Image Feature Significance for Self-position Estimation with Variable Processing Time

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Abstract. We have researched about an action planning method of an autonomous mobile robot with a real-time search. In the action planning based on a real-time search, it is necessary to balance the time for sensing and time for action planning in order to use the limited computational resources efficiently. Therefore, we have studied on the sensing method whose processing time is variable and constructed a self-position estimation system with variable processing time as an example of sensing. In this paper, we propose a self-position estimation method of an autonomous mobile robot based on image feature significance. In this method, the processing time for self-position estimation can be varied by changing the number of image features based on its significance. To realize this concept, we conceive the concepts of the significance on image features, and verify three kinds of equations which respectively express the significance of image features.

1 Introduction

An autonomous mobile robot is one of the most interesting targets in the field of the robotics. It is very expected not only in the industrial field but also in the community like an office, a hospital and a house in the future. Among various kinds of problems for an autonomous mobile robot, we have focused on and researched about its action planning methods with the real-time search [1][2]. In the action planning with the real-time search, a robot action is acquired through the recognition of the current situation and the action search on the ground. Therefore, the computational resource for the action planning is limited, and the situation around a robot changes every moment in a dynamic environment where the robot moves. Under these circumstances, we have to consider the balance between the time for recognition and the time for action search according to the situation around the robot in order to utilize the limited computational resource efficiently. This idea is based on Anytime Sensing which has been proposed by S.Zilberstein et.al[3], and one of crucial features in the action planning with the real-time search. As an example of recognition, we deal with a self-position estimation problem for the robot with vision and construct a self-position estimation system with variable processing time based on the above idea.

In this system, it is assumed that the robot estimates the current self-position by matching an acquired input image with stored images which indicate certain positions in the environment. The normalized correlation coefficient [7] is applied as a criterion
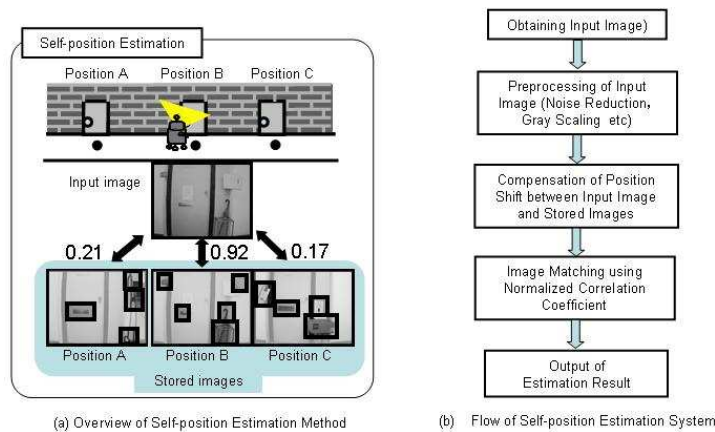
(a) Overview of Self-position Estimation Method   (b)   Flow of Self-position Estimation System

Fig. 1. Self-position Estimation System.

of the template matching. In order to use the limited computational resource efficiently, only image features in a stored image are used in the self-position estimation process. Moreover, the processing time for the self-position estimation is varied by changing the number of the image features utilized for the template matching. In this case, it is important that the number of the image features is varied according to priority in order not to deteriorate the performance of the self-position estimation.[5][6] To realize this idea, it is essential to decide how important each image feature is for the self-position estimation. By changing the number of the image features based on image feature importance, stable self-position estimation can be realized even if the time for the self-position estimation is shortened. According to these reasons, a new self-position estimation method with variable processing time is proposed based on image feature significance in this research. In this paper, the concepts based on image feature importance are conceived, and three types of equations are defined as an indicator of significance on image features. These equations are compared through some experimental results.

2   Self-Position Estimation with Variable Processing Time

2.1   Self-position Estimation System

As a framework of a self-position estimation problem, the robot moves in the indoor environment and estimates which key location it is around in the environment. It obtains images at key locations and image templates are generated with them as a preparation for the self-position estimation.At the self-position estimation, an input image is obtained and it is processed through image processing for noise reduction and gray scaling. Then, an input image matches stored image templates and the estimation result is output. In the case of Fig.1(a), the highest value of the similarity is one with the position B. Therefore, the output is the position B as the estimation result. In this paper, the normalized correlation coefficient(NCC) is applied as a criterion for the similarity.
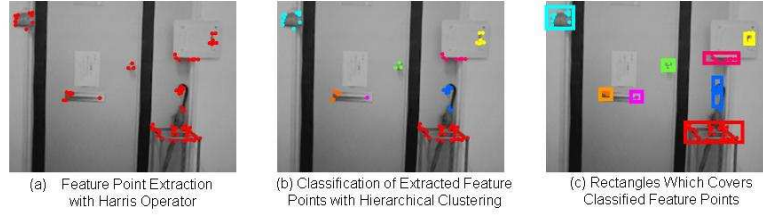
(a) Feature Point Extraction with Harris Operator

