

# Localization of Sensor Nodes in a Wireless Sensor Network Using the nanoLOC TRX Transceiver

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**Abstract**—A wireless sensor network consist of spatially distributed autonomous sensor nodes for data acquisition. Accurate localization of sensor nodes is a strong requirement in a wide area of applications. This paper describes the localization of sensor nodes using range measurements and trilateration with the Extended Kalman Filter. The commercially available nanoLOC sensor network is utilized for range measurements. Experimental results show, that a localization accuracy better than 0.5m can be achieved in most cases.

## I. INTRODUCTION

A wireless sensor network (WSN) consist of spatially distributed autonomous sensor nodes for data acquisition. Besides military applications and monitoring of physical or environmental conditions, robotics [1] and logistics [2] are typical application fields of WSN. Accurate localization of load carriers such as pallets or containers is a strong demand in many logistics applications. Via a WSN the location of nodes can be identified, so that the whole material flow process within a warehouse can be monitored. This paper studies the tracking of a forklift trucks (Fig. 1) using a nanoLOC WSN in conjunction with an Extended Kalman Filter.



Fig. 1. Forklift truck in a warehouse

Up to now several kinds of localization techniques are developed for the use in wireless networks. A review of existing techniques is given in [3]. These techniques can be classified by the information they use. These informations are: connectivity, Received Signal Strength (RSS), Angle of Arrival (AoA), Time of Arrival (ToA), Round-trip Time of Flight (RToF) and Time Difference of Arrival (TDoA).

Connectivity information is available in all kinds of wireless networks. The accuracy of localization depends on the range of the used technology and the density of the beacons. In cellular networks Cell-ID is a simple localization method based on cell sector information. In infrastructure mode of a Wireless LAN (WLAN), the access point (AP) to which the mobile device is currently connected, can be determined since mobile devices know the MAC hardware address of the AP, which they are connected to. In a WSN with short radio range, connectivity information can be used to estimate the position of a sensor node without range measurement [4].

RSS information can be used in most wireless technologies, since mobile devices are able to monitor the RSS as part of their standard operation. The distance between sender and receiver can be obtained with the Log Distance Path Loss Model described in [5]. Unfortunately, the propagation model is sensitive to disturbances such as reflection, diffraction and multi-path effects. The signal propagation depends on building dimensions, obstructions, partitioning materials and surrounding moving objects. Own measurements show, that these disturbances make the use of a propagation model for accurate localization in an indoor environment almost impossible [6]. A method to overcome this disadvantage is fingerprinting, which is introduced in [7] and uses a radio map. Fingerprinting is divided in two phases: In the initial calibration phase, the radio map is built by moving around and storing RSS values at various predefined points of the environment. In the localization phase, the mobile device moves in the same environment and the position is estimated by comparing the current RSS values with the radio map. A metric to compare the measured RSS values with the radio map is Euclidean distance proposed in [7]. Other approaches use a Bayesian algorithm [8] or Delaunay triangulation with lines of constant signal strength [9].

AoA determines the position with the angle of arrival from fixed anchor nodes using triangulation. In [10] a method is proposed, where a sensor node localizes itself by measuring the angle to three or more beacon signals. Each signal consists

of a continuous narrow directional beam, that rotates with a constant angular speed. Drawback of AoA based methods is the need for a special and expensive antenna configuration e.g. antenna arrays or rotating beam antennas.

ToA, RToF and TDoA estimate the range to a sender by measuring the signal propagation delay. The Cricket localization system [11] developed at MIT utilizes a radio signal and an ultrasound signal for position estimation based on trilateration. TDoA of these two signals are measured in order to estimate the distance between two nodes. This technique can be used to estimate the position of a node in a WSN [12] or to track the position of a mobile robot [13]. Ultra-Wideband (UWB) offers a high potential for range measurement using ToA, because the large bandwidth ( $> 500$  MHz) provides a high ranging accuracy [14]. The new WSN standard IEEE 802.15.4a specifies two optional signalling formats based on UWB and Chirp Spread Spectrum (CSS) with a precision ranging capability [15]. Nanotron Technologies distributes a WSN with ranging capabilities using CSS as signalling format.

