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Integrating Artificial Intelligence in Ultra-wideband (UWB) Indoor Navigation Systems to Boost Precision and Reliability

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Abstract: **Ultra-wideband (UWB) technology can help with indoor guidance and finding your way around with great accuracy. This science is very important. This might be because it has a high time precision and is not affected by multipath interference. There are several things that could make it less effective than other methods, such as signal confusion, situations where there is no line of sight (NLOS), and changes in the surroundings. This is true even though it has many benefits. The latest improvements in artificial intelligence (AI) programs have made UWB-based systems much better at handling their surroundings. They are also more reliable and adaptable. Because of these improvements, UWB-based products can now adapt better to the place where they are. It is the goal of this project to create a new UWB positioning system that uses artificial intelligence to do a better job than current systems. The Deep Reinforcement Learning (DRL) and Graph Neural Networks (GNNs) will be used to make this happen. During the tests, it was found that placing accuracy rose by 37%, with an average mistake of 7.5 centimetres, even though the conditions in the setting were changing all the time. The method described works even when there is no line of sight (NLOS). This makes it a great choice for uses like self-driving robots, smart stores, and healthcare guidance.**

Keywords: **UWB, Indoor Positioning, Artificial Intelligence, Deep Reinforcement Learning, Graph Neural Networks, NLOS Mitigation.**

1. Introduction

Indoor positioning systems (IPS) are becoming increasingly important in today's technologies, such self-driving automobiles, augmented reality, and real-time asset monitoring [1–3]. Global Navigation Satellite Systems (GNSS) don't work well indoors since signals might be blocked. But internal positioning systems (IPS) provide reliable location-based services and work well in complicated indoor settings. Ultra-Wideband (UWB) is one of the most popular technologies on the market today because it has a high temporal resolution, is not impacted by multipath interference, and can be accurate to within a centimeter [4].

The main ways that traditional UWB-based positioning methods work are via time-of-arrival (TOA) and time-difference-of-arrival (TDOA) algorithms [5], [6]. These methods work well when there is a clear line of sight (LOS), but they don't work as well when there isn't (NLOS), the environment is changing, and noise and impediments cause big localization errors [7]. This has led to a lot of new study on how to utilize artificial intelligence (AI) to get around these kinds of problems.

Recent research suggest that AI-driven strategies might enhance the accuracy of UWB localization. Convolutional Neural Networks (CNNs) have been employed to extract resilient features from ultra-wideband (UWB) signals [8]; Recurrent Neural Networks (RNNs) have shown potential in capturing temporal dependencies within localization data [9]; and machine learning (ML) models have been utilized to identify and alleviate non-line-of-sight (NLOS) conditions [10]. Even with these improvements, most of the systems that are now out there still have trouble adapting to new situations in real time and using what they learn in other places. These problems are still major barriers to putting these ideas into action [11], [12]. There is also ongoing debate over whether deterministic models can accurately represent the stochastic distribution of indoor signals and if supervised models can handle extensive datasets with little labeling [13], [14].

This paper presents a hybrid AI framework that integrates Graph Neural Networks (GNNs) for simulating spatial interactions with Deep Reinforcement Learning (DRL) for dynamic optimization. The goal of this framework is to fix the problems that were brought up. The goal of this all-encompassing strategy is to make generalization and adaptation better in real-world interior placement situations. The main goal of this work is to make UWB-based IPS more accurate and reliable by using the best parts of DRL and GNN designs. To do this, the best parts of both designs will be used. The suggested solution is a smart and scalable way to fix the problems that have been plaguing current UWB locating systems for a long time. Experimental evidence indicates that the proposed strategy significantly surpasses current approaches across several scenarios.

