A Novel UWB Indoor Positioning Algorithm Based on SVM

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Abstract. Ultra-wideband (UWB) is considered as a mainstream positioning technology in the field of indoor positioning by virtue of its high-precision positioning, low power consumption and strong penetration. However, indoor positioning still faces a series of challenges, such as NLOS problem. NLOS environments are particularly common in indoor positioning, where signal reflections, refractions, and scattering between buildings and obstacles can lead to performance degradation of traditional positioning algorithms. Aiming at indoor WSN localization scenarios, a SVM-based UWB Indoor Positioning (SUIP) algorithm based on Support Vector Machine (SVM) is proposed, which is applied in a public dataset with different scenarios. In the model optimisation of SUIP, a parameter selection method of SVM is designed through cross-validation. It is experimentally verified that SUIP can reduce positioning error and maintain the robustness efficiently in three-dimension NLOS scenarios compared with classical Chan algorithm.

Keywords: UWB · Support Vector Machine · Indoor Positioning

1 Introduction

Wireless Sensor Network (WSN) research is essential for applications like air quality monitoring, home automation, patient localization, and logistics management, where accurate node localization is crucial. GPS, is often unsuitable for WSNs due to high costs, energy consumption, large device sizes, and poor indoor performance. Researchers have thus focused on developing energy-efficient, low-cost, self-organizing WSN localization techniques that rely

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on wireless communication, multi-hop transmission, distributed processing, and high fault tolerance. Ultra-wideband (UWB) positioning technology has gained significant attention for indoor positioning, intelligent transport, and the Internet of Things due to its high accuracy, low power consumption, and strong anti-interference capabilities. Researchers have improved UWB positioning accuracy and stability by enhancing traditional algorithms like TOA, TDOA, AOA, integrating multi-sensor data, and AI techniques [1].

Despite challenges such as multipath effects and NLOS conditions, ongoing algorithm optimization and standardization efforts suggest a promising future for UWB in complex environments. This continuous research aims to provide efficient, cost-effective solutions for the diverse needs of real-world WSN applications. Jondhale S. *et al.* designed a new and efficient UWB tracking system based on RSSI that can track a single moving target and achieve high tracking accuracy regardless of target movement [2]. LOU P. *et al.* proposed an ultra-wideband UWB indoor navigation method based on digital twins [3], in which the perceptual-predictive feedback in cyber-physical space is utilised to effectively improve the accuracy of indoor positioning. Lee S. *et al.* used the artificial fish school algorithm (AFSA) for indoor target localization and tracking [4], and investigated the performance of the hybrid adaptive prey vision method with different numbers of artificial fish schools. QU J. compared the advantages and disadvantages of UWB technology with those of Bluetooth and Wi-Fi, and looked forward to the future development of UWB indoor positioning [5]. LIU A. *et al.* proposed a fusion method tightly coupled with a Dynamic Unscented Kalman Filter [6], which utilises odometry to identify and mitigate the effects of NLOS on UWB measurements. Wang Q. *et al.* proposed a novel indoor UWB NLOS-corrected localization method based on anchor point LOS/NLOS maps that utilizes priori environmental information [7], then selects LOS anchors for localization solving and corrects for observations affected by the NLOS anchors.

Support vector machine (SVM), as a powerful machine learning algorithm, has attracted much attention in recent years for its application in the field of wireless localization [8]. By using the classification idea and feature learning ability of SVM, researchers have successfully solved many challenges in wireless positioning. Kataria A. proposed a distance free localization strategy based on fuzzy logic [9]. This localization method uses SVM inputs to the signal strength received at anchor points near the sensor nodes and establishes the relationship between RSSI and distance through fuzzy analysis to assess the localization accuracy. Chriki A. *et al.* proposed a partitioned localization method based on RSSI measurements using SVM, with a comparison to an Artificial Neural Network (ANN) approach [10], which confirms the positioning accuracy of this localization scheme. ZHU F. *et al.* proposed a large-scale localization algorithm based on Fast SVM [11], which describes the minimum span by the concept of similarity metric and achieves a significant improvement in the classification rate. The overall research trend has transitioned from traditional algorithms to machine learning algorithms in complex, multipath, NLOS environments. However, in the case of fewer anchor nodes, there is still a lot of space for positioning algorithms in terms of stability and accuracy.

