Introduction

The demand for location-based services has risen in these years due to the rapid growth of mobile internet technology. However, due to the absence of line of sight and attenuation of GPS signals as they pass through walls, the usability of GPS or analogous satellite-based positioning system in interior contexts is limited. Indoor localization has been investigated for decades and a variety of indoor positioning solutions including WiFi[2, 27-35], Bluetooth [36-38], Radio-frequency Identification (RFID), Zigbee, Ultra-wideband (UWB), Ultrasound [39], Global System for Mobile Communication (GSM), magnetic field [40] and inertial sensors. However, each method has limitations in terms of accuracy, coverage, cost, complexity, and application. More importantly, the signal information may not be available in every context. Furthermore, the algorithms are often customized for a specific environment, so the performance of these single-signal systems cannot be generalized to every scenario.

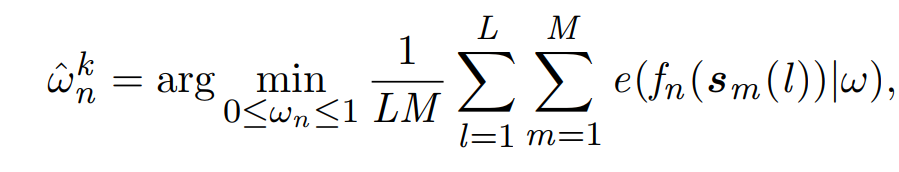
Altered fingerprint: Since the movement of access points or power adjustment can change the strength or presence of Wi-Fi signals, the traditional approach to maintaining positioning accuracy is to undertake site surveys regularly, which is time-consuming and costly. Therefore, He et al. [14] proposed the Localization with Altered APs and Fingerprint Updating(LAAFU) system to locate a target accurately and update fingerprints in the presence of altered AP signals. LAAFU system uses implicit crowdsourcing signals to update fingerprints and reduce survey number. Non-parametric Gaussian process regression is adopted to update fingerprint signals adaptively and transparently.

The adaptation of fingerprints to environmental change was investigated in [19-23]. The work in [19] and [22] introduced transfer learning techniques to adapt RSS measurements by transferring the knowledge from the old model to the altered one. [20] describes a modified Bayesian regression approach to estimate a posterior signal strength probability distribution over all locations based on online observations from WLAN access points(AP) by assuming a Gaussian prior centered around a logarithmic pass loss mean. Yin et al. [23] proposed a Location Estimation using Model Trees(LEMT) algorithm, creating a radio map from real-time signal strength information at reference points. Some traditional methods such as least variance of RSS values[21] can also be applied to assign lower weights to altered APs signals for each point in a cluster.

Weight allocation: After collecting a set of location estimates from multiple sources, it is crucial to achieve satisfactory fusion performances by selecting optimal weights. Determining an optimized weight can harness the advantages of different location estimation methods. There are two strategies to calculate weighting: supervised learning and unsupervised learning. Supervised learning attempts to learn the weighting allocation by using labeled data in the offline phase, where unsupervised learning learns the weighting allocation directly from online data.

Supervised Weights Learning

The majority of existing supervised weights learning is centered on minimizing localization errors in the offline phase utilizing available training data [1-9]. Weight training and weight selection are the two most essential aspects of supervised weight learning. As for weight training, the chosen weights should adequately reflect the intrinsic complementarity of the combined information. Current weights calculation is mainly focused on minimizing location errors [5] and maximizing the source efficiency [10]. Fang et al. [5] suggested searching the weight of the n-th positioning algorithm for the k-th grid point by minimizing the average localization error over the L training samples and M sources by the formula below:



,where e(fn(sm(l))|ω) is the localization error of the n-th function, the m-th source, and the l-th sample with the weight ω, and M is the number of the sources.

Rather than training distinct weights for different grid points, Fang et al. [12] suggested training various weights for different anchors by minimizing average positioning errors in the offline phase. The ultimate weights are selected from the anchor with the highest signal strength. In terms of accuracy and resilience, this method outperforms other traditional localization methods like LLS and MDS.

Some researchers proposed weight selection methods, including DFC [5], KAAL [1], and others [2] ,[9] , [11], [12]. Li et al. [13] used the nearest neighbor algorithm to search a suitable weight by directly matching the distance between the online observations and offline collected signals.

Unsupervised weight learning

There are two major unsupervised weights learning methods: conventional unsupervised weights learning and truth discovery.

Conventional unsupervised weights learning: Hu et al. [24] used a coefficient to combine measurements to determine the weighted mean of results to fuse PDR and WiFi. The coefficient is proportional to the absolute difference between the PDR and WiFi results. Guo and Ansari [25] advocated assessing the occurrences of localization outcomes to predict the most trustworthy localization result using the majority voting method.

Truth discovery methods: This method aims at finding the most reliable localization result from a pool of multiple positioning candidates. The most credible positioning result’s weight is set to 1, while the other positioning results’ weights are set to 0. Guo et al. [26] suggested an expectation-maximization algorithm by factoring the fingerprint quality into the genuine label estimate.

