2014 Sixth International Conference on Computational Intelligence and Communication Networks

Expansion RSS-based Indoor Localization Using 5G WiFi Signal

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***Abstract*—Indoor localization based on existent WiFi signal strength is becoming more and more prevalent and ubiquitous. Unfortunately, the WiFi received signal strength (RSS) is susceptible by multipath, signal attenuation and environmental changes, it is the major challenge for accurate indoor localization. In this paper, to overcome these limitations, we propose an indoor localization based on expansion RSS algorithm (ERA) to reduce the environmental interference. In addition, according to the detailed analysis of the 2.4G and 5G signal, we get that 5G WiFi signal is more stable than 2.4G, and experiment indicates the 5G signal is more accurate than 2.4G for indoor localization. Experimental results demonstrate the proposed algorithm exhibits superior performance in terms of localization accuracy and stabilization.**

Keywords- indoor localization; received signal strength(RSS); expansion RSS algorithm(ERA); 5G WiFi signal; localization accuracy; localization stabilization;

I. INTRODUCTION

Recently, indoor localization has received much attention for mobile devices localization with widely available WiFi signal, it can provide an accurate localization in indoor environment, such as shopping malls, airports, hospitals, subways, and university campuses. For outdoor localization environment, global navigation satellite systems (GNSS) such as GPS [1] have been used in a wide range of applications including tracking, transport navigation and guidance. Although GPS works extremely well in outdoor localization, unfortunately, it does not perform well in urban canyons, close to walls, construction, indoors, and in basement as the signal from the GPS satellites is too weak to come across most construction thus making GPS hard for indoor localization. Attempts of finding the accurate indoor localization, many indoor localization technologies are proposed, such as infrared [2], ultrawideband (UWB) [3], ultrasonic [4] , Bluetooth [5] , RFID (Radio Frequency Identification) [6], Zigbee [7], FM(frequency modulation) broadcast [8], Geomagnetism [9] and WiFi(Wireless Fidelity) [10],[11].

With the mobile computing technology and the increasing availability of WiFi networks have enabled more accurate localization in indoor environments. Most localization systems based on WiFi are available as commercial products as prototypes based on measurements on the received signal strength (RSS). WiFi based localization systems have several advantages. Firstly, in terms of cost effect, WLAN infrastructures implementation of localization algorithms does not need any additional hardware as network interface cards measure signal strength values from all wireless access points (APs) in range of the receiver. Therefore, RSS needed for localization can be obtained directly from network interface cards owned most mobile devices. Due to the ubiquity of WiFi networks, this mode of localization provides a particularly cost-effective solution for offering location based service (LBS) in commercial and residential indoor environments. For the low cost and wide availability without the need for additional hardware, the WiFi indoor localization is becoming increasingly prevalent and ubiquitous.

Although there are different choices for the localization measurement methods such as time of arrival (TOA) [12],[13], time difference of arrival (TDOA) [14], and angle of arrival (AOA) [15], channel state information (CSI) [16],[17] and received signal strength (RSS) [18],[19], RSS is generally the feature of choice for indoor WiFi localization due to its low cost without the need for additional hardware at our mobile devices. Most RSS-based indoor localization approaches adopt fingerprint algorithm as the basic scheme of indoor localization. The main theme is to collect fingerprint from the surrounding signatures at every reference point (RP) in the areas of workspace, and then building a fingerprint database. The position of the mobiles devices is determined by matching real time measurement RSS with the fingerprint database.

The fingerprint algorithm consists of two phases: an offline training phase, and an online localization phase. In the offline training phase, there are mainly two methods to build fingerprint map, empirical manual measurement [20],[21] and computed analytically based on the signal propagation model [22],[19]. Because signal propagation model is easily affected by environmental changes, normally, the fingerprint map is built with manual effort. In this phase, a creation of fingerprint map for reference points (RPs) survey where the position and RSS must be recorded. Basically, fingerprint map is a database of reference points at predefined points (coordinates) coupled with various radio signal strength characteristics, for example, RSS, signal angles, or propagation time called signal fingerprint. Step by step, for every fingerprint, there must be a measurement that includes the information about all positions and their received signal strength. When the localization system is beginning, the online localization phase, mobile devices detect signal properties at unknown point. Then, the real time

978-1-4799-6929-6/14 $31.00 © 2014 IEEE
DOI 10.1109/CICN.2014.117

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measurement signal strength values are compared with the fingerprint map to infer the position of the mobile devices. The key idea of fingerprint-based algorithm is to find the optimal nearest neighbor points. Attempts of finding the best matching algorithm and trying to improve the localization accuracy, many researchers propose the nearest neighbor (NN), k-nearest neighbor (KNN) [23], weighted k-nearest neighbor(WKNN) [24], Bayesian probabilistic model (BPM) [25], artificial neural network(ANN) [26] and support vector machine(SVM) [27] to obtain the optimal nearest neighbor points.