This paper proposes an SVM-based UWB Indoor Positioning (SUIP) algorithm, which innovatively transforms the continuous-space localization problem into a discrete-space classification problem. This transformation leverages the advantages of SVM for UWB indoor localization. Unlike traditional algorithms that struggle to model complex three-dimensional environments, SUIP excels by extracting high-dimensional features, demonstrating strong generalization, and effectively handling non-linear problems. The SUIP algorithm exhibits robust performance in tests using indoor UWB localization datasets.

The remainder of this paper is organized as follows. The system model and the complete algorithmic flow of SUIP are presented in Sect. 2. Section 3 describes the simulations of the proposed algorithm, comparing it with a traditional method to verify its efficiency. Finally, the conclusions of the paper are provided in Sect. 4.

2 SUIP Algorithm

2.1 System Model

In the proposed SUIP algorithm, UWB node localization problem is transformed into a multi-classfication problem. SUIP is based on the RBF kernel SVM, which transforms the known position of the mobile tag to be measured into the coordinates of the grid vertices in a closed cube space, and constitutes a training. The classification model is trained by an improved multi-classification SVM recognition scheme, and the sensor data of the to-be-tested tag with unknown location is used as a test set to predict the class of its coordinates, and the grid vertex coordinates are obtained to locate the to-be-tested mobile tag.

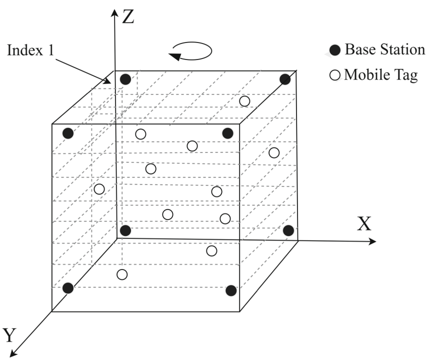


Fig. 1. UWB indoor positioning scene

As shown in Fig. 1, the indoor positioning scene is designed in a three-dimensional cubic space $[0, L] * [0, L] * [0, L]$ with side length L. Black nodes represent the base stations and white nodes represent the mobile tag coordinate positions. The three-dimensional cube is divided into identical small cubes with side length σ, and each small cube represents a category. At the same time, we map the coordinates into indexes in clockwise order from top to bottom, and construct pairs of the position coordinates of the white nodes with their indexes for the subsequent algorithms.

Assuming that there are M base station nodes and N sampling nodes, whose coordinates are (x_i, y_i) and (x_j, y_j) respectively. The Time Difference of Arrival (TDOA) measurement between the sampling node j to the base station node i and the sampling node j to the base station node 1 is r_{ji1}. The set of sampling nodes is:

$$D = \{(R_{j1}, v_j) | j = 1, ..., N\} \tag{1}$$

where $R_{j1} = [r_{j11}, ..., r_{jM1}] \in R^N$ is the input data and $v_j = \hat{x_j}$ or $v_j = \hat{y_j}$ is the output data. Least squares support vector machine(LS-SVM) localization defines the following optimisation criterion:

$$minJ(w, e) = \frac{1}{2}w^T w + \frac{1}{2}\gamma \sum_{j=1}^{N} e_j^2 \tag{2}$$

Obey the constraints:

$$v_j = w^T \varphi(R_j) + b + e_j \tag{3}$$

where w is the vector of weights, γ is the regularisation adjustment coefficient, e_j is the error variable, b is the deviation, and $\varphi(R_j)$ is the nonlinear mapping function. Through Eq. (2) and Eq. (3), the Lagrangian function can be obtained:

$$L(w, b, e, \lambda) = \frac{1}{2}w^T w + \frac{1}{2}\gamma \sum_{j=1}^{N} e_j^2 - \sum_{j=1}^{N} \lambda_j \{w^T \varphi(R_i) + b + e_j - v_j\} \tag{4}$$

where λ_j is the Lagrange multiplier. By the optimality conditions, it is obtained:

$$\begin{cases} \frac{\partial L}{\partial w} = 0 \to w = \sum_{j=1}^{N} \lambda_j \varphi(R_j) \\ \frac{\partial L}{\partial b} = 0 \to \sum_{j=1}^{N} \lambda_j = 0 \\ \frac{\partial L}{\partial e_j} = 0 \to \lambda_j = \gamma e_j \\ \frac{\partial L}{\partial \lambda_j} = 0 \to w^T \varphi(R_j) + b + e_j - v_j = 0 \end{cases} \tag{5}$$

