Empowering Bluetooth Angle of Arrival Positioning with Ultra-wideband for Industry 4.0

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Abstract

The shift from mass production to mass customization in the era of Industry 4.0 requires production and warehouse management to be more flexible and controllable. The precise location information of the resources (men, machines, materials) is significant to enable the orchestration of processes and operations. However, the massive resources and complicated industrial environment could impede the adoption of high-cost, shelter-sensitive and hard-to-deploy indoor positioning systems. Therefore, this paper proposes a novel solution that amalgamates Bluetooth Low Energy (BLE), featuring low energy consumption, low cost, and high scalability, and Ultra-wideband (UWB) technology that attains high location accuracy. A deep learning method is designed for angle of arrival (AoA) estimation to address the challenges of multi-path fading faced by BLE, thus enhancing location accuracy. UWB is innovatively employed to facilitate sampling and labeling job to underpin rapid deployment. The AoA training data can be collected on site during the operations, avoiding the impact on daily production. The experimental results show that the proposed solution achieving a positioning accuracy of 50 cm.

Keywords

Bluetooth Low Energy, Angle of Arrival, Ultra-wideband, Deep Learning, Industry 4.0.

1. Introduction

In Industry 4.0, the development of technologies such as the Internet of Things and edge computing has significantly improved the operational efficiency of paradigms like smart manufacturing and smart warehousing [1]. Within these paradigms, the acquisition and utilization of location information are of critical importance. To illustrate, real-time positioning technology can provide location information for both objects and personnel. In a warehouse setting, this information can be improve order picking and inventory management [2]. In the shopfloor, the precise location benefits the task allocation and vehicle routing planning. Additionally, positioning systems can issue alerts to prevent accidents by warning workers and vehicles when they approach hazardous areas [3]. Satellite-based systems like GPS and Beidou perform well outdoors but struggle indoors due to interference and obstructed lines of sight, making them less effective in complex industrial settings like warehouses and shopfloors [4], [5]. Nowadays indoor positioning systems have garnered increasing research in Industry 4.0 applications. The system must balance accuracy with a series of characteristics including technical cost, power consumption, and real-time performance in large-

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scale-deployment. The Angle of Arrival (AoA) positioning [6] is officially included in Bluetooth Core Specification 5.1 by Bluetooth Special Interest Group (SIG), which enhances the positioning accuracy of Bluetooth Low Energy (BLE) to the next level. In conjunction with the inherent characteristics of low power consumption and cost-effectiveness inherent to BLE, research on AoA technology offers a novel solution to meet the large-scale simultaneously positioning for Industry 4.0 applications.

How to calculate the accurate angle from the in-phase and quadrature (I/Q) data collected by the BLE array antenna deserves in-depth study. Traditional AoA algorithms such as multiple signal classification (MUSIC) [7], propagator direct data acquisition (PDDA) [8], signal subtraction subspace (SSS) [9] have been proven to be successful in laboratory test [10], but ones rely heavily on the computation capability. In [11], the application of the MUSIC algorithm on a BLE system is examined, but it is limited by its use of a uniform linear array (ULA), restricting the range of angle estimation. In [12], a theoretical analysis of the impact of phase noise on traditional subspace-based AoA estimation algorithms in BLE systems is presented. To reduce the computational complexity, [6] investigated the application of PDDA algorithm on BLE system in an empty indoor hall. The results show that the average positioning accuracy is less than one meter, but only a single receiver was used for the test, and the interference caused by the multipath effect was not considered.

