

Energy harvesting wearables can tell which train route you have taken

Marzieh Jalal Abadi^{*†}, Sara Khalifa^{*†}, Salil S. Kanhere^{*†} and Mahbub Hassan^{*†}

^{*}School of Computer Science and Engineering, University of New South Wales, Sydney, NSW 2052, Australia

Email: M.jalalabadi, s.khalifa, Mahbub.Hassan, salil.kanhere@unsw.edu.au

[†]National ICT Australia, Locked Bag 9013, Alexandria, NSW 1435, Australia

Email: Marzieh.abadi, Sara.Khalifa, salil.kanhere, Mahbub.Hassan@nicta.com.au

Abstract—Location privacy is an important concern for the users of mobile devices and this private information can be identified using the embedded motion sensors in these devices. This paper highlights the privacy leakage resulting from unrestricted access to seemingly innocuous generated patterns of vibration energy harvesting (VEH) circuits in mobile devices. We investigate that by monitoring the VEH generated patterns, a malware application can infer which train route the passenger has taken, violating her privacy. We collected real-world motion data for 4 distinct train routes in the Sydney metropolitan area. Our results show that the passenger's train route can be inferred with an average accuracy of 97.2% for a journey of 7 stations, confirming the rich contextual information embedded in VEH data and to light the associated privacy risks in releasing this data.

I. INTRODUCTION

Today's mobile devices (smartphones, smart watches, fitness bands, etc.) are equipped with a range of embedded sensors such as GPS, accelerometer, gyroscope, etc. These sensors can be used to infer contextual information such as location, activity, health, etc. and thus enable a range of applications [1]–[4]. However, unrestricted access to these sensor data traces may seriously compromise the privacy of users. Recent research has demonstrated that malicious applications with access to data collected from GPS [1], accelerometer [2] and even device battery profile [5] can accurately track the location of users as they move about in urban spaces.

In recent years, vibration energy harvesting (VEH) has emerged as a viable option for mobile devices to address the inadequacy of current battery technology. VEH harnesses power from human motions [6] and ambient sources [7]. Recent research [8] has demonstrated that VEH hardware instrumented in a mobile device can also serve as a motion sensor. This is due to the fact that different ambient vibrations and human motions produce a unique pattern of energy in the VEH circuit. Indeed, several research studies have demonstrated that the generated patterns of VEH hardware can be used directly to infer human activity [9], step counts [10], calorie expenditure [11], and transportation modes [12].

In this paper we reveal that the power generations of VEH contain rich information which can be used to infer the location of a user and thus compromise her privacy. We consider a scenario where a user has unknowingly installed a malicious application on their mobile device and granted

it permission to access the VEH patterns. For the sake of tractability, we demonstrate the attack in a scenario where the user is traveling on an urban train service with her mobile device and show that it is possible to precisely identify the train route (i.e. train line, start and end station). Train tracks create a vibration pattern that is distinct from other vehicles. A typical train ride consists of episodes of continuous motion interspersed with brief stoppages at train stations. Our key hypothesis is that the train tracks between any two consecutive stations (referred to as a segment) create a unique vibration characteristics that are reflected in the VEH data. We exploit this unique and repeatable pattern to identify individual segments. A typical train journey consists of several successive segments. We leverage this sequential nature of a trip to correct the occasional segment misclassifications and ultimately infer the entire trip.

To demonstrate the attack we collected real-world motion data for 4 distinct train routes in the Sydney metropolitan area. Our data set includes motion data from 36 trips and includes 360 segments from 40 train stations.

The specific contributions of the paper are as follows:

- 1) To the best of our knowledge, this paper is the first work to highlight the privacy leakage resulting from unrestricted access to seemingly innocuous VEH data in mobile devices.
- 2) We use a thresholding-based segmentation algorithm to extract the individual segments. The results show that we can extract about 82% of the segments by less than 10s error.
- 3) We employ different machine learning classifiers to recognise the individual segments. We used correlation feature selection algorithm to select the best feature set for our dataset. Our results show that 60.9% accuracy can be achieved using *ensemble* classifier for correctly identifying individual segments.
- 4) Exploiting the sequential properties of a train ride, we can achieve a trip inference accuracy of 97.2% for a journey of 7 stations. Our results are comparable to those reported in [13] for accelerometer data and confirm the rich contextual information embedded in VEH data. This raises concern that access to VEH data results in privacy risk of the users.