Even though fingerprint algorithm has been used successfully in indoor localization preliminarily, it exhibits several limitations when considering indoor environment. The major drawback of the fingerprint algorithm is that RSS is sensitivity to environmental changes such as object moving into the building, diffraction, and reflection, which result in changes in signal propagation. These challenges result mainly from the influence of obstacles on the propagation of electromagnetic wave. 2.4G signal is an unlicensed spectrum that different hardware and applications apart from WiFi can freely use this spectrum to cause interference. The most common instruments which use this frequency and can interfere with WiFi are microwaves that are the household electronic devices to emit interference in the 2.4G band, Bluetooth devices, telecommunications devices for the deaf, digitally enhanced cordless telecommunications phones, baby monitors, wireless speakers, wireless security cameras and so on. For getting accurate localization, a localization system must be able to overcome these challenges.

In this work, for solving the problem of the signal is unsteadiness, we propose an indoor localization system using 5G band signal and the expansion RSS algorithm(ERA), it aims at reducing the interference to build accurate fingerprint map and using the expansion RSS algorithm to improve the localization accuracy and stabilization.

The remainder of this paper is organized as follows: A brief description of indoor localization system is presented in Section 2. Section 3 describes the expansion RSS algorithm in detail. The characteristics of 2.4G and 5G band signal are analysed in Section 4. The experiment results and evaluations through implementation are listed in Section 5. Finally, Section 6 concludes the paper.

II. INDOOR LOCALIZATION SYSTEM

As in most fingerprint approaches, the proposed system consists of an offline training and an online localization phase. The offline training phase is responsible for collecting signal strength form each reference point (RP), and then recording it in the fingerprint database. At the online localization phase, the mobile devices collect the real time measurement RSS and compare it with the available fingerprint in the database.

A. Offline Training Phase

In the offline training phase, the workspace plan is decomposed into a grid of rectangular cells, whose number is indicated as N. The position estimation of the mobile devices will be limited to such cells. For each cell, the raw set of RSS time samples are collected from AP i at RP j with orientation o at the center of the cell. The RSS samples collected at each cell represents the position characteristic of such a cell. Since RSS varies noticeably due to interferences and environment conditions, several consecutive RSS measurements need to be collected at each cell with a period of time. Then, the average of the RSS time samples is computed and stored in fingerprint database. Such fingerprint map can be represented by $\Omega^{(o)}$:

$$\Omega^{(o)} = \begin{pmatrix} r_{1,1}^{(o)} & r_{1,2}^{(o)} & \cdots & r_{1,N}^{(o)} \\ r_{2,1}^{(o)} & r_{2,2}^{(o)} & \cdots & r_{2,N}^{(o)} \\ \vdots & \vdots & \ddots & \vdots \\ r_{L,1}^{(o)} & r_{L,2}^{(o)} & \cdots & r_{L,N}^{(o)} \end{pmatrix}$$

Where $r_{i,j}^{(o)}$ is a fingerprint from AP_i at AP_j with orientation o, for $i = 1,2,\cdots, L$, $j = 1,2,\cdots, N$, and $o \in \{\mathrm{forward}, back\}$. L is the total number of APs that can be detected, and N is the number of RPs.

B. Online Localization Phase

The major challenge for accurate RSS-based localization comes from the variations of RSS due to the dynamic and unpredictable nature of radio channel, and the RSS is easily affected by environmental changes, such as shadowing and multipath. It is variable that the RSS is received from same point at different time, so the real time measurement RSS is not too credible to accurate localization. To decrease the effect by variational signal, we expand the real time RSS before matching the fingerprint map. And three nearest neighbor points are obtained as described as n_a, n_b, n_c, the ultimate localization estimation is represented as $(\hat{x}, \hat{y})$:

$$\begin{cases} \hat{x} = \frac{1}{3}(x_{na} + x_{nb} + x_{nc}) \\ \hat{y} = \frac{1}{3}(y_{na} + y_{nb} + y_{nc}) \end{cases}$$