(b) Classification of Extracted Feature Points with Hierarchical Clustering

(c) Rectangles Which Covers Classified Feature Points

Fig. 2. Generation Method of Image Template.

$$R = \frac{\sum_x^M \sum_y^N \left\{ f(x,y) - \bar{f} \right\} \cdot \left\{ g(x,y) - \bar{g} \right\}}{\sqrt{\sum_x^M \sum_y^N \left\{ f(x,y) - \bar{f} \right\}^2} \sqrt{\sum_x^M \sum_y^N \left\{ g(x,y) - \bar{g} \right\}^2}} \qquad (1)$$

Eq.1 indicates the normalized correlation coefficient between two images F and G. They are grey-scale images whose size is $M \times N$. The parameters $f(x,y)$ and $g(x,y)$ are the brightness of the pixel at the coordinate (x,y) in each image F and G. The parameters $\bar{f}$ and $\bar{g}$ are the mean value of $f(x,y)$ and $g(x,y)$ respectively. When $f(x,y)$ is entirely identical to $g(x,y)$, the value of R is 1.0. On the other hand, when the image $f(x,y)$ is completely different from $g(x,y)$, R is -1.0. Here, it is assumed that $f(x,y)$ is an input image obtained at the current position of the robot, and that $g(x,y)$ is an image template stored in the robot. By the image template matching using this equation, it is estimated that the robot is around the position which is indicated by the image template with the highest value of R in the stored image templates.

2.2 Changing Method of Processing Time

The time for the image template matching occupies most of the processing time for the self-position estimation in this system. This is because NCC is the pixel-based calculation which requires computational resources. According to the above equation, the computational amount for calculating R is in proportion to the number of pixels. Therefore, only image features are utilized for the self-position estimation, and the number of the image features is changed in order to change its processing time.

The image features are extracted as some rectangle areas from a stored image through the image processing. shows. A set of extracted rectangles is called as an image template in this paper, and template generation method is described in the next section. The similarity between an input image and an image template is the average of NCC value on all rectangle areas utilized for the self-position estimation.

2.3 Generation Method of Image Templates

Fig.2 shows the generation method of the image template for the self-position estimation. First of all, feature points in each stored image are extracted with Harris operator[8] which is widely utilized for image feature extraction. As Fig.2(a) shows, a mass of feature points is extracted around the distinctive parts in a stored image. Thus, these points are grouped with hierarchical clustering as Fig.2(b). Then, a rectangle is created
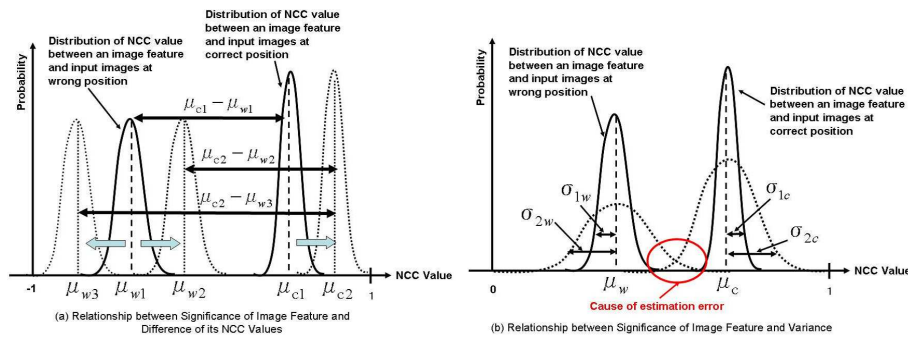
In the self-position estimation system, the current position is estimated as one which is indicated by the image template with the highest similarity for an input image. Therefore, the higher NCC values for the images obtained at correct position are better for the self-position estimation on an image feature. Moreover, the higher NCC values for the images obtained at wrong positions is worse for the self-position estimation on the image feature even if the NCC value is pretty high as Fig.3(a) shows. Therefore, the difference between NCC values at correct and wrong positions is important for the self-position estimation in addition to the absolute value of NCC at the correct position. Moreover, when the NCC values widely changes for various input images, the distribution of NCC value at the correct position overlaps the one at the wrong positions as Fig.3(b). This overlap causes the error of the self-position estimation. Therefore, the variance of NCC value should be also considered for stable self-position estimation.

