# Improving the accuracy of the autonomous mobile robot localization systems based on the multiple sensor fusion methods

Lan Anh Nguyen, Pham Trung Dung, Trung Dung Ngo, Xuan Tung Truong

***Abstract*—Localization system plays an important role in navigation frameworks of autonomous mobile robots. Because, it provides significant information for the remainder systems of the navigation frameworks. Recently, to improve the accuracy of the robot pose estimation system in dynamic environments, the mobile robots are equipped with a variety of sensors, such as wheel encoders, a global positioning system (GPS) sensor, and an inertial measurement unit (IMU) sensor. In this paper, we propose an improved localization system for autonomous mobile robots using multiple sensor fusion techniques. To accomplish that, an extended Kalman filter (EKF) algorithm is utilized to fuse the data from the wheel encoders, GPS and IMU sensors. The simulation results show that, our proposed localization system is able to provide higher accuracy of estimating mobile robot's pose than conventional systems.**

***Index Terms*—Autonomous mobile robots, localization system, navigation system, sensor fusion techniques.**

## I. INTRODUCTION

Localization is the problem of estimating robot's pose relative to its environment from sensor observations. To achieve autonomous navigation, the mobile robot must maintain an accurate knowledge of its position and orientation. Successful achievement of all other navigation tasks depends on the robot ability to know its position and orientation accurately. While a mobile robot moving in a real-world environment, it is equipped with a sensor system to know its position and orientation. Therefore, to localize successfully the robot have to determine both motion model and measurement model exactly [1]. However, there are a number of non-deterministic errors that remain, leading to uncertainties in robot pose estimation over time. Each errors are base on a distribution rule, either Gaussian or non-Gaussian. Therefore, in order to improve the accuracy of the localization system in the dynamic environment, it is necessary to first determine the cause of the disturbance, the type of noise distribution and how to eliminate such noise [2]. Because the noise randomly occurs during the robot's navigation, thus one of the common solutions used to compensate the noise caused by motion model and the measurement model is the sensor fusion with difference precision. In addition, each sensor measures only once or two parameters of the environment with limited accuracy. Moreover, using more sensors with higher accuracy will increase a quality of measurement. This is why the sensor fusion algorithms are thriving.

Several mobile robot localization systems have been proposed in recent years to improve the performance of the robot pose estimation [3], [4], [5], [6], [7] and [8]. An enhanced low-cost 3-D localization system is presented in [3]. In this paper, the authors made use of the Kalman filter algorithm to integrate the data from wheel encoders, MEMS-based inertial sensors, and GPS. In [4], the researchers presented a localization system of a mobile robot, which is equipped with 3–axis inertial measurement unit, an active beacon system, and wheel encoders. To do that, they utilized a low-pass filter and a Kalman filter algorithm to reduce noise of input sensors data and obtain more precise robot position and robot movement in real-time. In [5], the authors proposed a localization system of a mobile robot along an uneven path, where it cannot solely rely on encoders, GPS or accelerometer individually. In this system, the Kalman filter-based sensor fusion algorithm was implemented in order to get the best position estimation. A self-localization technique for autonomous mobile robot based on particle filtering in active beacon system is presented in [6]. Using ultrasonic sensor as a particle filter is applied to eliminate process and measurement noise. In [7], the authors presented a sensor fusion framework, that improves the localization system of mobile robots with limited computational resources. To do that, they employs an event based Kalman filter to combine the measurements of a global sensor and an inertial measurement unit on an event based schedule, using fewer resources but with similar performance when compared to the conventional methods. In [8], an adaptive neuron fuzzy inference system was proposed for fusing the GPS and IMU measurements to enhance performance estimation in low cost navigation system when the robot moves in a dynamic environment or slippery ground surfaces and uneven road conditions. In this paper, to improve the accuracy of the localization system of the autonomous mobile robot, which is equipped with wheel encoders, GPS and compass sensors, we propose an enhanced autonomous mobile robot localization system using the EKF.

The remainder of the paper is organized as follows. Section II describes the background information. Section III presents the proposed EKF sensor fusion algorithm with the measurement vector design in three different approaches. Section IV shows the experimental results. We conclude this paper in Section V.

