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Original scientific paper

UWB-INS Fusion Positioning Based on a Two-Stage Optimization Algorithm

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Abstract: Ultra-wideband (UWB) is a carrier-less communication technology that transmits data using narrow pulses of non-sine waves on the nanosecond scale. The UWB positioning system uses the multi-lateral positioning algorithm to accurately locate the target, and the positioning accuracy is seriously affected by the non-line-of-sight (NLOS) error. The existing non-line-of-sight error compensation methods lack multidimensional consideration. To combine the advantages of various methods, a two-stage UWB-INS fusion localization algorithm is proposed. In the first stage, an NLOS signal filter is designed based on support vector machines (SVM). In the second stage, the results of UWB and Inertial Navigation System (INS) are fused based on Kalman filter algorithm. The two-stage fusion localization algorithm achieves a great improvement on positioning system, it can improve the localization accuracy by 79.8% in the NLOS environment and by 36% in the (line-of-sight) LOS environment.

Keywords: inertial navigation system; Kalman filter; machine learning; optimal estimation; UWB

1 INTRODUCTION

With the development of positioning technology, demanding for high precision positioning of moving objects is increasing. In outdoor conditions, common positioning techniques include GNSS, GPS, etc. These methods are difficult to achieve the same effect in indoor conditions because there are many obstacles in the indoor environment, which can greatly weaken the electromagnetic signal from the satellite. In this context, UWB positioning technology was born, it has strong anti-interference ability, high transmission rate, high bandwidth, large system capacity, and strong penetration ability, achieving a high-level positioning effect in indoor conditions. The target can be positioned by the cooperation of multiple base stations, and the positioning accuracy is mainly affected by the NLOS error.

Fig. 1 shows the cause of the NLOS error. When there is an obstacle between the base station and the tag, the signal cannot reach directly, then the signal bounces and scatters. In the NLOS case, the propagation time and direction of the signal received by the base station are not the real value, which will cause positioning errors.

Figure 1 LOS (left) and NLOS (right)

Researchers have done a lot of research on error elimination of UWB positioning system. These methods can be summarized into the following two categories:

(a) Identifying the NLOS signals first, then eliminating the error of the identified NLOS signal in the subsequent process. For example: [1] uses support vector machine (SVM) to distinguish LOS and NLOS signals and extract the received power, maximum power, rise time, kurtosis and delay distributions as training features. Similarly [2, 3] train SVM by using the above channel features and combining the fitness between the slope distribution and the measured data. [4] introduces an NLOS recognition algorithm by executing correlation vector machine (RVM) with similar training features. [5] propose a delayed angular domain method to identify LOS/NLOS, which takes into account the diffusion of multiplex networks in the angular domain and the spatially selective fading of signals. In [6], characteristic parameters such as Riciank factor are considered to distinguish LOS signals from NLOS signals. [7] uses Denoising Channel State Information (CSI) to train ANN. In [8], NLOS and LOS signals are distinguished based on signal propagation path loss model or channel impulse response (CIR).

The core idea of class (a) method is to identify all NLOS signals first, filter out all these NLOS signals in the subsequent positioning process, and only use LOS signals to locate the target. It has two shortcomings:

1) In the environment without NLOS signal, positioning accuracy cannot be improved.

2) After NLOS signals are filtered out, there may not be enough LOS signals to complete the localization solution. For example, the Time of Arrival (TOA) method requires at least three base stations. If there are no more than three UWB signals after all NLOS signals are filtered, this method cannot be used to complete the location.

(b) Integrating the UWB system with other positioning technologies. Picking some localization techniques that are not sensitive to NLOS errors to fuse with UWB technology. The fusion system is robust to NLOS errors and achieves high accuracy. INS is an autonomous navigation system, which can provide the position, speed and attitude of the target without relying on any external information. INS system uses gyroscope and accelerometer to locate the object, so it is not affected by NLOS error. The core device of INS is inertial measurement unit (IMU), which has the advantages of small size, light weight, low cost, and high reliability. The error of INS system accumulates over time, and the fusion with UWB can eliminate the accumulated error. Literature [9, 10] has studied the positioning performance of different combination positioning systems. Among them, the combination positioning of UWB and IMU has become a better choice for combination positioning due to its high positioning accuracy and complementary advantages. For example, [11] uses Sage-Husa fuzzy adaptive filtering for INS/UWB combination positioning, and uses fading coefficient sliding window estimation method to detect and correct outliers, improving the positioning performance of indoor mobile robots.

