RESEARCH FEATURE

Kinetic-Powered Health Wearables: Challenges and Opportunities

Mahbub Hassan, Wen Hu, Guhao Lan, and Aruna Seneviratne, University of New South Wales, Sydney

Sara Khalifa, Data61—CSIRO

Sajal K. Das, Missouri University of Science and Technology

On-body health monitoring involves continuous sensing and wireless data transmissions, which severely impacts the battery life of wearable devices. However, rapid advances in kinetic energy harvesting (KEH) soon might obviate the need for battery recharging or replacement by harnessing human motion energy. The authors discuss the challenges and opportunities of KEH technology to help realize the ultimate vision of fully autonomous IoT-based healthcare.

A rapidly aging population combined with escalating chronic diseases have created a global crisis in healthcare. Sensor-rich wearable devices capable of collecting round-the-clock personal health and lifestyle data are seen as a significant aid in combating this crisis. Indeed, the wearable industry has seized the opportunity to release a smorgasbord of products for both collecting and analyzing such data. Wrist-worn devices such as Fitbit (https://www.fitbit.com) and Garmin's vívofit (https://explore.garmin.com/en-US/vivo-fitness) that track the number of steps, calories burned, sleep patterns, distance travelled, daily activity level, and many other useful metrics have achieved massive popularity in recent years. This trend is extending into the workforce. Gartner predicts that by 2018, two million employees will be required to wear some type of health-tracking device as part of their employment contract.[1] To help diagnose early signs of disease development, IBM's Watson now offers wearable developers a sophisticated supercomputer and cognitive computational system as a service that efficiently combines wearable data with clients' electronic medical records.[2]

While the healthcare benefits of wearables are beyond doubt, the devices' limited battery life is a serious impediment to their widespread adoption for 24/7 health monitoring, as Figure 1 shows. Health wearables include an array of sensors that monitor vital signs such as pulse rate, galvanic skin response (GSR), and body temperature as well as specialized motion sensors such as accelerometers and gyroscopes that can provide precise per-second

 0018-9162/18/$33.00

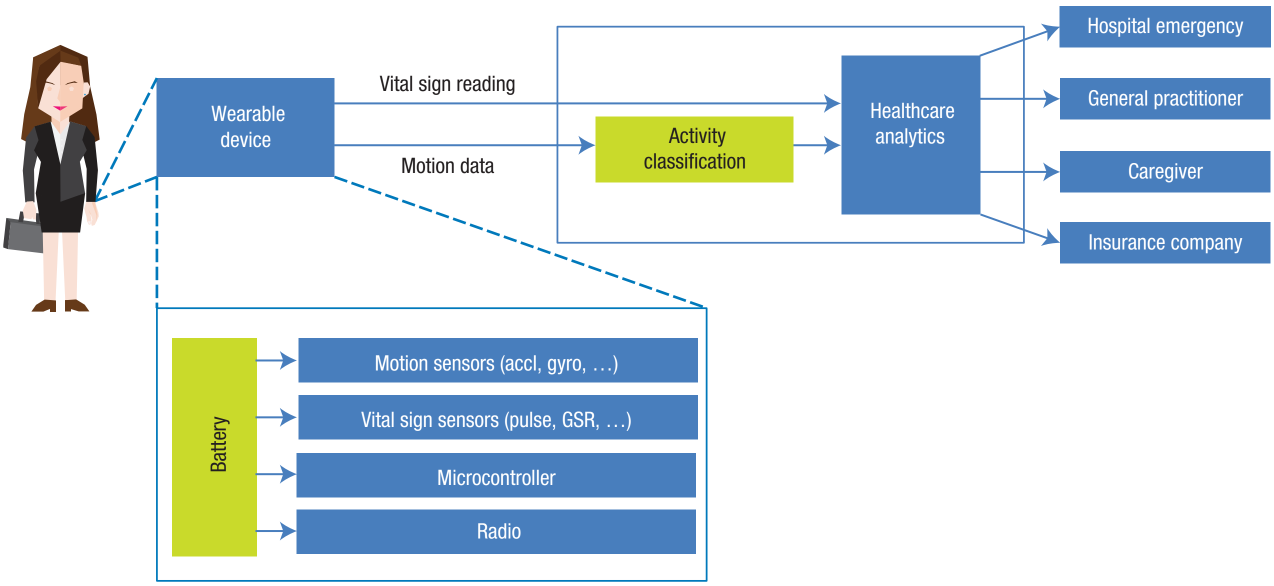

FIGURE 1. Wearable devices' limited battery life is a constraint on 24/7 health monitoring.

measurements of the body's 3D acceleration and angular velocity. The vital sign sensors provide "raw" health data while the motion sensors detect important user contexts such as activity, mobility, and location. Wearables also have a microcontroller unit to read the sensors and in some cases transmit the measurements to a nearby processing unit, such as a powerful smartphone, using an onboard radio. All of these circuits, when activated, consume battery power.

