

# Step detection from power generation pattern in energy-harvesting wearable devices

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**Abstract**—Energy-harvesting wearable devices generate power by converting natural phenomena such as human motion into usable electricity. We conduct an experimental study to validate the feasibility of detecting steps from the power generation patterns of a wearable piezoelectric energy harvester (PEH). Four healthy adults took part in the study, which includes walking along straight and turning walkways as well as descending and ascending stairs. We find that power generation exhibits distinctive peaks for each step, making it possible to accurately detect steps using widely used peak detection algorithms. Using our PEH prototype, we successfully detected 550 steps out of 570, achieving a step detection accuracy of 96%.

## I. INTRODUCTION

Step detecting wearable devices are increasingly being used for health monitoring [1], [2] and indoor positioning applications [3]–[7]. These devices use accelerometers to detect steps as human acceleration exhibits distinctive peaks when each step is taken. Step detection accuracies close to 100% can be achieved by using simple peak-detection algorithms that continuously monitor the accelerometer signal [8]. Figure 1 shows a real accelerometer trace from a wearable device carried by a subject walking along a straight indoor walkway. The peaks, which correspond to steps, are unmistakable.

While high step detection accuracy is considered a remarkable feature of the wearables, their power supply remained heavily dependent on batteries, which must be recharged or replaced. It is only recently that technological advancements in energy harvesting materials are creating some real opportunities for the wearables to generate some power of their own by converting natural phenomena such as human motion into usable electricity [9], [10]. This is a very important development, which may ultimately help realise battery-less wearable devices in the future.

The focus of our study is to propose and validate the concept of step detection directly from the patterns of power generation in wearable devices if human motion is used as the basis of energy harvesting. The concept is intuitive because if steps are known to show distinctive *acceleration peaks*, they are also expected to produce *power peaks* if power generation is based on motion (acceleration). The concept is also immensely beneficial from energy conservation points of view, because if steps can be detected directly from the power

generation patterns, then no power needs to be allocated to the accelerometer to measure acceleration. Finally, the proposed concept can help simplify the circuit board of the device by removing the accelerometer from it, which can further save the overall device power consumption as well as the form factor. All these benefits will contribute to realising health-tracking wearable Internet of things that are completely self-powered and too small to be noticeable.

To validate the concept, we have built a wearable prototype fitted with a piezoelectric energy harvester (PEH) to generate power from vibrations caused by motion. Four subjects volunteered to walk along straight and turning paths as well as descending and ascending stairs while wearing the prototype. We logged power generation data in terms of the AC voltage output of the PEH 1000 times per second during these walks and analysed these traces later to study their step detection potential. We find that, like acceleration, power traces also exhibit distinctive peaks for steps, which can be detected accurately using the widely used peak detection algorithms.

The contributions and outcomes of our study can be summarised as follows:

- We conduct the first experimental study to validate the concept of step detection from the power generation patterns in energy-harvesting wearable devices.
- We collect PEH power generation traces from four subjects under different walking scenarios including stairs, covering a total of 570 steps. The traces reveal that PEH power generation has distinctive peaks for human steps.
- We demonstrate that widely used peak detection algorithms can detect steps from PEH power generation patterns with an accuracy of 96%.

The rest of the paper is structured as follows. Section II provides a review of peak-detection algorithms widely used for detecting steps from accelerometer signals. The proposed PEH-based step detection, including the prototype development, data collection experiments, and threshold determination, is explained in section III. Results are presented in Section IV. We conclude the paper in Section VI.