In the rest of the paper, we first discuss the related work in Section II. The proposed attack including the three components are explained in the details in Section III. Finally we evaluate the method in Section IV followed by the conclusion of the paper in Section V.

II. RELATED WORK

Motion sensors such as accelerometers have been used in a wide range of applications and the findings show that they contains rich information to identify private information of users. Several prior works show that accelerometer is exploited as a low power sensor for activity recognition [14] and health monitoring [4]. Mannini et al. found that a single triaxial accelerometer worn on the wrist is sufficient to classify 4 broad activity classes with accuracy of 93.5% and it is feasible to detect some activities for real-time implementation [14]. Lohne-Seiler et al. utilised accelerometer to assess physical activity (PA) and link it to the prevention of disease in older adults aged 65-85 years [4]. A questionnaire was used to register self-reported health and the results show that the overall PA levels are associated with self-reported health. The recent study in [15] exploited gyroscope and accelerometer to identify the travelling route of the users. Nawaz et al. presents a passive route sensing framework that reads gyroscope and accelerometer measurements and recognises the travelled route using dynamic time warping algorithm. The results show that the performance of the route mining is similar to GPS and in addition it is more energy efficient. The capabilities of motion sensors are not restricted to context recognition of users but also the environment. For example Yi et al. demonstrated how to monitor bridges health by extracting their displacements induced by ambient effects [16]. Experimental results showed that the integration of GPS and accelerometer can be used as a reliable tool to characterise the dynamic behaviour of large structures such as suspension bridges undergoing environmental loads.

The new generations of mobile devices and wearables are expected to be equipped with new VEH circuits to ease the dependence on batteries by generating electrical energy from the device motion and ambient vibrations. In addition to the VEH capability of power generation, recent studies have shown that the generated patterns VEH circuits can be used as a new source of information to capture the device motion and ambient vibrations. The authors in [9] have used VEH as a motion sensor to classify human activities. Their results showed that VEH can achieve an average accuracy of 83% to recognise 14 different sets of activities. In addition to activity classification, VEH patterns have been proven to be informative for calorie expenditure estimation [11]. Lan et al. conducted an experimental study with data collected from 10 different subjects and for two different activities, walking and running. Their results showed that the calorie estimations obtained from VEH is very close to those obtained from a 3-axial accelerometer for most subjects. There have also been study on using VEH to detect the transportation mode of the users [12] and the initial demonstration showed that

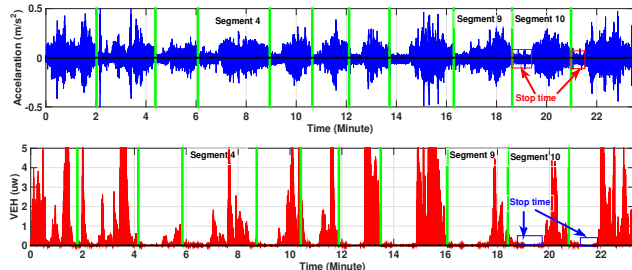


Fig. 1. The total acceleration, after removing gravity, the corresponding displacement and VEH for trace 9 in R_4

VEH achieves an average accuracy of 98.84% in determining whether the user is traveling by pedestrian or motorised modes. More over, an overall accuracy over 85% is achieved if a fine-grained classification is employed for three different motorised modes (car, bus, and train).

In this paper, we investigate that by monitoring the VEH generated patterns, a malware application can infer which train route the passenger has taken, violating her privacy. To the best of our knowledge, this study is the first work to highlight the privacy leakage resulting from unrestricted access to seemingly innocuous VEH data in mobile devices.

