

# JOURNAL OF SCIENCE



SAKARYA UNIVERSITY

## Sakarya University Journal of Science

ISSN 1301-4048 | e-ISSN 2147-835X | Period Bimonthly | Founded: 1997 | Publisher Sakarya University |  
<http://www.saujs.sakarya.edu.tr/en/>

Title: Real-Time Obstacle Avoidance Based on Floor Detection for Mobile Robots

Authors: Adem HİÇDURMAZ, Adem TUNCER

Received: 2020-01-13 13:39:02

Accepted: 2020-06-18 18:32:25

Article Type: Research Article

Volume: 24

Issue: 5

Month: October

Year: 2020

Pages: 845-853

How to cite

Adem HİÇDURMAZ, Adem TUNCER; (2020), Real-Time Obstacle Avoidance Based on Floor Detection for Mobile Robots. Sakarya University Journal of Science, 24(5), 845-853, DOI: <https://doi.org/10.16984/saufenbilder.674122>

Access link

<http://www.saujs.sakarya.edu.tr/en/pub/issue/56422/674122>

New submission to SAUJS

<http://dergipark.org.tr/en/journal/1115/submission/step/manuscript/new>



## Real-Time Obstacle Avoidance Based on Floor Detection for Mobile Robots

Adem HIÇDURMAZ<sup>\*1</sup>, Adem TUNCER<sup>2</sup>

### Abstract

Obstacle detection and avoidance are two main problems that demand solutions in the autonomous movement of mobile robots. To this end, the robots have been equipped with sensors and cameras. This study proposes a new method that allows mobile robots to move freely without any collision in an uncertain (i.e., both static and dynamic) workspace by processing images taken using a real-time webcam. In the study, a robot was allowed to move depending on the visibility and suitability of the floor in the images. These steps were repeated for each new image and, furthermore, the images were segmented based on an adaptive threshold obtained by calculating the statistical parameters. This segmentation was aimed to separate the floor from other areas in the study. Experimental results demonstrate that the proposed method is extremely successful to separate the floor from other regions and has a low cost and flexible method for obstacle avoidance.

**Keywords:** Mobile robot, Obstacle avoidance, Floor detection, Image segmentation, Adaptive threshold

### 1. INTRODUCTION

It is critical for a mobile robot to be able to move freely in a known or unknown environment by avoiding obstacles. Detecting and avoiding obstacles are among the most important and challenging issues to be considered in safe navigation. Various methods have been proposed to solve the obstacle avoidance problem. Some approaches use laser sensors [1], and some use ultrasonic sensors [2]. In addition to sensors,

vision-based methods are also used to avoid obstacles.

Various studies have been conducted on vision-based approaches using monocular [3, 4] or stereo [5] cameras. Vision-based systems provide significant information about the environment with a wide perspective [6]. An autonomous mobile robot using a camera can map an unknown environment with no prior information. Images taken with cameras can provide abundant

\* Corresponding Author: [ademhicdurmaz@gmail.com](mailto:ademhicdurmaz@gmail.com)

<sup>1</sup> Yalova University, Department of Computer Engineering, Institute of Science, Yalova, Turkey.  
ORCID: <https://orcid.org/0000-0001-7765-4529>

<sup>2</sup> Yalova University, Department of Computer Engineering, Engineering Faculty, Yalova, Turkey.  
E-mail: [adem.tuncer@yalova.edu.tr](mailto:adem.tuncer@yalova.edu.tr) ORCID: <https://orcid.org/0000-0001-7305-1886>

information about the environment, including brightness, color, and texture. In vision-based systems, images must be processed in real-time. The acquired images may contain various noises due to factors such as the amount of light, the brightness of the objects, and the angle of the camera, which cause deterioration in image quality. During image processing, segmentation and threshold techniques are applied to eliminate these negative effects and achieve successful results [7, 8]. Image segmentation, one of the most fundamental issues in image processing, subdivides a digital image into various parts of pixels [9].

