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A novel strategy of localization based on EKF for mobile robot*

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Abstract: This paper focuses on the accurate localization based on WSN (wireless sensor network) for indoor mobile robot using NLOS (non-line of sight) identification. For the traditional localization three measurement circles from observation are usually obtained to estimate the robot position, which brings up the larger errors in positioning. In order to resolve this problem, the position distributions calculated from multiple measurements are used to estimate the mobile robot location. Intersections of each two measurement circles are computed and distributions are fitted by using Gaussian. Expectations are taken as the observation values for extended Kalman Filter (EKF), which is applied to optimizing of localization. Also NLOS identifications are proposed to find the potential NLOS measurements which will severely deteriorate observation results. Efficiency of the presented localization algorithm with NLOS identification is illustrated via simulation experiments.

Key Words: mobile robot, localization, NLOS identification, Gaussian distribution, EKF

1 Introduction

Mobile robot is considered to be the representation of the highest level of electromechanical integration. Autonomous navigation is the basic function of the mobile robot, for which accurate localization is the premise [1, 2, 3]. Localization technology varies, as localization based on range estimation usually comes with the trilateration which needs at least three distances from the robot to the references with known positions to be estimated. And localization based on the data maps in [4] is considered to be the most popular of the range-free localization technologies.

Range-based localization is the most common way, for which GPS (Global Position Service) is a representation. For GPS in [5], at least three ranges from the satellites are needed which are estimated according the TOA (Time of Arrival) and trilateration is applied to the position of the object. Key point of localization based on range estimation is to get accurate distances. Several features are applied to range estimation, such as TOA, TDOA (Time Difference of Arrival), AOA (Angle of Arrival) and RSS (Received Signal Strength). Range estimation for indoor localization becomes difficult because of the complex conditions indoor. Ranges are always polluted by various errors, among which NLOS is the main source. The occlusion of information channel leads to NLOS propagation and range estimation errors. NLOS identification and mitigation are keys for indoor localization and large amount of works had been done such as the method considering the features of the data on statistics in [6] or the probability theory in [7].

In this paper, we firstly give a brief introduce for range estimation via RSS of WSN and localization for indoor mobile robot. Then a new method for localization based on RSS is presented in which the observed value of the position is replaced by the mathematical expectations of intersected points of each two circles (if they have) rather than the results of trilateration or least square method (LSM). EKF is applied to optimizing of the results of localization. Finally a novel strategy for NLOS identification is presented based on the motion model.

The rest of this paper is organized as follows. Section 2 is the brief overview of the related works. Section 3 gives the theories of range estimation based on RSS. In section 4, a new algorithm of localization and a new method for NLOS identification are presented. A simulation experiment is presented for the efficiency of the presented algorithm and method in section 5. Conclusions are given in the last part of this paper.

2 Related works

Indoor localization attracted significant attention because of the failure of GPS. Various methods are applied to indoor localization among which localization based on WSN becomes popular because of its high efficiency and flexibility. The existence of the NLOS errors is a deadly drawback of it. In this part, we give a brief overview of the researches on this problem.

Methods for NLOS identification include parameters methods and non-parameter methods. Non-parameter methods do not need range estimation mode and can be applied in different models such as RSS, TOA, and TDOA. In [10] a channel condition estimation algorithm that identifies the condition of the channel in UWB (Ultra Wideband) is proposed for NLOS identification and channel conditions are divided into LOS, NLOS-DP and NLOS-NDP based on TOA and RSS. In [11], the mean square error (MSE) and variances of estimated distances are applied to NLOS identification namely measurements with larger variances are considered NLOS. Measurements are classified into LOS and NLOS according to several features of them by using the least squares SVM in [12].

Identification based on parameters comes with advantages that estimated values of NLOS errors are available and it can throw mitigation to the measurements with the values on NLOS. In [5] variances of the measurements are calculated according to estimated ranges by curve fitting of RSS, those measurements with larger variances are considered NLOS

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errors and are mitigated by subtracting the mathematical expectation of NLOS. In [7] a combination of the hypothesis test of variances and the hypothesis test of arrangement of circular traces are applied. In hypothesis test of arrangement of circular traces a measurement is considered to be NLOS if a circle is surrounded by another one.

