Pervasive Self-powered Human Activity Recognition without the Accelerometer

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***Abstract*—Conventional human activity recognition (HAR) relies on accelerometers to frequently sample human motion (acceleration). Unfortunately, power consumption of accelerometers becomes a bottleneck for realising pervasive self-powering HAR as the amount of power that can be practically harvested from the environment is very small. Instead of using accelerometer, this paper advocates the use of energy harvesting power signal as the source of HAR when motion (kinetic) energy is being harvested to power the device. The proposed use of harvested power for classifying human activities is motivated by the fact that different activities produce kinetic energy in a different way leaving their signatures in the harvested power signal. Using information theoretic analysis of experimental data, we show that many standard statistical features provide significant information gain when the kinetic power signal is used for discriminating between different activities, confirming its potential use for HAR. We have evaluated activity recognition accuracy for kinetic power signal based HAR using 14 different sets of common activities each containing between 2-10 different activities to be classified. HAR accuracies varied between 68% to 100% depending on the set of activities. The average accuracy over all activity sets is 83%, which is within 13% of what could be achieved with an accelerometer without any power constraints.**

I. Introduction

Continuous human activity recognition (HAR) is becoming critical in many applications, including aged health care [1], [2], smart living [3], and indoor positioning [4], [5] to name a few. At the same time, there is a growing research and development momentum in realising various types of energy harvesting wireless devices [6]. These trends promise a new pervasive human activity monitoring paradigm where numerous wearable tiny devices continue to sense and monitor the human on a permanent basis.

Conventional HAR relies on accelerometers to frequently sample human motion (acceleration). Typically, a classifier is trained with a large number of samples collected during various types of activities, such as walking, running, standing, and so on. Later, when acceleration samples are presented to the classifier, it can recognise the activity using the trained model. A decade long research has confirmed that accelerometers are very effective in accurately detecting human activities.

Accelerometers are usually considered low-power electronics drawing only about a few μW per sample per second (Hz). However, when used in kinetic-powered devices, accelerometer power requirements is considered relatively high compared to the total kinetic power available, which is also measured in μW. A linear reduction in accelerometer power consumption is possible by reducing the sampling rates, but only at the expense of reduced accuracy for activity recognition.

In this paper, we investigate the possibility of achieving HAR using the *harvested power signal* instead of the acceleration. The proposed use of harvested power for classifying human activities is based on the observation that different activities produce kinetic energy in a different way leaving their signatures in the harvested power signal. Indeed, it was recently reported that we could harvest 612-813 μW if the user was running, but walking would generate only 155-202 μW [7]. Interestingly, due to the gravitational effect, going up the stairs would generate less power than going down the stairs [7], which indicates that we could even distinguish between these two very similar activities using the energy harvesting data. All these could be achieved without using any accelerometer thereby conserving the scarce power harvested from the environment.

The key contributions of this paper are summarised as follows:

- Using experimental data, we show that the power requirement of accelerometer for HAR ranges between 35-515% of the harvestable kinetic power. We also demonstrate 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.
- We propose the use of harvested power signal as a new source of realising HAR in a kinetic-powered device. By not using the acceleration for activity classification, the proposed HAR eliminates the need for accelerometer sampling, making HAR practical for self-powered devices. Applying information theoretic measures on experimental data, we demonstrate that kinetic power contains rich information for discriminating most typical activities of our daily life.
- We test the performance of kinetic power based HAR on

TABLE I
ACTIVITY SETS

Activity Set (AS)	Included Activities
AS 1	Walking (W), Running (R).
AS 2	Standing (S), Vacuuming (V).
AS 3	Going up the stairs (SU), Going down the stairs (SD).
AS 4	Standing on escalator going up (EU), Standing on escalator going down (ED).
AS 5	Standing, Walking, Going up the stairs, Going down the stairs.
AS 6	Standing, Walking, Going up the ramp (RU), Going down the ramp (RD).
AS 7	Standing, Walking, Standing on escalator going up, Standing on escalator going down.
AS 8	Going up the stairs, Going down the stairs, Standing on escalator going up, Standing on escalator going down.
AS 9	Going up the stairs, Going down the stairs, Going up the ramp, Going down the ramp.
AS 10	Standing, Walking, Running, Going up the stairs, Going down the stairs.
AS 11	Standing, Walking, Standing on escalator going up, Standing on escalator going down, Going up the ramp, Going down the ramp.
AS 12	Going up the stairs, Going down the stairs, Standing on escalator going up, Standing on escalator going down, Going up the ramp, Going down the ramp.
AS 13	Standing, Walking, Running, Going up the stairs, Going down the stairs, Vacuuming, Standing on escalator going up, Standing on escalator going down.
AS 14	Standing, Walking, Running, Going up the stairs, Going down the stairs, Vacuuming, Standing on escalator going up, Standing on escalator going down, Going up the ramp, Going down the ramp.

