Vision Based Navigation System of Autonomous Mobile Robot*

(Planning of Landmark Sensing Considering Environmental Conditions)

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We propose the Planning of Landmark Sensing (PLAS) considering environmental conditions for autonomous mobile robots. When a robot moves, the robot usually resets accumulated position errors by sensing the landmark. In previous works, these errors are estimated based on robot models, and Kalman Filter is used to reset the errors after the landmark sensing. Based on this method, only the relation of the robot and the landmark position is considered to influence the observation noise of Kalman Filter. But in the actual visual landmark sensing, environmental conditions, like position of lighting and brightness of room, are likely to cause the misrecognition of landmark. Then we consider environmental conditions for the observation noise. This helps our system to recognize the possibility of the misrecognition in bad sensing environments. As a result of the consideration of the environmental conditions, our navigation system can navigate robots precisely, even if the environments are not suitable for the landmark sensing.

Key Words: Moving Robot, Image Processing, Planning of Landmark Sensing, Kalman Filter, Navigation System, Inspection Robot, Learning, Adaptation, Environmental Conditions, Sensing Reliability

1. Introduction

In construction sites, robots have been expected to execute the dangerous and hard work as a substitute for human labors and a lot of robots for construction sites are studied^{(1),(2)}. But almost all works in these places require continuous movements. So the navigation system is required for autonomous mobile robots so as to identify their position and orientation correctly.

When a robot moves, the robot identifies its position and orientation based on outputs of encoders which are attached to the robot wheels. This method is called dead-reckoning. But if the robot moves based on the only dead-reckoning, accumulated position errors are created. Then other works introduced outer sensors, such as ultrasonic sensor^{(3),(4)}, laser range finder^{(5),(6)} and CCD camera^{(7),(8)}, in order to reset the accumulated position errors by measuring the relation between robots and environments. In these outer sensors, the CCD camera is used frequently, because it can recognize not only the landmark but also an unexpected obstacle.

We are developing the Air Conditioning Equipment Inspection Robot in Fig.1 for the purpose of automating the air volume inspection of air conditioning systems in constructing buildings. This robot finds out diffusers like in Fig.2 from its environment by using the CCD cameras, and moves to the place right under the diffuser. When the robot reaches under the diffuser, the robot lifts the sensor hood to the diffuser

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Fig. 1 Air conditioning equipment inspection robot

Circular Type Quadrangular Type

Fig. 2 Diffusers of air conditioning system (Anemo)

and measures the air volume flowing out from the diffuser. In our previous works, we proposed the navigation system of the robot which recognizes ceiling landmarks by the CCD cameras⁽⁹⁾, the recognition algorithm of landmark⁽¹⁰⁾ and the air volume inspection system⁽¹¹⁾. In these works, our system does not consider the measurement noise and the position error created during the robot movement. Then the robot is sometimes lost, because the robot does not sense the diffuser again during the movement after the robot senses at the start point.

In this paper, we propose a method of the Planning of Landmark Sensing (PLAS) which helps the navigation system to decide the landmark sensing point automatically. In other works⁽¹²⁾⁻⁽¹⁴⁾, the position errors of robots are estimated based on the robot model, and the Kalman Filter is used to reset the errors after the landmark sensing. In this method, only the relation of the robot and the landmark position is considered for the calculation of the observation noise of the Kalman Filter. But environmental conditions, like a position of lighting and brightness of room, are likely to cause the misrecognition of the landmark in usual landmark sensing by the CCD

Fig. 3 Model of a mobile robot

camera. Then we consider environmental conditions for the estimate of the observation noise of the Kalman Filter in order to realize the possibility of the misrecognition in case of bad sensing environments properly.

In PLAS, robots can plan good sensing points, because environmental conditions are considered for the estimate of the observation noise of the Kalman Filter. Further, the wheel noise of the robot model is adapted according to the floor condition of the building in PLAS. Using the proper value for the wheel noise is very important, because the position error created by the moving robot is estimated based on the robot model. But other works are using the fixed value for the wheel noise.

2. Modeling of Robot

When a mobile robot moves, the robot controls their actuators according to the moving wheel angle measured by the inner sensor such as encoders. But the robot always creates the accumulated position error because of the system noise or the uneven floor. In order to plan suitable landmark sensing points, we must estimate the robot error precisely based on the robot model. In this chapter, we explain our robot model.

