Human Context Detection from Kinetic Energy Harvesting Wearables

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ABSTRACT

Advances in energy harvesting hardware have created an opportunity for realizing self-powered wearables for continuous and pervasive Human Context Detection (HCD). Unfortunately, the power consumption of the continuous context sensing using accelerometer is relatively high compared to the amount of power that can be harvested practically, which limits the usefulness of energy harvesting. This chapter employs and infers HCD directly from the Kinetic Energy Harvesting (KEH) patterns generated from a wearable device that harvests kinetic energy to power itself. This proposal eliminates the need for accelerometer, making HCD practical for self-powered devices. The authors discuss in more details the use of KEH patterns as an energy efficient source of information for five main applications, human activity recognition, step detection, calorie expenditure estimation, hotword detection, and transport mode detection. This confirms the potential sensing capabilities of KEH for a wide range of wearable applications, moving us closer towards self-powered autonomous wearables.

Keywords: Self-powered Wearables, Kinetic Energy Harvesting, Piezoelectric Harvesters, Accelerometer, Activity Recognition, Step Counting, Calorie Expenditure Estimation, Hotword Detection, Transportation Mode Detection

INTRODUCTION

Recent advancements in wearable devices enable a wide era of human context-aware services in various domains, including healthcare (Osmani et al., 2008; Chipara et al.,2010), indoor positioning (Altun & Barshan, 2012; Khalifa et al., 2013), and fitness management (Albinali et al., 2010). Particularly, wearable sensors-based Human Context Detection (HCD) has recently become the focus of intense research and development, thus producing a wealth of tools and algorithms to accurately detect human context from data collected by the wearables (He et al., 2012). For example, a wearable sensor attached to the patient body can enable health care authorities to continuously monitor the current status of a patient from a remote centre. HCD then is expected to play a key role in reducing hospital costs by reducing the need for hospital admissions. Similarly, HCD can help individuals in monitoring their fitness level and having a better well-being by recognising various ambulation activities, such as walking, running, sitting, jogging, and so on. It has been confirmed that wearable technology coupled with HCD algorithms have the potential to improve the user's experience and quality of life.

The market of wearable devices is large, it has been found to be $20 billion in 2015 and expected to grow and reach $70 billion by 2025 (Harrop et al., 2015). Healthcare is considered the dominant sector of the wearable market, which combines medical, fitness, and wellness. It has big names such as apple, Fitbit, Google, Samsung, Nike, and Adidas. According to the International Data Corporation (IDC) Worldwide Quarterly Wearable Device Tracker report in 2016 the top leaders of the wearable market are Fitbit, Apple, Xiaomi, Samsung, and Garmin. A total of 78.1 million wearable units have been shipped in 2015, with 171.6% increase over 2014.

Almost all existing wearable products are powered by batteries. While battery technology has improved over the years, battery-powered devices cannot provide sustained operation without frequent charging. To achieve sustained operation, we either need to instrument the wearables with large batteries or be prepared to manually replenish the batteries when they die. Neither of these options is desirable because large batteries make the wearables heavy and less convenient to wear, while manual replacement is inconvenient and not a practical option for many elderly users, who may have to critically depend on such systems.

Over the past few years, a research trend in Energy Harvesting (EH) has emerged and gained the attention of the research community (Hamilton, 2012; Elvin & Erturk 2013). EH is commonly defined as the conversion of ambient energy such as vibrations, heat, wind, light, etc into electrical energy. EH devices can eliminate the need for battery replacement and significantly enhance the versatility of consumer electronics. In fact, significant advancements have been recently made in the EH hardware technology leading to many off-the-shelf products available at low cost. These developments point to future mobile devices that will be equipped with EH hardware to ease the dependence on batteries (Lee et al., 2013).

This means that it is conceptually possible to replace the battery of a wearable sensor with an EH unit to achieve perpetual sensing in many applications including HCD. Of all the ambient energy options, kinetic energy harvesting (KEH) is the most relevant option used for HCD because it can generate power directly from human motion and context. Advances in KEH hardware have motivated us to consider the concept of self-powered wearables for continuous and pervasive HCD, where numerous wearable tiny devices continue to sense and monitor the human on a permanent basis.

However, there is a caveat. KEH generally suffers from low power output (Bickerstaffe, 2015), which may challenge the power requirement of the wearable sensor's components, such as the accelerometer used for sampling human motion. Given that the sensor will also have to turn on its radio for occasional communications with a nearby sink, the power generated from energy harvesting is clearly too small to simply port the existing battery-powered wearables into energy-harvesting wearables. In fact, using energy harvesting to provide self-powered wearables is a very challenging problem that requires innovative sensing and communication solutions.

This chapter discusses a novel paradigm that may potentially overcome the power limitation of KEH, towards self-powered autonomous wearables. Although the primary purpose of KEH is to convert ambient vibrations into electric power, in principle, it could also be used as a potential sensor to detect or identify the source of the vibration. The ability to detect the vibration source can lead to many potential applications for the KEH hardware beyond its primary use of energy harvesting. More specifically, this novel approach employs KEH and infers information directly from the KEH patterns without using any other sensors such as accelerometers which need continuous power to operate. The underlying idea lies in the fact that different ambient vibrations generate energy in a different way producing different energy generation patterns in the KEH circuit. Because no actual sensor such as accelerometer is needed, a significant percentage of the limited harvested energy can be saved.

In this chapter, we discuss in more details the use of KEH patterns as a source of information for five main applications, human activity recognition, step detection, calorie expenditure estimation, hotword detection, and transport mode detection. This confirms KEH as a novel energy efficient source of information for a wide range of wearable applications, moving us closer towards self-powered autonomous wearables.

BACKGROUND

Human Context Detection

Human context has been initially perceived by the computer science community as a matter of the user location. However, in the last few years this notion has been generalised to all related aspects of the user (Orsi & Tanca, 2010). For example, a context-aware system may know the current physical activity of the user (walking, running, sitting, …etc), each step the user has taken, the daily calorie expenditure, and even what kind of transportation mode the user is using. In fact, Human Context Detection (HCD) is increasingly being used for a wide range of applications including healthcare (Osmani et al., 2008; Chipara et al.,2010) and fitness monitoring (Albinali et al., 2010), smart living, and localization (Altun & Barshan, 2012; Khalifa et al., 2013). Context-aware systems involves two basic processes: the acquisition of user's context using sensors and understanding of user's context by context modeling

There are two fundamentally different approaches to acquire the user's context, using infrastructure sensors (Wongpatikaseree et al., 2012; Singla et al., 2010) and wearable sensors (He et al., 2012). In the former, the sensors are installed at fixed locations to detect human context (e.g. physical activities) when a user visits these locations and interacts with the sensors. For example, cameras installed at fixed locations can be used to detect user activity whenever the user comes within their vicinity (Bodor et al., 2003; Poppe et al., 2010). However, deployment and maintenance of infrastructure sensors are costly. On the other hand, wearable sensors provide an alternative option by placing various types of sensors on the human body. For example, a wearable device in a wristband can help identify user's context by simply collecting and analysing data from the wearable. In existing wearable devices, accelerometer is the dominantly used sensor to acquire the user's context. Typically a triaxial accelerometer is used to measure the acceleration of the user in three dimensions. Machine learning techniques can be used then to model the context of the user from the acquired accelerometer data; this is called accelerometer-based human context detection. Consequently, wearable device can help achieving pervasive HCD without the need to deploy infrastructure sensors.