14 different sets of common activities each containing between 2-10 different activities to be classified. We find that HAR accuracies varied between 68% to 100% depending on the set of activities. The average accuracy over all activity sets is 83%, which is within 13% of what could be achieved with an accelerometer *not subjected to power constraints*.

The rest of the paper is organised as follows. Power consumption of accelerometers relative to the harvestable kinetic power is explored in Section II. This section also presents the derivation of the exponential model that captures the HAR accuracy as a function of power available to the accelerometer. We present the proposed concept of using energy harvesting data for HAR in Section III followed by its performance evaluation in Section IV. Related work is reviewed in Section V before concluding the paper in Section VI.

II. ACCELEROMETER POWER CONSUMPTION FOR HAR

The purpose of this section is to study the power consumption of the accelerometer relative to the power harvested in a kinetic-powered device. We are also interested in modelling the HAR accuracy degradation under power constraints. These objectives are achieved by evaluating HAR accuracy for a given set of activities by varying the sampling rate of the accelerometer. The harvestable power for a given set of activities is obtained using known models that estimate kinetic power generation from a given accelerometer trace.

TABLE II
FEATURE SET

Feature Name	Description
Mean	The central value of a window of samples
Standard deviation	A measure the amount of variation or dispersion from the mean.
Maximum	The maximum value in a window of samples
Inter-quartile Range	The difference between the upper quartile and the lower quartile of the window of samples
Root Mean Square	The square root of the arithmetic mean of the squares of the values of the window of samples. It is a measure of the magnitude of a varying quantity.
Mean Absolute Deviation	The mean of the absolute deviations from a central point. It measures dispersion or variability in values of the window of samples.
Skewness	A measure of the asymmetry of the probability distribution of the window of samples.
Kurtosis	A measure of the "peakedness" of the probability distribution of the window of samples.
Auto-Correlation	The cross-correlation of a signal with itself. It measures the similarity between observations as a function of the time lag between them.
Dominant Frequency	The maximum spectral component of the Fourier transform of the signal.
Power Spectrum Mean	The mean of the power spectrum of the signal.
Frequency Domain Entropy	The normalized information entropy of the discrete FFT component magnitudes of the signal.

A. Recognition Accuracy vs Sampling Rate and Power

Acceleration-based HAR requires periodic measurement of acceleration of the subject whose activity is to be recognised. Typically a 3-axial accelerometer is used to measure acceleration in three dimensions while the subject performs different activities. These data are then used to train a classifier, which is used later to detect activities from a given sample of acceleration values. Generally, the more frequent the measurements, the more information is available enabling more accurate classification. The frequency of measurement is called the sampling rate of the accelerometer, which is measured in Hz or number of measurements per second.

To perform a measurement, an accelerometer must be turned on for a few ms. Because the accelerometer consumes power when it is active, it is turned off when it is not measuring. Therefore, an accelerometer is continuously turned on and off, whose frequency is dictated by the sampling rate. As such, the average power consumption of accelerometer is a linear function of the sampling rate. For example, the data sheet of an ADXL150 accelerometer [8] shows that the accelerometer consumes about 5 μW on average per Hz, which means that it would require 50 μW if a sampling rate of 10 Hz was required for a given activity set.

Using a Samsung Galaxy Nexus smartphone in the hand, we have collected accelerometer traces from five different subjects for ten basic activities. Because different combinations of activities pose different challenges for classifications, we created 14 different sets of activities from these 10 basic activities as shown in Table I. The original data was collected at 100Hz, but

