Velocity Estimation from Visual Information using Environmental Property

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***Abstract*—In ecological psychology, it is considered that animals and insects use visual instead of distance information. In this paper, we take the mechanism of animals into consideration and address the method used to estimate the velocity of a robot by employing only one camera. Simulations are conducted and their accuracy is discussed.**

Keywords-velocity estimation; monocular camera; ecological psychology.

I. INTRODUCTION

Intelligent safety systems for automobiles, such as autonomous collision avoidance and navigation systems, have recently attracted considerable attention, leading to extensive research into developing effective autonomous vehicles. The DARPA ground challenge and the Google car are two examples [1]-[3]. The most common approach in these conventional studies is to create three-dimensional models of the environment. In this approach, the vehicles have sensors, such as laser range-finders, to measure distances to obstacles and create a precise three-dimensional model of the environment [4]-[8]. However, the creation of this environment model and the extraction of useful information involve huge computational costs. In contrast, although lower animals and insects do not have such distance sensors and their brains are very small, they behave adaptively even in unknown environments [9]-[11]. In ecological psychology, it is presumed that animals and insects use visual information instead of distance information.

This study considers the navigation mechanism of animals and addresses the method used to estimate the velocity of a robot using visual information. We focus on the ecological niche framework and assume that the average distance from obstacles is constant. Under this assumption, we derive an equation to estimate velocity from visual information. Simulations are conducted, and the error rate arising from the error of average distance is discussed.

This paper consists of the following parts. Section II defines the global coordinate system and explains the problem domain and the assumption in this paper. Section III describes a preliminary experiment that was conducted to discuss the validity of the assumption. Section IV proposes a method to estimate the velocity, and in Section V, simulations are conducted and the error rate of the proposed method is discussed. Section VI concludes this paper.

II. PROBLEM DOMAIN

In this study, we address the method of estimating the velocity of a robot by using only one camera; we employ no other sensors. In general, it is impossible to estimate velocity using a single camera. Hence, we make an assumption based on ecology. In ecology, it is reported that each animal occupies and exploits a unique niche. The size and variation of obstacles in its environment are aspects of this niche. Accordingly, we focus on the average distance from obstacles. The average distance depends on the niche and does not change rapidly. Therefore, in this study, we assume that the average distance from visible obstacles is known (i.e., it can be learned) and constant. Under this assumption, we derive an equation to estimate velocity from visual information. In practice, the average distance shows small variations; thus, we discuss the error rate of the estimated velocity arising from the error of average distance. The details are as follows.

We define the global and view coordinate systems as shown in Figure. 1, and we define the estimated average of distance as shown in Figure 2.

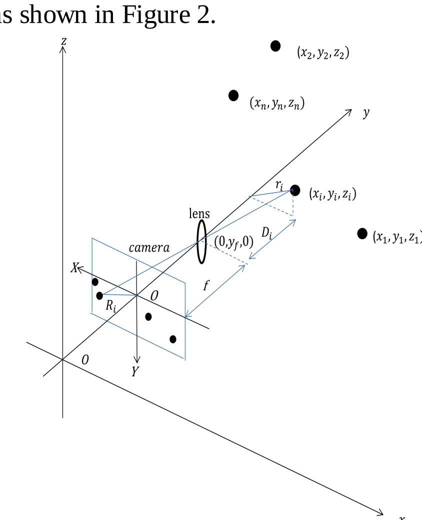

Figure 1. Definition of coordinate systems.

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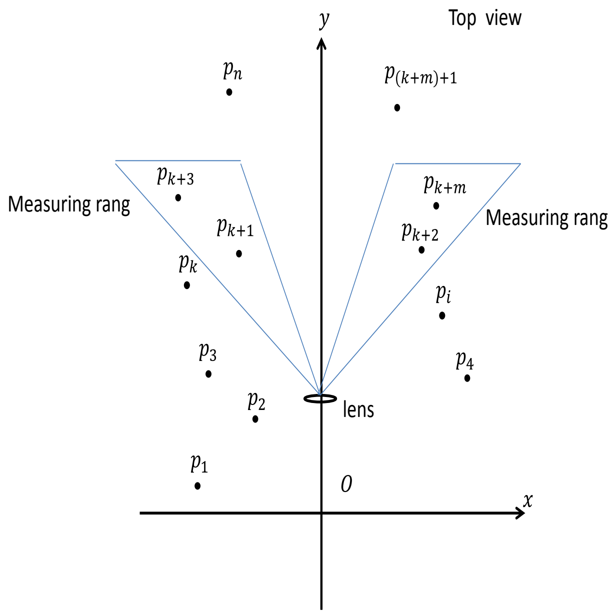

Figure 2. Definition of average distance.

