Engineering

Industrial & Management Engineering fields

Okayama University *Year* 2006

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Proceedings of the 2000 IEEE/RSJ International Conference on Intelligent Robots and Systems

Improvement of Odometry for Omnidirectional Vehicle using Optical Flow Information

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Abstract

Our research goal is to realize a robust navigation in indoor and outdoor environment for autonomous vehicle. An omnidirectional vehicle driven by four Mecanum wheels was chosen for our research platform. Mecanum wheel has 16 tilted rollers (45 degrees against the direction of wheel rotation) around the wheel, so the vehicle moves omnidirectionally by controlling these wheels independently. However, it has a disadvantage of odometry because of wheels' slippage. Particularly, when the robot moves laterally, same wheels' rotations generate different traveling distance according to a friction of a ground surface.

To cope with the problem, we estimate robot's position by detecting optical flow of ground image using vision sensor (visual dead-reckoning). The estimation method is inaccurate comparing with odometry, but it is independent from friction of ground surface. Therefore, the estimated vehicle position can be improved by fusing odometry and visual dead-reckoning based on maximum likelihood technique.

This paper describes an odometry method and a visual dead-reckoning method for omnidirectional vehicle, and fusion technique to improve the estimated position of the vehicle. Finally, experimental results support above technique.

1 Introduction

Our research goal is to realize a smart and robust navigation for autonomous vehicle in indoor and outdoor environment.

To realize a smart navigation, omnidirectional vehicle has an advantage for narrow passage navigation and obstacle avoidance. Therefore, we chose an omnidirectional vehicle for research platform driven by four Mecanum wheels, shown in Figure 1. Mecanum wheel has 16 tilted rollers (45 degrees against wheel axis) around the wheel. It enables omnidirectional motion by controlling 4 Mecanum wheels independently.

For robust autonomous navigation, one of the important issue is *positioning*. Odometry is the most popular method for positioning of wheeled vehicles, and accumulated error in odometry is usually reduced by fusing other positioning sensors.

Figure 1: Our Omnidirectional Vehicle

We implemented an odometry system for our omnidirectional vehicle by attaching an encoder to each wheel. However, in our experience, the error of estimated position is generated by friction of ground surface, particularly in lateral movement. To cope with the problem, we equipped CCD camera to get a series of ground images, and detects ground speed by flow image. The estimation is inaccurate comparing with odometry locally, however it is independent from friction of ground surface. It means that there is a chance to improve the accuracy of estimated position by fusing different information. In this paper, we apply the fusion method on our omnidirectional vehicle, and show Experimental results to support a validity of this method.

2 Related Work

This work relates to three research fields, omnidirectional mechanism, mobile robot localization, and visual dead-reckoning.

2.1 Omnidirectional Mechanism

To realize horonomic motion of vehicles, several types of omnidirectional mechanism were presented. [1] and [2] uses special wheels, which includes free rotating rollers.

We chose a mobile vehicle driven by Mecanum wheels because it is a commercial wheel chair for handicap people. The similar type vehicle (named "Uranus") was constructed and researched in Carnegie Mellon University [3].

Because of slippage problem, motion analysis for Mecanum wheel type vehicle is complicate. [4] described a brief of force and velocity analysis of it. In this research, we reconsider an odometry method for the vehicle driven by Mecanum wheels.

2.2 Mobile Robot Localization

Localization is a major topic in research area of mobile robot, and many algorithms and techniques have been proposed. [5] is a complete survey of current localization techniques. Our localization method uses Maximum Likelihood technique (e.g. [6]).

2.3 Optical Flow for Navigation

Recently, computing power increases drastically, and reasonable and high-speed vision processing board that calculates correlation is now obtainable. Therefore, optical flow (based on image correlation) can be calculated in quick and robust in standard PC now.

[7] presented detecting method of road information by optical flow. It clusters free space (on road) and other objects by tendencies of optical flow information. Also, vision odometry was presented in [8], that aims to estimate vehicle's position by detecting a ground pattern by CCD camera.

