International Journal of Advanced Information Science and Technology (IJAIST) ISSN: 2319:2682
Vol.4, No.4, April 2015 DOI:10.15693/ijaist/2015.v4i4.10-15

An Intelligent Indoor Location Learning Mechanism for Indoor Positioning System

Yi-Wei Ma[1], Jiann-Liang Chen[2], Jun-jie Liao[2] and Chia-Lun Tang[3]

[1]China Institute of FTZ Supply Chain, Shanghai Maritime University
[2]Department of Electrical Engineering, National Taiwan University of Science and Technology
[3]Advanced Research Center, Auden Techno Corp.

Abstract—**Traditionally, people use maps to locate themselves and their destination. However, rapid growth in the field of smart devices has brought new technological innovation that enables current indoor location to be determined by computing indoor position using Wi-Fi and smart devices. In this study, Near Field Communication (NFC) is utilized to obtain information about several set reference points. The environment provides users with current reference point data, and these reference points can be obtained and calculated to learning for strengthen positioning accuracy. As the environment changes, reliable reference point information can be obtained by reference point learning mechanism. This work proposes an indoor location learning mechanism (ILLM) that combines reference points and ant colony optimization for calculating making reliable indoor positioning information. The traditional learning method must be applied more than 150 times, while the proposed learning method only 100 times applied to yield the same positioning error rate as the environment varies. Therefore, the overall learning time is reduced. In this work, three APs are utilized for positioning in another research environment, the mean positioning error was reduced from 1.61m to 1.46m, so the mean accuracy rate was increased by 9.3%.**

Index terms -Received Signal Strength Indicator (RSSI), Time of arrival (TOA), Time Difference of Arrivals (TDOA), Angle of Arrival (AOA), Fingerprint-assisted, Ant colony.

I. INTRODUCTION

People sometimes want to know their current location when they are in outdoors. Identifying outdoor locations is not too difficult using current technology. However, people commonly loose themselves indoors owing to complex indoor designs, and because satellite and base stations cannot accurately find a location indoors when the indoor layout is complex. Therefore, the development of an effective indoor positioning system is important.

The accuracy and reliability of an indoor positioning system are undoubtedly its most important properties. Since indoor layouts may be complex, techniques that account for signal refraction, diffraction, diffusion and reflection by objects in the environment are required. A few current techniques are Time of Arrival (TOA) [1, 2], Time Difference of Arrivals (TDOA) [3, 4], Angle of Arrival (AOA) [5, 6] and Received Signal Strength Indication (RSSI) [7-10]. However, environmental factors reduce the accuracy of the results. Therefore, RSSI is utilized to receive signal strength data from devices and carry out positioning calculations.

Indoor positioning systems must be robust against environmental variations to keep down the complexity of their calculations while maintaining positioning accuracy. Reference [11] uses the reference point method to amend positioning errors. The present work thus focuses on reference points and uses learning curves for indoor positioning; whenever the indoor layout, reference points information is revised automatically, and errors are amended using sensors, improving the positioning accuracy.

Many studies emphasize on indoor positioning using methods that involve Wi-Fi [12], GPS [13, 14], RFID [15, 16], Bluetooth [17] and cameras [18], among others. Each device associated with these methods has its own advantages and disadvantages that depend on the environment in which it is used.

The rest of the paper is organized as follows. Section 2 presents the background of this study. Section 3 introduces the proposed indoor location learning mechanism for indoor positioning system. Section 4 presents the performance analysis of this study. Finally, conclusions are drawn in Section 5.

II. BACKGROUND KNOWLEDGE

A. Positioning technology development

Positioning systems are utilized in various fields, Different methods are utilized under various conditions, but GPS is the most widely used of all positioning systems. GPS depends on 29 GPS satellites in space, each of which is equipped with an atomic clock that is used to synchronize the time when it sends its position and time signal, which it does once every fixed number of cycles. The recipient of such a signal can compute its own position using the TOA method. Although the GPS positioning system operates globally and around round-the-clock, signal propagation is line-of-sight, so the signals are blocked in shielded areas. This work develops indoor positioning to determine current locations in spaces that are confined by obstacles.