## II. THE nanoLOC LOCALIZATION SYSTEM

Nanotron Technologies has developed a WSN which can work as a Real-Time Location Systems (RTLS). The distance between two wireless nodes is determined by Symmetrical Double-Sided Two Way Ranging (SDS-TWR). SDS-TWR allows a distance measurement by means of the signal propagation delay as described in [16]. It estimates the distance between two nodes by measuring the RToF symmetrically from both sides.

The wireless communication as well as the ranging methodology SDS-TWR are integrated in a single chip, the nanoLOC TRX Transceiver [17]. The transceiver operates in the ISM band of 2.4 GHz and supports location-aware applications including Location Based Services (LBS) and asset tracking applications. The wireless communication is based on Nanotron's patented modulation technique Chirp Spread Spectrum (CSS) according to the wireless standard IEEE 802.15.4a. Data rates are selectable from  $2 \text{ Mbit/s}$  to  $125 \text{ kbit/s}$ .

SDS-TWR is a technique that uses two delays, which occur in signal transmission to determine the range between two nodes. This technique measures the round trip time and avoids the need to synchronize the clocks. Time measurement starts in Node A by sending a package. Node B starts its measurement when it receives this packet from Node A and stops, when it sends it back to the former transmitter. When Node A receives the acknowledgment from Node B, the accumulated time values in the received packet are used to calculate the distance between the two stations (Fig. 2). The difference between the time measured by Node A minus the time measured by Node B is twice the time of the signal propagation. To avoid the drawback of clock drift the range measurement is performed twice and symmetrically. The signal propagation time  $t_d$  can be calculated as

$$t_d = \frac{(T_1 - T_2) + (T_3 - T_4)}{4}, \quad (1)$$

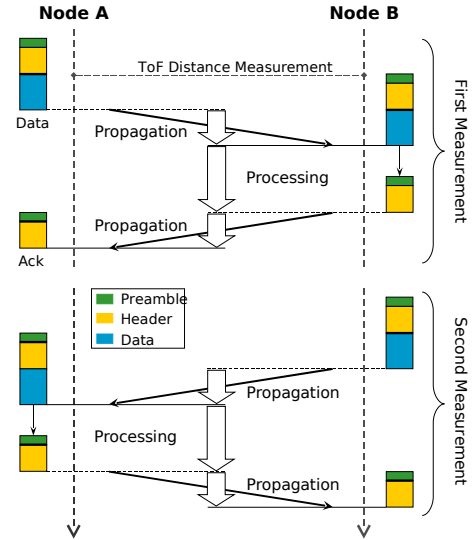


Fig. 2. Symmetrical Double-Sided Two Way Ranging [17]

where  $T_1$  and  $T_4$  are the delay times measured in node A in the first and second round trip respectively and  $T_2$  and  $T_3$  are the delay times measured in node B in the first and second round trip respectively. This double-sided measurement zeros out the errors of the first order due to clock drift [16].

Based on the nanoLOC TRX transceiver and the microcontroller ATmega 128L, the nanoLOC WSN can be used for developing location-aware and distance ranging wireless applications [18]. A mobile tag localizes itself by measuring the distances to a set of anchors as reference points. The anchors are located to predefined positions within a Cartesian coordinate system (Fig. 3). The tag position can be calculated by trilateration.

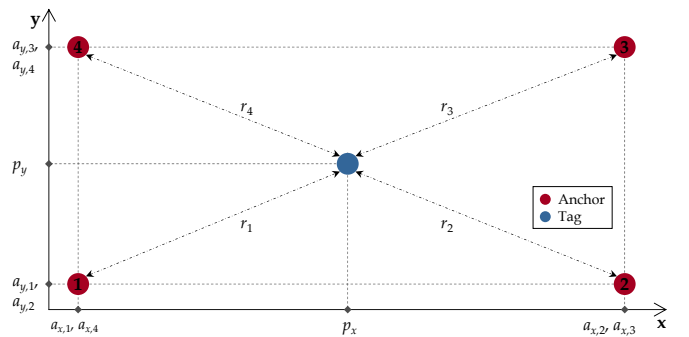


Fig. 3. Localization of a mobile tag based upon the distances to the four anchors

In the Fig. 3,  $(p_x, p_y)$  represents the x- and y-position of the mobile tag to be located. The positions  $(a_{x,i}, a_{y,i})$  with  $i \in \{1, 2, 3, 4\}$  are the x- and y-positions of the four anchors. The variables  $r_i$  incorporate the four distances between the tag and the anchor nodes. At least three distances are required to calculate the position of the tag.