Because vital signs do not change significantly every second, they can be sampled at a low frequency, such as once every hour, to conserve battery power. Thus, the impact of vital sign data collection on battery life is minimal. However, context detection requires continuous high-frequency 3D measurements (for example, 10 to 50 times per second) of the body's movements, and all of this data must be continuously transmitted to another processing device, which can quickly drain the battery power. As wearables' small form factor precludes the use of large and bulky batteries, users must frequently recharge or replace the battery. This constitutes a key obstacle to realizing the vision of fully autonomous IoT-based healthcare.

Health wearables must be able to run on a small battery for several years. Current battery capacity thus must improve dramatically. Historically, however, it has taken about a decade for battery capacity to double. This means we must look for alternate energy sources to power health wearables.

Kinetic energy harvesting (KEH), which uses special materials and processes to convert ambient motion or vibration energy into usable electricity, has made significant advances in recent years. As Table 1 shows, kinetic-powered IoT devices are already a reality in the industrial domains.

Given that any wearable is naturally subjected to human motion, we explored the question of whether KEH could solve the power problem of health wearables. In this article, we first discuss the challenges of and options for generating power from human motion. We observe that the KEH power available from wrist-worn devices is too small to significantly impact battery life. Next, we demonstrate that KEH can be used as a motion sensor for detecting human activities, which helps reduce power consumption and thus extends health wearables' battery life. However, our experiments also indicate that KEH currently is inferior to accelerometers for classifying human activities. Finally, we discuss trends in KEH

TABLE 1. Examples of kinetic-powered industrial IoT devices.

Manufacturer/product(s)	URL	Application domain
ReVibe Energy/modelA and modelD	http://revibeenergy.com	Structural health monitoring and industrial sensor networks
EnOcean/ECO 200	https://www.enocean.com	Self-powered switches and sensors for building automation
microGen Systems/AC and DC Power Cell	https://www.microgensystems.com	Construction, industrial, and automotive
Kinergizer/HiPER-D and HiPER-PM	http://kinergizer.com	Process control and asset monitoring
Midé/Volture	https://www.mide.com	Structural health monitoring
AdaptiveEnergy/Joule-Thief	http://www.adaptivenergy.com	Battery extension for wireless sensors

research and potential new opportunities to increase context detection accuracy for KEH.

CHALLENGES FOR KEH-POWERED HEALTH WEARABLES

Although in theory any wearable device could leverage human motion to power its electronics, successful application of KEH in health wearables faces significant practical challenges. First, 24/7 context detection requires devices to measure and transmit motion sensor values many times per second. The power consumption of health wearables is therefore several orders of magnitude higher than most industrial IoT devices, which are active only once every few hours or so. Second, compared to machine vibrations, human motion vibrations are very low frequency, which severely reduces the total electrical energy that can be harvested.

Existing efforts to increase power generation from human activities require users to wear either a heavy backpack[3,4] or a cumbersome outfit around a limb (see, for example, https://www.bionic-power.com). Although these methods can generate power on the order of watts, they can only be applied in certain niche domains, such as the military, exploration, and disaster relief, where users have to carry a lot of weight anyway. They are not practical for health-monitoring applications that require much simpler and smaller form-factor devices for user acceptance.

It is possible to generate power on the order of milliwatts by placing the energy harvester inside, say, the shoe, which is more practical for health monitoring than a heavy backpack. Indeed, researchers in both academia and industry are exploring shoe-based kinetic-powered health- and fitness-monitoring methods.[4] However, users are unlikely to wear shoes all the time, which makes such devices less practical for 24/7 health monitoring. On the other hand, wrist-worn devices such as Fitbit have proven to be popular for health and fitness monitoring. Unfortunately, only microwatts of power can be harvested from the wrist.[5] How to make the most efficient use of KEH to sufficiently power health wearables remains an open problem.

CONTEXT-SENSING OPPORTUNITIES FOR KEH

In this section, we present a novel approach to using KEH as a sensor for context detection, which extends the value proposition of KEH from strictly power generation to possible power conservation in health wearables. We first illustrate the built-in sensing mechanism available within a popular type of kinetic energy harvester that uses piezoelectric materials to convert motion or vibration into electrical energy, commonly referred to as a piezoelectric energy harvester (PEH). We then explain and provide quantitative analysis of the power-saving opportunities arising from PEH-based context detection. Finally, we share the results of experiments we conducted to benchmark the quality of PEH-based sensing against state-of-the-art techniques, which employ three-axial accelerometers for human activity recognition.

