NLOS Mitigation for Low-cost IR-UWB RTLS

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Abstract—**This paper proposes a method for mitigation of non-line-of-sight (NLOS) situations in a real time location system (RTLS) using an impulse radio ultra wide band (IR-UWB). Based on our experiment, we found that there is a slight chance to meet the line-of-sight (LOS) at all the readers of RTLS in a realistic scenario. In the NLOS environment, there are two problems of packet-miss error and multi-path error as well. To compensate for the packet-miss error, this paper presents a new algorithm (PPTi), which uses previous time information before the time difference of arrival (TDOA) positioning technique calculates the coordinate of the target. We also employed the Kalman Filter (KF) to mitigate multi-path error. Our proposed algorithm provides a 5.9% increased positioning success rate and a 25.6% decreased root mean square error (RMSE) in an NLOS environment.**

RTLS, IR-UWB, TDOA, Positioning, Tracking, NLOS

I. INTRODUCTION

In the past several years, there has been increasing interest in real time location systems (RTLS). Most of the RTLS's use the radio frequency (RF) signals for locating and tracking resources in real time. The RTLS is an attractive technology for various applications, such as patient and staff visibility tracking solutions, army personnel tracking solutions, warehouse tracking solutions, and oil and gas personnel tracking solutions. In particular, the RTLS market in the Asia Pacific region is expected to industrialize continuously in the forecast period [1].

Most of the RTLS's estimate a packet's arrival time to calculate the position of a tag. Because we know that the electric pulse travels at the speed of light, this information can be easily translated into distance information. Although there are other categories of positioning algorithms, such as scene analysis and proximity, most research focuses on the time-based method. In this paper, we focus on the time difference of arrival (TDOA) [2] method, which estimates the difference of arrival time at readers. The TDOA method is the most promising method considered in most of the product and standards in impulse radio ultra wide band (IR-UWB) [3].

Line-of-sight between the tag and readers is essential in order to calculate the position of the tag. If there is a blocking object between the tag and the readers the estimation of packet arrival can be severely compromised. Most of the positioning algorithms assume that there is a line-of-sight path between tag and reader. This, however, may not be true in a realistic scenario.

The contribution of this paper can be two-fold.

1. We show that the NLOS can be very serious in a realistic environment. This is verified by experiment with our RTLS. As far as we know, few papers have been published on NLOS in a realistic scenario.
2. We propose a pre-processing algorithm, which uses previous data to mitigate errors caused by NLOS. We also tested some filtering algorithms to find out the best filtering algorithm in an NLOS environment. We found that our proposed algorithm and filtering method improve positioning results in a realistic IR-UWB RTLS scenario.

There are researches that consider NLOS in RTLS [4]–[8]. The position of a tag can be calculated using only readers with LOS condition [4]. This method, however, needs many readers to respond to the bad NLOS condition. There is another research that employs a Kalman filter (KF) [9]–[11] to correct errors [5]. However, these consider 2.4GHz RF RTLS and do not consider the realistic scenario with IR-UWB. Our study considers a real environment in an IR-UWB RTLS. Most of the papers regarding NLOS with UWB focus on pulse shape analysis [6]–[8]. In this paper, we focus on the higher layer approach in order to mitigate NLOS error. Furthermore, our implemented system is a small, low-cost, and low-complex system that uses 1-bit ADC. Our system meets the on-going RTLS standard of IEEE 802.15.4f [12] and ISO/IEC 24730-6 [13].

According to our experiment, there are two major sources for problems, which are packet-miss and multi-path error. Although these problems are also known in the literature [14], [15], we found that this problem is serious. To improve positioning accuracy, we suggest the PPTi (Pre-positioning with Previous Time Information) algorithm (which uses previous information) when readers do not receive the transmitted packet or the received data is considered to be erroneous.

A filtering algorithm is also necessary to complement positioning data with errors. We propose a suitable filter, especially for the NLOS condition, and compare various filters. Performance criterion in this paper is the amount of positioning success and the root mean square error (RMSE) in positioning results.

This paper is organized as follows. In Section II, we show the effect of NLOS in a realistic scenario. The implementation details of our positioning system are also described in Section II. Section III describes the proposed PPTi algorithm and KF, which can mitigate NLOS problems. The results for the proposed method are presented in Section IV. Finally, Section

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V concludes the paper and provides a possible future direction for research on wireless positioning systems for NLOS.

II. PROBLEM

In this section, we show how terrible NLOS is in a realistic scenario. Before we focus on the problem, we briefly introduce our positioning system.