Our robot is moved by two driving wheels which move independently. Then we refer the robot model proposed by Komoriya⁽¹⁴⁾. We set the parameters like in Fig. 3. u_{rt} and u_{lt} are circumference speeds of right and left wheels. l is the distance between right and left wheels. u_{rt} and u_{lt} are system inputs. Then our system can be expressed like Eq. (1),

$$\mathbf{x}_{t+1} = f_t(\mathbf{x}_t, \mathbf{u}_t + \mathbf{v}_t) + \mathbf{w}_t \quad (1)$$

where

$$\mathbf{x}_t = (x_t, y_t, \theta_t)^T$$

$$\mathbf{u}_t = (u_{rt}, u_{lt})^T.$$

Here $\mathbf{v}_t$ is the wheel noise caused by the alternation of the wheel speed and $\mathbf{w}_t$ is the system noise. Both $\mathbf{v}_t$ and $\mathbf{w}_t$ are the white noise. Covariance matrixes of these are $\mathbf{V}_t$ and $\mathbf{W}_t$. $\hat{\mathbf{x}}_t$ is the estimate of the state vector $\mathbf{x}_t$, and $\mathbf{P}_t$ is the covariance matrix of the state vector $\mathbf{x}_t$. $\hat{\mathbf{x}}_t$ and $\mathbf{P}_t$ are altered by Eqs. (2) and (3)

$$\hat{\mathbf{x}}_{t+1} = f_t(\hat{\mathbf{x}}_t, \mathbf{u}_t) \quad (2)$$

$$P_{t+1} = A_t P_t A_t^T + F_t V_t F_t^T + W_t \quad (3)$$

$$A_t = \begin{bmatrix} 1 & 0 & -\frac{u_{rt} + u_{lt}}{2} \sin \theta_t \\ 0 & 1 & \frac{u_{rt} + u_{lt}}{2} \cos \theta_t \\ 0 & 0 & 1 \end{bmatrix},$$

$$F_t = \begin{bmatrix} \frac{1}{2} \cos \theta_t & \frac{1}{2} \cos \theta_t \\ \frac{1}{2} \sin \theta_t & \frac{1}{2} \sin \theta_t \\ \frac{1}{l} & -\frac{1}{l} \end{bmatrix}$$

3. Estimation of Position Error based on Extended Kalman Filter

3.1 Extended Kalman Filter

The robot estimates the position error based on the model in chapter 2, and the robot senses the landmark when the error reaches to the acceptable maximum position error E_p . Measured data includes the noise because of the system noise and the limit of resolving power of the CCD camera. Then we utilize the Extended Kalman Filter⁽¹⁵⁾ to estimate the position error after the measurement, because the noise of the measured data is the white noise in this study.

Measured data $y_t (l \times 1)$ is expressed by using the state vector x_t and observation noise q_t like Eq.(4).

$$y_t = h_t(x_t) + q_t \quad (4)$$

Here, $h_t(x_t)$ is the one dimensional non-linear vector function and can be differentiated by x_t . Then Eq.(4) approximates to Eq.(5) around $\hat{x}_t$.

$$h_t(x_t) = h_t(\hat{x}_{t/t-1}) + H_t(x_t - \hat{x}_{t/t-1}) \quad (5)$$

$$H_t = \left(\frac{\partial h_t}{\partial x_t} \right)_{x_t = \hat{x}_{t/t-1}} \quad (6)$$

Here, $H_t (l \times n)$ is the observation matrix. Then Eq.(7) is acquired by substituting Eq.(4) for Eq.(5).

$$y_t - h_t(\hat{x}_{t/t-1}) + H_t \hat{x}_{t/t-1} = H_t x_t + q_t \quad (7)$$

$$\eta_t = y_t - h_t(\hat{x}_{t/t-1}) + H_t \hat{x}_{t/t-1} \quad (8)$$

Further, Eq.(9) is acquired by substituting Eq.(8) for Eq.(7).

$$\eta_t = H_t x_t + q_t \quad (9)$$

Based on the Extended Kalman Filter, we can estimate the robot position similarly with the linear case. Then x_t and P_t are altered based on Eqs.(10) and (11).

