Adaptive Long-Term Wi-Fi Fingerprint-Based Indoor Localization

Subjects: Engineering, Electrical & Electronic
Contributor: Tesfay Gidey Hailu

This research delves into the challenges of Wi-Fi fingerprint-based indoor localization in dynamic environments, addressing the evolving nature of signal patterns and feature spaces over time. The study focuses on improving adaptive long-term localization accuracy by examining temporal variations in signal strength across 25 months. The research employs key methodologies such as mean-based feature selection, principal component analysis (PCA), and functional discriminant analysis (FDA) to examine signal features and address multicollinearity. The paper introduces an innovative algorithm, Ada-LT IP, which integrates data reduction and transfer learning techniques to enhance accuracy. The proposed method effectively mitigates signal fluctuations and reduces computational complexity, resulting in superior performance compared to current state-of-the-art approaches, as measured by mean absolute error. This research provides critical insights into enhancing adaptive long-term Wi-Fi indoor localization systems, paving the way for more reliable applications in real-world settings.

indoor localization | Wi-Fi fingerprinting | functional discriminant analysis | transferlearning | features extraction | computational complexity

1. Introduction

With the advent of the Internet of Things (IoT), along with the rollout of 5G and emerging 6G technologies, the significance of location-based services (LBS) has markedly increased. Accurate indoor positioning information is essential for a range of applications, including business location services, data mining, security monitoring, and venue management [1][2][3][4]. While global positioning system (GPS) technology operates effectively in outdoor settings, it proves inadequate for indoor localization due to weak signal reception in complex environments. Key challenges include limited line of sight, insufficient satellite signal penetration, and interference from internal obstacles, such as shadows and multipath fading [5][6][7][8][9]. As urbanization intensifies and a majority of activities shift indoors, the demand for reliable indoor positioning systems (IPSs) has surged. A variety of wireless technologies have emerged to address this need, including radio frequency identification (RFID) [10], Bluetooth [11], ultra-wideband (UWB) [12], Zigbee [13], inertial navigation [14], and visible light communication (VLC) [15]. However, the implementation of these technologies often incurs significant infrastructure costs. Effective IPSs leverage diverse signal characteristics—such as received signal strength (RSS), channel state information (CSI), angle of arrival (AOA), and time of arrival (TOA)—to accurately locate objects or individuals in environments where GPS signals are compromised. To meet the demands of indoor settings, these systems must provide high accuracy, rapid estimation times, and low power consumption. Nevertheless, the dynamic nature of indoor environments introduces variability in signal patterns, which can adversely affect positioning performance [16][17][18]. To achieve a balance between computational costs and accuracy, IPSs must optimize available resources while accounting for environmental factors and maintaining an acceptable margin of error. The mission of the application and the overall system cost are also critical determinants of positioning performance [19][20][21]. Among the various indoor positioning technologies, Wi-Fi fingerprint-based IPS (FPBIPS) stands out as a particularly promising solution owing to its cost-effectiveness and ease of implementation. However, FPBIPS is susceptible to challenges posed by multipath effects, shadowing, and scattering, which are influenced by the dynamic nature of indoor environments [22][23][24]. Additionally, signal attenuation in wireless communication systems—primarily attributed to path loss, shadowing, and multipath effects—can significantly degrade location accuracy [25]. **Figure 1** illustrates the impact of multipath on the received signal within an indoor setting.