### III. LOCALIZATION OF SENSOR NODES USING THE EXTENDED KALMAN FILTER

By monitoring a dynamic system, the interior process state such as position and velocity of mobile objects is not direct accessible. The distance measurements are subject to errors and noise. The Kalman Filter is an efficient recursive filter, which estimates the state of a dynamic system out of a series of incomplete and noisy measurements by minimizing the mean of the squared error. It is also shown to be an effective tool in applications for sensor fusion and localization.

The equations of the Kalman Filter fall into two groups: “predictor equations” and “corrector equations”. Based on the system input parameters, the current state estimate and error covariance estimate are projected forward to obtain the predicted *a priori* estimates for the next time step. This operation is called “time update”. Following an actual measurement is incorporated into the *a priori* estimate to obtain an improved *a posteriori* estimate. In other words the measurements adjust the predicted estimate at that time, so that this operation is denoted “measurement update”. As initial values for the primary estimation  $\hat{\mathbf{x}}_0$  and  $\mathbf{P}_0$  are passed. After each time and measurement update pair, the process is repeated with the previous *a posteriori* estimates. This recursive nature is one of the appealing features of the Kalman Filter and the essential advantage over other stochastic estimation methods. The filter recursively conditions the current estimate on all of the past measurements and can be used in real-time applications.

The basic filter is well-established, if the state transition and the observation models are linear distributions. In the case, if the process to be estimated and/or the measurement relationship to the process is specified by a non-linear stochastic difference equation, the Extended Kalman Filter (EKF) can be applied. This filtering is based on linearizing a non-linear system model around the previous estimate using partial derivatives of the process and measurement function.

Fig. 4 shows a complete picture of the operations of the EKF by presenting the specific predictor and corrector equations. The time update projects the *a priori* state and covariance estimates forward from time step to step. The first task during the measurement update is to compute the Kalman gain  $\mathbf{K}_k$ . The next step is to generate an *a posteriori* state estimate  $\hat{\mathbf{x}}_{k+1}$  as the result of the filter, in this case. The final step is to obtain the corresponding error covariance estimate  $\mathbf{P}_{k+1}$  for the next iteration.

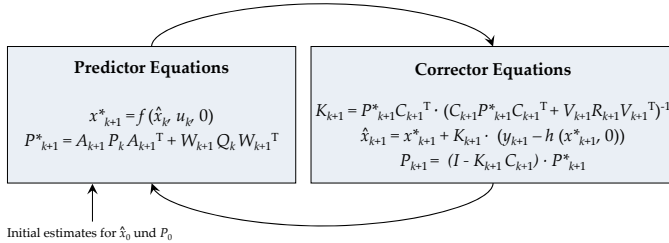


Fig. 4. Time update and measurement update equations of the Extended Kalman Filter

#### A. Design of the Extended Kalman Filter

The Extended Kalman Filter is suitable to determine the x- and y-position of the mobile tag with the measured distances to the four anchors. Using the trilateration method the anchor distances  $r_i$  with  $i \in \{1, 2, 3, 4\}$  are calculated as follow:

$$r_i = \sqrt{(p_x - a_{x,i})^2 + (p_y - a_{y,i})^2}. \quad (2)$$

To gain the unknown tag position, the equations in (2) are solved for  $p_x$  and  $p_y$ , and are transformed in matrices:

$$\mathbf{H} \cdot \begin{pmatrix} p_x \\ p_y \end{pmatrix} = \mathbf{z} \text{ with } \mathbf{H} = \begin{pmatrix} 2 \cdot a_{x,1} - 2 \cdot a_{x,2} & 2 \cdot a_{y,1} - 2 \cdot a_{y,2} \\ 2 \cdot a_{x,1} - 2 \cdot a_{x,3} & 2 \cdot a_{y,1} - 2 \cdot a_{y,3} \\ 2 \cdot a_{x,1} - 2 \cdot a_{x,4} & 2 \cdot a_{y,1} - 2 \cdot a_{y,4} \end{pmatrix},$$

$$\text{and } \mathbf{z} = \begin{pmatrix} r_2^2 - r_1^2 + a_{x,1}^2 - a_{x,2}^2 + a_{y,1}^2 - a_{y,2}^2 \\ r_3^2 - r_1^2 + a_{x,1}^2 - a_{x,3}^2 + a_{y,1}^2 - a_{y,3}^2 \\ r_4^2 - r_1^2 + a_{x,1}^2 - a_{x,4}^2 + a_{y,1}^2 - a_{y,4}^2 \end{pmatrix}. \quad (3)$$