3 RSS Range estimation model

Range estimation model based on RSS follows radio theory that signal strength presents deamplification while the increase of distance which can be expressed in LOS (Line of Sight) as

$$P(d) = P(d_0) + 10n\lg(\frac{d}{d_0}) + \xi \tag{1}$$

Where $P(d)$ is the signal strength at the points with distance d, $P(d_0)$ is the signal strength at the points with distance d_0 which usually comes as 1m. The propagation coefficient n characterizes the attenuate rate of signal strength. Measurement noise ξ usually comes as zero means Gaussian noise, namely $\xi \sim N(0,\sigma^2)$.

Signal strength always comes with errors caused by objects reflection or shadow in complex indoor environment, the relationship between d and P can be expressed as

$$P(d) = \begin{cases} P(d_0) + 10n_{LOS}\lg(\frac{d}{d_0}) + \xi, for\ LOS \\ P(d_0) + 10n_{NLOS}\lg(\frac{d}{d_0}) + \xi + \varepsilon, for\ NLOS \end{cases} \tag{2}$$

NLOS error ε comes with larger variance than LOS and non-zero means mathematical expectation. The distances between beacon nodes and mobile node can be estimated via the measured RSSs as

$$\hat{d} = \begin{cases} 10^{(P(d)-P(d_0)-\xi)/10n_{LOS}} & for\quad LOS \\ 10^{(P(d)-P(d_0)-\varepsilon)/10n_{NLOS}} & for\quad NLOS \end{cases} \tag{3}$$

We would like to rewrite the estimation $\hat{d}_{LOS}$ for LOS and $\hat{d}_{NLOS}$ for NLOS, and $\hat{d}_{NLOS} = \hat{d}_{LOS} + \Delta d$, Δd is the NLOS error. It is obviously that the ranges with errors lead errors of localization.

4 Proposed Algorithm and NLOS identification

In this section, we present a new range-based localization method based on RSS and a new method for NLOS identification. The common methods for localization usually come as trilateration that distances $\hat{d}_i = \sqrt{(x-x_i)^2 + (y-y_i)^2}$, where $P(x, y)$ is the coordinate of robot and (x_i, y_i) are the coordinates of the beacon nodes. With more than three estimated distances, an equation set can be written as

$$\begin{cases} \hat{d}_1 = \sqrt{(x-x_1)^2 + (y-y_1)^2} \\ \hat{d}_2 = \sqrt{(x-x_2)^2 + (y-y_2)^2} \\ \qquad \ldots\ldots \\ \hat{d}_i = \sqrt{(x-x_i)^2 + (y-y_i)^2} \end{cases} \tag{4}$$

$\hat{d}_i$ $i = 1,2..\mathrm{M}$ are distances estimated via RSSs. The solution of the equation set is the position of robot, as it is shown in figure 1.

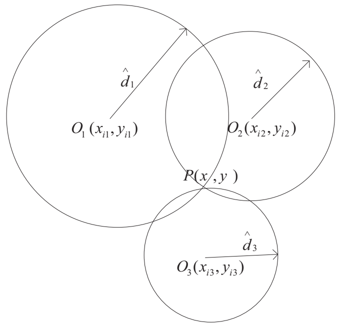


Figure 1. Trilateration

4.1 Assumptions

Before presenting the algorithm of localization, we would like to make the following assumptions.

1) There are M beacon nodes with known positions and one robot with a mobile node in the region, each beacon emits radio signal and the robot with mobile node receives it in ranges of signal strength.
2) Noise of measurement $\xi \sim N(0, \sigma_{Measurement}{}^2)$, NLOS errors $\varepsilon \sim N(\mu, \sigma_{NLOS}{}^2)$, and $\sigma_{NLOS} >> \sigma_{Measurement}$.
3) Most of measurements are under LOS condition and few under NLOS condition for each time.

4.2 Localization algorithm

We present a new algorithm for localization for robot with Gaussian fitting for coordinates and extended Kalman Filter (GFFC-EKF) which consists of three stages:

(1) Range estimation and computation of intersections for each two circles (if they have).

(2) Place intersections into the robot moving region on X axes and Y axes respectively. A Gaussian distribution is applied in fitting the frequency on X axes and Y axes, the mathematical expectations are taken as the observation values for extended Kalman Filter.

(3) Extended Kalman Filter for optimization.