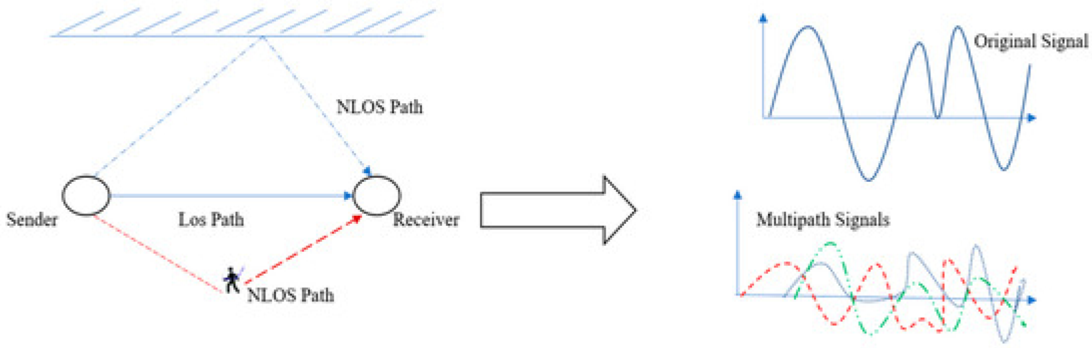

Figure 1. Multipath received signal effect of indoor environment scenario.

The variability of fingerprint values in indoor environments, influenced by factors such as device heterogeneity, measurement timing, user orientation, and channel conditions, significantly impacts positioning performance. This dynamic variability often leads to mismatches between stored and real-time fingerprints, posing a critical challenge for accurate indoor positioning. To address these issues, various fingerprint-matching strategies have been developed [26][27][28], broadly categorized into deterministic [29][30][31] and stochastic approaches [32][33][34]. To mitigate the challenges posed by complex indoor signal fluctuations, several FPBIPS methods have been proposed. One approach involves modeling signal jitter using the path loss model; however, this method is constrained by its dependence on map information and the assumption of a fixed receiver position [35][36][37]. In addition, machine learning (ML) algorithms have also been applied to RSS fingerprint-based indoor positioning problems, yet these techniques often fail to consider critical factors, such as leveraging related source domains, which could enhance the overall positioning accuracy and reduce the labor-intensive costs associated with offline fingerprint data collection [38][39][40]. In addition to that, recent advancements in addressing the inherent challenges associated with FPBIPS have been extensively documented in the literature. Various studies have proposed innovative algorithms and methodologies aimed at enhancing the resilience of these systems against signal fluctuations and the deterioration of fingerprints over time due to the dynamic nature of indoor environments [41][42][43][44][45]. For instance, advanced techniques and machine learning approaches have been demonstrated to significantly improve accuracy and robustness in environments with fluctuating signals and evolving conditions [44][45]. A novel multi-modal indoor localization method that integrates visual information, Wi-Fi signals, and lidar data, achieving high precision with an average 3D localization accuracy of 0.62 m and a mean square error of 1.24 m in two-dimensional tracking [44]. The study highlights the potential of hybrid techniques in enhancing location-based services within complex environments. Nevertheless, the performance relies on the accuracy and compatibility of the multimodal sensors used. In addition, the joint processing of multiple data sources might introduce additional overhead costs, which could limit deployment on low-power devices.