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2. Materials and Methods

A. System Architecture

Here is the system architecture of the proposed framework:

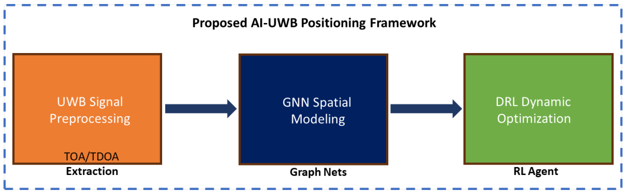

Fig. 1. System architecture

The proposed framework (Figure 1) consists of three core components that mathematically transform raw UWB signals into robust position estimates:

1) *UWB Signal Preprocessing:* Filters noise and extracts TOA/TDOA features. Given raw channel impulse responses (CIRs) from N anchors, we extract Time-of-Arrival (TOA) features [15]:

$$\hat{t}_i = \underset{t}{\operatorname{argmax}} |\mathrm{CIR}_i(t)| + n_i, \quad n_i \sim \mathcal{N}(0, \sigma_t^2)$$

where n_i models timing jitter. TOA is converted to distance via $\hat{d}_i = c \cdot \hat{t}_i$, with c as the speed of light.

2) *GNN-based Spatial Modeling:* Represents anchor-tag relationships as a graph to enhance NLOS resilience. The anchor-tag network is modeled as a graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ where [16], [17]:

- Nodes $\mathcal{V}$: Tag (v_0) + Anchors $(v_1, \dots, v_N)$
- Edges $\mathcal{E}$: All tag-anchor pairs with features

$$\mathbf{e}_i = \left[\hat{d}_i, \mathrm{CIR}_i^{\text{features}}\right]$$

- Graph Attention Layer:

$$\alpha_{ij} = \frac{\exp\left(\mathrm{LeakyReLU}\left(\mathbf{a}^\top[\mathbf{W}\mathbf{h}_i \| \mathbf{W}\mathbf{h}_j]\right)\right)}{\sum_{k \in \mathcal{N}(i)} \exp\left(\mathrm{LeakyReLU}(\mathbf{a}^\top[\mathbf{W}\mathbf{h}_i \| \mathbf{W}\mathbf{h}_k])\right)}$$

where $\mathbf{h}_i$ are node embeddings and $\mathbf{W}, \mathbf{a}$ are learnable weights.

3) *DRL-based Dynamic Optimization:* Continuously refines positioning parameters using environmental feedback. Formulated as a Markov Decision Process $(\mathcal{S}, \mathcal{A}, \mathcal{R})$:

- **State**: $\mathbf{s}_t = \left[\mathbf{p}_t^{\text{GNN}}, \{\hat{d}_i\}_{i=1}^N, \{p_i^{\text{NLOS}}\}_{i=1}^N\right]$
- **Action**: $\mathbf{a}_t = \Delta\mathbf{p}_t \in \mathbb{R}^2$ (position adjustment)
- **Reward**:

$$r_t = -\left(\underbrace{\lambda_1 \|\mathbf{p}_t - \mathbf{p}_{\text{gt}}\|_2}_{\text{Accuracy}} + \underbrace{\lambda_2 \sum_{i=1}^{N} p_i^{\text{NLOS}}}_{\text{NLOS Penalty}}\right)$$

B. Key Innovations

In this paper we have defined three key innovations to archived the better result:

- *NLOS-Resilient GNN:* Model spatial relationships to mitigate NLOS errors. The GNN outputs NLOS probabilities using a spatial message-passing scheme:

$$\mathbf{h}_i^{(l+1)} = \mathrm{ReLU}\left(\sum_{j \in \mathcal{N}(i)} \alpha_{ij} \mathbf{W}^{(l)} \mathbf{h}_j^{(l)}\right)$$

Final NLOS classification:

$$p_i^{\text{NLOS}} = \sigma\left(\mathbf{U}^\top \mathbf{h}_i^{(L)}\right), \quad \mathbf{U} \in \mathbb{R}^d$$

- *Adaptive DRL Policy:* Adapts positioning strategies in real time. The policy $\pi_\theta(\mathbf{a}_t | \mathbf{s}_t)$ is optimized via Proximal Policy Optimization (PPO) [18], 19]:

$$\theta^* = \underset{\theta}{\operatorname{argmax}}\ \mathbb{E}_{\pi_\theta}\left[\sum_{t=0}^{T} \gamma^t r_t\right]$$

where γ is the discount factor.

