Attendance monitoring in classroom using smartphone & Wi-Fi fingerprinting

Anand S, Kamal Bijlani, Sheeja Suresh, Praphul P
Amrita e-Learning Research Lab (AERL)
Amrita School of Engineering,
Amritapuri,
Amrita Vishwa Vidyapeetham,
Amrita University, INDIA
sanand@am.amrita.edu, kamal@amrita.edu, sheejasuresh@am.amrita.edu, ppraphul@am.amrita.edu

***Abstract*—Academic performance is directly affected by student attendance during the lecture hours. There are existing manual and automated attendance tracking systems that work to ensure that students attend the lectures without fail. However, the practical implementation of most automated systems have drawbacks such as high monetary cost, the need to install specialized hardware, and proneness to fake or proxy attendance. To address this, we propose a novel attendance marking system with which students may mark attendance using their smartphones. While applying facial recognition via the smartphone's front camera to determine the student's identity, the system also makes use of the campus Wi-Fi network to determine the student's location. The proposed system does not require high monetary cost or specialized hardware and yet incorporates adequate foolproof measures to counter fake or proxy attendance. Experimental studies with our system show that fingerprinting, which is the technique used here to determine indoor location, can achieve very good positioning accuracy even in classroom environments, where signal interference is usually very high.**

Keywords—Attendance, Indoor positioning, Fingerprinting

I. INTRODUCTION

Classroom presence plays a huge role in the knowledge that a student gains. It is important to ensure that the learner gets the right and direct guidance from the instructor in person. Research shows that there is a direct relation between regularity in classroom attendance and academic performance [1, 2]. For this purpose, institutions enforce a policy of manual attendance to be taken in classrooms by the instructors.

In recent years, systems were developed to automate the process of taking attendance in classrooms using technology. In addition to lessening the burden of manual attendance upon instructors, these systems save precious instruction time and improve the reliability of the attendance report. However, these systems have some drawbacks. Biometric systems [3], have high installation costs and only one student can provide attendance at a given time, which is still a time consuming process. Some attendance tracking systems require that the student identity cards with a specialized tag be swiped on a reader [4]. The major drawback in such systems is that the student's identity is dependent on the ID card alone, which is prone to fake or proxy attendance. Moreover, the setup for the above discussed systems cannot be altered quickly if a sudden need to change the classroom arises.

Attendance marking is done on our system from an application running on smartphones, which students are expected to carry. Though modern smartphones are more affordable than ever, usage of smartphones in classrooms could be seen as a distraction from education. But the benefits of smartphones in education and a mechanism to prevent undesirable usage of smartphones in the classroom is discussed in [5]. An attendance marking mobile application in which the student's presence is authenticated by applying facial recognition via the front camera of the smartphone when connecting to the classroom router is also discussed in [5]. The system assumes that the range of the classroom router is confined within the classroom walls only. The main drawback in that system is that students can easily provide attendance from outside the classroom as there may be open doors and windows. Moreover, Wi-Fi signals are only attenuated at walls, and not eliminated. A similar problem arises in the Bluetooth Low Energy (BLE) based attendance marking system [10].

Merely confirming the presence of the student via the smartphone will not solve the automated attendance problem, which is based on the following three authentication factors - student identity, presence at the right time, and presence at the right location. The first two factors can be realized quite easily using smartphones. But the problem is to ensure that the student marks his or her attendance from the right location.

To tackle indoor location tracking within the campus, we apply the fingerprinting technique [6] using the campus Wi-Fi network, which avoids the need to deploy specialized hardware for the purpose. It requires scanning of Received Signal Strength Indicator (RSSI) values from nearby Access Points (APs) using the smartphone. Fingerprinting involves a calibration mechanism which is used here to allow instructors to easily control the locations from which the students are permitted to provide attendance for respective courses. It ensures that sudden and unexpected requirements to change the lecture location from the regular classroom does not affect our system.

978-1-5090-6115-0/16 $31.00 © 2016 IEEE
DOI 10.1109/T4E.2016.20

Unique methods are employed to improve the positioning accuracy of the system. Since the student holds the phone up to the face to confirm identity, device proximity (to the student) and movement are controlled while performing the Wi-Fi scans. Also, we use the processing power of modern smartphones to perform a large number of Wi-Fi scans per second and take the mean for the calculations. Experiments show that it is possible to reduce the mean positioning error down to 1.6 m, even with a deterministic algorithm like k-NN.

