Babylonian Journal of Networking
Vol.2023, **pp**. 101–104
DOI: https://doi.org/10.58496/BJN/2023/013; ISSN: 3006-5372
https://mesopotamian.press/journals/index.php/BJN

Review Article

An Analytical Study on Improving Target Tracking Techniques in Wireless Sensor Networks Using Deep Learning and Energy Efficiency Models

Sahar Hamad Ahmed[1,*]

[1] *University of Anbar, Anbar, Iraq.*

ARTICLE INFO

Article History

Received 08 Sep 2023
Accepted 07 Nov 2023
Published 28 Nov 2023

Keywords

Wireless Sensor Network
Target Tracking
Deep Learning
Clustering Algorithms
Multi-Target Tracking
TensorFlow
Real-Time Monitoring

ABSTRACT

The work of Wireless Sensor Network (WSN) in goal tracking presentations, particularly in military, environmental, and surveillance operations, has garnered significant attention. In order to progress the accuracy, efficiency, and energy protection of these networks, a diversity of methods have been invented to resolve challenges such as real-time monitoring, multiple-target tracking, and resource optimization. This study examines a broad spectrum of algorithms and frameworks, such as energy-efficient methods, clustering methods, augmented state-based algorithms, and deep learning-based models, to address target tracking issues in WSNs. The outcomes emphasize the progress in the field, with a particular emphasis on enhancing tracking accuracy and reducing energy consumption, ranging from adaptive clustering methods to multi-sensor deep learning outlines. Recurrent neural networks (RNN), long short-term memory (LSTM), and prognostic models are instrumental in improving target detection, localization, and tracking. The examination also delves into the placement of WSN in a diversity of environments, including battlefields, intelligent transportation systems, and quantized areas, providing valuable visions into future trends and research orientations.

1. INTRODUCTION

The WSN is collected of numerous sensor components that are geologically organized to monitor the environment. Through a wireless edge, the nodes are capable of sensing, processing, and communicating with one another. The data is elated by the node using the multi-hop technique to communicate with the sink and other nodes. The bulges may be stationary or mobile, homogeneous or heterogeneous, and the network may have a single sink or multiple sinks to interface with the base station. The entire data is processed by an in-built processor in each node of the WSN before it is transmitted to other nodes. The requests of WSNs are vast and diverse, including environmental monitoring, military surveillance, object tracing, and healthcare monitoring [1]. The sensor network structure is illustrated in Figure (1.1).

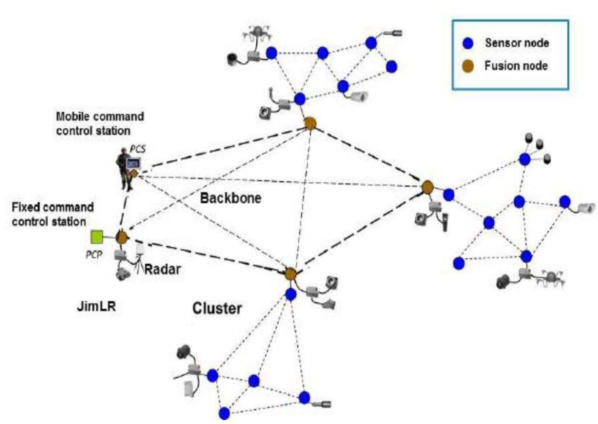

Fig .1. Wsn Architecture [2]

*Corresponding author. Email: sah19c1010@uoanbar.edu.iq

One of the most serious applications in WSN is target monitoring. Its impartial is to identify the presence of an animal, hunter, or other entity within a designated area, approximating its location, and subsequently updating the base position. Traffic tracking, humanoid tracking, animal tracking, and enemy tracking are among the numerous critical applications for which it is necessary to monitor a moving object [3]. Target tracking is the procedure of using a sensor network with diverse sensors to detect a moving object over time. Target tracing can be a resource-intensive and time-consuming procedure due to a variety of factors, such as the limited range of each node in the sensor network and the limited supply of energy [4]. Nevertheless, the positive implementation of conventional target track solutions in WSN applications is impeded by the constraints imposed by resource, power, sensing capability, communication, memory, and computational capability. The procedures for target checking in WSN should be capable of reducing computational complexity and effectively utilizing resources [5].

Target tracing is included of three primary components: (1) target detection (which includes humans, animals, and vehicles), (2) computation of the current position, and (3) prediction of the future position; [6]. In order to monitor mobile goals, it is necessary to detect their location in a circular manner within a network. The site technique based on received signal intensity (RSS) is currently in widespread use. In contrast to methods that depend on Time-of-Arrival, Time-Difference-of-Arrival, and Angle-of-Arrival, this method is cost-effective, hardware-free, and readily accessible [7].

A varied array of metrics, such as cluster creation, tracing accuracy, cluster head life time, miss rate, total energy consumed, distance between the source and object, and varying target speed, can be employed to conduct object tracking analysis [8].

