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Measurement of position based on correlative function in self-movement

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Abstract — This paper describes an effective method to estimate a position of an autonomous vehicle equipped with a single CCD-camera along indoor passageways. Using the sequential image data from the self-movement of the vehicle, the position is estimated by integrating the approximated motion parameters. The detection of the yaw angle that is one of the motion parameter is difficult in general, *e.g*, slip or error for noise, therefore the different detection is presented, which is, without shaft encoders, based on a projection function for 2D-image data and a cross-correlation function so as to be robust for noise. The approximated geometric function to estimate the position is used to reduce the computational effort. To verify the effectiveness of the method, the analysis and the computational results are shown through the simulations. Furthermore, the experimental results by using the test vehicle for the real indoor passageway are shown.

Index Terms **– autonomous vehicle, vehicle position, projection method, single-eye vision**

1 Introduction

In studies of an autonomous vehicle equipped with a TV-camera, the estimation of the vehicle position from a vision data in which the vehicle moves along indoor passageways plays an important role. The abilities of algorithms for the estimation by image processing have an effect on the total performance of the vehicle, because the size of the indoor vehicle is generally small, so the computational effort of the image processing must be reduced. Several approaches to estimate the vehicle position have been studied. There are two typical approaches such as the image processing for the static sequential image data [1, 2] and the analyzing the motion parameters from the optical flow[3, 4]. Unfortunately, they are not effective approaches for the small size vehicle, because their computational efforts are tremendous since it is needed to solve a set of nonlinear equations, or their results are weak for noise such as added noise or quantum error.

This paper describes an effective method to estimate a position of an autonomous vehicle equipped with a single CCD-camera along indoor passageways. In this method, using the sequential image data from the self-movement of the vehicle, the position is estimated by integrating the approximated motion parameters ; the distance and the yaw angle by the self-movement. The detection of the yaw angle is difficult in general, *e.g.* slip or error for noise, therefore the different detection, without shaft encoders, which is based on a projection function for 2D-image data and a cross-correlation function so as to be robust for noise is presented. Furthermore, the approximated geometric function to estimate the position is used in this method to reduce the computational effort. To verify the effectiveness of the method, firstly we analyze the error between the approximated geometric function and its actual function. Secondly, comparing with the usual image processing approach, the computational effort of this method is examined. Lastly, the experimental results by using the test vehicle for the real indoor passageway are shown.

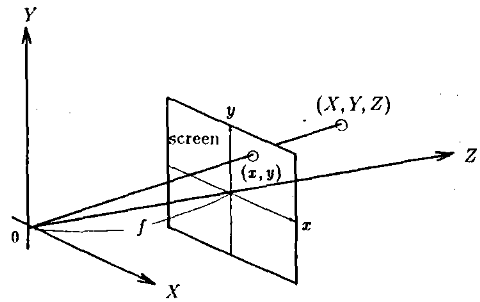

Fig.1 Camera model, f;focal length.

2 Geometric Interpretation

Most of indoor passageways can be figured with straight line segments, so we assume that the passageway is locally flat and straight in the near range with parallel both sides of the wall, then the geometry between the vehicle position and the passageway can be described in XZ-plane shown in Fig.2, in which 3D-coordinates with the origin at the focal point and the positive Z-axis shown in Fig.1. In Fig.2, L is the distance defined by the vehicle velocity during a certain interval time. We assume that the vehicle velocity v and the interval time Δt are constant, so L also constant and known. When the vehicle position $(X(t_{n-1}), Z(t_{n-1}))$ at time t_{n-1} moves to $(X(t_n), Z(t_n))$ at time $t_n = t_{n-1} + \Delta t$ along a curve line as an actual trajectory (Fig.2), our idea stands on approximating the curve line by a piecewise-straight line and a variation of the yaw angle. If the initial values of the motion parameters $(X(t_0), Z(t_0), \theta(t_0))$ are given, then the approximated position at time t_n is defined by the following equations

$$X(t_n) = X(t_0) + \sum_{i=1}^{n} L \sin\theta(t_i) \quad (1)$$

$$Z(t_n) = Z(t_0) + \sum_{i=1}^{n} L \cos\theta(t_i) \quad (2)$$

$$\theta(t_n) = \theta(t_0) + \sum_{i=1}^{n} \Delta\theta(t_i) \quad (3)$$

From the above equations, if detecting the variation of the yaw angle $\Delta\theta(t_i)$ at each time, the position can be estimated approximately under the condition $|\Delta\theta(t_i)| < \epsilon$; ϵ be defined by the camera angle of view.

