2010 2nd International Conference on Signal Processing Systems (ICSPS)

Automatic Floor Segmentation for Indoor Robot Navigation

Ma Ling
Department of Information and Communication Engineering
Tianjin Polytechnic University, TJPU
Tianjin, China
2006_maling@163.com

Wang Jianming
Department of Information and Communication Engineering
Tianjin Polytechnic University, TJPU
Tianjin, China
wangjianming@tjpu.edu.cn

Zhang Bo
Department of Information and Communication Engineering
Tianjin Polytechnic University, TJPU
Tianjin, China
316813299@qq.com

Wang Shengbei
Department of Information and Communication Engineering
Tianjin Polytechnic University, TJPU
Tianjin, China
wangshengbei@126.com

***Abstract*—Indoor autonomous robots can perform desired task in indoor environments without continuous human guidance, so navigation is indispensable for them. In the state of the art of vision-based navigation, one or more cameras are usually installed on a robot. This has led to a larger workload to deal with the data collected by cameras and arises the problem of delay. In the paper, we propose a novel vision-based navigation framework for indoor autonomous robots in which the camera is fixed on the ceiling. In the navigation scheme, a robot takes floor as their moving regions. So floor segmentation algorithm has to be designed to get floor regions in navigation images automatically. We adopted clustering analysis to implement automatic floor segmentation, and we also proposed a PCA based improved version of the algorithm to remove negative effect of shadow for segmented results.**

Keywords-YCbCr; K-means clustering; principal component analysis (PCA); floor segmentation; color feature extraction

I. INTRODUCTION

Autonomous mobile robot can be used in many special industry environments, such as non-man and non-dust workshops, dangerous and toxic situations, etc. With the rapid development of science and technology, the indoor mobile robot is trend to be more automatic and intelligent. The navigation technology of indoor mobile robot plays a very important part in the whole performance of the Mobile robot. As an important way of navigation, it affects the mobility and working efficiency of the mobile robot directly. Robot navigation refers to the ability to determine a robot current position and then to plan a path towards some goal location. For any mobile device, the ability to navigate in its environment is one of the most important capabilities of all. Staying operational, i.e. avoiding dangerous situations such as collisions and staying within safe operating conditions come first, but if any tasks are to be performed that relate to specific places in the robot environment, navigation is a must. In recent years, computer vision attracts a lot of attention for navigating a mobile robot in dynamic environments. Compared with other sensing systems, vision-based navigation is excellent and effective, and is one of the main research fields of autonomous mobile robot. Because of its abundant information, sensitivity, low cost, and the property of easily changing path and planning motion according to the requirement, the vision-based navigation has increasingly been an important research direction of autonomous mobile robot. The main technologies of vision-based navigation include navigation and obstacle avoidance, robot localization and the control system designing, etc. In this paper, we propose a novel navigation framework that the camera is fixed on the ceiling. When the robot is walking in the room, we must extract floor area where a robot could walk. We adopt several measures, such as color model conversion, PCA and K-means clustering, etc.

II. RELATED WORK

The vision-based navigation technology has become an important development direction of navigation technology. With a visual sensing system, wider view of field, rich and intensive data can be obtained for a mobile robot moving in a changing environment. At present, the vision-based navigation technology takes some features of objects as signposts, such as floor, lighting devices, baseboard, etc. The complexity of the algorithm for navigation can be simplified by the signposts.

Jiang Zemin *et al* [1] make use of baseboard for navigation. Du Juan and Li Wenfeng [2] use the features of floor tiles as signposts. The all above methods use the features of floor as signposts. But such signposts on the floor are obstructed easily by obstacles and moving objects. Chih-Jen Wu and Wen-Hsiang Tsai [3] use camera installed on the robot to capture the circular marks on the ceiling for navigation. This design approach makes the camera view less likely to be blocked and signposts are more conducive to be found for navigation. In this paper, the camera installed on the ceiling also can make the camera view less likely to be blocked.

So far, cameras are always installed on indoor robots to do navigation. This has led to a larger workload to deal with the data collected by the camera and arises the problem of delay [4]. Therefore we explored a novel navigation framework that the camera is fixed on the ceiling. Another advantage of adopting the system is that it can avoid the obstacle detection. In this case, the floor forms the largest proportion of the indoor surface, an automatic floor segmentation algorithm was presented which based on clustering algorithm. We also transform color space to YCbCr to remove the negative influence of shadow. In order to get better results, the algorithm of PCA is proposed in this paper. A group of experiment results were analyzed in different indoor condition. The purpose of the paper is to remove the shadow which is generated by the light and other external conditions, in order to accomplish the best effect of extracting the area of floor that the robot could walk on. The work in this paper also laid the ground for the further research in the field of detecting moving object, robot localization of the indoor vision-based navigation and robot motion planning. The following experiments show that the improved algorithm of automatic floor segmentation has relatively good segmentation results.