Proposes a tight combination positioning method based on extended finite impulse response (EFIR), which extracts the square value of the distance between the label and a single base station measured by UWB and IMU respectively, then inputs the difference of the two values into the subfilter as an observation vector [12]. Literature [13] proposed an improved extended Kalman filter, in which fault detection and isolation functions were added to correct the measurement data of UWB, and estimated the systematic errors of IMU.

The advantage of class (b) method is that it can still improve the positioning accuracy even in the environment without NLOS signal. However, when working in NLOS environment, the positioning stability and accuracy of class (b) method are inferior to those of class (a) method.

Inspired by the ideas of the two methods (a) and (b), this paper proposes a two-stage UWB-INS fusion localization method. In the first stage, an SVM-based NLOS signal filter is designed, and six-dimensional data is used as the feature vector of each training sample. In the second stage, UWB and INS positioning results are fused based on Kalman filter, and the insensitivity of INS to NLOS error is used to eliminate the influence of NLOS error. The two-stage algorithm combines the advantages of the two kinds of methods well. No matter working in NLOS environment or LOS environment, the algorithm can steadily improve the positioning accuracy. If there are no more than 3 UWB anchors working in the LOS environment, the filter in the first stage will temporarily stop working. It can ensure that there are enough UWB signals to complete the subsequent locating process.

2 METHODOLOGY

2.1 Overall Process

The overall process of our method is shown in Fig. 2. The input of stage 1 is the signals received by all UWB base stations, which may contain NLOS signals. After filtering by the SVM algorithm, only LOS signals are transmitted to Stage 2. In the second stage, the UWB system picks all LOS signals for positioning. Kalman filter fuses UWB and INS to obtain the optimal position estimation about the target.

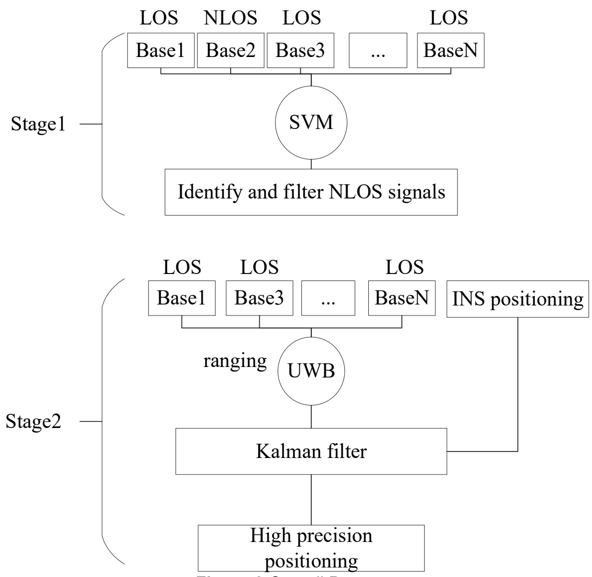


Figure 2 Overall Process

The methods among Fig. 2 will be described in detail in subsequent sections. The details of stage 1 are described in section 2.2, and stage 2 is in section 2.3. The experiment is in section 3.