Furthermore, achieving the desired accuracy with RSS-based fingerprinting requires a large number of labeled samples, which is expensive and time-consuming. Crowdsourcing approaches have been studied to create and update radio maps, aiming to eliminate the need for site surveying [46][47][48]. Algorithms are being developed to generate radio maps using user traces collected from the crowd. However, trace-matching algorithms based on inertial sensors often face issues with unstable posture and high-power consumption of smartphones [49][50][51]. While our work focuses on single-signal metrics, hybrid methods combining Bluetooth, Wi-Fi, UWB, and ZigBee [52] have been proposed to enhance indoor positioning. Other examples include the integration of Wi-Fi with Visual Light Positioning (VLP) [53] and Bluetooth Low Energy (BLE) [54]. A novel localization framework has been developed that integrates GNSS, Wi-Fi Fine Time Measurement (FTM), and built-in sensors to achieve precise meter-level accuracy [41]. The framework utilizes advanced techniques, including pedestrian dead reckoning and an adaptive multi-model extended Kalman filter, to ensure seamless indoor and outdoor positioning. Experimental results demonstrate substantial improvements in localization reliability, making it highly suitable for complex environments [41]. However, the framework's reliance on multiple data sources and algorithms can introduce complexity, requiring significant computational resources and careful calibration. Moreover, although these hybrid approaches can achieve meter-level localization accuracy, they may introduce complexities in system integration and increase overall costs. These contributions underscore the ongoing efforts to refine IPS performance in complex indoor settings while acknowledging the inherent limitations. In addition, a recent study in [55] has also proposed an innovative indoor localization system named iToLoc, which combines adversarial learning and semi-supervised techniques to address the limitations of existing FPBIPS methods. By utilizing a domain adversarial neural network, iToLoc effectively mitigates issues related to signal variability and device differences, achieving a localization accuracy of 1.92 m with over 90% success rate even after several months of operation. However, the impact of signal sampling fluctuations, the application of various data reduction techniques to extract significant predictors, and the use of positive knowledge transfer, which are critical aspects, have been overlooked in addressing the major challenges of indoor localization. Thus, in this paper, we propose a functional discriminant analysis method for feature extraction in Wi-Fi indoor localization systems. This paper employs advanced data reduction techniques to mitigate the overhead of fingerprint calibration by transforming Wi-Fi RSS values into a novel vector using linear transformation. The goal of this research paper is to enhance indoor localization performance for adaptive long-term Wi-Fi indoor positioning (adaptive LT Wi-Fi IP) by maximizing variance in a lower dimension while reducing computational complexity.

This study examines the temporal fluctuations in signal strength and proposes the implementation of transfer learning methodologies to enhance model performance in indoor positioning, even in scenarios with limited training data [56]. However, a key limitation of this approach lies in the presumption of similar data distributions between the training and testing datasets; discrepancies in these distributions can significantly impact model accuracy and reliability [57]. The dynamic nature of indoor environments is underscored by substantial variations in signal distributions observed between the training and testing datasets, as confirmed by the Mann–Whitney U test (see **Figure 2**). To mitigate this challenge, the study highlights the necessity for developing adaptable models capable of accommodating these environmental variations. Thus, the contributions of this paper include:

(1) We propose the application of functional discriminant analysis (FDA) in combination with transfer learning techniques to tackle the challenge of high offline fingerprint calibration overhead. To achieve this, we generate new feature spaces that focus on the most significant predictors. These predictors enhance the separability of the model, leading to improved accuracy in indoor positioning estimates.

(2) We examined the impact of sampling signal fluctuations on different algorithms in indoor localization scenarios. Multiple training samples were used to assess the influence of sampling fluctuations, while all collected testing samples for each month were used to evaluate algorithm robustness.

(3) We applied covariance analysis (CA) to reduce the multicollinearity problem of the various RSS values collected at a reference point (RP), aiming to minimize computational complexity.

(4) We compare the performance of different feature extraction methods, namely mean signal values, principal component analysis (PCA), and linear discriminant analysis (LDA/FDA), for adaptive LT Wi-Fi IP. We evaluate the effectiveness of these methods based on the achieved metrics and also investigate the hybrid effect of combining features extracted from multiple methods.

