Location Aware Schemes in IoT

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The rapid development in wireless technologies is positioning the Internet of Things (IoT) as an essential part of our daily lives. Localization is one of the most attractive applications related to IoT. In the past few years, localization has been gaining attention because of its applicability in safety, health monitoring, environment monitoring, and security.

Keywords: Internet of Things (IoT) ; Location of Things ; target localization ; wireless sensor network (WSN) ; review

1. Introduction

The Internet is a necessity for billions of people worldwide who need it to complete their daily tasks [1][2]. Furthermore, it provides various entertainment applications such as movies, music, and gaming. One estimate states that more than 58% of the world's population has access to the Internet to perform such daily tasks. The popularity and growth of the Internet exponentially increased (roughly 1170%) from 2000 to 2020 [3]. It is transforming the world into a global village where people can connect and communicate worldwide using the Internet.

The Internet allows different devices and appliances to connect and communicate, which led to a new domain called the Internet of Things (IoT) [4][5][6][7][8]. The IoT architecture consists of three layers: the physical layer, the network layer, and the application layer, as shown in Figure 1. The physical layer consists of various sensors attached to the subject. These sensors collect the data/information from the subject. Generally, the nature of data depends on the IoT application requirements. For example, localization-based applications require monitoring and collection of the locality information of the subject. Likewise, telehealth applications need to monitor the vitals of patients, and agricultural applications measure the temperature. The physical layer forwards the data to the network layer.

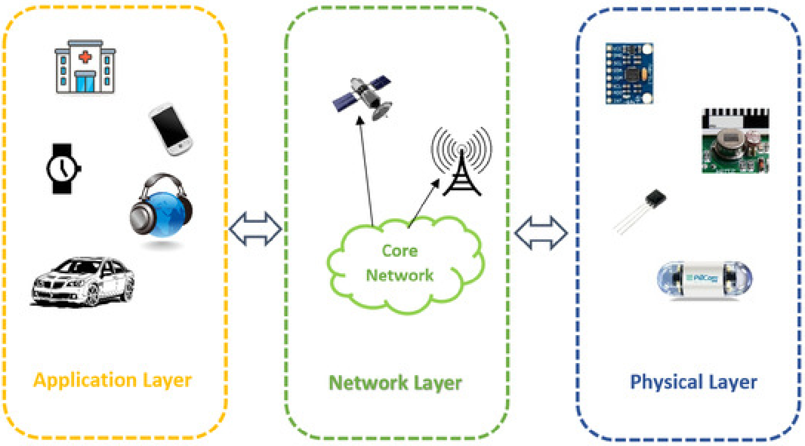

Figure 1. IoT architecture.

The network layer is the middle layer between the application and sensor layer in IoT architecture. The network layer aims to transmit the data/information from the sensors to the application layer. The medium of data transmission (wireless or wired) varies based on the application and requirements. Furthermore, the network layer tries to reduce the network's data traffic and overheads using optimization techniques. The application layer is the top layer that controls the services provided to the applications. This layer offers an interface to the user to control and manage the IoT devices. Furthermore, it provides services to the application depending on the nature of the application.

IoT is an extension of the Internet that envisions connecting all daily devices to the Internet for communications through interactions or sensing devices. These sensing devices are connected to form a network, termed a wireless sensor network (WSN) [9]. The IoT consisting of WSNs is essential for transforming the world into a smart world [10]. According to the Cisco Annual Internet Report [11], the number of IoT devices will rise from 6.1 billion to 14.7 billion by the end of 2023.

Among those 14.7 billion devices, more than 48% of them will assist users in performing daily tasks, such as home automation, security, and tracking applications. Therefore, they act as building blocks in smart cities, smart homes, smart transportation, smart healthcare, smart grids, and smart industry [12][13][14][15][16].

However, there exist numerous challenges in the development of such IoT applications. For example, health-related applications require rapid and reliable data transmission. Monitoring applications in smart environments require energy-efficient and robust protocols [17]. Similarly, there are challenges associated with cost, connectivity, and hardware limitations [18]. However, localization is one key challenge that needs to be addressed in the majority of smart applications. It is the process of acquiring an object or user's location through intelligent devices (sensors) in an indoor or outdoor environment. It is a critical requirement in most smart applications [19][20]. An exponential increase in smartphones, wristwatches, and other intelligent wireless IoT devices is motivating researchers to develop efficient localization schemes. As a result, we are witnessing a significant rise in localization schemes intended to operate in healthcare, agriculture, environmental work, and habitat monitoring [21][22][23].

2. Review of Location Aware Schemes in IoT

A comparison of the state-of-the-art studies is given in Table 1. From the table, it is clear that most of the existing surveys target a particular localization domain, i.e., outdoor or indoor.

Table 1. Comparison between this paper and published surveys.

References	Indoor Localization	Outdoor Localization	Smartphone Localization	Security	Energy Efficiency	Accuracy	Target Recovery	Target Prediction
[24]	✓				✓	✓		
[25]	✓				✓	✓		
[26]	✓				✓	✓		
[27]	✓			✓	✓	✓		✓
[28]	✓					✓		
[29]	✓			✓		✓		
[30]		✓			✓	✓		
[31]	✓	✓			✓	✓		✓
[32]	✓	✓				✓		
[33]	✓	✓		✓		✓		
[34]	✓		✓	✓	✓	✓		
[35]	✓		✓			✓		
[36]	✓	✓	✓			✓		✓
[37]	✓		✓		✓	✓		✓

References	Indoor Localization	Outdoor Localization	Smartphone Localization	Security	Energy Efficiency	Accuracy	Target Recovery	Target Prediction
Ours	✓	✓	✓	✓	✓	✓	✓	✓

The main focuses of already published surveys were accuracy, energy efficiency, target prediction, and security. They lack some critical KPIs, such as recovery, prediction, security, and localization with smart gadgets, i.e., smartphones. Only 28% of publications covered prediction; 35% covered security and localization with smartphones. Simultaneously, no published survey covered the target recovery KPI, which is an important indicator that affects the overall performance of the IoT-based localization scheme.

