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A Study on the Gradient Descent Based to Minimize Distance Loss in UWB Indoor Localization

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Abstract:

In recent years, indoor localization has garnered significant attention due to its applications in various domains such as asset tracking, navigation, and context-aware services. Ultra-Wideband (UWB) technology, with its high accuracy and robustness, has emerged as a promising solution for indoor positioning. However, achieving optimal localization accuracy remains a challenge. Factors such as Time of Arrival (TOA) errors, line-of-sight (LOS) conditions, and computational complexity impact the performance of UWB-based localization systems. This study delves into the use of gradient descent techniques and deep learning to minimize distance loss in UWB indoor localization. Specifically, we investigate the impact of gradient descent optimization on distance estimation accuracy, explore the trade-offs between learning rate, batch size, and hidden nodes in deep learning models, and compare the proposed approach with conventional UWB localization methods. Our findings demonstrate that deep learning-based optimization techniques can significantly improve the accuracy of UWB indoor localization.

Keywords —**Time of Arrival (TOA), Ultra-Wideband (UWB) technology, Indoor localization.**

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I. INTRODUCTION

A. Motivation and Problem Statement

After the COVID-19 pandemic, remote learning environments have rapidly proliferated, forcing many learners to study in isolation. This environmental change has led to problems such as reduced concentration, accumulated emotional fatigue, and decreased learning persistence. In particular, the lack of a feedback system that allows learners to share emotions and difficulties in real time hinders the effectiveness of self-directed learning. Most existing online learning platforms are function-oriented, focusing on features such as time tracking, progress management, and schedule sharing, while rarely integrating users' emotional states or immersion levels.

For example, Park et al. (2023) developed a real-time attention detection system using OpenCV and MediaPipe, achieving an accuracy of 97.85% [4]. However, it did not incorporate real-time feedback based on emotional states. This highlights a limitation of existing technologies that primarily focus on behavioral data while neglecting emotional support. As a result, learners experience psychological isolation, lack of motivation, and insufficient engagement, which can lead to decreased long-term academic performance. To address these challenges, this study proposes the "Study With Us" platform, which integrates emotion analysis, attention detection, and real-time interaction features. The platform goes beyond being a simple learning management tool and serves as a next-generation EdTech model that technically supports learners' internal states.

II. RELATED WORK

In the realm of indoor localization, advancements have centered around integrating Ultra-Wideband (UWB) technology, Kalman filters, Extended Kalman Filters (EKF), and Neural Networks to enhance accuracy and reliability. Borhan et al. (2023) [3] proposed a method combining Kalman and Moving Average filters to improve UWB-based localization accuracy, demonstrating superior error reduction compared to standard Kalman filtering. Karfakis et al. (2022) [4] introduced two UWB position prediction methods, employing an Extended Kalman Filter and a Neural Network (NN). The NN effectively represented sensor covariance, enhancing reliability by adapting to data loss.

Time of Arrival (TOA), Time Difference of Arrival (TDOA), and Received Signal Strength (RSS) techniques based on ultra-wideband technology are central to indoor localization. Specifically, an ultra-wideband based Time-Difference-of-Arrival (TDOA) positioning system has been proposed for real-time UWB multi-channel indoor positioning in industrial scenarios [5]. Furthermore, Lee et al. (2023) [6] proposed a machine learning-based compensation model to reduce distance errors caused by Non-Line-of-Sight (NLOS) conditions in UWB systems, thereby improving localization accuracy. In addition, Kim et al. (2022) [7] conducted research on optimizing model parameters in a deep learning-based UWB positioning system using gradient descent, thereby ensuring stable positioning performance in various indoor environments. The gradient descent-based approach proposed in this paper plays a pivotal role in training neural networks. It aims to minimize loss functions by iteratively adjusting model weights to obtain optimal localization accuracy. This paper will compare the results of using UWB and the gradient descent method.

III. METHODOLOGY

A. UWB Localization Technology

UWB can provide distance measurement, angle estimation, and real-time tracking for robot localization.

1. Distance Measurement between Tag and Anchors:
   - UWB systems measure the Time of Arrival (TOA) of UWB pulses.
   - By calculating the time taken for the signal to travel from the tag to the anchors, the system can estimate the distance.
2. Angle Estimation:
   - UWB allows for the determination of both distance and angle, which helps in narrowing down the possible positions of the robot.
3. Real-time Tracking using UWB:
   - Combining accurate distance measurements, angle estimation, and real-time tracking using UWB technology enables precise localization and tracking of moving robots within indoor environments

B. Proposed Algorithm: Deep Learning-Based Gradient Descent

In this study, we propose an algorithm that combines a deep learning model with gradient descent to minimize distance loss in UWB localization systems. This algorithm uses TOA data obtained from UWB sensors as input to predict the robot's position and optimizes the model parameters to minimize the error between the predicted and actual positions.

1. Data Collection and Preprocessing:
   - TOA data between UWB tags and anchors is collected.
   - The collected data undergoes noise reduction and normalization processes to be formatted appropriately for input into the deep learning model.

2. Deep Learning Model Design:
   - A deep neural network model based on a Multilayer Perceptron (MLP) is constructed.
   - The model consists of an input layer, several hidden layers, and an output layer.

- The input layer receives UWB distance measurement data, and the output layer predicts the robot's position in 2D or 3D space (e.g., (x,y) or (x,y,z)).
- An activation function (e.g., ReLU) is applied to each hidden layer to introduce non-linearity.
- The number of hidden nodes and the depth of the hidden layers influence the model's complexity and learning capability; thus, various configurations are experimented with to find the optimal structure.

