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Research Article

Development of an Autonomous Mobile Robot Doing Self-Position Estimation and Road Region Search

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ABSTRACT

This paper proposes an autonomous mobile robot expected to realize an intelligent robot that supports a human life. The proposed mobile robot has three main functions; self-position estimation, road region estimation, and route planning. Self-position estimation is performed by comparing local features obtained from the frontal images captured by the robot to a knowledge base. In road region estimation, the frontal image is separated into several regions to find the region where the robot can move. Furthermore, the route to the destination is planned by graph search. Experimental results show satisfactory performance of the proposed mobile robot.

1. Introduction

Robot technology has been widely used in industries. But, in recent years, it is largely expected in a welfare field and various kinds of service areas for supporting a human life. In particular, much attention has been focused on service robots [1] to help our daily life. These robots need to autonomously judge their actions in response to various usage situations, scenes, and environmental changes. Therefore, in recent years, researches on recognition and judgment on a drivable area for a mobile robot in surroundings have greatly advanced. GPS, LiDAR [2],[3] and cameras [4] are commonly used sensors for this purpose. GPS and LiDAR are, however, not able to acquire sensor signals in a specific environment. The former provides no information in a tunnel or indoors, whereas the latter is helpless without reflective objects such as buildings around it.

This paper proposes an autonomous mobile robot system that employs a camera and adapts to various environments and travel routes. To realize this, we propose a self-position estimation method using local features based on a camera. In the method, the ORB [5] (Oriented FAST and Rotated BRIEF [6]) technique is employed for detecting local features on an image. The ORB realizes high speed processing without affected by scaling, rotation and illumination. Since the calculation cost is high if the local features are used in their original form, BoF (Bag of Features [7]) is employed that converts the image features into feature vectors to reduce the calculation cost.

An autonomous mobile robot needs to find an area where it travels. For this purpose, the frontal image the robot acquires is separated into several regions employing GBS (Graph Based Segmentation [8]) and the regions are found that are similar to the initial robot travel region. For travelling autonomously to a destination, the robot must plan a route from the current location to the destination. In

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the method, numbers are given as labels to forks, corners and destinations, and route planning is performed based on backward search of a graph. The developed mobile robot travels to the destination employing the information on its self-position, the estimated road region and the planned route.

2. Self-Position Estimation of a Robot

Obviously, self-position estimation is of great importance for a mobile robot to travel to its destination. The proposed method uses local features on an image to know its present position. Here, local feature points are called local features in the method. Since many local features are extracted from a single image, comparing each local feature to a database increases calculation cost. Therefore, in the proposed method, extracted local features are converted to a histogram showing the frequency of occurrence of specific local features on the image by use of BoF. The robot's self-position is estimated by comparing the histogram to those prepared for each check point.

2.1. *Bag of Features*

Bag of Features (BoF) represents an image by a single feature vector. The process of BoF is shown as follows;

(i) Extracting local features from an image.
(ii) Creating Visual Words (VWs) by clustering the local features.
(iii) Creating a histogram of the image based on the Visual Words.

(i) *Extracting local features*

Local features are extracted using ORB in the proposed method. Fig. 1 shows an example of local features extracted by ORB. They are indicated by red circles in Fig. 1.

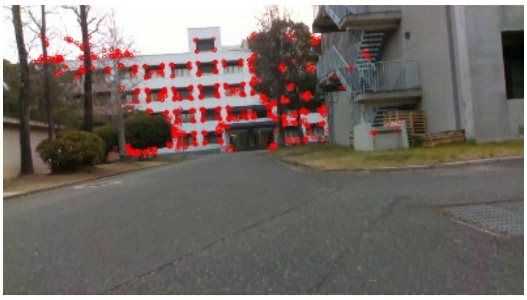

Fig. 1 Example of local features extracted by ORB.

(ii) *Clustering the local features*

Let us suppose that $\boldsymbol{F}_j$ $(j = 1,2,\dots,m)$ local features are extracted from an image. They are clustered by *K*- means++ [9] in a feature space. *K*-means++ is a clustering algorithm that improves the initial cluster problem of *K*-means [10].

(iii) *Creating a histogram*

After having clustered the local features, the center of each cluster $i (i = 1,\dots,n)$ is defined as VWs $\boldsymbol{V}_i (i = 1,2,\dots,n)$. A histogram representing a given image is created as follows. Given a local feature $\boldsymbol{F}_j$, a score s_{ij} showing the similarity between $\boldsymbol{V}_i$ and $\boldsymbol{F}_j$ is calculated to find $\boldsymbol{V}_{i^*}$ giving the maximum value of the score. Then a vote is given to bin i^* corresponding to $\boldsymbol{V}_{i^*}$. A histogram is made by performing the vote with all $\boldsymbol{F}_j$ $(j=1,2,\dots,m)$. This histogram provides an n-dimensional feature vector that represents the image.