II. Indoor Location Tracking

GPS is perhaps the best example of a technology that has been extensively applied in successful location tracking systems. But GPS will work reliably only in outdoor environments. Since our system has to estimate the user location within the university campus, only technologies that facilitate indoor location tracking can be used.

Indoor location tracking has been a hot topic for research in the past decade. Diverse technologies [7] exist for the purpose such as image processing, magnetic sensors, RFID, Bluetooth and more recently, Bluetooth Low Energy (BLE) [10]. Most of the technologies, with the exception of BLE are rather expensive and all of them require additional hardware to be deployed across the indoor environment. Wireless Fidelity or Wi-Fi can be used to track indoor location. Only requirement for this system is to ensure that signals from at least 5-6 Access Points are available throughout the campus or the indoor environment.

A. *Wi-Fi based indoor positioning*

Since university campuses have Wi-Fi Access Points deployed to provide access for staff and students, we choose to use it in this system to fulfill two aspects:

a) Enable the smartphone attendance marking application to work with the campus Wi-Fi network.

b) Estimate the smartphone's location within the campus.

While providing attendance via the smartphone application which confirms the student's identity by facial recognition, the student needs to be in the classroom assigned for the particular course. If the student's smartphone is detected to be present anywhere else within the campus, attendance marking will be refused by the system, thereby preventing fake or proxy attendance.

Indoor location tracking using Wi-Fi technology is based upon the fact that the signal from Wi-Fi routers varies in intensity with distance. The two major techniques that are used for finding indoor location using Wi-Fi signals are trilateration and fingerprinting [18].

B. *Trilateration*

Trilateration involves translating the Received Signal Strength Intensity to a physical distance measurement. It is possible to estimate the location of the wireless receiver if the RSSI values of at least 3 Access Points (APs) from the same floor is available and the location of the APs itself are known. But attenuations in the indoor environment significantly impact the RSSI value that is read by the receiver device. This is especially true in the classroom environment where signal interference is usually high because of the furniture setup and people presence. The modelling of the environment with a perfect path loss coefficient is rather tedious.

C. *Fingerprinting*

Fingerprinting involves two phases. Initially, the RSSI values from the available APs are recorded as a vector from a set of pre-determined locations that is spread across the indoor environment. In the next phase, the receiver device again scans for RSSI values. This time, the RSSI vector is compared against the set of previously recorded RSSI vectors and then depending upon the type of algorithm used, a best possible location estimate is returned. Since it takes into account the variation in RSSI, fingerprinting is the feasible technique that is applicable for classroom environments.

This system implements fingerprinting for the attendance marking scenario with novel measures to improve the RSSI acquisition procedure and thereby the overall positioning accuracy by taking into account the device proximity, device movement and temporal sampling.

III. Background Study and Related Works

In this section, the importance of attendance for academic performance, the various attendance marking systems and the need for this system are highlighted. We go on further to look at a few Wi-Fi based indoor location tracking systems and research work in the field.

Luca Stanca in [1] studies a large panel data set for evidence on the effects of attendance on academic performance and goes on to prove the co-relation between the two. Similarly, authors in [2] do a quantile regression analysis to establish the negative impact of absenteeism on academic performance.

The work done in [4] is a RFID attendance system which uses java programming to create a meaningful link between the data acquired by RFID hardware to automate the attendance register. RFID needs special tags to be embedded within the identity cards. But the identity card is not a sufficient proof for user identity as anybody can use it with the RFID hardware to provide attendance. Both [4] and the system is developed by Nippon Systems Development [8] require students to scan their cards over a reader. Both systems reduce the instructor's time and effort. But the overall time consumption for all the students put together is still large since only one student can mark attendance at a given time.

The system developed by Ichimura et al. [9] requires students to scan their Id cards, which has a digital image file of the student's portrait printed on it, over the NFC tag on their smartphones. However, it cannot confirm the student's identity nor the location prior to the marking of attendance.

The Bluetooth Low Energy (BLE) solution described in [10] ensures proximity by installing a BLE device in each classroom. It also cannot confirm the user identity. Moreover, it is based on the assumption that the range of the BLE device is restricted to the classroom alone.