$$\hat{x}_{t/t} = \hat{x}_{t/t-1} + K_t [y_t - h_t(\hat{x}_{t/t-1})], \quad \hat{x}_{0/-1} = x_0 \quad (10)$$

$$P_{t/t} = P_{t/t-1} - K_t H_t P_{t/t-1}, \quad P_{0/-1} = P_0 \quad (11)$$

$$K_t = P_{t/t-1} H_t^T [H_t P_{t/t-1} H_t^T + Q_t]^{-1} \quad (12)$$

$$Q_t = \begin{bmatrix} \sigma_r^2 & 0 \\ 0 & \sigma_a^2 \end{bmatrix}$$

Our system can plan the suitable sensing points by estimating the observation noise Q_t of the Extended Kalman Filter gain K_t according to the difference of

Fig. 4 Position of robot and landmark

environments.

3.2 Observation matrix

In this section, we explain the observation matrix used in the Extended Kalman Filter. Usual landmarks are classified to the line landmarks whose position are expressed like $ax + by + cz = 1$ in the robot coordinate systems, and spot landmarks which are expressed like (x, y, z) . Edges of the floor and the corridor are line landmarks, and the fluorescence lamp is a spot landmark. In our study, we utilize a spot landmark. Because the error of distance between the robot and the ceiling is small, we suppose that the landmark is on the same level plane with the robot. The relation between the robot and the landmark is expressed in Fig. 4. (x_t, y_t) is the robot position and (x_m, y_m) is the landmark position. Then the landmark distance r and the direction α are explained by Eqs.(13) and (14).

$$r = \sqrt{(x_t - x_m)^2 + (y_t - y_m)^2} \quad (13)$$

$$\alpha = \tan^{-1} \frac{y_t - y_m}{x_t - x_m} - \theta_t \quad (14)$$

Position r and direction α correspond to $h_t(x_t)$ in Eq.(4) and expressed like Eq.(15).

$$h_t(x_t) = \begin{bmatrix} h_t^{(1)}(x_t) \\ h_t^{(2)}(x_t) \end{bmatrix} = \begin{bmatrix} r \\ \alpha \end{bmatrix} \quad (15)$$

As a result, the observation matrix H_t is calculated by Eq.(6) and shown in Eq.(16).

$$H_t = \begin{bmatrix} \frac{\hat{x}_t - x_m}{\sqrt{D}} & \frac{\hat{y}_t - y_m}{\sqrt{D}} & 0 \\ -\frac{\hat{y}_t - y_m}{D} & \frac{\hat{x}_t - x_m}{D} & -1 \end{bmatrix} \quad (16)$$

$$D = (\hat{x}_t - x_m)^2 + (\hat{y}_t - y_m)^2$$

4. Planning of Landmark Sensing (PLAS)

In this chapter, we propose the Planning of Landmark Sensing (PLAS) considering environmental conditions. PLAS has the network structure like in Fig. 5. Inputs of network are environmental conditions and outputs are sensing reliability R and observation noise σ_r, σ_a . Sensing reliability R is used in the wheel noise adaptation, and observation noise σ_r, σ_a are used as the observation noise of the Extended

Fig. 5 System diagram of PLAS

Kalman Filter.

4.1 Environmental conditions

Inputs of PLAS are environmental conditions such as lighting condition, present position of robot and so on, which are likely to influence the measurement results. Brightness of the room and position of the lighting mostly influence the measurement results, because our system recognize the ceiling landmark by the CCD camera. We also consider the system noise of the camera system. Then we utilize 10 environmental conditions in Table 1 as the inputs of PLAS. Here, the membership grade of FTM IM of Input 8 means the output of the landmark recognition algorithm, Fuzzy Template Matching (FTM), which we proposed in the previous work⁽¹⁰⁾. In FTM, we model the landmark in the image by Fuzzy Template (FT), and the place which has the largest fitness value is decided to be a landmark place. Other inputs are explained in Fig. 6.

Here, the environmental conditions in Table 1 are considered to be useful for our system which recognizes ceiling landmarks, while other conditions would be considered to be useful in other systems.

4.2 Sensing reliability (R) and observation noise (σ_r, σ_a)

When we input the environmental conditions into PLAS, inputs are normalized to the value R_i by the reliability function which consists of gauss function Eq.(17).

$$G(a, b, c, I_i) = a \cdot \exp[-\{0.83255(I_i - c)/b\}^2] \quad (17)$$

Here, we define the each reliability function in Table 2 by experiments.