Eqn. 3 can be solved using the method of least squares:

$$\begin{pmatrix} \hat{p}_x \\ \hat{p}_y \end{pmatrix} = (\mathbf{H}^T \mathbf{H})^{-1} \mathbf{H}^T \cdot \mathbf{z} \quad (4)$$

The EKF addresses the general problem of estimating the interior process state of a time-discrete controlled process, that is governed by non-linear difference equations:

$$\begin{aligned} \tilde{\mathbf{x}}_{k+1} &= \mathbf{f}(\tilde{\mathbf{x}}_k, \mathbf{u}_k, \mathbf{w}_k) \\ \tilde{\mathbf{y}}_k &= \mathbf{h}(\tilde{\mathbf{x}}_k, \mathbf{v}_k). \end{aligned} \quad (5)$$

The state vector  $\mathbf{x}_k$  contains the tag position to be estimated as well as the first and second derivatives:

$$\mathbf{x}_k = (p_x \quad v_x \quad a_x \quad p_y \quad v_y \quad a_y)^T, \quad (6)$$

where  $p_x, p_y$  define the position,  $v_x, v_y$  represent the velocity and  $a_x, a_y$  define the acceleration. The optional input control vector  $\mathbf{u}_k$  is set to zero. The observation vector  $\mathbf{y}_k$  represents the observations at the given system and defines the entry parameters of the filter, in this case the results of the range measurements. The process function  $\mathbf{f}$  relates the state at the previous time step  $k$  to the state at the next step  $k + 1$ . The measurement function  $\mathbf{h}$  acts as a connector between  $\mathbf{x}_k$  and  $\mathbf{y}_k$ . The notation  $\tilde{\mathbf{x}}_k$  and  $\tilde{\mathbf{y}}_k$  denotes the approximated *a priori* state and observation,  $\hat{\mathbf{x}}_k$  typifies the *a posteriori* estimate of the previous step. Referring to the state estimation, the process is characterized with the stochastic random variables  $\mathbf{w}_k$  and  $\mathbf{v}_k$  representing the process and measurement noise. They are assumed to be independent, white and normal probably distributed with given covariance matrices  $\mathbf{Q}_k$  and  $\mathbf{R}_k$ . To estimate a process with non-linear relationships the equations in (5) must be linearized as follow:

$$\begin{aligned} \mathbf{x}_{k+1} &\approx \tilde{\mathbf{x}}_{k+1} + \mathbf{A}_k \cdot (\mathbf{x}_k - \tilde{\mathbf{x}}_k) + \mathbf{W}_k \cdot \mathbf{w}_k \\ \mathbf{y}_k &\approx \tilde{\mathbf{y}}_k + \mathbf{C}_k \cdot (\mathbf{x}_k - \tilde{\mathbf{x}}_k) + \mathbf{V}_k \cdot \mathbf{v}_k, \end{aligned} \quad (7)$$

where  $\mathbf{A}_k, \mathbf{W}_k, \mathbf{C}_k$  and  $\mathbf{V}_k$  are Jacobian matrices with the partial derivatives:

$$\begin{aligned} \mathbf{A}_k &= \frac{\partial \mathbf{f}}{\partial \mathbf{x}}(\tilde{\mathbf{x}}_k, \mathbf{u}_k, 0) & \mathbf{W}_k &= \frac{\partial \mathbf{f}}{\partial \mathbf{w}}(\tilde{\mathbf{x}}_k, \mathbf{u}_k, 0) \\ \mathbf{C}_k &= \frac{\partial \mathbf{h}}{\partial \mathbf{x}}(\tilde{\mathbf{x}}_k, 0) & \mathbf{V}_k &= \frac{\partial \mathbf{h}}{\partial \mathbf{v}}(\tilde{\mathbf{x}}_k, 0). \end{aligned} \quad (8)$$