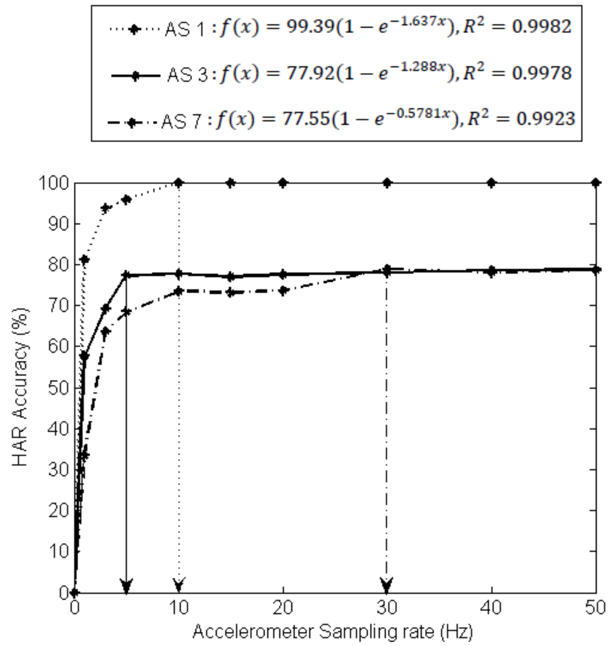


Fig. 1. HAR accuracy as a function of accelerometer rate for three different activity sets.

we later subsampled each of these traces at 1-50 Hz to study the effect of sampling rate on the activity recognition accuracy. In this study, we use K-nearest neighbour (KNN) classifier, which has been widely used by other researchers [9]–[11] due to its simplicity and effectiveness in activity classification. The KNN classifier is trained with 12 features (see table II) extracted from 5-sec windows with 50% overlapping of the accelerometer traces. Finally, for each sampling rate, we perform 10 fold-cross validation test to obtain the accuracy.

Fig. 1 shows the HAR accuracy as a function of sampling frequency of the accelerometer for three different sets, 1, 3 and 7. We make several observations. We can see that the HAR accuracy increases with increasing sampling rate, but its rate of increase continues to slow down as it approaches a limit (saturates). The characteristic of this growth in HAR accuracy is captured by the exponential function $f(x) = a(1 - e^{-\lambda x})$, where a is the limiting value of HAR accuracy and λ is a constant defining the shape or slope of the curve (curve fitting results shown in the legend). Note that different sets have different limiting values and they also reach the limiting value at different sampling rates, which we call *critical sampling rates*. For example, activity set 1 has a critical sampling rate of 10 Hz, because the accuracy does not improve any further beyond this rate, whereas the accuracy for set 7 continues to increase until 30 Hz.

A second observation is that the accuracy falls exponentially if the accelerometer is sampled below the critical sampling rate. This means that if there is not enough harvested power, then the accelerometer will be forced to operate at a lower sampling rate, which would cause exponential decrease in accuracy. This observation highlights the challenge facing the realisation of pervasive HAR using energy harvesting wearable devices. In the following section, we estimate the power that could be harvested for each activity set in Table I and compare it with the power requirements of the accelerometer.

TABLE III
AVERAGE HARVESTED POWER OF DIFFERENT ACTIVITIES

Activity	Average Harvested Power (μW)
Standing	0.063
Walking	53.50
Running	153.40
Stairs Up	44.94
Stairs Down	97.39
Vacuuming	29.94
Escalator Up	0.2198
Escalator Down	0.2522
Ramp Up	64.68
Ramp Down	56.02

B. Estimating Harvestable Kinetic Power

In the absence of commercially available kinetic energy harvesting portable devices that could be used to collect energy traces from users, we resort to mathematical estimations of kinetic energy from accelerometer traces. Specifically, we use a recently developed model by Gorlatova et al., [7] which has been shown to accurately estimate the amount of harvestable kinetic power from accelerometer data using a standard mass-spring damping system and validated using a comprehensive dataset collected from 40 participants going through unrestricted motions. Once the gravity is filtered out from the raw acceleration values, the filtered acceleration is converted to *proof mass displacement* using the Laplace domain transfer function:

$$z(t) = \mathcal{L}^{-1}\{Z(s)\} = \frac{A(s)}{s^2 + \frac{b}{m}s + \frac{k}{m}} \quad (1)$$

where m is the proof mass, k is the spring constant, b is the damping factor, $A(s)$ and $Z(s)$ denote, respectively, the Laplace transforms of $a(t) = \sqrt{a_x(t)^2 + a_y(t)^2 + a_z(t)^2}$, the overall magnitude of the acceleration, and $z(t)$, the proof mass displacement. Next, the resulted proof mass displacement, $z(t)$, is limited by the limit of the proof mass displacement, Z_L. Finally, the generated harvested power is determined by:

$$p(t) = b\dot{z}^2(t) \quad (2)$$

We used the configuration values, $m = 10^{-3}kg$, $Z_L = 10mm$, $k = 0.17$, and $b = 0.0005$, optimised in [7] for typical human activities. The entire procedure was implemented using MATLAB and SIMULINK. The outcome is a trace of kinetic power samples, which we use for further analysis.