Built-in PEH-based sensing mechanism

Figure 2 illustrates the energy-harvesting process of a PEH, which is designed to charge a rechargeable

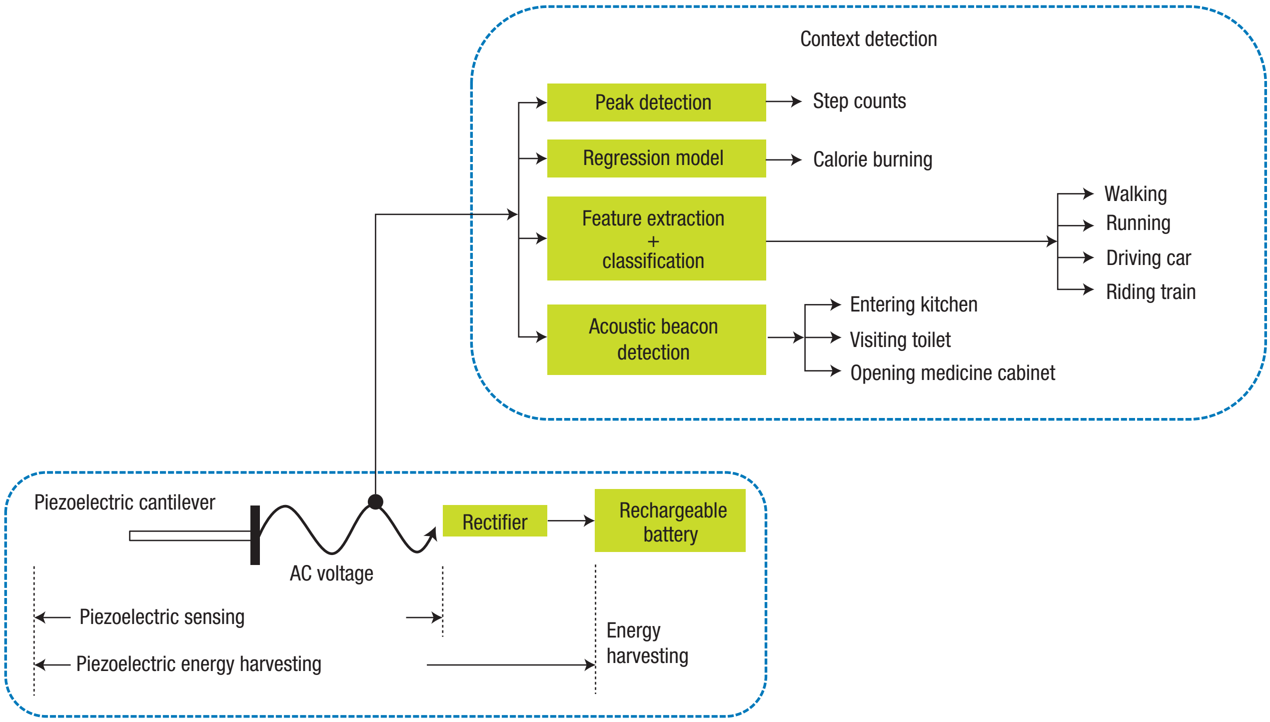

FIGURE 2. Converting energy to context in a piezoelectric energy harvester (PEH). The PEH uses kinetic energy harvesting to extract a range of health and lifestyle data without specialized motion sensors.

battery in a wearable. The PEH harvests energy from the vibrations of the piezoelectric cantilever, which generates continuous alternating current (AC voltage) that is converted to direct current (DC voltage) for eventual charging of the battery. The PEH therefore has a hidden built-in sensor that continuously senses the vibration of the wearable without consuming any battery power. With the device attached to the wrist, the vibrations and the consequent voltage wave are influenced by the actions performed by the user. Consequently, the harvested energy can be potentially converted to useful context data for healthcare monitoring.

Different methods can be applied to the received AC voltage data to detect different types of health and lifestyle information. For example, applying a peak detection algorithm to the voltage wave makes it possible to count steps because there would be vibration peaks each time the user's foot hits the ground, and applying a trained regression model to the energy wave can obtain calorie-burning estimations. Similarly, by extracting appropriate features from the energy and applying a trained classifier to them, it should be possible to monitor many contexts or activities of daily living such as whether the user is walking, running, driving a car, or riding a train.

Numerous other contexts can be detected from the piezoelectric voltage data by exploiting the PEH's ability to respond to sounds transmitted by a nearby speaker. For example, to monitor the activities of an elderly resident at home, acoustic beacons could be installed in the kitchen, bathroom, living room, and many other places that transmit sound beacons with unique identifiers. To track object interactions, sound beacons could also be fitted to important objects such as a medicine cabinet. Thus, every time the user visits these locations in the house or interacts with those objects, the health analytics system will be able to record it.