The matrix equation can be obtained from Eq. (5):

$$\begin{bmatrix} 0 & 1_M^T \\ 1_M & \Omega + \frac{1}{\gamma}I \end{bmatrix} \begin{bmatrix} b \\ \lambda \end{bmatrix} = \begin{bmatrix} 0 \\ v \end{bmatrix} \tag{6}$$

In this case, $v = [v_1, ..., v_N]^T$, $\Omega_{kl} = \varphi(R_k)^T \varphi(R_l)$, $\lambda = [\lambda_1, ..., \lambda_N]$. By Mercer's condition [12], the kernel function $K(\cdot)$ is related to the nonlinear mapping function $\varphi(\cdot)$ in the following way:

$$K(R_k, R_l) = \varphi(R_k)^T \varphi(R_l) \tag{7}$$

Assume that $(\hat{x}_j, \hat{y}_j)$ is the estimated coordinates of the mobile tag j, (x_j, y_j) is the true coordinates of the mobile tag j, r_{ji1} is the TDOA measurement between the mobile tag j with respect to the anchor node i and the mobile tag j with respect to the anchor node 1, and $R_{j1} = [r_{j11}, ..., r_{jM1}]$ is the distance vector. Therefore, the initial positioning of the mobile tag is:

$$v(R_j) = \sum_{i=1}^{N} \lambda_i K(R_{j1}, R_{l1}) + b \tag{8}$$

where parameters λ_i and b are obtained in the training phase. The output category judgement value $v(R_j)$ is obtained from the best λ_i and b in the localization phase. For the $K(\cdot)$, there are various forms of kernel functions, such as linear kernel, polynomial kernel, RBF kernel, Sigmoid kernel and so on.

2.2 Algorithmic Flow of SUIP

Algorithm 1. SUIP algorithm

Output: positioning result p_i

Input: the TDOA values $R_{i1}, i = 1, 2, ..., N$

Initialize width of small cube σ, length of moving area D, number of base stations N, penalty factor C, kernel function parameter γ, etc.

1: **for** each $p_i \in training\_set$ **do**
2: $index = f(p_i)$, according to Fig. 1
3: **end for**
4: The input TDOA values are constructed in pairs with the indexes of the true position mapping
5: **for** each $T = (R_{i1}, index) \in training\_set$ **do**
6: Set the kernel function, multiclassification model, penalty coefficients, kernel function coefficients γ, etc. for SVM
7: Input vector T into SVM classifier for training
8: Obtaining optimal parameters λ_i and b using cross-validation grid search, according to Eq. (8)
9: **end for**
10: **for** each *the TDOA values* $R_{i1} \in test\_set$ **do**
11: Use the SVM model to predict the output indexes
12: $p_i = f^{-1}(index)$, according to Fig. 1
13: **end for**
14: Positioning complete

The core idea of the SUIP algorithm is to transform coordinates into indexes, thereby converting the positioning problem into a multi-classification problem. This involves constructing TDOA-index pairs and utilizing an optimized SVM model for training. The trained SVM can then predict node positions based on the TDOA values. The flow of the proposed algorithm is outlined in Algorithm 1. The detailed positioning steps are as follows:

Step1: Preparation of the Training Set. Assuming M base stations, preprocess the TDOA values $R_{i1}, i = 1, 2, ..., M$ of the mobile tag for the first base station versus the mobile tag for the rest of the base stations. Meanwhile, the known mobile tag positions p_i, are collected and mapped to the coordinate indices index $= f(p_i)$ according to the scene devised in Fig. 1. The small squares are divided by $\sigma = 0.01m$ so that the accuracy of the localization can reach at most $0.01m$ level. The localization area is partitioned into small squares, each of which can then be mapped to a unique coordinate index. Therefore, the TDOA values and the coordinate indexes are used to form the training set.