III. NAVIGATION FRAMEWORK

In this paper, we propose a novel navigation framework that the camera is fixed on the ceiling, in order to avoid the detection of obstacles.And the navigation system which we adopted is used for indoor.

The processes of robot navigation are described as follows. After floor segmentation, we establish indoor navigation map with the grid method and achieve path planning. Then we could monitor the walking routes of robot by the algorithm of object tracking and the interference generated by other moving objects is eliminated by the algorithm of SIFT. In this paper, we mainly study the algorithm of automatic floor segmentation. The navigation framework is shown in figure 1.

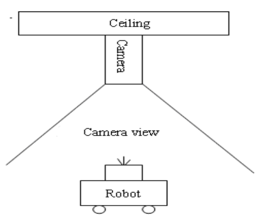


Figure 1. Navigation framework

The navigation framework which we adopted has some advantages as follows:

(1) Acquire the global information of the indoor venues effectively.

(2) Simplify the calibration of the camera, and locate the position of the robot easily.

(3) Stationary objects in the scene are stationary relative to the image captured by the camera, and it is easy to design algorithms to achieve navigation.

IV. AUTOMATIC FLOOR SEGMENTATION ALGORITHM

First of all, we assume that the floor surface forms the largest proportion of the indoor surface and has consistent color feature.

As shown in figure 2, in the same room, the material of the floor is generally same so the floor has almost the same color and texture features. But in different rooms, the color and texture features are different. Therefore, we must design a non-supervised algorithm to automatically adapt to the conditions of the floor in different rooms. In this paper, the problem is solved by clustering algorithm. We classify pixels into *n* groups according to the color characteristics. According to the clustering algorithm, the group with the largest number of pixels is floor.

Figure 2. An indoor image taken by a ceiling camera

The design ideas of automatic floor segmentation algorithm are shown in figure 3.

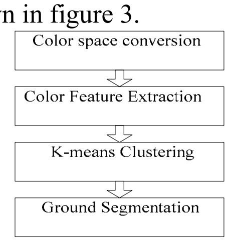


Figure 3. Automatic floor segmentation algorithm

A. Color Space Conversion

Objects in practical scenes often cast shadow. Shadow has severe effect on luminance components, but little on chroma components. Nevertheless the shadow under intense sunlight or incandescence lamp may be partly classified as a part of surrounding objects. When a region on the floor is covered by shadow, its luminance component is prone to be interfered by the changes of light, but the chroma components are stable [5].

Not only luminance but also chroma of a region will change if it is covered by shadow which is cast by moving objects on the floor. Luminance is very sensitive to the light intensity, while chroma maintains a comparative stability in the presence of light changes and shadow. Based on the stability, we select YCbCr colorspace [6]. Moving objects are extracted according to their chroma components' changes. For a pixel, it has three components. They including one luminance component Y and two chroma components Cb and Cr are statistical independent of each other. The shadow is removed in order to improve accuracy of the object's information.

RGB to YCbCr [7] transformation is the most commonly used color coordinate system for the compression of image and video signals. Y is the luminance component and Cb and Cr are the blue-difference and red-difference chrominance components. The primary red, green, blue inputs (R, G and B) can be converted as follows:

$$\begin{bmatrix} Y \\ Cb \\ Cr \end{bmatrix} = \begin{bmatrix} 0.2290 & 0.5870 & 0.1140 \\ -0.1687 & -0.3313 & 0.5000 \\ 0.5000 & -0.4187 & -0.0813 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \tag{1}$$

B. Image Feature Extraction

In the process of feature extraction, we have to divide the image into blocks first, because there are three disadvantages when we directly use the characteristic value of each pixel in image processing: (1) If each pixel is considered, computational complexity is increased, and clustering computation speed is influenced seriously. Thus the real-time performance of whole system is affected. (2) Pixel points scattered result in many small disconnected areas after the image is processed and the navigation map is distorted seriously. (3) The result of image processing is greatly influenced by noise.

Therefore, in this paper we use an image sub-block processing approach [8]. Take adjacent pixels in a rectangular as a unit and mean of the rectangular pixel region represents its pixel value, then take a rectangular as a pixel to participate in cluster computing.