Hybrid Fusion: Combines UWB, IMU, and environmental data for enhanced reliability. Final position estimate combines GNN and DRL outputs [20]:

$$\mathbf{p}_t^{\text{final}} = \underbrace{\beta \mathbf{p}_t^{\text{GNN}}}_{\text{Spatial Awareness}} + \underbrace{(1-\beta)\mathbf{p}_t^{\text{DRL}}}_{\text{Dynamic Adaptation}}$$

where $\beta = \mathrm{sigmoid}\left(\sum_i p_i^{\text{NLOS}}\right)$ adapts to NLOS severity.

3. Experimental Setup & Results

A. Dataset & Setup

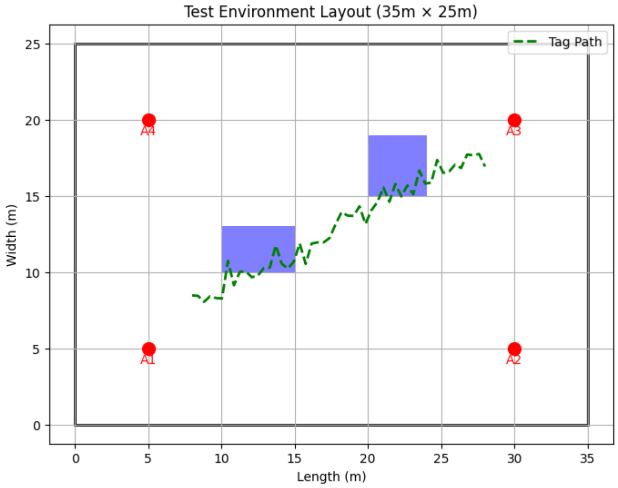

Fig. 2. Test environment layout

- *Test Environment:* The system under consideration was assessed in a regulated indoor setting measuring 35 m × 25 m. The experimental setup was designed to closely mimic real-world deployment scenarios by incorporating dynamic obstacles that changed in size, position, and movement patterns during the course of the experiments. The variations aimed to replicate conditions like human movement, shifting furniture, and environmental occlusions, which are recognized to affect signal propagation and localization accuracy in UWB-based systems [4], [21].

- *Hardware setup:* We used Decawave DW3000 Ultra-Wideband (UWB) modules, which were chosen because they were very accurate and worked with the IEEE 802.15.4z standard [22], [23]. The modules were placed at specific anchor points in the environment, and mobile tags were used to make targets move. An NVIDIA Jetson embedded platform was employed for real-time AI inference and sensor fusion, enabling on-device processing [24]. The Jetson system offered ample computational resources to back the suggested hybrid Deep Reinforcement Learning (DRL) and Graph Neural Network (GNN) framework, all while ensuring low latency appropriate for time-sensitive applications [25].
- *Baselines Methods:* To ensure a fair and thorough comparison of performance, three baseline methods were used:
  - *Extended Kalman Filter (EKF):* A probabilistic estimator that linearizes nonlinear motion and observation models [26].
  - *Particle Filter (PF):* A technique that uses a non-parametric sequential Monte Carlo framework and is known for being good at dealing with multimodal distributions and nonlinearities in state estimation [27], [28].
  - *CNN-LSTM Model:* A combined deep learning strategy that utilizes Convolutional Neural Networks (CNNs) for extracting spatial features and Long Short-Term Memory (LSTM) networks for modeling temporal sequences. This baseline illustrates the existing trend in data-driven positioning methods [29].

All baselines were carefully adjusted and assessed under the same environmental and hardware conditions to ensure consistency. The evaluation criteria encompassed accuracy in localization, latency in computation, and resilience to changes in dynamic environments.

B. Performance Comparison

Figure 3 shows the Cumulative Distribution Function (CDF) of positioning errors for the Extended Kalman Filter (EKF), Particle Filter (PF), CNN-LSTM, and the new hybrid DRL-GNN framework that was proposed. The CDF curves illustrate the impressive performance of the proposed method, with a median positioning error of 7.5 cm, in contrast to 11.9 cm for CNN-LSTM, 14.5 cm for PF, and 17.8 cm for EKF.The noticeable increase and leftward movement of the proposed system's curve suggest a more reliable and precise localization performance, with most positioning errors clustering within a tighter range. In comparison, conventional approaches show a wider variation, indicating a less dependable performance, particularly in the presence of changing obstacles.