$$T = \{(R_{i1}, index)|i = 1, 2, ..., M\} \tag{9}$$

Step2: Kernel Function Selection. For SVM, a suitable kernel function is crucial. The study currently uses the widely used Gaussian kernel function, also known as radial basis function(RBF) as the kernel function:

$$K(x_i, x_j) = \exp(-\frac{\|x_i - x_j\|^2}{2\sigma^2}) \tag{10}$$

The RBF function performs well in the case of linear indivisibility [13], which maps the samples to a high-dimensional space and is characterised by a wide convergence domain and a unique best approximation. For coordinate classification, the RBF function is a very good choice for its properties.

Step3: Training Phase. From Eq. (8), the coordinate category to which the TDOA value belongs can be judged, however, the positioning of mobile nodes is a multi-classification problem, for multi-classification SVM, it is necessary to design more than one classifier, at present, there are two strategies for solving multi-classification of SVM: *ovo* (one versus one) and *ovr* (one versus rest). The traditional 'one versus one' strategy requires one binary classifier to be trained for every two data, so that the number of classifiers needed to distinguish q categories is:

$$p = \frac{q(q-1)}{2} \tag{11}$$

However, locating mobile nodes requires a large amount of data to form the training set, which is computationally intensive and can take a long time to train, therefore, the current SUIP uses the *ovr* strategy. A decision tree hierarchy is currently used, where all the categories are first divided into one class with the rest of the classes, and then the rest of the classes are further divided into subclasses of one class with the rest of the classes, and so on until all the nodes comprise of only a single category, which is also a leaf of the decision tree. The multiclassification problem is decomposed into a series of binary classification problems, at which point the number of classifiers required to distinguish q categories is:

$$p = q \tag{12}$$

Not only reduces the amount of arithmetic, but also improves the training speed, the conversion process is shown in Fig. 2:

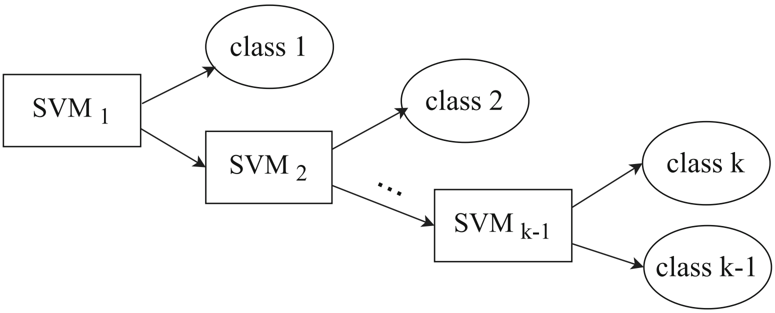


Fig. 2. Schematic diagram of the *ovr* multiclassification algorithm

Step4: Testing Phase. Based on the trained model parameters, it can be validated using a test set. The TDOA values $R_{i1}, i = 1, 2, ..., M$ of the mobile tag for the first base station versus the mobile tag for the rest of the base stations are preprocessed. at the same time, the mobile tag positions ${p_i}^*$ of the test set are collected to validate the algorithm's effect, and the TDOA values are composed into a test set:

$$T = \{(R_{i1})|i = 1, 2, ..., M\} \tag{13}$$

Then, the index of the node species is predicted using the model parameters. The coordinate indexes are reflected back to the cube centre of mass coordinates according to the model devised in Fig. 1, $p_i = f^{-1}(\text{index})$. Finally, the mobile tag positions ${p_i}^*$ is collected and compared with the predicted p_i to test the effect of the model.

