

OBSTACLE DETECTION USING STRUCTURED BACKGROUND

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Abstract: The paper presents an obstacle detection method for mobile robots using a structured background. This method is based on differences of appearance between obstacles and the background in the camera images. The basic idea is to cover the ground of the workspace with a known structure. If part of this structure is obscured, this can be detected and indicates the existence of an obstacle. The method uses a reference symbol, chosen to exhibit certain features, to construct a reference image of the structured background. To detect possible obstacles we calculate the Fourier descriptors (FD) of all contours included in a given image and compare them with those of the stored reference symbol. This enables us to recognize all reference symbols which are not obscured by obstacles. We then determine the positions and dimensions of all existing obstacles by calculating the occupied symbol areas. The method is implemented as part of a robot-vision system for fully automated stockkeeping. In this paper the results are shown using a MATLAB implementation.

1 INTRODUCTION

Obstacle detection is an important and essential task in a system with mobile robots (Al Zeer, Nabout and Tibken, 2006) and (Al Zeer, Nabout and Tibken, 2007). The method of detection depends on the available information about the obstacles and their environment.

There are various methods of obstacle detection, based on different approaches (Simmons, 1996) and (Sabe, Fukuch, Gutmann, Ohashi, Kawamoto and Yoshigahara, 2004). Two different types of strategies are distinguished. The first strategy is called range-based obstacle detection. This method is based on the measurement of the distance between the obstacle and an implemented sensor, such as an IR-Distance Sensor. The second method is called appearance-based obstacle detection, in which the obstacles, e.g. in a color picture, are separated from the background and classified using their appearance properties (Ulrich and Nourbakhsh, 2000).

Within our work an extended appearance-based method for obstacle detection has been developed, which does not use the appearance of an obstacle, but the appearance of the background. This method, obstacle detection using structure background, was developed for our robot-vision system (Al Zeer,

Nabout and Tibken, 2007) and allows a reliable detection and localization of obstacles. Grayscale images are available as part of a robot-vision system. These grayscale images are acquired by a camera system mounted on the ceiling of the workspace area. Therefore the calculation of the obstacle positions will be carried out by image evaluation. Objects in the workspace at the time of image acquisition are considered as static obstacles and they are taken into account in the calculation of collision-free routes. Objects that enter the workspace after the image acquisition are considered as dynamic obstacles (Borenstein and Koren 1990). These obstacles can be detected by the distance sensor which is mounted on the vehicle. Encountering a dynamic obstacle causes the vehicle to stop immediately and to provoke a re-imaging to calculate a new route. Several implementations of the new method will be described in detail and then their realization will be further illustrated.

The paper consists of four sections. In section 2 the principle of the method "obstacle detection using structured background" is explained. Section 3 is concerned with the selection of a suitable reference symbol. In section 4 some results related to the MATLAB implementation are shown and discussed.

2 OBSTACLE DETECTION

The basic idea of this method is to cover of the ground in the workspace with a known structure. If part of this structure is obscured by an obstacle, this can be detected. The structure can be generated by distributing reference symbols in a regular pattern in the workspace of the mobile robot. The distribution of symbols results in a regular and known pattern of contours in every picture of the workspace. Thus, the distribution of the center positions for the reference symbols comprises a matrix structure, similar to the pixel matrix of a bitmapped image.

The use of a symbol pattern as reference feature of the ground leads to an extension of the conceptual specifications of the developed robot-vision system. The implementation of a new strategy of obstacle detection in the robot-vision system was necessary, because it was observed that a guaranteed identification of obstacles through direct detection of objects is not possible because of lighting errors. The condition that the ground has to be covered with a symbol pattern is not an especially unrealistic burden, e.g. in the case of automated stockkeeping. To cover the floor of a warehouse with custom-patterned tiles, painted- or pasted- on symbols is a relatively simple requirement that does not involve a great effort or a high cost. Moreover, in the case of a robot-vision system, this requirement does not violate the principles or change the basic idea of the system.

To verify the results, using the robot-vision system, the extended method was implemented in Matlab and was tested under real conditions. Only common Matlab functions were used in the implementation. The obstacle detection using structure background is based on the following assumptions:

- First, an appropriate symbol pattern has to be applied to the workspace floor. The symbol used to generate the pattern must be suitable for accurate detection. The shapes of the symbol must differ greatly from the shapes of expected objects and also from possible shapes caused by noise and other errors.
- All symbols must be identical, i.e. they all have to be the same shape and size, and they must be arranged in a regular pattern with pre-defined distances to each other.
- The symbols must be large enough for the camera to render their shape and contours with sufficient accuracy. This depends on the resolution of the camera used and the distance between camera and ground.

- The symbols should not have reflective surfaces, so they will not cause reflection noise under bright lighting.

In order for the symbols to comprise a regular pattern on the ground, they have to be applied so that their centers form a regular grid, i.e. the distance between the centers of the symbols must be equal. In the following the individual steps of the newly developed method will be described in detail.