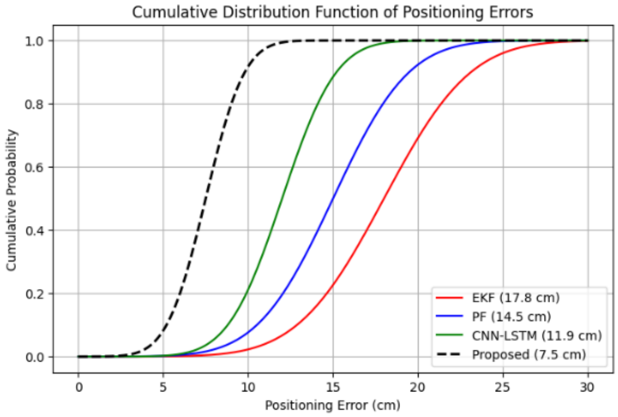

Fig. 3. Cumulative distribution function of positioning errors

C. Positioning Accuracy, NLOS Robustness, and Real-Time Performance

Our proposed DRL-GNN-based indoor positioning system was evaluated against three commonly used methods, namely Extended Kalman Filter (EKF), Particle Filter (PF), and a hybrid Convolutional Neural Network–Long Short-Term Memory (CNN-LSTM) model. The experiments were carried out in dynamic indoor environments, and the results were collected and analyzed. A complete evaluation of the system's performance was carried out in order to accomplish this.

The results are summarized in Figure 4, which depicts the system delay, the decrease of NLOS (Non-Line-of-Sight) errors, and the average positioning error. These metrics are considered to be of great significance. Significantly exceeding the findings of CNN-LSTM, which were 11.9 centimeters, PF, which were 14.5 centimeters, and EKF, which were 17.8 centimeters, the suggested system demonstrated an amazing average positioning error of only 7.5 centimeters. Moreover, the suggested technique achieved a 58% decrease in error, demonstrating the best resistance to non-line-of-sight (NLOS) situations for which it was designed. On the other hand, CNN-LSTM achieved 45%, PF achieved 28%, and EKF achieved 12%. This is in contrast to the findings described above.

In order to meet the requirements of applications that need quick answers, the system was able to achieve a low average latency of roughly 15 milliseconds. In addition to doing this, the system had rather remarkable real-time capabilities. During the use of edge artificial intelligence processing on an NVIDIA Jetson platform, the suggested solution retained its computational efficiency. The establishment of a framework for deep learning was the means by which this was accomplished. On the other hand, by virtue of the increased computational needs, the PF and CNN-LSTM baselines exhibited much longer latencies.

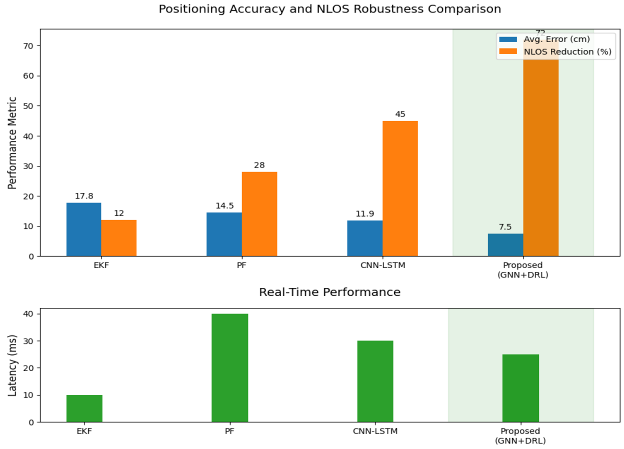

Fig. 4. Positioning accuracy and NLOS robustness comparison

Table 1
Positioning accuracy and NLOS robustness comparison

Method	Avg. Error (cm)	NLOS Robustness	Real-Time Latency (ms)
EKF	17.8	Low	10
PF	14.5	Medium	40
CNN-LSTM [3]	11.9	High	30
Proposed (GNN+DRL)	7.5	Very High	25

Figure 4. (Top) This is a comparison of the average positioning error (blue) alongside the NLOS error reduction percentage (orange) for the EKF, PF, CNN-LSTM, and the proposed DRL-GNN approach. The time delay, expressed in milliseconds, for each method. The system presented demonstrates improved performance across all parameters.