Beom-Ju Shin et al. explain their Wi-Fi based indoor positioning system using smartphones in [11]. Three RSSI samples are acquired for which the mean is calculated (if RSSI is above a certain threshold) and compared with RSSI vectors from the database to return a location estimate. The experiment is done in a single room only with four Wi-Fi APs installed in the room itself. The room is divided into 8 cells and shown in a mobile UI. The cell corresponding to the estimated location is highlighted when testing.

Carlos Figuera et al. have analyzed temporal sampling (number of samples over time) and spatial sampling (number of samples per unit area) processes involved in the acquiring of RSSI from Wireless APs in indoor scenarios [6]. They also propose algorithms to account for the RSSI fluctuation that may arise across various wireless receiver devices. Overall, the paper provides guidelines for the design of a cost-effective, high-performance measurement process.

Zhang Chong and Yu Hong Yang propose a hybrid algorithm in [12] for optimal accuracy and speed in location estimation. It combines a deterministic algorithm involving comparison of Euclidean distance and a probabilistic algorithm to increase both positional accuracy and the speed of estimation.

The 2014 Microsoft indoor localization competition [7] gave a platform for Dimitrios Lymberopoulos et al. to perform a systematic evaluation and comparison of indoor location technologies. They discuss the impact of change in environment and furniture setup on the positioning accuracy, the associated deployment overhead etc. The impact of furniture setup change was a difference in the positioning error by up to 4 m. Team 14 from this competition achieved a mean positioning error of 1.56 m using only existing Wi-Fi infrastructure, but their performance was based on a setup with 10 Access Points in a relatively small area of 300 m^2.

Some commercial applications offer location based rewards and incentives. In order to prevent the user from providing false location, a system to produce fingerprint evidence using error tolerant fuzzy extractor was developed by Chitra Javali et al. [13]. The fingerprint location evidence was secured so that it could not be shared with other users.

IV. THE PROPOSED SCHEME

In this section, we first describe the smartphone application, the overall architecture and the system flow. Then we explain the basis for our RSSI acquisition procedure.

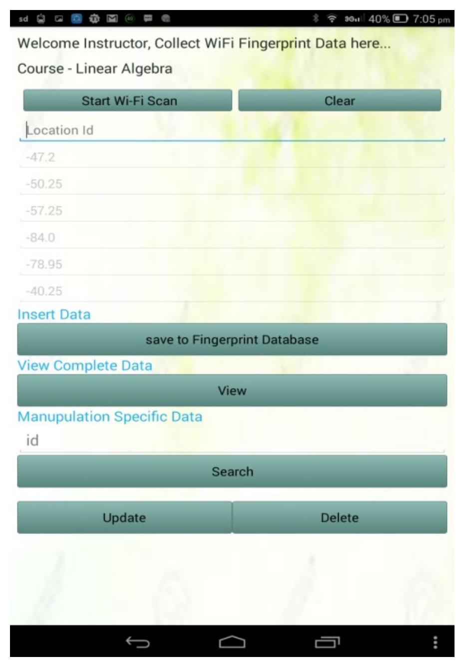
A. System Setup

The tool was developed and tested on the Android platform in smartphones. The identity of the user is confirmed using facial recognition via the front camera on the device. Using inertial sensors on the device, the tool prompts the user to bring up and hold the device at eye level (selfie style) to initiate the facial recognition. The RSSI values were stored on a MySQL database on a server hosted by apache tomcat.

There are two working modes in the tool:

a) Master mode: Scans for RSSI values to create and manage the fingerprint calibration data. The map of classrooms with the list of pre-determined locations is provided in this mode. The system admin team creates and maintains fingerprints for the areas external to the classroom (corridors etc.). The instructor can use this mode to decide which pre-determined locations correspond to the course and update the fingerprints for those locations and thereby for the course. If some other instructor already updated fingerprint for that location, it need not be done again unless the furniture setup is changed within the classroom. The RSSI values stored in the database can be viewed and managed in this mode as shown in figure 1.

