

Position Estimation Using Neural Network for Navigation of Wheeled Mobile Robot (WMR) in a Corridor

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Abstract: This paper describes position estimation algorithm using neural network for the navigation of the vision-based wheeled mobile robot (WMR) in a corridor with taking ceiling lamps as landmark. From images of a corridor the lamp's line on the ceiling in corridor has a specific slope to the lateral position of the WMR. The vanishing point produced by the lamp's line also has a specific position to the orientation of WMR. The ceiling lamps have a limited size and shape like a circle in image. Simple image processing algorithms are used to extract lamps from the corridor image. Then the lamp's line and vanishing point's position are defined and calculated at known position of WMR in a corridor. To estimate the lateral position and orientation of WMR from an image, the relationship between the position of WMR and the features of ceiling lamps have to be defined. But it is hard because of nonlinearity. Therefore, data set between position of WMR and features of lamps are configured. Neural network are composed and learned with data set. Back propagation algorithm(BPN) is used for learning. And it is applied in navigation of WMR in a corridor.

Keywords: position estimation, neural network, image processing, wheeled mobile robot

1. INTRODUCTION

The localization problem is critical to any autonomous vehicle. To complete this, the orientation and position of a vehicle with respect to the environment should be obtained. There are two kinds of vision-based approaches to solving the localization problem: the map approach [1~2] and the landmark approach [3~5]. The first requires a detailed map of the environment. The features extracted from sensor data are matched with the features in the map to estimate the vehicle location. But it is difficult to establish the correspondence between sensor data and the map. The second takes advantage of landmarks in the environment. The knowledge of landmark properties is utilized to locate the vehicle.

This paper describes lateral position and orientation estimation algorithm for the navigation of the vision-based wheeled mobile robot (WMR). These two kinds of information are required for WMR to drive safely in a corridor. The ceiling lamps are taken as landmark. However, the lamp's line on the ceiling in corridor has a specific slope to the lateral position of the WMR. The vanishing point produced by the lamp's line also has a specific position to the orientation of WMR. Therefore, we make up two spaces for the slope of lamp's line and the position of vanishing point. While WMR is driving, a camera captures front image and a board computer processes it. Then, the slope of the lamp's line and the position of vanishing point are produced by simple image processing algorithm. After then, we derive two linear approximation formulas from those two spaces. But their relationship is nonlinear. So there are some errors when two linear approximation formulas are used. To solve this problem, in this paper, neural network is composed and learned. Using the result, we estimate the lateral position and the orientation of the WMR for navigation.

The organization of this paper is as follows: In section 2, the relationship among the slope of the lamp's line, the position of vanishing point and the lateral position and the orientation of WMR is described. An algorithm to extract the image of the ceiling lamp is shown in section 3. Two method are compared to estimate the lateral position and orientation of WMR: linear approximation method and neural network. Algorithms about these are in section 4. In section 5, the

computer simulations and experiment results are shown. Section 6 includes concluding remarks and some future works.

2. RELATION BETWEEN WMR'S POSTURE AND LANDMARK

2.1 Relation between the slope of lamp's line and the lateral position of WMR

Fig. 1(a-b-c) shows corridor images that are captured by the camera at different lateral positions as Fig. 1. While the WMR is driving on the central line of the corridor, the lamp's line looks like a vertical line. However, the WMR is driving right or left from the central line, the lamp's line has a specific slope. That is, the slope of the lamp's line is influenced by the lateral position of WMR. But the position of vanishing point isn't. These are shown in Fig. 1(a-b-c).

To investigate this relation, images are taken at known lateral position and orientation of WMR in a corridor. These images were captured at intervals of 10cm, from -80cm to 80cm on the basis of center of corridor and intervals of 2.5°, from -12.5° to 12.5° on the basis of the front. From these images, the slope of lamp's line and the position of vanishing point were calculated. Using these data sets, relation plane was composed. Fig. 2 is the space that shows the relationship between the slope of the lamp's line, the lateral position and the orientation of the WMR.