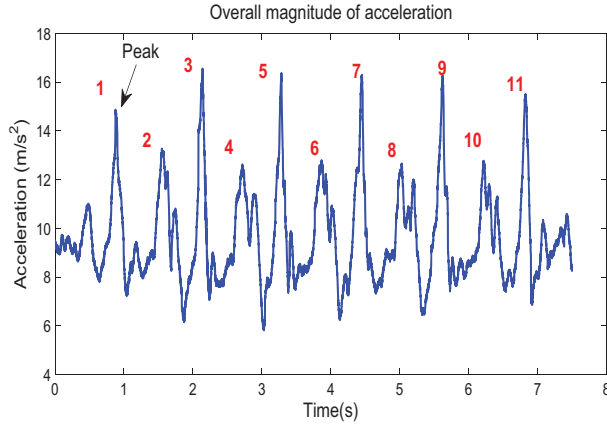


Fig. 1. The raw output patterns of an accelerometer from a wearable device attached to the waist of a subject walking along straight walkway for 11 steps.

## II. ACCELEROMETER-BASED STEP DETECTION

Step detection is usually defined as the automatic identification of the moments in time at which footsteps occur. In the literature, steps are usually detected by using the output of the accelerometer sensor. The accelerometer sensor records the acceleration in three different axes  $a_x(t)$ ,  $a_y(t)$ , and  $a_z(t)$ . The overall magnitude of the three axes,  $a(t) = \sqrt{a_x(t)^2 + a_y(t)^2 + a_z(t)^2}$ , is usually used to represent the accelerometer signal for step detection. Figure 1 shows the raw output patterns of an accelerometer from a wearable device attached to the waist of a subject walking along straight walkway for 11 steps. The peaks, which correspond to steps, are unmistakable as numbered.

One of the widely used methods for step detection is the peak detection. Several studies [3]–[7], [11], [12] showed that the peak detection method is precise enough to detect user steps. In this method, a step is detected when a local maxima (local peak) is detected. A local maxima is a data point that is larger than its two neighboring as shown in Figure 1. However, because of the irregular human movements and also the hardware noise, not all the detected peaks are valid steps. Some peaks could be very low in the amplitude and/or very close to each other. Two thresholds are used to filter out these peaks and recognize the valid steps:

- 1) The minimum peak height,  $T_1$ .
- 2) The minimum distance between every two consecutive peaks,  $T_2$ .

$T_1$  is determined based on the amplitude of the signal and  $T_2$  is determined based on the distance in time between every two consecutive peaks. Using these thresholds, the peaks that represent valid steps are only those peaks higher than  $T_1$  and separated by at least  $T_2$ .

## III. PROPOSED PEH-BASED STEP DETECTION

In this paper, we propose the power generation pattern of energy-harvesting wearable devices as a new source for step detection.

