A TDOA localization method for complex environment localization

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Abstract. Time Difference of Arrival (TDOA) algorithm is a widely used wireless network-based localization algorithm. However, with the increasing complexity of real-life localization environments, the disturbances of noise, perturbations and multi-path effect have limited the performance of the classical TDOA algorithm. In view of these, we design an Interaction-derived Sequence Selection (IDSS) method and an Interaction-derived Sequence Adjustment (IDSA) method to reduce localization error caused by Non Line of Sight (NLOS) environments. Furthermore, an Interacting Multiple Model (IMM) framework is proposed to deal with the localization problem in complex mixed environments. Experimental results demonstrate that the IDSS and IDSA methods can enhance TDOA localization performance in NLOS environments, and the IMM framework can maintain strong adaptability in complex mixed environments.

1. Introduction

In the current digital era, wireless networks have become widely available. This allows for the integration of wireless networks with many developing Internet of Thing (IoT) techniques, which provide more intelligent services to people. On this basis, one of the major functions of wireless networks - localization service - is gaining more and more attention. Wireless network localization is acting as the information supporter in people's life anytime and anywhere. For instance, transportation and logistics distribution, natural disaster rescue, important person tracking, etc. Though various systems such as Global Positioning System (GPS) can also applied to solve localization problems, none of them have advantages unique to wireless network-based localization methods. Taking an indoor scene as an example, on the one hand, the signal of satellite will be weakened by the closed environment, and on the other hand, the localization precision is intolerable for indoor environment applications. While, since wireless networks can be placed indoors easily, utilizing it for localization can result in higher precision and greater efficiency. Thus, it is obviously that the application of wireless localization in high precision demanding environments has a vast development space and tremendous application value.

Recently, wireless localization has been rapidly developed. In previous works, TDOA is one of the widely used algorithms that has been proven effective. But as real-world environments become more and more complex, especially in NLOS environments, classical TDOA algorithms have certain...
limitations in the process of practical application. To tackle this problem, in this work, we propose effective and unbiased TDOA-based methods to improve localization precision.

In summary, this work makes the following contributions:

- We propose two TDOA based methods, Interaction-derived Sequence Selection method and Interaction-derived Sequence Adjustment method, to effectively improve wireless localization precision. Experimental results illustrate that the precision of our optimized algorithms is increased and it can maintain better performance in NLOS environments.
- We design an Interacting Multiple Model framework which can combine with IDSS and IDSA algorithms. Experiments prove that it can achieve great localization performance in complex mixed localization environments.
- Numerous simulation experiments are conducted to verify the effectiveness of our proposed methods. In particular, considering the complexity of real-world environments, we design and build a suitable localization environment model, to simulate TDOA localization algorithms in both LOS and NLOS environments.

2. Related Work

Wireless network-based localization methods have been developed for a long time, earlier typical algorithms are generally based on ranging techniques to estimate the position of targets. Depending on the distance measurement approach, previous works can be roughly divided into several categories including Angle of Arrival (AOA)[1-3], Time of Arrival (TOA)[4-5], Received Signal Strength Indication (RSSI)[6-7], and so on. However, these methods have serious limitations when locating long-range targets or applied in NLOS environments. Most of the algorithms will be affected by signal precision, signal strength and time delay, which leads to localization failures in complex environments. Researches in recent years focus more on improving the TOA algorithm by adopting TDOA approach[8], dealing with the problem of time delay to raise the precision of localization[9]. TDOA algorithm solves the time measurement problem between given anchor nodes and tag nodes in wireless localization network, which eliminates distance difference caused by time delay, but the trouble of clock synchronization still exists between each anchor node[10]. In the case of localization with TDOA algorithm, two separate beams of signals are sent from a tag node to a fixed anchor node, then a hyperbolic model can be built from the difference arriving time between the two signal beams[11].

Meanwhile, though TDOA algorithm performs well in LOS environments, in practice, it is more common to perform localization in NLOS environments due to obstructions and other factors exist in real-world[12]. Actually, NLOS environments are unavoidable in dealing with problems such as indoor localization, urban obstruction localization, etc. The improvement of TDOA algorithms for NLOS environments have also been widely studied[13-14].