3 Simulations and Experiments

Performance Analysis of SUIP in LOS Environment. This paper adopts the const1-trial1 sub-dataset of the open source UWB dataset from the International Journal of Robotics Research (IJRR) [14] for the validation of the algorithms in the LOS environment. The recording environment of the dataset is an empty room without stationary as well as moving occlusions, which simulates a more ideal line-of-sight propagation environment. Since the higher the number of predicted localization points in the calculated result metrics, the greater the reliability of the metrics for assessing the localization performance. Therefore, for the data set with limited amount of data, this paper adopts the partition ratio of p=1:1 to obtain the training set and test set to further evaluate the performance of SUIP algorithm.

In order to improve the effectiveness of SUIP, the simulation part firstly carries out simulation experiments on the parameter selection. In this paper, we first explore the effect of different SVM model penalty coefficients C on the localization error with the iteration of flight points in LOS environment. Through theoretical analysis, the larger the penalty coefficient C is, the larger the penalty for misclassification is, and the results of localization on the dataset in Fig. 3 fit well with this theory. In Fig. 3, the localization results become more accurate and stable as C increases.

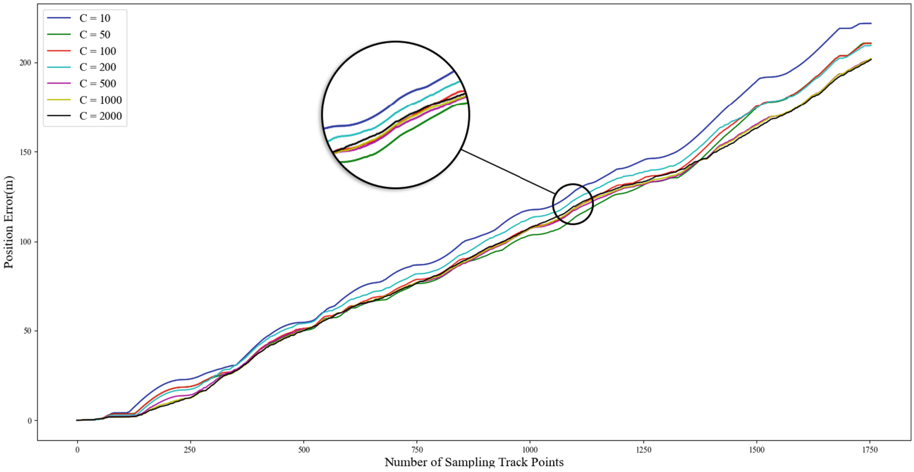


Fig. 3. Effect of different penalty coefficients C on localization error in LOS environment

Subsequently, this paper explores the influence of different SVM model RBF kernel function parameters γ on the position error with the iteration of flight points in LOS environment. Through theoretical analysis, the kernel function parameter γ determines the width of the Gaussian kernel, reflecting the influence of mapping a single sample to a higher-dimensional space, while the experimental trend in Fig. 4 shows that as the kernel function parameter γ decreases, the positional accuracy increases.

Through ten-fold cross-validation of the training set [15], this study obtained the parameter combination that performs best in the LOS environment. This parameter combination is $[C, \gamma] = [490, 0.5]$.

In this paper, SUIP is used to localize the coordinates using the above combination of parameters in this sub-dataset of the open source UWB dataset. Figure 5 are the three-dimension coordinate scatter plots of the predicted trajectories. It is obvious that the positioning trajectory of SUIP is more smoother and more closely aligns with the actual trajectory compared to the Chan algorithm [16].