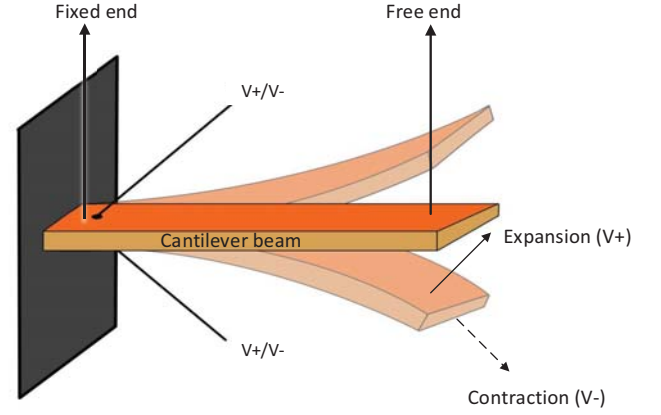
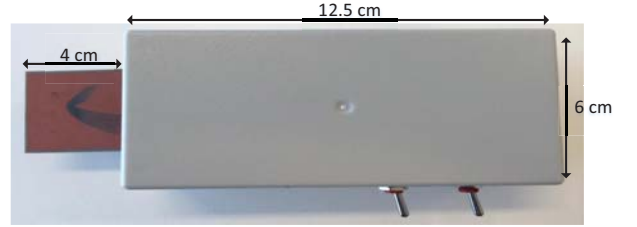
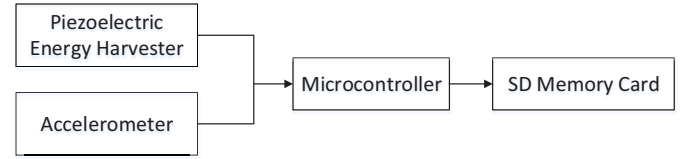
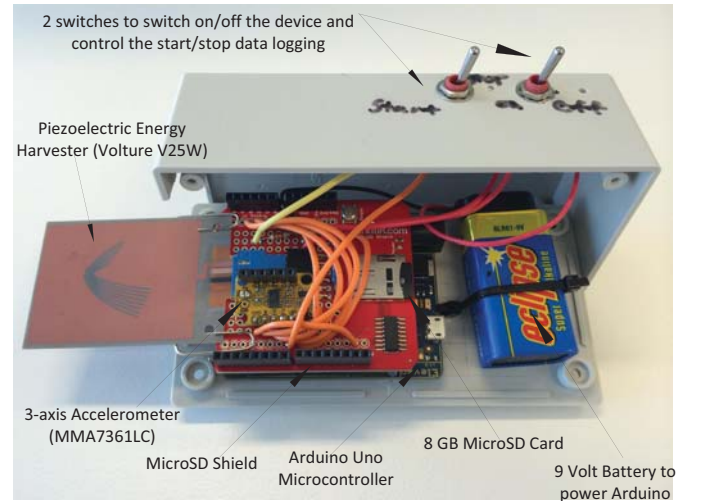


Fig. 2. A piezoelectric cantilevered beam.



(a) Block Diagram of our prototype's components (up) and external appearance (down).

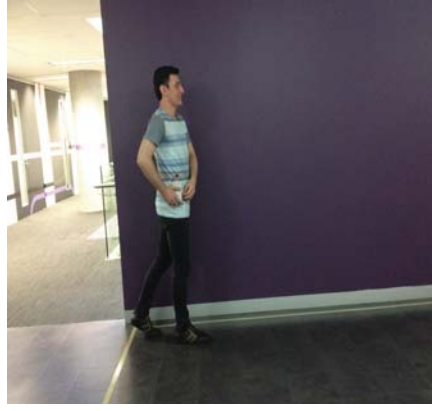


(b) Prototype's Internal Appearance.

Fig. 3. Prototype Development: (a) Block Diagram of our prototype's components (up) and external appearance (down), and (b) The internal appearance of the prototype.



(a) Device placement on the subject's body.



(b) Experimentation while turning walkways scenario.

Fig. 4. Experiments Design: (a) Device placement on the subject's body, and (b) Experimentation while turning walkways scenario.

Our objective is to investigate (a) whether the output pattern of a piezoelectric energy harvester (PEH) exhibits distinctive peaks for steps, which can be used for step detection, and (b) if it does, how much accuracy could be achieved for PEH-based step detection.

#### A. PEH Overview

PEH is the most favourable vibration energy harvesting transduction mechanisms due to their simplicity and compatibility with MEMS [13]. The piezoelectric effect was discovered in natural quartz crystals, but today's piezoelectric transducers are typically made from patented, proprietary ceramics.

Figure 2 shows a typical usage configuration of a piezoelectric cantilevered beam to implement a PEH. One end of the beam is fixed to the device, while the other is set free to oscillate (vibrate). When the piezoelectric material is subjected to a mechanical stress due to any source of environmental vibrations, it expands on one side and contracts on the other. Positive charges accumulate on the expanded side and negative charges on the contracted side, generating an AC voltage as the beam oscillates around the neutral position.

The amount of voltage is proportional to the applied stress, which means that each step taken by the human is expected to produce some peaks that would enable step detection from the voltage signal. In most applications, AC voltage is rectified to produce a DC, which can be used to power different devices, such as an accelerometer, a gyroscope, or a microphone. However, the focus of our study is to investigate whether the AC signals can be used directly to detect steps in a walking signals.