III. SYSTEM OVERVIEW

Here we present how our proposed attack uses VEH patterns to infer the user's train route. Our proposed system is composed of 3 main components: *segment extraction*, *segment classification*, and *trip inferring*. Segment extraction is mainly for extracting the intervals between every two consecutive stations from the VEH data trace (we refer to these intervals as segments). Then, the extracted segments are recognised using the segment classification component. Finally, the user's train route is inferred through the recognition of a sequence of segments using the trip inferring component. The details of those three components are discussed in this section.

Since, energy harvesting-based wearables are in their early stage of development, we employ the well-known mass-spring damping model to estimate VEH power patterns from accelerometer traces [6].

In this section, we first present how VEH power patterns are estimated from accelerometer traces, followed by the details of each component of our system.

A. VEH Model

To investigate the proposed privacy leakage of VEH data, we used a mathematical model which has been shown to accurately estimate VEH power patterns from accelerometer data using a standard mass-spring damping system [6]. This model has been validated using a comprehensive dataset including 40 participants going through unrestricted motions and the generated VEH power traces perfectly represent the motion data traces. The input of the model is raw accelerometer measurements in direction $\{x, y, z\}$ at time t , here denoted as $\{\hat{a}_x(t), \hat{a}_y(t), \hat{a}_z(t)\}$. The VEH power trace

TABLE I
FEATURE SELECTION, CLASSIFICATION FOR SEGMENT RECOGNITION

Statistical Features	Movement Features		
	Time Domain		Frequency Domain
Length	Median	Skewness	2 Dominant frequencies
Mean	Range	Kurtosis	Dominant frequency ratio
Maximum (MAX)	Minimum (MIN)	Absolute area	Mean of power spectrum
Standard deviation	Root mean square	Mean of peaks	Total energy of spectrum
Mean of absolute value	Mean of absolute deviation	Mean of distance between peaks	MIN of power spectrum
Number of samples higher than threshold 1, 2, 3	Number of datapoint cross mean	MAX distance between peaks	MAX of power spectrum
Spectral entropy	Coefficient variation	MAX of peaks	
Spectrum peak position	Interquartile range	Peak to peak	
6 First FFT components (1 – 6 Hz)	1 st and 3 rd Quartile	Peak to peak difference	

is generated from the overall magnitude of the acceleration $\hat{a}(t) = \sqrt{\hat{a}_x(t)^2 + \hat{a}_y(t)^2 + \hat{a}_z(t)^2}$. Since the earth gravity is included in the overall magnitude of the acceleration, first we removed this constant value from $\hat{a}(t)$. Then, the filtered acceleration, $a(t)$, is converted to *proof mass displacement* using the Laplace domain transfer function:

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

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 $a(t)$ and $z(t)$, the proof mass displacement. Next, the resulted proof mass displacement, $z(t)$, is restricted by the limit of the proof mass displacement, Z_L . Finally, the generated VEH power trace, $p(t)$, is calculated from:

$$p(t) = bz^2(t) \quad (2)$$

We used the configuration values, $m = 10^{-3}$ kg, $Z_L = 10$ mm, used in [6] to be consistent with small wearable devices restrictions. As it is proposed in [6], we exploited accelerometer measurements to identify k and b . The parameters are set to $k = 0.058$ kg.s² and $b = 2.6 \times 10^{-4}$ kg/s to optimise the harvested power for given vibration properties. The entire procedure was implemented using MATLAB and SIMULINK [17].

For each trace of accelerometer data, we used the model to identify its corresponding VEH power trace $p(t)$; we call it VEH data hereafter.