Furthermore, these surveys lacked detail and generic discussion in terms of protocols and techniques for localization schemes. Therefore, there is a need for a cross-domain survey that puts forward an in-depth discussion on the IoT-based localization scheme. A total of 40 papers were selected using the PRISMA approach. The key ideas of the selected papers are presented in Table 2. In addition to that, the selected studies were analyzed based on publishing details and target applications.

Table 2. Key ideas of selected papers.

Name	Overview
Delaney et al. [38]	This paper presents an energy efficient routing protocol using NHs model for tree structured WSN. Apart from energy efficiency, the proposed solution has the ability to present good results in a lossy network environment.
Alaybeyoglu et al. [39]	This paper presents an efficient tracking scheme for high speed targets. Additionally, the proposed scheme helps in reducing the target miss ratio during the whole tracking lifecycle.
Mirsadeghi et al. [40]	This paper presents an energy efficient prediction based target tracking scheme for WSN. The node closest to the object or with the highest energy is selected as a CH to prolong the network lifetime.
Patil et al. [41]	This paper presents an energy efficient WSHAN to improve the efficiency of target tracking target recovery.
Rouhani et al. [42]	This paper presents a solution to resolve the boundary target tracking issues using static clustering. The proposed solution is energy efficient, reasonably accurate and reliable in terms of target tracking.
Wahdan et al. [43]	This paper presents a hybrid solution of static networking clustering and dynamic CH. The dynamic CH uniformly utilize the energy of member SNs to prolong the network lifetime and prediction.
Zhou et al. [44]	This paper presents a fusion of MMA and PPHD for multi-target tracking in an urban area. Additionally, K-mean clustering is used to calculate the number of targets at any given time. The proposed scheme results in the tracking of dynamically changing unknown numbers of targets in urban areas.
Amudha et al. [45]	This paper presents a multi camera based scheme for target tracking. In this scheme, the camera near the mobile target is activated while all other cameras remain in a sleep state to conserve energy. In contrast, all the cameras are activated when a target is lost to improve the tracking.
Bhowmik et al. [46]	This paper presents an algorithm is to improve the overall coverage and target tracking. In addition to that, the proposed algorithm uses the FSM based RSSI tracking algorithm to make it more energy efficient.
Jinan et al. [47]	This paper presents a multi-model framework based on the PUESRF and JPDA. It results in improving the accuracy and precision of data that makes target tracking consistent.

Name	Overview
Darabkh et al. [48]	This paper presents an adaptive CH algorithm with an aim to achieve a better target tracking by efficiently electing CH and cluster members. The proposed algorithm is energy efficiency and improves the network scalability.
Khakpour et al. [49]	This paper presents a fusion of DCTT and PCTT against vehicular tracking in a Vehicular Ad-hoc Network. To improve the target prediction, The DCTT performs in a distributed manner while PCTT is used for a centralized prediction algorithm.
Joshi et al. [50]	This paper presents a static cluster based target tracking for the prediction that is independent of wireless network architecture (homogenous or heterogeneous). The proposed scheme uses a linear prediction technique to calculate direction and speed to improve the target prediction.
Xiao et al. [51]	This paper presents a novel ASMT using Bayesian estimation to efficiently track multiple targets. The ASMT provides high accuracy, precision based multi-target tracking, less computation and solves the data association problem in WSN very efficiently by using location state and velocity state.
Silva et al. [52]	This paper presents an energy efficient scheme with the ability to detect and highlight the fake node positioning and bogus data flooding.
Oracevic et al. [53]	This paper presents a SRPTT algorithm to prevent the rouge SN from faking its location or flooding the bogus packets in a WSN. The SRPTT maintains a balance between security and mobile target tracking by employing a reputation concept.
Alshamaa et al. [54]	This paper presents a novel zoning based localization technique for indoor target tracking. The proposed technique develops a belief function by combining fingerprint based target observation and evidence associated with sensor mobility to improve the accuracy of target tracking.
Chen et al. [55]	This paper presents an adaptive extended kalman filter to remove and update the noise covariance. The proposed solution results in improving the accuracy and reliability of target tracking.
Panag et al. [56]	This paper presents a DHSCA to uniformly utilize sensors during the tracking. The proposed algorithm simplifies the set-up phase time of the network resulting in reducing the overhead of the network.
Zhang et al. [57]	This paper presents a dynamic clustering-based adaptive filtering scheme for target tracking in a WSN. The proposed scheme consists of two stages hierarchal data aggregation technique, which results in accurate and energy efficient target tracking.
Qian et al. [58]	This paper presents an AUKF algorithm to enhance the robustness and accuracy of the recovery mechanism. The AUKF fine-tunes the noise covariance matrix to increase the accuracy and robustness of the recovery mechanism. The vigorous scheduling of static and mobile SNs improves the tracking probability with less energy consumption.
Zhang et al. [59]	This paper presents an algorithm based on a hybrid sensor network to estimate the target region via static sensors. Additionally, a movement algorithm is presented for nodes to select the location. The proposed solution results in conserving the energy by reducing the target tracking sensors.