However, the major challenge of wearable devices is the battery lifetime. A typical wearable device will need power for sensing, processing and communication which can quickly drain the battery life of the wearable. Accelerometer is widely used for sensing human motion and context. There are several types of accelerometers; however, the type that is used most in wearable and mobile devices is the capacitive accelerometer. In a capacitive accelerometer, a capacitor is formed by a "stationary" plate (the housing which moves with the base acceleration) and a "moving" plate attached to the seismic mass. The distance between these plates determines the capacitance which can be monitored to infer acceleration (change in capacitance related to acceleration). Bsching et al., (2012) tested the power consumption of six commonly used capacitive accelerometers when a 3.3v power supply and a 50 HZ sampling rate were used. Their results showed that accelerometers consume hundreds of microwatts at only 50 Hz sampling rate.

Moreover, the datasheets of the three widely used capacitive accelerometers ADXL150 (used in wearable sensors), SMB380 (used in Samsung Galaxy smartphones), LIS302DL (used in IPhone smartphones) showed that the average power consumption of the accelerometer is a linear function of the sampling rate (Yan et al., 2012). For example, Weinberg (2002) showed that the ADXL150 accelerometer consumes about 5 μW on average per Hz, which means that it would require 250 μW if a sampling rate of 50 Hz were required for a given activity set. The required sampling rate depends on the set of activities monitored and typically ranges from 1-50Hz (Ravi et al., 2005; Wang et al., 2005; Kwapisz et al., 2011; Khan et al., 2008). This means the battery must supply 5-250 μW to the accelerometer. This is simple for battery-powered wearable devices. However, it is an issue for energy harvesting wearable devices.

While it is possible to extend the battery lifetime by providing more energy-efficient solutions (Yan et al, 2012; Qi et al, 2013; Khalifa et al., 2013; Zappi et al., 2008), battery-powered sensors cannot provide sustained HAR without the need for frequent charging or battery replacement. This motivates us to explore Energy Harvesting (EH) solutions. EH is commonly referred to the conversion of ambient energy such as solar, kinetic, vibration, etc, into electrical energy. EH eliminates the need for battery replacement and significantly enhances the versatility of consumer electronics.

Kinetic Energy Harvesting Overview

In theory, electrical energy can be obtained from many types of energy, including kinetic (vibration) (Vocca & Cottone, 2014; Mitcheson et al., 2008), thermal (Xu et al., 2013) and radio frequency (Zungeru et al., 2012; Nintanavongsa et al., 2012). *Table 1* shows the power density estimates of typical ambient energy sources from Texas Instruments (Raju, 2008). Of all ambient energy options, kinetic energy harvesting (KEH) is the most relevant for wearables because it can power the wearable directly from human motion. Kinetic energy also produces 4 times as much energy as RF (as shown in Table 1) and is more abundant. A brief review of KEH is presented in this chapter.

Table 1. Power Density Estimates of typical ambient energy sources

Energy Source	Characteristics	Harvested Power Density
Vibration	Human Machine	4 $\mu W/cm^2$ 100 $\mu W/cm^2$
Light	Indoor (illuminated office) Outdoor (direct sun)	10 $\mu W/cm^2$ 10 mW/cm^2
Thermal (Heat)	Human Industrial	25 $\mu W/cm^2$ 1-10 mW/cm^2
Radio Frequency	GSN WIFI	0.1 $\mu W/cm^2$ 1 $\mu W/cm^2$
Source: Texas Instruments, Energy Harvesting White Paper 2008 (Raju, 2008).		

Kinetic energy harvesting (KEH) is a process of converting environmental vibrations into electrical energy. Kinetic EH and vibration EH are synonyms, environment around us is full of sources of kinetic or vibration energy such as natural seismic vibration (e.g. earthquakes), wind movement, sea waves, vehicular traffic, machinery vibration and human motion. In this chapter, we discuss the system architecture of a KEH -based device, the transduction mechanisms, the commercially available products implementing KEH, and the possible applications of KEH.

System Architecture

Figure 1 shows a block diagram of a KEH-based device. KEH-based Hardware typically comprises three parts: a transducer to convert vibration into electrical energy, an AC/DC converter to convert the AC generated from the transducer into regulated DC, and a battery or capacitor to store the harvested energy and provide a constant power flow to the load. The load normally consists of sensors (e.g. accelerometer), microprocessor, and Radio Frequency Transceiver.

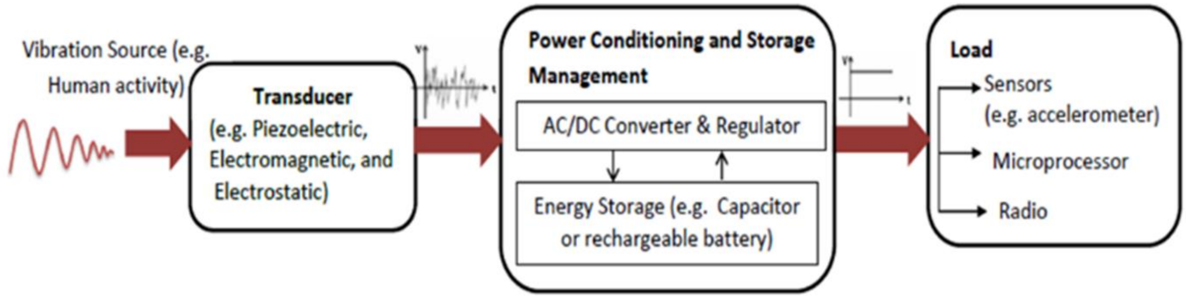


Figure 1. A block diagram of a KEH-based sensor

Transduction Mechanisms

From a hardware point of view, there are three main transduction mechanisms for converting vibration energy to electric power (Rao et al., 2013): piezoelectric, electromagnetic (capacitive), and electrostatic (inductive). Depending on the mechanism used, the operating principle differs.

- Piezoelectric harvesters make use of certain piezoelectric materials such as PZT and MFC, which have the ability to generate an electrical potential when subjected to a mechanical strain (Sodano et al., 2005; Kim et al., 2011). The resulting strain on the material will result in an output of alternating current which is converted into power.

- Electromagnetic harvesters make use of an oscillating mass (magnet) which traverses across a fixed coil, creating a varying amount of magnetic flux, inducing an alternating current that is converted to power (Chae et al., 2013).

- Electrostatic (capacitive) harvesters are based on separating the plates of an initially charged variable capacitor (varactor) using vibrations and converting mechanical energy into electrical energy (Boisseau et al., 2012). Electrostatic harvesters are widely used though they are not as popular as piezoelectric or electromagnetic transducers since Electrostatic harvesters need a polarization source to work and to convert mechanical energy from vibrations into electricity.

