RF-Based Vehicle Detection and Speed Estimation

Conference Paper · May 2012

DOI: 10.1109/VETECS.2012.6240184

Ahmed E. Kosba
University of Maryland, College Park

Moustafa Youssef
Egypt-Japan University of Science and Techn…

RF-based Vehicle Detection and Speed Estimation

Nehal Kassem
Department of CS. and Eng.
Egypt-Japan University of
Science and Technology (E-JUST)
Email: nehal.kassem@ejust.edu.eg

Ahmed E. Kosba
Department of Computer Engineering
Faculty of Engineering
Alexandria University
Email: ahmed.kosba@alexu.edu.eg

Moustafa Youssef
Wireless Research Center
Egypt-Japan Univ. of Sc. & Tech. (E-JUST)
and Alexandria University, Alexandria, Egypt.
Email:moustafa.youssef@ejust.edu.eg

***Abstract*—Developing a robust and reliable vehicle detection and speed estimation system that alerts drivers about driving conditions and helps them avoid joining traffic jams is an important problem that has attracted lots of attention recently. In this paper, we introduce a novel RF-based vehicle motion detection and speed estimation system (ReVISE). Our system leverages the fact that the presence of objects in an RF environment affects the received signal strength and hence, can be used to detect and identify different characteristics of the objects in an area of interest. Our long-term vision for ReVISE is to leverage common wireless networks, such as WiFi or cellular, to detect the density of traffic and estimate the car speed based on the mobile devices carried by users. This gives us an edge over the current techniques for traffic estimation as we do not require any specialized hardware and the cellular signal strength information is available from *all* cell phones, providing large-scale ubiquitous traffic estimation.**

We present the design and analysis of ReVISE including its vehicle detection and speed estimation modules. The detection module can differentiate between an empty street, stationary cars, and moving cars based on a multi-class SVM approach that uses features from the RF signal strength. We also present two novel speed estimation techniques based on statistical and curve fitting approaches. Evaluation of ReVISE in a real testbed shows that the proposed techniques can detect vehicle motion with an accuracy of 100% and estimate the vehicle speed with an accuracy of 90% in typical streets. This highlights the feasibility and promise of using RF for vehicle detection and speed estimation.

I. INTRODUCTION

Road traffic congestion is one of the major problems facing both developed and developing countries alike. With the number of vehicles on the roads exceeding one billion vehicles and increasing every day, road traffic congestion is going to exaggerate more and more. A vehicle motion detection system can help in identifying congested areas and rerouting cars around them.

A number of systems have been proposed for congestion estimation over the years. These systems can be categorized into two groups: infrastructure-based and distributed approaches. The infrastructure-based techniques include loop detectors [1], magnetic sensors [2], acoustic sensors [3], and computer vision techniques [4]. All these techniques require special hardware to be installed at the points where cars are to be detected. This limits their scalability and deployability due to cost issues.

On the other hand, distributed estimation techniques depend on sensors attached to the cars or the users. For example, the system in [5], [6] and the Mobile Millennium project [7] depends on GPS-enabled cars or high-end phones with users to detect congestion. These systems suffer from the limited availability of cars and high-end phones with GPS receivers, which is even worse in developing countries. Other systems that depend on the data collected by the cellular provider, e.g. [8], suffer from the accuracy of determining the location of the users and the granularity of congestion estimation.

In this paper, we propose a novel RF-based Vehicle detectIon and Speed Estimation system (ReVISE). This system makes use of the fact that the wireless signal strength of an RF environment is affected by the presence and motion of objects [9]–[11], and hence the wireless signals can be used to infer the state of the environment and identify objects in the area of interest. Although this signal strength information can be obtained by RF transmitters and receivers installed on the side of the road, ReVISE uses common wireless networks, like WiFi or cellular, to detect the traffic characteristics and estimate the car speed through mobile devices carried by users or laptops installed at the boundaries of the area. Compared to the current techniques, ReVISE does not require any special hardware as the cellular signal is received by ***all*** cell phones and its information can always be available. Therefore, a large-scale ubiquitous traffic estimation service can be provided through the usage of these huge information in detecting traffic conditions.

