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Auto-localization system for indoor mobile robot using RFID fusion

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SUMMARY

Autonomous mobile robots need accurate localization techniques to perform assigned task. Radio Frequency Identification Technology (RFID) has become one of the main means to construct a real-time localization system. Localization techniques in RFID rely on accurate estimation of the read range between the reader and the tags. This paper proposes an auto-localization system for indoor mobile robot using passive RFID. The proposed system reads any three different RFID tags which have a known location. The current location can be estimated using the Time Difference of Arrival (TDOA) scheme. In order to improve the system accuracy, the proposed system fuses the TDOA scheme for the three tags. A Kalman filter is used to minimize the estimated error and predict the next location. The simulation results validate the proposed framework.

KEYWORDS: Automation; Control of robotic systems; Design; Mobile robots; Robot localization; Sensor networks.

1. Introduction

Several methods have been proposed recently to solve the problem of localizing an autonomous mobile robot. Mobile robots offer services using a sensor network that has been built into indoor spaces such as offices, homes, and airports. The sensors and robots that are distributed within a space constitute the digital ecosystem. The indoor mobile robots interact with people. To ensure the safety and stability of human–robot interaction, more accurate and precise mobile robot localization systems are crucial. Indoor mobile robots have lots of potential applications in daily life, such as health care, home cleaning, and emergency supporting. The classical localization systems for mobile robots use dead-reckoning sensors such as gyroscopes and encoders.[1,2] Some other systems use combination of ultrasonic sensors, cameras, and the Global Positioning System (GPS).[3,4] These systems are subject to accumulation errors that can result in inaccurate performance such as in the dead-reckoning sensors. Moreover, these systems are constrained by environmental factors such as illumination in the case of Charge-Coupled Device (CCD) cameras, and outdoor conditions for the GPS. These problems are translated into uncertainties that diminish the accuracy and precision of mobile robot localization.[5,6]

The passive Radio Frequency Identification Technology (RFID) has been utilized for the researchers to recognize the position of the service robot. Several localization schemes were proposed using RFID passive tags, which are free from the problems of conventional sensor systems. Moreover, the RFID is gaining more ground by the day due to its ease of use, security, cost effectiveness, and ease of deployment. RFID has become one of the main means to construct a real-time locating system. Localization techniques in RFID rely on accurate estimation of the read range between the reader and the tags. Real-time localization systems use general procedures such as beacon transmission, beacon measurement such as time of arrival (TOA), time difference of arrival (TDOA), angle of arrival (AOA), time of flight (TOF), phase difference of arrival (PDOA), and received signal strength indicator (RSSI) and position determination using different types of algorithms such as trilateration, fingerprinting, and landmarks.[6–10]

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The AOA approach is used in angulations technique, which has to do with angle measurements. Location is measured by using two readers; one of the readers is used as a reference point based on its known distance and angle to the tag. Angle of reception of the signal to this reference node is used to determine the position of the other reader to the tag. This technique is very sensitive on effect of reflection. TOF is used when the distance information is available directly; this approach uses the computation of the time that a signal with known velocity will travel from a well-known reference point to a particular location. There is need for timing and clock synchronization within this system for accurate reading and computation of the distance of the object. Passive ultra high frequency (UHF) readers do not measure TOA, since the tag constantly responds to the reader. The RSS-based schemes are easily implementable, but the accuracy is highly dependent on the environment and the distance. In contrast, it is possible to get fairly high accuracy using TDOA.

Time difference of arrival uses cross-correlation process to calculate the difference in time of arrival of tag signal at multiple pairs of readers. The time delay defines a hyperbola of constant range difference from the receivers located at the foci. Each TDOA measurement yields a hyperbolic curve along which the source may be positioned. When multiple sources are used, multiple hyperbolas are formed and the intersection of sets of hyperbolas provides the estimated location.

In this paper, we propose an auto-localization system for indoor mobile robot using passive RFID. The proposed system reads any three different RFID tags having a known location. The current location is estimated using the TDOA scheme. The proposed system fuses the TDOA for the three tags to improve the location estimate. A Kalman filter (KF) is used to minimize the estimated error and predicts the next location.

The remainder of this paper is organized as follows. Section 2 describes the related work. In Section 3, a novel localization technique is proposed. Thereafter, Section 4 explains the KF details. Section 5 shows the simulation results of the proposed system using Matlab. Lastly, Section 6 will conclude this paper.