The procedure for finding i^* is formulated by the following equations;

$$i^* = \arg\max_i s_{ij}$$

$$s_{ij} = 1 - \frac{1}{2}\left\| \frac{\boldsymbol{V}_i}{\|\boldsymbol{V}_i\|} - \frac{\boldsymbol{F}_j}{\|\boldsymbol{F}_j\|} \right\| \tag{1}$$

2.2. *Self-position Estimation of the Robot*

In order to estimate the robot's self-position, the input images and keyframe images at branch points (junctions) are converted into histograms using BoF. The similarity of the histogram is then calculated and the robot's self-position corresponding to the input image is estimated. The procedure of the robot's self-position estimation is shown below.

(i) Histograms H_{in} and H_{key} of local features are created by BoF from the input image and the key frame image, respectively.
The similarity measure, $S_{SAD} (> 0)$, defined by

$$S_{\mathrm{SAD}} = \sum_{i=0}^{n-1} \left| H_{in} - H_{key} \right|_i \quad , \tag{2}$$

is calculated between H_{in} and H_{key}. Here $|\boldsymbol{a}|_i$ is the absolute value of the ith component of vector $\boldsymbol{a}$, and n is the number of classes of the VWs. Note that SAD means Sum of Absolute Difference.

(ii) To make the self-position estimation more accurate, the sum of the similarities of the past M input images is used. Let the similarity of frame f be denoted by S^f_{SAD}. Then, if

$$\sum_{f=f}^{f-M+1} S^f_{\mathrm{SAD}} < T_s \tag{3}$$

holds, it is judged that the robot is at the position where the key frame indicates. Here T_s is a predefined threshold.

3. Road Region Estimation

A road region is estimated from an image using an image segmentation technique. In the proposed method, GBS [8] is employed. It is a well-known image segmentation technique.

3.1. *Graph Based Segmentation*

Graph Based Segmentation (GBS) is one of the renowned image segmentation methods, which combines pixels with similar characteristic pixel values into multiple regions. The algorithm of GBS is shown below.

(i) Smoothing the input image $I(x, y)$ using the following equation.

$$L(x, y, \sigma) = G(x, y, \sigma) \cdot I(x, y) \quad (4)$$

$$G(x, y, \sigma) = \frac{1}{2\pi\sigma} \exp\left(-\frac{x^2+y^2}{2}\right) \quad (5)$$

Here σ is the standard deviation, $G(x, y, \sigma)$ is the Gaussian function, and $L(x, y, \sigma)$ is a smoothed image.

(ii) Creating a graph with the node v_i representing each pixel of the smoothed image and the edge e_q connecting adjacent pixels in the image. Using the illuminance difference between the pixels connected by an edge, the weight of the edge $w(e_q)$ is calculated by the following equation.

$$\omega(e_q) = \sqrt{(R_i - R_j)^2 + (G_i - G_j)^2 + (B_i - B_j)^2} \quad (6)$$

where, $R_\#$, $G_\#$, and $B_\#$ are the red, green and blue values of the node.

(iii) Assignment of a separate region $S_q (q = 1, \ldots, m)$ to each node where m is the total number of pixels in the image.

(iv) When nodes v_i and v_j connected by edge $e_q (q = 1, \ldots m)$ satisfy the following equation, the region S_i and S_j are combined.

$$\omega(e_q) \leq \min\left(\max_{e \in E_i}\{\omega(e)\} + \frac{c}{|S_i|}, \max_{e \in E_j}\{\omega(e)\} + \frac{c}{|S_j|}\right) \quad (7)$$

Here, c is a predetermined fixed value, $|S_\#|$ is the number of nodes constituting the region $S_\#$, and $E_\#$ is a set of edges connecting nodes in the region $S_\#$.

For all edges, the node is divided into several regions by determining the region connection by Eq. (7). If, with a certain region, the number of nodes is less than or equal to a threshold S_{th}, the region is merged with an adjacent region with which an edge connecting the two regions has the smallest weight among adjacent regions.

3.2. *Road Region Estimation*

In the proposed method, the road region is estimated by the following procedure;

(i) Divide the input image into regions using the GBS.

(ii) Set the robot's foot region as shown by a blue box in **Fig. 2**.

(iii) The maximum area including the foot region is a road region.

(iv) If the estimated road region A_R in (iii) is less than a threshold A_{th}, the road region of the past frame is used.

Fig. 3 shows an example of road region estimation. The gray area is the estimated road region.

4. Route Planning

The proposed method assumes the knowledge on a road map. Numbers are given as labels to junctions, corners and destinations on the map, all referred to as check points in the method, in advance. The relations on their connection are represented by a graph using the labels: A vertex corresponds to a label (or a check point), whereas an edge shows connection of two vertices: A weight is given to an edge according to the distance between two connected vertices.