Name	Overview
Li et al. [60]	This paper presents a sensor selection technique based on POMDP to reduce the sensor selection lagging. It results in improving the target tracking accuracy and reliability.
Darabkh et al. [61]	This paper presents an error and Energy-aware cluster head selection algorithm to improve the target localization. The proposed algorithm improves energy consumption and simplifies the selection of cluster members. Additionally, it reduces the packets overhead by minimizing the transmission of control messages.
Liu et al. [62]	This paper presents energy efficient scheme with low prediction accuracy. Apart from energy efficiency, it reduces the target miss rate probability.
Luo et al. [63]	This paper presents a scheme to improve the target tracking for an indoor environment using a CLTA.
Yu et al. [64]	This paper presents a mobile node-based target tracking scheme to enhance the target tracking accuracy and transmission reliability.
Vallas et al. [65]	This paper presents a Gaussian filter-based multi-sigma point filter to reduce the curse of dimensionality in high dimension systems. Furthermore, it improves the efficiency of tracking the multiple targets in a WSN.
Ghodousi et al. [66]	This paper presents an energy efficient tracking scheme using ARIMA and UKF. The ARIMA, after observing target in equal interval, predicts its future location while UKF estimates the target location. The proposed scheme preserves the energy of SNs and improves the network lifetime.
Liang et al. [67]	This paper presents a trust-based distributed KF scheme for secure and reliable target tracking.
Khan et al. [68]	This paper presents a dynamic clustering-based verifiable multi iteration scheme to improve target tracking. The proposed scheme improves the accuracy and reliability of tracking.
Liu et al. [69]	This paper presents an object localization scheme to provide better localization results on the sequences undergoing shape deformation and illumination changes.
Nguyen et al. [70]	This paper presents a solution to improve the accuracy of target tracking in harsh radio environments. The proposed scheme is efficient in both indoor and outdoor environments.
Ullah et al. [71]	This paper presents an underwater target tracking scheme intending to achieve energy efficiency and tracking accuracy.
Alberto et al. [72]	This paper presents a multi-model tracking system by unifying fingerprint-based tracking with neural networks. The proposed system also employs a Gaussian outliers filter with neural networks to further improve the tracking accuracy.
Liu et al. [73]	This paper presents a scheme for tracking multiple targets in a harsh environment accurately and precisely.

Name	Overview
Liu et al. [74]	This paper presents an AFS for accurate and efficient target tracking. The proposed scheme is robust and fault-tolerant with a low target loss rate. Moreover, PSO is used to fine-tune and improve the overall tracking performance.
Mahmoudreza et al. [75]	This paper presents a solution to tackle the multiple target tracking problems with accurate data association. It results in the prevention of false alarms.
Li et al. [76]	This paper presents a hybrid solution to provide accurate and reliable localization in harsh manufacturing workshops.
Reisinger et al. [77]	This paper presents an IMM tracking scheme unified with UKF to track the targets efficiently.

2.1. Distribution Based on Publishing Year

We aim to highlight the recent trends in target localization. Therefore, the papers from the last seven years (2014 and onward) are considered. The yearly distribution of the selected publications is presented in Figure 2. From the figure, it is depicted that there was less interest in localization in earlier years. However, it started rising from 2017. The last three years of research (2017–2019) comprised 67% of publications selected for this review. 2020 was just beginning when the papers were shortlisted. However, based on the trend, more contributions are expected in this domain than in past years.

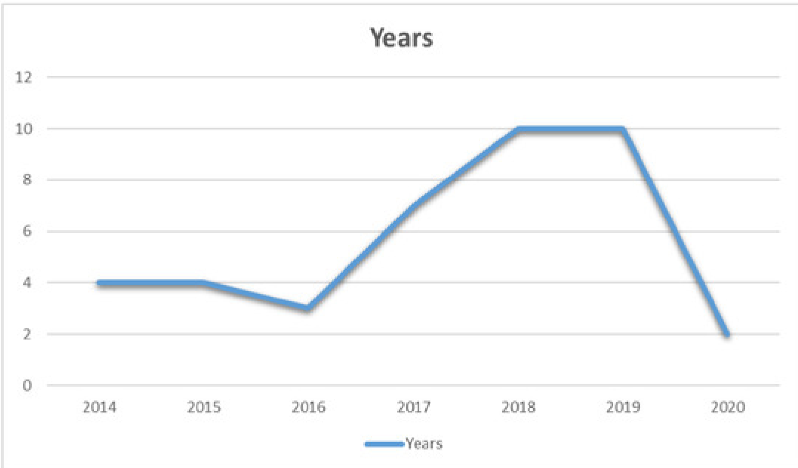

Figure 2. Distribution based on publication year.

2.2. Distribution Based on Publication Venue

This section aims to highlight the publication venue distribution. Our study includes various publication venues, such as IEEE, Elsevier, MDPI, and SAGE. The distribution of publications concerning the venues is presented in Figure 3. It was found that IEEE and Elsevier support most publications in the domain of target tracking—57.5% and 20%, respectively. Therefore, these two venues are recommended for localization in IoT.

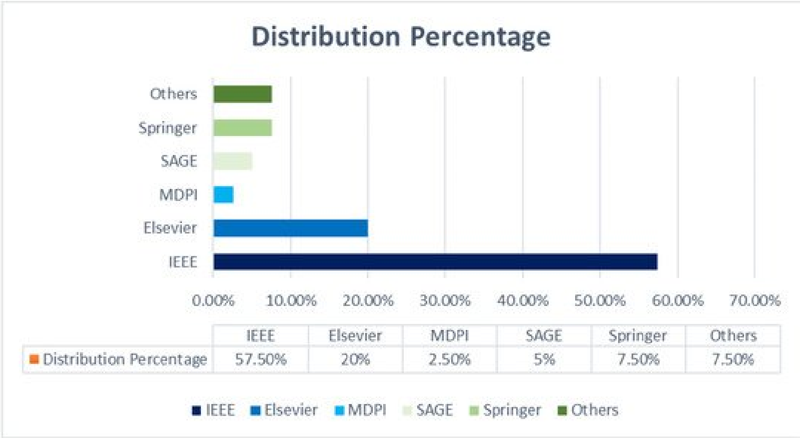

Figure 3. Distribution based on publishing venue.