Several past studies have focused on floor detection. Instead of detecting the obstacles, the areas where the robot can move freely are obtained by processing the floor images. Processing floor images for navigation without collision is practical and effective, especially for robots used in indoor environments. The floor-detection method establishes the separation of the floor and the obstacles at a low cost by processing the images obtained by the camera on the robot. No additional processing cost is required to determine the characteristics of the obstacles, such as location and dimensions.

In this study, we propose a novel floor-based detection approach for autonomous robots to effectively avoid obstacles, based on monocular vision. The major drawback to floor-based detection is that objects close to the floor, such as walls, cannot be detected. The motivation in this study was to perform segmentation by simple and fast filtering on images obtained simultaneously to distinguish between the floor and obstacles in the images taken and to determine the areas where the robot can move freely.

Classical segmentation methods can achieve very good results when the colors in the image are significantly different from each other [10]. While the obstacles have certain edge characteristics, the areas described as floor are variable, and it is very difficult to obtain features of the floor from the images. In our study, a statistical method was applied to the images to determine the floor areas. The image segmentation technique of thresholding was used. Thresholding is of great

importance in the detection process [11], and it is one of the most common and simple methods [12]. Since the effects of negative factors (light, shade, etc.) and colors in each image will vary, segmentation was performed with an adaptive threshold value. Comparisons between the segments were made according to the percentage change of the arithmetic mean (PCAM). The proposed method can be used effectively in static and dynamic environments.

The main contributions of this study are summarized as follows:

- An effective method based on a monocular camera that can be used to avoid collision has been proposed.
- The mobile robot is capable of navigating by avoiding obstacles in a known and unknown environment.
- Since obstacles are not detected separately, obstacle avoidance is achieved quickly and easily without the need for additional filters (e.g. Canny, Sobel, and Laplacian). Thus, the calculations are performed at a lower cost.
- To our best knowledge, this is the first study that uses the PCAM to find similarities or differences between segments.

## 2. LITERATURE REVIEW

Obstacle detection and avoidance have key roles in mobile robot navigation systems. To solve these challenging processes, numerous studies have been carried out, especially with vision-based systems. Li et al. [13] proposed image-based obstacle avoidance. They combined the dynamic window approach (DWA) and artificial potential field algorithm to determine the path of motion and to avoid obstacles. Kalogeiton et al. [14] used a stereo camera for mapping the environment for both obstacles and free space. After mapping the environment, the cognitive-based adaptive optimization (CAO) approach was used for the next optimum motion. Dönmez et al. [15] proposed a Gaussian controller method that would allow the robot to be advanced from an

initial position to the target position by determining the least costly path between the starting and target position on the images obtained from a camera mounted on the ceiling. Tuncer and Yildirim also [16] proposed a whole system for mobile robots including a vision-based path planning system using a camera mounted to the ceiling for locating the robot and obstacles. Mishra and Panda [17] proposed a multilevel color image segmentation method using entropy-based thresholding and bat algorithm. In the study, to measure the performance of the method, several objective functions, such as RMSE, PSNR, Jaccard similarity coefficient were used.

Some of the vision-based navigation studies include floor detection approaches. Benn and Lauria [12] proposed a two-stage method that can be used in dynamic environments, using a combination of image color segmentation and edge detection. Their study focused on separating the floor and obstacles from traversable space. The first stage uses segmentation for color images and the second stage uses the Canny filter and Hough transform to clarify the edges of the floor. However, since pixel-based evaluation and edge filters were emphasized in the study, objects that were very similar to the floor, such as the wall could be indistinguishable. Bhowmick et al. [18] relied on floor detection using a conventional breadth-first search-based region-growing technique to detect obstacles. However, they stated that the process was slow because of the many conditions in the study. Chun et al. [19] proposed detecting the floor candidate regions by exploiting the nonlinear diffusion method and detecting floor regions using the image segmentation technique. Li and Birchfield [20] proposed a combination of vertical edges, thresholding, and segmentation to approximate a wall-floor boundary. Their technique combined three visual cues for calculating the likelihood of horizontal intensity edge line segments defining the wall-floor boundary. Ling et al. [21] proposed a combination of k-means clustering and improved principal component analysis (PCA) methods for vision-based floor segmentation in indoor robot navigation, with a camera that was fixed on the ceiling. However, because the camera

was on the ceiling, objects that the robot could pass under could also be perceived as the floor.