2.2 UWB NLOS Signal Filter Based on SVM

We introduce the SVM classifier in stage 1 from three perspectives:

1) The input

The eigenvector of each UWB signal in this paper is defined as:

$$N=\{\text{firstPathAmp1, firstPathAmp2, firstPathAmp3, maxNoise, maxGrowthCIR, stdNoise}\} \tag{1}$$

The detailed interpretation of each element is:

- **firstPathAmp1**: first path amplitude-part1;
- **firstPathAmp2**: first path amplitude-part2;
- **firstPathAmp3**: first path amplitude-part3;
- **maxNoise**: maximum value of noise;
- **maxGrowthCIR**: The growth factor of the accumulator related to the received signal power;
- **stdNoise**: standard deviation of noise;

The above propagation channel characteristics can be collected in DW1000. We collected a total of 10000 samples from different sites, including two offices, a small apartment, a kitchen with a living room, a bedroom, a small workshop and a boiler room. The LOS/NLOS signals in the dataset were symmetrically distributed, with each class accounting for 50% of the samples. In addition, in order to avoid possible bias caused by different collection sites, this dataset was randomized.

2) The task

The SVM classifier maps the feature vectors of UWB signals into some points in the space. The task of SVM classifier is to draw a line to "best" distinguish the two types of UWB signals, so that if there are new samples in the future, this line can also make a good classification. SVM is suitable for small and medium-sized data samples, nonlinear, high dimensional classification problems. Taking two-dimensional features as an example, SVM will search for the partition hyperplane that can distinguish two categories and maximize the margin.

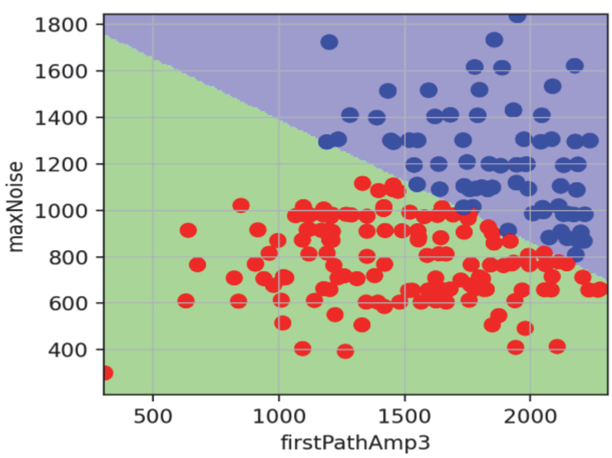


Figure 3 SVM classifier working in case of using two-dimensional features

As shown in Fig. 3, the hyperplane used to divide samples is a straight line when projected into a two-dimensional space. The NLOS signals (blue dot) and the LOS signals (red dot) are well distinguished by the line. In this paper, the input of the SVM classifier are six-dimensional features, these six features can be paired to form 15 two-dimensional planes.

3) The training process and result

The SVM algorithm constructed in this paper is built by python's sklearn library, the penalty coefficient is set to 1, and the kernel function uses "rbf". When dividing data set, the data set is divided into the training set, test set, and validation set according to the ratio of 7:2:1. After training on the training set for 5 epochs, the accuracy is finally verified on the validation set. The results show that the six-dimensional features of the UWB signal and SVM classifier proposed in this paper are practical and effective.

This paper introduces a UWB signal dataset, each sample contains a six-dimensional feature. These six-dimensional features can be projected into 15 two-dimensional planes. In order to better show the effect of the trained SVM classifier, we select the following six two-dimensions to show the classification result: (firstPathAmp1, firstPathAmp2), (firstPathAmp2, firstPathAmp3), (firstPathAmp3, maxNoise), (maxnoise, maxGrowthCIR), (maxGrowthCIR stdnoise), (stdnoise, firstPathAmp1), as shown in Fig. 4.