Table 2 summarises the advantages and disadvantages of the three transduction mechanisms. Generally speaking, piezoelectric and electrostatic systems are well suited to micro-scale (small scale) applications, while electromagnetic systems are preferable for macro-scale (medium scale) devices. Piezoelectric transducers are the most favorable due to their simplicity and compatibility with MEMS (Lefeuvre et al., 2006). Electromagnetic-based energy harvesters are usually bulky in size and difficult to integrate with MEMS. Moreover, electrostatic transducers need external voltage to operate. Many kinetic or vibration EH models have been recently developed (Gorlatova et al., 2014; Biswas & Quwaider, 2013; Yun et al., 2008). The main focus of these models is to optimise the parameters of the harvester to maximise the output harvested power. To maximise the output power, the harvester is mechanically tuned to an optimized resonant frequency present in the application environment.

Table 2. Transduction mechanisms of VEH

Type	**Advantage**	**Disadvantage**
Piezoelectric	No need for smart material Compatible with MEMS Compact configuration	Depolarization brittleness in PZT charge leakage
Electromagnetic	No need for smart material No need for external voltage source	Bulky size Difficult to integrate with MEMS
Electrostatic	No need for smart material Compatible with MEMS	External voltage source (or charger) is needed Mechanical constraints are needed

Commercially Available KEH/VEH Devices

Several kinetic or vibration energy harvesters are commercially available. The prevalent commercial VEH devices are based on the piezoelectric and electromagnetic transduction mechanisms. *Table 3* provides a list of the commercially available VEH devices. Perpetuum and Ferro Solutions produce electromagnetic-based VEHs, however, MID'E, MicroGen, PI Ceramic GmbH, and Smart Material produce piezoelectric-based VEHs. MicroStrain produces both electrodynamic generators (MVEH™ Harvester) and piezoelectric materials (PVEH™ Harvester). Recently, OMRON and Holst Centre/imec unveiled a prototype of an extremely compact electrostatic-based VEH. *Figure 2* shows some of the commercially available VEHs. Piezoelectric transducers are simple and compatible with MEMS. The characteristic of the products show that electromagnetic-based energy harvesters are usually bulky and not compatible with MEMS as mentioned previously. Moreover, the only electrostatic transducer is still under testing and not commercially available.

Table 3. Commercially available KEH/VEH devices

Manufacturer (Country)	Product	Material&	Dimensions (in) L × W × H	Weight (grams)	Output (in voltage)
Perpetuum (UK)	PMG FSH	Electromagnetic	3.4 × 2.6	1075	DC (5 V and 8 V)
Ferro Solutions (USA)	VEH 460	Electromagnetic	-	430	DC (3.3V)
LORD MicroStrain (USA)	PVEH&	Piezoelectric	1.87 × 1.75	185	DC (3.2 V)
	&MVEH&	Electromagnetic	2.25 × 2.56	216	DC (3.2 V)
MicroGen (USA)	BoLT PZEH	Piezoelectric	1.18 × 1.04 × 0.69	10	DC (3.3 V)
MID'E(USA)	Volture V25W	Piezoelectric	2.00 × 1.50 × 0.03	8	AC
PI Ceramic GmbH (Germany)	P-876.A11 DuraAct	Piezoelectric&	2.4 × 1.38 × 0.02	-	AC
Smart Material (USA	MFC M2503-P1	Piezoelectric	1.81 × 0.93 × 0.01	-	AC
OMRON and Holst Centre/imec	Still under testing	Electrostatic	1.96 × 2.36	15.4	DC

(a) Perpetuum *(b) Ferro Solution* *(c) MVEH MicroStrain* *(d) PVEH MicroStrain*

(e) MIDE Volture *(f) MicroGen* *(g) PI Ceramic* *(h) Smart Material (MFC* *(i) OMRON and Holst Centre/imec (under testing)*

Figure 2. Commercial kinetic or vibration energy harvesters (a) Perpetuum, (b) Ferro Solution (VED 460), (c) MicroStrain MVEH, (d) MicroStrain PVEH, (e) Mide Volture, (f) MicroGen, (g) PI Ceramic, (h) Smart Material (MFC), and (i) OMRON and Holst Centr

Most VEH devices are available as packaged systems, including the transducer, power conditioning circuit, and local storage. They provide a constant (regulated) DC voltage which is suitable to power multi-sensor nodes, controllers, peripherals, memory, etc; however, the intermediate outputs such as the AC voltage, or the unregulated DC, cannot be accessed. Some companies (such as MID\'E) make these intermediate outputs accessible by offering customizable energy harvesting evaluation kits, which provide modular components for power conversion and storage that afford plug-and-play compatibility with their transducers.

KEH Applications

KEH has a wide area of applications, such as medical implants, consumer applications, building technologies, vehicles and aerospace. A brief summary of how KEH can be used for each of these applications is presented below.

- Medical Implants: KEH can use a patient's own body movement and heartbeat to provide power for medical devices deployed inside the body, and which are vital to the life and well being of the patient.

- Consumer Electronics: KEH is suitable for many low-power consumer electronics, used as a sole power source or as a means to extend battery life.

- Building Technologies: KEH is suitable for building technology applications such as infrastructure sensing system battery and safety systems for buildings in the event of a power loss.

- Vehicles and Aerospace: KEH provides safe, reliable, cost effective solutions to those applications in which traditional power sources are not reliable or preferred, e.g. supplying power to tyre air pressure sensors (where batteries are difficult to change and hard-wiring is impossible), supplying power to sensors mounted inside an aircraft which monitor in-flight mechanical loads on the airframe.

KEH Limitation

KEH is mostly used for harvesting energy from machine vibrations because machines vibrate at high frequency, hundreds of Hz, which produces a reasonable amount of energy to sense and transmit data. However, KEH performance drops when harvesting energy from human motion because human motion has lower frequency (in the order of tens of Hz). The amount of power that can be practically harvested from human motion is too small to power all necessary functions of a wearable device. KEH from human activities can produce only limited power (measured in μW), which is not sufficient to simultaneously power all components in a wearable device including the accelerometer used to acquire user context.

Table 4 shows the power that could be generated using a commercial kinetic energy harvester for different activities (Olivares et al., 2010). It shows that some activities generate only a few μW which is much lower than what is required to sample the accelerometer at a sufficiently high rate for accurate context detection. Clearly, this will force the device to reduce the power to the accelerometer, i.e., use a lower sampling rate and accept a lower context detection accuracy, each time the user switches to one of the activities that produce small amount of power. Even if the harvested power is enough to operate the accelerometer at the required sampling rate, it reduces the amount that could be accumulated in the capacitor for future radio communications. Insufficient stored energy in the capacitor will force more aggressive duty cycling of the radio or more drastic reduction in the transmission power. In summary, when the power supply is limited by energy harvesting, powering the accelerometer trades off the quality of radio communication. In fact, using KEH to provide a self-powered HAR is a challenging problem that requires innovative sensing and communication solutions.