### 3. METHOD OVERVIEW

Since the variety and shape of obstacles in an indoor environment can be unlimited, the detection of the floor instead of the obstacles is the focal point of the proposed method. Various filters are available for detecting the edges of objects in an image. The most used filters are Canny, Sobel, and Laplacian. In the proposed approach, floor detection can be performed quickly and easily without the use of these filters. Image segmentation is one of the first and most important steps in image processing; in this process, an image is partitioned into multiple segments. Since light, shadow, and patterns are factors that have a significant impact on the pixel-based approach to floor detection, in this study, the image is divided into segments and then processed.

In the study, all the images were resized to the  $300 \times 535$ . Grid-based segmentation was applied to the images, as shown in Figure 1. As seen in the figure, the image is segmented to  $37 \times 5$  which performs well for images of the size  $300 \times 535$  in the experiments. The number of segments can be changed depending on the size of the image or robot.

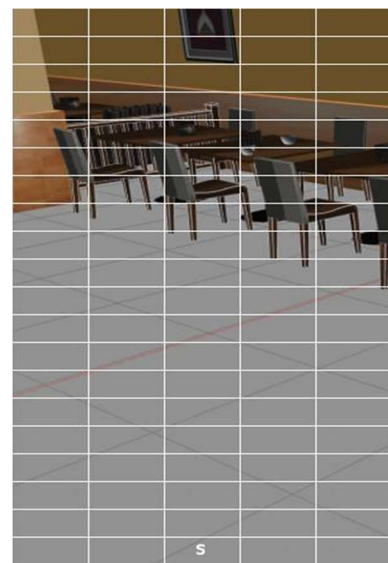


Figure 1 An example of image segmentation

The floor is always located in the lower half of the images. To reduce the possibility of errors and avoid unnecessary operations, the bottom half of the image is processed. The edges of the floor and the parts where the obstacles begin are important for the movement of the robot. Areas that are upper the obstacles in the images are not considered because they are not be related to robot movement. Even if there are errors in the detection of floor segments that are far from the robot, the image becomes clearer when the robot moves, when these segments are approached. Therefore, the floor segments which are close to the robot are notable, others are negligible. For all these reasons, ground detection is carried out by considering the segments close to the robot, not the entire image in the movement of the robot.

The sample segment, which is indicated by  $s$ , is selected from the bottom of the image because this will very likely be the floor. The arithmetic means of all the segments are calculated and compared with the segment  $s$ , which is detected as the floor. Values lower than the predefined threshold value are considered to be the floor. After comparing the segments, the floor segments are assigned a value of '0' and the other segments are assigned a value of '1' to obtain a filtered matrix. This study uses an adaptive threshold value instead of a fixed value. The PCAM is taken as the threshold value. For indoor images, the floor images may be similar to the images of other objects (wall, curtains, sofa, etc.). In this case, the threshold value must be changed dynamically to be effective. In this study, the threshold value is updated at the end of each new image captured by the camera. If the standard deviation of the filtered matrix is low, the threshold value is increased by one unit as a percentage, otherwise, it is decreased by one unit.

$$A = \frac{1}{n} \sum_{i=1}^n a_i \quad (1)$$

where  $A$  is the arithmetic mean of any segment,  $a$  is the pixel values, and  $n$  is the number of pixels, which is given by Equation 1. The PCAM is found by Equation 2.

$$p = |A - s(A)|/s(A) \times 100 \quad (2)$$

where  $p$  is the PCAM of two segments and  $s(A)$  is the arithmetic mean of the  $s$  segment. The filtered matrix is obtained by Equation 3.

$$FM_{ij} = \begin{cases} 0, & \text{if } t > p \\ 1, & \text{otherwise} \end{cases} \quad (3)$$

where  $FM$  is the filtered matrix,  $i$  and  $j$  are the dimensions of the matrix, and  $t$  is an adaptive threshold value.