However, there is a long way to achieve our long-term vision for ReVISE. Therefore, in this paper, we focus on the feasibility of using the RF signal strength information for vehicle detection and speed estimation as a first step towards our long-term vision. We use only one vehicle in our feasibility experiment. We leave the case of multiple vehicles for future work.

Figure 1 gives an overview of our vision for the ReVISE system. The system consists of: (1) signal transmitters, such as standard access points (APs) or cell towers, (2) monitoring points (MPs), such as standard laptops and cell phones with persons or at home, along with (3) an application server (AS) for training the system and estimating the traffic condition and car speed. Our contribution in this paper is three-fold:

- We show the feasibility of correctly differentiating between an empty street, a stationary car, and a moving car. Our approach depends on using a multi-class Support Vector Machine (SVM) classifier with novel features extracted from the wireless signal strength that can help

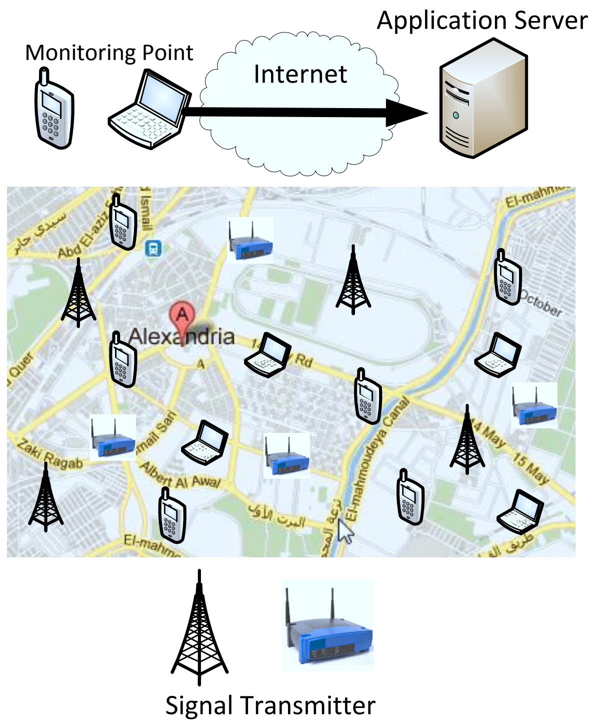

Fig. 1. ReVISE long-term ubiquitous vision for vehicle detection and speed estimation using standard wireless equipment. Mobile phones and other mobile devices with users or at homes and offices sense the signal strength from cell towers and/or WiFi access points. This signal strength information is used to train the system and estimate street states and car speed.

differentiate between the three states.

- We propose two techniques for vehicle speed estimation using statistical and curve-fitting techniques.
- We evaluate the proposed techniques in a real testbed.

Our results show that ReVISE can differentiate between the different states of the street based on the signal strength alone with an amazingly 100% accuracy. In addition, it can estimate the vehicle speed with 90% accuracy.

The rest of this paper is organized as follows: Section II presents the ReVISE System architecture and operation. Section III presents the experimental evaluation of the system and comparison between the proposed techniques. Section IV concludes the paper and gives some directions for future work.

II. The ReVISE System

In this section, we present the different components used in the ReVISE system. We start by an overview of the system architecture followed by a description of vehicle detection and speed estimation techniques.

A. System Overview

The ReVISE system is a software running in the application server that gathers the signal strength information from the monitoring points and processes them (Figure 2).

The ReVISE system works in two phases:

1) *Offline Phase:* During the offline phase, the system does parameter training and constructs an initial profile that is used during the next phase. In particular, it trains its SVM classifier and estimates the parameters to be used for speed estimation later. This is performed by the *Initial Profile Construction Module*.