2.3. Distribution Based on Publication Type

We have only considered conference proceedings and journal articles for the review. The distribution percentages of those publication types are presented in the form of a pie chart. From the Figure 4, it is clear that our results are mainly backed up by journal articles (67%).

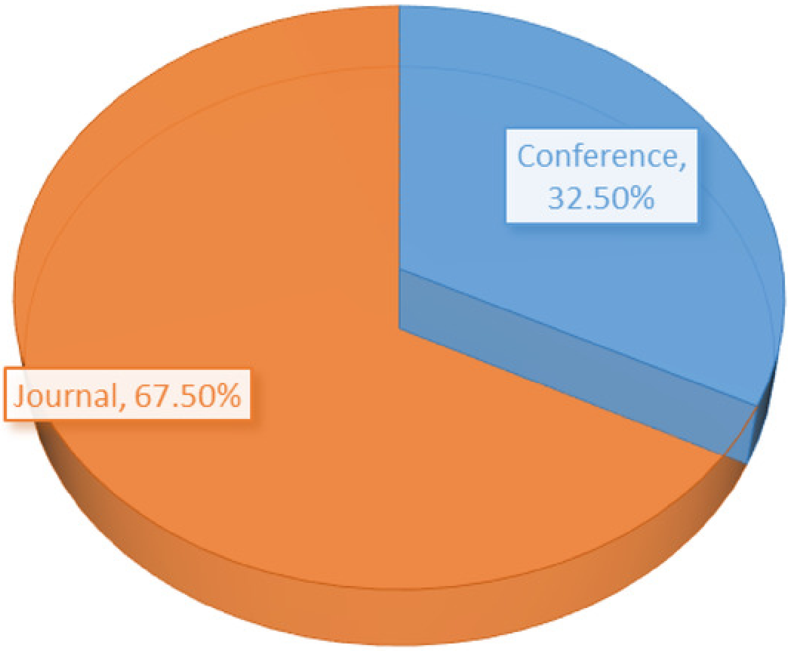

Figure 4. Distribution based on publication type.

2.4. Analysis Based on Localization KPIs

There are various localization KPIs, such as energy efficiency, localization accuracy, target prediction, target recovery, and security. Every paper is trying to address single or multiple KPIs. Table 3 lists the selected publications along with the target KPIs. The lifetime of sensors is a major concern in WSNs, as battery replacement is a tiring and time-consuming job. Additionally, low-battery or abandoned sensors can halt the performance of the overall network in emergencies.

Table 3. KPIs Addressed in Selected Papers.

Name	Energy Efficiency	Localization Accuracy	Target Prediction	Target Recovery	Security
Delaney et al. [38]	✓				
Alaybeyoglu et al. [39]	✓	✓	✓		
Mirsadeghi et al. [40]	✓	✓	✓		

Name	Energy Efficiency	Localization Accuracy	Target Prediction	Target Recovery	Security
Patil et al. [41]	✓	✓	✓	✓	
Rouhani et al. [42]	✓	✓			
Wahdan et al. [43]	✓	✓	✓		
Zhouet al. [44]		✓	✓		
Amudha et al. [45]	✓	✓		✓	
Bhowmik et al. [46]	✓	✓			
Jinan et al. [47]		✓	✓		
Darabkh et al. [48]	✓	✓	✓		
Khakpour et al. [49]		✓	✓		
Joshi et al. [50]		✓	✓		
Xiao et al. [51]		✓			
Silva et al. [52]	✓		✓		✓
Oracevic et al. [53]		✓	✓		✓
Alshamaa et al. [54]		✓			
Chen et al. [55]		✓	✓		
Panag et al. [56]	✓				
Zhang et al. [57]	✓	✓			
Qian et al. [58]			✓	✓	
Zhang et al. [59]	✓	✓			
Li et al. [60]	✓		✓		
Darabkh et al. [61]	✓	✓			
Liu et al. [62]	✓	✓	✓		
Luo et al. [63]		✓			

Name	Energy Efficiency	Localization Accuracy	Target Prediction	Target Recovery	Security
Yu et al. [64]		✓	✓		
Vallas et al. [65]		✓	✓		
Ghodousi et al. [66]	✓	✓	✓		
Liang et al. [67]		✓			✓
Khan et al. [68]	✓	✓			✓
Liu et al. [69]		✓	✓		
Nguyen et al. [70]		✓			
Ullah et al. [71]	✓	✓			
Alberto et al. [72]		✓			
Liu et al. [73]		✓			
Liu et al. [74]		✓	✓	✓	
Mahmoudreza et al. [75]		✓			✓
Li et al. [76]		✓			
Reisinger et al. [77]		✓	✓		

Furthermore, accurate predictions and identification of targets are desired in location-aware schemes. Therefore, energy efficiency, tracking accuracy, and target prediction are the most researched KPIs in target tracking of WSNs, as shown in Figure 5. In contrast, target recovery and security were explored in only 11% of the papers selected. These are also important aspects of localization that need the researcher’s attention in the future. In addition to the above analysis, a general overview of all the papers, including the proposed approach, network structure, number of targets, and performance parameters, is presented in Table 4.

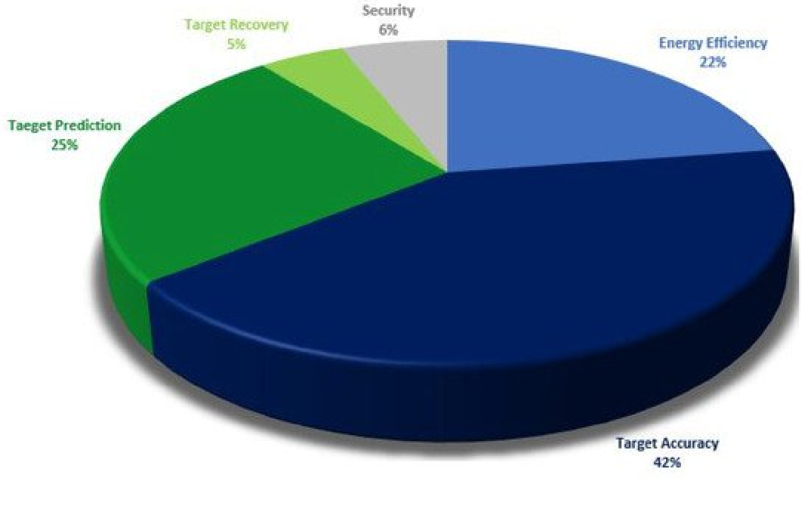

Figure 5. Distribution based on target challenges.