Stage 1: Suppose that M RSSs can be measured at time K, we firstly regard all of them are under LOS conditions and the distances are computed as follows

$$\hat{d}_i = 10^{(P_i(d)-P(d_0))/10n_{LOS}} \qquad i = 1,2...M \tag{5}$$

M distances and coordinates of the M beacon nodes can be gotten. Then equations $\hat{d}_i = \sqrt{(x-x_i)^2 + (y-y_i)^2}$ $i = 1,2...M$ represent M circles in the plane. The robot with mobile node must be at the only intersection of all the circles if the measurements are accurate. However noises do exist for each time, and the circles intersect at different points.

Each two circles may intersect at two points if the distance between centers of the circles is smaller than the sum of the radius, and each intersection is a potential position of the robot. Intersections of two circles can be computed by solving the equation sets as

$$\begin{cases} \hat{d}_l = \sqrt{(x-x_l)^2 + (y-y_l)^2} \\ \hat{d}_k = \sqrt{(x-x_k)^2 + (y-y_k)^2} \end{cases} k, l = 1,2...M, k \neq l \tag{6}$$

The amount of the intersections is C_M^2 if circles intersect with each other, but it is actually smaller. Then we get the matrix of the coordinates of the intersections as $I_{2\times m}$, m is the actual amount of the intersections.

According to the assumption that $\xi \sim N(0,\sigma_{Measurement}{}^2)$ and $\varepsilon \sim N(\mu,\sigma_{NLOS}{}^2)$, and operations on two Gaussian variables lead to Gaussian distribution or approximation Gaussian distribution. This means that coordinates we get also follow Gaussian distribution or approximation Gaussian distribution.

Stage 2: The coordinates we get in stage 1 are potential positions of the robot, and most likely follow Gaussian distribution. Most of measurements are under LOS conditions, namely most of the circles are indeed the circle we wanted (which means accurate), then most of the intersections are approximation of the position of robot.

In this stage, we count the times that the X coordinates and Y coordinates of the intersections fall into different regions, the regions are generated by cutting the X and Y axes from $x_i - \hat{d}_i$ to $x_i + \hat{d}_i$ and $y_i - \hat{d}_i$ to $y_i + \hat{d}_i$ into several pieces, in which $\hat{d}_i$ is the distance we measured in stage 1. However the region $x_i - \hat{d}_i \sim x_i + \hat{d}_i$ can be larger than the moving region which means $x_i - \hat{d}_i$ (or $y_i - \hat{d}_i$) is smaller than the left (or nether) boundary or the $x_i + \hat{d}_i$ ($y_i + \hat{d}_i$) is bigger than the right (or upper) boundary. Dealing with this, we exclude the regions that are out of the moving region from the regions above. We give a statistics of the intersections out of the regions and store the marked numbers of them in matrix $O_{2\times p}$. Interval of the regions may be a factor that affects the accuracy and computing velocity, weighting this we would like to set interval to be 1m.

The frequency of each region can be computed and we store it in vector $c_{1\times n}$, n is the amount of pieces the region contains. Then we fit the frequency $c_{1\times n}$ on X axes and Y axes with Gaussian distribution respectively, mathematical expectations are the results of observation and which are for the initial value of extended Kalman filter.

Stage 3: Extended Kalman Filter is the most popular tool for the optimal estimation of state variables for nolinear systems with Gaussian noise because of its high efficiency and concise form. The orientation of the mobile robot can be expressed as $P = (x, y, \theta)$, in which (x, y) is the position and θ is the angle of deviation as shown in Figure 2. Localization for robot means determining the pose of it, but in pure distance measurement localization systems we can only determine the position (x, y).

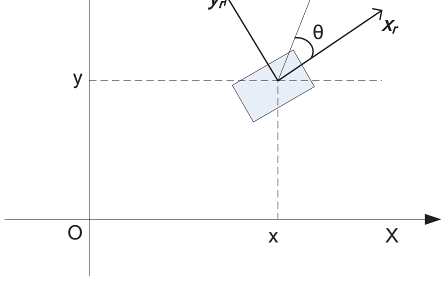


Figure 2. Brief schematic of posture of robot

Motion model of the robot can be the form as

$$\dot{S} = f(P,u) = \begin{bmatrix} \dot{x} \\ \dot{y} \\ \dot{\theta} \end{bmatrix} = \begin{bmatrix} v\cos\theta \\ v\sin\theta \\ \omega \end{bmatrix} \tag{7}$$