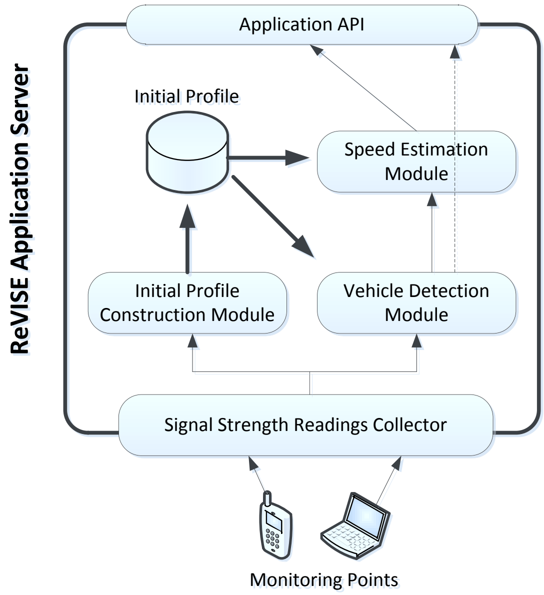

Fig. 2. ReVISE system architecture.

2) *Monitoring Phase:* During the monitoring phase, data of the received signal strength at the monitoring points are collected and classified to decide whether the street is empty, there is a stationary car, or a vehicle is passing (the *Vehicle Detection Module*). If a passing vehicle is detected, the system estimates its speed (the *Speed Estimation Module*). These decisions are taken based on the initial profile constructed in the offline phase.

In the balance of this section, we start by describing the testbed used for data collection followed by presenting our selected features for classification. We then describe the multi-class SVM classifier and two speed estimation techniques.

B. Experimental Testbed

Our experiment was conducted in a typical IEEE 802.11b environment with two access points and two monitoring points. We used two Cisco Aironet 1130AG series access points and two different laptops: one Dell Latitude D830 and one HP Pavilion ze5600 laptop both running Windows XP Professional and equipped with a D-Link Air Plus G+ DWL- 650+ Wireless NIC. APs represent the transmitting units while laptops represent the MPs.

A set of data was collected to evaluate the system performance. The testbed is located in a street 7.5 meters long and 5 meters wide. Figure 3 shows the layout for the experiment.

For the data collection, each one of the two MPs records samples from the two APs, giving a total of four data streams (one stream for each (MP, AP) pair). Samples were collected from the access points at the rate of one sample per second. Speed of the vehicle could not be accurately measured from the analog car speedometer. Therefore, we use the number of seconds taken to pass the area of the testbed as a measure

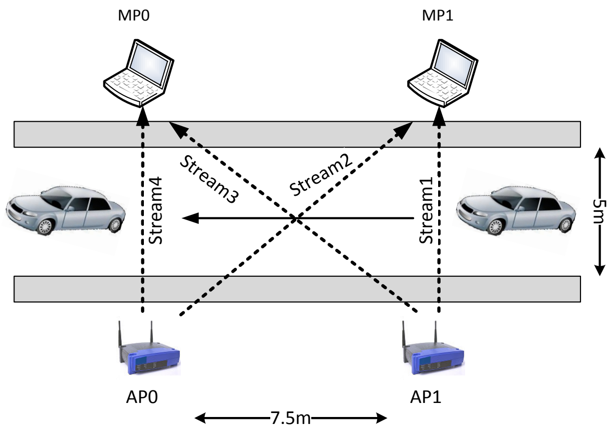

Fig. 3. Experiment layout.

for the vehicle speed. Sets of silence state readings, stationary vehicle readings and moving vehicle readings were collected. A total of about 45 minutes of data was collected. The data set contains four silence sets, four stationary vehicle sets and 20 moving vehicle sets. A moving vehicle set represents the motion of a crossing vehicle that enters and leaves the area of the testbed.