Due to the complexity of industrial indoor environments, traditional algorithms suffer from the impact of multipath effects, resulting in reduced angle estimation accuracy. In contrast, methods based on deep learning (DL) of the characteristics of I/Q values from multi-antenna element arrays outperform traditional signal processing methods in dealing with multipath effects [13]. Once trained, DL models can derive AoA information from the input data without requiring the complex calculations associated with traditional algorithms, thereby reducing computational costs [14]. In [15], the authors approach the problem of AoA estimation as a time series problem and employs a recurrent neural network (RNN) to learn deep features from the spatial power spectrum of BLE signals based on the PDDA algorithm as input features. The test results show that it outperforms the original PDDA algorithm. In [16], a DeepAoANet model is proposed which uses the I/Q-based spatial covariance matrix as a feature and is trained accordingly. The accuracy error of the training dataset is approximately 80% near 2.5 degrees, but only a ULA is used to output a one-dimensional angle. In [17], a variety of neural network architectures for AoA estimation using I/Q and RSSI values as inputs are proposed. In a series of simulations, the proposed algorithm exhibited superior performance compared to the benchmark PDDA algorithm, achieving a positioning accuracy of 70 cm. Despite their potential, DL models face challenges such as overfitting, where the models perform well on trained scenarios but poorly on unseen ones. Collecting more data to train the DL model can be one possible solution, but this requires large amount of time for data collection and labelling effort. The time-consuming and labor-intensive training work impede the large-scale deployment in industrial scenarios.

To tackle the issue of overfitting in DL models for AoA estimation, this paper proposes an improved method for calibrating ground truth labels in BLE data acquisition. UWB technology, known for its high accuracy in indoor positioning, faces limitations in large-scale industrial deployments due to its cost and power consumption. However, UWB can be leveraged to simplify the tagging process for extensive BLE data. During offline data collection, the X, Y, and Z coordinates from UWB are converted into angle information to serve as ground truth for model training. This data, combined with noisy BLE I/Q data, is used to train a supervised learning model for AoA estimation. It is crucial to smooth UWB positional information to minimize its inherent errors and their influence on the model. Furthermore, we introduce a DL model architecture for AoA estimation, which combines Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks, referred to as CL-AoA. This model effectively mitigates the impact of multipath effects on angle estimation, enhancing the robustness and accuracy of the positioning system. Our results show that the model has an error of approximately 2 degrees in the angle estimation.

The main contribution of this paper are as follows: first, we present the CL-AoA model which effectively mitigates multipath interference in angle estimation, thereby achieving high accuracy while maintaining low latency. Second, we introduce an automatic dataset ground truth labeling method that uses UWB technology for effortless labeling in BLE angle estimation. Workers carry a tag that combines UWB and BLE while moving around the factory. This setup allows the training data, including I/Q values and angle ground truth, to be labeled automatically. The remainder of this paper is structured as follows: Section 2 outlines the proposed architecture. Section 3 details the research methodology, including underlying principles, formulas, and the design of the CL-AoA model. Section 4 presents and discusses experimental results to validate the performance of the proposed methods. Finally, Section 5 provides the conclusions.

2. Overview Architecture

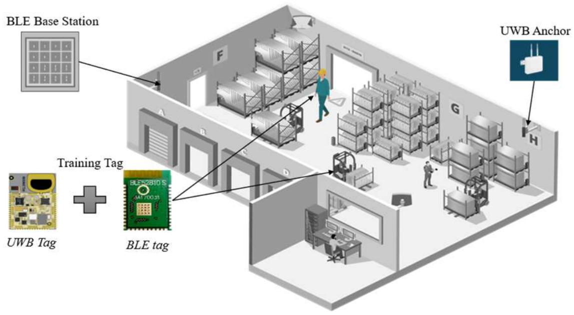


Figure 1: Training setup in Industry 4.0 scenario

2.1. Challenges

As shown in Figure 1, Industry 4.0 scenarios, such as workshops or warehouses, are complex due to the presence of numerous pieces of equipment, walls, and metal objects, which introduce significant signal noise and cause multipath effects. Multipath effects make it difficult for traditional techniques to compute azimuth (φ) and elevation (θ) angles properly, which lowers positioning accuracy. Consequently, the use of DL for angle estimation has been proposed [13], [15]. However, deploying DL methods in such scenarios faces several challenges. Firstly, DL requires the collection of substantial data during the offline stage. Traditional methods of data collection typically entail manual partitioning of regions for the purpose of collecting fixed-point data, which is a time-consuming and labor-intensive process in industrial settings. Secondly, while deploying the system and gathering data, it is essential to guarantee that the existing operational workflows remain uninterrupted.

2.2. Proposed methods

To address the challenges outlined above, this paper proposes a method that combines UWB and BLE for automatic dataset labeling and collection during the offline phase. The workflow of the proposed method, depicted in Figure 2, can be divided into three distinct phases: data collection and preprocessing, model training, and position estimation.