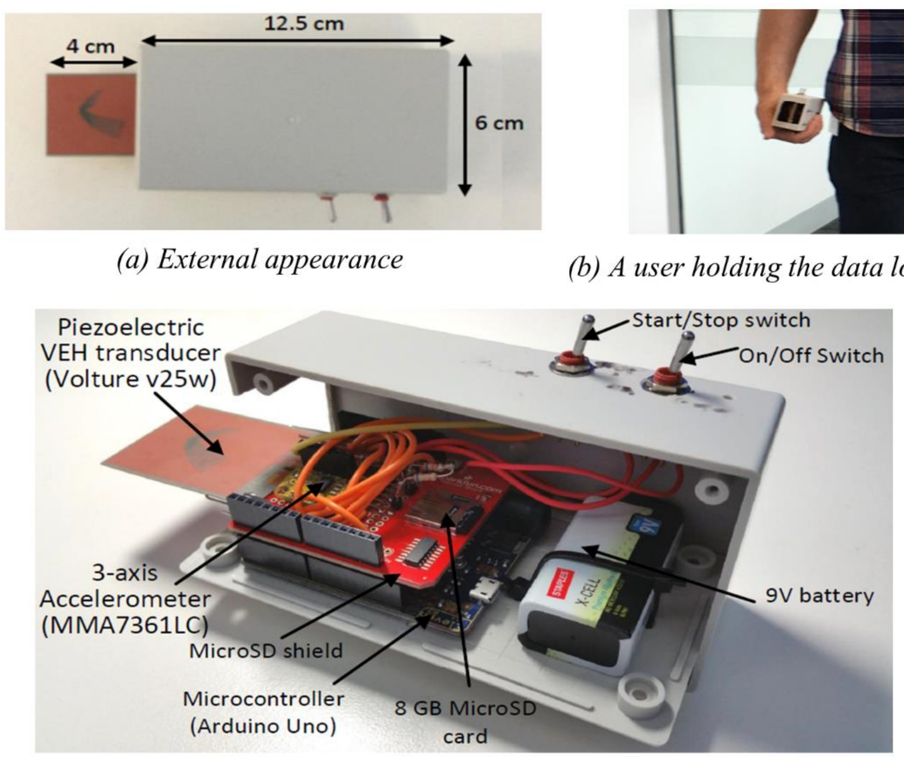
Table 4. Average Harvested Power for different activities when the device is attached to the shank

Activity	Average Harvested Power (μW)
Walking	10.30
Running	28.74
Cycling	0.36
Sitting	0.02
Lying	0.36

KEH-BASED HUMAN CONTEXT DETECTION

KEH-based Human Context Detection (HCD) aims at providing a self-powered HCD which does not need batteries to operate. It allows continuous and permanent monitoring of human activities, which will improve the user's experience and quality of life. KEH -based HCD is an alternative approach to HCD that does not use an accelerometer, which can have relatively high power requirements on relatively low-power energy harvesting wearables, but instead uses the generated KEH signal for HCD.

Since the wearables that rely on KEH to self-power themselves are still in their early stage of development, we built a KEH wearable prototype to evaluate the performance of the proposed KEH-based HCD. It is basically a data logger which records the generated signals of a commercially available piezoelectric KEH transducer, called Volture from MIDE (see www.mide.com). It provides AC voltage as its output. We also added a three-axis accelerometer (MMA7361LC) to the design for comparison purposes. We used an Arduino Uno as a microcontroller device for sampling the data from both the Volture and the accelerometer. We used a sampling rate of 1 kHz for data collection. We saved the sampled data on an 8-Gbyte microSD card, which we equipped to the Arduino using microSD shield. A 9V battery was used to power the Arduino. The data logger also includes two switches, one to switch on/off the device and the other to control the start and stop of data logging. *Figure 3* shows the external appearance of our data logger, a user holding the data logger during the data collection process, and the internal appearance of the data logger including the details of its components.



(a) External appearance

(b) A user holding the data logger

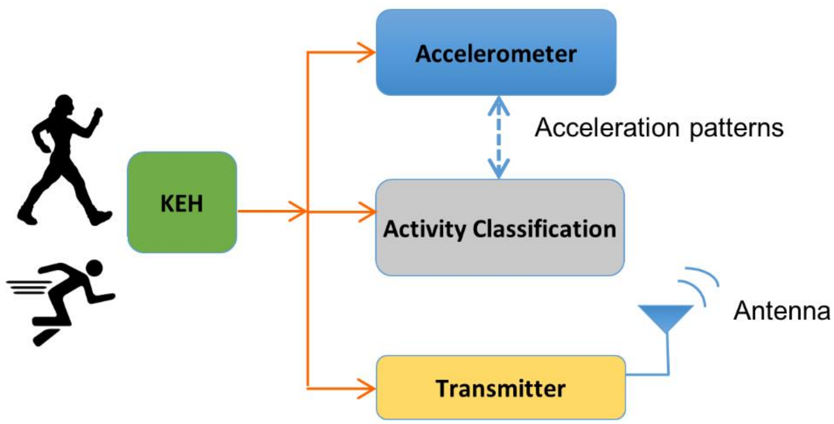
(c) Internal appearance

Figure 3. KEH data logger

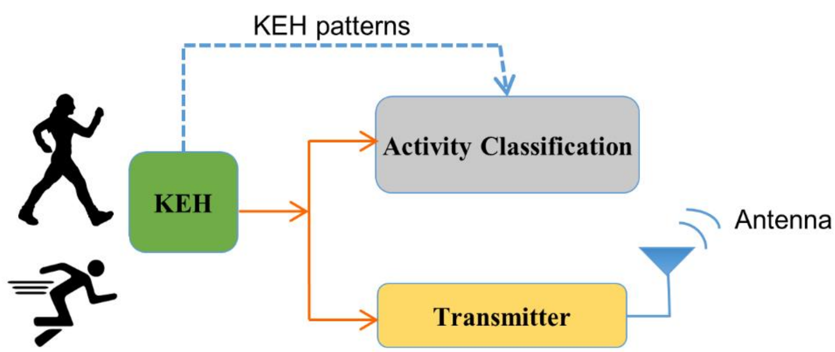
This data logger is used to collect KEH patterns for five main applications, human activity recognition, step detection, calorie expenditure estimation, hotword detection, and transport mode detection. In this chapter, we show the performance of using KEH patterns as a source of information for those five applications including the used algorithms in each application.

Activity Recognition

Human Activity Recognition (HAR) is becoming critical in many applications, including aged health care, fitness monitoring, and indoor positioning. Accelerometer has been widely used for human activity recognition as it is considered low-power electronics drawing only about a few μW per sample per second (Hz). However, we showed that accelerometer power requirements is considered relatively high when used in KEH powered devices (Khalifa et al., 2015a). Using experimental data, we showed that the power requirement of accelerometer for HAR ranges between 35-515% of the harvested kinetic power. We also demonstrated that down scaling power supply to the accelerometer reduces HAR accuracy exponentially. These results indicate that although accelerometers are considered low-power electronics in general, they can be the bottleneck of self-powered pervasive HAR. To address this challenge, we proposed the use of KEH patterns as a new source of realising HAR in a kinetic-powered device. *Figure 4* shows our proposal of using KEH patterns for HAR compared to the conventional use of acceleration patterns in a kinetic-powered device. Our proposal eliminates the need for accelerometer, making HAR practical for self-powered devices.