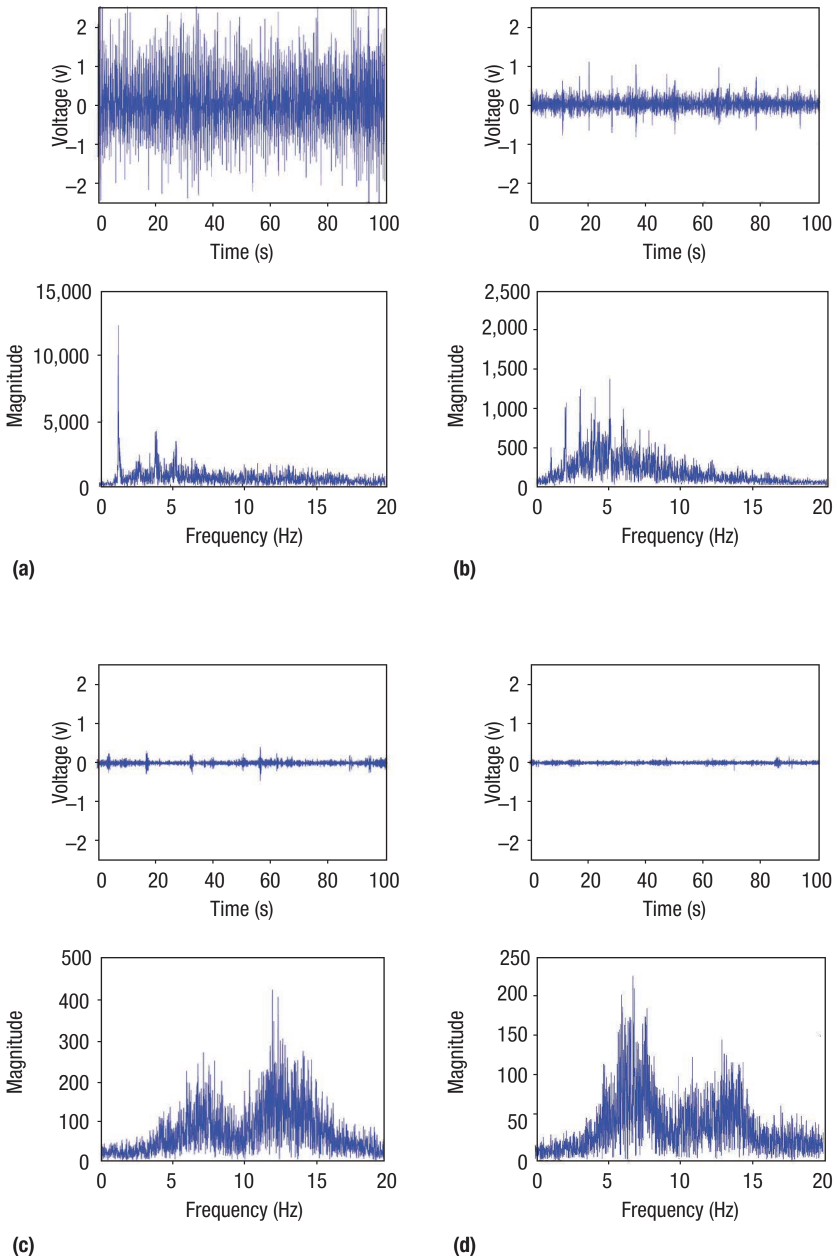

FIGURE 3. The impact of four daily activities on energy harvesting in both time and frequency: (a) running, (b), walking, (c) riding in a car, and (d) riding a train. The AC voltage signals were collected from a hand-held PEH carried by a person while doing these activities.

To assess the extent to which human activities affect the harvested energy, we had 10 volunteers carry a PEH in their hands while walking, running, riding in a car, and riding a train. The PEH was instrumented to record the AC voltage data in a storage card, and this data was later processed in our lab. Figure 3 plots the time-series data from one volunteer with their Fourier transforms. It is clear that the four activities distinctly influence the harvested energy in both time and frequency, which can be processed by sophisticated data analytics to detect and monitor the user's lifestyle. For example, from the time-domain amplitudes, we can see that running generates more energy than walking. Although the amount of energy harvested when the user was in the car or train was very similar, the frequency-domain patterns were different: energy was more focused (higher frequency) in the former scenario. The actual data varied from one volunteer to another, but the patterns were more or less consistent across all volunteers, showing that it is possible to detect activities from PEH signals.

Power savings with PEH-based sensing

To demonstrate how energy-based context detection could help power health wearables, we first illustrate the concept of duty cycling used in most low-power sensors and IoT devices to conserve system power.

Figure 4 shows duty cycling of a generic health wearable that reads sensor data at a given frequency and transmits this data to a nearby processing device using an onboard radio. Note

Parameter	PEH	ADXL335	ADXL377	MPU9250
P_{MD}	390 µW	1440 µW	1230 µW	333 µW
T_{MD}	0.55 ms	0.92 ms	1.47 ms	17.2 ms
$P_{MD} \times T_{MD}$	0.21 µJ	1.32 µJ	1.81 µJ	5.73 µJ