Basically, our approach is similar to above ideas. However, we do not rely on only visual information for positioning, but we use the information to support odometry system.

3 Odometry for Mecanum-wheel-type Vehicles

3.1 Target Vehicle

Our vehicle has four Mecanum wheels that enables omnidirectional motion. Originally, it is a commercial wheel chair, and it can be controlled by joystick. To construct autonomy on this vehicle, we removed the chair, and mounted CCD camera, an encoder for each driving motor and control PC. The driving motors are controlled by adjusting voltage of joystick port by D/A converter board.

Figure 2: A Mecanum Wheel

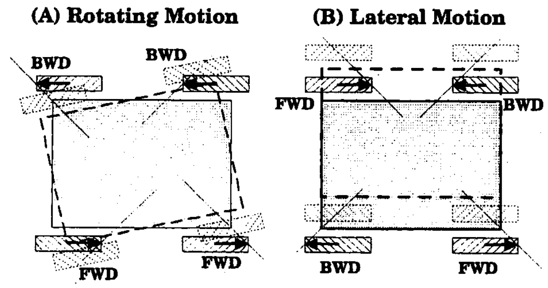
Figure 2 shows a photograph of one Mecanum wheel. It enables omnidirectional motion with free rotation of rollers, by controlling these wheels independently.

3.2 Kinematics

When Mecanum wheels move, each wheel location is somewhere along the direction of roller rotation because of free rollers' rotation. So, the vehicle's position and orientation are fixed singly by kinematics constraint of wheels' configuration (the other words, wheel base and tread never change). Note that the roller's directions of four Mecanum wheels are radiated roughly from a center of vehicle, so the position and orientation are calculable. Figure 3 shows an example of (A) rotation and (B) lateral movement for Mecanum wheel type vehicles.

3.3 Odometry Method

If there is no slippage between Mecanum wheels and ground surface, and if each roller is equipped in 45 degree tilted correctly, lateral traveling distance is



This figure shows a direction of the vehicle motion. "FWD" means that the moves forward, and "BWD" means that the wheel moves backward. Once the wheels rotate independently, the robot body moves from gray rectangle to the thick dotted rectangular. Note that all wheel locations are on the thin line of roller's rotation.

Figure 3: Mecanum Wheels' Motion

equal to forward traveling distance in the same wheels' rotation. However, an actual lateral traveling distance is shorter than actual forward traveling distance. It means that the wheel slippage affects very much when the robot moves laterally.

A following experimental result is one evidence of the problem. We controlled the robot by joystick, and measured a traveling distance of the vehicle on a p-tile surface. When the vehicle moves forward, each encoder counts 325 par one centimeter (average). On the other hand, when the robot moves laterally, encoder counts 348 par one centimeter (average).

On the basis of above pilot experiments, a tendency of distance shortage reappears on the same ground surface. We assume a virtual moving vector for each wheel rotation, which is expressed by a certain angle α from wheel's rotation direction (we call the angle "straying angle α"). Of course it is affected by the ground surface condition. Figure 4 shows a virtual moving vector for one Mecanum wheel.

A straying angle α for our vehicle is estimated by a relationship between forward traveling distance and lateral traveling distance par one wheel rotation.

$$\alpha = \arctan\frac{325}{348} = 43.03^\circ \tag{1}$$

Now we can calculate a velocity vector (dx, dy) and angular velocity ω by following equation.

$$dx = \frac{1}{4}(d_1 + d_2 + d_3 + d_4) \tag{2}$$

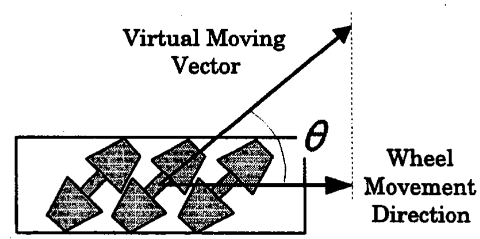


Figure 4: Moving Vector for one Mecanum Wheel

$$dy = \frac{1}{4}(-d_1 + d_2 + d_3 - d_4) \cdot \tan\alpha \tag{3}$$

$$\omega = (-d_1 + d_2 - d_3 + d_4) \cdot \beta \tag{4}$$

In above equations, d_1 indicates the differential movement of the front-left wheel. Similarly, d_2 corresponds to the front-right, d_3 corresponds to the rear-left, and d_4 corresponds to the rear-right (See Figure 5). β is also estimated experimentally.

