A new EKF SLAM algorithm of lidar-based AGV fused with bearing information

Huaxin Ye* and Charles C Zhou**
*Stevens Institute of Technology, Hoboken, NJ, USA, hye1@stevens.com
**Cascade Clean Energy, Cupertino, CA, USA, charles.zhou@ccleanenergy.com

ABSTRACT

Because of accumulation error from the variance of bearing in the conventional Extended Kalman Filter (EKF) algorithm, the Automated Guided Vehicle (AGV) using the lidar navigation for the Simultaneous Localization and Mapping (SLAM) needs to be guided with closed-loop route. This paper proposed a new EKF SLAM method fused with absolute bearing information provided by an electronic compass to enable more accurate map building with simple open-loop. This approach broke the EKF algorithm for SLAM application into two parts. The inner part of EKF compute the position and pose of AGV based on the encoder information and then correct the estimated result with the actual value of the compass. Such that the outer layer of EKF takes this corrected output from the inner to further estimate the position and pose of AGV and correct and map with lidar data. Simulation and experiment show that the algorithm can effectively reduce errors of AGV, even if the path is open-loop.

Keywords: automated guided vehicle, simultaneous localization and mapping, extended kalman filter, algorithm, laser guidance

1 INTRODUCTION

With the integration of global industrialization and informatization, manufacturing industry will become more automatic and intelligent. Meanwhile, AGV is widely used in various kinds of transportation tasks as a kind of advanced automated and intelligent logistics equipment. With the continuous progress of the technology, higher precision and stability of navigation and localization of AGV are also required.

Navigation methods of AGV have developed from the earlier electromagnetic navigation and tape navigation to laser navigation, inertial navigation and visual navigation [1]. Among these methods, laser navigation method conforms to the development trend of AGV navigation technology for higher positioning accuracy, higher routing flexibility and more intelligence.

To realize the navigation, lidar-based AGV has to know its location and pose when it's moving and create the environment map which determines its relative position at the same time. Environment map can clearly show the location of AGV, while the creation of map also relies on the AGV moving in initially unknown environment and unknown location to achieve relevant information. That is the Simultaneous Localization and Mapping (SLAM). During the SLAM process, AGV creates and updates the map, corrects its own location and pose.

Current SLAM approaches mainly include Particle Filtering method (PF), Graph-SLAM method, Scan Matching method (SM) and the Extended Kalman Filter method (EKF). The PF method searches a group of random samples in state space to approximate the probability density function, uses the sample mean to replace the integral operations, and obtain the minimum variance distribution of the state [2]. It has unique advantage in dealing with parameter estimation and status filtering of non-Gaussian and nonlinear time-varying systems. The Graph-SLAM method takes the SLAM problem as an optimization problem [3]. The objective function and constraints are defined, and it is solved using mathematical programming method. The SM method minimizes the metric distances between the scan characteristics or original data, and align the overlap of the scanning datasets [4]. It seeks the consistency of the datasets containing noise to build maps.

The EKF method is the most common method to solve the SLAM problem [5]. It linearizes the nonlinear system, uses the Kalman filter method to obtain the optimal estimation of system state. When used in AGV, the bearing variance will increase and the linearization errors will accumulate, that eventually results in inconsistent mapping estimation. In addition, EKF SLAM method relies heavily on closed-loop path of AGV. For instance, when AGV works in a new environment and the trajectory of motion is open loop, the map built by EKF SLAM method will have a larger error. In order to improve the accuracy of EKF SLAM method used in AGV and reduce the bearing variance, this paper presents an improved EKF SLAM method in which the additional absolute bearing information of compass is required, and closed-loop trajectory of AGV does not needed.

2 SLAM APPROACH BY USING EKF MODEL

2.1 SLAM Model

Essentially, SLAM is a problem about filtering. This paper defines the SLAM problem usually solved by using EKF model as joint posterior distribution of AGV's pose and the map at the current time. Considering the system noise and the measurement error, the filtering algorithm is used to estimate state variables and make optimal estimation of AGV's pose and the map[6].

Let $X_k = (x_k, y_k, \varphi_k)^{\mathrm{T}}$ be the pose of AGV on the time *k*, where x_k,y_k is the coordinates of AGV in the two-dimensional world coordinate system, φ_k is the orientation of AGV.