The BLE system comprises locators and tags, where the BLE tags transmit radio data packets with a Continuous Tone Extension (CTE) at a fixed frequency. Upon receiving the signal, the antenna array of the locator switches to collect I/Q data. This data undergoes quality analysis to filter out invalid samples, ensuring that only valid I/Q data is extracted as input features. UWB performs ranging using double-sided two-way ranging (DS-TWR) and outputs position data as X, Y, Z coordinates, which are subsequently converted into angle serving as ground truth labels for the CL-AoA model. To enhance robustness against multipath interference, BLE I/Q data is treated as time series data, leveraging the temporal correlations inherent in the signal, allowing the model to capture subtle variations in the data that are indicative of angle information. A combined CNN and LSTM model architecture is employed to learn and extract the angle information. The Least Squares (LS) algorithm is employed to estimate the positional information (X, Y, Z).

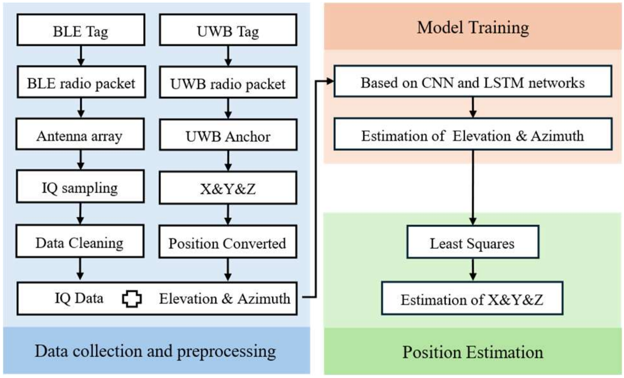


Figure 2: Workflow of the proposed method

3. Methodology

3.1. I/Q Sampling

The BLE tag is responsible for periodically transmitting BLE broadcast signals, which include CTE data. These data consist of a series of unwhitened, continuously modulated RF sinusoidal signals that define the time slots for antenna switching and sampling.

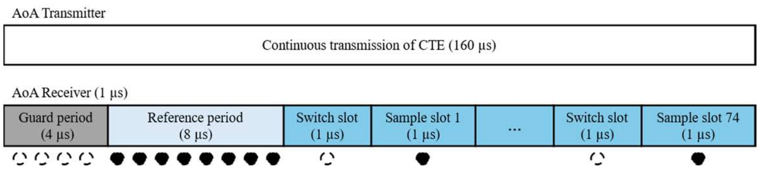


Figure 3: CTE timing rules

The CTE timing rules are presented in Figure 3, with a duration range of 16 to 160 μs, where the first 4 μs are a guard period followed by an 8 μs reference period. During this period, a single I/Q sample is collected at the reference antenna with a temporal resolution of 1 μs, resulting in a total of 8 reference samples. After this is the switching sampling period, during which alternate switching time slots and sampling time slots are defined. The time slots may be specified as either 1 μs or 2 μs. In this work, a total of 74 pairs of I/Q samples can be acquired during the switching sampling cycle. The collected I/Q data is presented in Eq. (1), where the first 8 groups are the reference period samples, and the rest are the sampling period. The discrete I/Q sample data can be utilized to calculate the signal Phase (ϕ) and Amplitude (A) at the current sampling moment using Eq. (2). By calculating the phase differences between the signals received by each antenna and considering the known geometry of the antenna array, the AoA information of the tag can be determined.

$$IQ_{Data} = \left[I_{ref1}, Q_{ref1}, \ldots, I_{ref8}, Q_{ref8}, I_1, Q_1, \ldots, I_{74}, Q_{74} \right] \tag{1}$$

$$A = \sqrt{I^2 + Q^2}, \phi = \arctan 2(Q, I) \tag{2}$$

3.2. Data Preprocessing

3.2.1. I/Q data cleaning

Due to environmental noise and inherent device defects, invalid data may be present in the collected I/Q samples. This paper chooses to perform quality analysis based on the phase difference, amplitude, amplitude difference, and Signal-to-noise Ratio (SNR) during the reference period. The SNR is an important metric for assessing the quality of the received signal. According to Eq. (2), A and ϕ can be calculate. Then, the power of the signal (P_{signal}) and the power of the noise (P_{noise}) can be computed as Eq. (3), where A_i is the amplitude at the *i-th* sampling time, and N is the total number of samples during the reference period. The SNR is then calculated as Eq. (4), and data with an SNR less than 20 dB is considered invalid and is filtered out to ensure the high quality of the I/Q data used for angle estimation.