III. ACCURATE LOCALIZATION BASED ON EXPANSION RSS ALGORITHM(ERA)

By analysing 2.4G and 5G WiFi signal, we get that absolute value of signal fluctuation is under 5 dBm as show in Figure 1, and about 93% fluctuation is within 5 dBm in all the measurement fluctuation (2.4G and 5G band signal). In our experiment, the 5G signal fluctuation is all within 5 dBm, and about 86% fluctuations are within 5 dBm in the 2.4G signal. To avoid the inaccurate nearest neighbor points are matching with the unauthentic real time RSS, before operating localization algorithm, the RSS is expanded ±5

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dBm, and then using it for localization. However, the 5G signal is more stable than 2.4G, form the Figure 1, about 86% fluctuations are within ±3 dBm, in order to expand the real time measurement RSS befittingly, but excessive expansion, the 5G signal only need the expansion of ±3 dBm in this work.

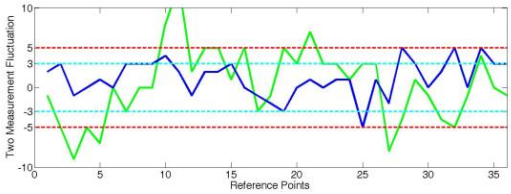


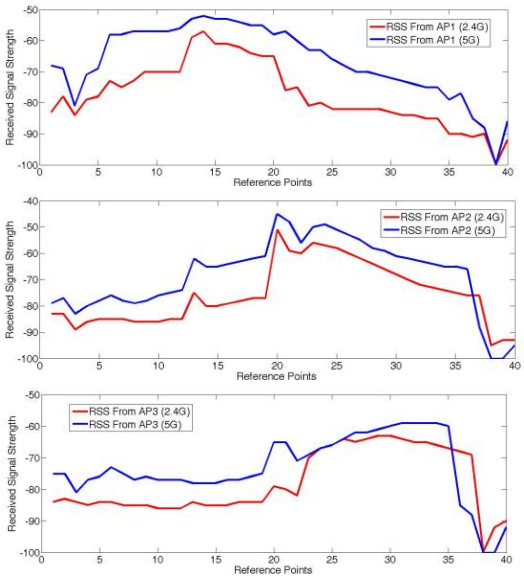
Figure 1. Signal fluctuation.

The real time measurement RSS is processed by the ERA, it will increase the real RSS characteristic of unknowed point to reduce the possible of matching false nearest neighbor points. The performance of ERA is described detailedly in Section 5.

IV. Stable 5G WiFi Signal-Based Localization

The indoor radio environment is quite complex. Due to the 2.4G is no permit limitation band, a wide variety of equipment use the band at the same time. It can not avoid to be interfered by the same frequency equipments that have introduced in Section 1. The interference signal will generate signal fluctuation when we detect the WiFi signal from surrounding access points.

In this section, we explore the impact of frequency band (2.4G and 5G) to evaluate the localization stabilization. While 2.4G signal is the only band originally used for WiFi, increasingly 5G signal is also used despite its poorer propagation characteristics resulting from higher frequency operation. Due to the 5G frequency band is less crowded, and it is far more available spectrum in 5G band. From Figure. 2, the signal strength of 5G is stronger than 2.4G. Generally, the stronger signal is more stable, and the stable signal can guarantee the high localization accuracy.



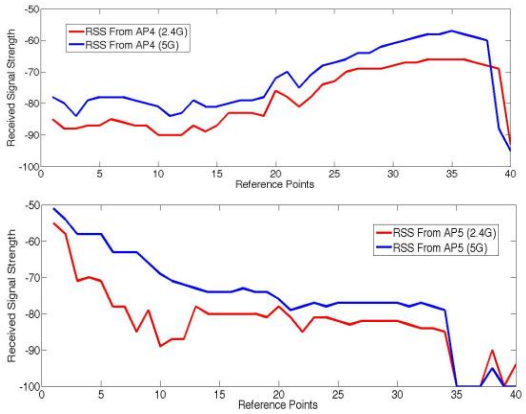


Figure 2. Received signal strength from different Aps

Besides this, from Figure. 3, we can get that the 5G signal is more stable than 2.4G in the same environment. From 30-st RP to 35-st RP, it indicates the 5G signal has poorer propagation characteristics resulting from higher frequency operation.