Table III shows the average harvested power for each activity[1]. Table IV presents the average harvested power for

[1]The average powers generated by some of the considered activities are slightly lower compared to the ones reported in [7]. This is due to the different holding positions of the sensing device. In our experiment, the device was held in hand while in [7] the sensors were placed in shirt and pant pockets.

TABLE IV
SAMPLING RATES AND POWER CONSUMPTIONS OF THE ACCELEROMETER FOR DIFFERENT ACTIVITY SETS

Activity Set	Average Harvested Power (μW))	Required Accelerometer Sampling Rate (Hz)	Required Power (μW))	Percentage of Harvesting Power consumed (%)	Achievable Accelerometer Sampling (Hz)
AS 1	103.45	10	50	**48.33**	20.69
AS 2	15.00	5	25	166.6	3
AS 3	71.17	5	25	**35.13**	14.234
AS 4	0.236	5	25	10593.2	0.047
AS 5	48.97	10	50	102.10	9.79
AS 6	43.56	30	150	344.35	8.71
AS 7	13.51	30	150	1110.3	2.70
AS 8	35.70	15	75	210.08	7.14
AS 9	65.76	15	75	114.05	13.15
AS 10	69.86	10	50	**71.57**	13.97
AS 11	29.12	30	150	515.11	5.82
AS 12	43.92	30	150	341.53	8.78
AS 13	47.46	20	100	210.70	9.49
AS 14	50.04	15	75	149.88	10.01

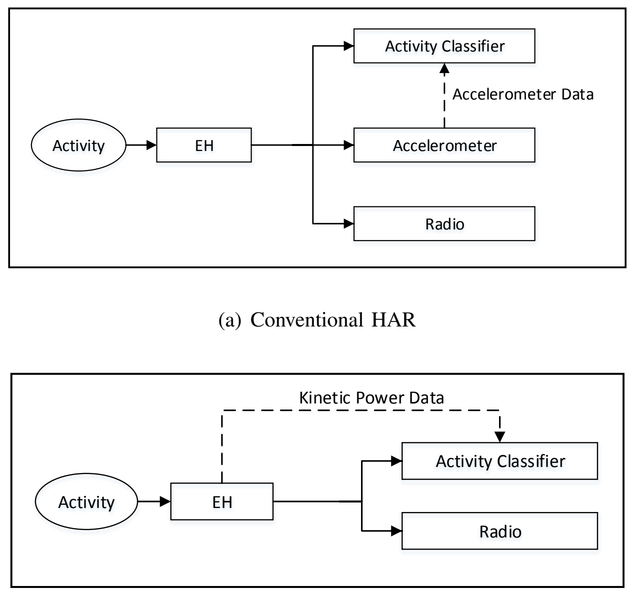
each activity set (column 2) along with the required sampling rates of the accelerometer to achieve the maximum (limiting) accuracy (column 3). Column 4 shows the power requirement of the accelerometer to achieve the maximum accuracy assuming a 5 μW power consumption per Hz on average. It means that the accelerometer can only work without power constraints as long as the harvested power (column 2) is grater than the powers in column 4. Column 5 shows the percentage of harvested power that would have been required by the accelerometer to work without power constraints.

As we can see that apart from a few activity sets (sets 1, 3, and 10), the accelerometer would require more power than could be harvested, forcing it to work under power constraints or at a reduced sampling rates as shown in the final column. Considering only the sets for which we have five or more activities to recognise, i.e., sets 10 to 14, we find from column 5 that the power requirement of the accelerometer is between 35-515% of the harvestable kinetic power. These results indicate that although accelerometers are generally considered low-power electronics, they become the bottleneck of self-powered HAR.

III. PROPOSED HAR USING HARVESTED POWER SIGNAL

Fig. 2 contrasts the proposed HAR architecture with conventional accelerometer-based HAR. In the conventional HAR, the acceleration samples are used to train a classifier which in turn is used to detect activities based on a window of acceleration samples. In contrast, no acceleration data is used in the proposed architecture. Instead, training and classification are accomplished entirely using the output signal of the kinetic energy harvester. Energy saved by not using the accelerometer can be used by other on-board units, such as the radio.

Fig. 3 compares the accelerometer signal with the estimated kinetic power signal when a subject went through a series of five activities in 35 seconds. It provides a clear visual confirmation that like the accelerometer signal, the power signal is also affected differently by different activities. Therefore, it should be possible to use kinetic power signal to achieve HAR. In the following section, we measure the discriminating ability of the kinetic power more formally using information theory and investigate the HAR accuracy that it can achieve for typical human activities.