It is also important to study the types of sensors used to track a target, as the target can be classified as cooperative or non-cooperative based on whether or not they are wearing a device that can be recognized by the sensing units (e.g., using RFID tagging to track animals). The goal is typically non-cooperative, which necessitates a more complex design of localization and monitoring algorithms [9].

The tracing algorithm has a considerable impact on the accuracy and calculation time of the target localization and tracking [10]. The monitoring strategies frequently employed for frequently are fuzzy-based, cluster-based, and mining-based predictions. The estimate of moving objects continues to be a difficult problem in WSN research, and it has not been extensively implemented [11].

Recurrent neural networks (RNNs) are an active method for addressing sequence problems, which are frequently encountered in the fields of machine translation, weather forecasting, and video motion recognition [12]. In realism, the goal tracking problem is a sequence problem. As a result, RNNs may be implemented to oversee target monitoring obligations [13]. One of the most well-known recurrent neural network topologies in deep learning is the long-short term memory network (LSTM). This paper suggests a goal tracking system that is both efficient and effective.

The system includes dynamic and static clustering techniques with the predictive tracking technique, which is an extension of RNNs, and the LSTM. As part of this investigation, two models from the LSTM were implemented. The object's direction of drive was confidential using the initial model, which was then used to determine its new position. The another model was working to predict the three nodes that would trace the object. This scheme will monitor both a single object and multiple objects, and it will calculate the energy consumption of both systems. Additionally, a novel algorithm was proposed to enhance the network's energy consumption and extend its lifespan.

2. RELATED WORK

In current years, significant progressions have been made in the arena of target tracking within WSN, with various innovative methodologies being developed. Some of these approaches have absorbed on prediction methods to improve tracking accuracy and reduce energy consumption, employing Kalman filters and particle filters. In 2015, Souza et al. presented the PRATIQUE technique, which is a prediction-based clustering approach aimed at reducing transmission costs and enhancing network efficiency. In 2017, Xiao and colleagues suggested a multi-target tracking algorithm based on state enhancement, which decreased computational complexity and improved tracking accuracy.

In 2019, Belmonte-Hernandez et al. presented the SWiBluX framework, intended for indoor localization using deep learning techniques, while other methods were developed to enhance energy efficiency, such as the dynamic clustering approach for target tracking proposed by Ahmad and Abbas in 2020. More lately, machine learning (ML) methods have been combined into target motion prediction procedures, educating efficiency and further reducing energy consumption.

TABLE I. SUMMARY OF METHODS USED FOR TARGET TRACKING IN WSNs

Year	Researchers	Proposed Approach	Advantages	Disadvantages
2015	Souza et al.	PRATIQUE: prediction-based clustering	Reduced transmission costs	Increased energy consumption with more clusters
2017	Xiao et al.	Multi-target tracking using state enhancement	Improved tracking accuracy and reduced complexity	Energy consumption not evaluated

2019	Belmonte-Hernandez et al.	SWiBluX framework for indoor localization using DL	Improved indoor localization accuracy up to 45%	Issues with energy consumption
2020	Ahmad and Abbas	Dynamic clustering approach to reduce energy consumption	Improved tracking accuracy and reduced energy usage	Effectiveness with multiple targets not assessed
2021	Choi and Yoo	RNN-based optimal duty cycle control approach	Reduced energy consumption while maintaining accuracy	Multi-target tracking challenges not addressed

3. CHALLENGES

Notwithstanding the important progressions in improving tracking accuracy and reducing energy consumption in WSNs, several challenges remain. First, multi-target following continues to be a major issue, as it requires additional resources and increases energy consumption. Second, harmonization of network nodes during tracking remains a challenge that needs innovative solutions. Finally, energy competence must be enhanced, especially in complex environments that require numerous sensors, while safeguarding high performance and accurate tracking.

4. CONCLUSION

Impartial tracing in wsn remnants a dynamic and developing field, with continuous improvements aimed at enhancing accuracy and reducing energy consumption. The studied exemplify the competence of deep learning models, augmented state-based algorithms, and predictive techniques in addressing challenges related to multiple target tracking. Emerging know-hows, such as RNNs and LSTM networks, have provided significant advancements in handling complex tracking scenarios, while adaptive clustering algorithms ensure optimized resource utilization. Moreover, energy real outlines are crucial for extending the operational lifetime of WSNs, particularly in large-scale deployments. Future work must emphasis on integrating more progressive machine learning techniques and exploring new applications of WSNs in increasingly diverse and complex environments, such as smart cities, precision agriculture, and industrial monitoring. By continuing to enhance the presentation and scalability of WSNs, the field will enable more efficient and reliable target tracking solutions across various sectors.

Conflicts Of Interest

The author declares no conflict of interest in relation to the research presented in the paper.

Funding

The author's paper explicitly states that no funding was received from any institution or sponsor.

Acknowledgment

The author would like to express gratitude to the institution for their invaluable support throughout this research project.