Our implemented RTLS is based on Impulse Radio Ultra Wide Band (IR-UWB) technology. Ultra Wide Band radios can provide high-precision localization (30cm resolution) due to their large bandwidths [3]. Furthermore, UWB can coexist with other wireless devices due to its unlicensed operation and low-power transmissions, and its low-cost, low-power transceiver makes it a good candidate for RTLS RF technology. Our system is a threshold-based, non-coherent, on-off keying system. A 1GHz, 1-bit ADC estimates the arrival time of a packet within nanoseconds. There are four receivers at the corners of a positioning field. The receivers are synchronized with the special clock distributor and have a dedicated Ethernet line in order to send the estimated time of packet arrival to a backend server. Position estimation is performed at the server with the TDOA (time difference of arrival) technique. The Least Square method, which minimizes the squared sum of errors, is employed to calculate the position. Fig. 1 simply shows the deployment of tag, readers, and server. The details of the implemented positioning system can be found in [16], [17].

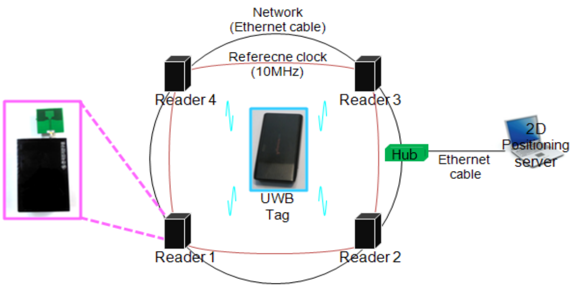


Figure 1. Network of our RTLS

Figure 2. Experience environment (9mx10m)

Experimental tests were conducted in a conference room, which are presented in Fig. 2. The size of the conference room is 9m x 10m. During these tests, a pedestrian, who was equipped with the UWB tag, walked around a round table (radius = 3.5m). The data updating frequency was 32Hz, the velocity of the tag was about 2m/s, and the path length was about 22m.

In our experiment, we put the tag on the chest of a person. The RTLS tag was attached on the front of the person's body, as in Fig. 3, and there were LOS conditions between the tag and readers #1 and #2. On the other hand, the tag could not see reader #3 or #4 at all.

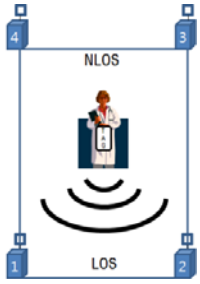


Figure 3. Example of NLOS environment

Table 1 shows the NLOS effect in regard to packet reception. It is remarkable that only 49 packets, out of 335 packets, were received at all four readers. Because we verified that our system could receive a LOS signal, it is certain that this result is purely coming from the NLOS effect. Only 14.6% of the transmitted packets could reach all the readers in a realistic scenario.

TABLE I. THE NUMBER OF TRANSMITTED PACKETS IN NLOS

Number of readers that received packet	***4***	***3***	***2***	***1***	***Total***
Number of packets	49	243	41	2	335
Percent (%)	14.627	72.537	12.239	0.597	100

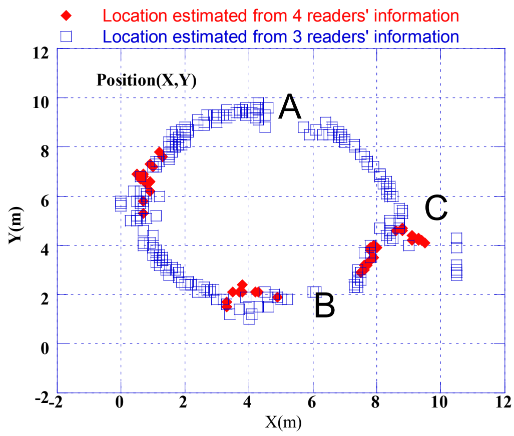


Figure 4. Comparision of LOS and NLOS in TDOA

Fig. 4 shows positioning results. Most of the points are calculated with time information from only three receivers. From the figure, we can see that there is a vacant spot, which is indicated as A and B, in the position tracking results. In this spot, transmitted packets couldn't be received at more than two receivers. Although one or two readers can receive the packet, the TDOA algorithm cannot calculate the position. In a positioning system, these blind spots can be a serious problem when we consider its real-time characteristic.

Furthermore, there are cases where the measured data carries errors. This case is indicated as C in Fig. 4. If there is a blocking object in the LOS path, a packet may arrive at a reader after it bounces off the opposite wall. In this case, the packet arrival time is much delayed. This effect results in huge errors in the positioning results.

III. PROPOSED ALGORITHM

This chapter describes the PPTi positioning algorithm as the proposed algorithm. We also describe KF in this section, as it was employed.