And the linearized system can be as

$$\begin{bmatrix} X_k \\ Y_k \\ V_k^x \\ V_k^y \end{bmatrix} = \begin{bmatrix} 1 & 0 & \Delta & 0 \\ 0 & 1 & 0 & \Delta \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} X_{k-1} \\ Y_{k-1} \\ V_{k-1}^x \\ V_{k-1}^y \end{bmatrix} \tag{8}$$

V is the velocity of the robot and Δ is the sampling interval. Observation model can be expressed as

$$z_i = h(P) = \begin{bmatrix} \sqrt{(x_i - x)^2 + (y_i - y)^2} \\ \arctan\dfrac{y_i - y}{x_i - x} - \theta \end{bmatrix} \tag{9}$$

Observation model degrade into $z_i = \hat{d}_i + \Delta d_i$ for pure distance localization system. Suppose that the motion model and the observation model can be expressed as

$$\begin{cases} x_{k+1} = f(x_k, k) + \Gamma_k \omega_k \\ z_{k+1} = h(x_{k+1}, k+1) + v_{k+1} \end{cases} \tag{10}$$

where $\omega_k \sim N(0, Q_k)$ and $v_k \sim N(0, R_k)$ are white Gaussian noises. Extended Kalman Filter contains the following steps [21, 22]:

$$\hat{x}_{k+1|k} = f(\hat{x}_{k|k}, k)$$

$$P_{k+1|k} = f_x(k) P_{k|k} f_x^T(k) + \Gamma_k Q_k \Gamma_k^T$$

$$\hat{x}_{k+1|k+1} = \hat{x}_{k+1|k} + K_{k+1}[z_{k+1} - h(\hat{x}_{k+1|k}, k+1)]$$

$$P_{k+1|k+1} = P_{k+1|k} - K_{k+1} h_x(k+1) P_{k+1|k}^T$$

$$K_{k+1} = P_{k+1|k} h_x^T(k+1)[h_x(k+1) P_{k+1|k} h_k^T(k+1) + R_{k+1}]^{-1}$$

Motion model of our system can be shown as equation (8), and the observation of the system can be linearized as

$$\begin{bmatrix} O_k^x \\ O_k^y \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} \begin{bmatrix} X_k \\ Y_k \\ V_k^x \\ V_k^y \end{bmatrix} \tag{11}$$

4.3 NLOS identification

In this section, we present a new method for NLOS identification. Let's consider the matrix $O_{2\times p}$ containing the marked numbers of the intersections out of the region. They have large probabilities to be measurements with NLOS errors with large biases, and we regard the intersections in $O_{2\times p}$ come with NLOS errors and search the marked numbers of the potential NLOS measurements. That is we can find the marked numbers of the measurements which cause the potential NLOS errors in $O_{2\times p}$ and we store them in N_1.

We give a prediction of the position at time k after getting the result at time $k-1$ via the linearized motion system model of the robot, and the prediction of the robot is $P^p(k) = (x^p(k), y^p(k))$ for time k. Distances from $P^p(k)$ to reference nodes can be $d_i^p(k) = \sqrt{(x_i^P(k) - x_i)^2 + (y_i^P(k) - y_i)^2}$ $i = 1,2...M$. Bias between prediction and measurements can be $Bia_i(k) = abs(\hat{d}_i(k) - d_i^p(k))$ $i = 1,2...M$ for each prediction and the average of the bias is $\bar{Bia}(k)$. Then we take the measurements with bias larger than $\bar{Bia}(k)$ as the potential NLOS and store them in $N2$.

The measurements which are considered to be potential NLOS are stored in the two vectors, we finally regard the measurements which are both in $N1$ and $N2$ as NLOS measurements, which refers the intersection of $N1$ and $N2$.

5 Simulation and Results analysis

In this section we present a simulation for our algorithm to evaluate its performance using Matlab. We set 7 beacon nodes in 100×100 m^2 area and two obstacles, 25 steps are taken along the trajectory. The variance of the noise under LOS condition is 3.3 and 5 for NLOS, and means of the LOS noise is 0 and 1 for NLOS. Errors of localization are defined as the Euclidean distances between the real positions (x_i^r, y_i^r) and the results (x_i^m, y_i^m), which means

$$error(i) = \sqrt{(x_i^r - x_i^m)^2 + (y_i^r - y_i^m)^2} \tag{11}$$

In this simulation, we would like to compare our algorithm with the PKCS-Rwgh from Yan Wang in [6] and we give a comparing to LSM. The flow chart of the presented algorithm and NLOS identification method is presented in figure 3.