Let $M_k = \left(m_1^{\mathrm{T}}, \cdots, m_i^{\mathrm{T}}, \cdots, m_n^{\mathrm{T}}\right)_k^{\mathrm{T}}$ be the map of AGV on the time *k*, where *n* is the number of landmarks and

$m_i = (x_i, y_i)^{\mathrm{T}}$,which is the coordinate of landmark *i* in a two-dimensional world coordinate system.

Let $Z_{0:k} = \{z_0, z_1, \cdots, z_k\}$ be AGV's observation of all landmarks on the time *k*.

Let $U_{0:k} = \{u_0, u_1, \cdots, u_k\}$ be the motion control input of AGV from time 0 to time *k*.

According to EKF model, SLAM problem can be determined as follows:

$$p(X_k, M_k | Z_{0:k}, U_{0:k}, X_0) \tag{1}$$

Equation (1) can be calculated based on the theory of Bayesian. We need to define a motion model and an observation model to describe the effect of the control input and the observation of system states.

AGV's motion model is expressed by probability distribution of the state transition matrix as:

$$p(X_k \mid X_{k-1}, u_k) \tag{2}$$

The observation model is defined as:

$$p(z_k \mid X_k, M_k) \tag{3}$$

Prediction and correction of AGV's pose and the map can also be called time update and observation update.

①Time update (Prediction):

$$\begin{aligned} &p(X_k, M_k | Z_{0:k-1}, U_{0:k}, X_0) \\ &= \int p(X_k | X_{k-1}, u_k)\, p(X_{k-1}, M_{k-1} \mid Z_{0:k-1}, U_{0:k-1}, \mathrm{x}_0)\, \mathrm{d}X_{k-1} \end{aligned} \tag{4}$$

②Observation update (Correction):

$$\begin{aligned} &p(X_k, M_k \mid Z_{0:k}, U_{0:k}, X_0) \\ &= \frac{p(z_k \mid X_k, M_k)\, p(X_k, M_k \mid Z_{0:k-1}, U_{0:k}, X_0)}{p(z_k \mid Z_{0:k-1}, U_{0:k})} \end{aligned} \tag{5}$$

Where $p(z_k \mid Z_{0:k-1}, U_{0:k})$ is a normalized constant.

When we know all control input $U_{0:k}$ and observation $Z_{0:k}$, formula (1) can be calculated by recursion with formula (4) and (5). The process is time update to the observation update to time update.

2.2 The Extended Kalman Filter Model to Realize SLAM

The EKF model is :

$$X_k = \mathrm{f}\left(X_{k\text{-}1}, u_k\right) + \Gamma_k w_k \tag{6}$$

$$z_k = \mathrm{h}\left(X_k, M_k\right) + v_k \tag{7}$$

Where f and h are respectively the motion model and the measurement model of AGV in the ideal condition with no noise, w_k and v_k are the Gauss noise with zero mean. Γ_k is the input matrix of noise and in this paper it's Jacobian matrix of u_k.

The EKF is separated to two steps which are as follows:

The prediction step:

$$\begin{bmatrix} \hat{X}_k^- \\ \hat{M}_k^- \end{bmatrix} = \begin{bmatrix} \mathrm{f}\left(\hat{X}_{k-1}, u_k\right) \\ \hat{M}_{k-1} \end{bmatrix} \tag{8}$$

$$P_k^- = \left[\begin{array}{c:c} FP_{MM}F^{\mathrm{T}} & FP_{XM} \\ \hdashline (FP_{XM})^{\mathrm{T}} & P_{MM} \end{array}\right]_{k\text{-}1} + \left[\begin{array}{c:c} \Gamma Q \Gamma^{\mathrm{T}} & 0 \\ \hdashline 0 & 0 \end{array}\right]_k \tag{9}$$

The update step:

$$\begin{bmatrix} \hat{X}_k \\ \hat{M}_k \end{bmatrix} = \begin{bmatrix} \hat{X}_k^- \\ \hat{M}_k^- \end{bmatrix} + K_k \left(z_k - \mathrm{h}\left(\hat{X}_k^- \right) \right) \tag{10}$$

$$P_k = \left(I - K_k H_k \right) P_k^- \tag{11}$$

$$K_k = P_k^- H_k^{\mathrm{T}} \left(H_k P_k^- H_k^{\mathrm{T}} + R_k \right)^{-1} \tag{12}$$