$$P_{signal} = \frac{1}{N}\sum_{i=1}^{N}|A_i|^2, P_{noise} = \frac{1}{N}\sum_{i=1}^{N}(A_i - \frac{1}{N}\sum_{i=1}^{N}A_i)^2 \tag{3}$$

$$SNR = 10 \times \log_{10}\left(P_{signal}/P_{noise}\right) \tag{4}$$

By analyzing the Z-scores of various parameters in the dataset, data filtering is conducted to ensure the integrity and reliability of the I/Q data used for angle estimation. The Z-scores for a given parameter x is calculated as Eq. (5), where μ is the mean and σ is the standard deviation of the parameter values in the dataset. $|Z|>3$ are considered as outliers and filtered out.

$$Z = (x-\mu)/\sigma \tag{5}$$

3.2.2. UWB-based labeling

Due consideration of factors such as cost and power consumption, this study only uses UWB in the offline stage, capitalizing on its high precision to facilitate the automatic labelling of BLE data samples. The UWB system comprises UWB tags and anchors. The positioning principle is to use ultra-short pulse signals and the DS-TWR [18] algorithm to determine the position and speed of the target by measuring the time delay of the signal and calculate the distance between the UWB tag and the anchor point. Then, trilateration can be employed to get the position information.

Each locator's position and orientation information is required, to transform the angles from the global coordinate system to the array's local coordinate system. Let the locator's position information be denoted as $(X_{loc}, Y_{loc}, Z_{loc})$ and its orientation information as (α, β, γ), where α, β and γ representing the rotation angles around the X, Y, and Z axes, respectively. The tag's positional information is denoted as $(X_{tag}, Y_{tag}, Z_{tag})$ .Calculate the relative position vector $(\Delta X, \Delta Y, \Delta Z)$ between the tag and the locator, and then use the rotation matrix R to transform the relative position vector from the global coordinate system to the locator's local coordinate system, denoted as $(X_{rel}, Y_{rel}, Z_{rel})$, as shown in Eq. (6).

$$\begin{cases} \begin{pmatrix} X_{rel} & Y_{rel} & Z_{rel} \end{pmatrix} = R \cdot \begin{pmatrix} \Delta X & \Delta Y & \Delta Z \end{pmatrix} = R_x(\alpha) \cdot R_y(\beta) \cdot R_z(\gamma) \cdot \begin{pmatrix} X_{tag} - X_{loc} & Y_{tag} - Y_{loc} & Z_{tag} - Z_{loc} \end{pmatrix} \\ R_x(\alpha) = \begin{pmatrix} 1 & 0 & 0 \\ 0 & \cos\alpha & -\sin\alpha \\ 0 & \sin\alpha & \cos\alpha \end{pmatrix}, R_y(\beta) = \begin{pmatrix} \cos\beta & 0 & \sin\beta \\ 0 & 1 & 0 \\ -\sin\beta & 0 & \cos\beta \end{pmatrix}, R_z(\gamma) = \begin{pmatrix} \cos\gamma & -\sin\gamma & 0 \\ \sin\gamma & \cos\gamma & 0 \\ 0 & 0 & 1 \end{pmatrix} \end{cases} \tag{6}$$

Then we can calculate φ and θ using the following formulas, where φ is the angle in the XY-plane from the X-axis, and θ is the angle from the XY-plane towards the Z-axis:

$$\varphi = \arctan 2(Y_{rel}, X_{rel}), \theta = \arctan 2(Z_{rel}, \sqrt{X_{rel}^2 + Y_{rel}^2}) \tag{7}$$

3.3. CL-AoA Architecture

Given the potential impact of various noise and interference sources on the collected I/Q data, this study employs a neural network architecture, CL-AoA, to learn deep features from the I/Q data for predicting 2D angle information. The proposed architecture, as illustrated in Figure 4, employs the spatial feature extraction capabilities of CNNs and the temporal modeling strengths of LSTMs. In this architecture, the noisy I/Q data from multiple antennas is treated as a 2D image. The CNN component is employed to extract spatial features from the I/Q data. Due to the temporal variation of the data from each antenna, the LSTM component is utilized to capture temporal dependencies, thereby enhancing the accuracy of the AoA estimation.