B. Indoor positioning method

Current positioning methods contains TOA, TDOA, AOA, TOA/AOA hybrid positioning method and RSSI.

- Time of Arrival (TOA):The TOA method calculates the distance between users from the delay times of the signals that are sent by users and received through three or more base stations, and thereby derives users' positions. The measurement of the signal propagation delay time requires that all base stations must satisfy time synchronization requirements.

- Time Difference of Arrivals (TDOA):The TDOA method calculates the distance between a user and a base station by measuring the time difference between he signals that arrive at two base stations through three or more base stations, and deriving a hyperbolic curve from each set, and then calculating the user's location.

- Angle of Arrival (AOA): The AOA method calculates position by measuring the direction from the user to a base station. Directional antennas are utilized to identify the source of the signal from the directional antennas to message from three fixed base stations to calculate the location of the user.

- Received Signal Strength Indicator (RSSI): RSSI receives the strength of radio signal from each AP of a user. The strength of the transmitted signal each AP is utilized to determine the radius, and then the user's location is calculated by trigonometric positioning accordingly.

- Trigonometric positioning: Three coordinates are known and related distance parameters are obtained using TOA or RSSI. Therefore, the intersection point identified and the location of the user can be thus obtained.

C.Ant Colony Optimization

This method of path optimization imitates a colony of ants that are cooperatively finding food. In nature, ants leave pheromones along their path as they look for food, enabling following ants to find the path they took. As the ants go back and forth along a path, the intensity of the pheromone increases. However, the pheromone dissipates over time, so paths from which it has dissipated are not chosen by ants that are searching for food. Over time, the ants thus find the optimal path [19, 20].

D.Sensors

- Accelerometer sensor:An accelerometer detects the rate of change of speed in a particular direction and along the three axes - x, y, and z. Change in one axis represents linear shift; change in two represents plane shift, and change in three represents three-dimensional shift. Accelerometers therefore have a wide range of applications [21]

- Orientation sensor:An orientation sensor obtains an azimuthal angle of a mobile phone that is laid flat. For example, the azimuth facing north is zero; the azimuth facing east is 90 degrees. The other two parameters that can be evaluated using such a sensor yield the degrees of vertical and horizontal rotations. An orientation sensor can be developed into an electronic compass, which not only specifies current location, but also measures the bearing of the user. The display of a smart phone or a tablet can be set up accordingly [22].

III. INDOOR LOCATION LEARNING MECHANISM (ILLM) ARCHITECTURE

A. Indoor positioning environmental field

Even if the number of AP in an indoor space suffices for interference, AP signals are commonly affected by the interior layout, decorations and furniture, influencing the positioning calculations. Hence, in this work, a device for collecting information concerning reference points is developed; it gathers data using NFC, and transports these data to a back-end server to start learning. Reliable learned reference point information is thus obtained and used to correct errors in calculations, improving indoor positioning.

The reference point learning method yields reliable reference information that current enables users to find a particular interior location. Users can transmit their required reference point information over the Internet. The system provides current reliable reference point information to users. As stated, decorations do not affect the accuracy of positioning. Whenever the indoor structure changes, the reference points begin to learn the current reference point information. In reference point learning, that is provided by users and continually send this information to the back-end server. The server then begins to learn by the ILLM method and to generate a learning curve. Reliable reference information can be obtained using the reference point learning method. When a user heads toward a particular interior space, user can learned information regarding the reference point information learning.

- Step1. The user has current RSSI information that is available to an NFC Reader.
- Step2. The NFC Reader continuously receives the information that is provided by users and sends the data to a back-end server to perform indoor positioning calculation.
- Step3. The back-end server performs reference point learning based on the received information, before repeating steps one and two. Reliable reference point information is thus learned.