B. Segment Extraction

The first component of our proposed attack is extracting the segments between every two consecutive stations. Segment extraction is a widely used method in speech recognition to determine the boundaries of acoustic units such as words, syllables and silence [18]. In this paper we exploit conventional thresholding-based algorithm which is used in speech recognition to extract the segments of a trace. Thresholding-based segmentation is simple and computationally efficient but its performance degrades in noisy environment. To address this limitation, adaptive thresholds which are subjected to the constraints of the experimental data are used to extract the segments [19]. In our study, the main idea of the segment

extraction component relies on the fact that a typical train journey consists of several successive segments separated by short stop intervals. During the stop interval, the train is stationary and it does not have acceleration in any direction; therefore the overall magnitude of acceleration, $a(t)$, and the corresponding VEH power traces have negligible variations. Figure 1 shows the overall acceleration $a(t)$ and its corresponding VEH for one of our experiments. In this experiment, the accelerometer data was collected from a journey composed of 11 segments. During the collection, we recorded the arrival time of the train at all stations to use them as true segments of the trace. We show these true segments with green lines in Figure 1. We can see that there are 11 segments separated by short stop time intervals. The amplitudes of the stop time intervals are much smaller than those of the segment intervals. Clearly these periodic short time intervals are well matched with the green line (arrival time at the stations) and determine the stop time.

To exploit thresholding-based approach, we apply a sliding temporal window from the first data point of the trace and calculate the percentage of the data point below a pre-defined threshold. We denote the window length by L_w that refers to the shortest stop time for a train. To select a universal minimum value for the stop time of the train, we chose $L_w = 10$ s. BY analysing our dataset, we found that the values of accelerometer measurements in stop time are often lower than 0.045 m/s², therefore we chose the threshold as $\lambda_1 = 0.045$ and considered the window as the *stop time* if over 93% of the samples within the window are lower than λ_1 . The value of percentage, 93%, is determined by examining different values to ensure most potential segments are extracted. The window is moved one by one for all the samples of the trace until all the stop times are found.

The instantaneous values of data are noisy due to temporary and occasional moves, therefore the algorithm might not detect all the segments using one definite value of λ_1 . To address this issue, we need to further check the extracted segments. We utilise a new parameter of L_{max} that represents the maximum length of the segment for traces. Once the trace is searched for λ_1 , we calculate the distance between all consequent segments; if the distance is higher than L_{max} , it means that some segments are missed. Therefore the algorithm increases the threshold for further search within the segments until the distance between any two adjacent segments does not exceed

L_{max} . Again we have tested different values of the thresholds for our dataset and the results show that the threshold value of $\lambda_2 = 0.052$ and $\lambda_3 = 0.064$ are precious enough to ensure all segments are extracted.

C. Segment Classification

In this section we exploit classification to recognise the individual segments. Due to random and short term movements derived from hand shakings and user interactions, the motion data are noisy and fluctuate over time. To eliminate the interference of such noises, we first employed the time window of w_s with no overlapping to the instantaneous values of each segment to smooth the raw data. Each window is estimated with the average of data points within w_s . In order to preserve the patterns of the segments, different size of w_s were examined and temporal window of $25s$ is selected. The smoothed segments are utilised for classification. Note that for brevity, we will drop the time index t from now onward.

1) *Class Definition*: As we mentioned earlier, each segment corresponds to a station interval. In our data campaign, we collected the data from North shore and Western lines of Sydney train transport that cover 9 and 11 segments respectively. The map of both lines is shown in Figure 2. Considering that a passenger may travel in 2 rail directions of a line, there are 40 classes in total for our dataset. We used this information to label all the segments; for instance the segments that represent Central station to Town Hall station are labeled as ‘a’.

2) *Feature Selection*: The potential features used for classification are categorised in 3 sets and we have summarised them in Table I. These features are extracted from the VEH data of each segment and used for classification .

- **Statistical Features**: We used 16 statistical features in both frequency and time domains and computed them for each segment. These features are able to effectively capture the general patterns of the train movements.
- **Movement Features**: In addition to statistical features, we used 26 features that present some motion and energy characteristics of the signal.
- **Peak Features**: The statistical and movement features represents the overall changes in the motion patterns but they do not represent any details about the geographical and local environments such as the turns or elevation of the routes. These local changes are reflected as sharp peaks and valleys in the motion data. We extracted the top 3 peaks of the data for each segment and used them as the peak features set. To identify one distinct peak for each local change, we first applied a temporal window size of $5s$, without overlapping, to the VEH data of the segment. Then we found the maximum values for each window and ranked them in a descending order. Three top ranking peaks were selected for window of $5s$. To avoid errors in peaks selection, we increased the size of the temporal window and repeated the process for several window sizes. Finally, we chose 3 peaks that won in most of the window sizes.