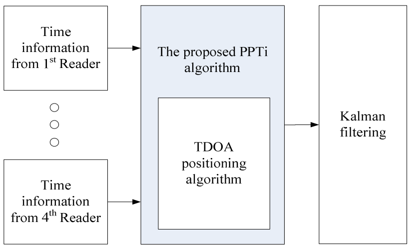


Figure 5. Block diagram of position awareness in proposed algorithm

The TDOA technique cannot calculate the position of a tag with two readers' information. Although it is possible to locate a tag with three readers' information, it is very risky because there is a high possibility of location error. The PPTi algorithm is an additional stage between information gathering and TDOA positioning, as in Fig. 5. Before the TDOA algorithm starts, the PPTi fills in the missing information using previous information. Although it is dangerous to use previous information, as it may carry outdated information, it is possible to increase positioning accuracy because the amount of timing data is critical in decreasing positioning error. This is verified in our experiment results.

Fig. 6 is a flow chart of the PPTi algorithm in the positioning server. Every reader that sampled the arrival time of a packet is supposed to send data to the server. The server waits for the packets from the readers and counts the amount of received data, which is denoted as *N*. The *N* of the LOS environment is obviously 4, and the *N* of the NLOS environment is 3 or 2, or even 1. In the case that *N* is 4, the server calculates six current TDOAs: TDOA21, TDOA31, TDOA41, TDOA32, TDOA42, and TDOA43. TDOA21 is the difference of packet arrival time at readers #1 and #2. Then, the server calculates the tag's position using this information. This is the same procedure used for the ordinary TDOA technique.

In the case that *N* is 3 or 2, the server figures out the missing readers and calculates the available three or one current TDOA information respectively. Unlike the case $N = 4$, the server adds the old, saved TDOA information to the missing current TDOA information for positioning. The server calculates the coordinates of the tag using the recycled TDOA information. After the server estimates the position of the tag, it confirms that this result is acceptable or not using threshold data. We figure out whether the difference between the current position and the previous position are smaller than the pre-determined threshold. If they are smaller than the threshold, the server outputs the calculated position and saves this position as the previous position. The server also saves the current TDOA as TDOA_old. If not, it returns to the 'wait' step. This threshold prevents the positioning system from accumulating positioning errors.