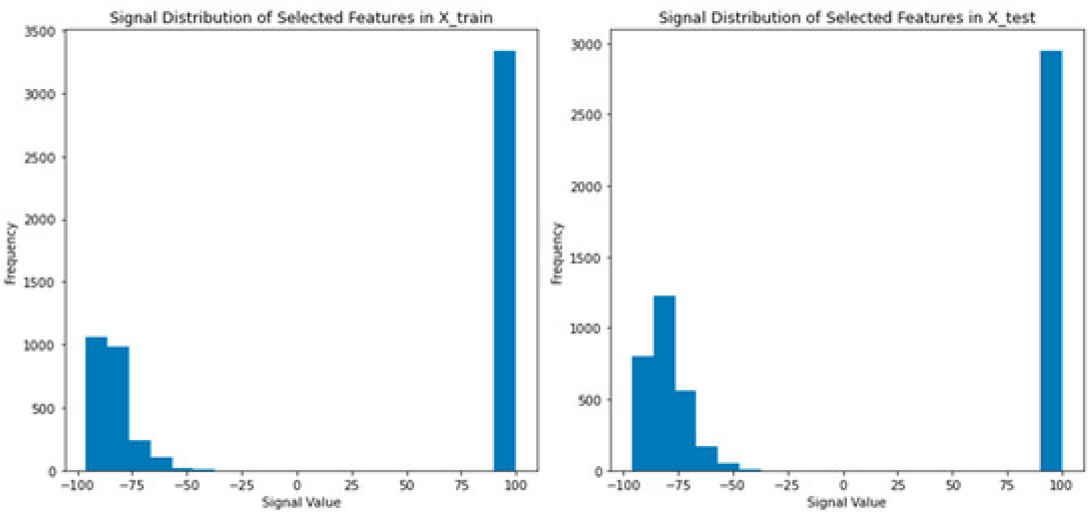

Figure 2. Signal distribution comparison between training and testing sample.

The rest of the paper is organized as follows: Related works are presented in Section 2. Section 3 describes the fingerprinting localization framework and its problem formulation. Experimental results, discussions, and evaluation metrics are presented in Section 4. Conclusions and recommendations are provided in Section 5.

2. Related Works

This study presents an overview of IPSs and explores the application of FDA for feature extraction in this domain. Indoor positioning (IP) has become an increasingly important research area, with applications in smart buildings, emergency response, and location-based services [58][59][60]. The paper discusses two main approaches for Wi-Fi-RSS-based IPSs: path loss model-based and fingerprinting. The path loss model-based approach relies on the relationship between RSS and distance to determine the target object's location [61][62][63]. However, due to the complex indoor environment, including factors such as non-line-of-sight (NLOS) propagation, multipath effects, and a dynamic environment, this distance-based approach cannot provide accurate geometric parameters [64][65]. In contrast, the fingerprint-based approach has gained significant attention in indoor localization as it does not rely on estimating geometric parameters and performs better than the distance-based approach in complex indoor environments [66][67]. Not only that, but also Wi-Fi-based RSS fingerprinting has gained popularity due to its advantages, including universal availability, privacy protection, and low implementation cost [22][23][24]. It is extensively used for communication purposes and holds great importance for terminals and sensor networks in IoT applications [1][2][3][4]. This approach involves two main phases: first, RSS fingerprints are collected from each Wi-Fi access point (AP) at multiple locations to create a radio map or fingerprint database, and then a predictive model is trained to establish the relationship between the signal and location [35][36][37].

However, this method has faced criticism for the high cost of creating wireless maps, which can be very expensive [44][45][46]. Attempts have been made to reduce the effort and time required for radio map generation, such as crowdsourcing [45] and simultaneous Wi-Fi localization and mapping, but these approaches have their own limitations [68]. Moreover, existing Wi-Fi networks are primarily designed for communication rather than positioning, and there is a need for robust and efficient algorithms to enhance their positioning performance. Nevertheless, the fingerprint-based approach still faces challenges in achieving robust and efficient positioning performance in dynamic indoor environments. Researchers have proposed several methods to deal with the dynamic indoor environment, which leads to low localization accuracy due to variations in fingerprint patterns over time. These methods can be classified into four groups: (i) probabilistic methods [69][70], (ii) machine learning methods [71][72], (iii) exploiting the quality of fingerprints of various signal features [73][74][75][76], and (iv) a fused group of fingerprints [77][78]. Although these methods have improved the location accuracy, they still suffer from fluctuations in the signal distribution and are not robust in indoor dynamic environments. Hybrid location systems (HPS) have been proposed to solve the single location problem, and the results demonstrate better location performance than the single system [79][80]. However, a hybrid base station falls outside the scope of this work and is not economically feasible. Additionally, computational complexity is a serious problem for hybrid systems based on indoor positioning.