Then, the standard deviation of the filtered matrix is calculated. The low standard deviation makes it difficult to distinguish between the floor and other things, such as a wall or curtains. This status indicates that the segments are close to each other in terms of the arithmetic mean value. In this case, the threshold value is reduced, otherwise, this value is increased. Thus, robust results are obtained for close segments. The filtered matrix provides effective floor information for robot navigation. Since the size of the filtered matrix is much smaller than the size of the original image, the trajectory planning on this filtered image can be done quickly.

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#### Algorithm 1. Pseudo-code of floor detection

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**Input** : Current frame as a matrix  $M$   
**Output** : Filtered matrix  $FM$   
 $s \leftarrow \text{getMatrixSampleAreaMean}(M)$   
 $t \leftarrow \text{threshold acceptable rate of changes}$   
 $v \leftarrow \text{reference variance value}$   
 $\text{row} \leftarrow \text{getRowByImageSize}(M)$   
 $\text{col} \leftarrow \text{getColByImageSize}(M)$   
**foreach**  $i=0$  to  $\text{gridrow}$  **do**  
    **foreach**  $j=0$  to  $\text{gridcol}$  **do**  
         $m = \text{getCurrentGridPartMean}()$   
         $p = \text{getPercentageofChange}(s,m)$   
        **if**  $t$  is greater than  $p$  **then**  
             $FM[i][j]$  is 0  
        **else**  
             $FM[i][j]$  is 1  
    **end**  
**end**  
**if** ( $FM.\text{variance} \leq v$ )  
    update threshold value ( $t=t+t \times 0.1$ )  
**return**  $FM$

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Algorithm 1 shows the pseudo-code of the floor detection used in the study. PCAM is calculated

using the steps followed in the algorithm. How many parts the image will be horizontally and vertically divided into is dynamically determined; then, the threshold in which the arithmetic mean change will be most effective is identified. The  $\nu$  value which is the reference variance value used in the algorithm is used to decide whether the threshold value should be updated. The threshold value is updated if the variance of the image is smaller than  $\nu$ , otherwise not update.

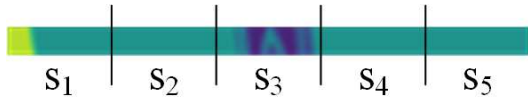


Figure 2 A horizontal part of the image consisting of 5 segments

Figure 2 shows the top row of the segmented image seen in Figure 1. A comparison of the variance, standard deviation, and arithmetic mean values of the sample segment  $s$  and five segments are shown in Table 1.

Table 1

Variance, mean and standard deviation values for sample  $s$  segment and 5 segments

Method	$s$	$s_1$	$s_2$	$s_3$	$s_4$	$s_5$
Variance	0.22	416.01	0	388.38	0	0
Arithmetic mean	121.66	81.63	68	40.45	68	68
Standard deviation	0.47	20	0	20	0	0

As shown Table 1, the variance of segment  $s$  is 0.22, the arithmetic mean is 121.66, and the standard deviation is 0.47. Moreover, although the variance and standard deviation values are very close to the  $s$  segment,  $s_2$ ,  $s_4$ , and  $s_5$  have very different arithmetic means. In this respect, the variance and standard deviation values used in image processing will be insufficient for distinguishing between the floor and the other objects. Therefore, PCAM has been proposed in the study.

#### 4. EXPERIMENTS

In this study, image segmentation was performed in a simple and fast way with the proposed method, and the effect of the PCAM was

determined to find the similarities between the segments. Experiments were performed on a machine with i7 1.8 GHz CPU and coded in Python programming language. The proposed algorithm is able to process an image in about 40 milliseconds. The method also works effectively in environments with dynamic obstacles.

Firstly, simulation studies with different images were carried out on the Robot Operating System (ROS) [22] framework to demonstrate the performance of the proposed algorithm. The Kinect cam was used to obtain the images in the ROS. The images were captured at 20 frames per second. The robot which used for simulations moves at 0.25 m/s when there is no obstacle, but slowdowns its speed when detected any obstacle.