Because in the analyzed system the predictor equation contains a linear relationship, the process function  $f$  can be expressed as a linear equation, where the transition matrix  $A_k$  is defined as:

$$A = \begin{pmatrix} 1 & T & T^2/2 & 0 & 0 & 0 \\ 0 & 1 & T & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & T & T^2/2 \\ 0 & 0 & 0 & 0 & 1 & T \\ 0 & 0 & 0 & 0 & 0 & 1 \end{pmatrix} \quad (9)$$

where  $T$  is the constant sampling time. The observation vector  $y_k$  contains the current measured distances to four anchors:

$$y_k = (r_1 \quad r_2 \quad r_3 \quad r_4)^T \quad (10)$$

The initial state estimate  $\hat{x}_0$  is calculated based on (3). For the subsequent estimation of the tag position  $(p_x, p_y)$  the functional values of the non-linear measurement function  $h$  must be approached to the real position. The function  $h$  comprises the trilateration equations (2) and calculates the approximated measurement  $\tilde{y}_k$  to correct the present estimation  $\tilde{x}_k$ . The equation  $\tilde{y}_k = h(\tilde{x}_k)$  is given as:

$$\begin{pmatrix} r_1 \\ r_2 \\ r_3 \\ r_4 \end{pmatrix} = \begin{pmatrix} \sqrt{(p_x - a_{x,1})^2 + (p_y - a_{y,1})^2} \\ \sqrt{(p_x - a_{x,2})^2 + (p_y - a_{y,2})^2} \\ \sqrt{(p_x - a_{x,3})^2 + (p_y - a_{y,3})^2} \\ \sqrt{(p_x - a_{x,4})^2 + (p_y - a_{y,4})^2} \end{pmatrix} \quad (11)$$

The related Jacobian matrix  $C_k = \frac{\partial h}{\partial x}(\tilde{x}_k)$  describes the partial derivatives of  $h$  with respect to  $x$ :

$$C_k = \begin{pmatrix} \frac{\partial r_1}{\partial p_x} & 0 & 0 & \frac{\partial r_1}{\partial p_y} & 0 & 0 \\ \frac{\partial r_2}{\partial p_x} & 0 & 0 & \frac{\partial r_2}{\partial p_y} & 0 & 0 \\ \frac{\partial r_3}{\partial p_x} & 0 & 0 & \frac{\partial r_3}{\partial p_y} & 0 & 0 \\ \frac{\partial r_4}{\partial p_x} & 0 & 0 & \frac{\partial r_4}{\partial p_y} & 0 & 0 \end{pmatrix} \quad \text{with} \quad \begin{aligned} \frac{\partial r_i}{\partial p_x} &= \frac{p_x - a_{x,i}}{\sqrt{(p_x - a_{x,i})^2 + (p_y - a_{y,i})^2}} \\ \frac{\partial r_i}{\partial p_y} &= \frac{p_y - a_{y,i}}{\sqrt{(p_x - a_{x,i})^2 + (p_y - a_{y,i})^2}} \end{aligned} \quad (12)$$

Given that  $h$  contains non-linear difference equations the parameter  $r_1, r_2, r_3$  and  $r_4$  as well as the Jacobian matrix  $C_k$  must be calculated newly for each estimation.

### B. Parameter Tuning

The effect of the Kalman estimation depends significantly on the parameters of the covariance matrices. To preferably gain an exact estimation, appropriate values for the process noise covariance  $Q_k$  and the measurement noise covariance  $R_k$  must be detected. The process noise covariance represents the accuracy of the estimates for the interior process state. The measurement noise covariance depends directly on the environment of the range measurements. Several experiments with different anchors show covariances in a range between 0.0216 and 0.354. The measurement noise covariance is chosen with  $R_k = 0.1328 \cdot I$  as mean variance of all experiments.

### C. Experiment Results

In a test series, the position of a forklift truck is tracked using the described method. The forklift truck shown in Fig. 1 can be operated in automatic and manual mode. The forklift truck moves in automatic mode along an oval course. The standard NanoLOC development kit which contains five sensor boards with sleeve dipole omnidirectional antennas is utilized for the experiment. Four anchor nodes (A1...A4) are placed at the edges of the course as shown in Fig. 5. The sampling time  $T$  is chosen to 0.3 s.