2. Related Research

There are many localization methods and applications in the literature. Errington *et al.*[11] proposed a localization algorithm based on the least-squares (LS) method. The lowest average error was between 20.49 cm and 75.53 cm. The accurate position and distances between the RFID reader and the RFID tags are not measured. If the RFID tags are found within the reader recognition area, their existence can be just checked. Position estimation error is generated according to the gap between the tags and the reader recognition area. Several algorithms have been proposed to solve these problems. Ma *et al.*[12] proposed the aforementioned scheme employing a tag arrangement pattern; this method depends on the mobile robot travel path. A triangular arrangement of RFID tags was proposed to reduce the estimation error. However, since this method depends on the gap between the tags, increasing numbers of RFID tags must be used to reduce error. Further studies examined encoder sensor systems used to compensate for limitations in RFID systems.[12–15] However, it was found that the error accumulation resulting from wheel slippage might cause the robot to veer off its intended course over long distances. CCD cameras have been used in the fusion system, but these systems are often hampered by illumination problems.[16] There have been many studies in which scholars have distinguished between the strong signal zone and the weak signal zone of a reader, so that the location of the tag situated within a reading zone of the reader can be statistically deduced.[17] Yet these studies have not considered real-time interferences that can cause delay in signals, resulting in the inaccurate estimation of the actual location of the target tag. Moreover, there have been studies on various statistical methods, use of multiple antennas, and use of directional antennas to overcome the inaccuracies caused by interference or noise from the surrounding environment.[18] Park *et al.*[19] proposed a method of using already disbursed tags for the purposes of locating and tracking a vehicle while overcoming environmental obstacles. The proposed method uses a two-reader detection model and the likelihood position estimation method to identify the location of a target vehicle. Choi *et al.*[20] introduced an algorithm that improves the localization by fusing an RFID system with an ultrasonic sensor system. Another study used a suitable tag's antenna in ultra high frequency band, expressly designed to obtain regular and stable RFID detection regions, to fuse RFID readings with the vehicle odometer data. A satisfactory performance is achieved, with an average position error of about 0.1 m.[21] As the robot estimates the direction it needs to go at a regular interval, the error will be

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propagated according to certain geometric relations between estimated directions and robot positions. Kim and Chong[22] proposed an effective direction correction algorithm which uses geometric relation between the estimated directions with respect to the robot position to overcome the disturbance environmental effect.

These previous works tried to solve the problem through the temporary exclusion of uncertainties without the direct consideration of the uncertainty associated with RFID systems. Moreover, most of the previous work accuracy is poor and in some cases depends on the tag density. Therefore, localization is only efficient in cases where RFID tag information is given continuously and where the mobile robot drives along a specific path which has high tag density.

Location estimate systems sometimes combine two or more of the classification approaches to achieve higher accuracy and precision depending on the complexity of the environment. The geometric approach is first considered, followed by the statistical scene analysis and then proximity-based. RSSI is a geometrical approach of estimating object location; this technique is based on the measurement of signal attenuation, the decrease of the signal strength relative to its original intensity. The amount of signal power received at the receiver antenna depends on the distance measured based on the fact that power transmitted reduces with respect to distance travelled by the signal within a complicated channel. Equations or functions describing the expected decrease in signal strength, given the distance such as the Friis equation, can be used to estimate location relative to the source of the signal.

The AOA approach is used in angulations technique, which has to do with angle measurements. Location is measured by using two readers; one of the readers is used as a reference point based on its known distance and angle to the tag. Angle of reception of the signal to this reference node is used to determine the position of the other reader to the tag. In 2D space, two angles and one distance measurement define a location, while in 3D space, two angle measurements, one distance, and one azimuth measurement are used to determine the location of the object. This technique is very sensitive on effect of reflection and scattering.

The TOF geometry location estimate technique is used when the distance information is available directly; this approach uses the computation of the time that a signal with known velocity will travel from a well-known reference point to a particular location. There is a need for timing and clock synchronization within this system for accurate reading and computation of the distance of the object.