To address the computational complexity of IPSs, various studies have used the application of PCA for data preprocessing aimed at reducing the dimension and noises of the original dataset [81][82][83]. These methods require intensive training dataset calibration overhead. However, the distribution of signal measurements for both training and testing did not account for the long-term effects of signal variations in the complex indoor environment. Moreover, studies have proposed LDA-based algorithms to eliminate the interference of environment and noise, generating a more stable and distinguishable fingerprint [84][85][86]. Additionally, several indoor localization algorithms have been proposed in the literature to improve indoor location estimation based on the functional discriminant analysis [87][88][89]. However, these methods have not considered the critical issues of offline fingerprint calibration overhead and have utilized CSI fingerprints, which demand extra hardware infrastructure cost compared to RSS fingerprints. Thus, the primary goal of this research study is to enhance the performance of long-term adaptive indoor localization systems that utilize RSS fingerprinting by reducing the computational complexity and resource requirements, both in terms of cost and time, through the application of transfer learning techniques in combination with several data reduction methods.

References

1. Brena, R.F.; García-Vázquez, J.P.; Galván-Tejada, C.E.; Muñoz-Rodriguez, D.; Vargas-Rosales, C.; Fangmeyer, J., Jr. Evolution of indoor positioning technologies: A survey. J. Sens. 2017, 2017, 2630413.
2. Chin, W.L.; Hsieh, C.C.; Shiung, D.; Jiang, T. Intelligent indoor positioning based on artificial neural networks. IEEE Netw. 2020, 34, 164–170.
3. Guo, X.; Ansari, N.; Hu, F.; Shao, Y.; Elikplim, N.R.; Li, L. A Survey on Fusion-Based Indoor Positioning. IEEE Commun. Surv. Tutor. 2020, 22, 566–594.
4. Basri, C.; El Khadimi, A. Survey on indoor localization system and recent advances of WIFI fingerprinting technique. In Proceedings of the 2016 5th International Conference on Multimedia Computing and Systems (ICMCS), Marrakech, Morocco, 29 September–1 October 2016; pp. 253–259.
5. Bergen, M.H.; Jin, X.; Guerrero, D.; Chaves, H.A.; Fredeen, N.V.; Holzman, J.F. Design and implementation of an optical receiver for angle-of-arrival-based positioning. J. Light. Technol. 2017, 35, 3877–3885.
6. Wann, C.D.; Yeh, Y.J.; Hsueh, C.S. Hybrid TDOA/AOA indoor positioning and tracking using extended Kalman filters. In Proceedings of the 2006 IEEE 63rd Vehicular Technology Conference, Melbourne, VIC, Australia, 7–10 May 2006; Volume 3, pp. 1058–1062.
7. Xiong, W.; Bordoy, J.; Gabbrielli, A.; Fischer, G.; Schott, D.J.; Höflinger, F.; Wendeberg, J.; Schindelhauer, C.; Rupitsch, S.J. Two efficient and easy-to-use NLOS mitigation solutions to indoor 3-D AOA-based localization. In Proceedings of the 2021 International Conference on Indoor Positioning and Indoor Navigation (IPIN), Lloret de Mar, Spain, 29 November–2 December 2021; pp. 1–8.
8. Alteneiji, A.; Ahmad, U.; Poon, K.; Ali, N.; Almoosa, N. Indoor localization in multi-path environment based on AoA with particle filter. In Proceedings of the 2020 3rd International

Conference on Signal Processing and Information Security (ICSPIS), Dubai, United Arab Emirates, 25–26 November 2020; pp. 1–4.