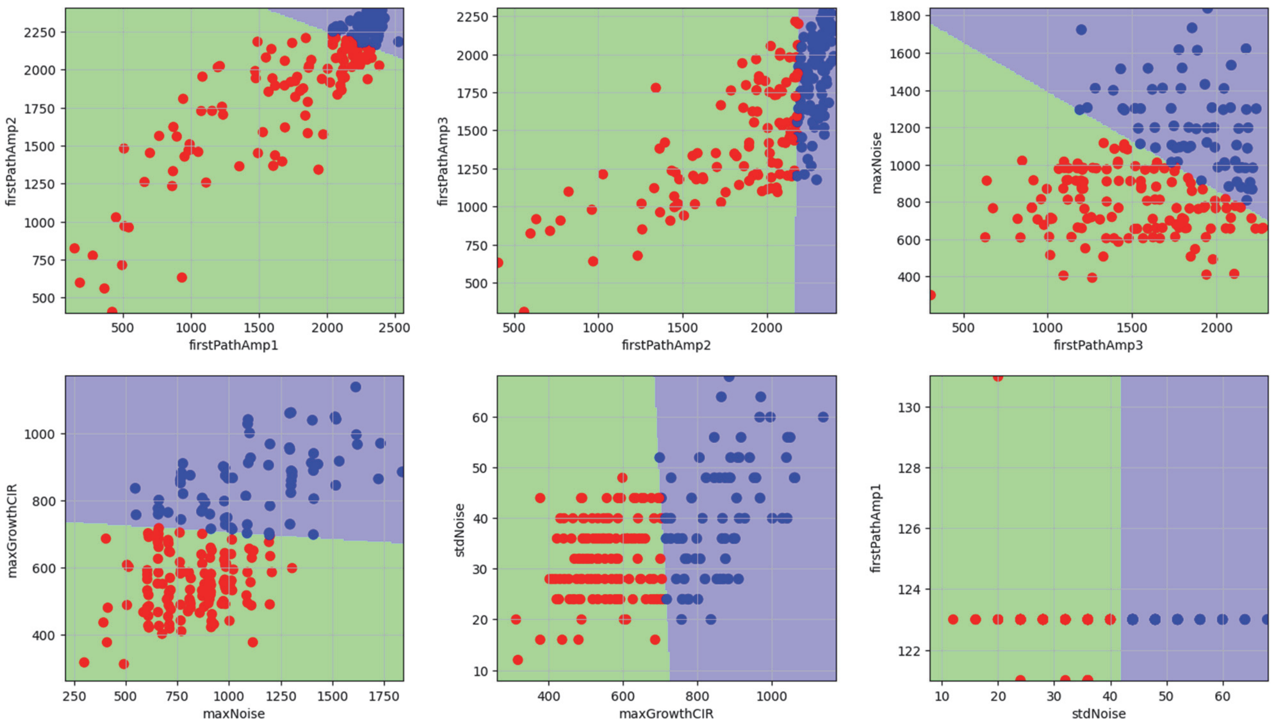


Figure 4 The effect of NLOS signal filter

In Fig. 4, the red dot is LOS signal, the blue dot is NLOS signal, and the coordinate axis is the factors of the feature vector.

The visualization results show that the projection results of hyperplane obtained by training SVM algorithm on any two dimensions can well divide NLOS signal and LOS signal. In addition, the figure shows that the values of firstPathAmp2, maxNoise and maxGrowthCIR of NLOS signal are significantly higher than those of LOS signal.

The accuracy of the final model on the validation set is 95.4%, which proves that the UWB NLOS signal filter can effectively classify the NLOS signals and LOS signals.

2.3 UWB-INS Fusion Positioning

In the first stage, an NLOS signal filter based on support vector machine is proposed. The recognition rate of NLOS signals reached 95.4%, but some NLOS signals still may not be filtered. In order to eliminate this part of NLOS error, a Kalman filter is used in stage two to fuse INS positioning information which is not sensitive to NLOS error.

Kalman filter is an optimal linear filter based on time sequence. It can predict the real state of the system at the next moment according to the state of the system at the last moment and the presuming state of the system. The Kalman filter algorithm can be simply composed of the following five equations:

(1) State prediction equation: This equation converts the state at the last moment into the state at the current moment according to the state transition matrix F.

$$x_t^- = Fx_{t-1} + Bu_{t-1} + Cv_{t-1} \tag{1}$$

(2) Prediction covariance matrix:

$$P_t = FP_{t-1}F_T + Q \tag{2}$$

(3) Calculate the gain of Kalman filter:

$$K_t = \frac{1}{P_t^- H^T (HP_t^- H^T + R)} \tag{3}$$

(4) Output target state:

$$x_t = x_t^- + K_t(z - Hx_t^-) \tag{4}$$

where, z is the measurement vector of the sensor. In this system, z is the coordinate value obtained by geometric calculation through UWB technology.