Phase difference of arrival allows coherent signal processing for improved range estimation performance. Signal with two or more frequencies are used and the phase difference observed at the two frequencies is used to estimate the location. This technique is used in both dual-frequency and multi-frequency approaches, a well-designed multiple frequency allows effective phase unwrapping and elimination of the range ambiguity. Phase wrapping is a critical issue in location estimation when the range is relatively large. In this approach, adequate frequency separation must be used since RFID system has a finite tag range. Decreasing or increasing the frequency separation amplifies or reduces the sensitivity of the phase difference to noise, thus leading to degrade or improve range estimation.

The TDOA technique measures the difference between the times of arrival of the same radio frequency (RF) signal at different locations. Location is computed from distance measurement from multiple reference positions. In two dimensions, the location is estimated using three non-collinear reference points, and in three dimensions, four non-coplanar reference points are used. The dimension of the location is equal to $(N-1)$, where N is the number of reference points being considered. TDOA uses cross-correlation process to calculate the difference in time of arrival of tag signal at multiple pairs of readers. The time delay defines a hyperbola of constant range difference from the receivers located at the foci; each TDOA measurement yields a hyperbolic curve along which the target may be positioned. When multiple sources are used, multiple hyperbolas are formed and the intersection of sets of hyperbolas provides the estimated location of the source. This technique is being employed in this paper.

3. Proposed Localization System

Let us formally define the problem of localization. We consider a global localization, where global means that the initial robot position is unknown. In order to estimate the robot position using the RFID system, the robot picks up any three tags, these tags have a known position as shown in Fig. 1. Three RFID readers are installed on the mobile robot to gather data of three tags. *Tag A* is a tag at position (x_A, y_A), likewise *Tag B* and *Tag C* respectively. Robot is positioned in 2D coordinate (x, y).

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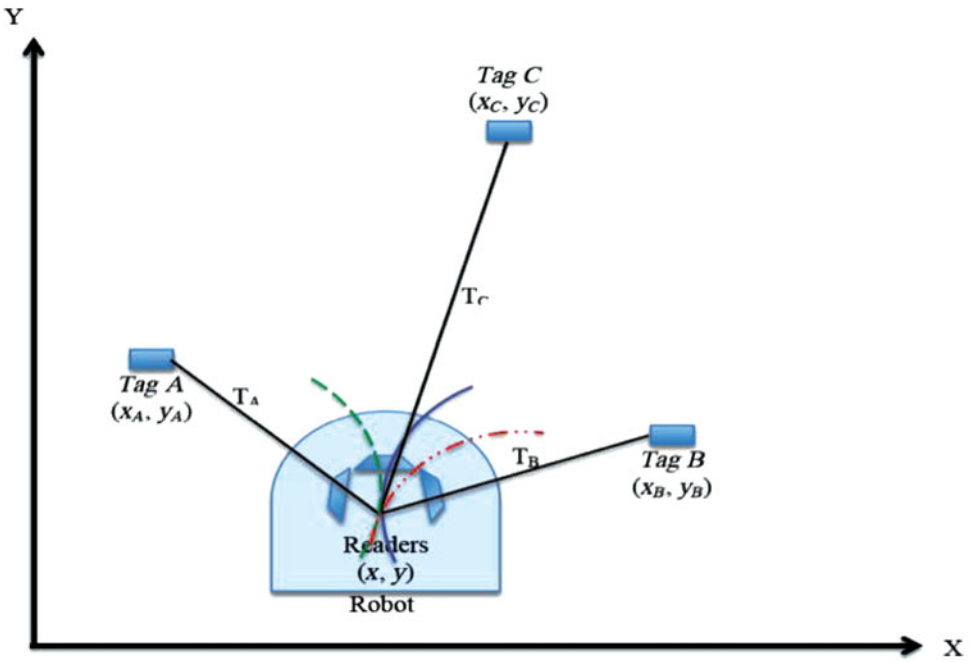


Fig. 1. Location estimation using TDOA.

Each tag pair gives a hyperboloid on which the robot lies. Location estimation is intersection of all hyperbolas. *N* tags provide *N*−1 hyperboloids intersecting on a single point of the robot. The current robot location can be estimated using the TDOA scheme. The proposed system fuses the TDOA for the three tags to improve the location estimate. A KF is used to minimize the estimated error and predicts the next location.