9. Lembo, S.; Horsmanheimo, S.; Honkamaa, P. Indoor positioning based on RSS fingerprinting in a LTE network: Method based on genetic algorithms. In Proceedings of the 2019 IEEE International Conference on Communications Workshops (ICC Workshops), Shanghai, China, 20–24 May 2019; pp. 1–6.
10. Cheerla, S.; Ratnam, D.V. RSS based Wi-Fi positioning method using multi layer neural networks. In Proceedings of the 2018 Conference on Signal Processing and Communication Engineering Systems (SPACES), Vijayawada, India, 4–5 January 2018; pp. 58–61.
11. Cheema, M.A. Indoor location-based services: Challenges and opportunities. SIGSPATIAL Spec. 2018, 10, 10–17.
12. He, S.; Chan, S.H. Wi-Fi fingerprint-based indoor positioning: Recent advances and comparisons. IEEE Commun. Surv. Tutor. 2015, 18, 466–490.
13. Wang, K.; Chen, Y.; Wang, Y.; Chen, X.; Chen, J. WiFi-based indoor positioning technologies for smart indoor spaces. IEEE Access 2020, 8, 199724–199742.
14. Giuliano, R.; Mazzenga, F.; Petracca, M.; Vari, M. Indoor localization system for first responders in emergency scenario. In Proceedings of the 2013 9th International Wireless Communications and Mobile Computing Conference (IWCMC), Sardinia, Italy, 1–5 July 2013; pp. 1821–1826.
15. Giordani, M.; Polese, M.; Mezzavilla, M.; Rangan, S.; Zorzi, M. Toward 6G networks: Use cases and technologies. IEEE Commun. Mag. 2020, 58, 55–61.
16. Zafari, F.; Gkelias, A.; Leung, K.K. A survey of indoor localization systems and technologies. IEEE Commun. Surv. Tutor. 2019, 21, 2568–2599.
17. Curran, K.; Furey, E.; Lunney, T.; Santos, J.; Woods, D.; McCaughey, A. An evaluation of indoor location determination technologies. J. Locat. Based Serv. 2011, 5, 61–78.
18. Youssef, M.; Agrawala, A. The Horus WLAN location determination system. In Proceedings of the 3rd International Conference on Mobile Systems, Applications, and Services, Seattle, WA, USA, 6–8 June 2005; pp. 205–218.
19. Xiang, Z.; Song, S.; Chen, J.; Wang, H.; Huang, J.; Gao, X. A wireless LAN-based indoor positioning technology. IBM J. Res. Dev. 2004, 48, 617–626.
20. Bahl, P.; Padmanabhan, V.N. RADAR: An in-building RF-based user location and tracking system. In Proceedings of the IEEE INFOCOM 2000. Conference on Computer Communications. Nineteenth Annual Joint Conference of the IEEE Computer and Communications Societies (Cat. No. 00CH37064), Tel Aviv, Israel, 26–30 March 2000; Volume 2, pp. 775–784.