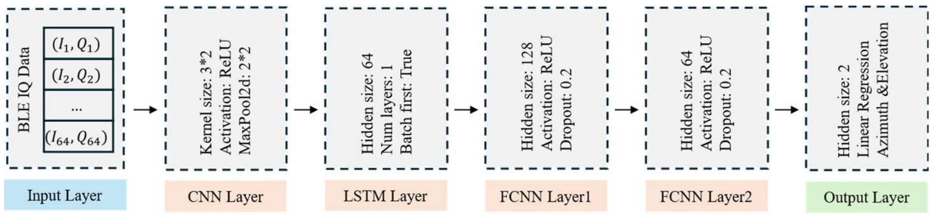


Figure 4: CL-AoA network architecture

Specifically, the CNN layers consist of two 2D convolutional layers, each with kernel sizes of 3×2 and utilizing the Rectified Linear Unit (ReLU) activation function. Each convolutional layer is followed by a 2×2 max pooling layer for down-sampling the data, reducing spatial dimensions and computation time. The output from the CNN layers is then fed into an LSTM layer with 64 hidden neurons to extract sequential features from the I/Q data. The subsequent fully connected layers, also using ReLU activation, process these features. To prevent overfitting, a dropout rate of 0.2 is applied. The output layer employs linear regression to predict the azimuth and elevation angles, with the mean squared error (MSE) used as the loss function to optimize the network. This hybrid architecture effectively captures both the spatial and temporal dynamics of the I/Q data, thereby improving the accuracy of AOA estimation.

3.4. Localization

In this study, the LS method is employed for position estimation [19]. Assume there are N base stations, each with a known position $loc_i=(x_i,y_i,z_i)$, where $i=1,2,\ldots,N$. Initialize target tag position as $loc_{tag}=(x,y,z)$. Each base station measures the azimuth φ_i and elevation θ_i angles to the target, and then using the rotation matrix R convert to the global coordinate system. The direction vector d_i can be expressed as follow:

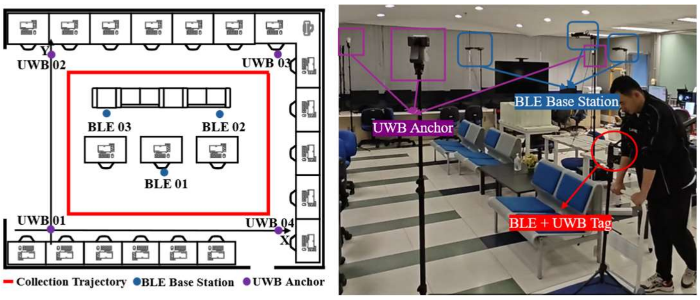
$$d_i=\left[(\cos\varphi_i\cos\theta_i),(\cos\varphi_i\sin\theta_i),\sin\varphi_i\right] \tag{8}$$

Compute the vector v_i from base station i to the target position loc_{tag}, then normalize v_i to obtain the unit vector $v_i^{norm}=v_i/\|v_i\|$.Sum the squared residuals from all base stations to obtain the residual function $R=\sum_{i=1}^{N}\| v_i^{norm}-d_i\|^2$, and then minimize the residual function R to obtain the estimated target position loc_{tag}. The LS method ensures that the solution minimizes the sum of the squared errors between the predicted and observed angles, providing an accurate estimate of the tag's position.

4. Experiment evaluation

4.1. Experimental Setup

The experimental were conducted in the Cyber-Physical Internet Laboratory of the Department of Industrial & Systems Engineering at The Hong Kong Polytechnic University. As illustrated in Figure 5 (a), the laboratory spans an area of approximately 80 square meters ($8m\times 10m$). The laboratory contains various equipment, including computers, BLE sensors, and furniture, ensuring that the BLE AoA tags are subjected to multipath interference similar to that in a warehouse scenario.



