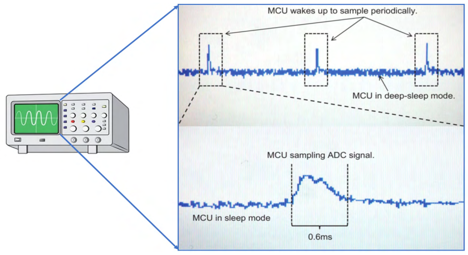

FIGURE 10. Profiling of voltage sampling.

TABLE 6. States of voltage sampling.

State	Time (ms)	Power (μW)
S1	0.6	480
S_sleep	null	6

than that reported in previous transportation mode detection systems such as [4], [6], [24].

For the duty-cycled transportation detection system, the average power consumption in data sampling can be obtained by the equation in [14], [42]. Based on the analysis in Section VI, a sampling rate of 100Hz and a window size of 5s is needed for the KEH-based system to achieve high recognition accuracy. With 100Hz sampling rate and 5s data collection, in case of data sampling, the proposed system consumes 135μJ.

Next, we evaluate the energy consumption of transmitting KEH voltage data via Bluetooth. We conduct power measurement of the Bluetooth Low Energy (BLE) beacon using the CC2650 wireless MCU. With the 100Hz sampling rate and 5s data sampling, the KEH-based system generates 500 samples. This results in 750 bytes data to be transmitted in total (in BLE packet). According to our measurement, the average transmission power of Bluetooth is 2.72mW. As a result, the energy consumption of data transmission for KEH-based system is 265.2μJ.

Based on the measurements, the energy consumption of KEH-based system to complete one classification is approximately 400.2μJ (note that the classification is executed in the cloud server).

VIII. CONCLUSION

In this paper, we propose an energy harvesting-based smart transportation mode detection system via AT-LSTM model. Extensive evaluation results show that the proposed system can achieve over 97% accuracy. Finally, we perform a detailed energy consumption profile to demonstrate that the proposed system significantly outperforms existing transportation mode detection system in terms of energy consumption. One limitation of our work is that the size of the designed prototype is relatively larger than common mobile devices. This problem can be addressed by using small size PEH. Moreover, as mentioned in the introduction, we have observed an increasing number of commercial products equipped with piezoelectric energy harvesters.

Therefore, the proposed system can be applied in any energy harvesting-based wearable devices such as smart shoes. We believe that with the development of technology, the size of energy harvester will be further reduced and embedded in more mobile devices in the near future.

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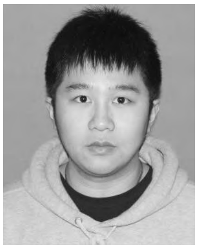

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