TABLE II
DATA COLLECTION DETAILS, SYDNEY TRAIN NETWORK

Line	Departure	Arrival	Route	Number of traces
North Shore	Central	Chatswood	R_1	10
	Chatswood	Central	R_2	8
West	Central	Strathfield	R_3	9
	Strathfield	Central	R_4	9

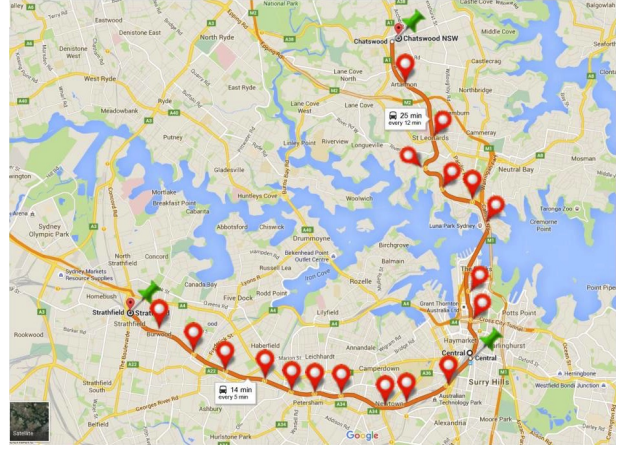


Fig. 2. Map of the Train Line in Our Experiments

3) *Classification Performance*: Each segment is represented with an array of 45 features. In order to create VEH dataset, we appended the VEH arrays of features and their corresponding classes for all segments. Multiple classifiers have been tested and the highest accuracy is achieved from the ensemble classifier [20] where random forest decision tree and AdaBoost Naïve Bayesian are its base classifiers.

The output of classifier could be presented as a single probability or in the form of confusion matrix. The former returns the average probability that all segments are correctly recognised and the latter represents the probabilities that a segment is detected as the other segments. Despite ensemble classifier achieves the best average accuracy comparing to the other classifiers, the confusion matrix shows that the recognition accuracy for some segments is still low. To compensate the low accuracy of segment recognition, we exploited the sequential property of the stations in a trip and used the confusion matrix as the output of classifier for our proposed trip inferring.

D. Trip Inferring

By now, we can recognise the individual segments of a trace and we will further explain how to figure the trip in this subsection. Assuming trip i is composed of n segments and using the sequential property of the trip, initially we created the sample space of the trip length n as S^n . Obviously the size of S^n is limited but depends on the number of segments in the route. For instance if m stations belong to a route, the sample space for trip length of n is $S^n = \{1 \rightleftharpoons n, 2 \rightleftharpoons n+1, \dots, m-n+1 \rightleftharpoons m\}$ and it consists of

$2 \times (m - n + 1)$ members. To infer trip i from its sample space, we exhaustively considered each element of j in S and introduced a new parameter of p_{tot}^{ij} for it. To compute p_{tot}^{ij} , first we identified the probabilities that each segment of trip i is mapped to the corresponding one in trip j . These probabilities are identified from confusion matrix of segment recognition. Then we obtain the sum of the probabilities; the result is p_{tot}^{ij} . Finally we chose the member in S with the highest p_{tot} as the inferred trip. This approach is promising because we considered all results for final inferring.

IV. SYSTEM EVALUATION

In this section, we examine the performance of our proposed attack on real data. The details of the experimental data are described in Section IV-A. We have noticed that the performance of individual components affect on the accuracy of trip inferring; therefore we present the evaluation of the components in isolation in Sections IV-B and IV-C followed with the performance of the combined components in Section IV-D.