$$\left[\hat{X}_k^{\mathrm{T}} \;\vdots\; \hat{M}_{\mathrm{new}}^{\mathrm{T}} \right]^{\mathrm{T}} = \left[\hat{X}_k^{\mathrm{T}} \;\vdots\; \hat{M}_k^{\mathrm{T}} \; \left(\mathrm{h}^{-1}\left(z_{\mathrm{new}} \right) \right)^{\mathrm{T}} \right]^{\mathrm{T}} \tag{13}$$

$$P_{\mathrm{new}} = \left[\begin{array}{c:c} P_k & P_k J_{\mathrm{h}^{-1} X}^{\mathrm{T}} \\ \hdashline J_{\mathrm{h}^{-1} X} P_k & J_{\mathrm{h}^{-1} X} P_k J_{\mathrm{h}^{-1} X}^{\mathrm{T}} + J_{\mathrm{h}^{-1}} R_k J_{\mathrm{h}^{-1}}^{\mathrm{T}} \end{array} \right] \tag{14}$$

Where $\hat{X}_k^-$ and $\hat{M}_k^-$ are respectively the predicted mean and the covariance of states. F is the Jacobian matrix of f. H_k is the Jacobian matrix of h. K_k is a gain matrix. z_{new} are new observed landmarks. h^{-1} is the inverse matrix of the measurement matrix. $\hat{M}_{\mathrm{new}}$ is the map with new landmarks added. $J_{\mathrm{h}^{-1} X}$ is the inverse matrix of h^{-1} to $\left[\hat{X}_k^{\mathrm{T}} \;\vdots\; \hat{M}_{\mathrm{new}}^{\mathrm{T}} \right]^{\mathrm{T}}$ which is a state vector. $J_{\mathrm{h}^{-1}}$ is the inverse matrix of h^{-1} to z_{new}.

3 A NEW EKF SLAM ALGORITHM

In the conventional EKF SLAM approach, velocity and angular velocity of lidar-based AGV are measured by the encoder. AGV's state can be predicted by using motion model, namely the prediction step. Then landmarks are measured by lidar and AGV's states are corrected by calculating the difference between observation and prediction, namely the update step. The two parts compose the complete EKF SLAM approach and its structure is shown as figure 1 (a).

This paper proposes a SLAM approach fused conventional EKF SLAM with absolute bearing information. The information of absolute bearing is provided by electronic compass installed on the AGV. Two layers of EKF are established. The inner layer EKF predicts AGV's position and pose by the encoder and corrects AGV's pose by electronic compass. The outer layer EKF uses the output of the inner EKF structure as the predictions of AGV's pose and corrects AGV's pose and the map of the environment by using the data acquired by lidar. The structure is shown as Figure 1 (b).

3.1 The Inner EKF Model

The model of independent inner EKF can be regarded as the solution of AGV's position. An encoder provides the input of motion model and an electronic compass provides the input of observation model.

(1)The motion model

Let the interval from time $k-1$ to time k be Δt. Linear trajectory is used to approximate the true trajectory of AGV. Firstly, The AGV walks along the direction of φ_{k-1} with speed υ_k in time period Δt and then rotates with angular velocity ω_k in time period Δt. According to equation(8), the motion model of AGV is obtained as follow:

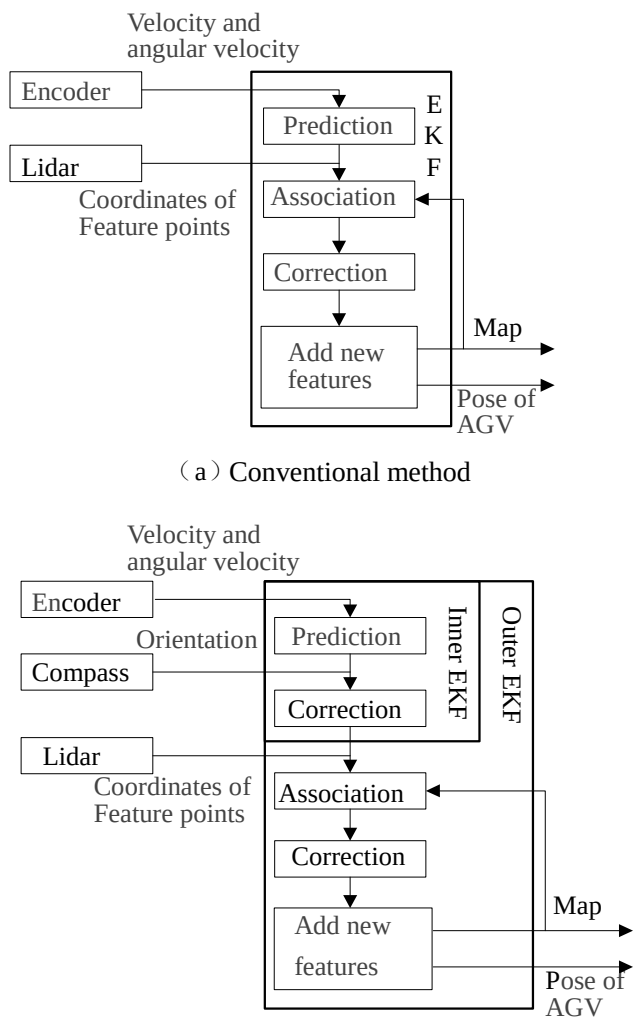

Figure 1: The structures of two kinds of EKF SLAM

$$X_k = X_{k-1} + \Delta t \begin{bmatrix} \cos\varphi_{k-1} & 0 \\ \sin\varphi_{k-1} & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \upsilon_k \\ \omega_k \end{bmatrix} + \Gamma_k w_k \quad (15)$$

Where υ is linear velocity of AGV, ω is angular velocity of AGV and random noise $w_k = \left[w_\upsilon, w_\omega \right]_k^{\mathrm{T}}$, where w_υ and w_ω are the random noise of linear velocity and angular velocity respectively.

(2)The observation model

We assume the noise of compass is zero-mean gaussian noise and the reading of compass is $z_{\mathrm{comp},k}$. Then the observation model is shown as follow:

$$z_{\mathrm{comp},k} = \varphi_{\mathrm{comp},k} + v_{\mathrm{comp}} \quad (16)$$

Where $\varphi_{\mathrm{comp},k}$ is true value of the compass and v_{comp} is zero-mean gaussian noise, that is $v_{\mathrm{comp}} \sim N\left(0, R_{\mathrm{comp}}\right)$ and R_{comp} is variance of v_{comp}. The acquisition data of e-compass is independent of the status variables of the system, so the bearing error of AGV estimated by compass will not be accumulated with time.

3.2 The Outer EKF Model

Because the inner EKF model is equivalent to the motion model of the outer EKF, we only need to build the observation model of the outer EKF. In this paper, the coordinate of the ith landmark m_i in the two-dimensional coordinate system is expressed as $\left(x_i, y_i\right)$. We assume that the coordinate system of lidar coincides with AGV's coordinate system and the coordinate of landmark m_i is $\left(x_i^{\mathrm{r}}, y_i^{\mathrm{r}}\right)$ in AGV's coordinate system. The measurement model of EKF SLAM is:

$$\begin{aligned} \mathrm{z}_{\mathrm{lasr},k,i} &= \mathrm{h}_i\left(X_k, m_i\right) + v_{\mathrm{lasr},k,i} \\ &= \begin{bmatrix} x_i^{\mathrm{r}} \\ y_i^{\mathrm{r}} \end{bmatrix} + v_{\mathrm{lasr},k,i} \\ &= \begin{bmatrix} \cos\varphi_{\mathrm{veh}} & \sin\varphi_{\mathrm{veh}} \\ -\sin\varphi_{\mathrm{veh}} & \cos\varphi_{\mathrm{veh}} \end{bmatrix} \begin{bmatrix} x_i - x_{\mathrm{veh}} \\ y_i - y_{\mathrm{veh}} \end{bmatrix} + v_{\mathrm{lasr},k,i} \end{aligned} \quad (17)$$

Where h_i is the observation model of the landmark m_i in ideal condition and $v_{\mathrm{lasr},k,i}$ is zero-mean gaussian noise.

4 SIMULATIONS AND ANALYSIS

In order to demonstrate the effectiveness and superiority of the algorithm, simulations were carried out on Matlab platform. Parameters of the AGV are shown in table 1 and figure 2 shows the simulation environment. The experimental environment covers an area of $80 \times 80\mathrm{m}^2$ and there are five waypoints as A, B, C, D and E. Forty-two landmarks are set up along the path of A-B-C-D-E-A. Two situations were simulated according to the open-loop and closed-loop path.