(a) Conventional accelerometer-based HAR in KEH powered devices



(b) Proposed KEH-based HAR

Figure 4. KEH-based HAR compared to accelerometer-based HAR in a kinetic-powered devices

Initially, We used a well know mass spring damping model to estimate KEH patterns form motion data due to the absence of commercially available kinetic energy harvesting portable devices that could be used to collect energy traces from users. By applying information theoretic measures on the estimated KEH patterns, we confirmed that KEH patterns contain rich information for discriminating typical activities of our daily life. We evaluated our proposal using 14 different sets of common activities each containing between 2-10 different activities to be classified. We showed an average accuracy of 83%, which is within 13% of what could be achieved with an accelerometer without any power constraints. However, the used KEH patterns were an approximation of the real data.

These results motivated us to build a data logger (whose components have been presented previously) to collect real KEH data and investigate whether the generated patterns by a real KEH hardware contain information about human activity as reported in our previous study from estimated KEH power patterns. We collected data for three different activities from ten different subjects holding the datalogger in hand.

Figure 5 shows the KEH patterns for three different activities: standing, walking, and running. This shows that the generated signal of a piezoelectric KEH transducer switches to clearly distinguishable patterns as the user changes her activities. Our experimental analysis showed that KEH-based HAR can achieve 98% accuracy for distinguishing three basic activities: standing, walking, and running, which as accurately as accelerometer-based HAR. We have also done some energy analysis which showed that KEH-based HAR consumes 72 % less energy compared to the conventional accelerometer-based HAR (Khalifa et al., 2015b).

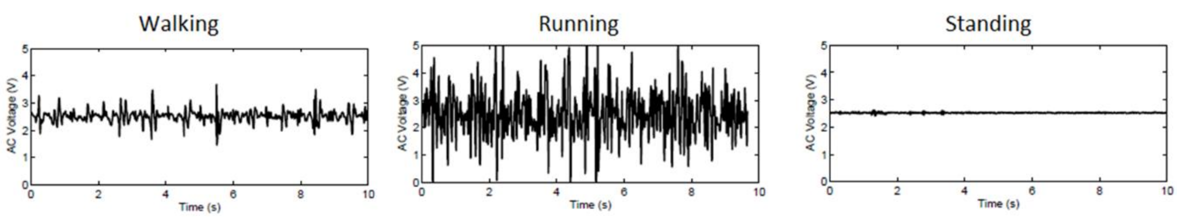


Figure 5. KEH patterns for three basic activities: walking, running, and standing

Following the power savings of not using accelerometer for HAR, we further reduced both on-node classification and communication overhead by proposing a new method that guarantees energy neutrality (Khalifa et al., 2016a). In this study, we used the kinetic energy accumulated in a fixed-length time window to transmit an unmodulated signal, called an "activity pulse". Because different human activities generate power at different rates, the transmission and receiving signal strengths are different among different activities. Thus, those signal strengths can be used to classify the activities. Energy neutrality is guaranteed because the transmission power of the activity pulse only uses the amount of energy harnessed in the last time window, and no additional energy is required to power any sensing or classification components in the wearable device.

Figure 6 shows our proposed architecture for energy neutral KEH-basedHAR. The KEH component in the architecture utilizes a capacitor to store the energy harvested for a given time window; and then uses all the stored energy to transmit an unmodulated signal, called an *activity pulse*. Because different activities generate power at different rates (Gorlatova et al., 2014), the receiving signal strengths are different among different activities. Thus, the signal strengths can be used to classify the activities. Assuming that the distributions of the received signal strengths of the activities are known, the classification can be done at the receiver side using Bayesian decision theory. Our proposed architecture guarantees the energy neutrality because we only use the accumulated energy in the last time window to transmit the activity pulse; no additional energy is required to power any sensing or classification components in the wearable device (Khalifa et al., 2016a).

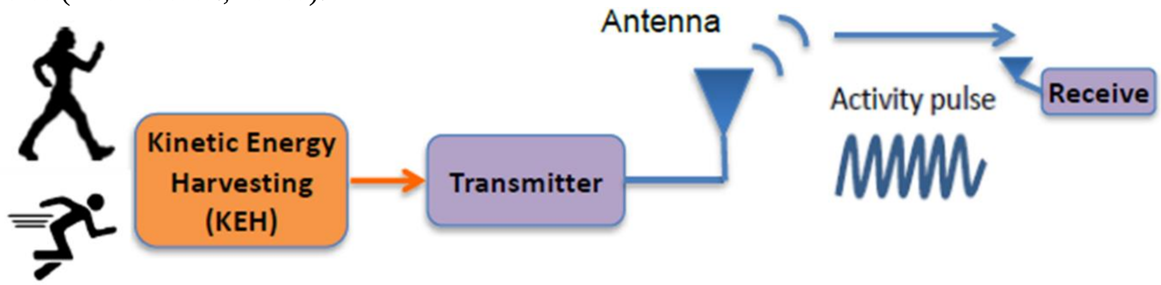


Figure 6. A proposed energy neutral KEH-based HAR

We evaluated the performance of our proposed idea of transmitting an "activity pulse" by collecting a real dataset from piezoelectric KEH prototype coupled with a Bluetooth prototype. We achieved an overall accuracy of 91% when the distance between the transmitter and the receiver is set to 30 cm. We also pointed out that the overall accuracy goes down to 85% and 65% when the distance is increased to 60 cm and 100 cm, respectively (Khalifa et al., 2016a).

Step Counting

Step detecting wearable devices are increasingly being used for health monitoring and indoor positioning applications. In the study shown in (Khalifa et al., 2015c), we conducted the first experimental study to validate the concept of step detection from the generated patterns of KEH wearables. Figure 7 shows the raw output patterns of a piezoelectric KEH from a wearable device attached to the waist of a subject walking along straight walkway for 11 steps.