A. Data Collection

In order to ensure the performance of the proposed attack, we collected the data from 2 different lines of Sydney train transport with distinct geographical features: *North shore line* and *Western line*. The map of both lines and their stations are shown in Figure 2. We collected 36 traces in total and the details are summarised in Table II. For North shore (Western) line, the trips start from Central station and end at Chatswood (Strathfield) station or reverses; therefore 2 routes are possible to travel for a line. We show them by R_1, R_2, R_3 and R_4 in Table II. There are 9 and 11 segments for North shore and Western lines respectively that results in 40 distinct segments in total for our dataset.

For each trace, one participant traveled by train over a route while using an Android smartphone, Samsung Galaxy SIII, and recorded the acceleration data with the sampling frequency of 100Hz. For all experiments, the train stopped at all stations. Moreover, to insure diversity in environmental conditions, the user travelled on old and new trains, at different days (weekday/weekend) and time (peak/off-peak) while sitting at different seats at upper or lower deck. The final dataset is collected from 40 distinct stations and covers 360 station intervals in total.

B. Evaluation of Segment Extraction

In order to employ the proposed algorithm for segment extraction, we chose $L_w = 10s$ and the thresholds as $\lambda_1 = 0.045$, $\lambda_2 = 0.052$ and $\lambda_3 = 0.064$. Apparently, the values of L_{max} depend on the train network and they are more than 210s in our experiments, therefore we chose $L_{max} = 210s$ for our dataset. Despite we select the parameters such that to maximise the segmenting precision, some errors still exist due to the use of one set of parameters for all traces; therefore it is necessary to evaluate the accuracy of segment extraction for all traces. We exploit Edit Distance [21] to measure the

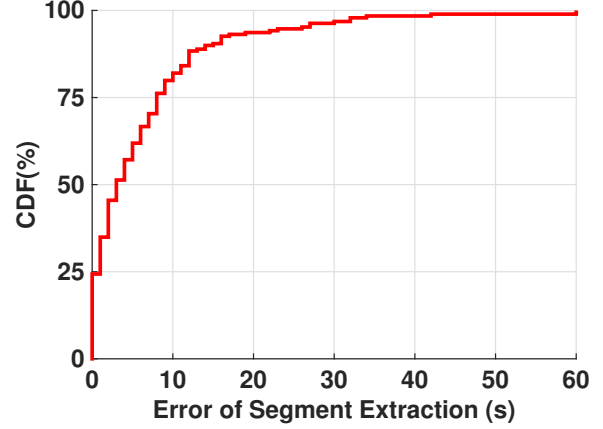


Fig. 3. CDF of error in segment extraction for accelerometer data.

TABLE III
COMPARISON OF AVERAGE ACCURACY FOR DIFFERENT CLASSIFIERS(%)

Ensemble	Logistic	Supported Vector Machine	Decision Tree	Naïve Bayes
55.5	49.1	49.6	40.2	53.1

TABLE IV
COMPARISON OF AVERAGE ACCURACY OF ENSEMBLE CLASSIFIER FOR DIFFERENT FEATURE SETS(%)

Features	VEH dataset
Statistical+Peak features(19)	53.3
All sets of features (45)	55.5
Selected features using CFS	60.9

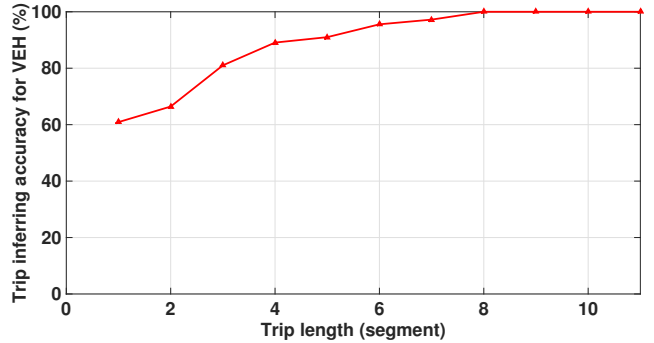


Fig. 4. Average accuracy of trip inferring for VEH

dissimilarity between true segment and extracted one and the result is the error of segment extraction in *second*. Figure 3 shows the CDF of the segment extraction. According to the figure, about 82% of the segments are extracted by less than 10s error. It means that the data may lose 10s of the segment from the beginning, end or both sides.