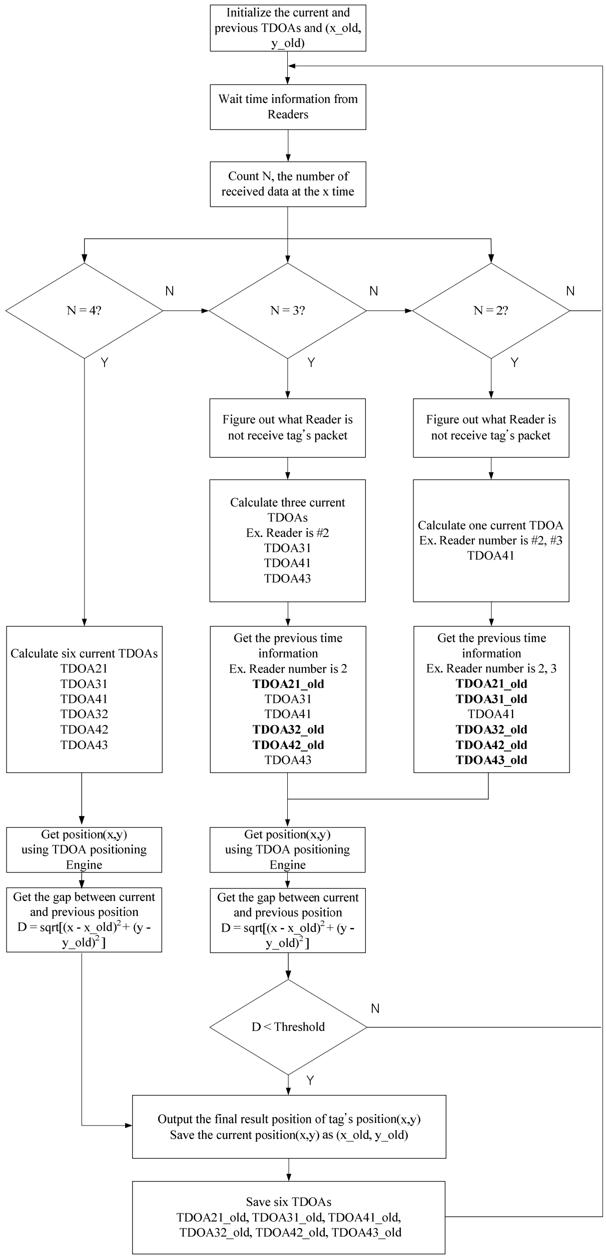


Figure 6. Flow chart of PPTi algorithm

KF is one kind of famous adaptive filter [15], [16]. It is used to estimate position according to the measurement error and state error of all the entries in the buffer. This can be adapted to RTLS because the tag is not fixed and moves infinitely. Although it is difficult to model a noise channel in a realistic environment, KF is frequently used in Location-based Service. We employed KF after we compared the performance of various filters on our system. Experiment results will be presented in Section IV. In this chapter, we briefly explain the KF model adapted to our system.

- State Model :

$$x_{k+1} = F_k x_k + G_k u_k + w_k. \quad (1)$$

- Observation Model :

$$y_k = H_k x_k + z_k. \quad (2)$$

The state equations and observation equations are expressed in (1) and (2). F, G and H are matrices; k is the time index; x is called the state of the system; u is a known input to the system; y is the measured output; and w and z are the noise. The variable w is called the process noise, and z is called the measurement noise.

$$\hat{x}_{k+1|k} = F_k \hat{x}_{k|k}. \quad (3)$$

$$P_{k+1|k} = F_k P_{k|k} F^T{}_k + Q_k. \quad (4)$$

The equations for the time and measurement updates are presented in (3) and (4). Again, notice how the time updates equation project the state and covariance estimates forward from time step k to $k+1$.

$$K_{k+1} = P_{k+1|k} H^T{}_{k+1} (H_{k+1} P_{k+1|k} H^T{}_{k+1} + R_{k+1})^{-1}. \quad (5)$$

$$\hat{x}_{k+1|k+1} = \hat{x}_{k+1|k} + K_{k+1}(y_{k+1} - H_{k+1}\hat{x}_{k+1|k}). \quad (6)$$

$$P_{k+1|k+1} = (I - K_{k+1} H_{k+1}) P_{k+1|k}. \quad (7)$$

The first task during the measurement data is to compute the kalman gain, K in (5). The measurement error covariance R approaches zero, the kalman gain, K, weights the residual more heavily. On the other hand, as estimates error, P approaches zero, the kalman gain, K, weights the residual less heavily. The next step is to actually measure the process to obtain z, and then to generate an a posteriori estimate by incorporating the measurement, as in (6). The final step is to obtain an a posteriori error covariance estimate via (7). After each time and measurement update pair, the process is repeated, with the previous a posteriori estimates used to project or predict the new a priori estimates.

This paper denotes the state model and the observation model of our RTLS in (11) and (12). The state vector x and measured output vector y consists of the position (x_x, x_y) and (y_x, y_y) for each one. The metrics in (1) and (2) are supposed as follows:

$$F = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, H = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, u = 0. \quad (8)$$

The known input to the system of u in (1) is expressed as 0, which is hard to input into the system and we do not expect to find the tag's next position. The measurement noise of z is given as 0.21, which is measured in our RTLS. The process noise of w is assumed to be 0.00002 for getting the smallest RMSE.

Suppose we have a linear system model, as described previously. Equations (3) and (4) define the basic equation of KF. This filter is explained for adaptive filters, as follows in the process of time k. (5), (6), and (7) are updated to estimation value, as follows in time k+1.

$$\begin{bmatrix} x_x(k) \\ x_y(k) \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x_x(k-1) \\ x_y(k-1) \end{bmatrix} + w. \quad (9)$$

$$\begin{bmatrix} y_x(k) \\ y_y(k) \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x_x(k) \\ x_y(k) \end{bmatrix} + z. \quad (10)$$

IV. SYSTEM EVALUATION

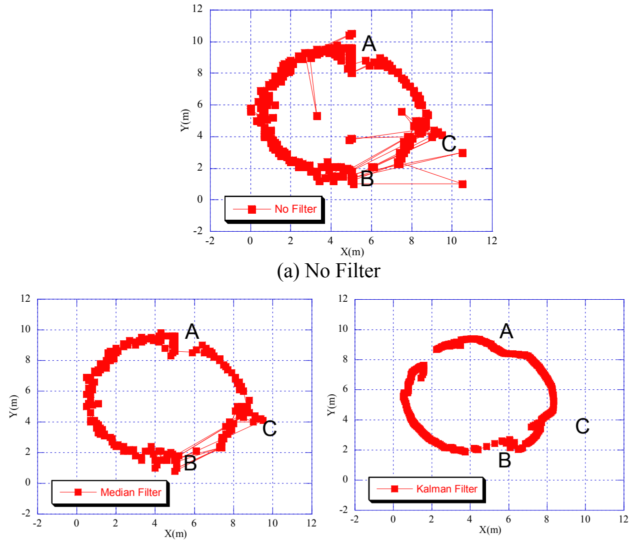
First, we show the effect of the difference threshold in Table II. The higher the threshold is, the more locations we get. The RMSE from the positioning results, however, shows better results with a lower threshold. This is obvious because including previous data provides more location estimation results but carries errors. The decrease of the RMSE means that the threshold plays the role of a filtering function. It is desirable to increase location data and decrease the RMSE. We determined the threshold as 4.5m, which provides a 91.9% positioning success rate.