The camera is located on the y-axis of the global coordinate system and moved forward at a constant velocity v. The lens is positioned at (0, y_f, 0). There are several static object, and the coordinates of their characteristic points p_i are denoted by (x_i, y_i, z_i), where n is the number of characteristic points. D_i is the distance between the lens and the i-th point, and it is expressed as $D_i = y_i - y_f$. R_i is the distance from the origin in the view coordinate system, r_i is the distance from the y-axis in the global coordinate system, and f is the focal length of the camera.As described above, we assume that each D_i is unknown. However, only the average distance from the visible characteristic points is estimated, as shown in (1):

$$\widehat{D} \approx \overline{D} = \frac{1}{m}\sum_{i=k+1}^{k+m} D_i \tag{1}$$

where only p_{k+1} to p_{k+m} are visible among all characteristic points (p_1 to p_n), as shown in Figure. 2. $\overline{D}$ is the actual average distance from the visible characteristic points, and $\widehat{D}$ is the predefined constant, estimated value of $\overline{D}$.

III. PRELIMINARY EXPERIMENT

To discuss the validity of the assumption written in Section II, we conducted preliminary experiment.

Figure. 3 shows setting of the experiment. We measured distance l_i and angle θ_i ever 5° from 30° to 75° and from 105° to 150°,then we move forward 2 m and measured again. From l_i and θ_i we calculated D_i and $\overline{D}$. Figure. 4 and Figure. 5 shows environments, and Table 1 and 2 shows experiment results

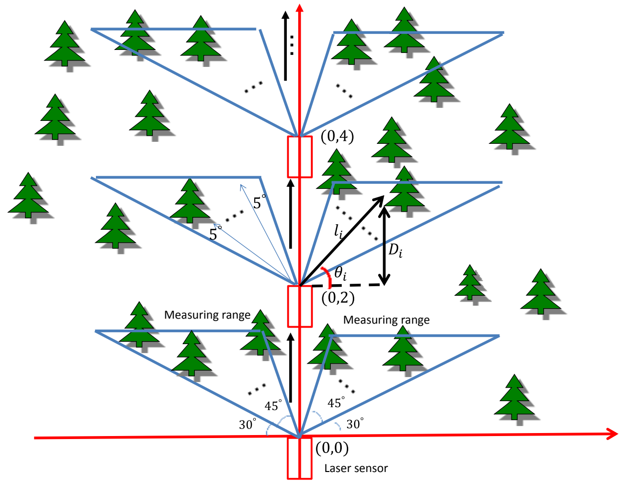

Figure 3. Range of measurement

Figure 4. Environment 1

Figure 5. Environment 2

TABLE 1. RESULT OF ENVIRONMENT 1

Measurement position	$\overline{D}$
(0,0)	2.73
(0,2)	2.99
(0,4)	2.87
(0,6)	2.96
(0,8)	2.88

TABLE 2. RESULT OF ENVIRONMENT 2

Measurement position	$\overline{D}$
(0,0)	12.15
(0,2)	12.03
(0,4)	12.83
(0,6)	12.32
(0,8)	12.13

Environment 1 is a passage way in a building and there is walls on its both sides. Though there are some objects, influence of these objects is filtered by the calculation of average. Thus the average distance does not change rapidly as shown in Table. 1. Environment 2 is a road between a building and a green zone, and the similar tendency is observed as shown in Table. 2. From these results, we can confirm that $\overline{D}$ is dependent on the environment, however, $\overline{D}$ does not change rapidly.

IV. VELOCITY ESTIMATION

Now, we estimate the velocity of the camera using the visual information R_i. From the geometric relationship, R_i is given by (2):

$$R_i = f\frac{r_i}{D_i} \tag{2}$$

Differentiating both sides of (2), we obtain (3):

$$\dot{R}_i = -f\frac{r_i}{{D_i}^2}\dot{D}_i \tag{3}$$

Dividing (2) by (3), we obtain (4):

$$\frac{R_i}{\dot{R}_i} = -\frac{\frac{fr_i}{D_i}}{\frac{fr_i}{{D_i}^2}\dot{D}_i} \tag{4}$$