Outputs of the network, sensing reliability $R(=O_1)$ and observation noise $\sigma_r(=O_2)$, $\sigma_a(=O_3)$, are calculated by Eq.(18). Here, n is the number of inputs, W_{ij} is the weight of node between R_i and O_j , and u_0 is the constant value.

Table 1 Inputs of PLAS

Input	Environmental Conditions	Parameters
I_1	Brightness of Room	B
I_2	Direction of Lighting	θ_l
I_3	Distance of Lighting	d_l
I_4	Tilting Angle of Camera	θ_{l1}
I_5	Target Rotation in Image	θ_{l2}
I_6	Direction of Landmark	θ_v
I_7	Distance of Landmark	d
I_8	Membership Grade of FTM	IM
I_9	Reliability of Present Position	$P_{11}+P_{22}$
I_{10}	Reliability of Present Orientation	P_{33}

Table 2 Reliability function

Input	Reliability Function	Unit
I_1	if($I_1 < 50$) $R_1 = 1 - G(1.25, 50, I_1)$ else $R_1 = 0$	lx
I_2	if($I_2 < 10$) $R_2 = 1 - G(1.3, 10, I_2)$ else $R_2 = 0$	m
I_3	if($I_3 < 90$) $R_3 = 1 - G(1.90, -180, I_3)$ else if($-90 \leq I_3 < 90$) $R_3 = G(1.90, 0, I_3)$ else $R_3 = 1 - G(1.90, 180, I_3)$	deg
I_4	$R_4 = G(1.45, 0, I_4)$	deg
I_5	if($I_5 < -67.5$) $R_5 = G(1.22, 5, -90, I_5)$ else if($-67.5 \leq I_5 < -22.5$) $R_5 = 1 - G(1.22, 5, -45, I_5)$ else if($-22.5 \leq I_5 < 22.5$) $R_5 = G(1.22, 5, 0, I_5)$ else if($22.5 \leq I_5 < 67.5$) $R_5 = G(1.22, 5, 45, I_5)$ else $R_5 = 1 - G(1.22, 5, 90, I_5)$	deg
I_6	$R_6 = G(1.90, 0, I_6)$	deg
I_7	$R_7 = G(1.10, 3, I_7)$	m
I_8	$R_8 = I_8$	-
I_9	$R_9 = G(1.0, 5, 0, I_9)$	m
I_{10}	$R_{10} = G(1.30, 0, I_{10})$	deg

Fig. 6 Environmental conditions

$$O_j = \text{sigmoid}\left(\sum_{i=1}^n W_{ij} R_i + \text{const}\right) \quad (18)$$

$$\text{sigmoid}(x) = \{1 + \tanh(x/u_0)\} / 2$$

Here, the weight of node W_{ij} are learned in various environments in advance. Sensing reliability R is used in the wheel noise adaptation of the next section, and observation noises σ_r, σ_a , are used as the observation noise Q_t of the Extended Kalman Filter. By using the outputs of PLAS, the observation noise Q_t always has the suitable value to the robot environments.

4.3 Wheel noise adaptation

In order to plan the suitable sensing point, we must use the suitable value for wheel noise V_t . But

the wheel noise is different according to the floor condition. The wheel noise on wooden floor and carpet are different for example. Thus, whenever the robot is introduced to the new environment, the robot is required to compensate the wheel noise automatically according to the floor condition so that the human operator may not give a new wheel noise to the robot. If we try to change the wheel noise according to the measurement results directly, we cannot get the suitable wheel noise, because the measurement results include the observation noise. Then both the measurement results and the observation noise should be referred for the estimation of the wheel noise V_i .

Here, x_{di} is a length of the robot movement estimated by the wheel control signal, and x_{ai} is a length of the robot movement estimated by the measurement results. n is the sensing number. In our system, we adjust the wheel noise based on Eq. (19) by using the sensing reliability R , whenever robot moves the regular length.

$$V_{t11} = V_{t22} = \sum_{i=1}^n \{R(x_{ai} - x_{di}/x_{di})^2/n\} \quad (19)$$

4.4 Planning of suitable sensing point

In other works⁽¹²⁾⁻⁽¹⁴⁾, the robot senses the landmarks, whenever the estimated position error is accumulated to the maximum acceptable error, whether robot is near the goal or the sensing condition is not suitable like in Fig. 7. But the robot usually confirms the position when it reaches the goal.