When the position $(X(t_{n-1}), Z(t_{n-1}))$ moves to $(X(t_n), Z(t_n))$, we define the corresponding pixels in the image data be (x, y) and

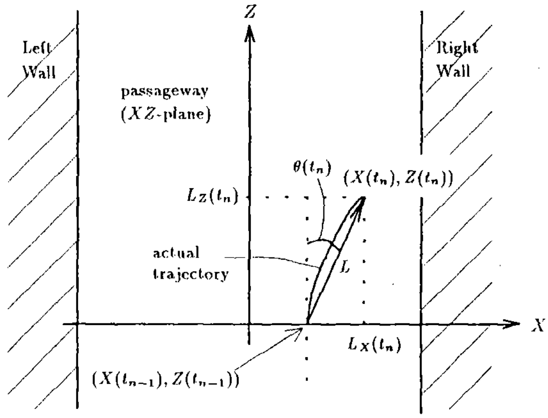

Fig.2 Geometric interpretation of the camera position in a passageway, and the approximated straight line segment for the actual trajectory.

$(x+dx, y+dy)$, respectively. Considering the geometric representations shown in Fig.1 and 2, through the algebraic manipulation, we obtain the following functions

$$dx = f\frac{HX - HZ\tan\Delta\theta(t_n)}{HZ + HX\tan\Delta\theta(t_n)} - f\frac{X(t_{n-1})}{Z(t_{n-1})} \quad (4)$$

$$dx = f\frac{Y(t_{n-1})}{HZ + HX\tan\Delta\theta(t_n)} - f\frac{X(t_{n-1})}{Z(t_{n-1})} \quad (5)$$

where

$$HX = (X(t_{n-1}) - L_X(t_n))$$
$$HZ = (Z(t_{n-1}) - L_Z(t_n))$$

and $L_X(t_n) = L\sin\theta(t_n)$ and $L_Z(t_n) = L\cos\theta(t_n)$.

The above equations are not solvable about $\Delta\theta(t_i)$, because there are four unknown variables ($X(t_i)$, $Y(t_i)$, $Z(t_i)$, $\theta(t_i)$) in eqs.(4) and (5). Now, in the actual environment as shown in Fig.2 where we examine the test vehicle, the following conditions are hold for enough short interval time Δt

$$Z(t_{i-1}) \gg L_Z(t_i)\,,\quad Z(t_{i-1}) \gg L_X(t_i)$$
$$Z(t_{i-1}) \gg (X(t_{i-1}) - L_X(t_i))\tan\Delta\theta(t_i) \quad (6)$$

The validity of these conditions will be discussed in the next section. Taking account of eq.(6), eqs.(4) and (5) are reduced to the approximated functions such that

$$dx \simeq -f\tan\Delta\theta(t_i) \quad (7)$$
$$dy \simeq 0 \quad (8)$$

The computational effort of eq.(7) is much reduced than that of eq.(4). Since eq.(8) means that dy is not affected by the variation of the yaw angle and does not vary during on enough short interval time, it is sufficient to detect only the lateral variation in the image data.

Note that (dx, dy) , of course, can be obtained directly from the two sequential image datum at time t_{n-1} and t_n, and then $\Delta\theta(t_n)$ may be obtained from eq.(7). However, this yields several problems such that how to specify the feature points, reduce quantum error and tremendous image processing, and so on. To avoid the problems, we show the different approach to obtain dx below.

3 Estimation of the Vehicle Position

3.1 Projection of the Image Data

The detection for the variation of the yaw angle requires not all of the information for 2D-image data, but only the lateral information in the image, so we define the projection function for the y-coordinate in the image

$$S(x, t_n) = \frac{1}{N}\sum_{y=0}^{N-1} p(x, y, t_n) \quad (9)$$

where $p(x, y, t_n)$ is the intensity of the image data at pixel (x, y) at time t_n and N is the size of the image data ($0 \leq x, y < N$), and $S(x, t_n)$ is interpreted as a projection function from 2D-image data on one-dimensional data.

Using eq.(9), the cross-correlation function is defined as

$$R(\tau, t_{n-1}, t_n) = \frac{1}{N\sigma(t_{n-1})\sigma(t_n)}\sum_{x=0}^{N-1} \times\left(S(x, t_{n-1}) - \overline{S(t_{n-1})}\right) \times\left(S(x+\tau, t_n) - \overline{S(t_n)}\right) \quad (10)$$

where

$$\overline{S(t_i)} = \frac{1}{N}\sum_{x=0}^{N-1} S(x, t_i)$$
$$\sigma(t_i) = \sqrt{\frac{1}{N}\sum_{x=0}^{N-1} S(x, t_i) - \overline{S(t_i)}}$$

The cross-correlation function contains the information of the lateral variation, thus the variation dx is extracted by using the following

$$dx = \max_{\tau} R(\tau, t_{n-1}, t_n) \quad (11)$$

The extracted value of dx is slightly different from the actual value, but it is expected that the value has a sufficient accuracy within the range discussed in the previous section. Since the detection above uses the statistical approach, it is expected that the detected dx is robust for a noise and a quantum error.