C. Evaluation of Segment Classification

In this section we investigate the accuracy of segment classification. We have used k -fold cross validation technique for evaluation. The Weka [22] machine learning software is used for our performance analysis. To verify the performance

of different classifiers, we present the accuracy of classification in Table III. Ensemble classifier that combines random forest decision tree and AdaBoost Naïve Bayesian is the selected classifier because it achieves highest accuracy.

To investigate the effect of different feature sets on the performance of classification, in Table IV we compare the average accuracy for different sets of features when ensemble classifier is employed. The data in the first and second row show the average accuracy of classification for different sets of features; the former used statistical and peak features and the latter exploited all 3 sets of features to create datasets. As we explained in Section III-C, there are 45 features for VEH data. To decrease the number of features, we employed Correlation Feature Selection [23] (CFS) technique to identify the most informative features and utilise them for our datasets. The average accuracy achieved from the selected features is shown in the third row. We observe that the average accuracy of classification improves to 60.9% if we use the selected features.

D. Trace Inferring

In order to evaluate the performance of the proposed trip inferring, we considered multiple trip lengths for all routes. Cross validation is also used for evaluating each trace independently. The average accuracy of the trip inferring is shown in Figure 4. Apparently the average accuracy is minimum for trip length of 1; this value is equal to the average accuracy of segment recognition (60.9%). However the average accuracy improves to 89% and 97.2% for VEH data if the user takes the train for 4 and 7 segments respectively. The accuracy of trip inferring reaches to 100% for trip length of 8. This is due to the fact that for larger trip length, the trip contains more segments and information therefore it can be inferred more accurately.

V. CONCLUSION AND FUTURE WORK

In this paper we highlight the privacy leakage resulting from unrestricted access to the generated patterns of VEH circuits in future mobile devices and wearables. We demonstrate that by monitoring VEH patterns, the passenger's trip can be inferred by identifying the station intervals (segments) of the route and exploiting the sequential property of the train ride. Using real-world motion data for 4 distinct train routes in the Sydney metropolitan area, we show that the passenger's train route can be inferred with an average accuracy of 97.2% for a journey of 7 stations, confirming the privacy risks in releasing such data. We suggest VEH data should be made privacy sensitive by restricting the access to this data. In our future work we will address how this privacy leakage can be remedied.