(5) Optimize the covariance matrix:

$$P_t = (I - K_t H)p_t^- \tag{5}$$

Among the Eqs. (2) to (6), x_t^- is the predicted state vector, F is the transfer matrix, x_{t-1} is the optimal vector output by the Kalman filter at the last moment, u_{t-1} is the output of the UWB sensor at the last moment, v_{t-1} is the output of the INS sensor at the last moment, B and C are the input matrixes, p_t^- is the current moment prediction covariance matrix, Q is the prediction of process noise covariance matrix, K_t is the Kalman gain, x_t is the optimal target state vector at the current time, and p_t is the optimal noise matrix at the current time

The calculation process can be divided into two parts, the filtering calculation loop and the gain calculation loop, the two parts depend on each other. In a computational cycle, Kalman filter has two information updates: time update and measurement update. In the above five formulas, each step of the state is to obtain the prior estimate of the current calculation period based on the previous calculation period. The system noise covariance matrix Q and the measurement noise covariance matrix p_t^- affect the Kalman gain K_t. The Kalman gain K_t determines whether the state estimate is closer to the prior estimate or the measured value in the state estimation equation.

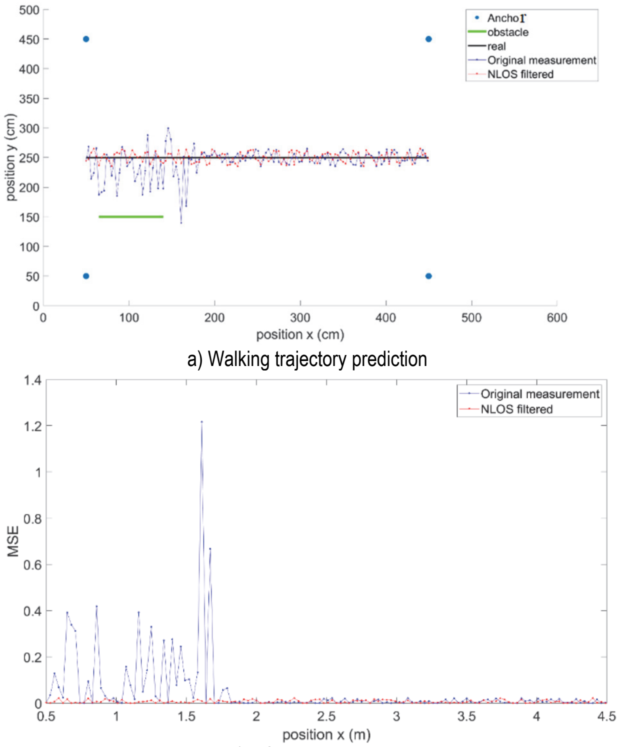
3 EXPERIMENT

In order to verify the effectiveness of the proposed two-stage model, four base stations are built in the indoor scenario, one of which is affected by NLOS error. This paper conducts comparative experiments from three parts: 3.1 Stage 1 effect analysis 3.2 Stage 2 effect analysis 3.3 Overall model promotion analysis.

3.1 Effect of Stage 1 Algorithm

The specific process of the experiment is as follows: the experimenter arranges four base stations in an indoor space, and the coordinates of the four base stations (unit cm) are (50, 50), (450, 50), (50, 450), (450, 450). An obstacle was placed at a certain position in the area to make NLOS environment. The experimenter wore a tag, marched along a line marked in advance, and observed the position of the target point output by the positioning system. Two groups of experiments were conducted, only one group using the UWB NLOS signal filter proposed in stage 1. Comparing the experiment result.