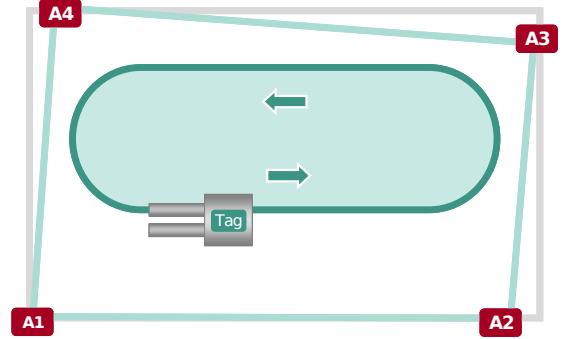


Fig. 5. Trajectory of the fork lift truck

Fig. 6 presents the result of this experiment. The red dashed line shows the course of the forklift truck with the starting point indicated as triangle. The raw trilateration (green dots) calculated with Eqn. (4) shows large peak errors of up to several meters. Large errors occur because the line-of-sight (LOS) propagation on the transmission path between the tag and anchor nodes is blocked in some positions. So the signal propagation is conducted through reflection and scattering which results in large ranging errors. This phenomenon is the main source for the observed errors in the raw trilateration. The estimated position of the EKF (blue line) removes the measurement noise and shows an accuracy better than 0.5 m in most cases.

### IV. CONCLUSIONS AND FUTURE WORKS

In this paper, the accuracy of localization with the nanoLOC TRX transceiver is evaluated. The position accuracy of the estimation is better than 0.5m in most cases. The main source for ranging errors is non-line-of-sight (NLOS) and multi-path signal propagation. As already mentioned, the trilateration method just requires three ranging information. An approach to detect NLOS measurements is to measure the distance to more than three anchor nodes and to use this redundancy to detect errors. These measurements have to be disregarded in order to improve the accuracy and reliability. Another technique to mitigate NLOS and multi-path errors is the Biased Kalman Filter presented in [19]. This filtering uses the estimated standard deviation to mitigate the NLOS error through increasing parameters of the measurement noise covariance matrix.

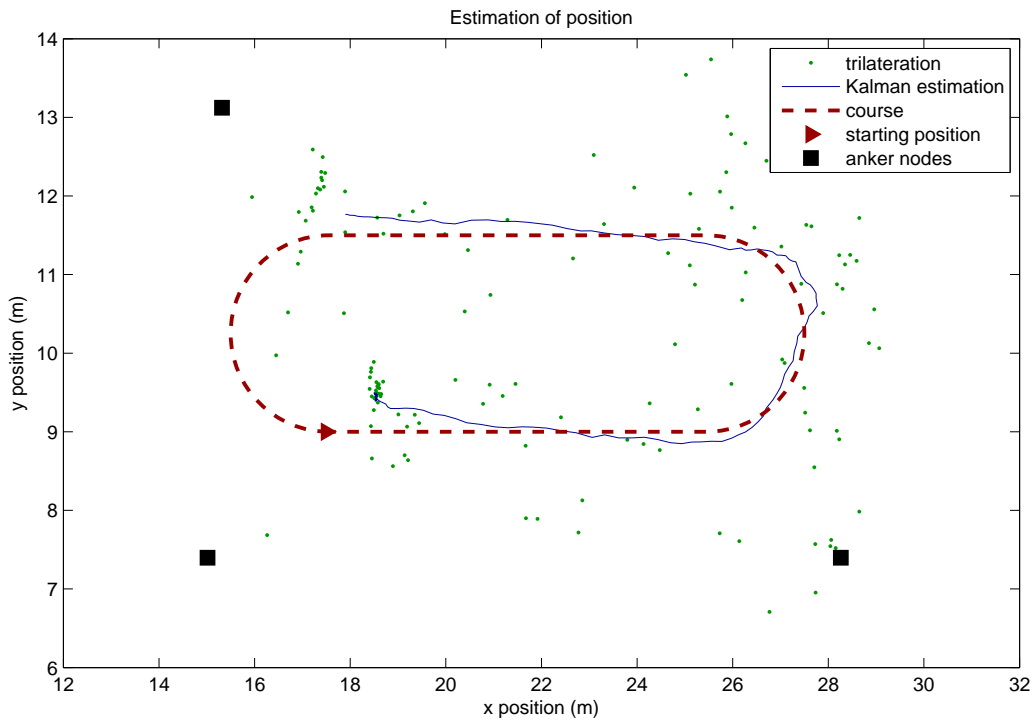


Fig. 6. Results of the Extended Kalman Filtering

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