Table 4. Overview of selected papers.

Ref.	Proposed Approach	Network Structure	Number of Targets	Performance Parameters	Tool
[38]	ETX-NH	Tree	Single	PDR: 96%	TOSSIM
[39]	PF-DLSTA	Tree	Single	N/A	NS2
[40]	Low Power Target Prediction Mechanism	Dynamic Cluster	Single	MR: 0.69%	N/A
[41]	WSHAN	Dynamic Cluster	Single	EE: 37%	MATLAB
[42]	BCTT	Static Cluster	Single	EE: 48%	Omnet++
[43]	SCDCH	Static Cluster	Single	N/A	MATLAB
[44]	PPHD-MMA	Dynamic Cluster	Multiple	N/A	N/A
[45]	VGTR	Dynamic Cluster	Single	TMR: 99% reduction	MATLAB
[46]	DCTC with Fuzzy Sensing	Tree	Single	N/A	TinyOS and nesC
[47]	JPDA, PUESRF	Dynamic Cluster	Multiple	N/A	N/A
[48]	IPAH	Dynamic Cluster	Single	EE: 40% improved, LE: 52% improved	MATLAB
[49]	DCTT, PCTT	Static Cluster	Single	N/A	NS2 + TOSSIM
[50]	Prediction based object tracking algorithm	Static Cluster	Single	PA: 99%	NS2
[51]	ASMT	Static Cluster	Multiple	FR: >14%	N/A
[52]	GTPM	Dynamic Cluster	Single	N/A	NS2
[53]	SRPTT	Static Cluster	Single	N/A	Java Simulator
[54]	Extended observation model, 2^{nd} mobility model	Static Cluster	Single	N/A	N/A

Ref.	Proposed Approach	Network Structure	Number of Targets	Performance Parameters	Tool
[55]	AEKF	Static Cluster	Single	RMSE: 32.53%	N/A
[56]	DHSCA	Static Cluster	Single	N/A	Fortran PowerStation 4.0
[57]	ACDF	Dynamic Cluster	Single	N/A	N/A
[58]	AUKF	Static Cluster	Single	N/A	MATLAB
[59]	HNTA	Hybrid Cluster	Multiple	N/A	N/A
[60]	Adaptive sensor selection algorithm with POMDP	Dynamic Cluster	Multiple	N/A	N/A
[61]	EEA-IAH	Dynamic Cluster	Single	N/A	MATLAB
[62]	LPPT	Static Cluster	Single	Reduce MR: 36.34%, EE: 5.2 times	Omnet++
[63]	CLTA	Dynamic Cluster	Single	LE: 0.65 m	MATLAB
[64]	FTS	Tree	Single	LE: >50 improvement	MATLAB
[65]	DMGIF	Dynamic Cluster	Multiple	N/A	N/A
[66]	ARIMA, AUKF	Dynamic Cluster	Single	N/A	Opnet + MATLAB
[67]	Trust-based distributed Kalman filtering.	Dynamic Cluster	Single	N/A	N/A
[68]	Dynamic cooperative multilateral sensing	Dynamic Cluster	Single	LE: 19% improved	MATLAB
[69]	ELM compressive sensing	Dynamic Cluster	Single	N/A	MATLAB

Ref.	Proposed Approach	Network Structure	Number of Targets	Performance Parameters	Tool
[70]	LEMon, LEMon-M	Static Cluster	Single	Outdoor and Indoor LE: 10 m and 2 m improved	N/A
[71]	Distance and angle-based localization	Dynamic Cluster	Single	LE: 90% improved, ABL: 104.9 m	N/A
[72]	SWiBluX	Dynamic Cluster	Single	LE: 45% improved	N/A
[73]	TS PM-PHD	Dynamic Cluster	Multiple	N/A	N/A
[74]	AFS for MC-SSN	Tree	Single	LE: <0.2%	N/A
[75]	AIE-MCMCDA	Dynamic Cluster	Multiple	LE: 0.39–4.12%	N/A
[76]	CS-BnB, BnB-AMCL	Dynamic Cluster	Single	LE: 0.005 m/0.111 deg	4WS4WDr
[77]	IMM, UKF	Dynamic	Multiple	EE: 4 times	N/A