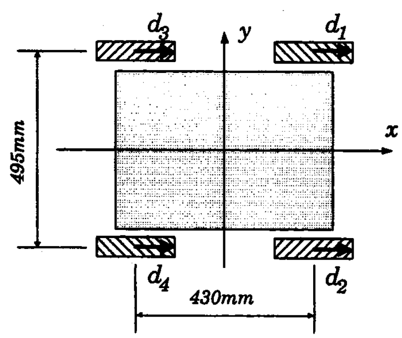


Figure 5: Coordination of our Omnidirectional Vehicle

We have done several experiments to evaluate an availability of the odometry. Figure 6 shows one experimental result, and the vehicle estimates its position correctly on the p-tile surface.

3.4 Slipping Problem of Mecanum wheels

If the robot moves on a uniform surface, we can apply above odometry method directly for Mecanum wheel type vehicle. However, if the robot enters a different friction's ground (e.g. the vehicle comes into a carpet room from p-tile corridor), an actual traveling distance of lateral movement changes.

To estimate how much the ground surface affects in lateral movement, we tested the vehicle on several

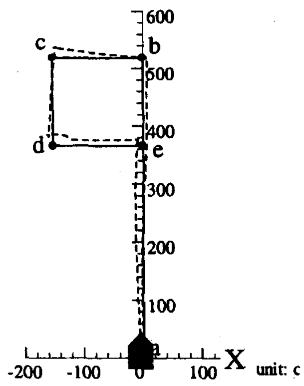


Figure 6: Experimental Result of Dead Reckoning

kinds of surfaces, and calculates each straying angle α of each ground. Table 1 shows the results.

Table 1: Value α in several Ground Condition

Condition	$\alpha(deg)$
P-Tile	43.03
Asphalt	42.60
Carpet	41.71

According to above experiment, it generates maximum 5 percent error on a carpet floor comparing with p-tile's parameters for our omnidirectional robot.

If there is a pre-knowledge about the ground surface condition, we can change the straying angle α based on the knowledge. However, if there is no information about the ground condition, it is impossible to estimate without external sensors. Therefore, we applied visual dead reckoning for position estimation to cope with different ground surface, shown in next section.

4 Visual dead-reckoning

4.1 Main Idea

In assumption of flat ground and fixed camera, a location of a ground point can be projected to a certain pixel on camera image. Therefore, we put a CCD camera at the front of the vehicle (with 45 degree tilted) to detect a ground image, shown in Fig.7. Then, the vehicle speed can be estimated by detecting flow speeds of images.

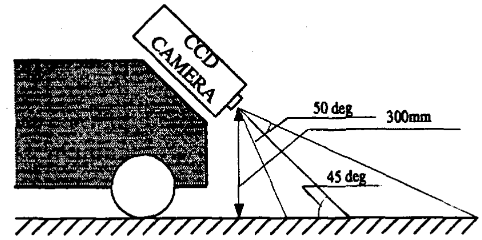


Figure 7: Configuration of Vision Sensor

To detect optical flows of ground image, we use an image processing board, FUJITSU Tracking Vision. It calculates 80 points of correlation between template image (16×16 *pixels*) and search space image (24×24 *pixel*) within 60 milliseconds. Then vehicle position can be estimated by integral of these speed vectors. In our current implementation, we realized only lateral motion to evaluate our method.

4.2 Problems

A problem for visual dead-reckoning is an accuracy. Once we use optical flow technique for positioning, it generates quantized errors. Currently, maximum length of moving vector is 8 pixels, so it has a potential of more than 10 percent errors. Also, once the vehicle speed exceeds, it happens to fail matching because the reference image area may be out of range. Currently, we experiment with slow vehicle speed (less than 10 [cm / sec]) because of limitation of hardware speed.