Fig. 2 Example of the robot's foot region

Fig. 3 Example of estimation of a road region

Given an initial position and a destination, the route having the minimum weight is searched on the graph backwards from the destination to the initial position. Then a route is finally produced which the robot tracks.

5. Algorithm on Autonomous Movement

An autonomous movement algorithm of the robot is shown in the following;

(i) Find the road region from the input image using GBS and the foot region.
(ii) Separate the road region into three sub-regions and calculate the areas of the three sub-regions. If the areas are all less than a threshold, **pause**. Otherwise, face the sub-region having the largest area.
(iii) **Move** forward.
(iv) Obtain local features from the input image and estimate the robot's self-position.
(v) If the estimated self-position matches one of the key frames, judge if it is the destination. If yes, **stop**. If not, turn to the direction specified in the route plan. Go to (i).
(vi) If the estimated self-position does not match any of the key frames, go to (i).

6. Experiment

6.1. *Experimental Environment*

In the experiment, the proposed robot system is evaluated by whether or not the robot reaches the destination autonomously in an outdoor environment. Two different routes, A and B, with different destinations are set. Route A contains more number of junctions (referred to as check points) than route B and higher precision in self-position estimation is required. On the other hand, route B has a rotary on the way and a robot needs travel along a curved line at the spot. The robot travels these routes five times each. If an emergency stop is required due to the passage of a vehicle or the like while travelling, the trial is interrupted and restarted after the passage. Table 1 shows the parameters related to the experiment. The travel speed of the robot is 0.2 [m/s] and the rotation speed is 0.2 [rad/s].

6.2. *Experimental Results*

Table 2 shows the results of the experiment. In Table 2, '○' indicates that the robot reached the destination successfully, whereas '×' indicates failure. The processing time was 65.4 [ms/frame]. The travel of the robot was successful 3 times out of 5 with route A, whereas it was successful 4 times out of 5 with route B. As for the weather, 2 times out of 4 were successful when it was fine, whereas 5 times out of 6 were successful when cloudy.

7. Discussion

In the performed experiment, as shown in Table 2, the destination could be reached in many cases (70%) regardless of the travel route and the weather. This is thought to be due to the high accuracy of self-position estimation and road region estimation.
However, in the second and the third experiment on route A and the first experiment on route B, the destination could not be reached. Failure with the first experiment on route A results from misdetection of a check point when successive check points exist. It is necessary to raise the ability of self-position estimation further by designing a stronger classifier.
Failure with the second experiment is incomplete estimation of the road region caused by a shadow. When a shadow is on the road region, the part that is originally the same region with a neighbor region is separated from the neighbor like the one in the white circle as shown in Fig. 4. Moreover, in the method, the road region to move next is determined by selecting the region having the maximum area among the three separated sub-regions. Hence the existence of a shadow on the road may mislead the selection. More robust road region estimation not influenced by a shadow needs to be developed.

Table. 1 Parameters used in the experiment

No. dimensions of ORB	32
No. features	1000
No. clusters	500
No. learning images	12 places × 5 frames

Table. 2 Experimental results

	1	2	3	4	5
route A	○	×	×	○	○
route B	×	○	○	○	○

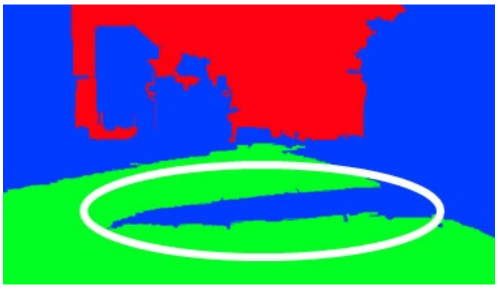

Fig. 4 Example of a shadow region on a road

Use of depth information obtained from a RGB-D camera may be useful for solving the difficulty.
Failure with the first experiment on route B results from the inclination of the road surface near the roadside. The inclination of the road surface becomes larger toward the end of the roadside. This has a negative effect on driving close to the roadside. Actually, the travel closes to the roadside didn't go well only by coping with fine adjustment of the traveling direction. It is necessary to calculate the inclination of the road surface from, e.g.,

images and to adjust traveling direction of the robot early. The depth information which a RGB-D camera provides might be of some help.
Detection of a road region where fewer pedestrians or obstacles exist is also within the scope of the present study. This function may help the robot choose an easier way when there is an alternative route such as a rotary.

8. Conclusion

This paper proposed an autonomous mobile robot system which does self-position estimation by scene recognition at a check point on the road using local features on a fed image, and travels forward by detecting a road region connected to its present position by performing region segmentation on the image. The route to the destination was decided in advance by graph, representing a road map, search. In the experiment, satisfactory performance was achieved with the robot travel on two routes and two kinds of weather. Further studies to equip higher functionality with the proposed robot system include use of depth information for more accurate detection of a road region not influenced by shadows or for detecting the inclination of a road surface, and design of a stronger classifier to find a check point regardless of the weather.

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