2.2 Relation between the position of vanishing point and the orientation of WMR

Fig. 3(a-b-c) shows corridor images that are captured by the camera at orientation as Fig. 3. When the WMR is heading straightforward, the position of vanishing point is located at the centers of images. However, if WMR is heading leftward or rightward, the position of vanishing point moves to right or left from the center point. These are shown in Fig. 3(a-b-c).

By the same way, using the data set in section 2.1, relation plane like Fig. 4 is configured and shows the relationship between the slope of the lamp's line, the lateral position and the orientation of the WMR.

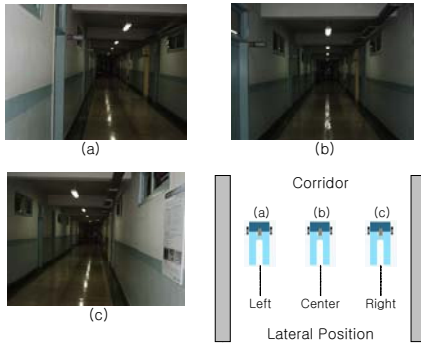


Fig. 1. The variation of the slope of lamp's line according to the lateral position of WMR

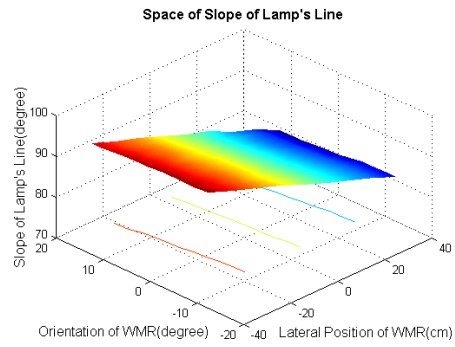


Fig. 2. Relationship between the lateral position, orientation of the WMR and the slope of the lamp's line

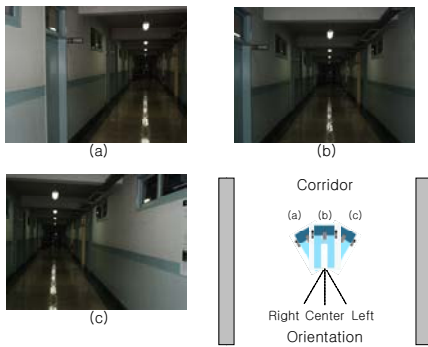


Fig. 3. The variation of the position of vanishing point according to the orientation of WMR

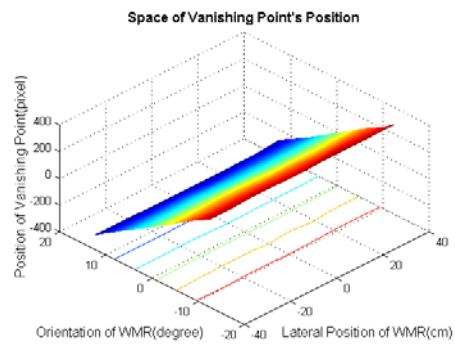


Fig. 4. Relationship between the lateral position, orientation of the WMR and the position of vanishing point

2.3 Definition of landmark's features

In this paper, lamps on the ceiling are taken as landmark. In corridor image, there are two feature according to the lateral position and orientation of WMR : the slope of lamp's line and the position of vanishing point.

These features are represented in Fig. 5. The slope of lamp's line is defined as the angle between vertical line and the line that is generated by the lamps. Vanishing point is defined as the cross point of horizontal line and lamp's line. The position of vanishing point is the distance from center of image.

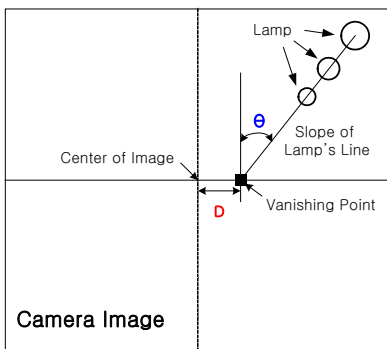


Fig. 5. Defining the slope of lamp's line and the position of vanishing point

3. IMAGE PROCESS ALGORITHM

For the estimation of the lateral position and the orientation of the WMR, we take the lamp on the ceiling as landmark. From the image of the corridor, we try to extract a simple image of the ceiling lamp. Therefore, we make up a simple image process algorithm as Fig. 6. Fig. 7(a) is a camera image of the corridor. We also apply threshold value to Fig. 7(a).