References

1. Castellacci, F.; Viñas-Bardolet, C. Internet use and job satisfaction. Comput. Hum. Behav. 2019, 90, 141–152.
2. Scheerder, A.J.; van Deursen, A.J.A.M.; van Dijk, J.A.G.M. Negative outcomes of Internet use: A qualitative analysis in the homes of families with different educational backgrounds. Inf. Soc. 2019, 35, 286–298.
3. World Internet Users Statistics and 2020 World Population Stats. Internet World Stats. 2020. Available online: (accessed on 29 March 2021).
4. Yaqoob, I.; Hashem, I.A.T.; Ahmed, A.; Kazmi, S.A.; Hong, C.S. Internet of things forensics: Recent advances, taxonomy, requirements, and open challenges. Future Gener. Comput. Syst. 2019, 92, 265–275.
5. Srinivasan, C.; Rajesh, B.; Saikalyan, P.; Premsagar, K.; Yadav, E. A review on the different types of internet of things (IoT). J. Adv. Res. Dyn. Control. Syst. 2019, 11, 154–158.
6. Jagannath, J.; Polosky, N.; Jagannath, A.; Restuccia, F.; Melodia, T. Machine learning for wireless communications in the Internet of Things: A comprehensive survey. Ad Hoc Netw. 2019, 93, 101913.
7. Malik, H.; Alam, M.M.; Pervaiz, H.; Le Moullec, Y.; Al-Dulaimi, A.; Parand, S.; Reggiani, L. Radio resource management in NB-IoT systems: Empowered by interference prediction and flexible duplexing. IEEE Netw. 2019, 34, 144–151.
8. Khan, S.Z.; Malik, H.; Sarmiento, J.L.R.; Alam, M.M.; Le Moullec, Y. Dorm: Narrowband iot development platform and indoor deployment coverage analysis. Procedia Comput. Sci. 2019, 151, 1084–1091.
9. Kumar, D.P.; Amgoth, T.; Annavarapu, C.S.R. Machine learning algorithms for wireless sensor networks: A survey. Inf. Fusion 2019, 49, 1–25.
10. Shafique, K.; Khawaja, B.A.; Sabir, F.; Qazi, S.; Mustaqim, M. Internet of Things (IoT) for Next-Generation Smart Systems: A Review of Current Challenges, Future Trends and Prospects for Emerging 5G-IoT Scenarios. IEEE Access

2020, 8, 23022–23040.

11. Cisco Annual Internet Report-Cisco Annual Internet Report (2018–2023) White Paper. Available online: (accessed on 29 March 2021).
12. Hassija, V.; Chamola, V.; Saxena, V.; Jain, D.; Goyal, P.; Sikdar, B. A Survey on IoT Security: Application Areas, Security Threats, and Solution Architectures. IEEE Access 2019, 7, 82721–82743.
13. Hamdan, O.; Shanableh, H.; Zaki, I.; Al-Ali, A.R.; Shanableh, T. IoT-Based Interactive Dual Mode Smart Home Automation. In Proceedings of the 2019 IEEE International Conference on Consumer Electronics (ICCE), Las Vegas, NV, USA, 11–13 January 2019; pp. 1–2.
14. Trappey, A.J.C.; Trappey, C.V.; Govindarajan, U.H.; Sun, J.J.H. Patent Value Analysis Using Deep Learning Models—The Case of IoT Technology Mining for the Manufacturing Industry. IEEE Trans. Eng. Manag. 2019, 1–13.
15. Saleem, Y.; Crespi, N.; Rehmani, M.H.; Copeland, R. Internet of Things-Aided Smart Grid: Technologies, Architectures, Applications, Prototypes, and Future Research Directions. IEEE Access 2019, 7, 62962–63003.
16. Saboor, A.; Mustafa, A.; Ahmad, R.; Khan, M.A.; Haris, M.; Hameed, R. Evolution of Wireless Standards for Health Monitoring. In Proceedings of the 2019 9th Annual Information Technology, Electromechanical Engineering and Microelectronics Conference (IEMECON), Jaipur, India, 13–15 March 2019; pp. 268–272.
17. Tang, J.; So, D.K.C.; Zhao, N.; Shojaeifard, A.; Wong, K. Energy Efficiency Optimization with SWIPT in MIMO Broadcast Channels for Internet of Things. IEEE Internet Things J. 2018, 5, 2605–2619.
18. Zaidan, A.; Zaidan, B. A review on intelligent process for smart home applications based on IoT: Coherent taxonomy, motivation, open challenges, and recommendations. Artif. Intell. Rev. 2020, 53, 141–165.
19. Rahman, A.; Li, T.; Wang, Y. Recent advances in indoor localization via visible lights: A survey. Sensors 2020, 20, 1382.
20. Elbes, M.; Alrawashdeh, T.; Almaita, E.; AlZu’bi, S.; Jararweh, Y. A platform for power management based on indoor localization in smart buildings using long short-term neural networks. Trans. Emerg. Telecommun. Technol. 2020, e3867.
21. Giri, A.; Dutta, S.; Neogy, S. Fuzzy logic-based range-free localization for wireless sensor networks in agriculture. In Advanced Computing and Systems for Security; Springer: Singapore, 2020; pp. 3–12.
22. McAllister, T.D.; El-Tawab, S.; Heydari, M.H. Localization of Health Center Assets Through an IoT Environment (LoCATE). In Proceedings of the 2017 Systems and Information Engineering Design Symposium (SIEDS), Charlottesville, VA, USA, 28 April 2017; pp. 132–137.
23. Song, Y.; Zhang, X.; Zhang, M.; Wang, J. Research of node localization algorithm based on wireless sensor networks in marine environment monitoring. J. Comput. Methods Sci. Eng. 2018, 18, 69–83.
24. Zafari, F.; Gkelias, A.; Leung, K.K. A survey of indoor localization systems and technologies. IEEE Commun. Surv. Tutor. 2019, 21, 2568–2599.
25. Yassin, A.; Nasser, Y.; Awad, M.; Al-Dubai, A.; Liu, R.; Yuen, C.; Raulefs, R.; Aboutanios, E. Recent advances in indoor localization: A survey on theoretical approaches and applications. IEEE Commun. Surv. Tutor. 2016, 19, 1327–1346.
26. Oguntala, G.; Abd-Alhameed, R.; Jones, S.; Noras, J.; Patwary, M.; Rodriguez, J. Indoor location identification technologies for real-time IoT-based applications: An inclusive survey. Comput. Sci. Rev. 2018, 30, 55–79.
27. Laoudias, C.; Moreira, A.; Kim, S.; Lee, S.; Wirola, L.; Fischione, C. A survey of enabling technologies for network localization, tracking, and navigation. IEEE Commun. Surv. Tutor. 2018, 20, 3607–3644.
28. Liu, M.; Cheng, L.; Qian, K.; Wang, J.; Wang, J.; Liu, Y. Indoor acoustic localization: A survey. Hum. Centric Comput. Inf. Sci. 2020, 10, 2.
29. Jang, B.; Kim, H. Indoor positioning technologies without offline fingerprinting map: A survey. IEEE Commun. Surv. Tutor. 2018, 21, 508–525.
30. Vo, Q.D.; De, P. A survey of fingerprint-based outdoor localization. IEEE Commun. Surv. Tutor. 2015, 18, 491–506.
31. Zhuang, Y.; Hua, L.; Qi, L.; Yang, J.; Cao, P.; Cao, Y.; Wu, Y.; Thompson, J.; Haas, H. A survey of positioning systems using visible LED lights. IEEE Commun. Surv. Tutor. 2018, 20, 1963–1988.
32. Do, T.H.; Yoo, M. An in-depth survey of visible light communication based positioning systems. Sensors 2016, 16, 678.
33. Ferreira, A.F.G.; Fernandes, D.M.A.; Catarino, A.P.; Monteiro, J.L. Localization and positioning systems for emergency responders: A survey. IEEE Commun. Surv. Tutor. 2017, 19, 2836–2870.
34. Xiao, J.; Zhou, Z.; Yi, Y.; Ni, L.M. A survey on wireless indoor localization from the device perspective. ACM Comput. Surv. (CSUR) 2016, 49, 1–31.