References

[1] X. Guo, L. Li, N. Ansari, and B. Liao, “Knowledge aided adaptive localization via global fusion profile,” IEEE Internet Things J., vol. 5, no. 2, pp. 1081–1089, Apr. 2018

[2] X. Guo, L. Li, N. Ansari, and B. Liao, “Accurate WiFi localization by fusing a group of fingerprints via a global fusion profile,” IEEE Trans. Veh. Technol., vol. 67, no. 8, pp. 7314–7325, Aug. 2018

[3] L. Wang and W.-C. Wong, “Fusion of multiple positioning algorithms,” in Proc. 8th Int. Conf. Inf. Commun. Signal Process. (ICICS), Singapore, Dec. 2011, pp. 1–5.

[4] S.-H. Fang, T.-N. Lin, and K.-C. Lee, “A novel algorithm for multipath fingerprinting in indoor WLAN environments,” IEEE Trans. Wireless Commun., vol. 7, no. 9, pp. 3579–3588, Sep. 2008

[5] S.-H. Fang, Y.-T. Hsu, and W.-H. Kuo, “Dynamic fingerprinting combination for improved mobile localization,” IEEE Trans. Wireless Commun., vol. 10, no. 12, pp. 4018–4022, Dec. 2011

[6] S.-H. Fang, C.-H. Wang, T.-Y. Huang, C.-H. Yang, and Y.-S. Chen, “An enhanced ZigBee indoor positioning system with an ensemble approach,” IEEE Commun. Lett., vol. 16, no. 4, pp. 564–567, Apr. 2012

[7] Y. Gwon, R. Jain, and T. Kawahara, “Robust indoor location estimation of stationary and mobile users,” in Proc. IEEE Conf. Comput. Commun. (INFOCOM), vol. 2. Hong Kong, Mar. 2004, pp. 1032–1043

[8] X. Guo, L. Chu, and X. Sun, “Accurate localization of multiple sources using semidefinite programming based on incomplete range matrix,” IEEE Sensors J., vol. 16, no. 13, pp. 5319–5324, Jul. 2016

[9] X. Guo, F. Hu, N. R. Elikplim, and L. Li, “Indoor localization using visible light via two-layer fusion network,” IEEE Access, vol. 7, pp. 16421–16430, 2019.

[10] D. Taniuchi and T. Maekawa, “Robust Wi-Fi based indoor positioning with ensemble learning,” in Proc. IEEE 10th Int. Conf. Wireless Mobile Comput. Netw. Commun. (WiMob), Larnaca, Cyprus, Oct. 2014, pp. 592–597.

[11] S.-H. Fang, C.-H. Wang, T.-Y. Huang, C.-H. Yang, and Y.-S. Chen, “An enhanced ZigBee indoor positioning system with an ensemble approach,” IEEE Commun. Lett., vol. 16, no. 4, pp. 564–567, Apr. 2012.

[12] S.-H. Fang and T.-N. Lin, “Cooperative multi-radio localization in heterogeneous wireless networks,” IEEE Trans. Wireless Commun., vol. 9, no. 5, pp. 1547–1551, May 2010.

[13] H. Li, H. Meng, K. Zheng, and H. Zhao, “An indoor localization scheme based on data fusion in wireless networks,” in Proc. 10th Int. Conf. Commun. Netw. China (ChinaCom), Shanghai, China, Aug. 2015, pp. 807–812.

[14] Kourosh Khoshelham and Sisi Zlatanova. 2016. Sensors for indoor mapping and navigation. Sensors 16, 5 (2016).

[15] L. Pei, M. Zhang, D. Zou, R. Chen, and Y. Chen. A survey of crowd sensing opportunistic signals for indoor localization. Article 4041291 (2016), Jun 2016

[16] J. Shang, X. Hu, F. Gu, D. Wang, and S. Yu. 2015. Improvement schemes for indoor mobile location estimation: A survey. Math. Prob. Eng. 2015, Article 397298, May 2015

[17] Moe Z. Win, R. Michael Buehrer, George Chrisikos, Andrea Conti, and H. Vincent Poor. 2018. Foundations and trends in localization technologies—Part I. Proc. IEEE 106, 6 (2018), 1019–1021.

[18] Moe Z. Win, R. Michael Buehrer, George Chrisikos, Andrea Conti, and H. Vincent Poor. 2018. Foundations and trends in localization technologies—Part II. Proc. IEEE 106, 7 (2018), 1132–1135

[19] Z. Sun, Y. Chen, J. Qi, and J. Liu, “Adaptive localization through transfer learning in indoor Wi-Fi environment,” in Proc. IEEE 7th Int. Conf. Mach. Learn. Appl., 2008, pp. 331–336.