#### B. PEH Prototype

In order to investigate PEH-based step detection, we built a prototype to collect the output of a PEH. Our prototype includes a product called Vulture from MIDÉ [14], which implements a piezoelectric energy harvester providing AC voltage as its output. We added a 3-axis accelerometer (MMA7361LC) to the prototype for comparison purposes. An Arduino Uno

has been used as a micro-controller device for sampling the data from both the Vulture and the accelerometer. A sampling rate of 1 KHz has been used for data collection. The sampled data has been saved on an 8GB microSD card which has been equipped to the Arduino using microSD shield. A nine volt battery has been 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. The hardware platform and the internal appearance of the data logger are shown in figures 3(a) and 3(b), respectively.

#### C. Data Collection Experiments

Our data has been collected from the National ICT Australia (NICTA) building. Four subjects, two male and two female, between 26 to 35 years of age, volunteered to participate in this research study. The subjects were asked to place the prototype at their waist as shown in Figure 4. Four different walking scenarios have been considered in our experiment design:

- Straight walkways (7.5 meters long).
- Turning walkways (a square path of  $4 \times 4$  meters, 16 meters in total).
- Ascending Stairs.
- Descending stairs.

Each of these walking scenarios have been done two times by each subject. All subjects performed all the walking scenarios at normal walking speed. A switch has been used to start and stop data collection at the beginning and end of each scenario. Subjects were asked to stop and wait a few seconds after and before each scenario. To allow a natural walking style, the subjects were not asked to count their steps. Instead, one more volunteer was responsible to monitor the walking of each subject and count the actual number of steps have been taken in each scenario. Using this way, we had the ground truth values which are used in the performance evaluation stage. In total, we have 570 steps from all subjects, experiments and scenarios.

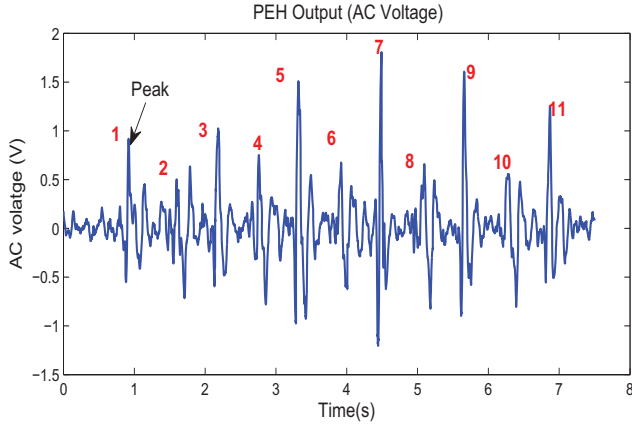


Fig. 5. The raw output patterns of a piezoelectric energy harvester (PEH) from a wearable device attached to the waist of a subject walking along straight walkway for 11 steps.

#### D. Thresholds Determination

Figure 5 shows the raw output pattern of a PEH from a wearable device attached to the waist of a subject walking along straight walkway for 11 steps. We clearly see the step occurrences in the output pattern of a PEH output signals. This confirms that, like acceleration, power traces also exhibit distinctive peaks for steps, which can be detected accurately using widely used peak detection algorithms. Note that some steps are observed to be higher than other steps in both the accelerometer and PEH outputs as the signals have been collected for a waist placement. As a result, the steps taken by the leg that is closer to the device have bigger effect on the output signals.

As explained in Section II, in order to detect a valid step, two thresholds are required. The minimum peak height,  $T_1$ , and the minimum distance between every two consecutive peaks,  $T_2$ .  $T_1$  is determined based on the amplitude of the signal and  $T_2$  is determined based on the distance in time between every two consecutive peaks. These thresholds are usually determined experimentally.