Threshold value can be determined by experiment. The resulting image is shown in Fig. 7(b). However, it includes the ceiling lamp image and also unnecessary light reflections region.

Here, we define two rules as Eq. (1) and Eq. (2) to extract the image of the ceiling lamp.

$$\text{Rule1: } A1 < a \text{ number of pixel of object} < A2 \quad (1)$$

$$\text{Rule2: } \sigma^2 \text{ of specific object} < T \quad (2)$$

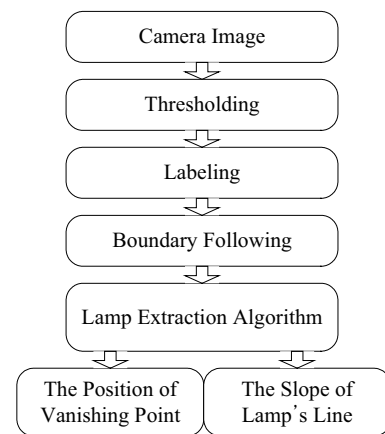


Fig. 6. Image process algorithm

Eq. (1) is introduced for get rid of unnecessary noise and big light reflective areas. The resulting image is shown in Fig. 7(c). But there are some unnecessary objects. In Fig. 7(c), the image of the ceiling lamps looks like a circle. From the features of the circle, we can find out that the variation of the distance between the center point and the boundary points is small. For this reason, Rule 2 is introduced to remove small

light reflective areas. The resulting image is shown in Fig. 7(d). In conclusion, these two simple rules work well to get the desired lamps image.

Here, the center point of object is calculated by Eq. (3). Where CX_n and CY_n is the centroid of object, n is a number given through labeling, m_i is the number of pixel of object, and x_i and y_i is position of pixel.

$$CX_n = \frac{1}{m_i} \sum_{i \in n} x_i, \quad CY_n = \frac{1}{m_i} \sum_{i \in n} y_i \quad (3)$$

Here, $n = 1, 2, \dots, k$

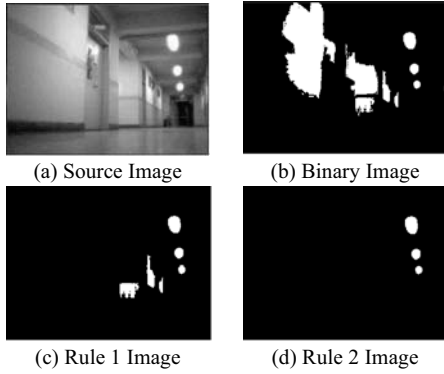


Fig. 7. Lamp extraction process

4. LATERAL POSITION AND ORIENTATION ESTIMATION ALGORITHM

4.1 Linear approximation method

While WMR is driving on the floor in corridor, the front image is captured with the CCD camera. The slope of the lamp's line and the position of vanishing point are computed using proposed simple image process algorithm. When such data are applied to the spaces, two approximated lines concerned with the lateral position and the orientation of the WMR are produced as Fig. 8 and Eq. (4). This means that there are many lateral position and orientation that have the same slope of lamp's line and the position of vanishing point. But when two lines are drawn in the same space, there is only one cross point, which is real lateral position and orientation of WMR in a corridor.

$$\begin{pmatrix} P_{WMR} \\ \theta_{WMR} \end{pmatrix} = \begin{pmatrix} -4.5284 & 0.0064 \\ 0.03487 & -0.0441 \end{pmatrix} \begin{pmatrix} \theta_{Lamp} \\ D_{Lamp} \end{pmatrix} + \begin{pmatrix} 403.64 \\ -4.001 \end{pmatrix} \quad (4)$$