(a) Conventional HAR

(b) Proposed HAR

Fig. 2. HAR Architectures: (a) Conventional accelerometer-based HAR and (b) Proposed HAR based on kinetic power signal

IV. PERFORMANCE EVALUATION

The main purpose of this section is to evaluate the HAR accuracy when kinetic power signal is used to classify the different activities in a given activity set. But first, we provide an information theoretic analysis to formally assess the discriminating capacity of kinetic power signal for typical human activities.

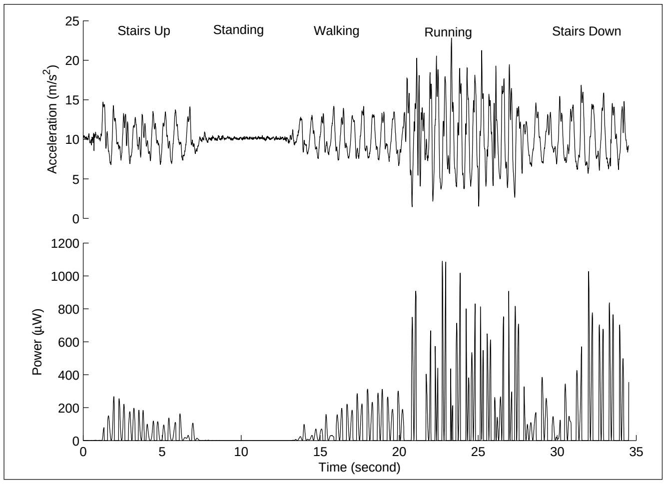


Fig. 3. The accelerometer trace (the magnitude of the three axes) and the corresponding harvested power trace for the activity sequence: stairs up-standing-walking-running-stairs down .

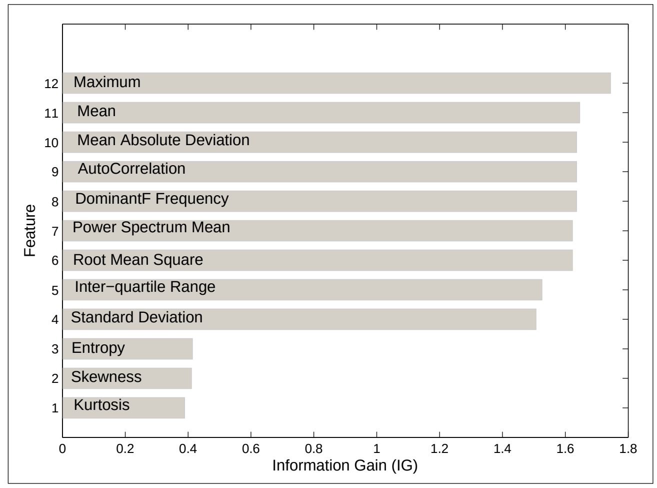


Fig. 4. Information gain of kinetic power signal of AS 14 for 12 features commonly used for HAR

A. Information Gain

Information gain (IG) is a measure that determines how useful a given feature is for discriminating between the classes (activities) to be learned [12]. The IG of feature f_i measures the expected reduction in entropy caused by partitioning the data (instances) according to this feature. The calculation of information gain is based on calculating the entropy H(S) of a set of classes S.

$$H(S) = -\sum_{i=1}^{n} p_i \log_2 p_i \tag{3}$$

where n is the number of different activity classes and p_i is the proportion of all instances belonging to the i^{th} class. The information gain is then calculated using:

$$Gain(S, f_i) = H(S) - \sum_{v \in Values(f_i)} \frac{|S_v|}{|S|} H(S_v) \tag{4}$$

where S_v is the subset of S for which feature f_i has a value v (i.e., $S_v = s \in S|Values(f_i) = v$) and $|S|$ denotes the cardinality of the set S.

A feature that cannot help with classification has a zero IG. If the kinetic power signal does not contain any useful information for activity classification, then it will be difficult to find a feature with positive IG. Next, we compute IG for a range of commonly used statistical features on the kinetic power samples. The outcome for activity set 14 is shown in Fig. 4 and the average for all sets with 5 or more activities, i.e., sets 10-14, are shown in Table V . We see that there are many features with significant IG, confirming that the kinetic power signal contains rich information that can be used to train a classifier to detect activities (see the following subsection).