The landmark recognition in bad sensing condition is likely to cause the misrecognition. Then we plan the sensing point based on the map information before the robot starts and during the movement. In the planning, we consider the following two rules.

(a) When the sensing point is near the goal (if the distance between the goal and the sensing point is less than D_s),

(b) If the difference between the position error of before sensing and after sensing is small (less than ΔE),

If a sensing point satisfies above rules, we compensate the sensing point by reducing the maximum acceptable position error based on Eq. (20) like in Fig. 8.

$$E_p^{(+)} = E_p^{(-)} - \beta(E_p^{(-)} - E_g)/n \quad (20) \\ (0 < \beta \leq 1)$$

In this equation, E_p is the acceptable position error, and E_g is the difference between the maximum acceptable position error and the position error of the robot at the goal. We usually use $\beta=1$. But if the number of sensing increases after the compensation compared with before, we use $\beta < 1$ and plan the sensing point again. Here, (+) means the error after the compensation, and (-) means the error before the

(a) In case of near sensing point to landmark

(b) In case of unsuitable sensing point for sensing

Fig. 7 Decision of sensing point in previous method

Fig. 8 Compensation of sensing point

compensation.

Here, this planning of sensing is done by PLAS. But because the brightness of room (B) and membership grade of FTM (IM) are unknown at the start point, we use the fixed value for these parameters. Then we plan the sensing point based on the only map information at the start point. But our robot plan the sensing point again after the each sensing, and actual values are used for the brightness of room (B) and membership grade of FTM (IM) in this case. Figure 9 explains the procedure of planning of landmark sensing in this work.

5. Simulation

In the simulation, we use the course in Fig. 10, on which there are 17 points right under the landmarks (Quadrangular Type Anemo and Circular Type Anemo). The robot passes the each point once in a round. The order of the landmark which the robot visits is defined in the map in advance. We change the lighting position and brightness of the room in this course. Here the robot has the map which includes the information of landmark and lighting position, and fixed value $V_{t11} = V_{t22} = 0.000001$ are used for the wheel noise.

Figure 10(a) is the case of average brightness

Fig. 9 Flowchart of decision of sensing point

Fig. 10 Simulation results

and location of lighting, Fig. 10(b) is the case of too near lighting from landmark and Fig. 10(c) is the case that brightness of the room is different locally. Brightness of the room in Fig. 10(a) and (b) is

Table 3 The number of sensing in each condition

Landmark	(a)Average Environment	(b)Too Near Lighting	(c)Changed Brightness
1	5	5	5
2	2	2	3
3	2	2	3
4	6	8	6
5	2	3	2
6	2	3	2
7	5	5	4
8	3	3	3
9	7	8	6
10	3	3	3
11	3	3	3
12	6	8	7
13	5	6	5
14	3	2	3
15	13	16	10
16	2	2	2
17	2	2	2
Total	71	81	69

equally 1000 [lx]. Table 3 indicates the sensing number which the robot senses during the movement from one landmark to another.

As results of simulation, if the lighting is located too near to the landmark or the room is too dark, sensing number tends to increase. And sensing numbers are likely to decrease, as the brightness of the room becomes the normal condition. These results show that PLAS plans the suitable sensing points according to the sensing environments.

6. Experiments

6.1 Air conditioning equipment inspection robot

The robot, which we use in experiments, is Air Conditioning Equipment Inspection Robot⁽⁹⁾⁻⁽¹¹⁾ in Fig. 1. This robot is developed to automate the measurement of air volume flowing out from air diffusers.

The system diagram of our robot is shown in Fig. 11. This robot has 2 CPU. One CPU controls actuators and air conditioning equipment inspection system, and the other controls camera system and navigation system. Two CPU communicate by RS-232C.

In this section, we explain the specifications of our robot.

6.1.1 Image recognition system Diffusers of air conditioning system are not only landmarks of navigation system but also the targets of the inspection for this robot. Diffusers are recognized by two CCD cameras. One camera (Main Camera) is located in front of the robot with the revolving device which can pan and tilt in order to find out any landmark from the environment. The other (Small Camera) is

Fig. 11 System diagram of robot

located on the center of the robot facing to the upper direction and the robot uses this camera right under the landmark in order to compensate its position and orientation. For the recognition algorithm, we use Fuzzy Template Matching (FTM)⁽¹⁰⁾, and a recognition of a diffuser requires about four seconds by using two transputers. FTM can recognize landmarks precisely, and the error of image recognition is 4 pixels in the image on the average.