Obtain reference point information.

- Step1. If users want to obtain the latest reliable reference point information for positioning, they can send a data requirement to the server.
- Step2. When a server receives users' requirements, it provides those users with the latest learned information.

B. System Architecture

The function of the system architecture can be described by two flowcharts one for positioning, and the other for the reference point algorithm for doing correction. In the positioning process, sensors and the reference point method are used to correct or reduce errors based on obtained RSSI information. The reference point learning algorithm calculates reference data concerning reference points by ant colony optimization; accelerating the learning process, and increases the reliability of the information.

The positioning procedures, shows that after the system begins by performing the first positioning process. As the first coordinate is obtained and errors are corrected using reference point data, the data become increasingly reliable. Finally, the condition of the user is determined from changes in the readings from the sensors. The system determines whether a user moves and if so, in which direction, and the current coordinate of the user is adjusted accordingly.

C. ILLM Environment

The RSSI signal is obtained mainly from the previously known positions of APs, and the user's location and direction are derived accordingly. Therefore, a smart phone that is equipped with an accelerometer sensor and a direction sensor is required needed, and four wireless APs must be set up in the interior space. In the research environment in this work, the four APs are denoted as AP1, AP2, AP3 and AP4, which are placed in different positions in the indoor environment.

The chart of the position of indoor environment is mapped to mobile phone and the display of the smart phone. The indoor map is displayed on a grid; the dots represent the APs, and the squares represent the reference points. As the value of RSSI from each AP is obtained, errors are corrected based on the reference information.

D. Coordinate calculation method and reference point information corrected

To increase the accuracy of positioning causing wireless signal errors, triangulation positioning method that use messages from four APs messages to calculate coordinates are used, and messages from three APs are picked. Four position coordinates can be obtained the coordinate of the center calculated therefrom.

Errors are corrected using reference information. Every reference point records information about the APs in the research environment, and begins the learning process accordingly. A learning curve is obtained for each AP and converted to an RSSI value to calculate reliable reference point information. Reference point information learning by using ant colony optimization imitates the leaving of a pheromone by ants that are looking for food, which enables following ants to find an already followed path. This method improves reference point information and diminishes the importance of historical data over time, yielding reliable information quickly even in a changing environment.

First, this work present the problem as a path and then the RSSI values are converted into paths, each associated with a recorded intensity in all instances of pheromone. The thickness of the pheromone represents the weight of the path. Currently used paths are strengthened and other information is diminished in importance, resulting in an increasingly efficiently learning process. In this work, a real reference point learning curve is obtained using SSID information. The required RSSI information in indoor environment is obtained, and reliable reference information is obtained by learning. Each RSSI value will be calculated to obtain the difference between curves. Next, this result is compared with the output of the ILLM algorithm that is proposed herein. The ILLM algorithm not only yields current information by adjusting the weights, but also adjusts the attenuation parameters in the learning process. Therefore, when the RSSI is excessive, the evaluated attenuation parameters can be utilized to reduce the rate of attenuation of those paths, while the attenuations of the other parts are increased, yielding rapid results.

IV. PERFORMANCE ANALYSIS

Reference point information comes mainly from users proactively who provide current AP information. Those users their devices provide signal information learning curve is calculated. Four APs supply signals in the research environment in this work. The RSSI of each AP is examined under fixed conditions. The RSSI information that is provided by APs varies slightly even in a fixed environment, affecting the degree of reliability of reference point positioning. Larger RSSI values are obtained closer to the APs, where the drifting range is smaller. Farther from an AP, space factors have a stronger effect, and the drifting range is higher. The ILLM algorithm that is proposed in this work can be utilized to eliminate the drifting factors and obtain reliable and fixed reference data, for the purpose of corrected errors, as shown in Figure 1.