There are many features that can be used in the area of the floor, such as the color, texture, etc. In this paper, color information is used for clustering. We extract the mean pixel value of the $n \times n$ pixels as the characteristic value which is very essential before clustering algorithm.

C. K-means Clustering

Cluster analysis or clustering is the assignment of a set of observations into subsets so that observations in the same cluster are similar in some sense. Data clustering attempts to participate data points into disjoint group such that data belonging to same cluster are similar while data belong to different clusters are dissimilar. One of the most popular and efficient data clustering methods is the K-means [9].

Simply speaking K-means clustering is an algorithm to classify or to group objects based on features into k groups. K is a positive integer number. The grouping is done by minimizing the sum of squares of distances between data and the corresponding cluster centroid [10]. Thus the purpose of K-mean clustering is to classify the data.

The K-means algorithm, probably the first one of the clustering algorithms proposed, is based on a very simple idea: Given a set of initial clusters, assign each point to one of them, and then each cluster center is replaced by the mean point on the respective cluster. These two simple steps are repeated until convergence. A point is assigned to the cluster which is close in Euclidean distance to the point.

D. Floor Segmentation

After clustering, Find out the group with largest number of pixels, and then mark the pixels of the group as black. The other pixels are marked as white. Then the image is divided into two parts. The black area is the region that the robot could walk on.

Figure 4 is the result after running this algorithm on figure 2.

Figure 4. The result of this algorithm

We can see that the algorithm has extracted the most of the floor. But in the upper part of the picture you will find that the area of floor and the area of non-floor are reverse if you observe carefully. So shadow generated by the light has a serious influence on the result. We have to adopt an improved algorithm to get better result.

V. The Improved Algorithm of Automatic Floor Segmentation

Although often used in practice, K-means has several drawbacks. The number of clusters has to be determined in advance and the algorithm is dependent upon the starting centroid locations. What's more, weakness of arithmetic mean is not robust to outliers. Very far data from the centroid may pull the centroid away from the real one. These can distort the centroid positions and ruin the clustering. In the segmentation algorithm, the above-mentioned issues are also generated, because shadow has a great influence on clustering effect. We use the algorithm of principal component analysis (PCA) to solve these issues.

PCA is a way of identifying patterns in data, and expressing the data in such a way as to highlight their similarities and differences [11]. Since patterns in data can be hard to find in data of high dimension, where the luxury of graphical representation is not available, PCA is a powerful tool for analyzing data. The other main advantage of PCA is that once you have found these patterns in the data, you can compress the data by reducing its dimensions, without much loss of information.

The algorithm of PCA has a certain effect on shadow suppression and it can achieve the principal information of the image [12]. Using the principal components, the data is mapped into the new feature space. Then, the K-means algorithm is applied to the data in the feature space. The final objective is to distinguish the different clusters much accurately.

The design ideas of the improved algorithm of automatic floor segmentation are shown in figure 5.

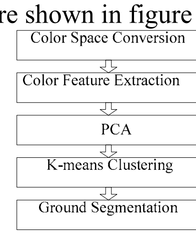


Figure 5. The improved algorithm of automatic floor segmentation

After obtaining the floor area, we need some simple image processing [13]. Firstly remove all connected components which are fewer than 5 pixels away from the binary image, and then use the algorithm of opening. Opening can be used to remove small objects, protrusions from objects, and connections between objects. This can make the boundaries of floor region much clear.

The result processed by the improved algorithm is shown in figure 6.

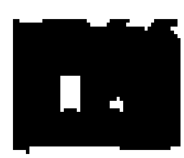


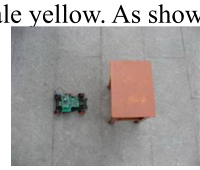
Figure 6. The result of the improved algorithm

Figure 7. Ten groups of sample image

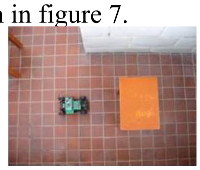
Comparing figure 4 with figure 6, we can see that the improved algorithm of automatic floor segmentation can get better result.

VI. Experimental Results and Discussion

As to verify the ability and precision of the improved algorithm of automatic floor segmentation, we take photos of ten different floor environments. For each environment, we have ten pictures. These are: (a) Corridor, the gray granite floor. (b) Corner of the corridor, dark red, regularly shaped floor tiles. (c) In the toilet, the color of the floor is oyster white, regularly shaped floor tiles. (d) In the office, the color of the floor is pale yellow. (e) In the canteen, textured marble floors. (f) In the library, stone floor of gray. (g) In the library, white, regularly shaped floor tiles. (h) In office building, carpet of light green. (i) In the restaurant, black marble floors. (j) In the laboratory building, marble floors of pale yellow. As shown in figure 7.