An interesting observation is that the Maximum feature, i.e., the maximum power in a window of 5-sec, provides the most information gain beating the Mean feature. This is interesting

TABLE V
AVERAGE INFORMATION GAIN FOR ACTIVITY SETS 10 TO 14

Feature	Average IG
Maximum	1.5299
Mean Absolute Deviation	1.4388
Mean	1.4364
Auto-correlation	1.4364
Dominant Frequency	1.4364
Standard Deviation	1.4131
Power spectrum mean	1.4109
Root mean square	1.4109
Inter-quartile Range	1.3615
Skewness	0.4476
Frequency Domain Entropy	0.4148
Kurtosis	0.4090

because in the literature [7], it is often mentioned that the average kinetic power of different activities are different, which may give the impression that the Mean kinetic power would be the key for activity classification. In the following subsection, we will compare the accuracies that could be obtained by using different power features.

B. Classification Accuracy

In this subsection we use the same method used in Section II to obtain HAR accuracy. There are some subtle differences in how we obtain the features from the acceleration and the kinetic power traces. For the accelerometer traces, we consider both single, i.e., the overall acceleration, and 3-axial data, which means we extract 12 features for the single but 36 features for the 3-axial traces. For the kinetic power, we only have a single trace, so only 12 features are extracted. Table VI compares the accuracies of kinetic power signal based HAR when different power features are used in isolation and also when all of the 12 features are used. First, we find that the Maximum feature provides better accuracy than the Mean, as it is expected from the IG results presented in the previous subsection. Second, using multiple features together does not

TABLE VI
ACCURACIES FOR KINETIC POWER BASED HAR

Activity Set	EH-based HAR Accuracy (%)		
	Using Maximum Feature	Using Mean Feature	Using 12 Features in Table II
AS 1	96.20	93.59	98.43
AS 2	100	100.00	100
AS 3	90.93	61.53	65.97
AS 4	82.67	60.00	63.21
AS 5	86.88	63.24	80.00
AS 6	81.84	60.26	67.35
AS 7	88.19	74.50	56.46
AS 8	86.21	61.36	61.07
AS 9	68.40	30.96	31.84
AS 10	84.06	55.53	79.73
AS 11	79.52	53.98	46.53
AS 12	73.91	41.80	41.39
AS 13	78.57	51.83	60.93
AS 14	72.00	41.51	49.00
Average	83.53	60.72	64.42

TABLE VII
COMPARISON OF ACCURACIES FOR ACCELEROMETER-BASED AND KINETIC POWER BASED HAR

Activity Set	HAR Accuracy (%)		
	Power	Accelerometer (Overall)	Accelerometer (3-axial)
AS 1	96.20	100	100
AS 2	100	100	100
AS 3	90.93	80	93.20
AS 4	82.67	62.14	100
AS 5	86.88	76.24	96.06
AS 6	81.84	64.47	95.86
AS 7	88.19	73.04	99.90
AS 8	86.21	63.07	96.50
AS 9	68.40	55.78	92.20
AS 10	84.06	81.21	94.64
AS 11	79.52	57.19	96.96
AS 12	73.91	51.71	94.25
AS 13	78.57	72.88	98.16
AS 14	72	64	95.45
Average	83.53	71.55	96.66

Power: using a single feature (max).
Accelerometer (Overall): using 12 Features (see Table II)
Accelerometer (3-axial): using 36 features (12 features (see Table II) from each axis)

provide any accuracy gain. This is a surprising result because it is well known that for accelerometer-based HAR, many features are to be used in combination to achieve high accuracy and in fact for our data set we have also found the same. It is also known that the use of the individual acceleration components in x, y, and z directions, albeit more complicated, improves accuracy significantly. We therefore evaluate two sets of accuracies for the accelerometer-based HAR, one with the overall acceleration and the other applying the 12 features on each of the three components.

HAR accuracies for accelerometer are shown in Table VII along with those obtained for the kinetic power based HAR with the Maximum feature used for classification. We see that kinetic power based HAR performs better than accelerometer-based HAR when only the overall acceleration is used and remains with 13% on average when individual acceleration components are considered. These results are encouraging because Table VII presents the best case results for the accelerometer, i..e, when the accelerometer is *not power constrained*. As shown in Table IV, the accelerometers in a self-powered device may often have to operate under power constraints due to lack of enough kinetic power.

Next, we take a closer look into the classification results to identify the source of lower accuracy for the kinetic power based HAR. We examine the sets that achieved the three lowest accuracies in Table VII. These are sets 9 (68.40%), 12 (73.91%), and 14 (72%). We find that these are the sets that contain the activities going up the ramp (RU) and going down the ramp (RD). In our experiments we collected data when subjects walked over ramps with small slopes with angles ranging between 10°-30°. For such low-angle ramps, they are very similar to the walking (on the surface) activity.