35. Davidson, P.; Piché, R. A survey of selected indoor positioning methods for smartphones. IEEE Commun. Surv. Tutor. 2016, 19, 1347–1370.

36. Guo, G.; Chen, R.; Ye, F.; Peng, X.; Liu, Z.; Pan, Y. Indoor Smartphone Localization: A Hybrid WiFi RTT-RSS Ranging Approach. IEEE Access 2019, 7, 176767–176781.

37. Jadaa, K.J.; Kamarudin, L.M.; Ahmad, R.B. Detection and Tracking Survey for Smart Home Using Wireless Sensor Network. J. Eng. Appl. Sci 2019, 14, 3119–3129.

38. Delaney, D.T.; Higgs, R.; O'Hare, G.M. A stable routing framework for tree-based routing structures in WSNs. IEEE Sens. J. 2014, 14, 3533–3547.

39. Alaybeyoglu, A.; Kantarci, A.; Erciyes, K. A dynamic lookahead tree based tracking algorithm for wireless sensor networks using particle filtering technique. Comput. Electr. Eng. 2014, 40, 374–383.

40. Mirsadeghi, M.; Mahani, A. Low power prediction mechanism for wsn-based object tracking. Procedia Technol. 2014, 17, 692–698.

41. Gupta, A.; Patil, S.; Zaveri, M. Lost target recovery in wireless sensor network using tracking. In Proceedings of the 2012 International Conference on Communication Systems and Network Technologies, Rajkot, Gujarat, India, 11–13 May 2012; pp. 352–356.

42. Rouhani, S.; Haghighat, A.T. Boundary static clustering target tracking in wirless sensor networks. In Proceedings of the 2015 6th International Conference on Computing, Communication and Networking Technologies (ICCCNT), Dallas-Fortworth, TX, USA, 13–15 July 2015; pp. 1–6.

43. Wahdan, M.A.; Al-Mistarihi, M.F.; Shurman, M. Static cluster and dynamic cluster head (SCDCH) adaptive prediction-based algorithm for target tracking in wireless sensor networks. In Proceedings of the 2015 38th International Convention on Information and Communication Technology, Electronics and Microelectronics (MIPRO), Opatija, Croatia, 25–29 May 2015; pp. 596–600.

44. Zhou, M.; Zhang, J.J.; Papandreou-Suppappola, A. Multiple target tracking in urban environments. IEEE Trans. Signal Process. 2015, 64, 1270–1279.

45. Amudha, J.; Arpita, P. Multi-Camera Activation Scheme for Target Tracking with Dynamic Active Camera Group and Virtual Grid-Based Target Recovery. Procedia Comput. Sci. 2015, 58, 241–248.

46. Bhowmik, S.; Das, S.; Giri, C. Tree based tracking target in wireless sensor network. In Proceedings of the 2016 International Conference on Advances in Computing, Communications and Informatics (ICACCI), Jaipur, India, 21–24 September 2016; pp. 390–397.

47. Jinan, R.; Raveendran, T. Particle filters for multiple target tracking. Procedia Technol. 2016, 24, 980–987.

48. Darabkh, K.A.; Albtoush, W.Y.; Jafar, I.F. Improved clustering algorithms for target tracking in wireless sensor networks. J. Supercomput. 2017, 73, 1952–1977.

49. Khakpour, S.; Pazzi, R.W.; El-Khatib, K. Using clustering for target tracking in vehicular ad hoc networks. Veh. Commun. 2017, 9, 83–96.

50. Joshi, P.; Joshi, A. Prediction Based Moving Object Tracking in Wireless Sensor Network. Int. Res. J. Eng. Technol. 2017, 4, 3365–3368.

51. Xiao, K.; Wang, R.; Zhang, L.; Li, J.; Fun, T. ASMT: An augmented state-based multi-target tracking algorithm in wireless sensor networks. Int. J. Distrib. Sens. Netw. 2017, 13, 1550147717703115.

52. Silva, A.; Zhou, F.; Pontes, E.; Simplicio, M.A.; Aguiar, R.; Guelfi, A.; Kofuji, S. Energy-efficient node position identification through payoff matrix and variability analysis. Telecommun. Syst. 2017, 65, 459–477.

53. Oracevic, A.; Akbas, S.; Ozdemir, S. Secure and reliable object tracking in wireless sensor networks. Comput. Secur. 2017, 70, 307–318.