As a result, the position $(X(t_n), Z(t_n))$ is estimated from eqs.(1)-(3) by using $\Delta\theta(t_n)$ which is calculated by substituting dx in eq.(11) into eq.(7).

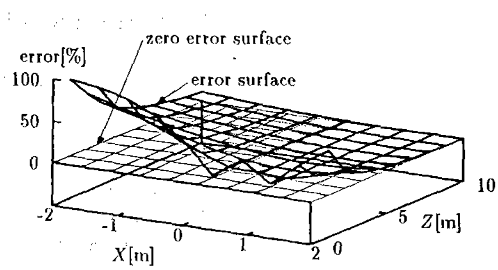

Fig.3 Difference between theoretical and approximate value.

3.2 Effectiveness of the Method

In this section, we verify the validity of the resultant $\theta(t_n)$ in eq.(7) with respect to the degree of the approximation and the robustness for the noise. To verify the degree of the approximation, we show the surface of the relative error in Fig.3, which is derived by subtracting the approximated value in eq.(7) from the actual value in eq.(4). The ranges are $|X| \leq 2$[m] and 0[m] $< Z \leq 10$[m], and valid for the test vehicle in the real indoor passageway. From the figure, the error decrease with Z, but increases with the absolute value of X. However, the error is accurate within 10[%] for the ranges $|X| \leq 2$[m] and $Z \geq 3.3$[m], and it is an allowable error whenever the test vehicle observes objects within the range.

Next, to verify robustness for the noise, two virtual sequential

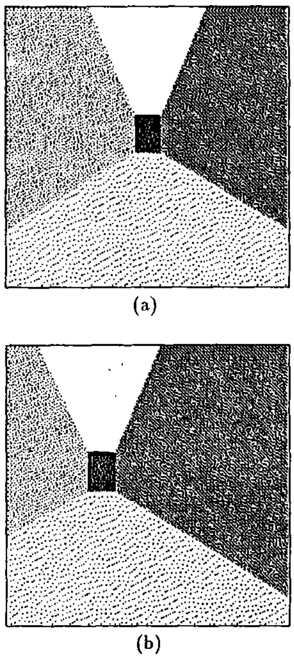

Fig.4 Virtual image datum of a passageway,(a); image at t_0 , (b);image at t_1.

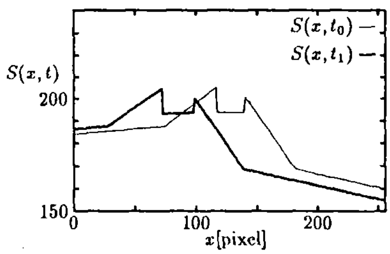

Fig.5 Projection functions for the datum in Fig.4.

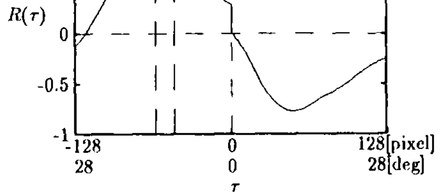

Fig.6 Cross-correlation function for the projections in Fig.5 , A^0 = 0.81 at 10.0[deg], A = 0.82 at 11.2[deg].

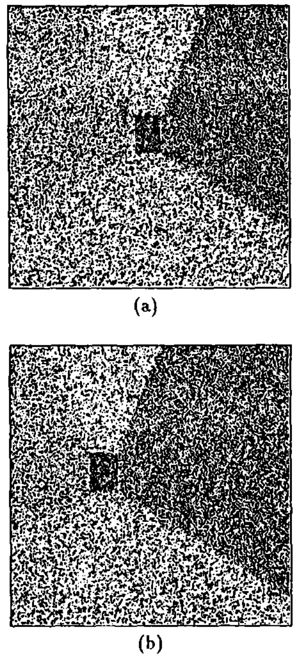

Fig.7 Virtual image datum with added noise, (a);image at t_0 , (b);image at t_1.

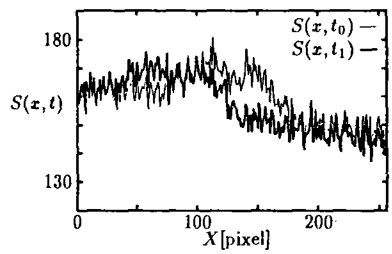

Fig.8 Projection functions for the datum in Fig.7.

image data are prepared. Fig.4(a) shows a virtual image data of a passageway observed with the initial values $X(t_0) = Z(t_0) = 0$[m], $\theta(t_0) = 0$[deg], and Fig.4(b) shows another virtual image data after the vehicle moving with $L = 0.2$[m] and right rotation by $\theta(t_1) = 10$[deg]. From these image data, the results of the projection function and the cross-correlation function are shown in Fig.5 and 6, respectively. In Fig.6, A^0 is the actual maximum value at $\theta(t_1) = 10$[deg] and A be the resultant maximum value from eq.(11). The result shows that the error is sufficiently small in use of the test vehicle.