Tag A and *Tag B* are at known locations; robot can be located onto a hyperboloid. The receivers do not need to know the absolute time at which the pulse was transmitted, only the time difference is required. With the third tag *Tag C* at the third location, this would provide the second TDOA measurement and hence locate the robot on the second hyperboloid. The intersection of these two hyperboloids describes a curve on which the robot lies. The unknown location of the robot to be determined is in (x, y) coordinate. A multilateration algorithm comprising three tags at known location *A*, *B*, and *C*, and TOA *T* of pulses from the robot at (x, y) to each of the tag location is the distance divided by the speed of light *c*. The corresponding TOA at each reader is given by the following equations:

$$T_A = \frac{1}{c}\sqrt{(x - x_A)^2 + (y - y_A)^2}, \tag{1}$$

$$T_B = \frac{1}{c}\sqrt{(x - x_B)^2 + (y - y_B)^2}, \tag{2}$$

$$T_C = \frac{1}{c}\sqrt{(x - x_C)^2 + (y - y_C)^2}. \tag{3}$$

The calculations of TDOA (τ) with *Tag A* at the reference coordinate yields:

$$\tau_A = \frac{1}{c}\sqrt{x^2 + y^2}, \tag{4}$$

$$\tau_B = T_B - T_A = \frac{1}{c}\left(\sqrt{(x - x'_B)^2 + (y - y'_B)^2} - \sqrt{x^2 + y^2}\right) + \text{measurement noise}, \tag{5}$$

$$\tau_C = T_C - T_A = \frac{1}{c}\left(\sqrt{(x - x'_C)^2 + (y - y'_C)^2} - \sqrt{x^2 + y^2}\right) + \text{measurement noise}, \tag{6}$$

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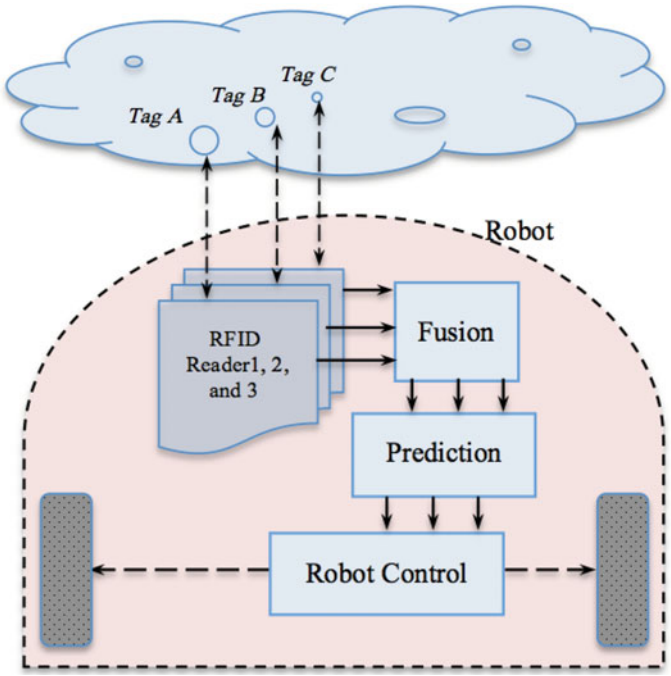


Fig. 2. Proposed localization system.

where (x'_B, y'_B) is the location of *Tag B* with respect to the origin located at site *Tag A*, and (x'_C, y'_C) is the location of *Tag C* with respect to the origin located at site *Tag A*. The multilateration system was solved for the unknown location (x, y) in real time with respect to site *Tag A*. Since the solution to the model is an over determined system that is the number of equations outnumbers the number of the unknowns, also that the system is the nonlinear least square minimization problem, the Levenberg–Marquardt (LM) algorithm was adopted to find an optimization solution to the systems. The LM algorithm is an iterative technique that locates the minimum of a function that is expressed as the squares of nonlinear functions,

$$S(\beta) = \sum_{i=1}^{m} [y_i - f(x_{i,}\beta)]^2, \tag{7}$$

where β is a parameter vector; $x_{i,}$ and y_i are independent and dependent variables; $S(\beta)$ is the sum of the squares of the deviations.[23]

Figure 2 shows the entire system. The proposed system fuses TDOA for the three tags, and a KF is used to minimize the estimated error and predict next location.

4. Kalman Filter

Kalman filter is a set of mathematical equations that provides an efficient computational solution to discrete time data filtering problems, in essence removing extraneous noise from a given stream of data. The filter is very powerful in several aspects: It supports estimations of past, present, and even future states. It is an optimal predictor in the case of Gaussian uncertainties, and it can do so even when the precise nature of the modeled system is unknown. Moreover, KF is the best linear estimator for any other distribution.