With the advent of intelligence, research on wireless localization has shifted to the study of exploiting information between various anchor nodes to construct precise and complex systems[15]. Some researchers have also applied latest techniques, such as machine learning and deep learning, combining with wireless localization algorithms to obtain more robust results[16-18]. Nevertheless, considering the resource and cost limitations of localization systems, the TDOA algorithm is still the most mainstream wireless localization method. Therefore, we adopt TDOA as a basis, and carry out the improvement of TDOA localization algorithm, which enables it to adapt to the requirements of complex environments.

3. Method

3.1. Kalman Filter

The TDOA algorithm that only relies on hyperbolic model for localization has a measure of bias, while the advantage of Kalman filtering is to implement an iterative process of filtering based on localization models. It can affect the localization results through model switching and data integration during iterative process. The basic principle of Kalman filtering are two equations: the model
transformation equation and the filter external interaction equation. These two equations are calculated separately and work together to make a better fit for localization data processing:

\[ s_k = A s_{k-1} + w_{k-1} \]
\[ z_k = G s_k + v_k \]

where \( k \) means \( k \)-th iteration, \( s_k \) represents the model transformation value during the filtering process, \( z_k \) is actual measurement value to be solved, and it is also a reflection of the interaction derived value of the final target node localization result obtained from the filter. \( A \) denotes an \( n \times n \) square matrix, in which the time transfer value is included, and different time transfer values can be set according to different localization situations. \( G \) is also an \( n \times n \) square matrix with the value of \( n \) determined by the number of anchor points involved in TDOA localization. \( w_k \) represents error values in NLOS environments, and \( v_k \) represents noise level during the external interaction of Kalman filtering, where the noise value can be either gaussian distributed white noise, or other noise applicable to wireless network localization.

An iteration of Kalman filtering involves the updating of two main parameters, one is the model transformation value \( s_k \) and the other is the error covariance matrix \( P_k \), the following steps briefly describe the iterative process:

1. Calculate model transformation values \( \hat{s}_k \).
2. Error covariance matrix \( \hat{P}_k \) is updated using \( A \) and \( \hat{P}_{k-1} \). Considering the effect caused by the noise under NLOS environments, noise covariance matrix \( Q \) is added to the calculation:
   \[ \hat{P}_k = A \hat{P}_{k-1} A^T + Q \]
3. Solving for interaction-derived sequence value \( e_k \):
   \[ e_k = z_k - G s_k \]
4. Calculate Kalman gain \( K_k \) of the first update process, and apply the results to the second update process to complete the effective connection of two process:
   \[ K_k = \hat{P}_k G^T (G \hat{P}_k G^T + R_k)^{-1} \]
5. Calculate model transformation value \( \hat{s}_k \) from Kalman gain \( K_k \) and interaction-derived sequence value \( e_k \):
   \[ \hat{s}_k = \hat{s}_k + K_k e_k \]
6. Update error covariance matrix \( \hat{P}_k \) again:
   \[ \hat{P}_k = (1 + K_k G^T) \hat{P}_k \]

After finishing the above processes, one Kalman filtering iteration is done.

3.2. Interaction-derived Sequence Selection
Regarding the principle of Kalman filtering, it is obvious that data of each iteration will affect the result of next iteration, and this effect will continue to the end of entire localization process. Then if the data of one iteration is incorrect, it will have a transfer effect on the subsequent localization process. Although the correction based on filter itself can reduce the influence of data with large deviation values in localization process, however, the Kalman filter is not able to select error data independently. To tackle this problem, we proposed the interaction-derived sequence selection method, which can make localization results meet expected requirements.

The selection of interaction-derived sequence values is related to the setting of selection criteria. For different localization scenarios and different localization objects, an error threshold is not always the same. Specifically, we select \( e_k \) that exceeds error threshold, and let the Kalman gain \( K_k \) in this iteration to be zero:

\[
K_k = \begin{cases} 
0, & e_k \geq \varepsilon \\
K_k, & e_k < \varepsilon 
\end{cases}
\]
where $\varepsilon$ represents error threshold. Therefore, we can know from the above equation that the value of $\hat{s}_k$ and $\bar{P}_k$ will be equal to $\bar{s}_k$ and $\bar{P}_k$, which means the effect caused by the estimated value of current iteration vanishes.