21. Zhou, G.; Xu, S.; Zhang, S.; Wang, Y.; Xiang, C. Multi-floor indoor localization based on multi-modal sensors. Sensors 2022, 22, 4162.
22. Huang, L.; Yu, B.; Du, S.; Li, J.; Jia, H.; Bi, J. Multi-Level Fusion Indoor Positioning Technology Considering Credible Evaluation Analysis. Remote Sens. 2023, 15, 353.
23. Ferris, B.; Fox, D.; Lawrence, N.D. Wifi-slam using gaussian process latent variable models. In Proceedings of the 20th International Joint Conference on Artifical Intelligence, Hyderabad, India, 6–12 January 2007; Volume 7, pp. 2480–2485.
24. Du, X.; Liao, X.; Liu, M.; Gao, Z. CRCLoc: A crowdsourcing-based radio map construction method for WiFi fingerprinting localization. IEEE Internet Things J. 2021, 9, 12364–12377.
25. Fang, S.H.; Lin, P.; Lin, T.N. Indoor localization by a novel probabilistic approach. In Proceedings of the 2007 IEEE 8th Workshop on Signal Processing Advances in Wireless Communications, Helsinki, Finland, 17–20 June 2007; pp. 1–4.
26. Njima, W.; Ahriz, I.; Zayani, R.; Terre, M.; Bouallegue, R. Smart probabilistic approach with RSSI fingerprinting for indoor localization. In Proceedings of the 2017 25th International Conference on Software, Telecommunications and Computer Networks (SoftCOM), Split, Croatia, 21–23 September 2017; pp. 1–6.
27. Singh, N.; Choe, S.; Punmiya, R. Machine learning based indoor localization using Wi-Fi RSSI fingerprints: An overview. IEEE Access 2021, 9, 127150–127174.
28. Roy, P.; Chowdhury, C. A survey of machine learning techniques for indoor localization and navigation systems. J. Intell. Robot. Syst. 2021, 101, 63.
29. Scherhaeufl, M.; Pichler, M.; Schimbaeck, E.; Mueller, D.J.; Ziroff, A.; Stelzer, A. Indoor localization of passive UHF RFID tags based on phase-of-arrival evaluation. IEEE Trans. Microw. Theory Tech. 2013, 61, 4724–4729.
30. Giovanelli, D.; Farella, E.; Fontanelli, D.; Macii, D. Bluetooth-based indoor positioning through ToF and RSSI data fusion. In Proceedings of the 2018 International Conference on Indoor Positioning and Indoor Navigation (IPIN), Nantes, France, 24–27 September 2018; pp. 1–8.
31. Yang, F.; Xiong, J.; Liu, J.; Wang, C.; Li, Z.; Tong, P.; Chen, R. A pairwise SSD fingerprinting method of smartphone indoor localization for enhanced usability. Remote Sens. 2019, 11, 566.
32. Wang, W.; Li, T.; Wang, W.; Tu, Z. Multiple fingerprints-based indoor localization via GBDT: Subspace and RSSI. IEEE Access 2019, 7, 80519–80529.
33. Dai, Q.; Qian, B.; Baotoeng, G.O.; Guo, X.; Ansari, N. GRIDLoc: A Gradient Blending and Deep Learning based Localization Approach Combining RSS and CSI. IEEE Wirel. Commun. Lett. 2024. early access.

34. Farid, Z.; Nordin, R.; Ismail, M.; Abdullah, N.F. Hybrid indoor-based WLAN-WSN localization scheme for improving accuracy based on artificial neural network. Mob. Inf. Syst. 2016, 2016, 6923931.
35. Liu, Z.; Dai, B.; Wan, X.; Li, X. Hybrid wireless fingerprint indoor localization method based on a convolutional neural network. Sensors 2019, 19, 4597.
36. Zhang, L.; Tan, T.; Gong, Y.; Yang, W. Fingerprint database reconstruction based on robust PCA for indoor localization. Sensors 2019, 19, 2537.
37. Abdi, H.; Williams, L.J. Principal component analysis. Wiley Interdiscip. Rev. Comput. Stat. 2010, 2, 433–459.
38. Jolliffe, I.T.; Cadima, J. Principal component analysis: A review and recent developments. Philos. Trans. R. Soc. A Math. Phys. Eng. Sci. 2016, 374, 20150202.
39. Liu, D.; Liu, Z.; Song, Z. LDA-based CSI amplitude fingerprinting for device-free localization. In Proceedings of the 2020 Chinese Control And Decision Conference (CCDC), Hefei, China, 22–24 August 2020.
40. Sanam, T.F.; Godrich, H. Device free indoor localization using discriminant features of CSI a canonical correlation paradigm. In Proceedings of the 2018 52nd Asilomar Conference on Signals, Systems, and Computers, Pacific Grove, CA, USA, 28–31 October 2018; pp. 423–427.
41. Yuan, Y.; Liu, X.; Liu, Z.; Xu, Z. MFMCF: A novel indoor location method combining multiple fingerprints and multiple classifiers. In Proceedings of the 2019 3rd International Symposium on Autonomous Systems (ISAS), Shanghai, China, 29–31 May 2019; pp. 216–221.
42. Wang, J.; Wang, X.; Peng, J.; Hwang, J.G.; Park, J.G. Indoor fingerprinting localization based on fine-grained CSI using principal component analysis. In Proceedings of the 2021 Twelfth International Conference on Ubiquitous and Future Networks (ICUFN), Jeju Island, Republic of Korea, 17–20 August 2021; pp. 322–327.
43. Liu, W.; Cheng, Q.; Deng, Z.; Chen, H.; Fu, X.; Zheng, X.; Zheng, S.; Chen, C.; Wang, S. Survey on CSI-based indoor positioning systems and recent advances. In Proceedings of the 2019 International Conference on Indoor Positioning and Indoor Navigation (IPIN), Pisa, Italy, 30 September–3 October 2019; pp. 1–8.
44. Subhan, F.; Saleem, S.; Bari, H.; Khan, W.Z.; Hakak, S.; Ahmad, S.; El-Sherbeeny, A.M. Linear discriminant analysis-based dynamic indoor localization using bluetooth low energy (BLE). Sustainability 2020, 12, 10627.
45. Hailu, T.; Edris, T. MultiDMet: Designing a Hybrid Multidimensional Metrics Framework to Predictive Modeling for Performance Evaluation and Feature Selection. Intell. Inf. Manag. 2023, 15, 391–425.