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## II. BACKGROUND INFORMATION

### A. *Kinematic Model of The Mobile Robot*

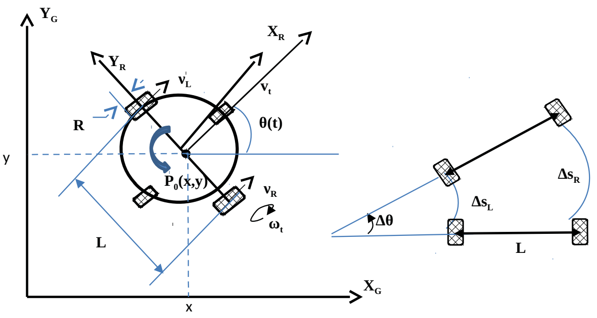



Fig. 1. The global reference frame and the robot reference frame.

We can describe the pose of the mobile robot as a vector with three elements $[x, y, \theta]^T$, as shown in Fig. 1. Assume $\triangle S_R$ and $\triangle S_L$ are distances traveled by the right and left wheels of the robot in interval time $T_s$, respectively. As a result, the linear incremental displacement $\triangle S$ and the orientation $\triangle\theta$ of the robot are defined as follows:

$$\triangle S = \frac{\triangle S_L + \triangle S_R}{2}; \quad \triangle\theta = \frac{\triangle S_R - \triangle S_L}{L} \tag{1}$$

where, L denotes the distance between two robot's wheels. For the differential drive robot, the position can be estimated starting from a known position by integrating the movement. Thus, after each interval time $T_s$, the incremental travel distances of the robot $\triangle x$ and $\triangle y$ on the global reference frame are:

$$\triangle x = \triangle S\cos(\theta + \frac{\triangle\theta}{2}); \quad \triangle y = \triangle S\sin(\theta + \frac{\triangle\theta}{2}) \tag{2}$$

Therefore, the state of the mobile robot at the time $k$ is governed as follows:

$$\begin{bmatrix} x_k \\ y_k \\ \theta_k \end{bmatrix} = \begin{bmatrix} x_{k-1} \\ y_{k-1} \\ \theta_{k-1} \end{bmatrix} + \begin{bmatrix} \triangle S_k\cos(\theta_{k-1} + \triangle\theta_{k-1}/2) \\ \triangle S_k\sin(\theta_{k-1} + \triangle\theta_{k-1}/2) \\ \triangle\theta_{k-1} \end{bmatrix} \tag{3}$$

Equation (3) is also known as the odometry motion model of the mobile robot [2]. Assume, a control command of the robot is $\mathbf{u}_k = [v_k, \omega_k]^T$ with the linear velocity command $v_k$ and the angular velocity command $\omega_k$. Hence, $\triangle S_k = v_{k-1}T_s$, and $\triangle\theta_{k-1} = T_s\omega_{k-1}$. Finally, we obtain the kinematic model of the mobile robot in (4) using (3). This system model will be used in rest of the paper.

$$\begin{bmatrix} x_k \\ y_k \\ \theta_k \end{bmatrix} = \begin{bmatrix} x_{k-1} \\ y_{k-1} \\ \theta_{k-1} \end{bmatrix} + \begin{bmatrix} v_{k-1}T_s\cos(\theta_{k-1} + 0.5T_s\omega_{k-1}) \\ v_{k-1}T_s\sin(\theta_{k-1} + 0.5T_s\omega_{k-1}) \\ T_s\omega_{k-1} \end{bmatrix} \tag{4}$$

### B. *Extended Kalman Filter*

Extended Kalman filter [9] is widely used in many different applications, especially in the field of mobile robots. Let us assume that a process has a state vector $\mathbf{x}_k \in \Re^n$ and the state of the process is governed by the non-linear stochastic difference equation:

$$\mathbf{x}_k = f(\mathbf{x}_{k-1}, \mathbf{u}_k, \mathbf{w}_k) \tag{5}$$

with a measurement $\mathbf{z} \in \Re^m$, that is

$$\mathbf{z}_k = h(\mathbf{x}_k, \mathbf{v}_k) \tag{6}$$

where, $\mathbf{x}_k, \mathbf{z}_k$ are the state and measurement vectors in the time step $k$, respectively; $f$ is a non-linear function, that relates the state at the previous time step $k-1$ to the state at the current time step $k$. It is also included a driving function $\mathbf{u}_k$ and a zero-mean process noise $\mathbf{w}_k$; $h$ is the non-linear function that relates the state $\mathbf{x}_k$ to the measurement $\mathbf{z}_k$; $\mathbf{w}_k$, $\mathbf{v}_k$ are the random variables and represent the process and measurement noises, respectively. They are assumed to be independent to each other with normal probability distributions (7).