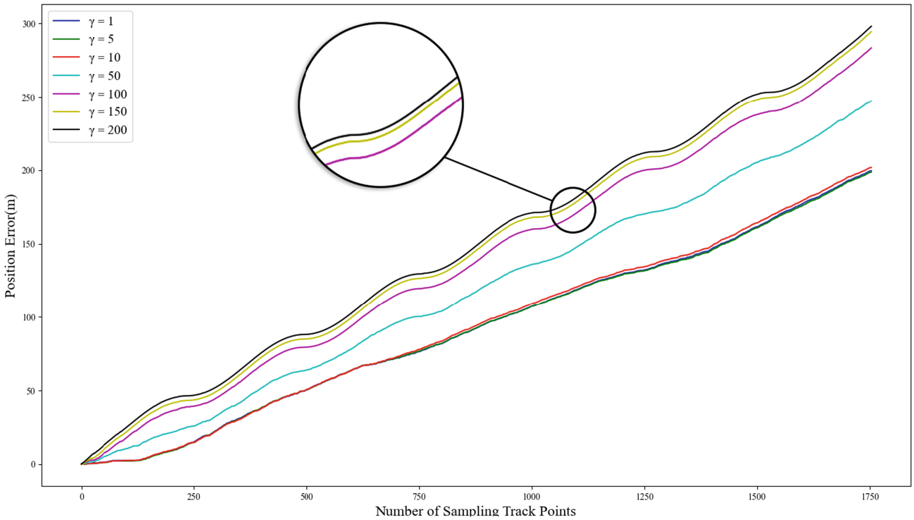


Fig. 4. Effect of different kernel function parameters γ on localization error in LOS environment

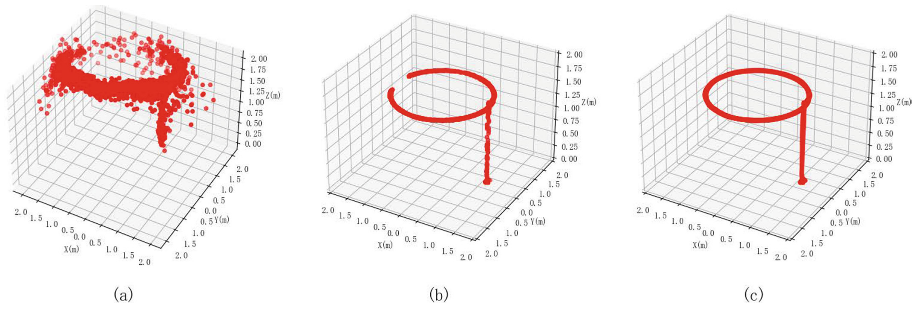


Fig. 5. (a) is the Chan algorithm positioning trajectory in LOS environment, (b) is the SUIP algorithm positioning trajectory in LOS environment, and (c) is the real trajectory of the flight in LOS environment

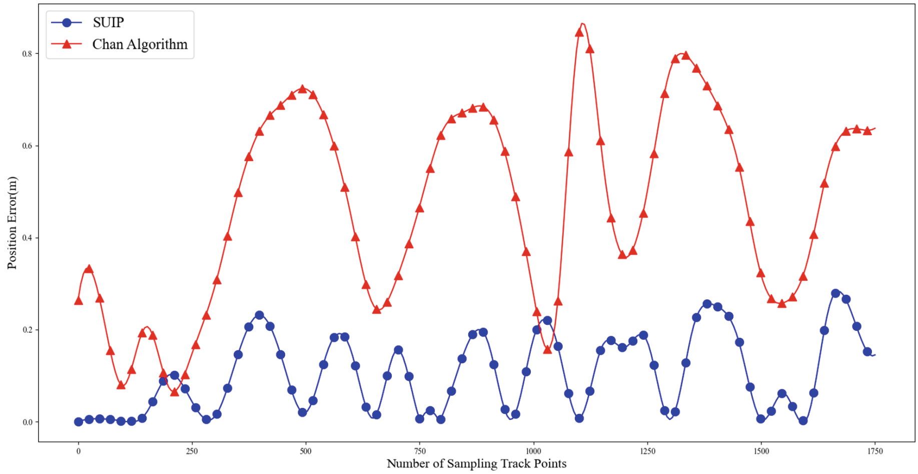


Fig. 6. Comparison of localization errors between SUIP and Chan algorithms in LOS environment