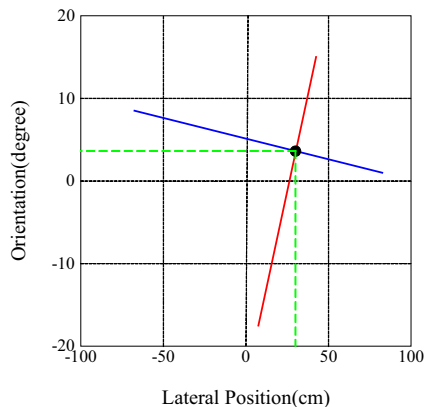


Fig. 8. Lateral position and orientation of WMR by means of linear approximation method

But the relations are nonlinear. Therefore, when simulation was carried out using this method, there are rather big estimation errors.

4.2 Neural network method

To reduce the above-mentioned estimation errors, a neural network is constructed like Fig. 9. As a learning method, backpropagation algorithm is used.

The transfer function of each node is sigmoid function and the output of each node is Eq. (5).

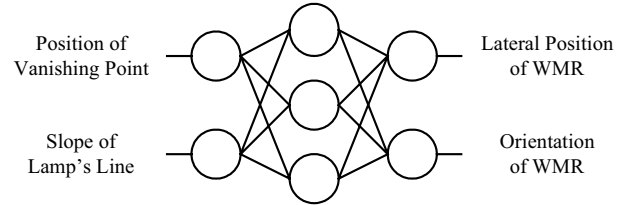


Fig. 9. Neural network model

$$u_j^{k+1} = \sum_{p=1}^N W_{jp}^k \cdot a_i^k \quad (p = i, j) \quad (5)$$

While learning, the error in each node is Eq. (6).

$$\delta_j^{k+1} = a_i^{k+1} (1 - a_i^{k+1}) e_i^k \quad (6)$$

And the variation of weights is Eq. (7).

$$W_{ij}(t+1) = W_{ij}(t) + \eta \cdot \delta_j^{k+1} \cdot a_i^k + \Delta W_{ij}(t) \quad (7)$$

5. SIMULATIONS AND EXPERIMENT

5.1 Computer simulation

Computer simulation was carried out using both linear approximation method and neural network.

Fig. 10 is the simulation results by means of linear approximation. The estimation error of lateral position is ranged from -3.658cm to 2.544cm and that of orientation is from -0.57° to 1.018° .

Fig. 11 is the simulation results by means of neural network. The estimation error of lateral position is from -1.604cm to 1.397cm and that of orientation is from -0.624° to 0.374° .

Table 1 shows RMS (root mean square) error, which represents degree of dispersion. As shown, estimation error is improved about 37.9% in lateral position and 35.3% in orientation when neural network is used as compared with linear approximation.

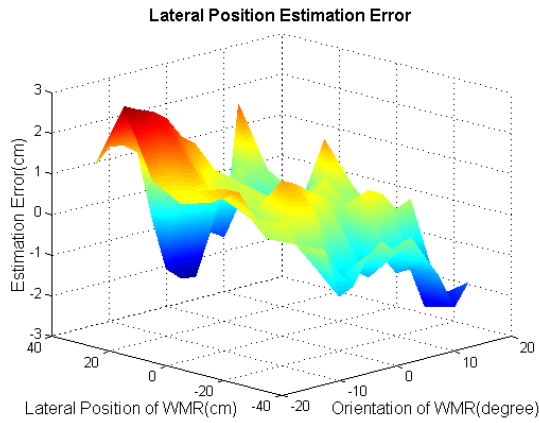
Table 1. RMS error

Method RMS Error	Linear Approximation	Neural Network	Improvement by NN
Lateral Position	1.135 cm	0.705 cm	37.9%
Orientation	0.400°	0.259°	35.3%

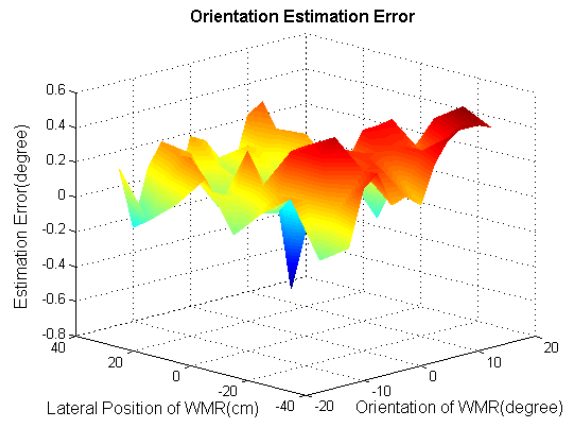
5.2 Navigation Experiment

Fig. 12 is the picture of the wheeled mobile robot for experiment in our laboratory and the program GUI.