C. Feature Selection

ReVISE aims at using the signal strength information to differentiate between three states: empty street, stationary car, and moving car. We have two candidate features per stream: the mean and the variance of signal strength. Figure 4 shows the relation between the mean of the signal strength and the three states for the four different streams. The figure shows that the presence of a car in the wireless environment affects the mean of the signal strength. The change of the signal strength can be negative or positive due to the multipath propagation effects [12]. In some cases, the mean of the signal strength cannot differentiate between two states (e.g. stationary and moving car using Stream 2). However, combining features from the different streams and using other features should help in resolving this ambiguity.

Figure 5 shows the relation between the variance of the signal strength and the three states for the four different streams. The figure shows that the movement of a car in the wireless environment affects the variance signal strength which is expected due to the changes of the wireless channel. The stationary car effect on the variance is similar to that of the silence period. It is interesting that in some cases, the variance in the presence of a stationary car is less than the variance in the silence state (Stream 3). This is due to the attenuation of the signal strength which leads to reduced variance. Again, combining features from the different streams and using other features, such as the mean, should help in clearly differentiating between the different states.

From these two figures, we use both the mean and variance of the signal strength as features to discriminate between the three states.

Figure 6 shows the relation between the variance of the signal strength and the number of seconds taken by the vehicle

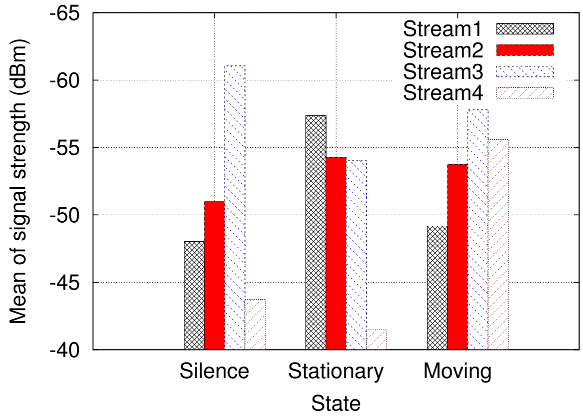

Fig. 4. Average signal strength for different states.

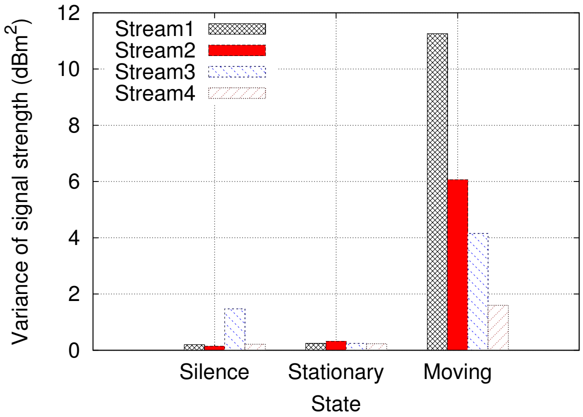

Fig. 5. Variance of signal strength for different states.

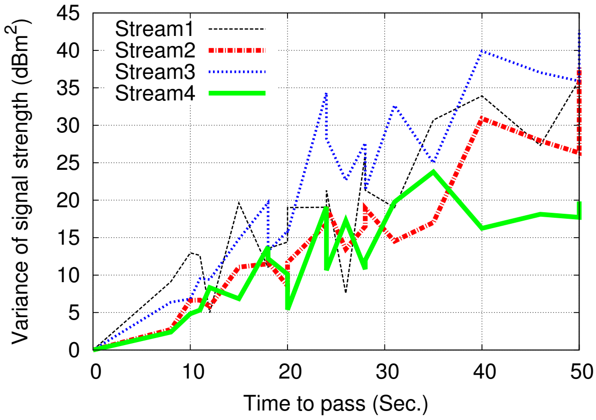

Fig. 6. Variance of the RSS versus the number of seconds the car takes to pass the testbed area.

to pass the area. The figure shows that the variance of the signal strength decreases when the car speed increases. This is expected as the car effect on the signal strength decreases as its speed increases. This relation can be used to estimate the speed of the moving vehicle.