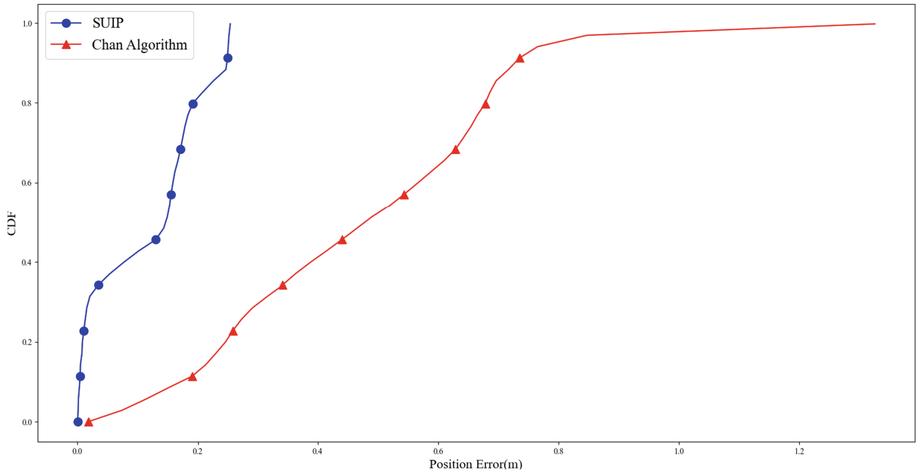
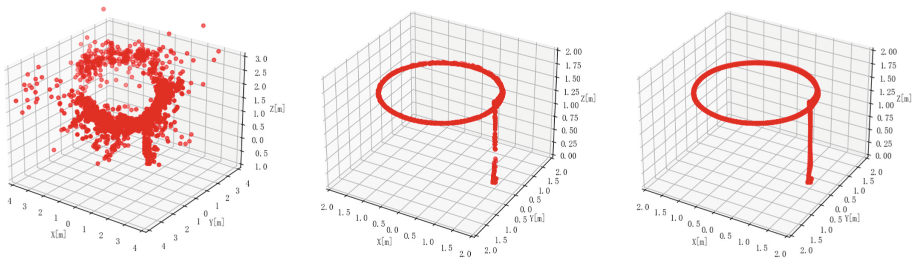


Fig. 7. CDF comparison of SUIP and Chan algorithms in LOS environment

In LOS environment, Fig. 6 and Fig. 7 show the positioning errors of the SUIP and Chan algorithms, and the cumulative error distribution function for both algorithms, respectively. It can be clearly seen that the positioning error of SUIP algorithm is basically in the interval [0.0 m-0.3 m], and its maximal error is reduced by about 65% compared with Chan algorithm. By calculating the RMSE of the two algorithms over the entire flight segment, it can be concluded that the Chan algorithm has an RMSE of 15.37 cm, while the SUIP algorithm achieves an RMSE of 9.64 cm. This indicates a 37.27% improvement in localization performance for SUIP in LOS scenarios. Additionally, the CDF distribution curve shows that SUIP has a higher probability of being distributed within smaller positional error intervals, demonstrating superior performance.

Performance Analysis of SUIP in NLOS Environment. In this paper, the const4-trial6 sub-dataset of the publicly available dataset is taken for the validation of NLOS. The recording environment of the dataset is a room with two stationary wooden block obstacles and a metal block obstacle moving back and forth in the left-right direction, which is placed to simulate a more desirable non-line-of-sight propagation environment. Same as the LOS environment, this paper adopts a p=1:1 segmentation ratio to obtain the training and test sets for further evaluation of the performance of the SUIP algorithm.

Through ten-fold cross-validation on the training set, this study obtained the best performing parameter combination in the NLOS environment. This parameter combination is $[C, \gamma] = [503, 1.2]$. The above parameter combination is utilised to locate the coordinates using SUIP. Figure 8 also clearly illustrates that the positioning trajectory of the SUIP algorithm is smoother and more closely aligns with the actual trajectory compared to the Chan algorithm.



(a) (b) (c)

Fig. 8. (a) is the Chan algorithm positioning trajectory in the NLOS environment, (b) is the SUIP algorithm positioning trajectory in the NLOS environment, and (c) is the flight true trajectory in the NLOS environment

In the NLOS environment, Figs. 9 and 10 show the positioning errors of the SUIP and Chan algorithms, as well as the cumulative error distribution function for both algorithms, respectively. It is evident that the SUIP algorithm's positioning error predominantly falls within the interval [0.00 m-0.25 m], which is comparable to its performance in the LOS environment. This significantly reduces the positioning error in the NLOS environment, with its maximum error reduced by approximately 87.5% compared to the Chan algorithm. By calculating the RMSE over the entire flight segment, it can be concluded that the Chan algorithm has an RMSE of 27.51 cm, while the SUIP algorithm achieves an RMSE of 11.64 cm, marking a 57.68% improvement in localization performance in the NLOS scenario. The CDF error analysis also shows that the SUIP algorithm has a higher probability of falling within smaller positional error intervals.