$$\mathbf{w}_k \sim N(0, \mathbf{Q}_k); \quad \mathbf{v}_k \sim N(0, \mathbf{R}_k); \quad E(\mathbf{w}_k, \mathbf{v}_k) = 0 \tag{7}$$

In practice of course one does not know the individual values of the noise at each time step. However, one can approximate the state and measurement vector without them as follows:

$$\widehat{\mathbf{x}}_k^- = f(\widehat{\mathbf{x}}_{k-1}, \mathbf{u}_k, 0) \tag{8}$$

and

$$\widehat{\mathbf{z}}_k = h(\widehat{\mathbf{x}}_k, 0) \tag{9}$$

The basic operation of the EKF filter is the same as the linear discrete Kalman filter. Hence, the equations for the EKF filter also fall into two phases: (i) time update equations, and (ii) measurement update equations. The time update equations are responsible for projecting forward the current state and error covariance estimates in time, to obtain the a priori estimates for the next time step. The measurement update equations are responsible for the feedback for incorporating a new measurement into the a priori estimate to obtain an improved a posteriori estimation.

EKF filter time update equations:

$$\widehat{\mathbf{x}}_k^- = f(\widehat{\mathbf{x}}_{k-1}, \mathbf{u}_k, 0) \tag{10}$$

$$\mathbf{P}_k^- = \mathbf{F}_k\mathbf{P}_{k-1}\mathbf{F}_k^T + \mathbf{W}_k\mathbf{Q}_{k-1}\mathbf{W}_k^T \tag{11}$$

EKF filter measurement update equations:

$$\mathbf{K}_k = \mathbf{P}_k^-\mathbf{H}_k^T(\mathbf{H}_k\mathbf{P}_k^-\mathbf{H}_k^T + \mathbf{V}_k\mathbf{R}_k\mathbf{V}_k^T)^{-1} \tag{12}$$

$$\widehat{\mathbf{x}}_k = \widehat{\mathbf{x}}_k^- + \mathbf{K}_k(\mathbf{z}_k - h(\widehat{\mathbf{x}}_k^-, 0)) \tag{13}$$

$$\mathbf{P}_k = (I - \mathbf{K}_k\mathbf{H}_k) + \mathbf{P}_k^- \tag{14}$$

where, $\widehat{\mathbf{x}}_k^- \in \Re^n$ is a priori state estimation at step $k$ given knowledge of the process prior to step $k-1$; $\widehat{\mathbf{x}}_k \in \Re^n$ is a posteriori state estimation at step $k$ given measurement $\mathbf{z}_k$; $\mathbf{P}_k^-$ is an a priori estimation error covariance matrix; $\mathbf{P}_k$ is an a posteriori estimation error covariance matrix; $\mathbf{Q}_k$ is the process noise covariance (the covariance of the noise associated to the motion model); $\mathbf{R}_k$ is the measurement noise covariance at step $k$ (Note subscript allowing it to change with each measurement); $\mathbf{K}_k$ is the Kalman gain; $\mathbf{F}_k$ and $\mathbf{H}_k$ are the Jacobian matrix of partial derivatives of the function $f$ and $h$ with respect to $\mathbf{x}$, respectively, and computed in (15).

$$\mathbf{F}_k = \frac{\partial f(\mathbf{x}_{k-1}, \mathbf{u}_k)}{\partial \mathbf{x}_{k-1}}; \quad \mathbf{H}_k = \frac{\partial h(\mathbf{x}_k)}{\partial \mathbf{x}_k} \tag{15}$$

$\mathbf{W}_k$ is the Jacobian matrix of partial derivatives of the function $f$ with respect to $\mathbf{w}$; and $\mathbf{V}_k$ is the Jacobian matrix of partial derivatives of the function $h$ with respect to $\mathbf{v}$.

$$\mathbf{W}_k = \frac{\partial f(\mathbf{x}_{k-1}, \mathbf{u}_k)}{\partial \mathbf{w}}; \quad \mathbf{V}_k = \frac{\partial h(\mathbf{x}_k, \mathbf{u}_k)}{\partial \mathbf{v}} \tag{16}$$