In this work, $\hat{x}_k$ represents the suitable estimate of the true tag location in 2D planes,

$$\hat{x}_k = (x_k, y_k)^T . \tag{8}$$

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The KF model assumes that the real state at time k evolves from the state at $k-1$. Thus, the process equation is given as:

$$\hat{x}_{k+1} = A\hat{x}_k + w_k, \tag{9}$$

where w_k is called process noise and assumed to be zero-mean white noise process. The coordinate of observation vector z_k is as follows:

$$\hat{Z}_k = (x_k^{\cdot},\ y_k)^T. \tag{10}$$

The output/observation/measurement vector is given by:

$$z_k = C\hat{x}_k + v_k, \tag{11}$$

where v_k is called measurement noise and assumed to be zero-mean white noise process too. The extrapolation of the most recent state estimate to the present time (prediction phase) of the location filter is shown as follows:

$$M_k^{-1} = P_k^{-1} + C_k^T R_k^{-1} C_k, \tag{12}$$

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k(z_k - C_k\hat{x}_{k|k-1}), \tag{13}$$

$$K_k = M_k C_k^T R_k^{-1}, \tag{14}$$

$$\hat{x}_{k+1|k} = A_k\hat{x}_{k|k} + w_k, \tag{15}$$

$$P_{k+1} = A_k M_k A_k^T + Q_k, \tag{16}$$

where A is the scale transition matrix, C is the state transition matrix applied to the previous state $\hat{x}_k$, Q_k is the covariance of the process noise w_k, and R_k is a covariance of the measurement noise v_k. The calculation of Kalman gain (K) not only depends on the known measurement error covariance R_k but also on the state estimation covariance P_k. A and C matrices are given as:

$$A = \begin{bmatrix} A_x & 0 \\ 0 & A_y \end{bmatrix}, \tag{17}$$

$$C = \begin{bmatrix} H_x & 0 \\ 0 & H_y \end{bmatrix}. \tag{18}$$

The update phase substitutes unit matrices C and A into Eqs. (14) to (16) for the computation of the measurement update of the robot location. The measurement updates the correct value.

The measurement noise v_k has different covariance matrix for each of the nodes and changes with time. The covariance of the measurement noise at instant i for node k is:

$$\left(R_i^k\right)^{-1} = \begin{cases} \begin{bmatrix} (100\sqrt{k})^{-1} & 0 \\ 0 & (100\sqrt{k})^{-1} \end{bmatrix} & \text{for i} \le \dfrac{T_f}{2} \\ \begin{bmatrix} (100\sqrt{k})^{-1} + 50^{-1} & 0 \\ 0 & (100\sqrt{k})^{-1} + 50^{-1} \end{bmatrix} & \text{for i} > \dfrac{T_f}{2} \end{cases}. \tag{19}$$

5. Simulation Results

In this section, the efficiency of the proposed localization system is illustrated through Matlab simulation. A room of dimension size 6 m × 6 m was simulated and the tags are placed at a fixed position as shown in Fig. 3. The robot moves in the room and uses its three readers to calculate TOA for each tag using Eqs. (1) to (3), then calculated time delay (TDOA) in Eqs. (4) to (6) of paired tags and assumed measured delay of 0.2, 0.3, and 0.4 sec for each tag pair (*Tag A Tag B*, *Tag A Tag C*,