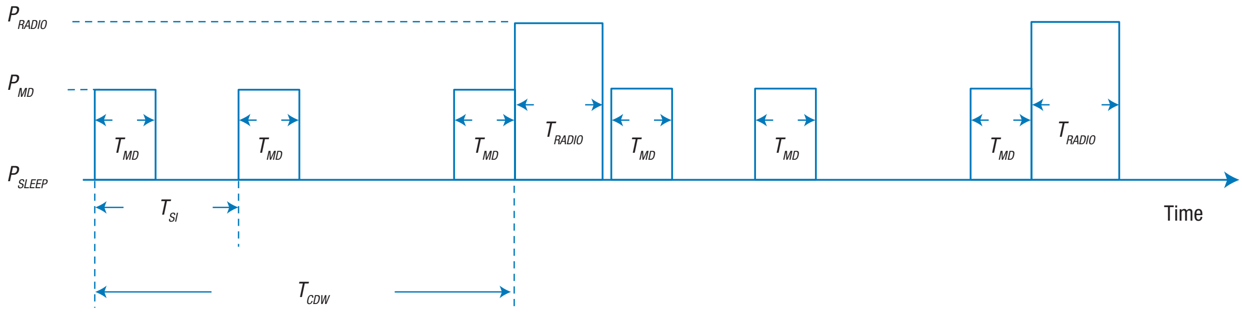

FIGURE 4. Power-consumption parameters of a duty-cycled system. T_{SI}: sampling interval; T_{MD}: time to read a sample; P_{MD}: average system power consumed during a sample reading from the sensor; T_{CDW}: length of one cycle of data collection; T_{RADIO}: time to transmit all data from one cycle; P_{RADIO}: radio power consumption; P_{SLEEP}: system power consumption during sleep.

that the system does not stay active all the time, which would rapidly drain the battery. Instead, it sleeps most of the time and wakes up only when it needs to either read sample data from the sensor or transmit the sampled data using the radio. Similarly, the radio is only activated when the data needs to be transmitted. Because turning the radio on and off each time the data are to be transmitted consumes significant power, usually the sampled sensor data are stored in a local buffer and the radio is activated once in a while to transmit all buffered data in a batch. Such batch data transmission amortizes radio power consumption over many samples. For human activity monitoring, feature extraction and classification are usually done over a few seconds, which is referred to as the context detection window (CDW). The radio therefore can be activated once every T_{CDW}, which is the length of the window in seconds.

Now the overall system power consumption for the wearable can be defined as

$$P_{CONTEXT} = \frac{E_{SM} + E_{RD} + E_{SLEEP}}{T_{CDW} + T_{RADIO}}. \quad (1)$$

The numerator shows total energy consumption from sampling (E_{SM}), transmitting (E_{RD}), and sleeping (E_{SLEEP}) for one cycle of data collection and transmission. The denominator is the length of one such cycle, which is the time to collect the samples (T_{CDW}) plus the time it takes to transmit them (T_{RADIO}). Except for T_{CDW}, which is a design choice for the context detection analytic, all other variables depend on the choice of hardware for implementing the wearable.

To obtain practical power consumption data, we instrumented a Texas Instruments SensorTag, which is representative of many low-power IoT devices with a variety of sensors, and measured the power consumption of sampling and radio transmission using an oscilloscope. In particular, we considered three different accelerometers. MPU9250 is a digital inertial measurement unit (IMU) from InvenSense that comes with the SensorTag, and it is connected to the microcontroller unit (MCU) using the Inter-Integrated Circuit (I2C) bus. In contrast, ADXL335 and ADXL377 are analog accelerometers from Analog Devices that are connected to the

TABLE 2. Power consumption for detecting contexts of varying complexity.

Context complexity	Sampling rate	PEH			ADXL335			ADXL337			MPU9250		
		E_{SM}	E_{RD}	Power	E_{SM}	E_{RD}	Power	E_{SM}	E_{RD}	Power	E_{SM}	E_{RD}	Power
Simple	10 Hz	2.10 µJ	9.52 µJ	17.56 µW	13.20 µJ	18.40 µJ	37.20 µW	18.10 µJ	18.40 µJ	42.03 µW	57.30 µJ	18.40 µJ	79.93 µW
Moderate	25 Hz	5.2 µJ	14.44 µJ	25.43 µW	33.00 µJ	33.16 µJ	69.71 µW	45.25 µJ	33.16 µJ	82.82 µW	143.25 µJ	33.16 µJ	176.90 µW
Complex	50 Hz	10.50 µJ	23.80 µJ	39.75 µW	66.00 µJ	57.76 µJ	125.86 µW	90.50 µJ	57.76 µJ	149.50 µW	286.50 µJ	57.76 µJ	335.40 µW

MCU using the analog-to-digital (ADC) channels. We also measured power consumption of sampling the voltage of a PEH. The MCU of the SensorTag has a built-in Bluetooth Low Energy (BLE) radio, which we used to measure the data transmission power. Here we assume the wearable will use BLE to communicate with a nearby edge device, such as a smartphone, which in turn can send the data to the cloud using 4G technology.

Some of the parameters in Figure 4 are not dependent on the type of sensors used, while others vary based on the sensor type. For example, system power consumption during sleep (P_{SLEEP}) and radio power consumption (P_{RADIO}) were measured at 6 µW and 2 mW, respectively, for all sensors. On the other hand, T_{MD} and P_{MD}, which respectively define the time to read a sample and the average system power consumed during sample reading from the sensor, are influenced by the type of sensors used. The table in Figure 4 shows P_{MD} and T_{MD} for different sensors. We observed that use of PEH, which does not consume any external power to operate, reduces energy consumption for each sample collection. A small amount of energy savings for each sampling translates into significant power savings for the overall system.