From (4), we obtain (5):

$$D_i = -\frac{R_i}{\dot{R}_i}\dot{D}_i \tag{5}$$

Alternatively, as the objects are static, the velocity of the camera can be expressed by (6) using the temporal change of D_i.

$$v = -\dot{D}_1 = -\dot{D}_2 = \cdots = -\dot{D}_i = \cdots = -\dot{D}_n \tag{6}$$

From (5) and (6), we obtain (7):

$$D_i = \frac{R_i}{\dot{R}_i}v \tag{7}$$

From (7), we can obtain the sum of the distances from the visible characteristic points (p_{k+1} to p_m), and thus, we obtain (8):

$$\sum_{i=k+1}^{k+m} D_i = v\sum_{i=k+1}^{k+m}\left(\frac{R_i}{\dot{R}_i}\right) \tag{8}$$

From (1) and (8), we obtain (9):

$$v = \frac{\overline{D}}{\frac{1}{m}\sum_{i=k+1}^{k+m}\frac{R_i}{\dot{R}_i}} \tag{9}$$

In this paper, we utilize a predefined estimated value $\widehat{D}$ instead of the actual average $\overline{D}$. Therefore, the estimated velocity of the camera $\hat{v}$ is given by (10):

$$\hat{v} = \frac{\widehat{D}}{\frac{1}{m}\sum_{i=k+1}^{k+m}\frac{R_i}{\dot{R}_i}} \tag{10}$$

We conduct simulations using this method in the next section.

V. SIMULATION

We conduct simulations to discuss the accuracy of the proposed estimation method. In the simulations, we set all the characteristic points on horizontal planes (z = 0) to simplify the environments. Figures. 6–9 show the simulation environments. The small circles denote the characteristic points and the triangle denotes the visible area.

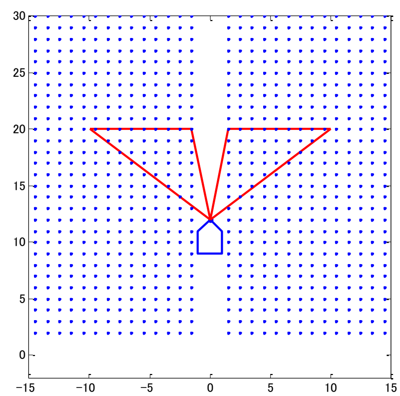

Figure 6. Environment 1 (regular pattern, 900 points).

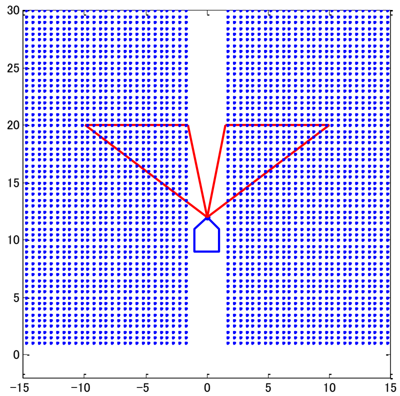

Figure 7. Environment 2 (regular pattern, 3600 points).

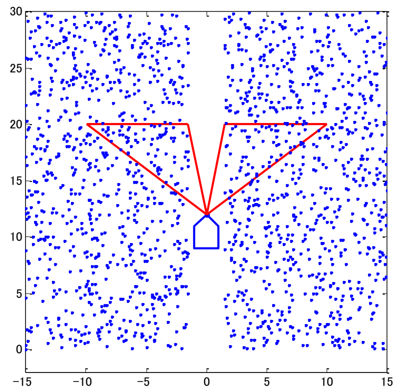

Figure 8. Environment 3 (random pattern, 900 points).

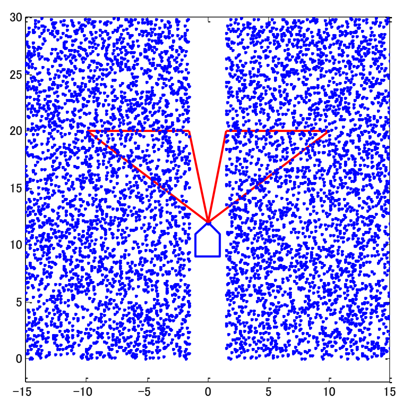

Figure 9. Environment 4 (random pattern, 3600 points).

The characteristic points are set at a regular interval in Environment 1 (Figure. 6) and 2 (Figure. 7), and are set randomly in Environment 3 (Figure. 8) and 4 (Figure. 9). The density of the characteristic points is the same in Environment 1 and 3, and in Environment 2 and 4.