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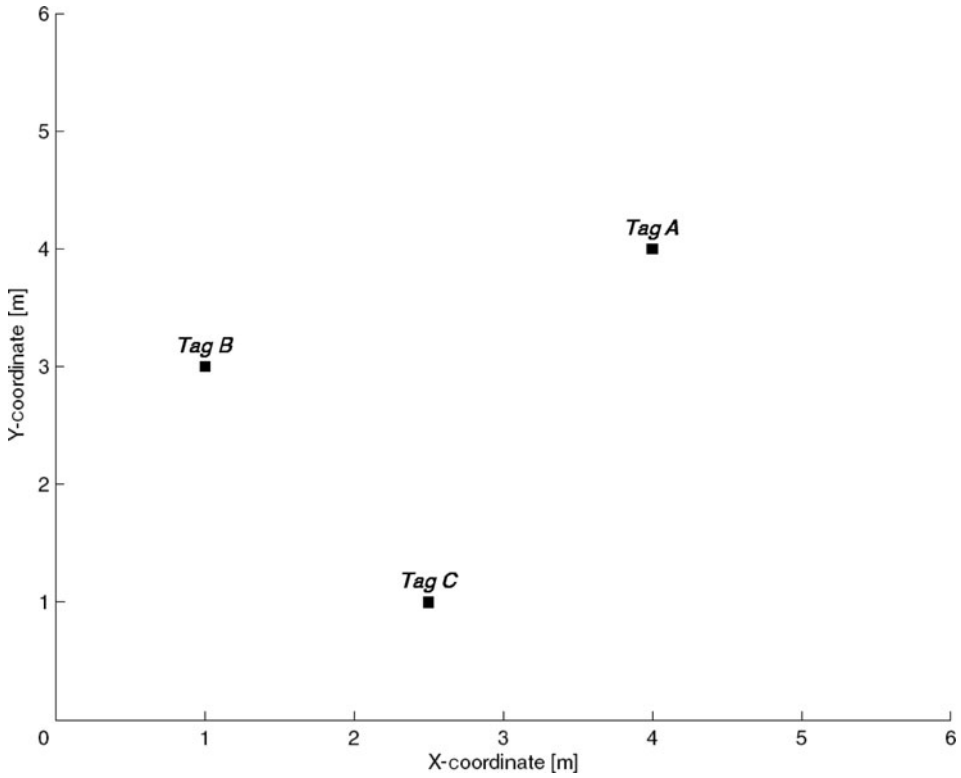


Fig. 3. Tag positions.

and *Tag B Tag C*). Figure 4 shows the simulation of actual and estimated robot position at different 10 locations. Figure 5 shows the error between the actual position and the estimated position for both *X* and *Y* coordinates. In Fig. 5, you can note that position seven has an error of 40 cm in coordinate. Thus, a KF is used to minimize the estimated error and predicts the next location.

In our simulation, the covariance process noise of model Q and the covariance of measurement noise R values are:

$$Q = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, \quad R = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}.$$

The values used for the system defined in Eqs. (9) and (11) are:

$$A = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, \quad C = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}.$$

This estimated robot position, the output of the TDOA technique, is used as input into the KF algorithm. Figure 6 shows the KF performance compared with the actual robot position. There are five iterations between each position. Apparently, the proposed system improved by using KF, and this is clear in Fig. 7. The maximum error of the proposed system is 2.5 cm.

6. Conclusions

We have proposed an auto-localization system for indoor mobile robot using passive RFID. The proposed system reads any three different RFID tags, which have a known location. The current location can be estimated using the TDOA scheme. The proposed system fuses the TDOA for the three tags to improve location estimate. A KF was used to minimize the estimated error and predict next location. The simulation results validate the proposed framework. Real implementation of the proposed system will be considered for future work.

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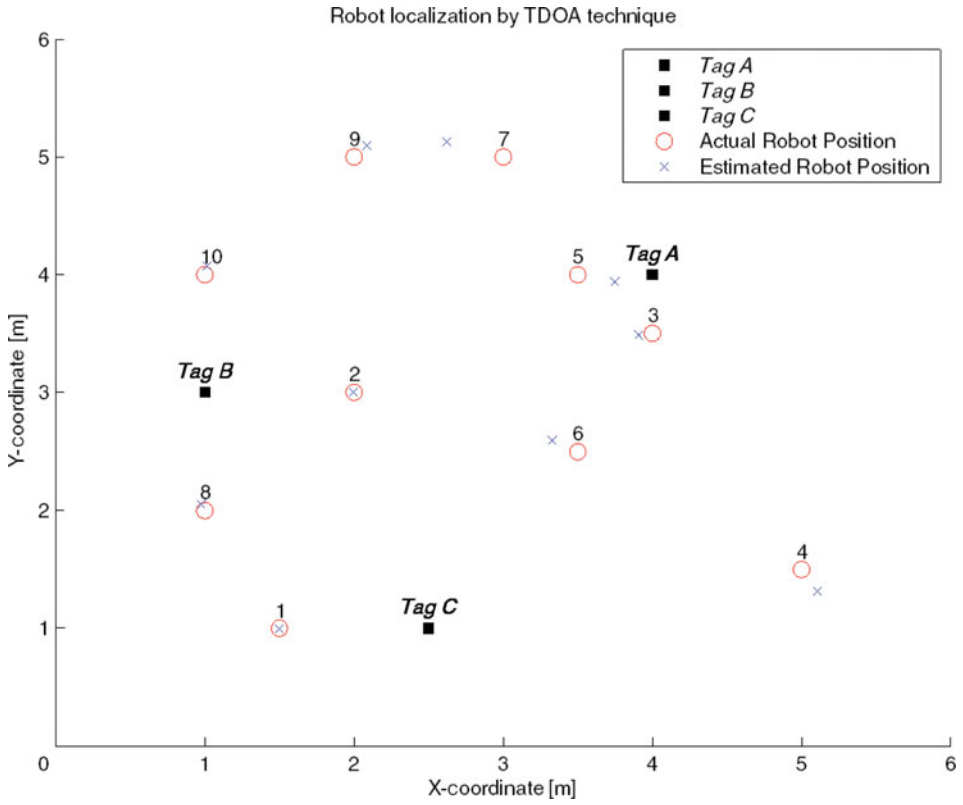