5 Fusion of Odometry and Visual Dead-Reckoning

In section 3 and 4, we noted that (1) odometry for Mecanum wheel vehicle is easily affected by a ground friction, and (2) visual dead-reckoning is inaccurate.

These methods are completely independent, so the odometry can be improved by fusing visual dead reckoning. We apply standard Maximum Likelihood Technique (e.g. [6]) to fuse both estimated positions.

5.1 Model of Odometry

Let the "actual" vehicle position and velocity be vector $P[t]$ and $V[t]$. Then, these vectors are expressed by following equations.

$$P[t] = [x[t] \;\; y[t] \;\; \theta[t] \;\;]^T \quad (5)$$

$$V[t] = [v_f[t] \;\; v_s[t] \;\; \omega[t] \;\;]^T \quad (6)$$

where $(x[t]\ ,\ y[t])$ is a location of the vehicle, and $\theta[t]$ is an orientation of it. $v_f[t]$ and $v_s[t]$ are velocities of front direction and side direction (note that it is omnidirectional vehicle), and $\omega[t]$ is an angular velocity of the vehicle.

An actual position of the vehicle is updated by following recursive equation,

$$P[t+\tau] = P[t]+\tau \begin{bmatrix} v_f[t]\cos\theta[t] - v_s[t]\sin\theta[t] \\ v_f[t]\sin\theta[t] + v_s[t]\cos\theta[t] \\ \omega[t] \end{bmatrix} \quad (7)$$

where τ is a sampling time. Theoretically, an error term caused by quantization of calculation is necessary in above equation, but it is omitted here for simplicity.

Once a function $f[P[t], V[t]]$ is defined as a right side of (7), actual position of the vehicle can be approximated by following equations,

$$\begin{aligned} P[t+\tau] &= f[P[t], V[t]] \\ &= f[\hat{P}[t] + \Delta P[t], \hat{V}[t] + \Delta V[t]] \\ &\simeq f[\hat{P}[t], \hat{V}[t]] + \\ &\quad J[t]\Delta P[t] + K[t]\Delta V[t] \quad (8) \\ &= \hat{P}[t+\tau] + \Delta P[t+\tau] \quad (9) \end{aligned}$$

where "**estimated**" position and velocity by odometry are expressed as $\hat{P}[t]$ and $\hat{V}[t]$, and "**error**" of position and velocity are expressed as $\Delta P[t]$ and $\Delta V[t]$. Also, $J[t]$ and $K[t]$ are as follows.

$$\begin{aligned} J[t] &= \left.\frac{\delta f[P,V]}{\delta P}\right|_{\hat{P}[t],\hat{V}[t]} \\ K[t] &= \left.\frac{\delta f[P,V]}{\delta V}\right|_{\hat{P}[t],\hat{V}[t]} \end{aligned}$$

According to above equations, positioning error $\Delta P[t+\tau]$ can be expressed by following equation.

$$\Delta P[t+\tau] = J[t]\Delta P[t] + K[t]\Delta V[t] \quad (10)$$

To estimate how much error (in position and orientation) is produced, we use a covariance matrix, defined as $\Sigma P[t] = E(\Delta P[t] \cdot \Delta P[t]^T)$. It is a covariance of errors between position parameters : $\Delta x, \Delta y, \Delta\theta$. By using (10), it can be calculated recursively as follows.

$$\begin{aligned} \Sigma P[t+\tau] &= E(\Delta P[t+\tau]\Delta P[t+\tau]^T) \\ &= J[t]\Sigma P[t]J[t]^T + \\ &\quad K[t]\Sigma V[t]K[t]^T \quad (11) \end{aligned}$$

Covariance matrix of velocity $\Sigma V[t+\tau]$ is expressed by following style.

$$\Sigma V[t] = \begin{bmatrix} \sigma_{v_f}^2 & \sigma_{v_f v_s} & \sigma_{v_f \omega} \\ \sigma_{v_f v_s} & \sigma_{v_s}^2 & \sigma_{v_s \omega} \\ \sigma_{v_f \omega} & \sigma_{v_s \omega} & \sigma_{\omega}^2 \end{bmatrix} \quad (12)$$

where σ_{v_f} (or σ_{v_s} or σ_ω) means variance of error in front (or side or angular) direction. $\sigma_{v_f v_s}$ means covariance of effectiveness between v_f and v_s.