PEH and accelerometer have different output signals. In our prototype, accelerometer gives acceleration in  $m/s^2$  but PEH gives AC voltage in *volt*. As shown in Figures 1 and 5, the amplitude (the range of the output) is different for accelerometer than PEH.  $T_1$  has been found experimentally in our data to be  $11 m/s^2$  for accelerometer and  $0.2 volt$  for PEH.  $T_2$  has been found to be  $0.4 millisecond$  for both accelerometer and PEH. This is due to the fact that, at normal walking speed, human approximately takes two steps per second.

#### IV. RESULTS

In this section, we investigate the performance of PEH-based step detection and compare it to accelerometer-based step detection. Table I shows the experimentally determined thresholds for both the accelerometer and PEH signals based on our data.

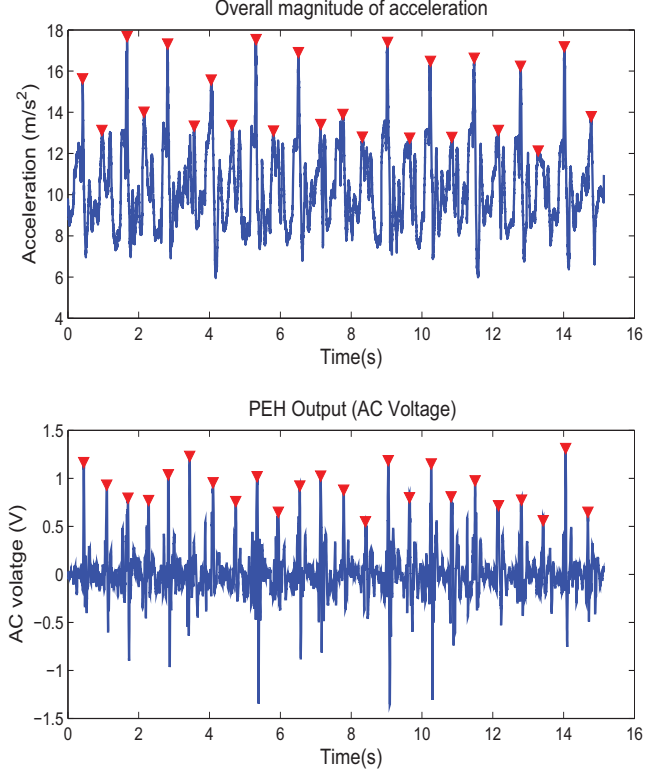


Fig. 6. The accelerometer and PEH output patterns with the detected steps marked on both of them, when a turning walkways scenario is considered.

TABLE I  
EXPERIMENTALLY DETERMINED THRESHOLDS FOR STEP DETECTION  
ALGORITHM FOR BOTH ACCELEROMETER AND PEH.

Accelerometer Thresholds	$T_1 = 11 m/s^2$ $T_2 = 0.4 ms$
PEH Thresholds	$T_1 = 0.2 volt$ $T_2 = 0.4 ms$

Figure 6 shows the identified steps using the previously determined thresholds for both accelerometer (overall magnitude) and PEH signals when square walking scenario and waist placement of the device are considered. The accuracies of the step detection algorithm in both the accelerometer and PEH cases are calculated using Equation 1.

$$Accuracy = (1 - \frac{|Actual - Estimated|}{Actual}) \times 100\%, \quad (1)$$

where *Actual* is the actual step count and *Estimated* is the estimated step count.

Tables II, III, IV, and V show the accuracies (%) of PEH-based step detection for the four considered scenarios: straight line, turning walkways, ascending, and descending stairs, respectively. These tables also show the actual number



TABLE II  
PEH-BASED STEP DETECTION ACCURACIES FOR STRAIGHT WALKWAYS  
SCENARIO FOR EACH SUBJECT AND OVER ALL THE SUBJECTS.