Using the same datum in Fig.4 but with added noise ; appearance frequency of 40[%] and random intensity from 0 to 255 gray scale (Fig. 7), the result by the same manner above is shown in Fig.9. Comparing the results in Fig.6 with that is 9, it is found that the method to detect $\theta(t_i)$ is robust for the noise.

The computational time of the method using the two sequential image data takes 0.15[sec] for calculating $\theta(t_n)$ on PC computer (CPU : Pentium 90MHz). This cost is sufficiently small comparing with the usual image processing such as an extraction of the edge line or the calculation of the optical flow.

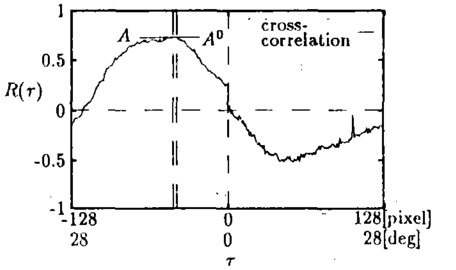

Fig.9 Cross-correlation function for the projections in Fig.8 , A^0 = 0.73 at 10.0[deg], A = 0.73 at 10.8[deg].

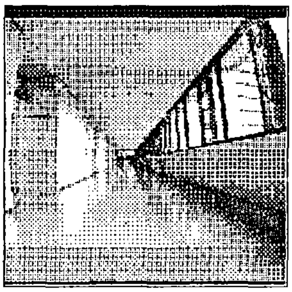

Fig.10 Scene of a real passageway.

4 Experimental result

In this section, installing the proposed method in a test vehicle, which is small size (100[cm] × 30[cm]) and equipped with a single CCD-camera, we examine the accuracy for the estimated position along the real indoor passageway shown in Fig.10. The size of the image are 256 × 256 pixels spatial resolution with 8 bit gray scale, and the image sequence consists of 26 frames. Fig.11 shows experimental results (solid line) obtained by the method and the real measured values (diamond mark) of the vehicle positions. Fig.11(a) shows the measured value of $\theta(t_n)$. Comparing the measured value with the real value, it is found that the error is sufficiently small. Fig.11(b) shows the measured value of $X(t_n)$, and Fig.11(c) shows the measured value of $Z(t_n)$. Here, $X(t_n)$ is the sine of $\theta(t_n)$ (see eq.(1)), $Z(t_n)$ is the co-sine of $\theta(t_n)$ (see eq.(2)). Therefore, the error of $X(t_n)$ is large as compared with the error of $Z(t_n)$, because the value of $\theta(t_n)$ is small ($|\theta| < 30$[deg]) in this experiment. However the position of the vehicle is estimated sufficiently.

5 Conclusion

In the proposed method, its the processing takes a sufficient short time, thus it is very effective for the real-time processing as long as the autonomous vehicle moves on the real indoor passageway. Here, the error of the estimated position increases with the iteration times of the estimation, because the position is estimated by integrating the approximated motion parameters. Therefore, the other method of measuring position is needed to correct the estimating error and then measure the initial values of the motion parameters again. To do that, we use a method that is extraction of the edge line consists of the feature of the passageway. However, its processing takes a very long time, so we use this method at long interval (one processing by 10 iterations) to correct the error. Using it and the proposed method has an advantage to reduce the computational effort with keep the error small sufficiently.

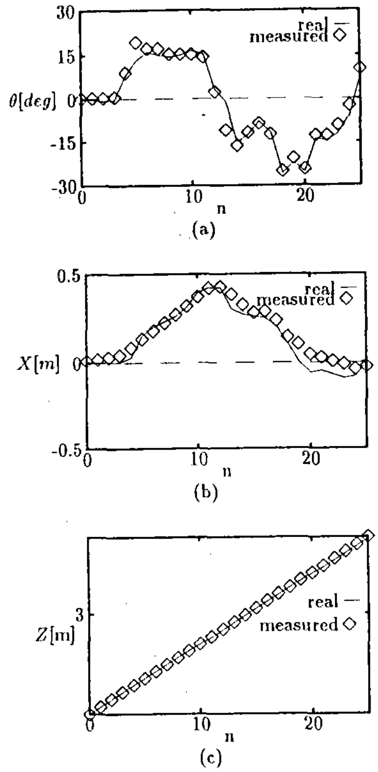

Fig.11 Experimental results in use of the test vehicle for the real passageway, sampling rate=0.15[sec], $\theta(t_0)$ = 0[deg], $X(t_0)$ = 0[m], $Z(t_0)$ = 0[m].

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