MSE (root mean square error) is used to evaluate the quality of localization results.



a) Walking trajectory prediction

b) MSE comparision

Figure 5 Effect of stage 1 algorithm

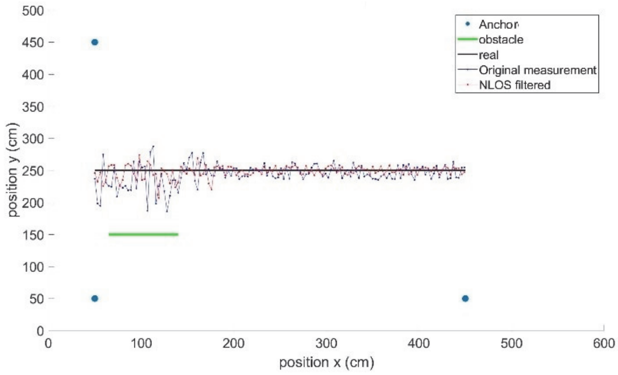
Fig. 5b is the MSE solution result of Fig. 5a. The blue line in Fig. 5a shows: when there is no NLOS error, the original positioning system performs well. However, when NLOS error occurs in one of the base stations, the positioning effect is greatly shifted and the MSE waveform produces a high peak. This indicates that the original UWB positioning system is seriously affected by NLOS error. After introducing the NLOS filter in stage I, the positioning result is shown by red line. It can be seen that the positioning system is no longer seriously affected by NLOS signals, which means the SVM-based NLOS signal filter greatly improves the anti-NLOS error ability of the UWB positioning system.

However, the algorithm in stage 1 still has shortcomings: 1) When there is no NLOS environment, the algorithm has no improvement on the localization result. 2) The filter in stage I still has 4.6% recognition error for NLOS signal. In order to improve these two shortcomings, we propose the algorithm of stage two.

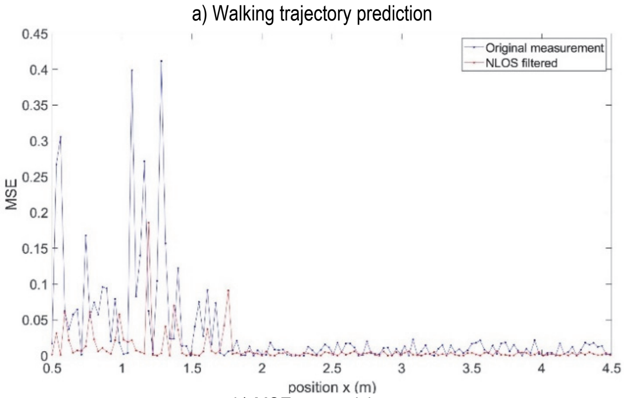
3.2 Effect of Stage 2 Algorithm

When testing the effect of the algorithm in stage 2, the overall process of the experiment is similar to the test of stage 1, and the result is shown in Fig. 6. The coordinates of the four UWB anchors are still (50, 50), (450, 50), (50, 450), (450, 450), and the obstacle is in the same position. In this section, we only use the stage 2 algorithm to improve the positioning effect.

From Fig. 6, it can be seen that when the experimenter is in the interval between 200 and 450 on the horizontal coordinate, there is no NLOS signal, and the algorithm in stage 2 can still improve the positioning accuracy to a certain extent. When the experimenter is walking in the interval between 50 and 200 of the abscissa, there is NLOS environment. In this case, for there is no NLOS signal filter, the positioning result of UWB will be shifted greatly, which will affect the positioning accuracy of the fusion positioning algorithm. Although the Kalman filter algorithm can also reduce the influence of NLOS error, it cannot achieve the same effect as the stage 1 algorithm in NLOS environment.