D. Vehicle Detection Module

During the monitoring phase, the vehicle detection module uses a multi-class SVM classifier to determine the current state: silence, stationary car, moving car. This is based on a set of $2n$ features collected from the different streams (mean and variance of the signal strength for each of the n streams).

Since SVMs were originally designed as binary classifiers to differentiate between two classes, we construct a multi-class SVM classifier. We use the *all-against-one* algorithm [13] to decompose the multi-class problem into several binary problems using SVMs as binary classifiers. For our case, we construct three two-class classifiers using all the binary pair-wise combinations of the three classes: silent-stationary, silent-moving, and stationary-moving. Each classifier is trained using the samples of the first class as positive examples and the samples of the second class as negative examples. The classifiers are then combined using the max-wins algorithm, i.e. the selected class is determined by choosing the class voted by the majority of the classifiers.

E. Speed Estimation Module

Once the vehicle detection module detects that there is a passing vehicle, the *Speed Estimation Module* is called to estimate the speed of the passing vehicle. We propose two algorithms for estimating the speed of the passing vehicle: a statistical approach (based on Figure 5) and a curve-fitting approach (based on Figure 6).

1) Statistical Technique: This technique is based on the idea that the time taken by a vehicle to pass an area of interest is a measure of the vehicle's speed. This time can be measured by observing the change in variance (Figure 5) of border streams that bound the area (like Stream 1 and Stream 4 in Figure 3). Entering the area of interest causes an increase in the variance of the stream lying at the entrance; exiting the area of interest ends the increase in the variance of the stream lying at the exit. The time between these two events can be taken to estimate the vehicle speed.

The change in the variance is detected by comparing two moving variances estimates of the signal strength of a single stream, each of them has a different window size: a long window variance represents the static environment, while the short window variance represents the current state. If the difference between moving variances of the two signal behaviors exceeds a certain threshold, then a change in the variance is detected. This technique does not need any training.

2) Curve Fitting Technique: Based on the relation between the variance of the signal strength and the vehicle speed indicated in Figure 6, we use a curve fitting approach to capture this relation for each stream. Therefore, given the current estimated variance, the fitted curve is used to estimate the car speed.

To combine the estimated speeds from the different streams, we use the weighted averaging of all streams where the weight is the R-square value [14]. The R-Square value is the square of the correlation coefficient between the original and the modeled data values. It provides a measure of how well future outcomes are likely to be predicted by the fitted curve. All R-square values are normalized to one by dividing by the summation of the R-square values of all streams.

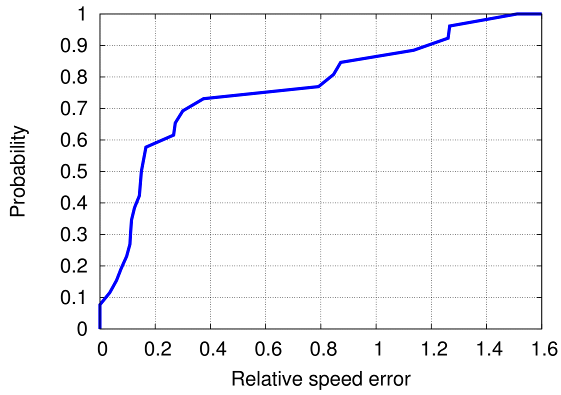

Fig. 7. CDF of the relative speed error for the statistical technique.

$$\text{Combined speed} = \Big(\sum_{k=1}^{n} R_k^2 \times \text{Speed}_k\Big) / \Big(\sum_{k=1}^{n} R_k^2\Big)$$

Where R_k^2 and Speed_k are the R-square value and estimated speed of stream k repetitively.