Fig. 4. Simulation of TDOA technique showing actual and estimated robot positions.

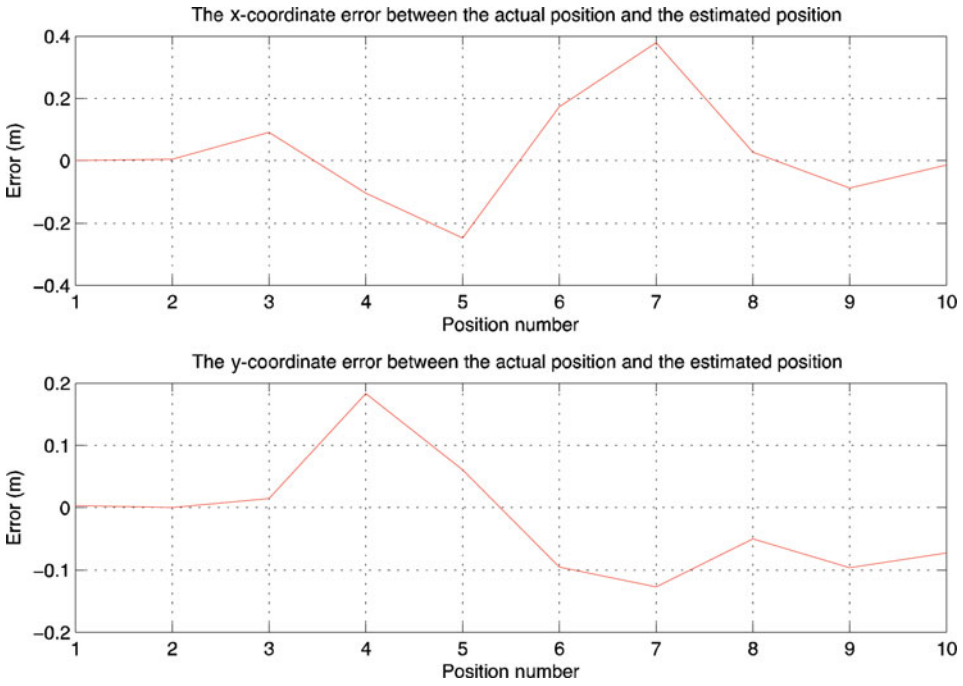


Fig. 5. The error between the actual position and the estimated position using TODA.