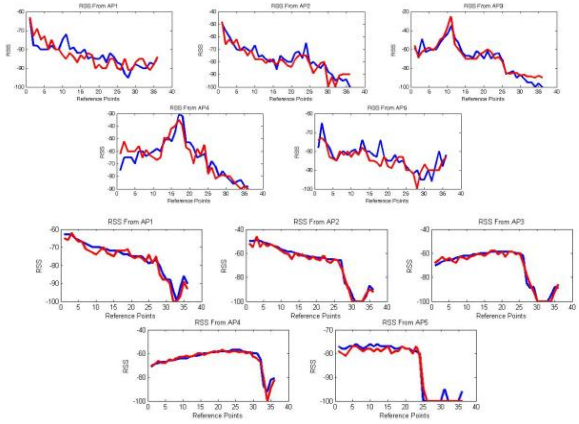


Figure 3. Twice received signal strength from different APs at all APs (2.4G and 5G)

Today more and more APs have double frequency band, and the 5G signal seem to be much more adapted for indoor localization than 2.4G signal. Due to a lack of co-channel interference, it can be feasible to use more stable RSS for the purpose of accurate localization. So the 5G signal is selected as localization estimation in this paper, and the accuracy analysis is presented in Section 5.

V. Experiments and Evaluations

A. Experiment Setup

In this section, we present the implementation and experimental evaluations of the proposed algorithm. The fingerprint database is collected by iPhone 5, its network card can detect both 2.4G and 5G signal. The workspace is equipped with WiFi environment by five TP-LINK WDR6300 routers that can emit 2.4G and 5G WiFi signal. Five APs are placed in the teaching building of our university. The total dimension of area is 36×25.8 meters,

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consisting of hallways and some classrooms. We collect 40 reference points evenly form the hallways region, and obtain WiFi fingerprint database using iPhone 5 with the application software that is a custom mobile application to collect RSS and build the fingerprint map automatically. When collecting the fingerprint map, the mobile devices are kept at the same height of approximately an adult's breast and sometimes rotated horizontally at the same position to face different directions. Both RPs and unknowed points are collected over several hours. In particular, for the RPs data, 20 samples at each RP with a rate of 1 sample/second are collected. For the unknowed points, altogether 40 unknowed points are collected by a user walking through the hallway area.

Besides that, according to [8], [28], Manhattan distance performs slightly better than Euclidean distance, and our workspace is a regular rectangle, we use the Manhattan distance as the standard of error analysis. The Manhattan distance is an expressions of geometric metric space. It is defined as the sum of the absolute differences of values between a real time measurement RSS from fingerprint as indicated by the following equation:

$$ManDist(r_{k,s}^{(o)}, r_{i,j}^{(o)}) = \sum_{j=1}^{N} | r_{k,s}^{(o)} - r_{i,j}^{(o)} |$$

B. *The Performance of ERA-based Localization Using 5G WiFi Signal*

This section evaluates the performance of ERA as detailed description in Section 3. From section 4, the 5G signal is more stable than 2.4G, if both two signal can be received by our mobile devices, the 5 GHz signal should have priority to be used for localization estimation. we compare the proposed algorithm with traditional KNN algorithm, and the localization result is showed in Figure 4. The result indicates the 5G based localization is more accurate than 2.4G, and no matter 2.4G and 5G signal, the ERA performs better than traditional KNN algorithm.

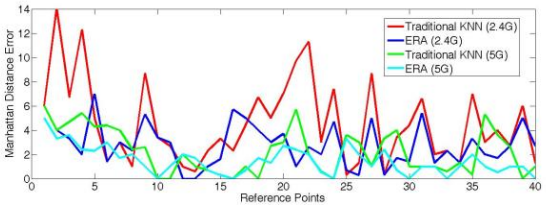


Figure 4. Average error of all algorithms(2.4G and 5G signal)

In addition, we also analyse the average error and standard deviation to evaluate the localization stabilization. From Figure 5 and 6, regardless of 2.4G and 5G signal, the average error of ERA is smaller than traditional KNN algorithm as well as the standard deviation. The average error of ERA (2.4G), ERA (5G), traditional KNN (2.4G) and traditional KNN (5G) is 2.8025, 1.4800, 4.5700 and 2.2350 respectively as show in Figure 5. Beside localization accuracy, the localization stabilization is also important for localization system. In our experiment, the standard deviation of ERA (2.4G), ERA (5G), traditional KNN (2.4G) and traditional KNN (5G) is 3.2290, 1.3437, 11.6129 and 3.4187 respectively. The more less standard deviation that implies the localization is more stable. It indicates that not only localization accuracy but also localization stabilization is improved by ERA.