Subject No.	Experiment No.	Actual # of steps (Ground Truth)	Estimated # of steps	Accuracy (%)
S1	E 1	12	12	100
	E 2	12	12	
S2	E 1	12	12	100
	E 2	12	12	
S3	E 1	11	12	100
	E 2	12	12	
S4	E 1	12	12	96.15
	E 2	13	14	
Accuracy (%) overall subjects			99.04	

TABLE III  
PEH-BASED STEP DETECTION ACCURACIES FOR TURNING WALKWAYS  
SCENARIO FOR EACH SUBJECT AND OVER ALL THE SUBJECTS.

Subject No.	Experiment No.	Actual # of steps (Ground Truth)	Estimated # of steps	Accuracy (%)
S1	E 1	24	24	100
	E 2	24	24	
S2	E 1	25	25	100
	E 2	25	25	
S3	E 1	21	21	100
	E 2	21	21	
S4	E 1	27	27	100
	E 2	27	27	
Accuracy (%) overall subjects			100	

of steps (ground truth), the estimated number of steps for each individual subject per each experiment.

Our analysis shows 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.

By looking at the step counts for each scenario, we found that only one placement in the straight walkway scenario shows overcount. On the other hand, in ascending and descending stairs, the results were more inclined to undercount than overcount. Figures 7 and 8 show the accelerometer-based and PEH-based step detection for ascending stairs of subject 3, experiment 2 and for descending stairs of subject 2, experiment 2, receptively. Some steps have been missed by the PEH-based step detection due to the irregular shape of the signal in these scenarios, leading to some false negative errors. These false negative errors could be due to the use of a universal threshold which might not be a correct choice because of the different styles of motion between normal walking and ascending/descending stairs.

In total, over all subjects and all walking scenarios, 550 steps out of 570 have been successfully detected achieving a 96% step detection accuracy when PEH patterns are used, compared to 100% accuracy when the accelerometer is used.

All of our results were based on a waist placement of

TABLE IV  
PEH-BASED STEP DETECTION ACCURACIES FOR ASCENDING STAIRS  
SCENARIO FOR EACH SUBJECT AND OVER ALL THE SUBJECTS.

Subject No.	Experiment No.	Actual # of steps (Ground Truth)	Estimated # of steps	Accuracy (%)
S1	E 1	17	15	94.12
	E 2	17	17	
S2	E 1	17	17	100
	E 2	17	17	
S3	E 1	18	16	80.56
	E 2	18	13	
S4	E 1	18	17	97.22
	E 2	18	18	
Accuracy (%) overall subjects			92.97	

TABLE V  
PEH-BASED STEP DETECTION ACCURACIES FOR DESCENDING STAIRS  
SCENARIO FOR EACH SUBJECT AND OVER ALL THE SUBJECTS.

Subject No.	Experiment No.	Actual # of steps (Ground Truth)	Estimated # of steps	Accuracy (%)
S1	E 1	17	17	94.12
	E 2	17	15	
S2	E 1	17	15	82.35
	E 2	17	13	
S3	E 1	18	18	100
	E 2	18	18	
S4	E 1	18	18	97.22
	E 2	18	17	
Accuracy (%) overall subjects			93.42	

the prototype on the subjects' body. Previous studies [15]–[17] have shown that different placement of the accelerometer sensor on the subject's body affects the step detection accuracy. To investigate this criteria for PEH signals, we have conducted a simple experiment to compare waist placement to hand placement of the prototype. One volunteer was asked to hold our prototype in her hand and walk along straight walkway for 11 steps.

Figure 9 shows the PEH's output signals for waist and hand placement of the device. One observation is that the steps have less contribution to the peaks of the signal. The reason for this is because, in hand holding position, the leg movement is not contributing to the signal's output, making the step occurrences are not clear. This means that, for hand placement, PEH-based step detection will be more challenging. Further experimentation is still needed in this direction.

## V. RELATED WORK

Step detection algorithms have been widely used for health monitoring and indoor positioning applications [3]–[7]. In these applications, steps are usually detected by using the output of the accelerometer sensor. Three different algorithms have been discussed in the literature for step detection: peak detection, zero-crossing detection, and moving variance detection.