Fig.4 shows the relationship between the size of the image feature and its significance. This is the concept from the viewpoint of the computational resources. As mentioned in Section 1, the computational resources is limited in the action planning with the real-time search, therefore it is important to utilize the computational resources efficiently. Here, let two rectangles drawn in Fig.4 stand for image features for the estimation of a certain position. As mentioned in Section 2.2, computational amount for the self-position estimation is in proportion to the number of pixels of an image feature. Therefore, if the NCC values of these two image features are very similar as this figure shows, it is apparent that the small image feature is better than the large one. According to this reason, the size of image features should be considered on the image feature significance.

3.2 Equations of Image Feature Significance

Based on the above concepts, the three kinds of equations are formulated as a indicator of significance on image features.

$$E_1 = k_1 \mu_c + (\mu_c - \max_j \mu_{w(j)}) \tag{2}$$

$$E_2 = k_1 \mu_c + \{(\mu_c - k_2 \sigma_c) - \max_j (\mu_{w(j)} + k_2 \sigma_{w(j)})\} \tag{3}$$

$$E_3 = E_2 - k_3 \frac{S_p}{\sum_{q=1}^h S_q} \tag{4}$$

μ_c, μ_w : mean value of NCC of correct or wrong images

σ_c, σ_w : variance of NCC of correct or wrong images

j : number of positions

$k_1 \sim k_3$: weight

S_p : number of pixels of image features

h : number of image features

Eq.(2) indicates the significance on an image feature which considers only the mean value of NCC at the correct position and the difference of NCC values between the correct position and wrong ones.In this equation, the first term is the absolute value of NCC

for an input image obtained at the correct position. The second term is the difference of NCC values between the correct and wrong positions. k_1 is a weight in order to balance these two parameters. The larger this value becomes, the more important the image feature becomes for the self-position estimation. Eq.(3) indicates the significance on an image feature which considers the variance of NCC values at the correct and wrong positions.The larger the variance of NCC values becomes, the smaller the second and third terms become. Eq.(4) indicates the image feature significance which considers the computational amount for the self-position estimation in addition to the quality of the self-position estimation. The second term is a percentage of the pixel of an image feature for all image features. Therefore, the second term becomes large when the size of an image feature becomes large.

4 Experimental Results and Verification

4.1 Experimental Setup

In order to examine the proposed method, we performed some experiments. First of all, six image templates were generated which respectively distinguished from the position A to the position F. The value of significance was calculated for each image feature in a image template according to the above equations. The weights in Eq.2, Eq.3 and Eq.4 were 0.14, 1.20, and 1.20 respectively. These parameters were decided experimentally. Then, a real robot performed the self-position estimation with the acquired image templates in a real environment. In this experiment, the number of the image features was changed from one up to five according to the priority given by each equation of the image feature significance. The self-position estimation was performed a hundred times at each key location.

4.2 Generated Image Templates

Fig.5 shows the image templates which were generated with the method in Section 2.3. As this figure shows, rectangles which cover distinctive parts in each stored image were generated as an image template. Fig.6 shows the top five rectangles ranked by each equation expressed in Section 3.2 for the templates of Position E. This is because the rank of the image features in this image template changed characteristically. As this figure shows, unique image features have higher priority in each image template. Moreover, comparing image features ranked by Eq.(2) with ones by Eq.(3), the ranking of some image features changes. This is because image features which are ranked lower in Eq.(3) are much influenced by the robot motion, therefore, the variance of NCC values becomes large. In addition, image features with a larger size are ranked lower by Eq.(4) in comparison with ones ranked by Eq.(4). This is because larger image features are ranked by Eq.(4) from the viewpoint of the computational resources.