Generally speaking, the harder the context to detect, the higher the required sampling rate for collecting more high-resolution information for that context.[6] For example, if the context is whether the person is moving or staying still, then sampling only once or twice per second is sufficient. However, if we need to detect context from a very large number of possible activities the person is engaged in at a given time, then we need to sample at a much higher frequency. Equation 1 indicates that the power consumption of the wearable will increase if the sensor is sampled more frequently, and vice versa. This is because the sampling rate within a given cycle increases E_{SM} and E_{RD}. Thus, ultimate power consumption will depend on the type of context detections required by a particular health-monitoring application.

For one second of C_{DW} (T_{CDW} = 1 sec), Table 2 shows the power consumption for detecting contexts of varying complexity. We can see that using PEH signals instead of conventional accelerometers can reduce the power consumption of context detection significantly. The more complex the context detection task, the higher the power savings. For example, for a complex context detection that requires sampling at 50 Hz, conventional context detection using an ADXL337 accelerometer in a SensorTag would consume 149 µW. By adopting the concept of energy-based context detection, the health wearable can detect the same context by consuming only 39 µW, which would extend the battery life by a factor of 3.8.

Quality of PEH-based context detection

After demonstrating the significant potential power savings of energy-based context detection, we examined the quality of such context detection with PEH signals. For this experiment, we used an Arduino Uno fitted with a Midé V25W piezoelectric cantilever and a Freescale MMA7361LC accelerometer. Ten volunteers carried the device in their hands while performing five different activities: standing

TABLE 3. Classification accuracy of PEH-based and conventional accelerometer-based sensing on different activity sets.

	< *S*, *W*, *R*, *SU*, *SD* >				< *S*, *W*, *R* >			
	Standard features		Standard + vibration features		Standard features		Standard + vibration features	
Classifier	**PEH**	**MMA7361LC**	**PEH**	**MMA7361LC**	**PEH**	**MMA7361LC**	**PEH**	**MMA7361LC**
Nearest neighbor	70.21%	95.44%	80.11%	95.81%	100%	100%	100%	100%
Decision tree	76.34%	87.02%	79.76%	88.19%	98.95%	98.95%	98.95%	97.38%
Support vector machine	72.89%	90.43%	72.89%	88.89%	100%	100%	100%	100%
Naive Bayes	70.58%	84.69%	70.58%	85.44%	98.95%	98.43%	98.95%	100%

(S), walking (W), running (R), going up stairs (SU), and going down stairs (SD). Each volunteer collected 300 seconds of data for S and W, 240 seconds of data for R, and 200 seconds of data for both SU and SD. To avoid any accuracy loss due to lack of samples, we used a very high sampling rate, 1 kHz, for both the PEH and the accelerometer. All data were stored on a local storage card for postprocessing.

Table 3 shows the accuracies obtained for both the PEH and the accelerometer using four machine learning classifiers well known for their ability to recognize human activities: nearest neighbor (NN), decision tree (DT), support vector machine (SVM), and naive Bayes (NB). To adjust for the differing amounts of training data per activity, all accuracies are calculated as a weighted average, where the weight of an activity represents how frequently it appears in the training data.

For the activity set that includes all five activities (< *S*, *W*, *R*, *SU*, *SD* >), the first two columns report accuracies when the classifiers are trained using a set of "standard" features known to achieve good performance with accelerometer data. For these standard features, we observe that the PEH's best performance, 76.34 percent with DT, is 19 percent lower than the best performance achieved with the accelerometer, 95.44 percent with NN. We then repeated the classification experiments by adding seven special features well known for quantifying vibration (https://www.bksv.com/media/doc/br0094.pdf), which we refer to as vibration features that mainly contain metrics related to various peak-to-peak measurements of the signal.[7] The second two columns of Table 3 show that the classification accuracies increased significantly for the PEH when the vibration features were used, but they had no noticeable effect for the accelerometer. With vibration features, the PEH was able to achieve accuracies up to 80 percent with NN, which is 15 percent lower than that of the accelerometer.

W, SU, and SD are similar activities that require highly precise sensing data for accurate distinction. To assess PEH performance when the activity set does not contain similar activities, we evaluated activity classification performance with the activity set < *S*, *W*, *R* >. As the third and fourth columns of Table 3 show, the PEH and accelerometer both achieved nearly 100 accuracy regardless of the classifier used. This indicates that a PEH could be as reliable as an accelerometer for applications that aim to detect activities that are not too similar. In this capacity, a PEH could useful sensor for detecting a wide range of human contexts.

LOOKING INTO THE FUTURE

Significant research is ongoing to further boost the density of energy generation in PEHs. Here we survey six trends and analyze their potential opportunities for human context detection in health wearables.

Multi-axis PEH. While currently available PEHs are limited to harvesting energy from a single vibrational axis, recently proposed novel harvesting models indicate that it might be possible to harvest kinetic energy from multiple dimensions.[8] Such multi-axis energy harvesters will undoubtedly provide much richer information about human motion compared to existing harvesters.