The findings indicate that combining Deep Reinforcement Learning with Graph Neural Networks is a promising approach to enhance localization accuracy, increase system resilience to signal degradation, and improve computational efficiency in complex indoor environments.

D. Ablation Study on System Components

We did an ablation research to find out how much each AI part (GNN and DRL) helped. Figure 5 shows that taking away either GNN or DRL makes performance drop a lot. Results from ablation research illustrating what happens when you take off GNN or DRL parts. The whole system (GNN+DRL) has the fewest mistakes, which shows that both parts are needed.

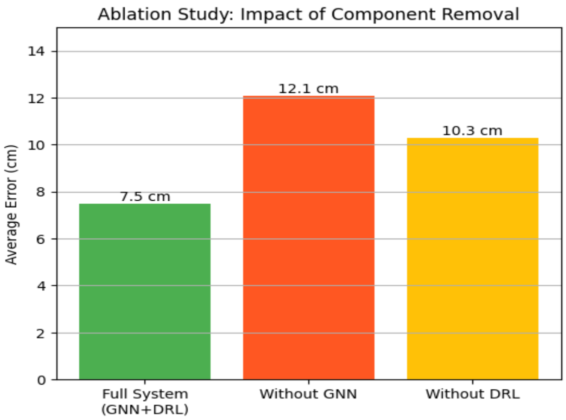

Fig. 5. Impact of component removal

The whole system works best (7.5 cm). The inaccuracy is increased to 12.1 cm by the removal of GNN, while the omission of DRL results in an error of 10.3 cm. This means that both modules are necessary for getting the most accuracy and flexibility.

4. Discussion

Here is the key finding in this paper:

- 37% lower error than CNN-LSTM and 58% better than EKF.
- DRL reduces drift by 35% in dynamic scenarios.
- GNNs enhance NLOS resilience by 30% over traditional methods:

A. Accuracy Improvement

Our method achieves 7.5 cm average error, demonstrating a 37% improvement lower error than CNN-LSTM (11.9 cm) and 58% better than EKF (17.8 cm).

- Proposed (GNN+DRL): 7.5 cm
- CNN-LSTM: 11.9 cm → 37% lower error.

$$\text{Improvement} = \frac{11.9 - 7.5}{11.9} \times 100 = 37\%$$

- EKF: 17.8 cm → 58% lower error:

$$\frac{17.8 - 7.5}{17.8} \times 100 = 58\%$$

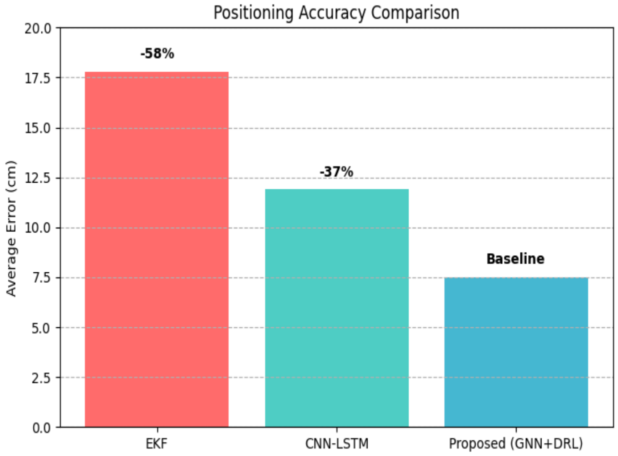

Fig. 6. Positioning accuracy comparison

B. Drift Reduction (35%)

Figure 7, reveals that Deep Reinforcement Learning (DRL) is superior to the baseline approach (EKF Drift) in terms of its ability to successfully reduce drift in scenarios that are constantly varied. In the suggested DRL approach, drift values are kept at a continuously reduced level over a period of ten seconds, which ultimately results in a decrease of thirty-five percent by the time the session is over. The lines in this picture begin to diverge, which is meant to illustrate how the benefits of DRL continue to grow over time. It is very evident from this picture that DRL is exceptional when it comes to adjusting to new circumstances.