46. Ferris, B.; Fox, D.; Lawrence, N.D. Wifi-slam using gaussian process latent variable models. In Proceedings of the 20th International Joint Conference on Artifical Intelligence, Hyderabad, India, 6–12 January 2007; Volume 7, pp. 2480–2485.

47. Kjærgaard, M.B.; Treu, G.; Ruppel, P.; Küpper, A. Efficient indoor proximity and separation detection for location fingerprinting. In Proceedings of the 1st International ICST Conference on Mobile Wireless Middleware, Operating Systems and Applications, Chicago, IL, USA, 30 June–2 July 2010.

48. Yang, Z.; Wu, C.; Liu, Y. Locating in fingerprint space: Wireless indoor localization with little human intervention. In Proceedings of the 18th Annual International Conference on Mobile Computing and Networking, Istanbul, Turkey, 22–26 August 2012; pp. 269–280.

49. Rai, A.; Chintalapudi, K.K.; Padmanabhan, V.N.; Sen, R. Zee: Zero-effort crowdsourcing for indoor localization. In Proceedings of the 18th Annual International Conference on Mobile Computing and Networking, Istanbul, Turkey, 22–26 August 2012; pp. 293–304.

50. Alzantot, M.; Youssef, M. Crowdinside: Automatic construction of indoor floorplans. In Proceedings of the 20th International Conference on Advances in Geographic Information Systems, Redondo Beach, CA, USA, 6–9 November 2012; pp. 99–108.

51. Constandache, I.; Gaonkar, S.; Sayler, M.; Choudhury, R.R.; Cox, L. Enloc: Energy-efficient localization for mobile phones. In Proceedings of the IEEE INFOCOM 2009, Rio de Janeiro, Brazil, 19–25 April 2009; pp. 2716–2720.

52. Luo, R.C.; Hsiao, T.J. Indoor localization system based on hybrid Wi-Fi/BLE and hierarchical topological fingerprinting approach. IEEE Trans. Veh. Technol. 2019, 68, 10791–10806.

53. Chong AM, S.; Yeo, B.C.; Lim, W.S.; Pratap, S. Integration of UWB RSS to Wi-Fi RSS fingerprinting-based indoor positioning system. Cogent Eng. 2022, 9, 2087364.

54. Huang, Q.; Zhang, Y.; Ge, Z.; Lu, C. Refining Wi-Fi based indoor localization with Li-Fi assisted model calibration in smart buildings. arXiv 2016, arXiv:1602.07399.

55. Li, D.; Xu, J.; Yang, Z.; Tang, C. Train Once, Locate Anytime for Anyone: Adversarial Learning-based Wireless Localization. ACM Trans. Sens. Netw. 2024, 20, 1–21.

56. Yong, L.H.; Zhao, M. Indoor positioning based on hybrid domain transfer learning. IEEE Access 2020, 8, 130527–130539.

57. Zhang, Y.; Wu, C.; Chen, Y. A low-overhead indoor positioning system using CSI fingerprint based on transfer learning. IEEE Sens. J. 2021, 21, 18156–18165.