In Fig. 7, the performance of various filtering algorithms is compared. Original data carries many errors in Fig. 7 (a). The median filter, in Fig. 7 (b), provides improved results compared with the original data, but errors still remain. Adopting KF eliminates most of the outlined points, in Fig. 7 (c). Based on these experiments, we employed KF as the filter algorithm for the NLOS environment.

Fig. 8 compares our proposed method to original data in two dimensional plots. We can clearly see that PPTi fills the blind spot in the original results, which is denoted as A and B when we compare Fig. 8(a) and 8(b). When we employed KF with PPTi, the result is much improved when compared to the original results. Although KF can eliminate outliers by itself, we can see that employing KF with PPTi can provide improved results when we compare Fig. 8(c) and 8(d).

TABLE II. EFFECT OF THRESHOLD

	The proposed PPTi positioning				
Threshold(m)	***6.0***	***4.5***	***3.0***	***1.5***	***0.5***
Positioning success rate (%)	98.2	91.9	89.6	86.3	74.3
No. of positioning success	328	308	300	289	249
RMSE (m)	0.7323	0.5983	0.5736	0.5131	0.4782

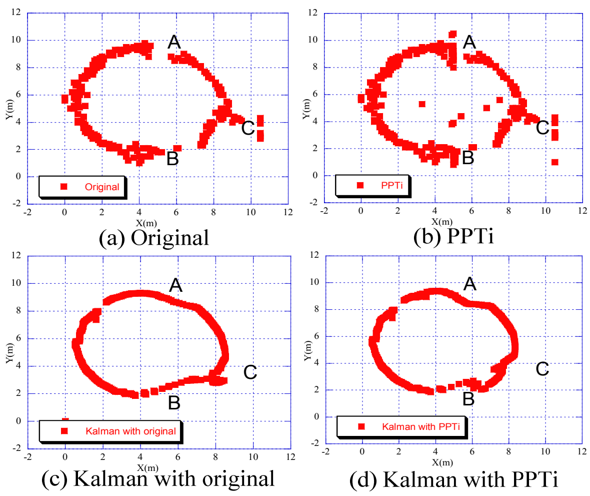


(a) No Filter

(b) Median Filter

(c) Kalman Filter

Figure 7. Comparison of filtering methods



(a) Original

(b) PPTi

(c) Kalman with original

(d) Kalman with PPTi

Figure 8. Comparisons of positioning results in 2D plots

TABLE III. DETAILS OF POSITTIONING RESULT COMPARISON.

	Original		**PPTi**	
	TDOA	***Kalman***	***TDOA***	***Kalman***
The No. of Positioning Success	288 (86.0%)	288 (86.0%)	308 (91.9%)	308 (91.9%)
RMSE (m)	0.6705	0.3931	0.4002	0.2921

Finally, Table III summarizes the performance of the PPTi positioning algorithm. It is certain that the PPTi algorithm provided a 5.9% increased positioning success rate when compared to the results without PPTi. Even from the RMSE point of view, the PPTi provided a 40.3% decreased RMSE when compared with the results of the original, pure TDOA method. These results confirm that the PPTi algorithm can compensate for positioning error. In other words, to utilize previous information, even if it is outdated, is better than nothing, as the amount of information is critical in mitigating error. In the case that KF is employed with both methods, PPTi still provided a 25.6% decrease of RMSE. From these results we can conclude that PPTi improves positioning performance, and PPTi with KF is a suitable method for the mitigation of NLOS error.

V. CONCLUSION

In the paper, a serious problem in a NLOS environment was introduced. We showed that the proposed PPTi algorithm can fill the blind spot and improve positioning accuracy. Although this paper and results are based on experiment using IR-UWB system, the algorithm and results can be applied to RTLS that has an inherent NLOS environment. The NLOS scenarios that are important to the success of RTLS must be considered seriously in the future.

ACKNOWLEDGMENT

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