Low-resonance PEH. It is conceptually possible to build a PEH that resonates at frequencies much lower than those of the current devices used in high-frequency industrial IoT applications.[9] This implies that in the future we can expect a much better match between human frequency and PEH resonance frequency. In other words, many low-frequency human vibrations not adequately registered by existing high-resonance energy harvesters will be properly captured. The availability of low-resonance PEH will help extract much more refined signals of human motion, thereby boosting the accuracy of wearable context sensing.

Nanotechnology-based ultrasensitive PEH. Existing bulk materials have limited sensitivity to vibrations—they can only react to vibrations with amplitudes higher than a given threshold. As such, our capability to sense human vibrations are limited by the threshold properties of the bulk material. It is now becoming feasible to manufacture materials at nanoscale and engineer molecular structures that can achieve far greater sensitivity than bulk materials. Piezoelectric ZnO nanowire[10] is one such recent innovation that offers extreme sensitivity to vibrations of ultrasmall magnitude for mechanical-energy-harvesting purposes. This technology is still in research labs, but once it becomes available for commercialization we will have the opportunity to detect miniscule human vibrations readily from energy harvesters. Such ultrasensitive signals could help differentiate many fine-grain activities, such as sitting and standing, which is difficult to do with current bulk PEH signals.

Self-tuning PEH. Different human activities produce vibrations at slightly different frequencies. Existing PEHs have a fixed resonance frequency, making it difficult to capture vibrations from all activities with equal precision. Researchers at the University of California, Berkeley,[11] recently invented a method that lets a PEH self-tune its resonance frequency to adapt to the changing vibrations of the environment. This discovery is expected to help build PEHs for wearables that will resonate with the frequency of the user activity, thus producing not only more energy from human motion but also stronger context signals for health analytics.

PEH array. Researchers at Chongqing University recently demonstrated that it is possible to micromachine five piezoelectric cantilevers in a single substrate to produce an array of five individual energy harvesters in a single microelectromechanical system (MEMS).[12] Although the use of PEH arrays is purely motivated by the need to produce more energy from the harvesting device, it opens up a fascinating new avenue for PEH-based context detection research. A PEH array can be paralleled to some extent with so-called multiple antenna technologies, such as multiple-input and multiple-output (MIMO), used in wireless communications to increase the received signal quality. A PEH array makes it possible to receive multiple vibration signals, which could contain some independent information about the vibration source. For example, a PEH array configured with different resonance frequencies for different cantilevers will produce independent energy signals, which might capture different aspects of the same context and thus provide a diversity opportunity in context detection. Indeed, researchers have recently argued that an array of piezoelectric cantilevers responding to a set of very narrow frequency bands is superior to an accelerometer in detecting typing input through skin.[13] The superiority of piezoelectric cantilevers in this application is due to the fact that only a specific set of frequencies is conducted through the human skin in response to tap input. A flat response curve of accelerometers in this case leads to the capture of irrelevant vibrations, which increases the signal-to-noise ratio.

Hybrid PEH. Finally, materials scientists have found ways to combine the piezoelectric and the electromagnetic effects in the same structure, thus generating energy harvesting from both effects at the same time.[14] Again, this trend is motivated by the need for increasing the total energy generation from ambient vibrations. However, because the energy generation from piezoelectric harvesting is different from that of electromagnetic harvesting, it opens up new possibilities for multimodal context sensing using the same sensing hardware.

It is clear that compared to existing energy harvesters, which offer very limited functionality, we will have a plethora of new types of energy-harvesting signals available in future self-powered health wearables. How to detect an expanding range of human activities and contexts from these diverse energy signals will be a challenging task. To this end, we can leverage the recent advances in machine learning algorithms, such as deep learning constructs,[15] to detect complex activities and contexts with higher accuracy. Energy-based human context detection therefore opens the door to a new research direction for wearable sensing and health monitoring. It might even lead to cross-disciplinary research opportunities for joint optimizations of both energy harvesting and context sensing within the same platform.

Although several KEH solutions have been successfully deployed in industry, KEH generates too little energy for health wearables due to their limited form factor and attachment restrictions and the low frequency of motion of human activities. Despite this, KEH could significantly improve device battery life due to its potential for detecting context from harvested energy. Existing energy harvesters are inferior to accelerometers for classifying human activities but as the technology evolves may prove to be accurate context-sensing devices. C

REFERENCES

1. D.C. Plummer et al., *Top Strategic Predictions for 2016 and Beyond: The Future Is a Digital Thing*, Gartner, 2 Oct. 2015; https://www.gartner.com/doc/3142020/top-strategic-predictions-future-digital.

ABOUT THE AUTHORS

MAHBUB HASSAN is a professor in the School of Computer Science and Engineering at the University of New South Wales, Sydney (UNSW Sydney). His research interests include mobile networks, nanoscale wireless sensor networks, self-powered and energy-harvesting wireless networks, the Internet of Things (IoT), and wearable computing. Hassan received a PhD in computer science from Monash University. He is a Senior Member of IEEE. Contact him at mahbub.hassan@unsw.edu.au.