3.3. Interaction-derived Sequence Adjustment

The core idea of the IDSS method is to select $e_k$ that exceed error threshold $\varepsilon$, and any measurement with $e_k$ greater than error threshold is considered invalid. Thus, one of the key steps of IDSS is to choose a suitable error threshold. Here we propose the interaction-derived sequence adjustment method, which is dedicated to avoiding the difficulty of choosing error threshold, so that the data of each iteration can be effectively included in subsequent iterations of the filter. For the adjustment of IDSA, an adjustment factor $\alpha$ is added to iteration process. Similar to the IDSS method, IDSA also evaluates interaction-derived sequence value $e_k$ before adjusting Kalman gain $K_k$. Since $e_k$ has positive or negative values which correspond to the comparison of estimated and updated values, respectively, a positive value indicates that the estimated value is large, while a negative value indicates that the estimated value is small. Hence, the adjustment strategy is as follows:

$$K_k = \begin{cases} K_k / \alpha, & e_k \geq 0 \\ K_k \times \alpha, & e_k < 0 \end{cases}$$

The IDSA method with the addition of an adjustment factor can achieve two-way correction of processed data. In view of the greater flexibility to choose the value of adjustment factor, a larger adjustment factor can be selected when dealing with data with high deviations, while for cases with low deviations, an adjustment factor close to 1 can achieve effective performance.

3.4. Interacting Multiple Model

The interactive multi-model is proposed to explore the study of multiple continuous manoeuvring targets under passive localization. The main purpose of IMM is to reduce the impact of time delay on localization results. In the IMM model, which involves both LOS and NLOS localization environment states, the distance measurement equation is as follows:

$$R_k(t) = h_k(t) + b_k + c_k w_k(t)$$

$$b_k = \begin{cases} 0, & \text{LOS} \\ b_k, & \text{NLOS} \end{cases}$$

$$c_k = \begin{cases} \sigma, & \text{LOS} \\ \sqrt{\sigma^2 + \sigma_{\text{NLOS}}^2}, & \text{NLOS} \end{cases}$$

where $R_k(t)$ denotes measured values between a label node and the $k$-th anchor node at time $t$, $h_k(t)$ represents truth distance values between the two nodes at time $t$, $b_k$ represents the error caused by environment and takes different values depending on the localization environment, $c_k$ indicates noise distribution obeys different standard deviations in different environments. In NLOS environments, the standard deviation of noise $\sigma_{\text{NLOS}}$ should be set greater than 1.

The IMM is essentially a cyclic process similar to Kalman filter as shown in Figure 1. The equation is established as follows:

$$x_k(t+1) = F x_k(t) + C v_k(t)$$

$$R_k(t) = G x_k(t) + b_k^{\text{NLOS}} + c_k(t) w_k(t)$$
The first equation is label node movement equation, and the second equation is measurement value equation, where the matrix $F$ contains time transfer values, the matrix $C$ is a mean-variance transfer matrix, the matrix $G = I$ allows the transformation of movement equation into measurement value equation:

\[
F = \begin{bmatrix}
1 & T & 0 & 0 \\
0 & 1 & 0 & 0 \\
0 & 0 & 1 & T \\
0 & 0 & 0 & 1
\end{bmatrix},
C = \begin{bmatrix}
T^2/2 & 0 \\
T & 0 \\
0 & T^2/2 \\
0 & T
\end{bmatrix}
\]

Similar to Kalman filtering, the update process is as follows:

\[
\hat{X}_{k,oj}(k) = \sum_{i=1}^{r} \hat{X}_{k,i}(k-1)m_{k,i}(k-1)
\]

\[
P_{k,oj}(k) = \sum_{i=1}^{r} \left[ P_{k,i}(k-1) + \left( \hat{X}_{k,i}(k-1) - \hat{X}_{k,oj}(k-1) \right) \left( \hat{X}_{k,i}(k-1) - \hat{X}_{k,oj}(k-1) \right)^T \right] m_{k,i}(k-1)
\]

In the implementation of IMM, Kalman filtering is still used. By applying Kalman filtering, the above two variables are iterated.