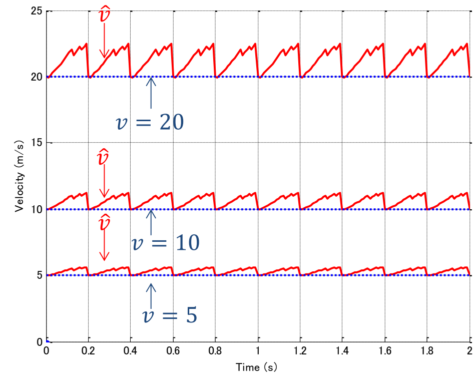

Figure 10. Results of Environment 1

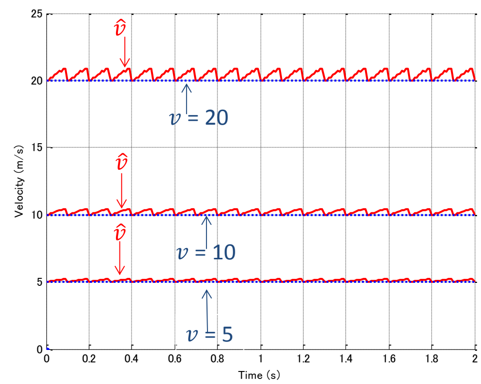

Figure 11. Results of Environment 2

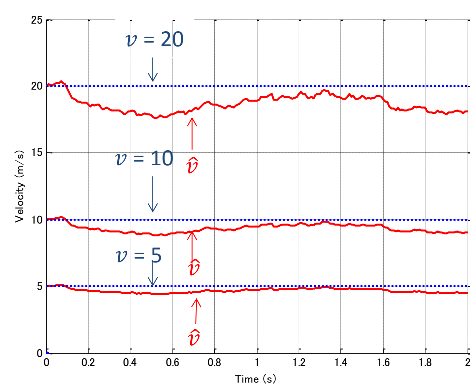

Figure 12. Results of Environment 3

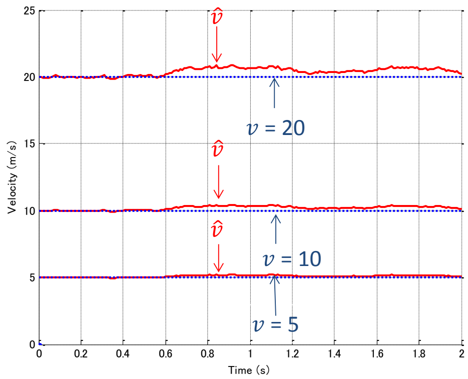

Figure 13. .Results of Environment 4

We conducted simulations at different velocity (v = 5, 10, 20) in every environment. Figure. 10–13 show the results, and based on them, we can infer that the velocity can be estimated. However, the estimated velocity has a small oscillating error. In a precise sense, the average distance $\overline{D}$ is not constant and it oscillates because, while the camera is moving, some characteristic points go out of view and others come into view. At the same time, the sum of $R_i/\dot{R}_i$ also oscillates, and it counterbalances the oscillation of $\overline{D}$. Thus, the actual v is determined as a constant value, as shown in (9).However, as shown in (10), we employ a constant $\widehat{D}$ instead of $\overline{D}$ in the simulations because the actual $\overline{D}$ is unknown. As $\widehat{D}$ is constant and the sum of $R_i/\dot{R}_i$ oscillates, the estimated velocity $\hat{v}$ also oscillates, which causes the error. Therefore, the amount of error depends on the variation of $\overline{D}$. And the error rate of $\hat{v}$ is the same as the error rate of $\widehat{D}$. In the environments, there are a large number of characteristic points and they are uniformly distributed. Hence, the error becomes small, as shown in Figure. 12 and 13.

In summary, we can conclude that the velocity can be estimated using only one camera, and the error rate of the estimated velocity is dependent on the error rate of $\widehat{D}$ and is independent of the actual velocity. As the variance of the error of distance is dependent on the density of characteristic points, the variance of the error of velocity is also dependent on the density of characteristic points.

VI. CONCLUSION

In this paper, we addressed a method for the velocity estimation of a robot from visual information. We focused on the property of the environment and assumed that the average distance from the visible characteristic points was constant and predefined. Under this assumption, we proposed a method for velocity estimation. Simulations were conducted and the results showed that the velocity could be estimated with a small error, which depended on the environment.

Our future work is to develop a prototype system and conduct experiments in real environments, and discuss effectiveness of the proposed framework in practical use.

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