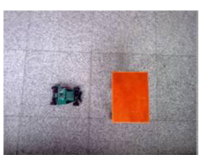
(a)The first group



(b) The second group

(c) The third group

(d) The fourth group

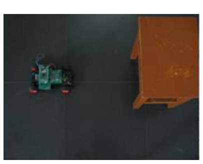


(e) The fifth group

(f) The sixth group

(g) The seventh group

(h) The eighth group



(i) The ninth group

(j) The tenth group

First we use the improved algorithm of automatic floor segmentation to get the results. Then we compare them with the results by manual segmentation to get correct segmentation rates. The results by manual segmentation are the correct results in theory. For example, figure 8 is the processed result of figure 7(a) by manual segmentation. To get segmentation correct rates, the results of manual segmentation are compared with the results of improved algorithm. The segmentation correct rates of different groups are shown in table I. Line numbers (one, two, three……) represent group numbers. Column numbers represent the number of pictures in each group.

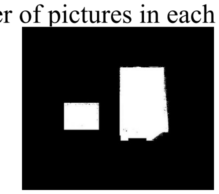


Figure 8. The processed result of figure 7(a) by manual segmentation

Among the ten conditions, the distribution of correct segmentation rates is shown in figure 9. Abscissa (1、2、3……) represents group number, ordinate represents correct segmentation rate.

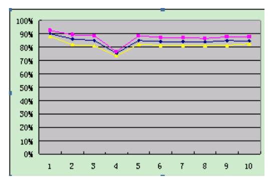


Figure 9. The distribution of correct segmentation rates

The blue curve shows the distribution of mean. The red curve shows the distribution of maximum. The yellow curve shows the distribution of minimum. We can see from the blue curve, the mean correct segmentation rates of the ten groups are about 85%. Within each group the difference value between the maximum and minimum is not exceed 10%.

TABLE I. THE TABLE OF CORRECT SEGMENTATION RATE

	1 (%)	**2 (%)**	**3 (%)**	**4 (%)**	**5 (%)**	**6 (%)**	**7 (%)**	**8 (%)**	**9 (%)**	**10 (%)**	**mean （%）**	**maximum （%）**	***minimum（ %）***

one	92.7	90.3	91.3	88.1	89.7	91.4	90.9	88.4	89.7	90.4	90.3	92.7	*88.1*
two	88.8	89.4	83.2	84.5	81.8	88.0	85.7	86.5	88.4	87.0	86.7	89.4	*81.8*
three	83.2	88.5	82.5	86.6	80.9	86.3	84.9	85.3	87.7	85.2	85.1	88.5	*80.9*
four	73.3	75.7	75.0	75.7	76.8	75.0	76.5	75.8	74.0	76.4	75.4	76.8	*73.4*
five	87.9	88.4	83.6	84.9	82.4	86.3	84.1	83.5	86.7	83.5	85.1	88.4	*82.4*
six	82.3	87.3	81.3	85.7	81.3	85.8	83.1	84.4	86.3	84.4	84.2	87.3	*81.3*
seven	84.9	87.3	83.6	85.8	83.7	84.9	86.5	82.4	83.5	81.5	84.3	87.3	*81.5*
eight	81.4	83.7	82.6	83.5	86.7	83.5	84.7	85.5	81.7	83.6	83.7	85.5	*81.4*
nine	86.9	87.9	84.7	85.0	81.3	85.8	84.9	82.4	85.9	84.6	84.9	87.9	*81.3*
ten	*82.5*	*84.7*	*83.5*	*84.5*	*87.5*	*84.8*	*85.4*	*86.3*	*82.5*	*84.1*	*84.6*	*87.5*	*82.5*

The following is results analysis of the first group which is the best and the fourth group which is the worst.

The first group: Corridor, the gray granite floor. Correct segmentation rates are as follows: 92.65%, 90.28%, 91.29%, 88.08%, 89.74%, 91.35%, 90.89%, 88.37%, 89.73%, 90.38%.

The mean correct rate is 90.28%.

We select one image of the first group to analyze the segmentation result and its correct segmentation rate is 90.28%. Its original image is shown in figure 10.