The path is open-loop when AGV moves along the path of A-B-C-D-E in the simulation. Standard deviation of noise caused by compass is set as one degree. The pose error of AGV was shown in figure 3 after 100 times simulations. It shows that when path is open-loop, the position errors and bearing errors caused by using the conventional method will diverge with time going by. While the position errors and bearing errors caused by the method proposed in this paper maintain in the vicinity of zero. The simulation shows that the method proposed in this paper can reduce pose error of AGV effectively when its path is open-loop. Besides, AGV can create an accurate environment map under the condition of a closed-loop path.

Table1: Parameters of the simulation

Parameter	Value
Noise standard deviation of velocity（m/s）	0.3
Noise standard deviation of angular velocity（rad/s）	π/180
Noise standard deviation of distance measured by lidar（m）	0.1
Noise standard deviation of angle measured by lidar（rad）	π/180
The maximum distance measured by lidar（m）	30
The angle of view of lidar（°）	180

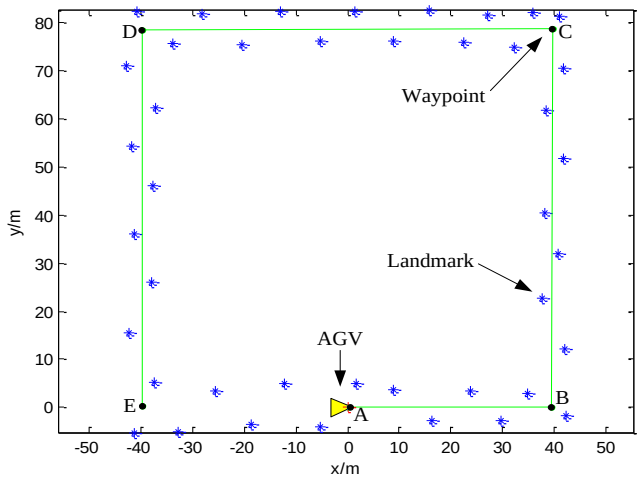

Figure 2: Simulation environment

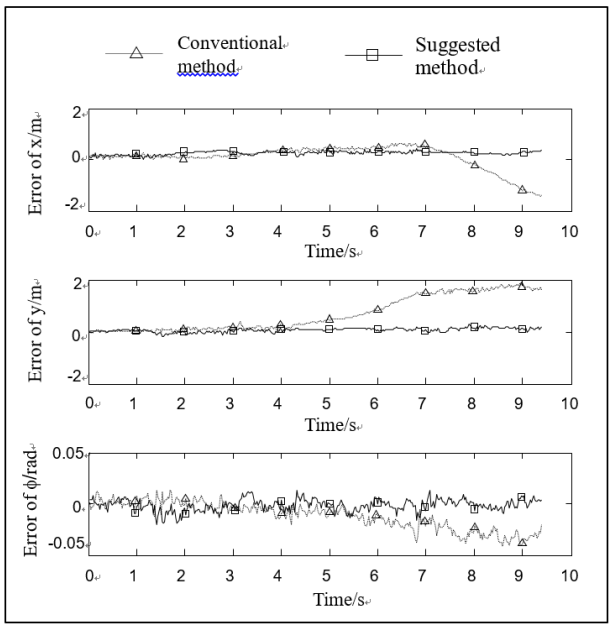

Figure 3: Error comparison of two methods

It's about 100 seconds when AGV moves from waypoint E to waypoint A along the closed-loop path of A-B-C-D-E-A in the simulation. Standard deviation of noise caused by compass is set as one degree. The average values of evaluation index for AGV in simulations with open-loop and closed-loop path of all time are shown in table 2. These evaluation indexes are similar with that of reference [7]. Comparative data indicates that the conventional EKF SLAM relies heavily on closed-loop path to reduce pose error of AGV and then establish a relatively accurate environment map. While the idea of EKF SLAM fused with absolute bearing information proposed in this paper can build relatively accurate map without depending on the closed-loop path.

5 EXPERIMENTS AND DISCUSSION

In order to further verify the effectiveness of suggested theories and methods, self-developed AGV experimental platform with laser navigation system was used to accomplish localization and mapping experiments. The experimental environment is a semi-closed and vacant room whose length is 7.35m and width is 4.85m. ICP (Iterated Closest Points) algorithm was adopted to obtain the AGV's estimated pose as the true value[8]. By comparing the estimated error of AGV's pose between the EKF SLAM approach fused with absolute bearing information proposed in this paper and conventional EKF SLAM approach, it can be illustrated that the former method was better than the latter.