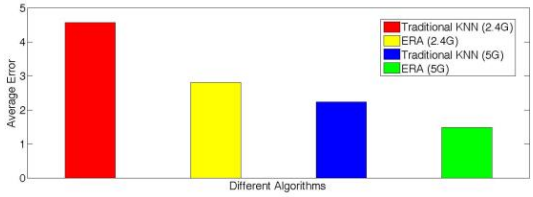


Figure 5. Average error of all algorithms(2.4G and 5G signal)

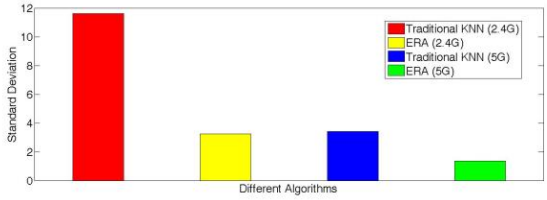


Figure 6. Standard deviation of all algorithms(2.4G and 5G signal)

VI. EXPERIMENTS AND EVALUATIONS

This paper focuses on improving the localization accuracy and stabilization by the ERA approach. By analysing the change rule of WiFi signal, about ±5 dBm of fluctuation is in the 2.4G and 5G signal, so the real time measurement RSS is not accurate as localization estimation, before matching the fingerprint map, the real time measurement RSS need expansion to reduce the environmental interference, and then matching with the fingerprint map. However, the 5G WiFi signal is more table than 2.4G, to avoid to expand enough, and the most fluctuation of 5G WiFi signal is within ±3 dBm, so the 5G WiFi signal only need the expansion of ±3 dBm. Experimental results indicate the proposed algorithm is more accurate and stable than traditional KNN algorithm.

In the future, we intend to perform this algorithm to apply it in larger fingerprint database, as well as to investigate the performance of the proposed algorithm in the more complex environment and the multi-layered buildings.

ACKNOWLEDGMENT

This work was supported by National Natural Science Foundation of China under grant project No.61232004 and No.61103085.

REFERENCES

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[1] N. Bulusu, J. Heidemann, and D. Estrin, "Gps-less low-cost outdoor localization for very small devices," Personal Communications, IEEE, vol. 7, no. 5, pp. 28–34, 2000.

[2] C. Lee, Y. Chang, G. Park, J. Ryu, S.-G. Jeong, S. Park, J. W. Park, H. C. Lee, K.-s. Hong, and M. H. Lee, "Indoor positioning system based on incident angles of infrared emitters," in Industrial Electronics Society, 2004. IECON 2004. 30th Annual Conference of IEEE, vol. 3, pp. 2218–2222, IEEE, 2004.

[3] A. Shahi, A. Aryan, J. S. West, C. T. Haas, and R. C. Haas, "Deterioration of uwb positioning during construction," Automation in Construction, vol. 24, pp. 72–80, 2012.

[4] V. Filonenko, C. Cullen, and J. Carswell, "Investigating ultrasonic positioning on mobile phones," in Indoor Positioning and Indoor Navigation (IPIN), 2010 International Conference on, pp. 1–8, IEEE, 2010.

[5] S. Li, Y. Lou, and B. Liu, "Bluetooth aided mobile phone localization: a nonlinear neural circuit approach," ACM Transactions on Embedded Computing Systems (TECS), vol. 13, no. 4, p. 78, 2014.

[6] N. Li and B. Becerik-Gerber, "Performance-based evaluation of rfidbased indoor location sensing solutions for the built environment," Advanced Engineering Informatics, vol. 25, no. 3, pp. 535–546, 2011.

[7] L. Luoh, "Zigbee-based intelligent indoor positioning system soft computing," Soft Computing, vol. 18, no. 3, pp. 443–456, 2014.

[8] Y. Chen, D. Lymberopoulos, J. Liu, and B. Priyantha, "Indoor localization using fm signals," Mobile Computing, IEEE Transactions on, vol. 12, no. 8, pp. 1502–1517, 2013.

[9] J. Chung, M. Donahoe, C. Schmandt, I.-J. Kim, P. Razavai, and M. Wiseman, " Indoor location sensing using geo-magnetism," in Proceedings of the 9th international conference on Mobile systems, applications, and services, pp. 141–154, ACM, 2011.

[10] N. Alsindi, Z. Chaloupka, N. AlKhanbashi, and J. Aweya, "An empirical evaluation of a probabilistic rf signature for wlan location fingerprinting," 2014.