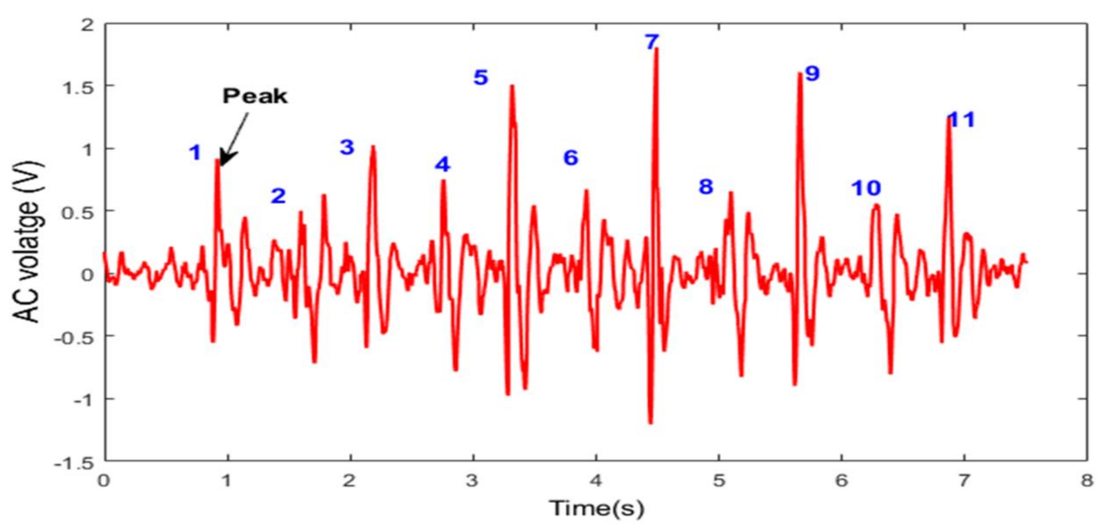


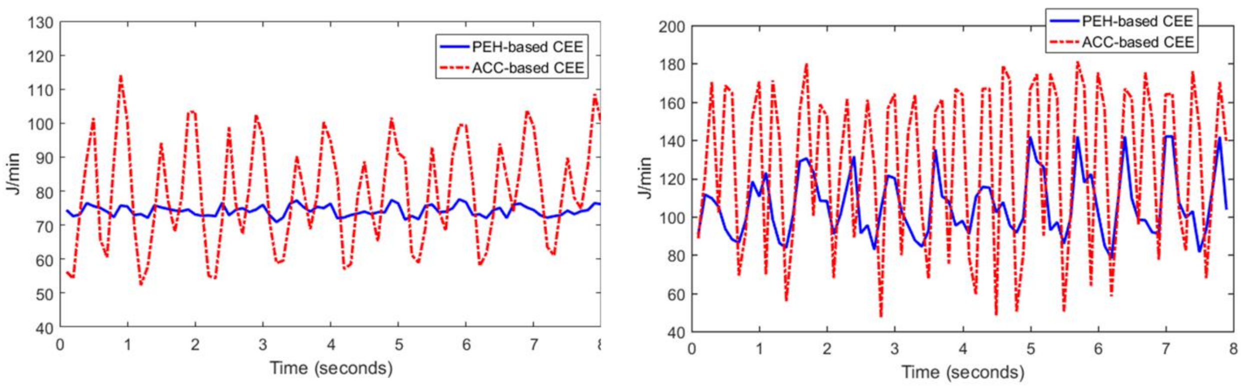
Figure 7. The raw output patterns of a piezoelectric KEH harvester from a wearable device attached to the waist of a subject walking along straight

Figure 7 shows that KEH patterns exhibit distinctive peaks for steps, which can be detected accurately using widely used peak detection algorithms. We collected data from four different subjects under different walking scenarios, including walk along straight and turning paths as well as descending and ascending stairs, covering a total of 570 steps. Our analysis showed that PEH-based step detection can be achieved with 99.08% and 100% accuracy for straight and turning walkways, respectively. However, the accuracies for ascending and descending stairs scenarios are 92.97% and 93.42%, respectively. In total, over all subjects and all walking scenarios, 550 steps out of 570 have been successfully detected achieving 96% step detection accuracy when PEH patterns are used, compared to 100% accuracy when the accelerometer is used. All of our results in this study (Khalifa et al., 2015c) were based on a waist placement of the KEH hardware on the subjects' body. Therefore, more experimentation is still needed to study the effect of different device placements on the results.

Calorie Expenditure Estimation (CEE)

Calorie expenditure estimation (CEE) is valuable in monitoring many health problems, such as obesity, an epidemic which is predicted to be the most preventive health problem in the future.

Unlike the conventional works that highly rely on accelerometers for CEE, we conducted the first experimental study in (Lan et al., 2015) to assess the suitability of using KEH data for accurate CEE. We used KEH prototype to collect real data from ten different subjects for two different activities, walking and running. *Figure 8* shows the instantaneous estimation results of KEH-based and ACC-based CEE for both walking and running activities.



(a) Walking (b) Running

Figure 8. The instantaneous estimation results of KEH-based and ACC-based CEE for both walking and running activities.

Figure 8 shows that although the instantaneous estimations of the proposed KEH-based method are different from that of the accelerometer-based, the averages of the KEH-based CEE over a period of time (one second or longer), are very close to that of the accelerometer-based CEE. The authors used a standard statistical regression model to drive the results. *Figure 9* plots the mean of the estimated calorie expenditure over one second of the KEH-based and accelerometer-based methods for both walking and running activities. The results show that for most subjects, the calorie estimations obtained from KEH patterns are very close to those obtained from a 3-axial accelerometer (Lan et al., 2015).

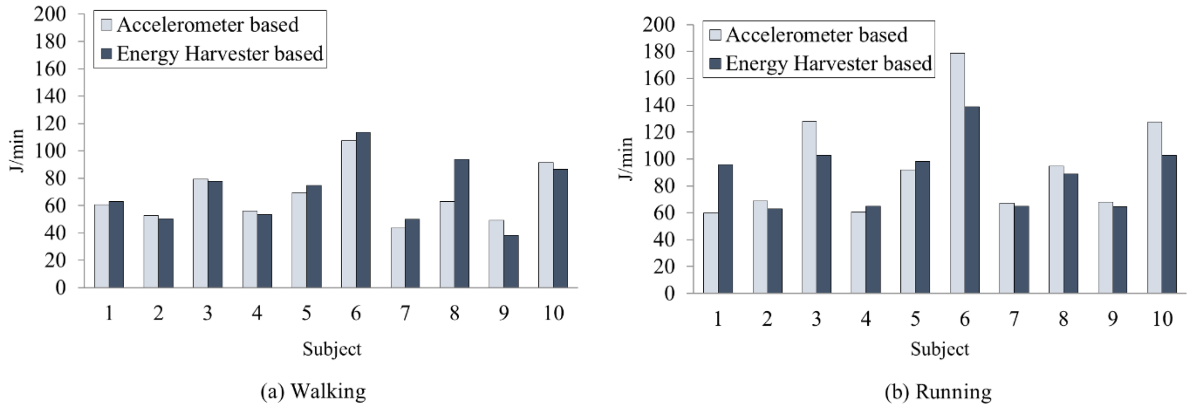


Figure 9. The mean of the estimated calorie expenditure over one second of the KEH-based and accelerometer-based methods for both walking and running activities.

Hotword Detection

Detecting hotwords, such as ``OK Google", is a recent method used by voice control applications to allow verbal interaction with devices by delineating user commands from background conversations. Pervasive hotword detection requires continuous sensing of audio signals, which results in significant energy consumption when a microphone is used as an audio sensor.

We conducted the first experimental study to validate the feasibility of using the vibration energy harvested (VEH) patterns generated from human speech as a potential new source of information for detecting hotwords, such as ``OK Google" (Khalifa et al., 2016b). *Figure 10* shows the architecture used in our study for VEH-based hotword detection. The generated AC voltage data is continuously fed to a trained binary classifier, which classifies the input signal into either hotword or non-hotword. No actions will be taken during the normal conversation (speech contains no hotword), but if hotword is detected, the system will switch to the command mode.