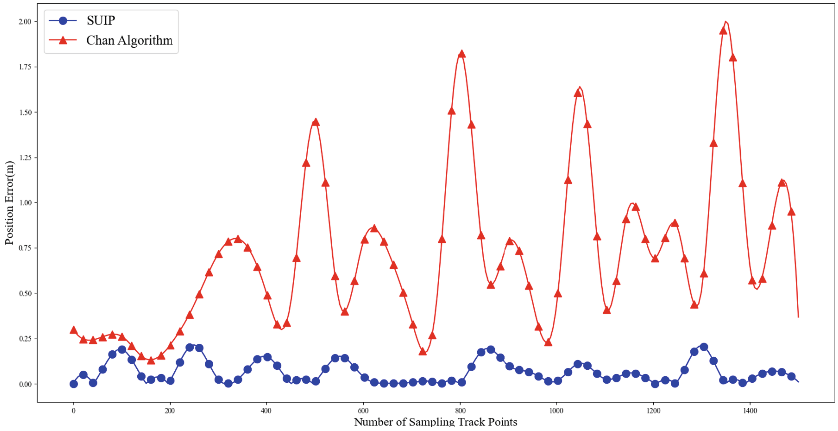


Fig. 9. Comparison of localization errors between SUIP and Chan algorithms in LOS environment

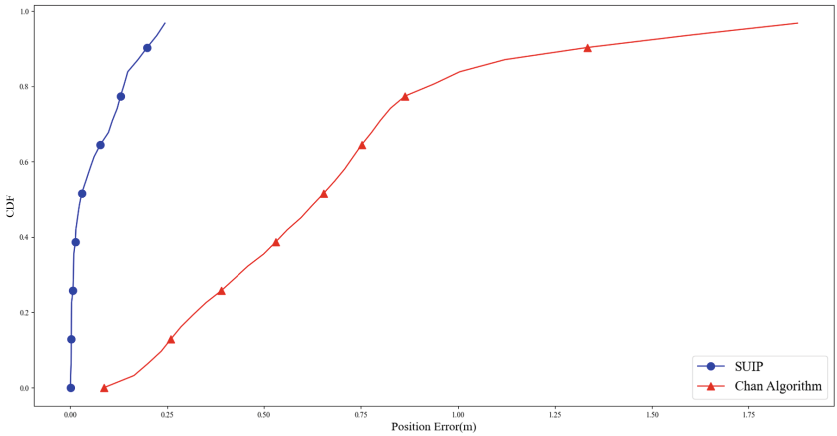


Fig. 10. CDF comparison of SUIP and Chan algorithms in NLOS environment

Overall, the results from the dataset indicate that the SUIP algorithm significantly enhances UWB indoor localization performance in both LOS and NLOS scenarios. The algorithm demonstrates a consistent ability to maintain lower positioning errors across varying environmental conditions. And the performance improvement is attributed to SUIP's ability to handle non-linearities and extract high-dimensional features, which are crucial in complex indoor settings. Consequently, SUIP provides a reliable and efficient solution for UWB indoor localization.

4 Conclusions

In this paper, a SVM-based UWB indoor positioning algorithm (SUIP) is innovatively proposed by combining SVM with indoor localization of UWB, and the superiority of SUIP algorithm is verified using the UWB dataset on IJRR. In addition, in order to improve the effectiveness of algorithm, this paper firstly investigates the influence of SVM model parameters on the positioning accuracy, and then selects the best parameters to train the test set. The experimental results show that SUIP has good localization accuracy and high stability even in NLOS environment. Compared to the classical Chan algorithm, it improves the localization accuracy by 37.27% in the LOS environment and 57.68% in the NLOS environment. The method discussed in this paper provides a new and feasible research idea for further using machine learning tools to solve the UWB indoor positioning problem and maintain the positioning reliability of wireless sensor networks.

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