We present the result of localization and localization errors compared with PKCS-Rwgh and LSM in figure 4, figure 4(a) gives an intuitive image of the localization, and Figure 4(b) presents the error curves of the algorithms. It is obvious that our algorithm gains a better performance than others with smaller errors. The mean of errors for our algorithm is 1.1919m compared to 1.667m for PKCS-Rwgh and 2.2205m for LSM. Table 1 presents the marked numbers of the measurements polluted by NLOS errors and the results of NLOS identification, most of the NLOS measurements are identified successfully in the presented method.

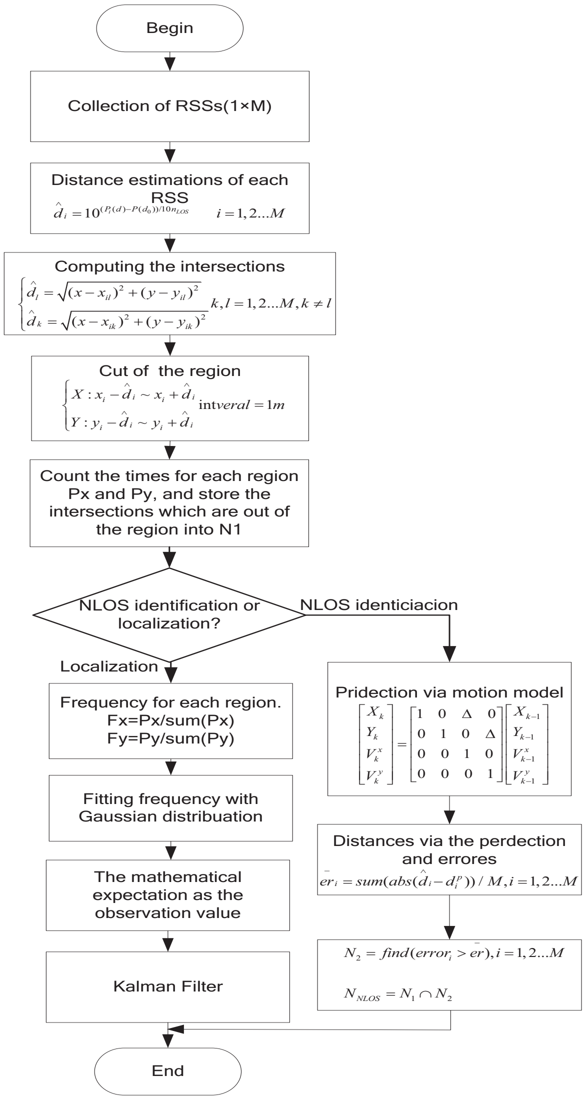
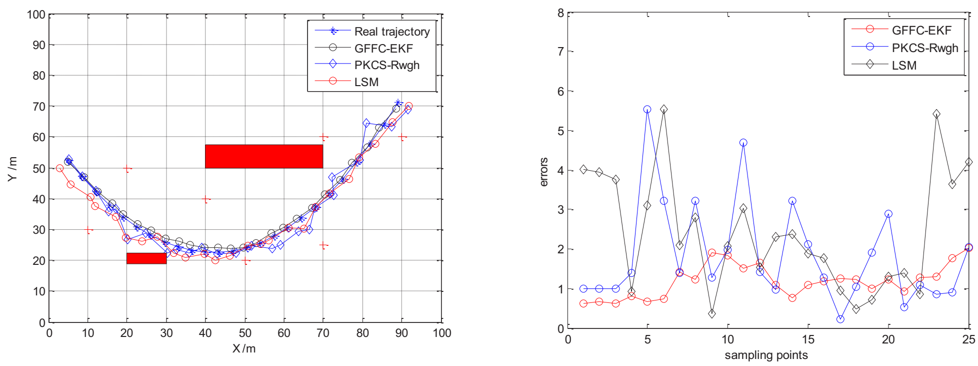