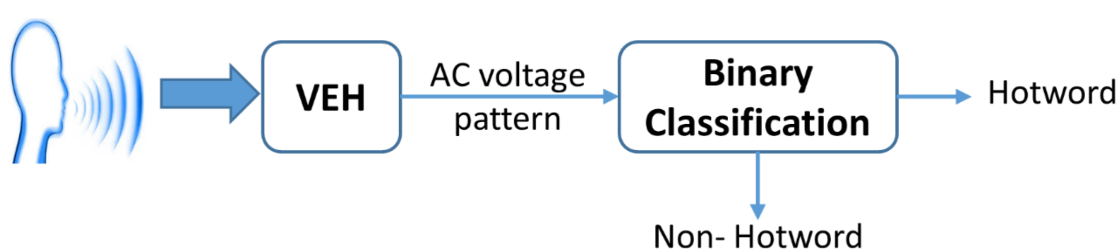


Figure 10. VEH-based hotword detection

We conducted a comprehensive experimental study involving 8 subjects using our KEH datalogeer. We chose the phrase "OK Google" as a repetitive of the hotwork category and three choices of a non-hotword phrases "fine, thank you", "good morning", and "how are you". *Figure 11* shows the VEH patterns for silence and when the four phrases are spoken by one of the subjects involved in the study.

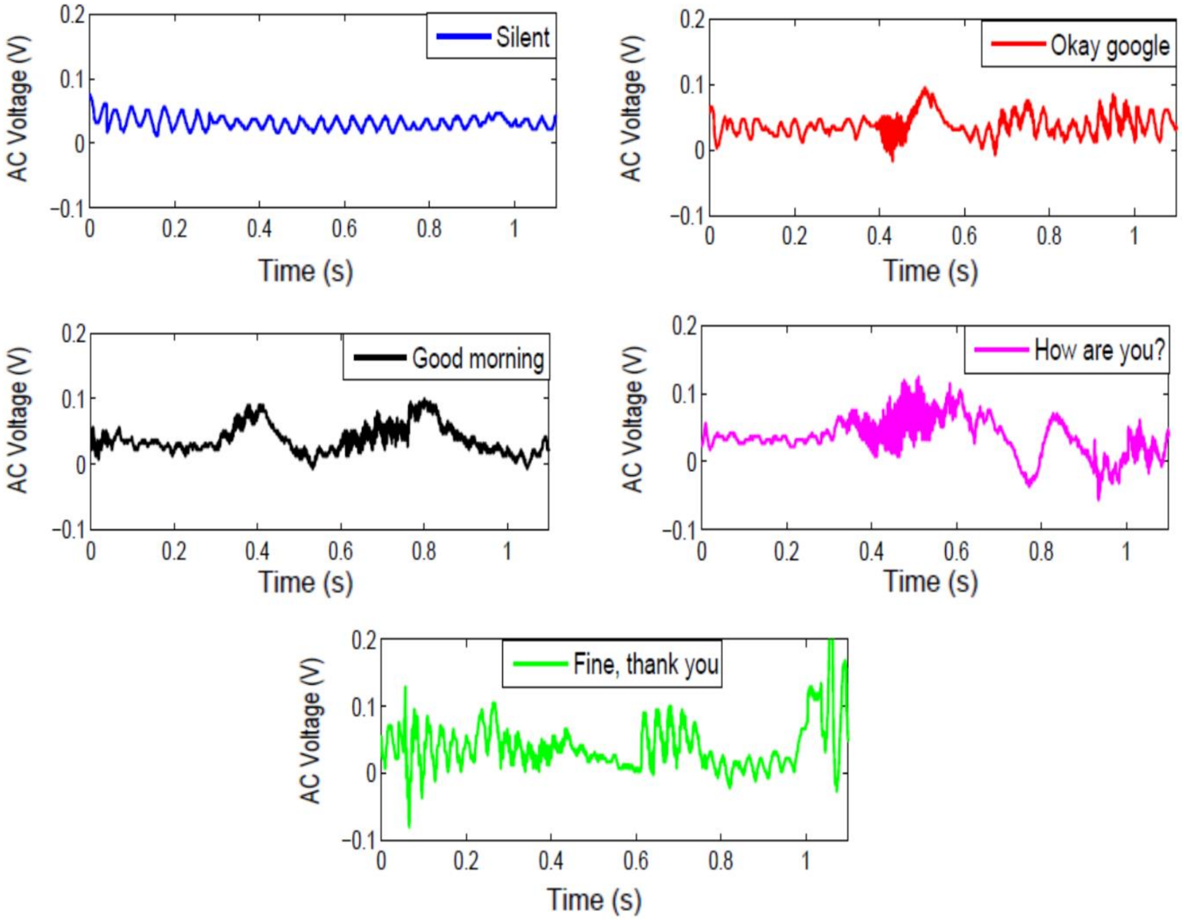


Figure 11. VEH patterns for silence and when the four phrases are spoken

We see that the voltage produced by silence is significantly lower than those produced by voice. We also notice that silence has a more periodic voltage pattern, which captures the background (noise) vibrations, while the voltage is markedly biased in the positive direction when phrases are spoken. This is expected because, in this scenario, sound waves continuously hit directly on one surface of the piezoelectric beam causing it to vibrate asymmetrically around the neutral position. The experiments involved the analysis of two types of hotword detection, speaker-independent, which does not require speaker-specific training, and speaker-dependent, which relies on speaker-specific training.

Our results showed that a simple Decision Tree classifier can detect hotwords from KEH signals with accuracies of 73% and 85%, respectively, for speaker-independent and speaker-dependent detections (Khalifa et al., 2016b). We further demonstrate that these accuracies are comparable to what could be achieved with an accelerometer sampled at 200 Hz.

Transportation Mode Detection

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, accelerometer and GPS are the dominantly used signal sources which quickly drain the limited battery life of the wearable devices.

However, we investigated the feasibility of using the output voltage from the KEH device as the signal source to achieve transportation mode detection (Lan et al., 2016). *Figure 12* gives the high-level overview of the KEH-based transportation mode detection system. Instead of relying on any accelerometer or GPS signal, the proposed system exploits the AC voltage generated from the KEH wearable devices as the signal to achieve transportation mode 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 harvesting devices should contain distinctive features to distinguish different transportation modes.

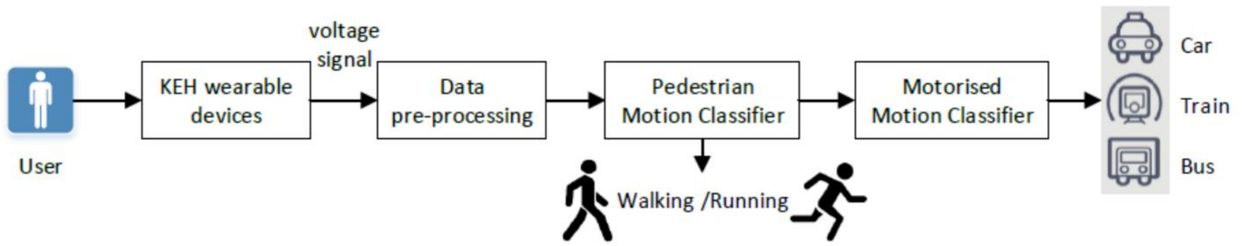


Figure 12. Overview of KEH-based transportation mode detection

The system decomposes the overall detection task into three subtasks. First, the raw voltage signal from the KEH device is going through the data pre-processing which applies a lowpass filter to eliminate possible noise. In addition, we have designed a stop-detection algorithm to classify and filter the stop/pause data out from the voltage signal profile. *Figure 13* shows a trace of the VEH voltage signal recorded during a train trip with an illustration of stop/pause periods of the train. Then, in the second level of classification, a pedestrian motion classifier is applied on the processed voltage signal; the classifier determines whether the person is traveling via walking/running. When the pedestrian motion classifier determines the ongoing traveling as non-pedestrian mode, the process progresses to the motorized motion classifier which determines whether the user is in a motorized transport, and what kind of vehicle is used.