a) Walking trajectory prediction



b) MSE comparision

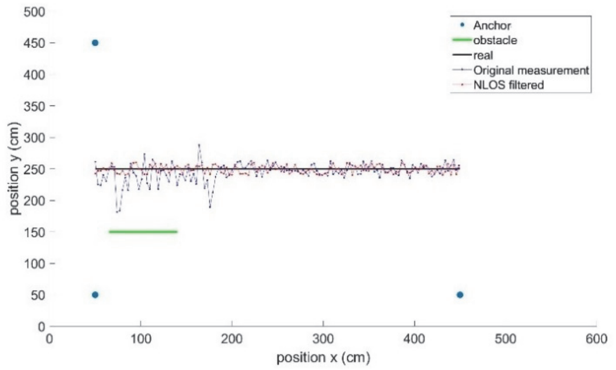
Figure 6 Effect of stage 2 algorithm

3.3 Effect of the Whole Two-Stage Algorithm

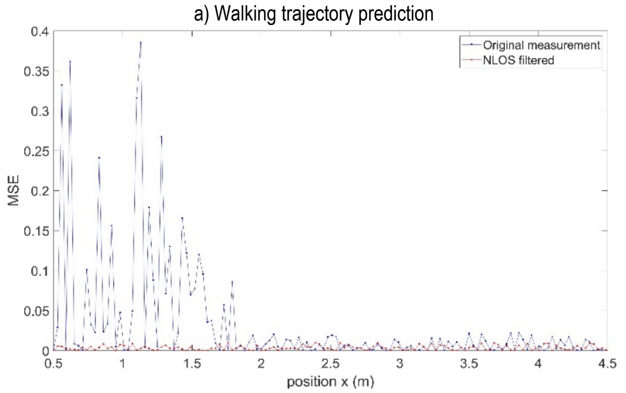
By fusing stage 1 and stage 2, the two-stage algorithm in Fig. 2 is finished. The experimental results are as shown in Fig. 7.

Fig. 7 shows that the two-stage algorithm can perfectly make up for the deficiency of the single-stage algorithm. As can be seen from Fig. 7b, when the experimenter is in the range of 2 ~ 4.5 m, no NLOS environment, the two-stage algorithm can improve the positioning effect which is not possible when using stage 1 alone. When the experimenter is in the range of 0.5 ~ 2 m, with NLOS environment, the performance of the two-stage algorithm is much greater than that of only using the stage 2 algorithm.

In order to avoid the chance of experiment, several experiments were conducted and the results were averaged. The results of the experiment are shown in Tab. 1. When working in the NLOS environment, the two stage algorithms work together to greatly improve the accuracy of positioning. When working in LOS environment, the first stage algorithm loses its function but the second stage algorithm still works. From the table we can be seen that the algorithm can improve the localization accuracy by 79.8% in the NLOS environment and by 36% in the LOS environment.



a) Walking trajectory prediction



b) MSEcomparision

Figure 7 Effect of the whole two-stage algorithm

Table 1 Experiment summary

Method	MSE / cm^2	Accuracy / cm	Improving
a) NLOS environment			
Original	3956	63.2	
Only stage 1 (SVM classifier)	275	16.6	73.7%
Only stage 2 (UWB-INS fusion)	380	19.5	69.2%
Stage1 + Stage2	**164**	**12.8**	**79.8%**
b) LOS environment			
Original	240	15.5	
Only stage 1 (SVM classifier)	240	15.5	0
Only stage 2 (UWB-INS fusion)	98	9.9	36%
Stage1 + Stage2	**98**	**9.9**	**36%**

4 CONCLUSION

UWB is a carrier-less communication technology that transmits data using narrow pulses of non-sine waves on the nanosecond scale. The UWB positioning system uses the multi-lateral positioning algorithm to accurately locate the target, and the positioning accuracy is seriously affected by the non-line-of-sight (NLOS) error. The existing non-line-of-sight error compensation methods lack multidimensional consideration. To combine the advantages of various methods, a two-stage UWB-INS fusion localization algorithm is proposed. In the first stage, a SVM-based UWB NLOS signal filter is proposed, which can filter the NLOS signal with accuracy of 95.6%. In the second stage, we constructed a fusion algorithm using Kalman filter, fusing UWB and INS localization results. Experimental results show that the algorithm can improve the localization accuracy by 79.8% in the NLOS environment and by 36% in the LOS environment.

Experimental results show that the proposed method can improve the localization accuracy in both NLOS and LOS environments and achieves a good effect. It also provides a new idea of two-stage algorithm to improve the positioning accuracy of UWB.

However, the two-stage algorithm still has some future improving direction:

(a) In the stage 1 SVM classifier, instead of discarding all NLOS signals, it might be possible to deploy compensation for them.

(b) There may be a more effective algorithm than Kalman filtering in the stage 2 UWB-INS fusion method.

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