REFERENCES

- [1] A. Thiagarajan, J. Biagioni, T. Gerlich, and J. Eriksson, "Cooperative transit tracking using smart-phones," in *Proceedings of the 8th ACM Conference on Embedded Networked Sensor Systems*. ACM, 2010, pp. 85–98.
- [2] Y. Zheng, Y. Chen, Q. Li, X. Xie, and W.-Y. Ma, "Understanding transportation modes based on gps data for web applications," *ACM Transactions on the Web (TWEB)*, vol. 4, no. 1, p. 1, 2010.
- [3] T. Y.-H. Chen, A. Sivaraman, S. Das, L. Ravindranath, and H. Balakrishnan, "Designing a context-sensitive context detection service for mobile devices," 2015.
- [4] H. Lohne-Seiler, B. H. Hansen, E. Kolle, and S. A. Anderssen, "Accelerometer-determined physical activity and self-reported health in a population of older adults (65–85 years): a cross-sectional study," *BMC Public Health*, vol. 14, no. 1, p. 1, 2014.
- [5] Y. Michalevsky, A. Schulman, G. A. Veerapandian, D. Boneh, and G. Nakibly, "Powerspy: Location tracking using mobile device power analysis," in *24th USENIX Security Symposium (USENIX Security 15)*, 2015, pp. 785–800.
- [6] M. Gorlatova, J. Sarik, G. Grebla, M. Cong, I. Kymissis, and G. Zussman, "Movers and shakers: Kinetic energy harvesting for the internet of things," *ACM SIGMETRICS Performance Evaluation Review*, vol. 42, no. 1, pp. 407–419, 2014.
- [7] M. F. B. A. Rahman and S. L. Kok, "Investigation of useful ambient vibration sources for the application of energy harvesting," in *Research and Development (SCOREd), 2011 IEEE Student Conference on*, December 2011.
- [8] S. Khalifa, M. Hassan, A. Seneviratne, and S. K. Das, "Energy-harvesting wearables for activity-aware services," *IEEE Internet Computing*, vol. 19, no. 5, pp. 8–16, Sept.-Oct. 2015.
- [9] S. Khalifa, M. Hassan, and A. Seneviratne, "Pervasive self-powered human activity recognition without the accelerometer," in *Pervasive Computing and Communications (PerCom), 2015 IEEE International Conference on*. IEEE, 2015, pp. 79–86.
- [10] S. Khalifa, M. Hassan, and A. Seneviratne, "Step detection from power generation pattern in energy-harvesting wearable devices," in *2015 IEEE International Conference on Data Science and Data Intensive Systems*, December 2015.
- [11] G. Lan, S. Khalifa, M. Hassan, and W. Hu, "Estimating calorie expenditure from output voltage of piezoelectric energy harvester-an experimental feasibility study," in *Proceedings of the 10th EAI International Conference on Body Area Networks (BodyNets)*, 2015.
- [12] G. Lan, W. Xu, S. Khalifa, M. Hassan, and W. Hu, "Transportation mode detection using kinetic energy harvesting wearables," in *Pervasive Computing and Communications, 2016 IEEE International Conference on*. IEEE, 2016.
- [13] J. Hua, Z. Shen, and S. Zhong, "We can track you if you take the metro: Tracking metro riders using accelerometers on smartphones," *arXiv preprint arXiv:1505.05958*, 2015.
- [14] A. Mannini, S. S. Intille, M. Rosenberger, A. M. Sabatini, and W. Haskell, "Activity recognition using a single accelerometer placed at the wrist or ankle," *Medicine and science in sports and exercise*, vol. 45, no. 11, p. 2193, 2013.
- [15] S. Nawaz and C. Mascolo, "Mining users' significant driving routes with low-power sensors," in *Proceedings of the 12th ACM Conference on Embedded Network Sensor Systems*. ACM, 2014, pp. 236–250.
- [16] T.-H. Yi, H.-N. Li, and M. Gu, "Wavelet based multi-step filtering method for bridge health monitoring using gps and accelerometer," *Smart Structures and Systems*, vol. 11, no. 4, pp. 331–348, 2013.
- [17] S. Khalifa, "Inertial Kinetic Energy Harvesting Model," <http://www.mathworks.com/matlabcentral/fileexchange/53585-inertial-kinetic-energy-harvesting-model>.
- [18] K. Waheed, K. Weaver, and F. M. Salam, "A robust algorithm for detecting speech segments using an entropic contrast," in *Circuits and Systems, 2002. MWSCAS-2002. The 2002 45th Midwest Symposium on*, vol. 3, Aug 2002, pp. III–328–III–331 vol.3.
- [19] A. Ljolje, J. Hirschberg, and J. P. van Santen, "Automatic speech segmentation for concatenative inventory selection," in *Progress in speech synthesis*. Springer, 1997, pp. 305–311.
- [20] T. G. Dietterich, "Ensemble methods in machine learning," in *Multiple classifier systems*. Springer, 2000, pp. 1–15.
- [21] A. Marzal and E. Vidal, "Computation of normalized edit distance and applications," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 15, no. 9, pp. 926–932, Sep 1993.
- [22] M. Hall, E. Frank, G. Holmes, B. Pfahringer, P. Reutemann, and I. H. Witten, "The WEKA Data Mining Software: an Update," *ACM SIGKDD explorations newsletter*, vol. 11, no. 1, pp. 10–18, 2009.
- [23] M. A. Hall, "Correlation-Based Feature Selection for Machine Learning," Ph.D. dissertation, The University of Waikato, 1999.