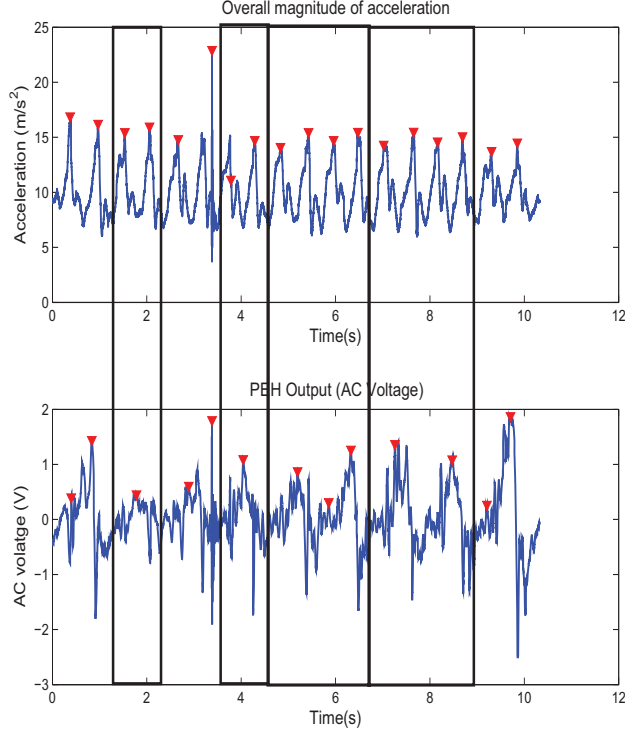


Fig. 7. Showing the false negative errors of PEH-based step detection when ascending stairs scenario of subject 3, experiment 2 is considered.

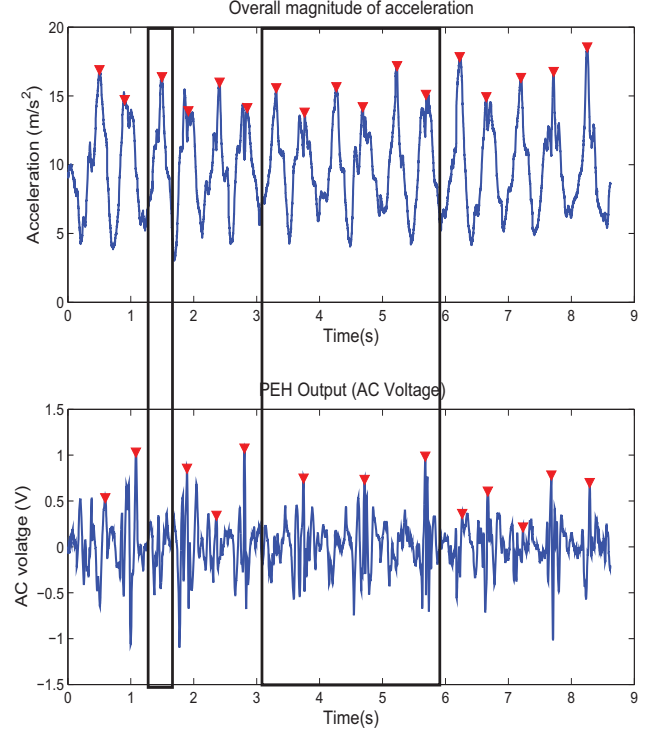


Fig. 8. Showing the false negative errors of PEH-based step detection when descending stairs scenario of subject 2, experiment 2 is considered.