Figure 10. One original image of the first group

Its automatic segmentation result is shown in figure 11.

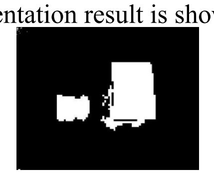


Figure 11. Its segmentation result

Its manual segmentation result is shown in figure 12.

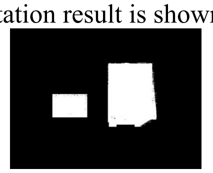


Figure 12. Its manual segmentation result

Analysis of segmentation result is as follows: The correct segmentation rate of the group is higher, because illumination and floor color are uniform, so the result is less affected by shadow.

The fourth group: The photo is photographed in the office, the color of the floor is pale yellow. Correct segmentation rates are as follows: 73.34%, 75.73%, 74.03%, 75.03%, 75.67%, 76.83%, 74.95%, 76.52%, 75.83%, 76.42%. The mean correct rate is 75.44%.

We select one image of the fourth group to analyze the segmentation result and its correct segmentation rate is 75.03%. Its original image is shown in figure 13.

Figure 13. One original image of the fourth group

Its automatic segmentation result is shown in figure 14.

Figure 14. Its segmentation result

Its manual segmentation result is shown in figure 15.

Figure 15. Its manual segmentation result

Analysis of segmentation result is as follows: The correct segmentation rate of the group is lower, because reflected light on the stool is so strong that color information is lost seriously.

From the experimental results we can see that the improved algorithm of automatic floor segmentation has relatively good segmentation results.

VII. CONCLUSIONS

In this paper, we propose a novel navigation framework that the camera is fixed on the ceiling. The advantage of the framework is that the detection of obstacles is avoided and the workload is reduced in dealing with the data collected by the camera. The algorithm restrains the noise of shadow which is generated by the light and other external conditions. And it accomplishes the better effect of extracting floor region that the robot could walk on. The work in this paper also laid the ground for the further research in the field of detecting moving object, robot localization of the indoor vision-based navigation and robot motion planning.

Considering the light and shadow, the algorithm has its special application conditions: (1) Shadow cannot be so strong. Otherwise, the color information of the floor will be corrupted severely. (2) The color of obstacles cannot be too close to the color of the floor, because we adopt color information for clustering algorithm. (3) The reflected light on floor and obstacles cannot be too strong because it also makes color information lost. So the algorithm remains to be improved.

REFERENCES

[1] Jiang Zemin, Yang Yi, Fu Mengyin and Wang Meiling, “Indoor visual navigation based on parallels,” J. Robot, vol. 29, no. 2, pp. 128-139, 2007.

[2] Du Juan and Li Wenfeng, “ground-based feature recognition for indoor robot visual navigation,” Sciencepaper Online, http://www.paper.edu.cn.

[3] Chih-Jen Wu, Wen-Hsiang Tsai, “Location estimation for indoor autonomous vehicle navigation by omni-directional vision using circular landmarks on ceilings,” Robotics and Autonomous Systems, vol. 2, no. 57, pp. 546-555,2009.

[4] Lu Shaofang and Liu Dawei, “A survey of research situation on navigation by autonomous mobile robot and its related techniques,” J. Transactions of the Chinese Society for Agricultural Machinery, vol. 3, no. 2, pp. 113-116, 2002.

[5] G. S. Xiang and X. Y. Wang, “Background reconstruction and object extraction based on color and object tracking,” J. Chinese Journal of Mechanical Engineering, vol.19, no.3, 2006.

[6] R. Chapuis and R. Chausse, “A Dynamic Vision Algorithm to Locate a Vehicle on a Nonstructured Road,” Robotics Research, May 2000.

[7] T. Ebrahimi and C. Home, “MPEG-4 natural video coding an overview,” Signal Processing:Image Communication, no. 15, pp. 365-385, 2000.

[8] R. Kenneth and Castleman, Digital Image Processing, Beijing: Tsinghua University Press, 1998.

[9] J. A. Hartigan and M. A. Wang, A, “K-means clustering algorithm,” Applied Statistics, 1979.

[10] E. Shechtman and M. Irani, “Matching local self-similarities across images and videos,” CVPR, 2007.

[11] I. T. Jolliffe, Principal Component Analysis, Springer Verlag,1986.

[12] D. Nister, H. Stewenius, “Scalable recognition with a vocabulary tree,” CVPR, 2006.

[13] A. Buades, B. Coll and J. M. Morel, “A non-local algorithm for image denoising,” CVPR, 2005.