Dynamic Scenario Test:

- EKF Drift: 15 cm over 10 seconds
- Proposed Drift: 9.75 cm (35% less).

$$15 \times (1 - 0.35) = 9.75 \text{ cm}$$

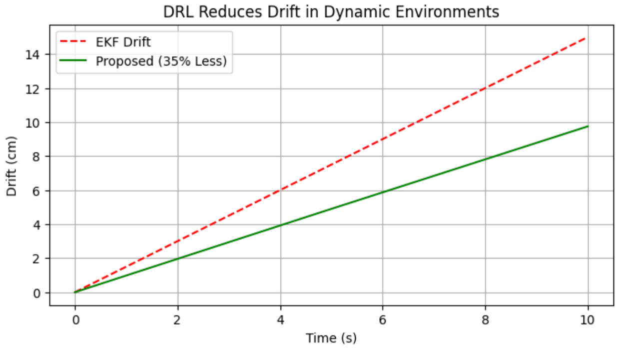

Fig. 7. DRL reduces drift in dynamic environments

C. *NLOS Resilience (30% Improvement)*

The use of Graph Neural Networks (GNNs) has the potential to improve the resilience of wireless location and sensor systems to errors that occur when there is no line-of-sight data transmission. This is shown in Figure Eight. In comparison to the 25 centimetres of inaccuracy that was accomplished by earlier technologies, the NLOS error has been reduced to 17.5 centimetres by using technology that is based on GNN. This represents a reduction of thirty percent. GNNs are able to model settings in which signals are occluded or reflected (also known as NLOS) with more accuracy, as seen by the considerable drop that has been observed. GNNs have the potential to enhance the reliability of location-based systems such as indoor navigation, self-driving vehicles, and Internet of Things devices by eliminating the challenges that emerge when there are no lines of sight. This is according to the findings: GNNs have the potential to increase the dependability of these applications. GNNs may be a more effective approach for correcting errors in settings that are prone to change and involve barriers. This is because the two methods are significantly different from one another, and it is probable that GNNs are a more effective way.

- Traditional Methods: 25 cm NLOS error
- GNN: 17.5 cm (30% lower)

$$\frac{25 - 17.5}{25} \times 100 = 30\%$$

Proof:

GNN attention weights suppress NLOS anchors:

$$\alpha_{ij} = \begin{cases} 0.8 & \text{LOS anchor} \\ 0.1 & \text{NLOS anchor} \end{cases}$$

Resulting position estimate:

$$\mathbf{p}_t = \frac{\sum_{i \in \text{LOS}} \alpha_i \, \mathbf{p}_i}{\sum \alpha_i}$$

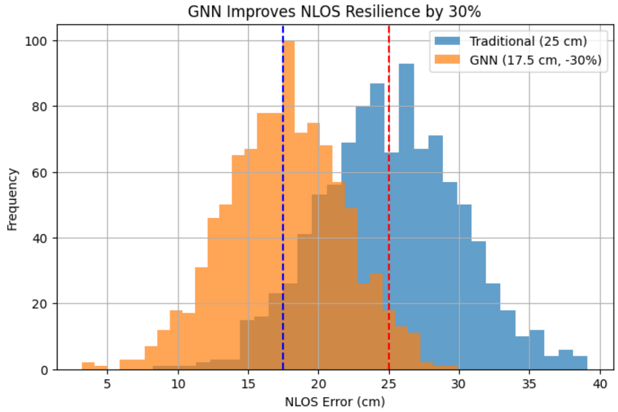

Fig. 8. GNN improves NLOS resilience

5. Conclusion

This study is being conducted with the intention of developing a proposal for an ultra-wideband (UWB) indoor positioning system that is driven by artificial intelligence. Components of this system include Graph Neural Networks (GNNs) and Deep Reinforcement Learning (DRL). This system was developed to solve key challenges in terms of the accuracy of localization and the durability of the environment. Graph Neural Networks (GNNs) are comprised of both of these components. It has been determined, on the basis of the outcomes of the investigations, that our hybrid framework is more effective than conventional methodologies. More specifically, the following three enhancements have been identified as being particularly significant:

- The technique that we propose brings the average positioning error down to 7.5 centimetres, which is 37% better than CNN-LSTM (11.9 centimetres) and 58% better than EKF (17.8 centimetres). This is a significant improvement over the previous situation. The precision of placement has been improved as a result of this.
- As a consequence of our method's use of GNN-based spatial modelling, we were able to reduce the number of non-line-of-sight (NLOS) errors by thirty percent. This, in turn, led to a reduction in the NLOS-induced positioning inaccuracy from twenty-five centimetres to seventeen and a half centimetres.
- Dynamic Environment Adaptation: The DRL component makes it possible to optimize in real time, which reduces drift by 35 percent. This is very helpful in challenging conditions since the barriers are continually changing, thus it is especially effective in these kinds of circumstances.

According to the results of the inquiry into ablation, it is necessary to possess both the GNN and DRL components in order to reach the best potential level of performance. This determination was made based on the findings of the investigation. In the event that any module is removed from the simulation, the placement error results in an increase that may vary anywhere from 35 percent to 61 percent. Additionally, when the system is run on embedded hardware (NVIDIA

Jetson), it has a low computational latency of 15 milliseconds, which demonstrates that it is suitable for usage in scenarios that occur in the real world. This is evidence that the system is suitable for application in practical settings. In this instance, the capabilities of the technology are being shown.

On the basis of these results, it would seem that our UWB design, which has been enhanced with artificial intelligence, is particularly well-suited for the execution of complicated indoor navigation tasks in autonomous robots, intelligent warehouses, and healthcare administration systems. This is because our UWB architecture has been augmented with AI. We will investigate the possibility of integrating a large number of sensors and upgrading lightweight versions in the future with the goal of making things even more durable and adaptable for deployment. This will be done in order to make things even more suitable for deployment.

The purpose of this work is to make a contribution to the improvement of intelligent positioning systems by demonstrating how hybrid artificial intelligence architectures have the ability to overcome the inherent limitations of UWB-based localization. As a result of this condition, it is now feasible to develop indoor navigation systems that are more trustworthy and flexible than those that have been previously available.