(a) (b)

Figure 5: Layout scene of the laboratory

The UWB anchors and tags use Qorvo's DWM1001-DEV module development board to obtain positional information. The BLE tags utilize the BRD4184 and operate in a non-connected communication mode, transmitting data packets with CTE on data channels excluding 37, 38, and 39, as specified by the Silicon protocol. The BLE locator employs Silicon EFR32BG22 development board and the BRD4185A antenna array to collect raw I/Q sample data. In this experiment, as depicted in Figure 5 (b), BLE and UWB tags were combined and mounted on a trolley's stand. An operator pushed the trolley along the red trajectory shown in Figure 5 (a), simulating the movement of a forklift in the factory. Throughout the process, a total of 140,000 IQ data samples were collected. The proposed method was employed to automatically label the ground truth angles using the positional information from the UWB system.

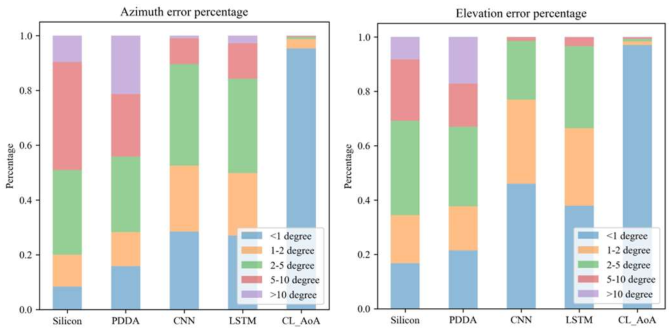
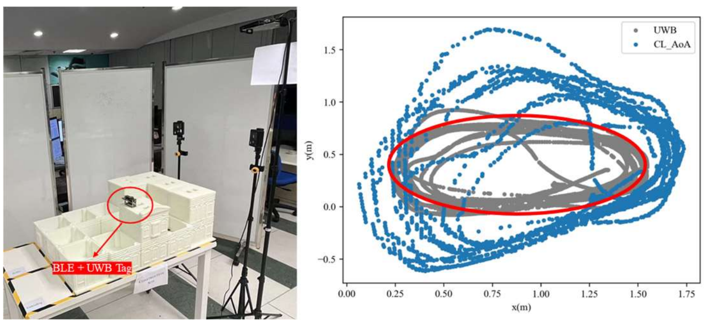


Figure 6: Angle estimation error comparison

4.2. Results and Analysis

The experimental results, which include error distribution for both azimuth and elevation angles, are illustrated in Figure 6. Overall, the DL-based methods outperform the traditional methods. The CL-AOA network demonstrates superior performance in the experiments, achieving 98% of angle errors within 2 degrees. This indicates its robustness in significantly mitigating the impact of multipath effects on AoA estimation.



(a) (b)

Figure 7: Position estimation scenario and results

In the position estimation comparison experiment, an $2m \times 1m$ area within the laboratory was selected as the test site, as shown in Figure 7 (a). To increase the complexity of the environment, three partitions were added. An operator carried the tags and moved around the perimeter of a table to collect data. The UWB positioning results were used as the benchmark for comparison. Using the CL-AoA model trained from angle estimation, angles were derived from the received I/Q data. The LS method was then employed to estimate positions based on these angles. The results are shown in the right-hand side of Figure 7 (b), where the red line represents the ideal position trajectory. The proposed method achieves a positioning accuracy within approximately 0.5 meters. This level of accuracy demonstrates the feasibility of deploying the proposed method in Industry 4.0 environments.

5. Conclusion

In this study, an automatic dataset labeling method for BLE data samples based on UWB in Industrial 4.0 environments is proposed. This method significantly reduces the workload in the data collection stage and ensure the normal operation of the factory business processes. We then introduced a CL-AoA model architecture, which effectively reduce the impact of multipath effects on angle estimation. Experimental results show the proposed method demonstrated that 98% of the angle errors in the test set were within 2 degrees. Additionally, the position estimation accuracy was within 0.5 meters.

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