Figure 4 shows the real experimental environment and its plane model. The speed of the AGV is 0.1m/s and it takes 280s to accomplish the 14.3m path in this environment.

Figure 5 shows the estimated pose error of AGV by using two kinds of method. It can be seen from the graph that the estimated pose error caused by using proposed method in this paper is stable. It floats up and down around zero, superior to conventional method. Mean square root(rms) error of pose estimated by two methods are 0.0091m and 0.0268m respectively, as shown in table 3.

Table 2: The average values of evaluation indexes

Method	Path	Rms error of AGV's position（m）	Rms error of AGV's bearing（rad）	The ormalized estimated squared error of AGV's pose
Conventional method	Open-loop	0.7120	0.0116	3.8429
	Closed-loop	0.5105	0.0081	3.8187
Suggested method	Open-loop	0.2079	0.0051	3.4628
	Closed loop	0.2059	0.0048	3.4757

(a)Real environment (b)Plane model

Figure 4: Experimental environment

Table3: RMS error of two methods

Ways	RMS error
Conventional method	0.0268m
Suggested method	0.0091m

Figure 6 shows trajectories of AGV estimated by two methods. As shown in the graph, the trajectory of AGV estimated by the method proposed in this paper is closer to the true trajectory, while the trajectory estimated by the conventional method is far away from the real estimated path. According to reference [9], in order to compare two methods more directly, grid map was built according to the estimated trajectory of AGV and the map is obtained as shown in figure 7. From the grid map it can be seen that the environmental boundary contour established by the conventional method is fuzzy, while the environmental boundary contour established by the method proposed in this paper is relatively clear.

6 CONCLUSIONS

The conventional EKF SLAM approach is able to achieve certain accuracy in localization and mapping when the AGV's trajectory is closed-loop. But the accuracy can not meet the requirement under the circumstance a higher flexibility is needed. (changeable environment and open-loop motion path). The EKF SLAM approach fused with bearing information of compass can effectively compensate for the insufficient. Localization of AGV and mapping of the environment with enough precision can be achieved even though the motion path is unknown. The method is also superior to the conventional approach when the path is open-loop.

Nowadays AGV has been widely used in warehousing and manufacturing. In the future, AGV can also be used in tobacco, pharmaceutical, food, chemical industry for handling operations have clean, safe, no pollution emissions and other special requirements. And all kinds of dangerous sites such as the battlefield demining or nuclear radiation environment.