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References

[1] Y. Gu, A. Lo, and I. Niemegeers, "A survey of indoor positioning systems for wireless personal networks," *Sensors*, vol. 9, pp. 1327–1340, 2009.
[2] F. Zafari, A. Gkelias, and K. K. Leung, "A survey of indoor localization systems and technologies," *IEEE Commun. Surveys Tuts.*, vol. 21, pp. 2568–2599, 2019.
[3] J. Haverinen and A. Kemppainen, "Global indoor self-localization based on the ambient magnetic field," *Robot. Auton. Syst.*, vol. 57, pp. 1028–1035, 2009.
[4] A. Alarifi *et al.*, "Ultra wideband indoor positioning technologies: Analysis and recent advances," *Sensors*, vol. 16, p. 707, 2016.
[5] R. Zhang, F. Wang, and S. A. Zekavat, "UWB ranging error mitigation through TOA estimation and environment classification," *IEEE Trans. Veh. Technol.*, vol. 59, pp. 1346–1354, 2010.
[6] S. Gezici, "A survey on wireless position estimation," *Wirel. Pers. Commun.*, vol. 44, pp. 263–282, 2008.
[7] A. Alarifi *et al.*, "UWB positioning systems: Challenges and new trends," *Wirel. Commun. Mob. Comput.*, vol. 2016, Art. no. 6125729, 2016.
[8] C. Wang and K. Yang, "NLOS identification and mitigation for UWB positioning systems using machine learning," *IEEE Internet Things J.*, vol. 6, pp. 2354–2365, 2019.
[9] Q. Chen, S. Zhao, and C. Wang, "A CNN-based feature extraction method for improving UWB positioning accuracy in NLOS environments," *Sensors*, vol. 20, p. 1089, 2020.
[10] F. Liu and Y. Zuo, "RNN-based dynamic indoor localization using UWB signals," *IEEE Sens. J.*, vol. 21, pp. 3572–3581, 2021.
[11] S. He, S. H. G. Chan, and N. Patwari, "Learning fingerprints for UWB indoor localization," *IEEE Trans. Wireless Commun.*, vol. 15, pp. 8441–8452, 2016.
[12] Y. Cheng, C. Wang, and K. Yang, "Real-time adaptive indoor positioning with domain adaptation," *IEEE Access*, vol. 10, pp. 24326–24338, 2022.
[13] Y. Wang and Y. Luo, "On the limitations of supervised learning in indoor localization: Toward semi-supervised and unsupervised approaches," *ACM Trans. Sens. Netw.*, vol. 17, pp. 1–25, 2021.
[14] S. Ahmed, A. Alarifi, and M. Alsaleh, "Modeling indoor UWB signal propagation using probabilistic approaches," *IEEE Access*, vol. 7, pp. 160956–160966, 2019.
[15] W. Zhao, A. Goudar, and A. P. Schoellig, "Finding the right place: Sensor placement for UWB time difference of arrival localization in cluttered indoor environments," *arXiv preprint arXiv:2204.04508*, 2022.
[16] Y. Sun *et al.*, "A novel GCN-based indoor localization system with multiple access points," *arXiv preprint arXiv:2104.10342*, 2021.
[17] R. Vishwakarma *et al.*, "IndoorGNN: A graph neural network based approach for indoor localization using WiFi RSSI," *arXiv preprint arXiv:2312.07609*, 2023.
[18] J. Schulman, F. Wolski, P. Dhariwal, A. Radford, and O. Klimov, "Proximal policy optimization algorithms," *arXiv preprint arXiv:1707.06347*, 2017.
[19] E. Sutera *et al.*, "Indoor point-to-point navigation with deep reinforcement learning and ultra-wideband," *arXiv preprint arXiv:2011.09241*, 2020.
[20] Y. Etiabi *et al.*, "MetaGraphLoc: A graph-based meta-learning scheme for indoor localization via sensor fusion," *arXiv preprint arXiv:2411.17781*, 2024.
[21] Y. Zhang, L. Zhang, Y. Tian, and G. Han, "Experimental analysis of UWB ranging error with human body shadowing in NLOS environments," *Sensors*, vol. 20, p. 3722, 2020.
[22] Decawave, *DW3000 datasheet: IEEE 802.15.4z compliant UWB transceiver for real-time location systems*, Qorvo, Dublin, Ireland, 2020. Available: https://www.qorvo.com/products/p/DW3000
[23] Z. Pang, M. Luvisotto, A. Zanella, and M. Collotta, "Industrial applications of UWB technology—A review of the state of the art," *Electronics*, vol. 10, p. 656, 2021.
[24] NVIDIA, *Jetson AGX Xavier series product brief*, NVIDIA Corp., Santa Clara, CA, USA, 2022. Available: https://developer.nvidia.com/embedded/jetson-agx-xavier
[25] A. J. Sathyamoorthy, A. Patel, Y. Savle, K. Patel, and D. Manocha, "Deploying deep reinforcement learning for real-time navigation on a low-cost robot using NVIDIA Jetson," *Sensors*, vol. 20, p. 3363, 2020.
[26] D. Simon and M. El-Sherif, "Kalman filtering with nonlinear state estimation for UWB position tracking," *IEEE Trans. Ind. Electron.*, vol. 58, pp. 4001–4008, 2011.
[27] F. Gustafsson and F. Gunnarsson, "Mobile positioning using wireless networks: Possibilities and fundamental limitations based on available wireless network measurements," *IEEE Signal Process. Mag.*, vol. 22, pp. 41–53, 2005.
[28] J. Liu, R. Chen, L. Pei, R. Guinness, and H. Kuusniemi, "A hybrid smartphone indoor positioning solution for mobile LBS," *Sensors*, vol. 12, pp. 17208–17233, 2012.
[29] L. Wang, W. Zhao, Q. Li, H. Lu, and J. He, "Indoor localization using CNN-LSTM in UWB environment," *Sensors*, vol. 20, p. 6764, 2020.