While navigate the corridor, front image is captured and processed by proposed simple image process algorithm. As the result of this, the slope of lamp's line and the position of vanishing point are calculated and the lateral position and orientation of WMR is estimated through neural network..

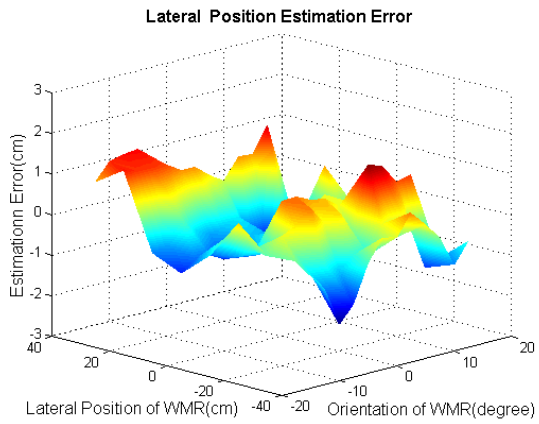


(a) Estimation error of lateral position

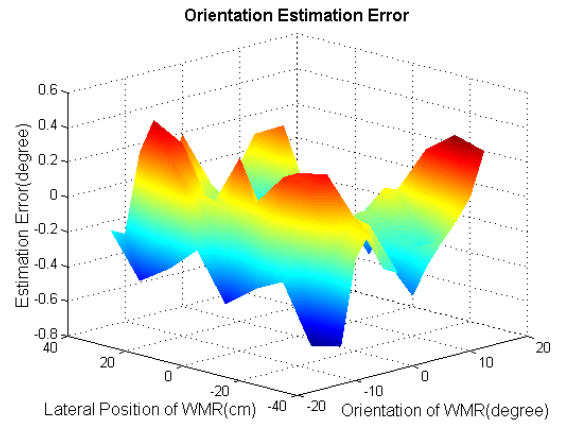


(b) Estimation error of orientation

Fig. 10. Estimation error by means of linear approximation method



(a) Estimation error of lateral position



(b) Estimation error of orientation

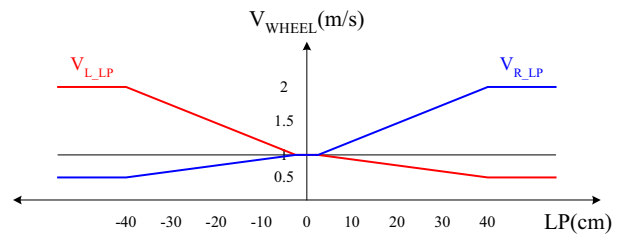
Fig. 11. Estimation error by means of neural network

The wheel velocity for compensation of the error is controlled by the velocity profiles like Fig. 13. According to the estimated lateral position, right and left wheel velocities are calculated in Fig. 13(a), which is V_{L_LP} and V_{R_LP} . Also according to the estimated orientation, two actuated wheel velocities are calculated in Fig. 13(b), which is $V_{L_θ}$ and $V_{R_θ}$. These values are combined by Eq. (8). Here, R_{LP} and $R_θ$ is the weight. In our experiment, R_{LP} and $R_θ$ was fixed with 0.2 and 0.15.