III. EXPERIMENTAL EVALUATION

In this section, we introduce the experiments conducted to evaluate the ReVISE system. We used the testbed described in Section II-B. We start by presenting the metrics used for evaluating the system. The results of the different modules are then provided.

A. Evaluation Metrics

We use the false positive and false negative rates to quantify the detection performance of the multi-class SVM classifier. For speed estimation, we use the 25th, 50th, and 75th percentiles in addition to the CDF of the relative speed error between the estimated and the actual speed.

B. Performance Evaluation

In this section, the results of the system evaluation are presented with the contribution of each module in those results.

1) Vehicle Detection Module: To evaluate this module, a 7-fold cross-validation technique was applied on the testbed data. The result of cross-validation method was 100% accuracy indicating zero false positive and false negative rates. This amazing high accuracy of detection highlights the promise of using RF signals for car detection.

2) Speed Estimation Module: To evaluate the speed estimation techniques, we use a set of 20 moving vehicles.

Statistical technique: Figure 7 shows the CDF of relative speed error between the predicted and the actual speed using the testbed. The figure shows that the median relative speed error of the statistical technique is 0.15.

Curve fitting technique: We experimented with three different degrees for the fitted curves: linear, quadratic, and cubical. Figure 8 shows the CDF of relative speed error between the predicted and actual speed using the testbed data. The figure shows that the quadratic and linear curve fitting almost give the same errors with a slight advantage to the quadratic fit.

Technique	Statistical	Linear fitting	Quadratic fitting	Cubic fitting
25th percentile relative speed error	0.10	0.07	0.05	0.13
Median relative speed error	**0.15**	**0.13**	**0.11**	**0.30**
75th percentile relative speed error	0.58	0.16	0.17	0.43

TABLE I
RELATIVE SPEED ERROR PERCENTILES FOR THE DIFFERENT SPEED ESTIMATION TECHNIQUES.

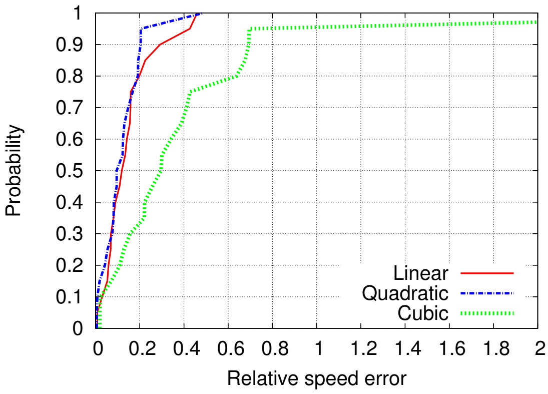

Fig. 8. Relative speed error CDF for the curve fitting technique.

The cubic curve fitting is the worst because of the over-fitting problem. The same problem was observed with higher fitting degrees.

Table I summarizes the median error for the different speed estimation techniques. The table shows that the quadratic fitting technique is the best technique in terms of accuracy. Also, the results show that the curve fitting technique outperforms the statistical technique in accuracy. However, the statistical technique does not require any training phase. Therefore, it may be preferred in some situations.

IV. CONCLUSION AND FUTURE WORK

In this paper, we presented the design and analysis of the ReVISE system that enables vehicle motion detection and speed estimation using already installed wireless networks without using any special hardware. ReVISE uses a multi-class SVM classifier to provide the detection capability. Two methods were proposed for speed estimation: the first method is based on a statistical technique that depends on the significant change in the signal strength of the border streams when a vehicle enters or exits the area of interest. The other method is based on a curve-fitting technique that captures the relation between the signal strength and vehicle speed.

The feasibility of ReVISE was evaluated in a real testbed. The results showed that the accuracy of the detection technique is 100%. For the speed estimation, the results showed that the quadratic curve fitting has the best accuracy compared to other degrees of fitting with an accuracy of 90%. However, the statistical technique may be appealing in some situations as it does not require training.