4.3 Performance of Self-position Estimation

In order to examine the image feature significance ranked by Eq.(2), Eq(3) and Eq.(4), the experiment of the self-position estimation with a real-robot was performed. In this
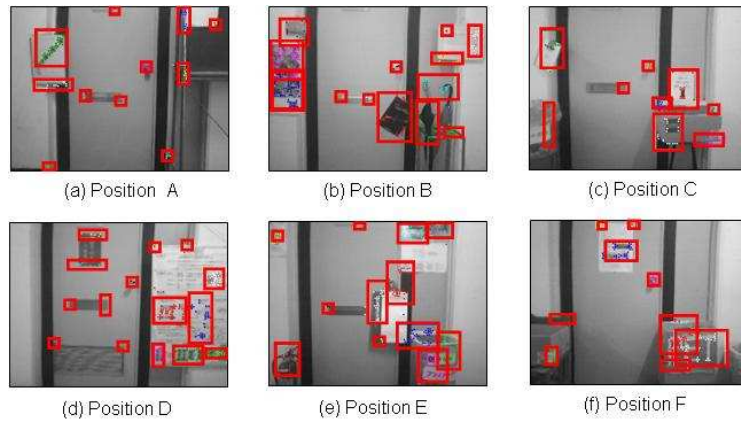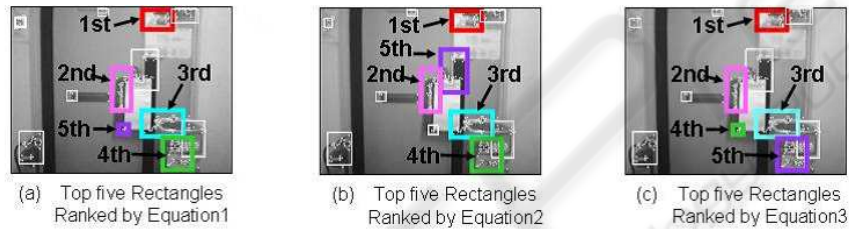
Fig. 5. Generated Templates.

Fig. 6. Comparison of Image Feature Ranking(Position E).

experiment, the number of the image feature changed according to the priority ranked by each equation, and the self-position estimation was performed with only selected image features. The robot succeeded the estimation of its current position at all positions in all trials. In order to compare the quality of each equation, the relationship between the performance of the self-position estimation and each equation on image feature significance was examined. In addition, the relationship between the processing time and each equation on image feature significance was also examined.

Fig.7 shows the difference of NCC values between the correct and wrong positions on the image template of the position E. The larger this value becomes, the more clearly the image template can distinguish the correct position from wrong ones. According to this result, all image templates have almost same quality Fig.8 shows the processing time for the self-position estimation when the number of the image features in an image template changes. As Fig.8 shows, the processing time with the image template ranked by Eq.4 is the shortest in all equations. This is because Eq.4 considers the computational resources for the self-position estimation. According to these results, Eq.4 is the best indicator of image feature significance.
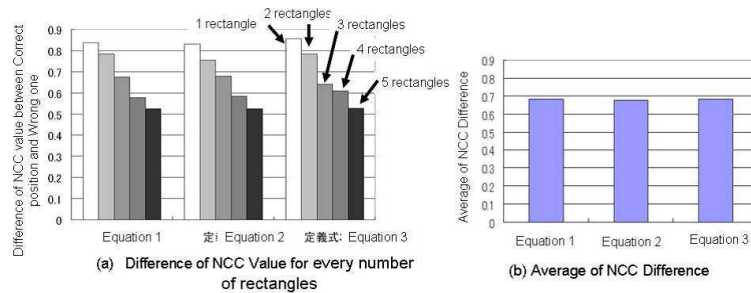
Fig. 7. Difference of NCC values between the correct and wrong positions for the template.
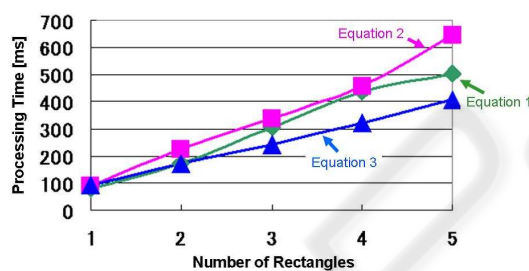

Fig. 8. Processing Time for Self-position Estimation.

5 Conclusions

A new self-position estimation method with variable processing time was proposed based on image feature significance in this research. It was demonstrated that the stable and efficient self-position estimation could be realized with an image template based on image feature significance even if the number of the image feature was changed. For the future work, the self-position estimation with an omni-directional image will be tackled based on the proposed method. Moreover, it will be examined how the environmental change influences the performance of the self-position estimation.

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