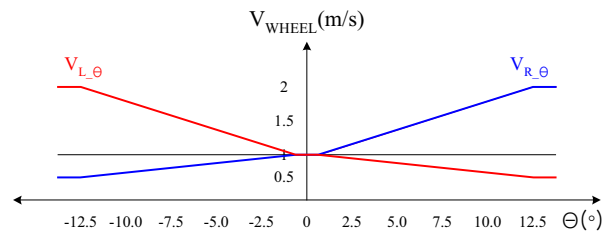
$$\begin{pmatrix} V_L & V_R \end{pmatrix} = \begin{pmatrix} R_{LP} & R_θ \end{pmatrix} \begin{pmatrix} V_{L_LP} & V_{R_LP} \\ V_{L_θ} & V_{R_θ} \end{pmatrix} \quad (8)$$



Fig. 12. WMR and program GUI



(a) Wheel velocity according to the lateral position



(b) Wheel velocity according to the orientation

Fig. 13. Velocity profiles of actuated wheel

Fig. 14 shows the lateral position and orientation of WMR in a corridor while driving. As shown, WMR was driven well at the center without collision with the wall and Fig. 15 shows the actuated wheel velocities.

While driving, WMR swerve from the course because of the

irregularity of the road. Nevertheless, WMR converge to the course by the wheel velocity profiles in Fig. 13.

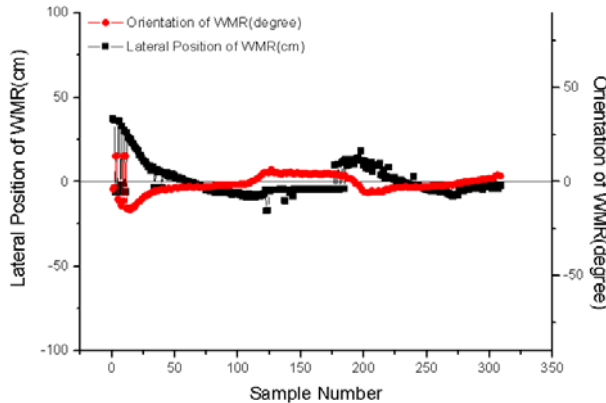


Fig. 14. Lateral position and orientation of WMR while driving

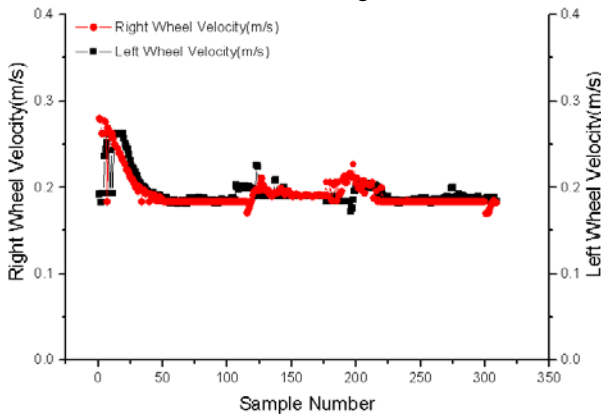


Fig. 15. Velocity of actuated wheels while driving

6. CONCLUSION

This paper described lateral position and orientation estimating algorithm for the navigation of a vision-based Wheeled Mobile Robot (WMR) in a corridor.

The ceiling lamps were taken as landmark and simple image processing algorithm was used to extract lamp's image from a camera image using geometrical feature of the lamp such as shape and size.

The relation planes were made up for the slope of lamp's line and the position of vanishing point. To define the relationships among them, two linear approximate formulas were driven from these two spaces. But there were rather large estimation error because of nonlinearity.

To reduce the estimation error, a neural network was proposed and learned by the backpropagation algorithm. As the result of simulation using neural network, RMS error was reduced up to 37.9% in lateral position and 35.3% in orientation.

Finally, PC-based WMR is composed and proposed algorithms were installed in them for an experiment. WMR could navigate the corridor without the collision with the wall. The distance covered is about 10m and the mean velocity of WMR is 0.2m/sec.

But the angle of view in the camera is limited. Therefore, when a vision system is mounted on the WMR and the orientation of the WMR is above certain degree, no lamp images is not captured. To overcome this disadvantage, another method or sensor must be considered. Also, to drive the mobile robots in an unknown environment is crucial work.

That must be investigated in the future.

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