[20] M. Atia, A. Noureldin, and M. Korenberg, “Dynamic online-calibrated radio maps for indoor positioning in wireless local area networks,” IEEE Trans. Mobile Comput., vol. 12, no. 9, pp. 1774–1787, Sep. 2013

[21] N. Alikhani, V. Moghtadaiee and S.A. Ghorashi. Fingerprinting Based Indoor Localization Considering the Dynamic Nature of Wi-Fi Signals. *Wireless Pers Commun* 115, 1445–1464, Jul. 2020

[22] V. W. Zheng, E. W. Xiang, Q. Yang, and D. Shen, “Transferring localization models over time,” in Proc. 23rd Nat. Conf. Artif. Intell., 2008, vol. 3, pp. 1421–1426

[23] J. Yin, Q. Yang, and L. M. Ni, “Learning adaptive temporal radio maps for signal-strength-based location estimation,” IEEE Trans. Mobile Comput., vol. 7, no. 7, pp. 869–883, Jul. 2008

[24] K. Hu, X.-Y. Liao, and M. Yu, “Research on indoor localization method based on PDR and Wi-Fi,” in Proc. 10th Int. Conf. Wireless Commun. Netw. Mobile Comput. (WiCOM), Beijing, China, Sep. 2014, pp. 653–656.

[25] X. Guo and N. Ansari, “Localization by fusing a group of fingerprints via multiple antennas in indoor environment,” IEEE Trans. Veh. Technol., vol. 66, no. 11, pp. 9904–9915, Nov. 2017

[26] X. Guo, L. Li, F. Xu, and N. Ansari, “Expectation maximization indoor localization utilizing supporting set for Internet of Things,” IEEE Internet Things J., vol. 6, no. 2, pp. 2573–2582, Apr. 2019

[27] M. Kotaru, K. Joshi, D. Bharadia, and S. Katti, “SpotFi: Decimeter level localization using WiFi,” ACM SIGCOMM Comput. Commun. Rev., vol. 45, no. 4, pp. 269–282, Aug. 2015.

[28] X. Guo, S. Zhu, L. Li, F. Hu, and N. Ansari, “Accurate WiFi localization by unsupervised fusion of extended candidate location set,” IEEE Internet Things J., vol. 6, no. 2, pp. 2476–2485, Apr. 2019

[29] M. Zhang, W. Shen, Z. Yao, and J. Zhu, “Multiple information fusion indoor location algorithm based on WiFi and improved PDR,” in Proc. 35th Chin. Control Conf. (CCC), Chengdu, China, Jul. 2016, pp. 5086–5092.

[30] J. Niu, B. Wang, L. Cheng, and J. J. P. C. Rodrigues, “WicLoc: An indoor localization system based on WiFi fingerprints and crowdsourcing,” in Proc. IEEE Int. Conf. Commun. (ICC), London, U.K., Jun. 2015, pp. 3008–3013.

[31] F. Evennou and F. Marx, “Advanced integration of WiFi and inertial navigation systems for indoor mobile positioning,” EURASIP J. Adv. Signal Process., vol. 2006, p. 164, Dec. 2006

[32] L. Li, X. Guo, N. Ansari, and H. Li, “A hybrid fingerprint quality evaluation model for WiFi localization,” IEEE Internet Things J., vol. 6, no. 6, pp. 9829–9840, Dec. 2019.

[33] P. Zhang, Q. Zhao, Y. Li, X. Niu, Y. Zhuang, and J. Liu, “Collaborative WiFi fingerprinting using sensor-based navigation on smartphones,” Sensors, vol. 15, no. 7, pp. 17534–17557, 2015.

[34] Y. Du, D. Yang, and C. Xiu, “A novel method for constructing a WiFi positioning system with efficient manpower,” Sensors, vol. 15, no. 4, pp. 8358–8381, 2015

[35] C. Basri and A. El Khadimi, “Survey on indoor localization system

and recent advances of WiFi fingerprinting technique,” in Proc. 5th Int. Conf. Multimedia Comput. Syst. (ICMCS), Marrakesh, Morocco, Oct. 2016, pp. 253–259.

[36] Y. Wang, Q. Ye, J. Cheng, and L. Wang, “RSSI-based Bluetooth indoor localization,” in Proc. Int. Conf. Mobile Ad Hoc Sensor Netw. (MSN), Shenzhen, China, Dec. 2015, pp. 165–171

[37] H. Zou, C, et al. 2017. Accurate Indoor Localization and Tracking Using Mobile Phone Inertial Sensors, WiFi and IBeacon. *IEEE International Symposium on Inertial Sensors and Systems (INERTIAL)*.

[38] M. Castillo-Cara, J. Lovón-Melgarejo, G. Bravo-Rocca, L. Orozco-Barbosa, I. García-Varea, “An Empirical Study of the Transmission Power Setting for Bluetooth-Based Indoor Localization Mechanisms.” Sensors. 2017; 17(6):1318.

[39] J. Qi, G-P. Liu, “A Robust High-Accuracy Ultrasound Indoor Positioning System Based on a Wireless Sensor Network”. *Sensors*. 2017; 17(11):2554.

[40] Y. Shu, B. Cheng, G. Shen, C. Zhao, L. Li, and F. Zhao. 2015. Magicol: Indoor localization using pervasive magnetic field and opportunistic WiFi sensing. IEEE Journal on Selected Areas in Communications 33, 7 (2015), 1443–1457.