## III. THE PROPOSED SYSTEM

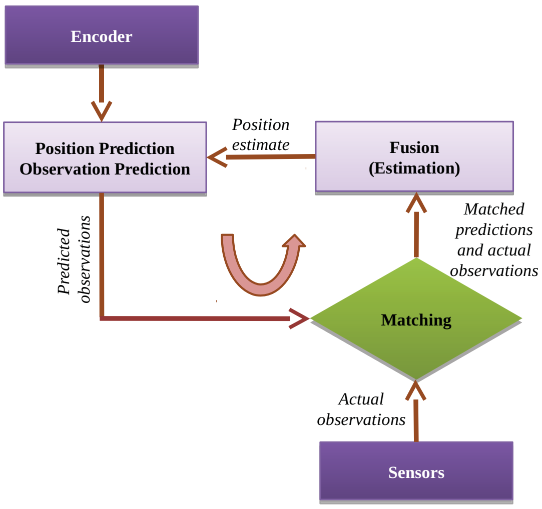



Fig. 2. The block diagram of the proposed autonomous mobile robot localization systems based on the multiple sensor fusion methods.

In the real-world environment, the autonomous mobile robot is equipped with a sensor system to perceive the its surrounding environment. In the sensor system, encoder, GPS and IMU is utilized to determine the position of the mobile robot. However, each sensor has its own advantages and disadvantages. Thus, to improve the accuracy of the mobile robot localization system, we utilize the EKF to fuse the data from aforementioned sensors. To accomplish that, we propose a block diagram of the mobile robot localization system, as shown in Fig. 2. As can be seen in Fig. 2, the encoder is used in the prediction phase of the EKF filter. Whereas, the GPS or/and compass are utilized in the correction phase.

The EKF filter linearizes the state of a system about an estimation of the current mean and covariance. This can be done only if the linearization errors are small in the update time interval [10]. In our work, we assume that the sensors frequencies are high enough, leading the time interval is short enough. Furthermore, without loss of generality, we assume that the process noise is non–additive and measurement noise is the additive. Therefore, the motion model is presented in (5). And the measurement model is presented in (17), that is modified from (6).

$$\mathbf{z}_k = h(\mathbf{x}_k) + \mathbf{v}_k \tag{17}$$

where, $\mathbf{x}_k = [x_k, y_k, \theta_k]^T$ is the state vector defined in (4); $\mathbf{z}_k$ is the measurement vector; $\mathbf{v}_k \sim N(0, \mathbf{R}_k)$ is the measurement noise with the covariance matrix $\mathbf{R}_k$; $\mathbf{u}_k = [v_k, \omega_k]^T$ and $\mathbf{w}_k \sim N(0, \mathbf{Q}_k)$ in (5) are the input control vector of the robot and the process noise with the covariance matrix $\mathbf{Q}_k$, respectively;

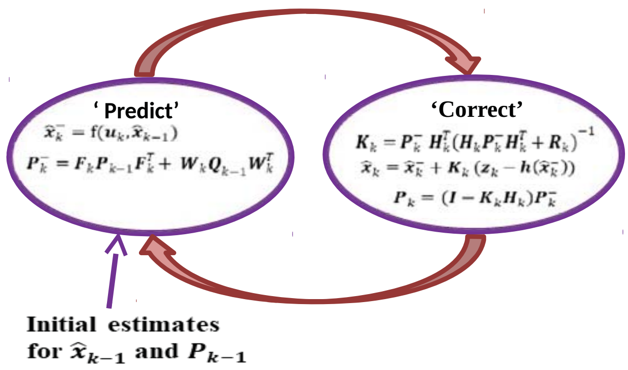



Fig. 3. The extended Kalman filter-based mobile robot localization system.

$v_k$ is the linear velocity and $\omega_k$ is the angular velocity of the robot; and $\mathbf{Q}_k$ is defined in (18), as presented in [1].

$$\mathbf{Q} = \begin{bmatrix} (\alpha_1|v_k| + \alpha_2|\omega_k|)^2 & 0 \\ 0 & (\alpha_3|v_k| + \alpha_4|\omega_k|)^2 \end{bmatrix} \tag{18}$$

In addition, because the measurement noise is the additive noise, therefore equation (12) is rewritten as follows:

$$\mathbf{K}_k = \mathbf{P}_k^- \mathbf{H}_k^T (\mathbf{H}_k \mathbf{P}_k^- \mathbf{H}_k^T + \mathbf{R}_k)^{-1} \tag{19}$$