4. Experimental Results and Analysis

4.1. Experiment Settings
Localization Environment. In order to compare methods in the same localization environment, so as to facilitate the comparative analysis of experimental results, we uniformly set the number of label nodes involved in the process of localization to 25, and the generation method is linear generation with straight line movement. The number of anchor nodes involved is 4, the radius of localization environment is set to 50 meters, the distribution of anchor nodes is square distribution, and the order of the main anchor node is 1, its position is set to the origin of coordinates.

4.2. Parameter Settings.
The setting of important parameters mainly includes the error threshold $\epsilon$ in IDSS method and the adjustment factor $\alpha$ in IDSA method. In view of our environment is a wireless network with a radius of 50 meters, and its maximum effective coverage area is a square area of $100 \times 100$, so the maximum value of the error threshold is set to 33% of noise standard deviation. For the adjustment factor, since the localization environment built by us has a localization radius of 50 meters which belongs to short-distance localization, thus the error caused by NLOS environment will not cause much impact, so the adjustment factor should be set close to 1. In this experiment, we manually set its value to 1.2.
4.3. Simulation of IDSS and IDSA methods

In the simulation, we use standard Kalman filter, Chan algorithm[19] and our proposed method to locate the target in 4 localization environments with noise standard deviation of 1m, 2m, 3m and 4m respectively, where the localization environment with higher noise standard deviation can be regarded as a simple simulation of a NLOS environment. The experimental results are shown in Figure 2.

When the standard deviation of noise is equal to 1, i.e., in a relatively LOS localization environment, all methods can have effective localization results. However, as the noise continues to increase, the impact of NLOS has an increasing effect on TDOA algorithms, and the standard Kalman filtering method and Chan algorithm both show different degrees of localization distortion. By comparing the localization results of our improved TDOA methods with those of standard Kalman filter and Chan algorithm in different noise environments, it intuitively shows that our methods can fit the path better than others, and have ability to maintain robustness in NLOS environments.

4.4. Simulation of IMM framework

In order to investigate the effectiveness of the IMM-based TDOA algorithm in a complex localization environment, we use an environment transformation matrix $M_{env}$ to represent the state of localization environment. In experiments, we conduct 5 times of environmental transformation.
Figure 3. Simulation results of IMM-based TDOA algorithm in a complex transformed environment, the subfigure (b) is a partial of subfigure (a).

We set the initial position of the label node to (1000,1000), and the main anchor node is located at the origin of coordinate axis (0,0). The tag node has a certain velocity $v = 20 \text{ m/s}$ during localization process. The number of observations of the labeled nodes in each localization environment is set to 500, since there are 5 transformations of localization environments, 2500 observations are in total. The performance of the IMM-based TDOA algorithm in different localization environments can be well analyzed by monitoring distance values between tag nodes and anchor nodes, which are shown in Figure 3.

Taking a look in Figure 3(a), it can be clearly observed that the distance measured by TDOA varies more significantly for every 500 intervals than that measured by IMM-based TDOA algorithm, due to the change of localization environment. Such a change in localization environment makes the TDOA algorithm, which used to be closer to real distance values, fluctuate to a larger extent. However, the implemented IMM-based TDOA algorithm has better localization performance in both LOS and NLOS environments, its localization results are significantly better than basis TDOA algorithms, demonstrate that it is able to adapt to complex environmental transitions.

5. Conclusion
TDOA algorithm is a key algorithm in wireless network localization. For the problem of insufficient localization precision of classical TDOA algorithm in NLOS environment, in this paper, we propose two Kalman filter-based improved methods, IDSS and IDSA. Both of them can overcome the impact of environmental noise on localization precision, and can be adapted to the NLOS environment. Meanwhile, for the complex environment with state transitions, we propose the IMM framework, which can locate distance well in combination with above algorithms. Since our work assumes that signal reception efficiency is 100%, future work can focus on the effective reception of propagating signals to solve the problems of signal attenuation and obstruction in real-world localization process.

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