(a)



(b)

Fig. 1. Model screenshots of the application (a) Previously acquired fingerprint data is viewed for six locations (b) Master mode interface used to trigger Wi-Fi scans, store, and view and manipulate fingerprint data

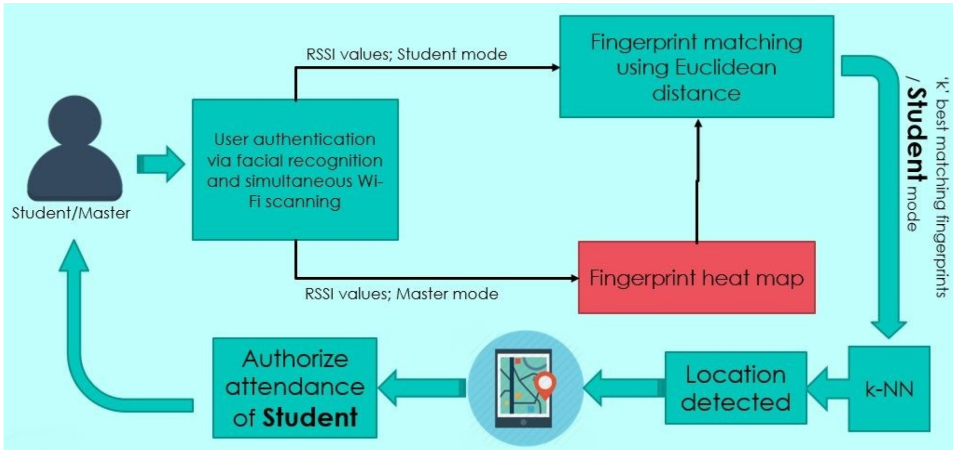


Fig. 2. Block diagram showing the flow of the system

b) Student mode: Similar to the admin mode, the student mode first scans for RSSI values. The k-NN algorithm is then used to find the three best fingerprint matches using Euclidean distance from the existing fingerprints. The mean positioning error is a direct consequence of the magnitude of 'k'. But a 'k' value of one results in greater maximum errors [16]. We selected the 'k' value to be three as it gave optimal results. From the coordinates of the three locations, an average coordinate is calculated and returned for authentication. If the coordinate is confirmed to be within the classroom, attendance will be approved. Otherwise, the student is prompted to try again. The system flow is illustrated in figure 2.

To confirm the location of the user, the tool scans for the signals from available Wi-Fi Access Points. But this is done exactly during the time when the user brings the device to eye level. While facial recognition only requires the face to be motionless and lighted properly, performing Wi-Fi scans during that time gives a few advantages in improving location accuracy. The basis of our RSSI Acquisition procedure is given in the following sub-sections.

B. Device proximity

The proximity of the receiver or smartphone device to the user affects the RSSI [14]. It's a major factor in the accuracy of any signal strength based indoor positioning system, which cannot be controlled in real time indoor navigation scenarios. But this attendance marking system scans for RSSI values at the same time it applies facial recognition to confirm the user's identity. The user has to hold the device at a minimum distance in order to capture his/her face within the frame. Also, by controlling the orientation with the help of inertial sensors in the smartphone, the system ensures that the device is kept at eye level from a distance. The uniformity in the scanning mechanism reduces RSSI variation to an extent and boosts the overall accuracy of this system.

C. Device Movement

RSSI values read by a moving wireless device is different than that of a stationary device. Indoor positioning systems such as the one described in [15] consider device movement. Our system, on the other hand scans for RSSI values only during the facial recognition process during which the user has to stop moving the smartphone around. Thus the possibility of device movement is eliminated.

D. Temporal Sampling

Taking just one sample RSSI value will not account for the variation in RSSI. Acquiring multiple RSSI samples over time and calculating the mean always improves the accuracy of the system. For example, 3 RSSI values are taken and the mean is calculated in the algorithm used in [11]. In [16], experiments were done to calculate RSSI deviation for up to 20 samples before settling upon 5 samples for optimum accuracy and speed. Such experiments prove that more RSSI samples are always better. But very large number of RSSI samples were never taken in these systems. One reason is that the reduction in RSSI deviation reduced with more samples [6]. But the major reason is that each Wi-Fi scan took a long time to complete. The time taken by a Nokia E60 to complete a Wi-Fi scan [17] was about 13 seconds. Especially in real time indoor navigation scenarios, such time consumption was never practical or worth it. But with the advent of modern affordable smartphones, time taken for performing Wi-Fi scans has reduced drastically. On the lower end, the Lenovo S5000-h with a 1.2 GHz Quad Core Processor could perform about 50 Wi-Fi scans in about 2 seconds. On the upper end, the OPPO Find 7 with a 2.5 GHz Quad Core Processor could perform double the number of scans in the same duration. Location accuracy was tested with only a few to a large number of samples. We restricted the final count to 100 samples as accuracy improvement was getting constricted with more samples and also to ensure that the Wi-Fi scans don't take more than 3-4 seconds, the typical duration for which the users hold up the smartphone for authentication.