54. Alshamaa, D.; Mourad-Chehade, F.; Honeine, P. Tracking of mobile sensors using belief functions in indoor wireless networks. IEEE Sens. J. 2017, 18, 310–319.

55. Chen, Y.M.; Tsai, C.L.; Fang, R.W. TDOA/FDOA mobile target localization and tracking with adaptive extended Kalman filter. In Proceedings of the 2017 International Conference on Control, Artificial Intelligence, Robotics & Optimization (ICCAIRO), Prague, Czech Republic, 20–22 May 2017; pp. 202–206.

56. Panag, T.S.; Dhillon, J. Dual head static clustering algorithm for wireless sensor networks. AEU Int. J. Electron. Commun. 2018, 88, 148–156.

57. Zhang, H.; Zhou, X.; Wang, Z.; Yan, H.; Sun, J. Adaptive consensus-based distributed target tracking with dynamic cluster in sensor networks. IEEE Trans. Cybern. 2018, 49, 1580–1591.

58. Qian, H.; Fu, P.; Li, B.; Liu, J.; Yuan, X. A novel loss recovery and tracking scheme for maneuvering target in hybrid WSNs. Sensors 2018, 18, 341.

59. Zhang, C.; Fei, S. A Movement Algorithm for Target Group Tracking in Wireless Sensor Networks. In Proceedings of the 2018 37th Chinese Control Conference (CCC), Wuhan, China, 25–27 July 2018; pp. 7226–7230.

60. Li, W.; Han, C. A Novel Sensor Selection Algorithm for Multi-Target Tracking in Wireless Sensor Networks. In Proceedings of the 2018 Chinese Automation Congress (CAC), Xi'an, China, 30 November–2 December 2018; pp. 2854–2858.

61. Darabkh, K.A.; Alsaraireh, N.R. A yet efficient target tracking algorithm in wireless sensor networks. In Proceedings of the 2018 15th International Multi-Conference on Systems, Signals & Devices (SSD), Yasmine Hammamet, Tunisia, 19–22 March 2018; pp. 7–11.

62. Liu, A.; Zhao, S. High-performance target tracking scheme with low prediction precision requirement in WSNs. Int. J. Ad Hoc Ubiquitous Comput. 2018, 29, 270–289.

63. Luo, J.; Zhang, Z.; Liu, C.; Luo, H. Reliable and cooperative target tracking based on WSN and WiFi in indoor wireless networks. IEEE Access 2018, 6, 24846–24855.

64. Yu, X.; Liang, J. Genetic fuzzy tree based node moving strategy of target tracking in multimodal wireless sensor network. IEEE Access 2018, 6, 25764–25772.

65. Vilà-Valls, J.; Closas, P.; Bugallo, M.F.; Míguez, J. Distributed Multiple Gaussian Filtering for Multiple Target Localization in Wireless Sensor Networks. In Proceedings of the 2018 52nd Asilomar Conference on Signals, Systems, and Computers, Pacific Grove, CA, USA, 28–31 October 2018; pp. 1439–1443.

66. Izadi-Ghodousi, Z.; Hosseinpour, M.; Safaei, F.; Mohajerzadeh, A.H.; Alishahi, M. An Efficient Target Tracking in Directional Sensor Networks Using Adapted Unscented Kalman Filter. Wirel. Pers. Commun. 2019, 109, 1925–1954.

67. Liang, C.; Wen, F.; Wang, Z. Trust-based distributed Kalman filtering for target tracking under malicious cyber attacks. Inf. Fusion 2019, 46, 44–50.

68. Khan, M.A.; Khan, M.A.; Rahman, A.U.; Malik, A.W.; Khan, S.A. Exploiting cooperative sensing for accurate target tracking in industrial Internet of things. Int. J. Distrib. Sens. Netw. 2019, 15, 1550147719892203.

69. Liu, E.; Chu, Y.; Zheng, L. Object Tracking Based on Compressive Features and Extreme Learning Machine. IEEE Access 2019, 7, 45994–46003.

70. Nguyen, C.L.; Raza, U. LEMOn: Wireless Localization for IoT Employing a Location-Unaware Mobile Unit. IEEE Access 2019, 7, 40488–40502.

71. Ullah, I.; Liu, Y.; Su, X.; Kim, P. Efficient and accurate target localization in underwater environment. IEEE Access 2019, 7, 101415–101426.

72. Belmonte-Hernández, A.; Hernández-Peñaloza, G.; Gutiérrez, D.M.; Álvarez, F. SWiBluX: Multi-Sensor Deep Learning Fingerprint for precise real-time indoor tracking. IEEE Sens. J. 2019, 19, 3473–3486.

73. Liu, L.; Ji, H.; Zhang, W.; Liao, G. Multi-sensor multi-target tracking using probability hypothesis density filter. IEEE Access 2019, 7, 67745–67760.

74. Liu, Q.; Lin, J.; Mao, Y. Adaptive Fuzzy Tree System for Target Tracking in Mission Critical Sensor Networks. IEEE Access 2019, 7, 184676–184685.

75. Mahmoudreza, H.; Hamid, K.; Mohammadtaghi, B. Augmented input estimation in multiple maneuvering target tracking. J. Syst. Eng. Electron. 2019, 30, 841–851.

76. Li, G.; Huang, Y.; Zhang, X.; Liu, C.; Shao, W.; Jiang, L.; Meng, J. Hybrid Maps Enhanced Localization System for Mobile Manipulator in Harsh Manufacturing Workshop. IEEE Access 2020, 8, 10782–10795.

77. Fruhwirth-Reisinger, C.; Krispel, G.; Possegger, H.; Bischof, H. Towards Data-driven Multi-target Tracking for Autonomous Driving. In Proceedings of the 25th Computer Vision Winter Workshop (CVWW), Rogaska Slatina, Slovenia, 3–5 February 2020.