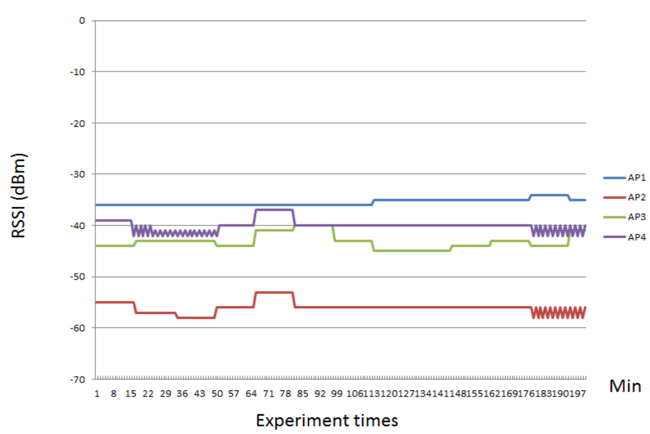


Figure 1. RSSI value status

A.Learning Curve of the pattern changes

Interior layout affects indoor positioning. Reference point information, based on stable arrangements of signals, is reliable. However, when an interior space is re-decorated or its layout is changed to satisfy retail requirements, for example, and the reference point information is not updated, errors are generated in positioning. Therefore, reliable reference point data must be learned. Both the traditional statistical method and the ILLM method are examined herein. In the traditional statistical method, when an interior layout changes, old data are still used. Executing the process of learning reference point information more than 150 times yields the desired weight and stable reference point information, as shown in Figure 2.

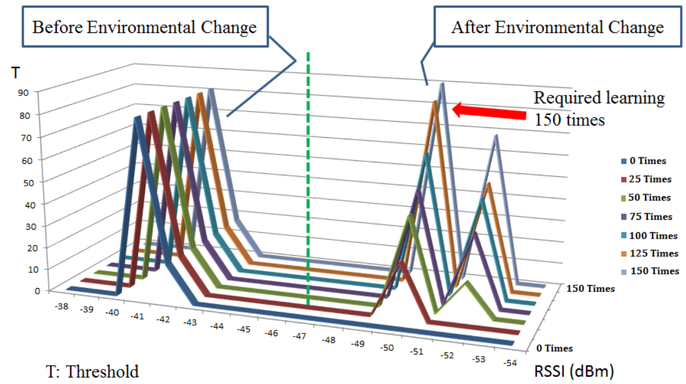


Figure 2. Reference point learning status change (traditional statistics)

ILLM restarts the learning process when the indoor layout changes, and then accelerates decay of historical data. Data do not affect the current learning curve, which emphasizes the current reference point information. Also, an 80% threshold requirement can be satisfied after executing the learning process 100 times, as shown in Figure 3.

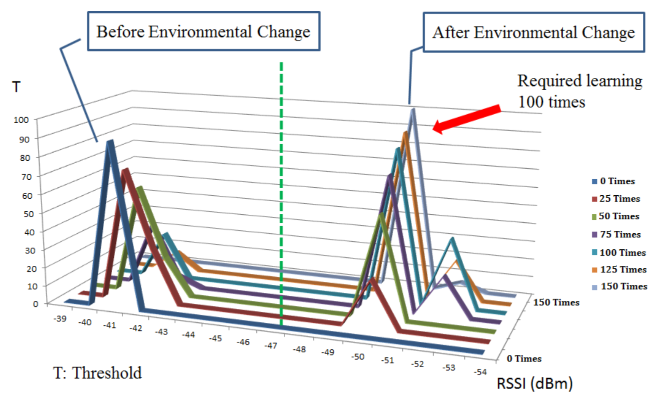


Figure 3. Reference point learning status change (ILLM)

In this work, three to five APs are utilized to investigate the impact of accurate on positioning. Three to five APs are set up in the environment according in the arrangement that was described in this work, the influence of error on positioning areas is discussed.