After the successful results from the simulation studies, floor detection was performed on the real images, and these were presented here. Figure 3 shows: (a) the image taken from a real environment, (b) the filtered image according to the variance, (c) the filtered image according to the standard deviation, and (d) the filtered image according to the PCAM. The noise, which is a light, shadow, and a floor with a pattern, makes it difficult to detect the floor. For example, as seen in the image, there is a carpet with patterns. However, with the proposed method, as shown in Figure 3(d), the floor in the actual environment image can be easily detected.

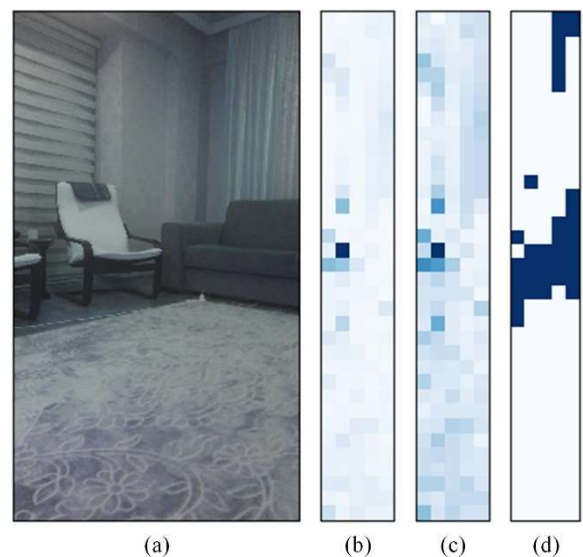


Figure 3 (a) Original image (b) variance (c) standard deviation (d) PCAM



Since the threshold value may vary depending on the complexity and size of the images, it has no fixed value. Experiments were carried out with different initial threshold values for the same image, and the appropriate value was determined according to the similarity ratio of the sample floor segment and other segments in the image. Therefore, the initial threshold value for the images given in the study was considered as 40, and at each step, the threshold value is updated according to the variance value of the filtered image. The arithmetic means of the sample segment and other segments were compared and the segments with at least the same threshold value were marked as “1” and the others as “0”.

In Figure 4, an obstacle is placed in the environment, and the effect of the method is observed when the environment is dynamic. It is clear that the proposed method can better detect the obstacle and distinguish it from the floor. This allows the mobile robot to easily distinguish between the floor and the obstacles in dynamic environments during autonomous navigation.

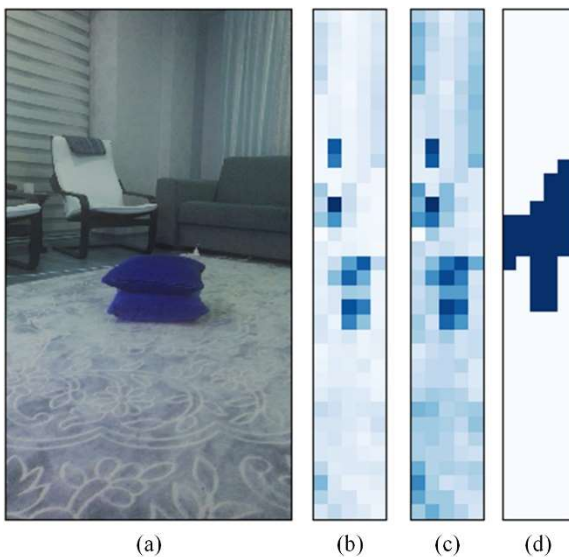


Figure 4 (a) Original image (b) variance (c) standard deviation (d) PCAM

Even if the floor and objects can be distinguished, it is a little more difficult to distinguish objects that are similar to the floor. For example, in general, the floor and wall have similar features. As can be seen in the Figure 5, although the distinction between floor and wall is difficult, the

difference between the proposed approach can be clearly determined.