- 1) The peak detection algorithm is one of the widely used methods for step detection [3]–[7]. It searches for the peaks and valleys of the waveform by selecting thresholds in order to identify a distinct step. The step is detected when a valid maximum peak and a valid minimum peak are detected in sequence in a certain interval.
- 2) The zero crossing detection algorithm determines the number of steps by counting the number of times the signal crosses the zero level and dividing it by two [4], [18]. The division by two is due to the observation that the signal crosses the zero level twice in each step during the walking mode.
- 3) The moving variance detection algorithm implements the moving variance filter while keeping in view that acceleration variance has a trend to increase with respect to the step length [18]. Then the local mean acceleration is calculated for each sample of the overall acceleration. This followed by applying after to make the foot activity more prominent. Finally, a step is detected when the acceleration variance is above a certain threshold level.

Ayub et al., [18] have shown that the zero crossing detection algorithm is more robust than the moving variance detection algorithm for step detection. On the other hand, Kang et al., [4] have shown that the zero crossing and the peak detection algorithms are precise enough to detect user steps.

In our work, we have used the peak detection algorithm to demonstrate the feasibility of detecting steps from the output voltage of a PEH wearable. However, it would be interesting to study the performance of the two other algorithms when the PEH signal is used for step detection. To the best of our knowledge, this is the first study to demonstrate that step detection is viable using PEH wearables.

## VI. CONCLUSION

In this paper, we have proposed the concept of step detection directly from the patterns of power generation in wearable devices if human motion is used as the basis of energy harvesting. This proposal is particularly beneficial from energy conservation points of view, because if steps can be detected directly from the power generation patterns, then no power needs to be allocated to accelerometer to measure acceleration. By doing so, the accelerometer can be removed from the design leading to further save of the overall device power consumption as well as the form factor.

Using experimental data, we have shown that steps can be accurately detected from PEH power generation patterns with

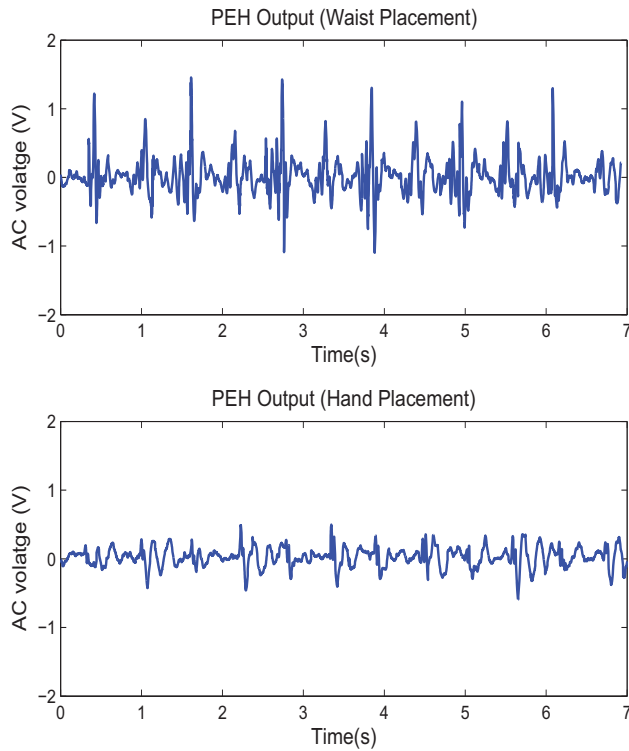


Fig. 9. Comparing PEH's output patterns for two different placement of the prototype on the person's body: waist placement (up) and hand placement (down).

an accuracy of 96% on average. We believe that the proposed idea will contribute towards the realisation of more pervasive and permanent step detection. To our knowledge, this is the first study investigating the viability of step detection using piezoelectric energy harvesting signals. More experimentation is still needed to study the effect of different device placements on the results.

Although this is a specific research focused on step detection only, the positive outcomes imply that PEH signals may have a wide range of applications for sensing and tracking human health. For example, it may be possible to identify a "waking signature" of person that could help realise various applications including user authentication or detecting abnormal walking behaviour. Investigations of these applications remain the focus of our on-going efforts [19]–[21]

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