References

[1] P. Krishnaveni and J. Sutha, "Novel deep learning framework for broadcasting abnormal events obtained from surveillance applications," Journal of Ambient Intelligence and Humanized Computing, pp. 1–15, 2020.
[2] B. Pannetier, J. Dezert, and G. Sella, "Multiple target tracking with wireless sensor network for ground battlefield surveillance," in 17th International Conference on Information Fusion (FUSION), 2014, pp. 1–8.
[3] K. A. Darabkh, W. Y. Albtoush, and I. F. Jafar, "Improved clustering algorithms for target tracking in wireless sensor networks," The Journal of Supercomputing, vol. 73, no. 5, pp. 1952–1977, 2017.
[4] M. J. Saeed, L. Han, and M. K. Muyeba, "An energy efficient and resource preserving target tracking approach for wireless sensor networks," in 2014 9th International Symposium on Communication Systems, Networks & Digital Sign (CSNDSP), 2014, pp. 232–237.
[5] K. Xiao, R. Wang, L. Zhang, J. Li, and T. Fun, "ASMT: An augmented state-based multi-target tracking algorithm in wireless sensor networks," International Journal of Distributed Sensor Networks, vol. 13, no. 4, 2017, Art. no. 1550147717703115.
[6] É. L. Souza, R. W. Pazzi, and E. F. Nakamura, "A prediction-based clustering algorithm for tracking targets in quantized areas for wireless sensor networks," Wireless Networks, vol. 21, no. 7, pp. 2263–2278, 2015.
[7] X. Lu, J. Liu, W. Qi, and Q. Dai, "Multiple-target tracking based on compressed sensing in the Internet of Things," Journal of Network and Computer Applications, vol. 122, pp. 16–23, 2018.
[8] D. Charanya and G. V. Uma, "Tracking of moving object in wireless sensor network," International Journal of Computer & Communication Technology, vol. 3, no. 5, 2012.

[9] S. Mendieta Moreton, "Multi-Target Localization and Tracking with Wireless Sensor Networks for Digital Storytelling," M.S. thesis, NTNU, 2017.
[10] T. Wang, X. Wang, W. Shi, Z. Zhao, Z. He, and T. Xia, "Target localization and tracking based on improved Bayesian enhanced least-squares algorithm in wireless sensor networks," Computer Networks, vol. 167, 2020, Art. no. 106968.
[11] P. Mansur and S. Sreedharan, "ANN based dual prediction for object tracking in wireless sensor networks," 2017.
[12] H. Yang and B. Sikdar, "A protocol for tracking mobile targets using sensor networks," in Proceedings of the First IEEE International Workshop on Sensor Network Protocols and Applications, 2003, pp. 71–81.
[13] L. Deng, D. Li, and R. Li, "Improved IMM algorithm based on RNNs," in Journal of Physics: Conference Series, vol. 1518, no. 1, 2020, Art. no. 012055.
[14] W. L. Yeow, C. K. Tham, and W. C. Wong, "Energy efficient multiple target tracking in wireless sensor networks," IEEE Transactions on Vehicular Technology, vol. 56, no. 2, pp. 918–928, 2007.
[15] J. Vilà-Valls, P. Closas, M. F. Bugallo, and J. Míguez, "Distributed multiple Gaussian filtering for multiple target localization in wireless sensor networks," in 2018 52nd Asilomar Conference on Signals, Systems, and Computers, 2018, pp. 1439–1443.
[16] Y. Lei, Y. Wu, and A. J. K. Chowdhury, "Multi-target tracking algorithm in intelligent transportation based on wireless sensor network," Open Physics, vol. 16, no. 1, pp. 1000–1008, 2018.
[17] L. Paris and M. H. Anisi, "An energy-efficient predictive model for object tracking sensor networks," in 2019 IEEE 5th World Forum on Internet of Things (WF-IoT), 2019, pp. 263–268.
[18] A. Belmonte-Hernández, G. Hernández-Peñaloza, D. M. Gutiérrez, and F. Alvarez, "SWiBluX: Multi-sensor deep learning fingerprint for precise real-time indoor tracking," IEEE Sensors Journal, vol. 19, no. 9, pp. 3473–3486, 2019.
[19] C. Wu, C. Zhao, and H. Gong, "Energy-efficient target tracking algorithm for WSNs," 3D Research, vol. 10, no. 1, pp. 1–10, 2019.
[20] T. Ahmad and A. M. Abbas, "EEAC: An energy efficient adaptive cluster based target tracking in wireless sensor networks," Journal of Interdisciplinary Mathematics, vol. 23, no. 2, pp. 379–392, 2020.
[21] R. Verma, R. Rajesh, and M. S. Easwaran, "Modular multi target tracking using LSTM networks," arXiv preprint arXiv:2011.09839, 2020.
[22] S. H. Choi and S. J. Yoo, "Recurrent neural network-based optimal sensing duty cycle control method for wireless sensor networks," IEEE Access, vol. 9, pp. 133215–133228, 2021.