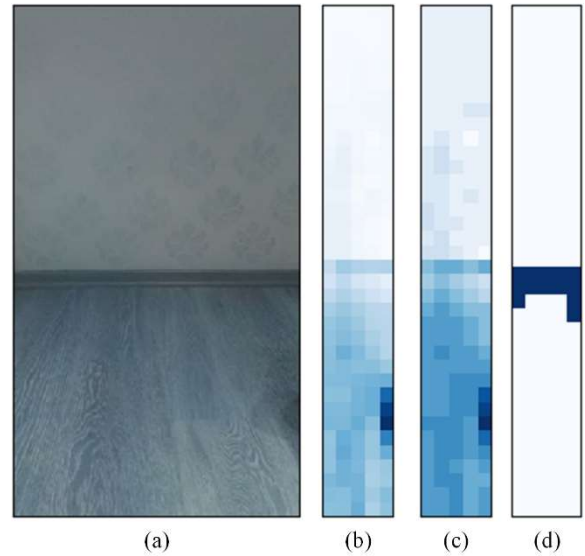


Figure 5 (a) Original image (b) variance (c) standard deviation (d) PCAM

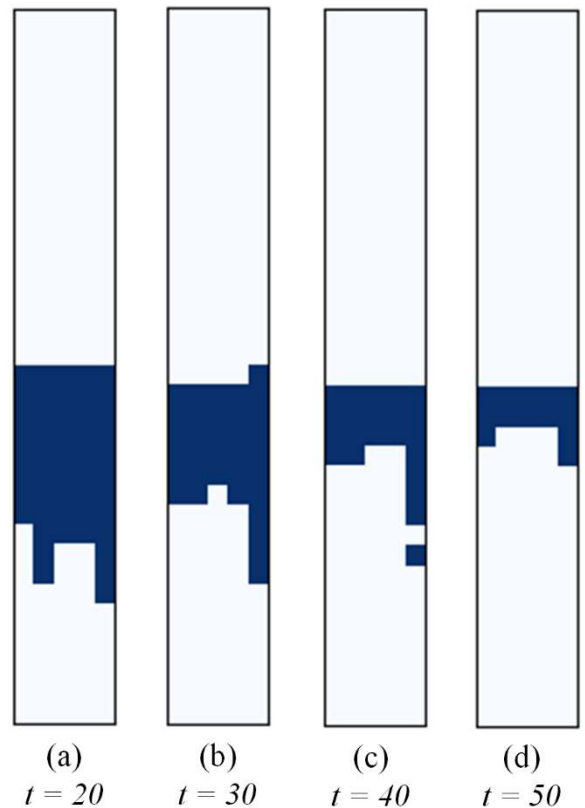


Figure 6 Effect of different threshold values

In addition, experiments in which the threshold values for the image of Figure 5 are applied as 20, 30, 40, and 50 are shown in Figure 6 to show the

effect of the initial threshold values. The appropriate threshold value for this image appears to be 50. The effect of adaptive threshold value on the separation of floor and wall is quite effective and, in this respect, the threshold value is used adaptively in the study.

## 5. CONCLUSION

This study proposed a new image-based floor detection approach in an indoor environment for autonomous mobile robots. The floor was detected using image segmentation and an adaptive threshold. Then, the segments were compared according to PCAM to determine which segments constitute the floor. To the best of our knowledge, the present study is the first to use the PCAM for the identification of the similarities or differences between the segments. However, it should be noted that even if the floor and the wall are similar, the floor can easily be separated from the wall. Additionally, as the proposed method does not require any prior knowledge of the environment, it can be applied to real-time problems.

The experimental results show that the proposed algorithm reaches 92% accuracy, which shows successful in separating the floor from other regions making it a highly flexible method for obstacle avoidance. Hence, it can be concluded that the proposed provides successful results at a low cost without the need for additional filters that are used in image processing.

### *Funding*

The authors received no financial support for the research, authorship, and/or publication of this paper.

### *The Declaration of Conflict of Interest/ Common Interest*

No conflict of interest or common interest has been declared by the authors.

### *Authors' Contribution*

AH: Literature review, research, methodology, simulation, writing the initial draft.

AT: Supervision, research, methodology, interpretation, writing-revision, and finalizing.

### *The Declaration of Ethics Committee Approval*

The authors declare that this document does not require an ethics committee approval or any special permission.

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