WEN HU is a senior lecturer in the School of Computer Science and Engineering at UNSW Sydney. His research interests include novel applications, low-power communications, security, and compressive sensing in sensor network systems and the IoT. Hu received a PhD in computer science from UNSW Sydney. He is a Senior Member of ACM and IEEE. Contact him at wen.hu@unsw.edu.au.

GUOHAO LAN is a PhD student in the School of Computer Science and Engineering at UNSW Sydney. His research interests include mobile and pervasive computing, cyber-physical systems, and wireless sensor networks. Contact him at guohao.lan@unsw.edu.au.

ARUNA SENEVIRATNE is the foundation Professor of Telecommunications in the School of Electrical Engineering and Telecommunications at UNSW Sydney. His research focuses on the use of machine learning to improving the performance, reliability, and security of IoT systems. Seneviratne received a PhD in electrical engineering from the University of Bath. Contact him at a.seneviratne@unsw.edu.au.

SARA KHALIFA is a research scientist at Data61—CSIRO in Sydney, Australia. Her research interests include ubiquitous and pervasive computing, smart wearables, the IoT, energy harvesting, and pattern recognition. Khalifa received a PhD in computer science from UNSW Sydney. Contact her at sara.khalifa@data61.csiro.au.

SAJAL K. DAS is a professor of computer science and the Daniel St. Clair Endowed Chair at the Missouri University of Science and Technology. His research interests include wireless sensor networks, cyber-physical systems, the IoT, smart environments, big data analytics, and security. Das received a PhD in computer science from the University of Central Florida. He is an IEEE Fellow. Contact him at sdas@mst.edu.

2. R. Sen, "Building Smarter Wearables for Healthcare, Part 1: Examining How Healthcare Can Benefit from Wearables and Cognitive Computing," IBM developerWorks, 04 Aug. 2015; https://www.ibm.com/developerworks/library/cc-smarter-wearables-healthcare-concepts/index.html.
3. L. C. Rome et al., "Generating Electricity while Walking with Loads," *Science*, vol. 309, no. 5741, 2005, pp. 1725–1728.
4. L. Xie and M. Cai, "Human Motion: Sustainable Power for Wearable Electronics," *IEEE Pervasive Computing*, vol. 13, no. 4, 2014, pp. 42–49.
5. M. Gorlatova et al., "Movers and Shakers: Kinetic Energy Harvesting for the Internet of Things," *IEEE J. Selected Areas in Comm.*, vol. 33, no. 8, 2015, pp. 1624–1639.
6. T. Y.-H. Chen et al., Designing a Context-Sensitive Context Detection Service for Mobile Devices, tech. report MIT-CSAIL-TR-2015-029, Massachusetts Inst. of Technology, 24 Sept. 2015; https://dspace.mit.edu/handle/1721.1/98905.
7. S. Khalifa et al., "HARKE: Human Activity Recognition from Kinetic Energy Harvesting Data in Wearable Devices," *IEEE Trans. Mobile Computing*, vol. 17, no. 6, 2018, pp. 1353–1368.
8. E. Aktakka and K. Najafi, "Three-Axis Piezoelectric Vibration Energy Harvester," Proc. 28th *IEEE Int'l Conf. Micro Electro Mechanical Systems* (MEMS 15), 2015; doi: 10.1109/MEMSYS.2015.7051166.
9. H. Li, C. Tian, and Z.D. Deng, "Energy Harvesting from Low Frequency Applications Using Piezoelectric Materials," *Applied Physics Reviews*, vol. 1, no. 4, 2014; https://doi.org/10.1063/1.4900845.
10. Z.L. Wang and W. Wu, "Nanotechnology-Enabled Energy Harvesting for Self-Powered Micro-/Nanosystems," *Angewandte Chemie Int'l Ed.*, vol. 51, no. 47, 2012, pp. 11700–11721.
11. C.G. Gregg, P. Pillatsch, and P.K. Wright, "Passively Self-Tuning Piezoelectric Energy Harvesting System," *J. Physics: Conf. Series*, vol. 557, 2014; http://iopscience.iop.org/article/10.1088/1742-6596/557/1/012123/pdf.
12. H. Yu et al., "A Vibration-Based MEMS Piezoelectric Energy Harvester and Power Conditioning Circuit," *Sensors*, vol. 14, no. 2, 2014, pp. 3323–3341.
13. C. Harrison, D. Tan, and D. Morris, "Skinput: Appropriating the Body as an Input Surface," *Proc. SIGCHI Conf. Human Factors in Computing Systems* (CHI 10), 2010, pp. 453–462.
14. W. Chen, Y. Cao, and J. Xie, "Piezoelectric and Electromagnetic Hybrid Energy Harvester for Powering Wireless Sensor Nodes in Smart Grid," *J. Mechanical Science and Technology*, vol. 29, no. 10, 2015, pp. 4313–4318.
15. P. Vepakommaz et al., "A-Wristocracy: Deep Learning on Wrist-Worn Sensing for Recognition of User Complex Activities," *Proc. IEEE 12th Int'l Conf. Wearable and Implantable Body Sensor Networks* (BSN 15), 2015; doi:10.1109/BSN.2015.7299406.