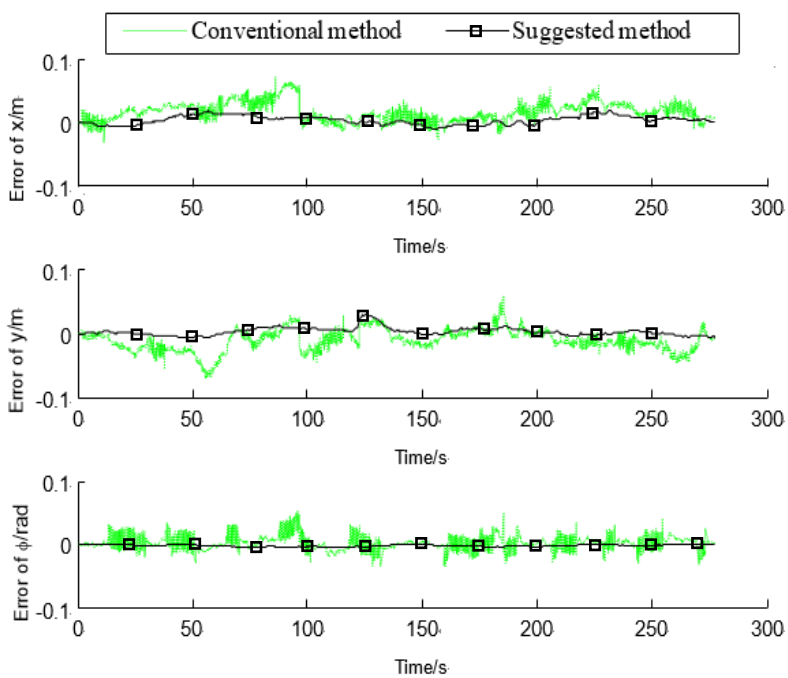

Figure 5: Comparison on estimated pose errors

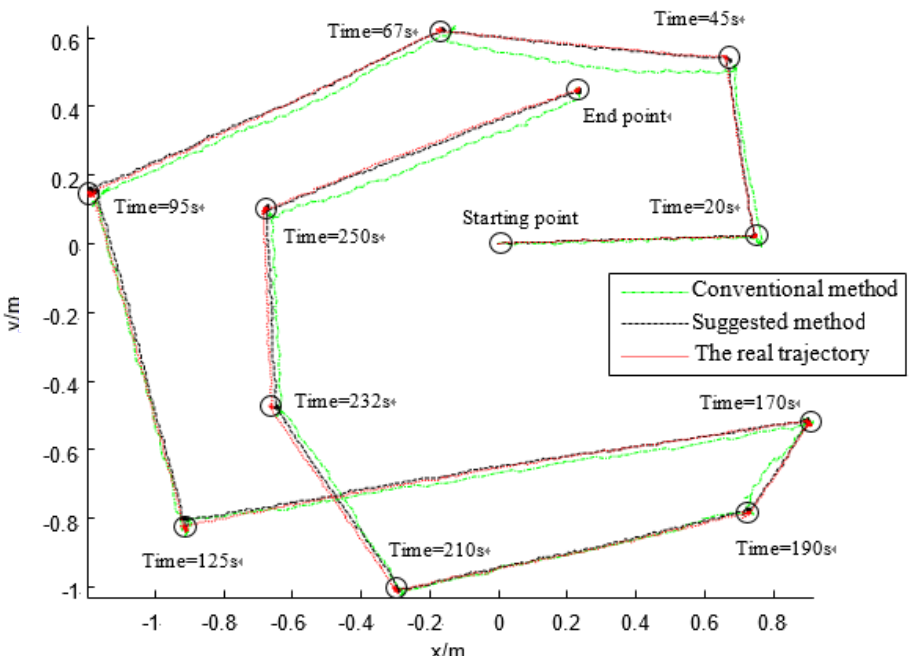

Figure 6: Comparison on estimated track of AGV by two ways

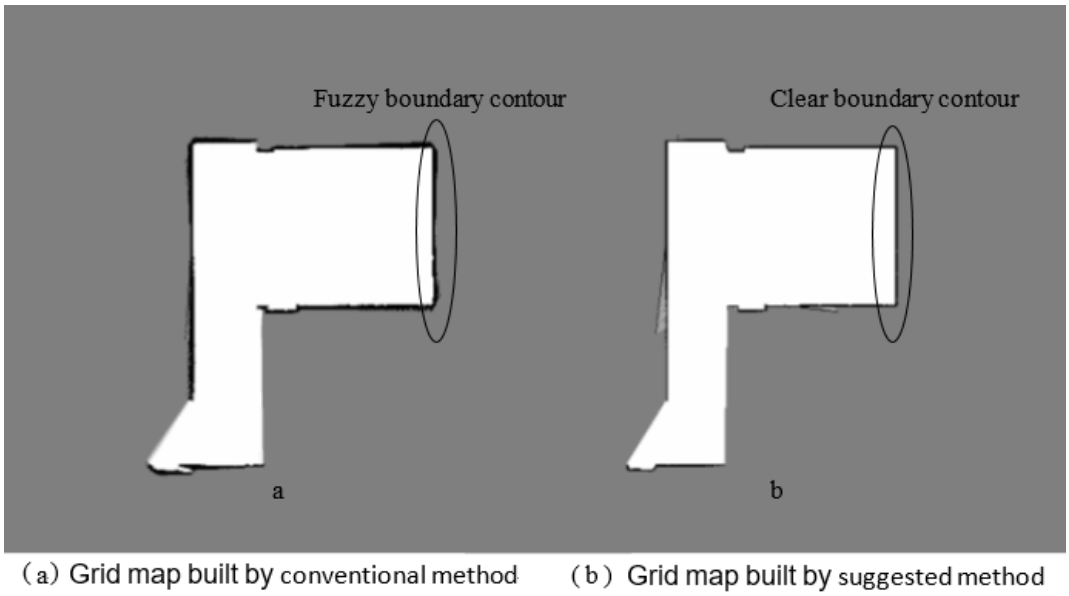

Figure 7: Comparison on grid Map created by two ways

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