6.1.2 Navigation system Our robot has a map of the moving space, and navigation system confirms the present robot position on the map whenever it senses the landmark. The map includes not only the movable area but also the positions of the landmarks and the lighting on the ceiling. The navigation system navigates the robot according to the map until the inspections of all diffusers are finished. The navigation system also controls the total sequence of the robot including movement, inspection and so on.

6.1.3 Actuator This robot has 2 driving wheels and 2 casters (total 4 wheels). This robot moves at the speed of 2 km/h (maximum speed) by the combined movement of forward, reverse and rotation.

6.1.4 Air conditioning equipment inspection system This robot has a sensor hood above the robot to measure the volume and the temperature of the air flowing out from diffusers of air conditioning system. When the robot reaches right under the diffuser, the robot lifts and attaches the sensor hood to the ceiling diffuser, and measures the volume and the temperature of the air flowing out from the diffuser.

6.2 Experimental method

In the experiments, we made the robot move on

Fig. 12 Experimental course

the experimental course in Fig. 12 continuously with the navigation system with PLAS and the previous our navigation system. Each system navigates the robot so that the robot may start under Landmark 0 and return under the Landmark 0 via under Landmark 1 to 6. Under the each landmark, the robot compensates its position and orientation in order to inspect a air diffuser. During the navigation of each system, we made the lighting on and off in order to change the sensing condition. Here the lighting is 50cm from the diffuser.

6.3 Experimental result

Figure 13 shows the trajectories of the robot in the experiments. The navigation system with PLAS navigates the robot continuously without losing sight of landmarks, while the previous navigation system loses sight of the landmark in case the lighting is on at the Landmark 5. In Fig. 13(b), the sensing number increases during the movement, although the lighting is on. This is because robot can recognize the diffuser without the lighting in the daytime, and the observation noise of the Extended Kalman Filter is rather smaller in case the lighting is off than in case lighting is on.

Here, the previous system does not sense landmark during the movement from one diffuser to another, because it does not estimate the accumulated position error during the movement. But in PLAS, the robot senses the landmark on the way to one landmark from another, if only the position error, estimated by the robot model, accumulates to the acceptable error.

Table 4 and Fig. 14 indicate the alternation of the number of the sensing and wheel noise V_t , when we made the robot move on the experimental course in Fig. 12 continuously. As results, the number of the sensing decreases according to the convergence of the wheel noise V_t . This result shows sensing points are planned more suitable points, as the wheel noise

(a) In case of navigation by PLAS (Lighting is on)

(b) In case of navigation by PLAS (Lighting is off)

(c) In case of navigation by previous system (Lighting is on)

Fig. 13 Robot trajectories

converges on the suitable value during the iteration.

In these experiments, we could prove PLAS can navigate the robot precisely in the bad sensing condition by increasing the number of the sensing. Further PLAS can adapt the wheel noise to the robot environment and find out the best sensing point in any environment.

7. Conclusions

In this paper, we proposed the Planning of Landmark Sensing (PLAS) considering environmental

Table 4 Alternation of the number of sensing and wheel noise

Round	Main Camera Sensing (Times)	Small Camera Sensing (Times)	Total Sensing (Times)	Image Recognition Accuracy	Average of Error (mm)	Wheel Noise V_i
1	11	34	45	0.795	76.43	0.0020
2	23	19	42	0.785	57.86	0.0053
3	22	20	42	0.89	54.07	0.0040
4	22	19	41	0.905	44.66	0.0047

Fig. 14 Alternation of the number of sensing and wheel noise

conditions for autonomous mobile robots.

Characteristics of our work are

(i) PLAS estimates the observation noises of the Extended Kalman Filter based on the environmental conditions such as the lighting position and the brightness of the room,

(ii) PLAS plans the suitable sensing points by estimating the accumulated position error based on the robot model and the Extended Kalman Filter and

(iii) PLAS compensates the wheel noise of the robot model automatically during the movement.

As results, PLAS can plan the suitable sensing points according to the robot environments.

In present system, we utilize only the lighting position and the brightness of the room for the environmental conditions actually. Then we must try to find out the parameters which can influence the measurement results, and add them to inputs of PLAS.

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