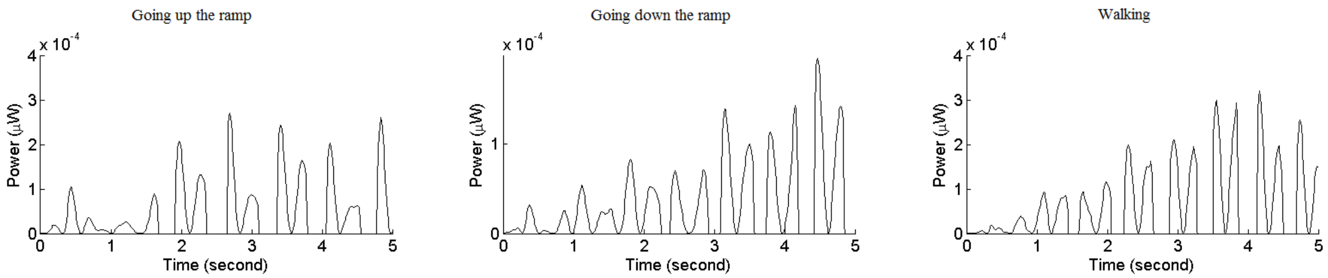
A 3-axial accelerometer is fundamentally advantaged in separating RU, RD, walking, or any other very similar human activities due to the multi-dimensional measurement of the motion, hence achieving very high accuracy for all activity sets in our experiments including sets 9, 12, and 14. By measuring acceleration in three dimensions, new discriminating opportunities arise, which is not possible with a single-dimensional power measurement.

The advantage of a 3-axial accelerometer against the single-dimensional harvested power signal is illustrated in Figure 5 by plotting the samples from three activities, RU, RD, and walking. We see that the signals of these three activities look very similar whether acceleration or power samples are used. Even when each axis is considered separately, they look very similar. However, when we consider the acceleration signals in y and z directions together, we find two clear discriminating patterns between the three activities.

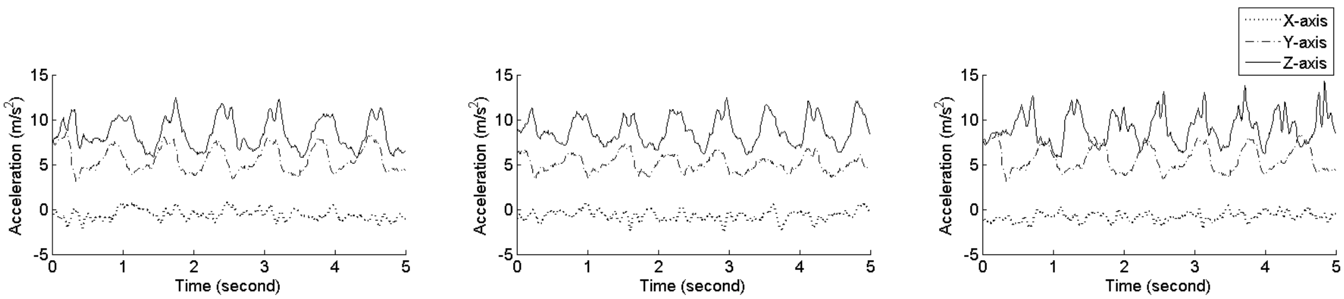
The y and z acceleration signals closely follow the shape of a sinusoidal wave due to the periodic motion of walking and the tilting of the smartphone in the hand, but they have a phase shift relative to each other. The relative shift for walking is the maximum (close to 180°) and minimum for RU. We also see that the offsets between these two signals are different for different activities. During training, a classifier quickly learns such important differences, which allows it to accurately distinguish the activities from each other. However, when a single-dimensional power signal is used, the classifier does not have access to such information, leading to confusions. Whether we can extract multi-dimensional motion information from the harvested power signal remains an open question.

V. Related Work

Our work is related to energy-efficient HAR because we reduce the power consumption of the HAR process in a self-powered device by not using the accelerometer. Reducing HAR power consumption is also important in battery-powered devices, which motivated many researchers to look for new ways to reduce battery consumption of HAR. We can categorise them in three basic approaches, reducing the sampling rate of the accelerometer, reducing the classification



(a) Kinetic power signal for RU, RD, and W. Classification Accuracy=74.10%



(b) 3-axial accelerometer signal for RU, RD, and W. Classification Accuracy=94.31%

Fig. 5. A comparison of kinetic power signal (a) with 3-axial accelerometer signal (b)

complexity, and reducing the number of accelerometers placed on the human body.