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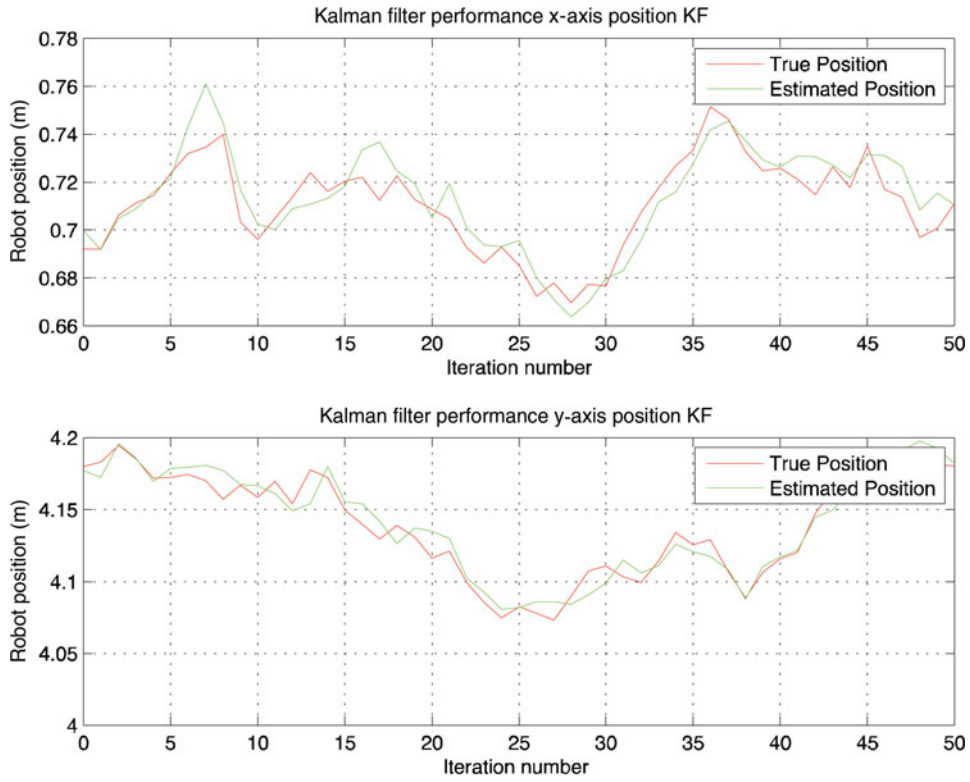


Fig. 6. KF performance.

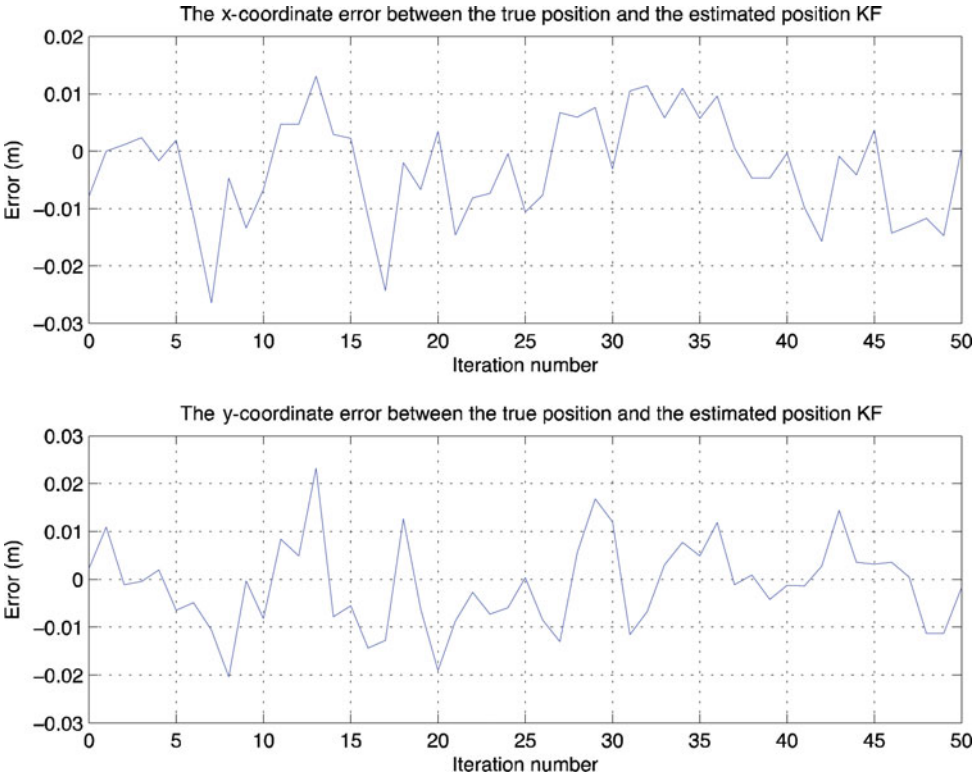


Fig. 7. The error between the actual position and the estimated position using KF.

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Conflict of Interests

The author declares that there is no conflict of interests regarding the publication of this paper.

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