As a result, the EKF-based localization system for mobile robots is shown in Fig. 3. Where, $\mathbf{F}_k$ is the Jacobian matrix of partial derivatives of the function $f$ with respect to state $\mathbf{x}$ and is defined in (20), where $\beta_{k-1} = \theta_{k-1} + 0.5T_s\omega_{k-1}$.

$$\mathbf{F}_k = \frac{\partial f(\mathbf{x}_{k-1}, \mathbf{u}_k)}{\partial \mathbf{x}_{k-1}} = \begin{bmatrix} 1 & 0 & -v_{k-1}T_s \sin\beta_{k-1} \\ 0 & 1 & v_{k-1}T_s \cos\beta_{k-1} \\ 0 & 0 & 1 \end{bmatrix} \tag{20}$$

In reality, the robot's motion is subjected to noise. Leading to the actual velocities differ from the commanded ones $\mathbf{u} = [v, \omega]^T$. Therefore, we will model this difference by a zero–centered random variable with finite variance. More precisely, let us assume the actual velocities are driven by $\hat{\mathbf{u}} = \mathbf{u} + \mathbf{w}$.

$$\begin{bmatrix} \hat{v} \\ \hat{\omega} \end{bmatrix} = \begin{bmatrix} v \\ \omega \end{bmatrix} + \begin{bmatrix} \epsilon_1 \\ \epsilon_2 \end{bmatrix} \tag{21}$$

where, $\mathbf{w} = [\epsilon_1, \epsilon_2]^T$ is the process noise. In other words, $\mathbf{w}$ is replaced by $\mathbf{u}$ in (16). Thus, the Jacobian matrix $\mathbf{W}$ defined in (16) is rewritten as follows:

$$\mathbf{W}_k = \begin{bmatrix} T_s \cos\beta_{k-1} & -0.5v_{k-1}T_s^2 \sin\beta_{k-1} \\ T_s \sin\beta_{k-1} & 0.5v_{k-1}T_s^2 \cos\beta_{k-1} \\ 0 & T_s \end{bmatrix} \tag{22}$$

where, $\beta_{k-1} = \theta_{k-1} + 0.5T_s\omega_{k-1}$. The size of matrices $\mathbf{F}$ and $\mathbf{Q}$ depend on the structure of the mobile robot. Whereas, the size of matrices $\mathbf{z}$, $\mathbf{H}$ and $\mathbf{R}$ depend on a number of measurements or sensors. In addition, Jacobian matrix $\mathbf{H}_k$ is defined by the sensor types, that are utilized for measurement. In this paper, we make use of encoder, GPS, compass sensors. GPS sensor provides the position of the mobile robot $(x, y)$. Compass sensor measures the robot's heading $\theta$. Thus, the measurement model and Jacobian matrix $\mathbf{H}_k$ were derived for each sensor in the next subsections. Moreover, to eliminate the cumulative error when using only the wheel encoders or

TABLE I
MEAN ERROR FOR THE THREE APPROACHES

| Sensors | Sinusoidal trajectory | Circular trajectory |
|---|---|---|
| Encoder | 37.4074 | 35.1793 |
| Encoder + GPS | 0.2303 | 0.2477 |
| Encoder + Compass | 0.1630 | 0.2032 |
| Encoder + GPS + Compass | 0.1455 | 0.1533 |

TABLE II
MEAN SQUARE ERROR FOR THE THREE APPROACHES

| Sensors | Sinusoidal trajectory | Circular trajectory |
|---|---|---|
| Encoder | 6.1162 | 5.9312 |
| Encoder + GPS | 0.0289 | 0.0217 |
| Encoder + Compass | 0.0189 | 0.0243 |
| Encoder + GPS + Compass | 0.0081 | 0.0115 |

the dead - reckoning method, and improve the performance of the localization system, in this paper, we propose four approaches, including: (i) using only encoder; (ii) combining encoder and GPS; (iii) combining encoder and compass; (iv) combing encoder, GPS and compass.