Reducing the sampling rate of the accelerometer is a widely used method to save the system energy. However, this reduction is always achieved at the expense of the recognition accuracy. Therefore, improving the trade-off between sensor energy consumption and accuracy of HAR has been the focus of many research studies. The authors in [13], [14] used a single activity monitoring technique to adjust the sampling rate and classification set of features to a choice that is optimal for this activity and hence to reduce system energy overheads without violating user accuracy requirements. In A3R [13], they used sets of two classification features: Time domain and frequency domain. However, AdSense [14] explores the feature set space by Genetic Programming techniques and finds the optimal feature set that effectively reduces both the classification and the sampling rates.

When a large number of activities are to be classified, the classifier model can be very complex. Higher complexity leads to higher CPU usage and battery usage. Therefore, one way to reduce HAR battery consumption would be to reduce classifier complexity. The authors in [15] provided an adaptive HAR which, instead of using a single complex classifier based on a large set of features, employs multiple simple classifiers each trained to classify only a subset of the activities using a small number of features. Then at runtime, depending on the current context, the system switches to the right classifier as the given set of activities to recognise changes with the context.

An alternative approach to extend the battery life time of HAR systems has been to reduce the number of accelerometers to be used [16]. This approach works when the data collected by body sensors are transmitted to a base station (PC or a smartphone) to be analysed and classified. Such studies tried to exploit the redundant and unreliable accelrometers in order to reduce the communication cost between the sensor nodes and the base station, and hence extend the life time of the monitoring system.

While it is possible to extend the battery life time of HAR through the previously mentioned ways, battery-powered sensors cannot provide sustained HAR without the need for battery replacement. Recently, a new research trend in energy harvesting [6] has gained the attention of the research community. Energy harvesting 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. Many energy harvesting models have been recently developed [7], [17]–[20]. The main focus of these models is to optimise the parameters of the harvester to maximise the output harvested power. These recent advances in energy harvesting devices have motivated us to consider the concept of self-powered pervasive HAR. The novelty of our work is in the use of the harvested power to classify the activities that generate the power, which to our knowledge has not been addressed before.

VI. Conclusion and Future Work

Although accelerometers are considered low-power electronics in general, our study has revealed that the accelerometer becomes the *power bottleneck* in realising self-powered

HAR. We have shown that the kinetic power signal itself contains signatures for the human activities that are to be classified and recognised. A standard KNN classifier can detect many activities with very high accuracies using only the kinetic power signal and not using the accelerometer at all. Since the kinetic power is readily available from the energy harvesting circuit, HAR based on kinetic power signal conserves a significant fraction of the scarce harvested power that would have been consumed by the accelerometer. Thus, the proposed use of energy harvesting signal for HAR can be considered a key enabler for realising the vision of pervasive self powered human activity recognition.

This paper is the first detailed study of recognising human activity directly from the energy harvesting signal. Although we have shown that good HAR accuracies are possible for many common activities, we have also found that the kinetic power signal cannot distinguish very similar activities, such as walking on a flat surface and walking on a ramp, with high accuracy. For such cases, an accelerometer has a clear advantage with its 3-axial measurement capability, which provides more detailed (multi-dimensional) motion information of these activities leading to high recognition accuracy. An interesting future work would be to investigate the possibility of extracting multi-dimensional (multi-axial) motion information from the kinetic power signal. One possibility could be to consider energy harvesting methods capable of harvesting kinetic power separately from each components of human motion. This would yield three separate power signals, one for each axis, enabling more advanced training of the classifier similar to a HAR based on a 3-axial accelerometer.

In this work, we used a mathematical model to estimate the harvestable kinetic power from accelerometer traces because portable kinetic energy harvesting devices are currently not available. A natural continuation of the current work would be to build a portable kinetic energy harvester and validate the current results with real harvestable kinetic power data. The portable device could also be used to further validate existing mathematical models that estimate kinetic power data from human motion data.

We have analysed HAR accuracy when the accelerometer and the energy harvester are used in a *mutually exclusive* manner. A logical future direction is to consider a hybrid system where a 3-axial accelerometer is sampled at a low sampling rate (low power consumption), but the classifier is trained using both the acceleration samples as well as the kinetic power signal, thus enabling very accurate HAR with low power consumption. The hybrid system combines the advantages of both signals to realise a more flexible HAR with a goal to achieve a better accuracy-power tradeoff than the one possible with the mutually exclusive method.

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