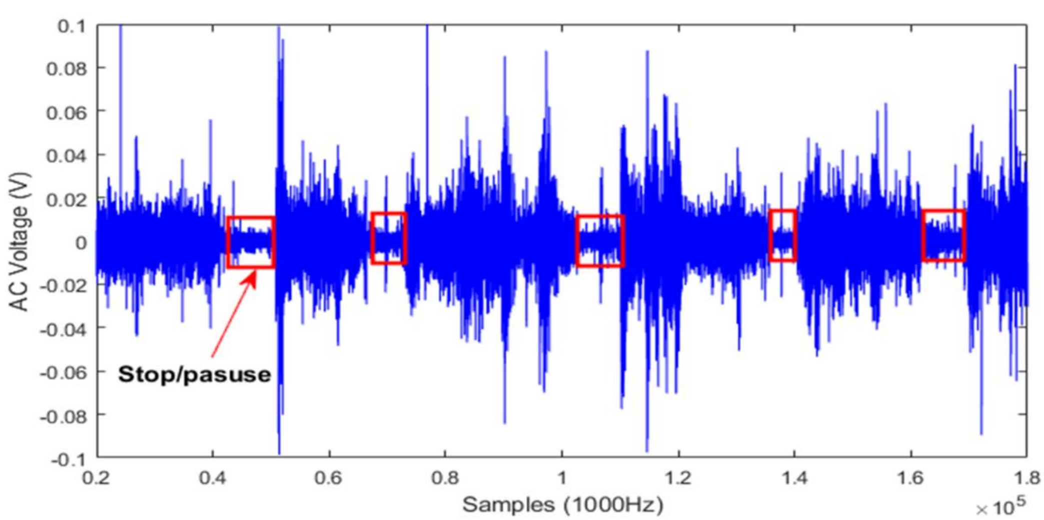


Figure 13. Illustration of stop/pause periods of a vehicle (train)

To develop and evaluate the performance of our approach, we collected over 3 hours of data trace using our KEH data logger. We collected four traces of data by 4 volunteers for pedestrian motions (walking/ running) and three motorized modes (bus, driving, and train) for different traveling routes across Sydney on different days. *Figure 14* compares the voltage generated by pedestrian motions (walking and running) and motorized motions (bus, car, and train). We can observe that the amplitudes of voltage from the pedestrian motions are much higher than that from the motorized motions. Intuitively, this is because when traveling by vehicles, people's motion is relatively stationary (assuming the user is sitting or standing in the vehicles during the trip), thus, the output voltage from the KEH device is quite low. On the contrary, when people are walking/running, the KEH device experiences considerably heavier vibration, and thus, generates higher voltage. Our results show that an accuracy of 98.84% can be achieved in determining whether the user is traveling by pedestrian or motorized modes, using threshold-based classification algorithm. However, in a fine-grained classification of three different motorized modes (car, bus, and train), an overall accuracy of 85% is achieved using voltage peak based learning algorithm (Lan et al., 2016).

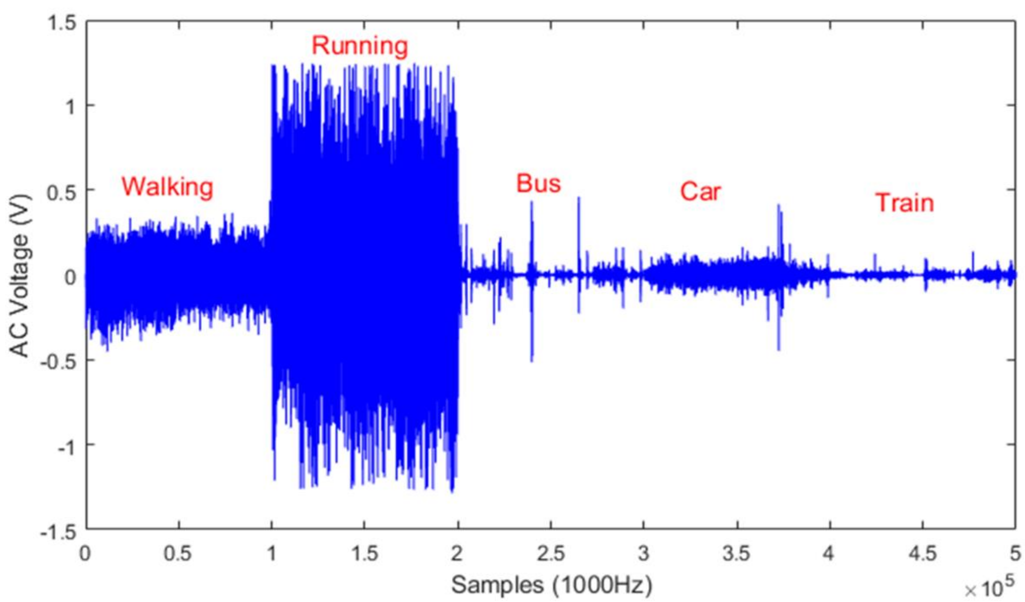


Figure 14. A comparison of KEH voltage signal from different transportation modes

In this chapter, we present our studies of using KEH patterns as a source of information for five main applications, human activity recognition, step detection, calorie expenditure estimation, hotword detection, and transport mode detection. *Table 5* summaries the data collection details, the algorithms used, and the accuracy reported in each study, confirming KEH as an efficient source of information for a wide range of wearable applications.

Table 5: A summary of our studies of using KEH patterns as a source of information for different applications and the corresponding data collection campaign, the algorithms used, and the accuracy reported for each application.

Application	Data Collection	Proposed Algorithm	Accuracy
Human Activity Recognition	10 Subjects (6F, 4 M) 5 different activities 2 holding positions	K-nearest neighbour algorithm	81% for hand 87% for waist
Step Counting	4 subjects Different walking scenarios, including walk along straight and turning paths as well as descending and ascending stairs, covering a total of 570 steps.	Peak detection algorithm	96%
Calorie Expenditure Estimation	10 subjects 2 different activites walking, running	Standard statistical regression	88% for walking and 84% for running
Hotword Detection	8 subjects (4 F, 4 M) 6 instances (30 hotwords, 30 non-hotwords) per subject Hotword: OK Google Non-hotwords Good Morning, How are you? Fine, thank you	Decision tree classifier	73% for speaker-independent 85% speaker-dependent
Transport Mode Detection	3 hours of data trace for three motorized modes (bus, driving, and train) Different traveling routes across Sydney different days.	Voltage peak based learning algorithm	85%

CONCLUSION

This chapter shows the potential use of KEH as a novel source of information for a wide range of wearable applications including, human activity recognition, step detection, calorie expenditure estimation, hotword detection, and transport mode detection. Unlike existing sensors, like microphones, or accelerometers, KEH does not require any power supply to operate, offering a unique power saving opportunity if used as a sensor for these applications.

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