V. EXPERIMENTS

Before the final accuracy testing over a large area with multiple classrooms, we performed a relatively smaller test in a smaller area. It was to fix the number of RSSI samples to be taken at every pre-determined location. Using the existing Wi-Fi AP distribution, every pre-determined location used six RSSI values.

Fig. 3. Reduction in the positioning error as more RSSI samples are used

We tested the tool in 21 pre-determined locations, spaced out at a distance not exceeding 5-6 m. All locations were pre-determined near walls and furniture, where RSSI fluctuations tend to be higher [7]. Both calibration and testing satisfied the conditions of device proximity and movement, as discussed in the previous section. From the results that we acquired in figure 3, we decided to settle with 100 RSSI samples as there is no real time navigation constraint for our scenario and the total scan time was typically 3-4 seconds. This is different from other Wi-Fi based indoor location tracking techniques, in which the number of RSSI samples used are much lower.

The final testing was done with 9 classrooms placed next to three corridors in the first three floors of an Amrita University building. Each classroom had an area of 12m * 6m. Eight Pre-determined indoor locations were identified in each classroom and around 28 locations were identified in the corridors from the first three floors. All locations were distributed evenly with a distance not exceeding 5-6 m.

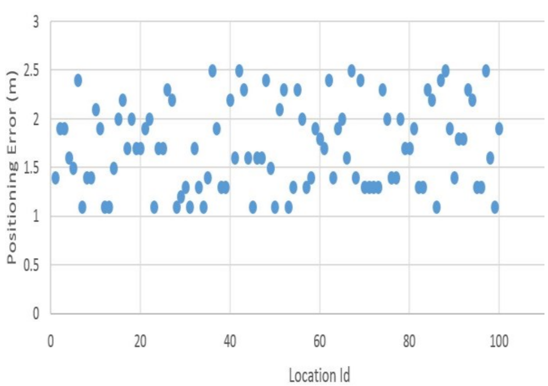


Fig. 4. Positioning accuracy test at 100 locations

VI. RESULTS & ANALYSIS

The accuracy achieved with our setup is described in figure 4 where the positioning error for each of the location tested is given. With the overall positioning error between 1-2.5 m, the estimation of whether the device is inside the classroom proved to be correct 94 out of 100 times. The positioning error in the incorrect estimations did not exceed 1.5 m, which could be used as the minimum threshold requirement for the device to be within the perimeter of the classroom during system implementation. It shows that careful control of the RSSI acquisition procedure can give respectable accuracy for an indoor positioning system using Wi-Fi fingerprinting, even with a simple algorithm like k-NN. Such an implementation is applicable for the attendance marking scenario with facial recognition though it may not practically possible for real time indoor navigation systems.

Acquiring fingerprint for one pre-determined location within a classroom takes maximum 4 seconds. This system requires that the process be repeated 7 times for each classroom. Given the time required for maneuvering across the locations, the whole fingerprint acquiring process for every classroom can be completed within a minute. Change in furniture setup can change the positioning error by up to 4 m [7]. If that happens, the re-calibration of the Fingerprint heat map within the classroom can be done in a very short time.

Similar to other automated attendance systems using biometric and RFID technologies, this system also requires implementation effort. But the monetary cost involved is almost negligible. The effort involved in maintaining the fingerprint calibration (needed within the classroom when furniture setup changes) consumes only a minute. We get an automated, low cost attendance marking system which quickly and reliably determines student identity and location at the correct time. If the need to change the lecture location from the regular classroom arises unexpectedly, the re-calibration mechanism also allows instructors to change the classroom location for a course without notice to the system administrators.

VII. CONCLUSION

This paper showed that it is possible to achieve an affordable, fast and secure automated attendance marking system in classroom using smartphone and Wi-Fi Fingerprinting technique that incorporates a controlled RSSI acquisition procedure and a simple k-NN algorithm. Further scope of this research will be to look into delivering Location Based Services (LBS) for teachers and students using this tool, and further increase of positioning accuracy using probabilistic algorithms, such as the Bayesian filter.