### A. Global Position Systems (GPS)

GPS sensor provides the position of the mobile robot in the ground plane $\widehat{\mathbf{z}}_k = [x_k, y_k]^T$. Therefore, the Jacobian matrix $\mathbf{H}$ is determined as follows:

$$\mathbf{H}_{Gps} = \frac{\partial h(\mathbf{x}_k)}{\partial \mathbf{x}_k} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix} \tag{23}$$

### B. Compass

Compass sensor is a navigation device used for determining the direction relative to the Earths magnetic poles. Thus, it can be utilized to measure the heading of the mobile robot. Then the measurement vector is $\widehat{\mathbf{z}}_k = \theta_k$.

$$\mathbf{H}_{Com} = \frac{\partial h(\mathbf{x}_k)}{\partial \mathbf{x}_k} = \begin{bmatrix} 0 & 0 & 1 \end{bmatrix} \tag{24}$$

### C. Combining GPS and compass in the measurement model

Then the measurement vector is $\widehat{\mathbf{z}}_k = [x_k, y_k, \theta_k]^T$. Therefore, the Jacobian matrix $\mathbf{H}_k$ is defined as follows:

$$\mathbf{H}_{GC} = \frac{\partial h(\mathbf{x}_k)}{\partial \mathbf{x}_k} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \tag{25}$$

## IV. SIMULATION RESULTS

### A. Simulation Setup

To verify the usefulness of our localization system, we have implemented and tested the proposed system in a Matlab based simulation. In order to accomplish that, we created two scenarios, which their sizes are 75 x 60[$m^2$] and 55 x 40[$m^2$], as shown in Fig. 4(a) and Fig. 5(a), respectively. The kinematic model of the differential drive mobile robot introduced in Section II-A is made use of. In the first scenario, the trajectory of the mobile robot is the sinusoidal trajectory. The initial pose of robot is $(0, 0, 0)$, the goal pose is $(76, 32, 28)$, and the traveling time is 52[s]. Whereas, the trajectory of the robot is the circular trajectory with anti-clockwise direction in the second scenario. The initial pose of the robot is $(0, 0, 0)$, the diameter of the circle is 40[m], and the traveling time is 63[s]. The maximum linear velocity and angular velocity of the mobile robot are 2[m/s] and 0.4[rad/s], respectively, in both scenarios. The sampling time of the EKF filter is 100 [ms].

From the equations of the process shown in Fig. 3, it is recognizable that the efficiency of the EKF filter mainly depends on the estimation of white Gaussian noises $\mathbf{w}_k$ and $\mathbf{v}_k$. Moreover, the noises are featured by covariance matrices $\mathbf{Q}_k$ and $\mathbf{R}_k$ respectively. Therefore, determining the values for the parameters of $\mathbf{Q}_k$ (18) and $\mathbf{R}_k$ adjudicate the quality of the EKF filter. The covariance matrix $\mathbf{Q}_k$ is predetermined as constant by our experiences, as follows:

$$\mathbf{Q} = \begin{bmatrix} 0.01 & 0 \\ 0 & 0.0685 \end{bmatrix} \tag{26}$$

The measurement noise $\mathbf{v}_k$ with the covariance matrix $\mathbf{R}_k$ is predefined in (27). In which, if the measurement data is the coordinates $(x, y)$, the covariance matrix is $\mathbf{R}_{(x,y)}$, while the measurement data are $(x, y, \theta)$, the covariance matrix is $\mathbf{R}_{(x,y,\theta)}$. In addition, if the measurement signal is only the angle $\theta$, the covariance matrix is $R_\theta = 0.0685$

$$\mathbf{R}_{(x,y)} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}; \quad \mathbf{R}_{(x,y,\theta)} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0.0685 \end{bmatrix} \tag{27}$$

To compare the experimental results between approaches, a statistical data analysis of all the experiments is carried out. To do that, the Mean Error (ME) and Mean Square Error (MSE), which are computed in (28), are utilized in this paper.

$$ME = \frac{1}{n}\sum_{k=1}^{n} NE_k; \quad MSE = \frac{1}{n}\sum_{k=1}^{n}(NE_k - ME)^2 \tag{28}$$

where, n is the number of samples, NE is calculated in (29).