Figure 4 shows the measurements of error rate based on the aforementioned arrangement, revealing that RSSI signal drifting causes errors in positioning. Averaging the information in the figure reveals that the error that is generated using three APs exceeds that using four or five APs, using four as opposed to five APs yields no significant difference in error, so four APs were utilized in this work.

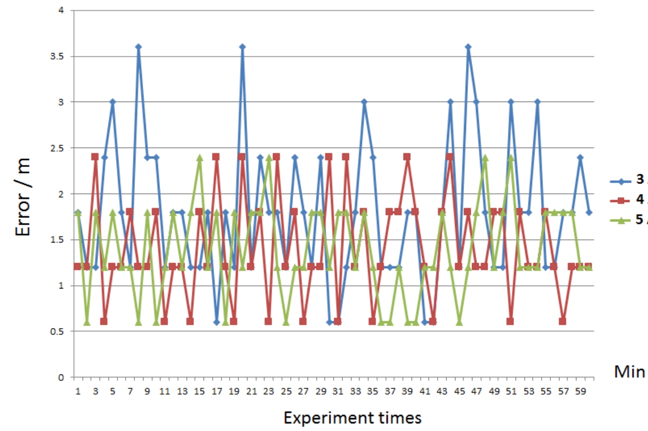
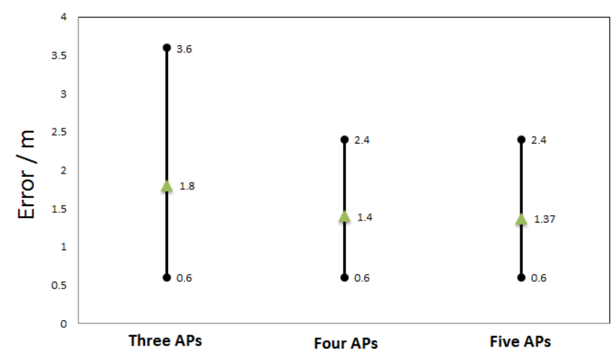


Figure 4. AP numbers affect positioning (Error rate)

Figure 5 shows the errors that are caused by RSSI signal drifting when using three, four or five APs are utilized. Averaging the data in this figure shows that the error that is generated when three APs are utilized exceeds that generated when four or five APs are used. When three APs are utilized in the test environment, the average error is 1.8m; increasing the number of APs above four APs does not significantly change the error so four APs are utilized.



	Three APs	Four APs	Five APs
Maximal	3.6m	2.4m	2.4m
Minimal	0.6m	0.6m	0.6m
Average	1.8m	1.4m	1.37m

Figure 5. AP numbers affect positioning (Average error rate)

B. Reference point uncorrected impact on the positioning

When adding reference point information can improves the accuracy of the positioning. The average error in reference point corrected impact on the positioning is better than that without the addition of reference point data, so the error rate can be reduced by adding a reference point.

Reliable reference point data can be obtained by reference point learning, and the error rate can be reduced using such data. Reference point information that is obtained by reference point learning mitigates the problem of message flow. Following the learning process, reliable data concerning the reference point, as shown in Figure 6.

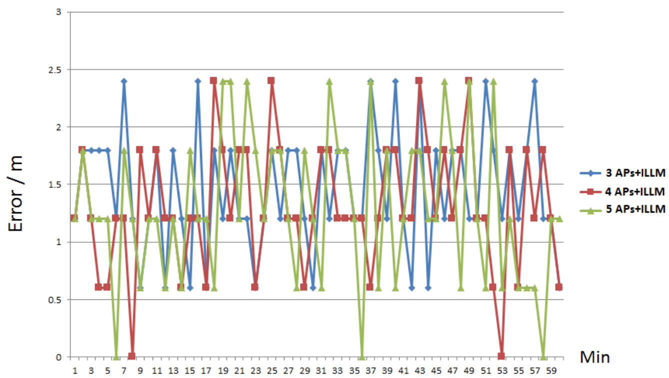


Figure 6 AP numbers and ILLM impact on positioning (Error rate)