3. Loss Function Definition:
   - A loss function is defined to minimize the Euclidean distance error between the predicted robot position $(x\hat{},y\hat{})$ and the actual robot position (x,y).
   - Mean Squared Error (MSE) is used as the loss function:

$$L = \frac{1}{N}\sum_{i=1}^{N}((\hat{x}i - x_i)^2 + (\hat{y}i - y_i)^2)$$

where N is the number of data samples.

4. Model Optimization using Gradient Descent:
   - A gradient descent optimizer (e.g., Adam, SGD) is used to minimize the defined loss function.
   - The model's weights W and biases b are updated at each training step according to the gradient of the loss function:

$$W_{t+1} = W_t - \alpha\frac{\partial L}{\partial W_t}$$

$$b_{t+1} = b_t - \alpha\frac{\partial L}{\partial b_t}$$

Here, α is the learning rate, which determines the step size of model updates.

- The learning rate and batch size significantly affect the model's convergence speed and final performance, so optimal values are found through hyper-parameter tuning.

IV. RESULTS

In this study, a simulation environment was set up to verify the effectiveness of the proposed deep learning-based gradient descent method. UWB anchors were placed at fixed positions, and a robot moved along a specific trajectory, collecting TOA data from UWB tags. The collected data was used as input for the proposed model, which then predicted the robot's position.

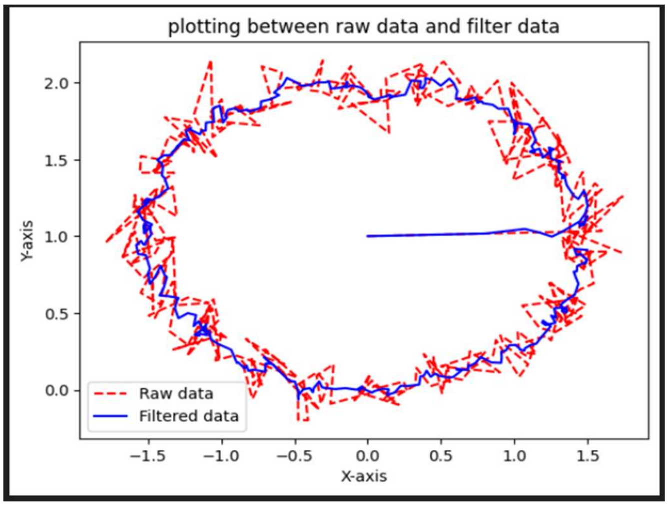

Figure 1. Robot moving trajectories by gradient descent and UWB positioning methods

Figure. 1 illustrates the robot's moving trajectories traced by the gradient descent-based UWB positioning method and a conventional UWB positioning method. As shown in the figure, the method incorporating gradient descent predicts the robot's trajectory much closer to the actual path, demonstrating a significantly reduced prediction error compared to the conventional UWB positioning method. This indicates that gradient descent effectively optimized the model parameters, corrected measurement errors, and improved positioning accuracy.

Table 1. presents the robot's position by UWB positioning methods and the filter result by

gradient descent, where "Optimized Position" refers to the results obtained through gradient descent.

Based on these results, it is evident that the gradient descent method can effectively reduce errors in UWB positioning systems. This method, characterized by iterative adjustments based on gradient information, demonstrates a capacity to fine-tune model parameters, resulting in a noteworthy decrease in localization errors. This suggests that it can be selected as an optimized proposed method for UWB positioning systems. In particular, the application of deep learning models contributed to further enhancing prediction accuracy by learning complex nonlinear relationships. The appropriate setting of hyper-parameters, such as learning rate, batch size, and the number of hidden nodes, played a crucial role in the model's convergence speed and final performance. For instance, an overly large learning rate can lead to divergence, while a too small learning rate can slow down convergence [8]. In this study, cross-validation was used to explore the optimal combination of hyper-parameters to achieve stable and high accuracy.

Table 1. The position of robot by UWB positioning methods and filter result by gradient descent

Robot Position		**Optimized Position**	
X-axis	Y-axis	X-axis	Y-axis
0.034	0.997	0.758	0.996
0.491	2.133	0.610	1.710
-0.521	1.662	0.492	1.882
-1.721	1.321	-1.472	1.420
-1.381	0.000	-0.351	0.325
1.125	0.215	1.325	0.512

V. CONCLUSION

In conclusion, the integration of the gradient descent method with UWB-based indoor localization systems proves advantageous, notably surpassing traditional UWB methods. This approach, through leveraging gradient information, iteratively refines model parameters, effectively reducing localization errors and enhancing accuracy in UWB positioning systems. The gradient descent method emerges as an optimized proposed solution, offering a systematic means of fine-tuning localization models for improved position estimates. Through this study, we confirmed that deep learning-based gradient descent can significantly improve the accuracy and reliability of UWB indoor localization.

In future work, we will apply more complex deep network-based approaches, such as Recurrent Neural Networks (RNNs) or Convolutional Neural Networks (CNNs), to optimize distance loss in UWB localization systems [9]. Furthermore, research will be conducted to enhance robustness against various obstacles and Non-Line-of-Sight (NLOS) conditions in real-world environments. Finally, our goal is to develop more precise and stable indoor localization solutions by integrating various sensor fusion technologies (e.g., accelerometers, gyroscopes) to complement the limitations of UWB systems [10].

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