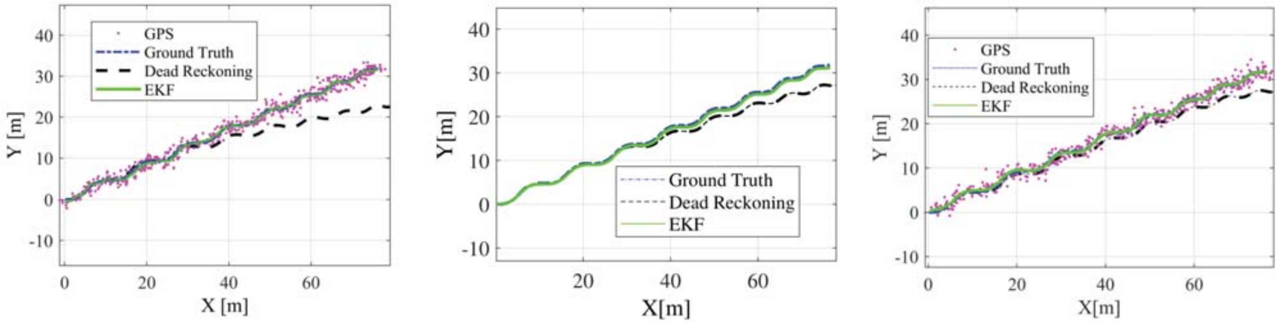
$$NE_k = \sqrt{(x_{ekf} - x_{true})^2 + (y_{ekf} - y_{true})^2} \tag{29}$$

In this study, we have collected 520000 samples in the sinusoidal scenario and 630000 in the circular scenario.

### B. Experimental Results

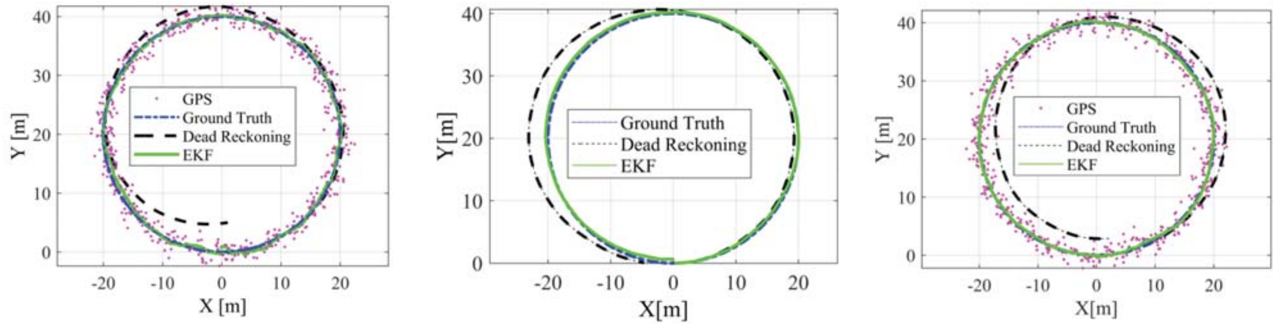
The experimental results of the two conducted experiments are shown in Figs. 4, 5, Table I, and Table II. Figure 4 and 5 show the trajectories of the mobile robot, including: The blue dash lines are the expected trajectories (ground truth); The black dash lines are the trajectories derived from the encoder data (the dead reckoning method); The magenta dots are the GPS data; and The green dash lines are the estimated trajectories of the mobile robot using our proposed localization system. Whereas, Table I and Table II illustrate the statistical data analysis of the two conducted experiments.

As can be seen in Figs. 4 and 5, the black dash lines are very far from the ground truth trajectories of the mobile robot, because the errors are accumulated over time during the robot's navigation. This is the weakness of the dead reckoning




(a) Encoder and GPS (b) Encoder and Compass (c) Encoder, GPS and Compass

Fig. 4. The sinusoidal trajectories of the mobile robot in three approaches.




(a) Encoder and GPS (b) Encoder and Compass (c) Encoder, GPS and Compass

Fig. 5. The circular trajectories of the mobile robot in three approaches.

method. In contrast, the green lines are approximated to the real robot's trajectories in three approaches and both sinusoidal and circular trajectories. This illustrates that, the proposed EKF-based localization system is able to provide the higher accuracy than the dead reckoning method. In addition, Table I and Table II depict that using approach III the values of the mean error and mean square error are smallest, and those values in approach I are biggest, in both sinusoidal and circular trajectories. This indicates that, the proposed localization system with approach III outperforms conventional system in terms of accuracy of estimating the pose of the mobile robot in dynamic environments.

## V. CONCLUSION

We have presented an enhanced localization system for autonomous mobile robots in dynamic environments using multiple sensor fusion techniques. To do that, an EKF algorithm is utilized to fuse the data from the sensors, including the wheel encoders, the global positioning system sensor, and the inertial measurement unit sensor. We have conducted two experiments corresponding with two sinusoidal and circular trajectories of the autonomous mobile robots. The simulation results indicate that, our proposed localization system is capable of providing higher accuracy mobile robot's pose than existing systems.

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