[11] R. S. Campos, L. Lovisolo, and M. L. R. de Campos, "Wi-fi multifloor indoor positioning considering architectural aspects and controlled computational complexity," Expert Systems with Applications, vol. 41, no. 14, pp. 6211–6223, 2014.

[12] M. Heidari and K. Pahlavan, "A new statistical model for the behavior of ranging errors in toa-based indoor localization," in Wireless Communications and Networking Conference, 2007. WCNC 2007. IEEE, pp. 2564–2569, IEEE, 2007.

[13] P.-H. Tseng, K.-T. Feng, Y.-C. Lin, and C.-L. Chen, "Wireless location tracking algorithms for environments with insufficient signal sources," Mobile Computing, IEEE Transactions on, vol. 8, no. 12, pp. 1676–1689, 2009.

[14] M. Bocquet, C. Loyez, and A. Benlarbi-Delai, "Using enhanced-tdoa measurement for indoor positioning," Microwave and Wireless Components Letters, IEEE, vol. 15, no. 10, pp. 612–614, 2005.

[15] C.-H. Lim, B. P. Ng, and D. Da, "Robust methods for aoa geo-location in a real-time indoor wifi system," Journal of Location Based Services, vol. 2, no. 2, pp. 112–121, 2008.

[16] K. Wu, J. Xiao, Y. Yi, D. Chen, X. Luo, and L. M. Ni, "Csi-based indoor localization," Parallel and Distributed Systems, IEEE Transactions on, vol. 24, no. 7, pp. 1300–1309, 2013.

[17] Z. Yang, Z. Zhou, and Y. Liu, "From rssi to csi: Indoor localization via channel response," ACM Computing Surveys (CSUR), vol. 46, no. 2, p. 25, 2013.

[18] A. Jaffe and M. Wax, "Single-site localization via maximum discrimination multipath fingerprinting," IEEE Transactions on Signal Processing, vol. 62, no. 7, pp. 1718–1728, 2014.

[19] M. Ficco, C. Esposito, and A. Napolitano, "Calibrating indoor positioning systemswith low efforts," Mobile Computing, IEEE Transactions on, vol. 13, no. 4, pp. 737–751, 2014.

[20] C. Wu, Z. Yang, and Y. Liu, "Smartphones based crowdsourcing for indoor localization," 2014.

[21] A. Danalet, B. Farooq, and M. Bierlaire, "A bayesian approach to detect pedestrian destination-sequences from wifi signatures," Transportation Research Part C: Emerging Technologies, vol. 44, pp. 146–170, 2014.

[22] I. Bisio, M. Cerruti, F. Lavagetto, M. Marchese, M. Pastorino, A. Randazzo, and A. Sciarrone, "A trainingless wifi fingerprint positioning approach over mobile devices," 2014.

[23] P. Torteeka and X. Chundi, "Indoor positioning based on wi-fi fingerprint technique using fuzzy k-nearest neighbor," in Applied Sciences and Technology (IBCAST), 2014 11th International Bhurban Conference on, pp. 461–465, IEEE, 2014.

[24] B. Shin, J. H. Lee, T. Lee, and H. S. Kim, "Enhanced weighted knearest neighbor algorithm for indoor wi-fi positioning systems," in Computing Technology and Information Management (ICCM), 2012 8th International Conference on, vol. 2, pp. 574–577, IEEE, 2012.

[25] D. Madigan, E. Einahrawy, R. P. Martin, W.-H. Ju, P. Krishnan, and A. Krishnakumar, "Bayesian indoor positioning systems," in INFOCOM 2005. 24th Annual Joint Conference of the IEEE Computer and Communications Societies. Proceedings IEEE, vol. 2, pp. 1217–1227, IEEE, 2005.

[26] M. Zhou, Y. Xu, and L. Tang, "Multilayer ann indoor location system with area division in wlan environment," Systems Engineering and Electronics, Journal of, vol. 21, no. 5, pp. 914–926, 2010.

[27] F. Yu, M. H. Jiang, J. Liang, X. Qin, M. Hu, T. Peng, and X. R. Hu, "An indoor localization of wifi based on support vector machines," in Advanced Materials Research, vol. 926, pp. 2438–2441, Trans Tech Publ, 2014.

[28] A. Farshad, J. Li, M. K. Marina, and F. J. Garcia, "A microscopic look at wifi fingerprinting for indoor mobile phone localization in diverse environments," in Indoor Positioning and Indoor Navigation (IPIN), 2013 International Conference on, pp. 1–10, IEEE, 2013.

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