We experimented in try and error to find suitable value of (12) by referring experimental results.

Above all, we obtain vehicle's position $P[t]$ and covariance matrix $SigmaP[t]$ recursively.

5.2 Model of Visual Dead-reckoning

Equations for visual dead-reckoning are the same as equations for odometry shown in section 5.1, only sampling time τ and covariance matrix of $\Sigma V[t]$ are different. The values of $\Sigma V[t]$ for visual dead-reckoning are also calibrated by experimental results.

5.3 Experimental Result: Error Ellipsoid

Figure 8 shows one experimental result of Error Ellipsoid. In this experiment, the vehicle was moved 480 centimeters laterally by operator's joystick control. Half of the ground surface was concrete, and the other half was artificial turf that had large friction for Mecanum wheel. A parameter of "straying angle α" for odometry was set for p-tile ground.

Upper line of dots represents estimated positions by odometry, and lower line of dots represents estimated positions by visual dead-reckoning. Both start point was the same. (It is shifted one of it just for display.)

We can see that the estimated traveling distance by odometry is longer than expected one because of wheels' slippage.

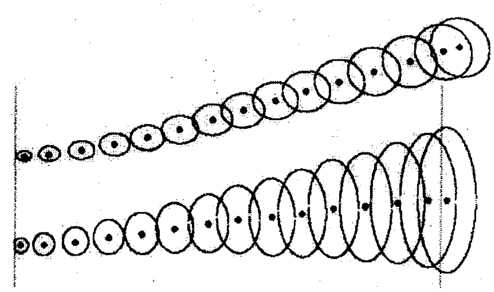


Figure 8: Experimental Result : Error Ellipsoid

5.4 Fusion by Maximum Likelihood Method

To fuse the information of odometry and visual dead-reckoning, we use Maximum Likelihood estimation, as following equations.

$$\Sigma_{fu} = \left(\Sigma_{op}[t]^{-1} + \Sigma_{vp}[t]^{-1}\right)^{-1} \quad (13)$$

Where $\Sigma_{op}[t]$ is covariance matrix of position based on odometry, $\Sigma_{vp}[t]$ is covariance matrix of position based on visual dead-reckoning, and Σ_{fu} means fused covariance matrix. By using (13), estimated position is updated by following equation.

$$\hat{P}_{fu} = \Sigma_{fu}\Sigma_{vp}^{-1}\hat{P}_{su} \quad (14)$$

Figure 9 shows the fusing result of experiment shown in Figure 8. In this experiment, fusion is done in every 1 second, and the estimated traveling distance of lateral direction was improved comparing with odometry only.

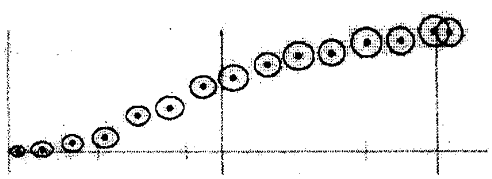


Figure 9: Experimental Result : Fusion Result

6 Conclusion and Future Works

We described odometry and visual dead-reckoning for omnidirectional vehicle driven by Mecanum wheels. Both methods have merits and demerits, so we fused them by Maximum Likelihood technique to improve the estimated vehicle position.

Currently, we have a big problem about an accuracy of visual dead-reckoning which is calculated by optical flow, so we can not rely on that information very much. It can be improved by closing CCD camera to the ground, and expanding searching area for optical flow detection.

We also consider about dynamic estimation of "straying angle α" to adapt ground surface. Theoretically, visual dead-reckoning result is independent from odometry estimation, so it can estimate a value of "straying angle α" during vehicle navigation.

Acknowledgments

Dr. Maeyama helped us to analize a detail of positioning method for mobile robot. I would like to thank him very much.

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