V. Conclusion

This work develops an intellectual reference point-assisted indoor positioning system that focuses on favorable accuracy and efficiency. This work makes the following contributions. Combines NFC in indoor positioning with NFC technology to support learning of positioning. Establishes the Indoor Location Learning Mechanism, which yields reference point information by learning in a changing environment. Makes corrections to accurate using accelerometer sensors and orientation sensors, yielding accurate changes in displacement in the positioning process. Finally, charts demonstrate that reference point learning with the ILLM, proposed in this study, is more efficient than the traditional method. The number of applications of the learning process is reduced from the original 150 times to 100 times, so the duration of the process is shortened from 150 minutes to 100 minutes, and the learning efficiency is increased. Obtaining reliable information and calculating the position of indoor environment using a learning curve reduces the error. In the test environment with three APs, the average error is reduced from 1.61m to 1.46m, so the positioning accuracy is improved by 9.3%.

References

[1]. Y. Geng, J. He, H. Deng and K. Pahlavan, "Modeling the effect of human body on TOA ranging for indoor human tracking with wrist mounted sensor," Proceedings of the International Symposium on Wireless Personal Multimedia Communications, pp.1-6, 2013.
[2]. G. Amin and S. Stavros, "A hybrid TDoA-ToA localization method," Proceedings of the International Conference on Telecommunications, pp.1-4, 2013.
[3]. J.Y. Yoon, J.W. Kim, W.H. Lee and D.S. Eom, "A TDoA-based localization using precise time-synchronization," Proceedings of the International Conference on Advanced Communication Technology, pp.1266-1271, 2012.
[4]. K. Enda, M.H. Kabir, F. Ono and R. Kohno, "High accuracy tag tracking system based on TDOA in medical network," Proceedings of the International Symposium on Medical Information and Communication Technology, pp.1-4, 2012.
[5]. N. Ngoc, L. Thu and Y. Shin, "A new approach for positioning based on AOA measurements," Proceedings of the International Conference on Computing, Management and Telecommunications, pp.208-211, 2013.
[6]. J.R. Jiang, C.M. Lin, F.Y. Lin and S.T. Huang, "ALRD: AoA localization with RSSI differences of directional antennas for wireless sensor networks," Proceedings of the International Conference on Information Society, pp.304-309, 2012.
[7]. P.K. Sahu, E.H.K. Wu and J. Sahoo, "DuRT: Dual RSSI trend based localization for wireless sensor networks," Sensors Journal, vol.13, no.8, pp.3115-3123, 2013.
[8]. J.Y. Wang, C.P. Chen, T.S. Lin, C.L. Chuang, T.Y. Lai and J.A. Jiang, "High-precision RSSI-based indoor localization using a transmission power adjustment strategy for wireless sensor networks," Proceedings of the International Conference on High Performance Computing and Communication, pp.1634-1638, 2012.
[9]. C. Liu, D. Fang, Z. Yang, X. Chen, W. Wang, T. Xing, N. An and L. Cai, "RDL: A novel approach for passive object localization in WSN based on RSSI," Proceedings of the IEEE International Conference on Communications, pp.586-590, 2012.
[10]. H. Zhang, J. Zhang and H. Wu, "An adaptive localization algorithm based on RSSI in wireless sensor networks," Proceedings of the International Conference on Cloud Computing and Intelligent Systems, pp.1133-1136, 2012.
[11]. Y. Yu, J. He, O. Wang, F. Liu and C. Xu, "A query-driven indoor location system based on smartphone," Proceedings of the First IEEE Workshop on Enabling Technologies for Smartphone and Internet of Things, pp.25-29, 2012.
[12]. S. Boonsriwai and A. Apavatjrut, "Indoor WIFI localization on mobile devices," Proceedings of the International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology, pp.1-5, 2013.
[13]. R.W. Ouyang, A.K.S. Wong and K.T. Woo, "GPS localization accuracy improvement by fusing terrestrial TOA measurements," Proceedings of the IEEE International Conference on Communication, pp.1-5, 2010.
[14]. H. Kim, C. Park, Y. Cho, C. Shin, J. Park and D Park, "A study on a ratiometric GPS iteration algorithm for indoor localization," Proceedings of the International Conference on Computing and Convergence Technology, pp.32-35, 2012.
[15]. Z. Li, Z. Zhou, C. He and X. Huang, "Advances in RFID-ILA: The past, present and future of RFID-based indoor location algorithms," Proceedings of the Chinese Control and Decision Conference, pp.3830-3835, 2012.
[16]. J.L. Brchan, L. Zhao, J. Wu, R.E. Williams and L.C. Perez, "A real-time RFID localization experiment using propagation models," Proceedings of the IEEE International Conference on RFID, pp.141-148, 2012.
[17]. N. Mair and Q.H. Mahmoud, "A collaborative Bluetooth-based approach to localization of mobile devices," Proceedings of the International Conference on Collaborative Computing: Networking, Applications and Worksharing, pp.14-17, 2012.
[18]. Y. He, Y. Liu, X. Shen, L. Mo and G. Dai, "Noninteractive localization of wireless camera sensors with mobile beacon," Proceedings of the IEEE Transactions on Mobile Computing, pp.333-345, 2013.
[19]. A. Aggarwal and J.S. Bhalla, "Efficient use f artificial neural networks for path finding using fuzzy logic based Ant-Colony System algorithm," Proceedings of the Next Generation Information Technology Summit Confluence,