ACKNOWLEDGEMENT

We are grateful for the support and facilities provided by the Amrita E-Learning Research Lab and Amrita Vishwa Vidyapeetham University.

REFERENCES

[1] L. Stanca, "The Effects of Attendance on Academic Performance:Panel Data Evidence for Introductory Microeconomics", J. Econ. Educ., vol. 37, no. 3, pp. 251–266, 2006.

[2] Pranab Kumar Pani and Pallavi Kishore, "Absenteeism and performance in a quantitative module A quantile regression analysis", Journal of Applied Research in Higher Education, Vol. 8 Iss: 3, pp.376 – 389, 2016

[3] Yash Mittal, Aishwary V arshney, Prachi Aggarwal, Kapil Matani and V K Mittal, "Fingerprint Biometric based Access Control and Classroom Attendance Management System", IEEE INDICON, pp. 1-6, 2015

[4] R.B. Kuriakose and H.J. Vermaak, "Developing a Java based RFID application to automate student attendance monitoring", Pattern Recognition Association of South Africa and Robotics and Mechatronics International Conference, pp. 48-53, 2015

[5] Mahesh G, Jayahari KR and Kamal Bijlani, "A Smart Phone Integrated Smart Classroom", Next Generation Mobile Applications, Services and Technologies, 2016

[6] Carlos Figuera et al., "Time-Space Sampling and Mobile Device Calibration for WiFi Indoor Location Systems", IEEE transactions on Mobile Computing, VOL. 10, NO. 7, JULY 2011

[7] Dimitrios Lymberopoulos, Jie Liu and Xue Yang, "A Realistic Evaluation and Comparison of Indoor Location Technologies: Experiences and Lessons Learned", The 14th ACM/IEEE Conference on Information Processing in Sensor Networks, pp. 178-189, 2015

[8] Nippon Systems Development, Attendance management web System http://www.systemgear.com/product/pdc300/school.html (Last accessed on July 17, 2016)

[9] Ichimura Takumi amd Kamada Shin: Attendance Management System with NFC (Near Field Communication) on Nexus, Symposium on Mobile Interactions 2013, pp.139-140, Mar. 2013

[10] Shota Noguchi, Michitoshi Niibori, Erjing Zhou and Masaru Kamada, "Student Attendance Management System with Bluetooth Low Energy Beacon and Android Devices", 18th International Conference on Network-Based Information Systems, pp. 710-713, 2015

[11] Beom-Ju Shin et al., "Indoor WiFi Positioning System for Android-based Smartphone", Information and Communication Technology Convergence, pp. 319-320, 2010

[12] Zhang Chong and Yu HongYang, "Indoor Matching Location Algorithm Based on WIFI Signal Strength", International Conference on Communications, Circuits and Systems (ICCCAS), pp. 116-119, 2013

[13] Chitra Javali, Girish Revadigar, Daniel Pletea and Sanjay Jha, "Location Fingerprint Evidence and Authorisation using WiFi Channel Characteristics", IEEE International Conference on Pervasive Computing and Communications Demonstrations, pp. 1-3, 2016

[14] K. Kaemarungsi and P. Krishnamurthy, "Properties of indoor received signal strength for WLAN location fingerprinting," in Mobile and Ubiquitous Systems: Networking and Services. MOBIQUlTOUS, pp. 14–23, 2004

[15] Kun Hou and Ruizhong Wei, "Indoor Location Based on WiFi", IEEE 19th International Conference on Computer Supported Cooperative Work in Design, pp. 331-336, 2015

[16] Nicolas Le Dortz, Florian Gain and Per Zetterberg, "Wifi Fingerprint Indoor Positioning System using Probability Distribution Comparison", IEEE International Conference on Acoustics, Speech and Signal Processing, pp. 2301-2304, 2012

[17] Damian Kelly, Ross Behant, Rudi Villing and Sean McLoonet, "Computationally Tractable Location Estimation on WiFi Enabled Mobile Phones", Signals and Systems Conference (ISSC), pp. 1-6, 2009

[18] Sumana Das, Thiago Teixeira and Syed Faraz Hasan, "Research Issues Related to Trilateration and Fingerprinting Methods", International Journal of Research in Wireless Systems, pp. 33-35, 2012