Currently, we are expanding the system in different directions including combining the two techniques of speed estimation for better accuracy and applying filtering techniques to enhance the quality of the data, and evaluating the system in larger testbeds. Expanding the system to work in a multi-vehicle environment with standard wireless equipment arbitrary located is another direction towards our long-term ubiquitous vision for ReVISE.

ACKNOWLEDGMENT

This work is supported in part by a grant from the Egyptian Science and Technology Development Fund (STDF).

REFERENCES

[1] B. Coifman and M. Cassidy, “Vehicle reidentification and travel time measurement on congested freeways,” *Transportation Research Part A: Policy and Practice*, vol. 36, no. 10, pp. 899–917, December 2002.

[2] S. Y. Cheung, S. Coleri, B. Dundar, S. Ganesh, C.-W. Tan, and P. Varaiya, “Traffic measurement and vehicle classification with a single magnetic sensor,” Institute of Transportation Studies, UC Berkeley, Institute of Transportation Studies, Research Reports, Working Papers, Proceedings, Sep. 2004.

[3] B. Fazenda, H. Atmoko, F. Gu, L. Guan, and A. Ball, “Acoustic based safety emergency vehicle detection for intelligent transport systems,” in *ICCAS-SICE, 2009*, August 2009, pp. 4250 –4255.

[4] T. Zielke, M. Brauchkmann, and W. von Seelen, “Cartrack: computer vision-based car following,” in *Applications of Computer Vision, Proceedings, 1992., IEEE Workshop on*, nov-2 dec 1992, pp. 156 –163.

[5] J. Yoon, B. Noble, and M. Liu, “Surface street traffic estimation,” in *MobiSys*, 2007, pp. 220–232.

[6] P. Mohan, V. N. Padmanabhan, and R. Ramjee, “Nericell: rich monitoring of road and traffic conditions using mobile smartphones,” in *Proceedings of the 6th ACM conference on Embedded network sensor systems*, ser. SenSys ’08. New York, NY, USA: ACM, 2008, pp. 323–336.

[7] “Mobile millennium project.” [Online]. Available: http://traffic.berkeley.edu/

[8] D. Valerio, A. D’Alconzo, F. Ricciato, and W. Wiedermann, “Exploiting cellular networks for road traffic estimation: A survey and a research roadmap,” *IEEE VTC Spring*, 2009.

[9] M. Youssef, M. Mah, and A. Agrawala, “Challenges: device-free passive localization for wireless environments,” in *Proceedings of the 13th annual ACM international conference on Mobile computing and networking*, ser. MobiCom ’07. ACM, 2007, pp. 222–229.

[10] A. E. Kosba, A. Abdelkader, and M. Youssef, “Analysis of a device-free passive tracking system in typical wireless environments,” in *Proceedings of the 3rd international conference on New technologies, mobility and security*, ser. NTMS’09. IEEE Press, 2009, pp. 291–295.

[11] A. E. Kosba, A. M. Saeed, and M. A. Youssef, “RASID: A Robust WLAN Device-free Passive Motion Detection System,” in *PerCom’12: Proceedings of the Tenth IEEE International Conference on Pervasive Computing and Communications, 2012*.

[12] M. Youssef and A. Agrawala, “Small-scale compensation for WLAN location determination systems,” in *WCNC’03: proceedings of the IEEE Wireless Communications and Networking, 2003.*, pp. 1974–1978.

[13] D. G. Gjorgji Madzarov and I. Chorbev, “A multi-class svm classifier utilizing binary decision tree,” *Informatica (Slovenia)*, vol. 33, no. 2, pp. 225–233, 2009.

[14] A. C. Cameron and F. A. Windmeijer, “An r-squared measure of goodness of fit for some common nonlinear regression models,” *Journal of Econometrics*, vol. 77, no. 2, pp. 329 – 342, 1997.