Figure 3. Flow chart of localization and NLOS identification



(a) results of localization

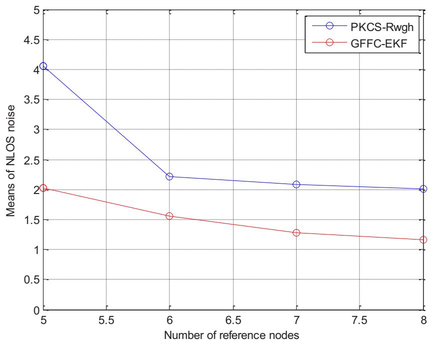
(b)localization errors of each point

Figure 4. Results of simulation

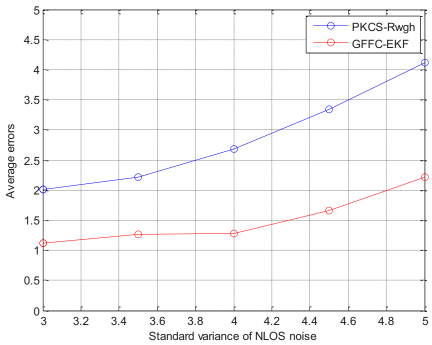
We also present simulations with fewer beacon nodes compared with the PKCS-Rwgh, figure 5(a) presents the average of errors with different amount of beacon nodes. Experiments with larger variance NLOS are presented in figure 5(b), and Figure 5(c) presents the average errors with larger means for NLOS. Obviously, algorithm in this paper gains a better performance with different values of means and variance of the noise.

Table 1 Results for NLOS identification.

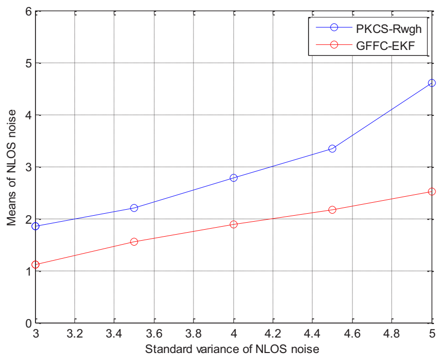
Number of times	NLOS (0 for NO, 1 for YES)	The marked numbers for NLOS
1	0 0 0 0 1 1 0	5 6 0
2	0 0 0 0 1 1 0	5 6 0
3	0 0 0 0 1 1 0	5 6 0
4	0 0 0 0 1 1 0	5 6 0
5	0 0 0 0 1 1 0	5 6 0
6	0 0 0 0 1 1 0	5 6 0
7	0 0 0 0 1 1 0	5 6 0
8	0 0 0 0 1 0 0	0 5 0
9	0 0 0 0 1 0 0	0 5 0
10	0 0 0 0 1 0 0	0 5 0
11	0 0 0 0 1 0 0	0 5 0
12	0 0 0 0 1 0 0	0 5 0
13	0 0 0 0 1 0 0	0 5 0
14	0 0 0 0 1 0 0	0 5 0
15	0 0 0 0 1 0 0	0 5 0
16	0 0 0 0 1 0 0	0 5 0
17	0 0 0 0 1 0 0	0 5 0
18	0 0 0 0 1 0 0	0 5 0
19	0 0 0 0 1 0 0	5 0 0
20	0 0 0 0 0 0 0	2 0 0
21	0 0 0 0 0 0 0	2 0 0
22	0 0 0 1 0 0 0	0 4 0
23	1 0 0 1 0 0 1	1 4 7
24	1 0 0 1 0 0 1	1 4 7
25	1 0 0 1 0 0 1	1 4 7



(a) Average errors with different amount of nodes



(b)Average errors with different standard variance



(c)Average errors with different means of noise

Figure 5. Average errors under different situation

Our algorithm gains satisfactory performance. Though the computing burden increases in a way, the high accuracy of localization and nice performance of NLOS identification of the presented algorithm are of significance for indoor robot localization based on WSN.

6 Conclusion

A new algorithm for robot localization and a new method for NLOS identification based on range estimation via RSS are presented in this paper. The intersections of each two circles are computed and frequency of intersections is fitted using Gaussian distribution in localization algorithm. The mathematical expectations are applied to the observation values for extended Kalman Filter.

A new method is presented for NLOS identification, which contains the stage of investigation the results of localization and the stage of predicting the position of the robot via the motion model. The efficiency of the presented algorithm for localization and method for NLOS identification are proved by simulation experiments, the presented algorithm improves the accuracy of localization and the method gains nice performance of NLOS identification.

The works in this paper can be applied in designing of systems for mobile robot localization in indoor environment via WSN. Future work for us will be centered on localization of mobile robot in unknown environment via WSN or other sensors. And also methods for accurate localization with fewer reference nodes are key points.

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