pp.69-75, 2013.
[20]. M.S. Daoud, A.A. Hopgood, M.A. Al-Fayoumi, H.M. Mimi, "A new routing area displacement prediction for Location-Based Services based on an enhanced ant colony," Proceedings of the IEEE International Conference on Systems, Man and Cybernetics, pp.3247-3252, 2014.
[21]. M. Youssef, M.A. Yosef and M. El-Derini, "GAC: Energy-efficient hybrid GPS-accelerometer-compass GSM localization," Proceedings of the IEEE Global Telecommunications Conference, pp.6-10, 2010.
[22]. J.S. Leu and H.J. Tzeng, "Received signal strength fingerprint and footprint assisted indoor positioning based on ambient Wi-Fi signals," Proceedings of the IEEE Vehicular Technology Conference, pp.1-5, 2012.

Authors Profile

Yi-Wei Ma is a lecturer in China Institute of FTZ Supply Chain, Shanghai Maritime University.HereceivedthePh.D.degree in Department of Engineering Science at National Cheng Kung University, Tainan, Taiwan. His research interests include internet of things, digital home network, cloud computing,embedded system,multimedia p2p streamingand ubiquitous computing.

Jiann-Liang Chen was born in Taiwan on December 15, 1963. He received the Ph.D. degree in Electrical Engineering from National Taiwan University, Taipei, Taiwan in 1989. Since August 2008, he has been with the Department of Electrical Engineering ofNational Taiwan University of Science and Technology, where he is a distinguished professor now. His current research interests are directed at cellular mobility management and personal communication systems.

Jun-jie Liao He received the M.S. degree in Electrical Engineering of National Taiwan University of Science and Technology, Taipei, Taiwan. His research interests include digital home network, and indoor positioning system.

Chia-Lun Tangwas born in Miaoli, Taiwan, in 1974. He received the M.S. and Ph.D. degrees in electrical engineering from National Sun Yat-Sen University, Kaohsiung, Taiwan, in 1998 and 2001, respectively.Since 2001 to 2006, he worked for the Industrial Technology Research Institute, Hsinchu, Taiwan. And he had been a Manager of RF Communication System Technology Department there. Since 2007, he joined in the Auden Techno Corp., Taoyuan, Taiwan, and he has been a RF Chief Technical Officer there. His current research interests include the designs of smart phone, tablet antenna, tunable antenna solution and high integrated antenna module.