2.1 Creating a Reference Symbol

The reference symbol is used as a basis of comparison for the detection system, so its Fourier descriptors (FDs) are detected and saved (Nabout, 1993).

Figure 1 shows an example for such a symbol. Here "h" is the height, "b" the width, and "c" the center (center of area) of the symbol. The symbol orientation is chosen in suitable way to cover the maximum area of the workspace.

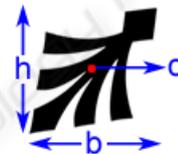


Figure 1: Reference symbol.

The center of gravity of the symbol area can be calculated according to the following general Eq. (1) (Nabout, 1993)

$$\begin{aligned} X_c &= \frac{1}{F} \sum_{i=1}^n \int_{x_i}^{x_{i+1}} x y dx \\ Y_c &= \frac{1}{2F} \sum_{i=1}^n \int_{x_i}^{x_{i+1}} y^2 dx \end{aligned} \quad (1)$$

Here, (X_c, Y_c) are the coordinates of the center of the symbol, whose contours were approximated by a polygon with n vertices.

The contour features of the symbol are computed using the contour extraction methods described in (OKE) (Nabout, 1993). Consequently, the original grayscale image is first converted to a binary image. Then the contours of the reference symbol are extracted using the OKE method. Freeman-code is used to describe the contours (cf. Figure 2 and Figure 3).

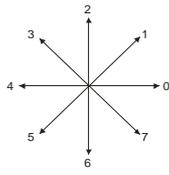


Figure 2: Freeman-Code. Figure 3: Contours of the reference symbol.

The OKE method consists of the following steps:

1. Segmentation of the image into overlapping 2*2 or 4*4 windows.
2. Evaluation of these windows according to the extraction rules in time with the image sample rate (extraction of basic contour elements).
3. Sorting of the contour elements to generate closed contours.

For the reference symbol used here (Fig. 3), the following Freeman chain was obtained using the MATLAB implementation.

```
0000006665666666656666654444445444455665665666656666666
6666666666666666766667666766764544444445444222222222222
22221222212221222122355655656565665665666566656666666
6566666444544444543222221222122121212121212123555555556
55655565656565656565654444445444445422221222212222101010
10110110110111111111113455455454545445444454434221222
221220010000000100010001001001010101010110110113454454445
44445444444544444444444444322212222222007007000070000
700000000000000000001000010001010122222122222000010000
001
```

The starting point of the Freeman-chain is in this example (86, 10). The extracted contour is shown in figure 3.

To approximate the contour of the reference symbol the KKA method (cf. Nabout) is used. The KKA method is carried out as follows:

1. Segmentation of the chain of contour elements into partial sequences that satisfy certain conditions.
2. Detection of noise chains and merging them with neighboring chains.
3. Sorting of partial chains, approximation of curved contour parts.

After these steps, the FDs of the reference symbol are calculated by a Fourier-analysis and are saved in a data structure. Fig. 4 shows the symbol after contour approximation.

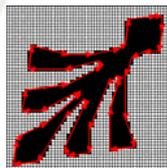


Figure 4: The approximated contour of the symbol of Fig.1.

2.2 Creation of a Reference Image

To create a reference image, the workspace floor is covered with symbols forming a grid structure as described above. Then an image of the empty workspace without obstacles is acquired (Figure 5).

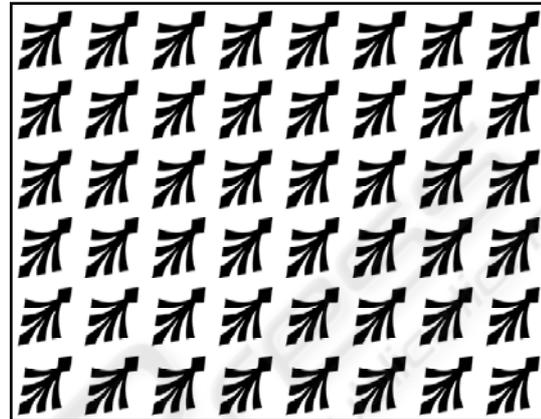


Figure 5: Workspace floor with reference symbols.

The reference image should be created under real conditions. The acquisition parameters are set so that all the symbols in the picture are completely visible. Since a camera-acquired image always contains other contours in addition to the symbols (noise, errors, etc.), as a first step *all* the contours in the picture are extracted and approximated using the OKE and KKA-methods and saved in the form of polygonal approximations. To remove the contours created by noise we adopt a length filter using an upper and lower threshold for the contour length. Subsequently, the FDs and centers of area gravity for the symbol polygons are computed. In our example, the reference image contains 48 symbols. By comparing the FDs of the extracted polygon with the FDs of the reference symbol, all existing symbols in the reference image can be detected. Their centers then determine the grid structure (Figure 6).

[47, 45	47, 138	:
146, 45	:	744, 322
247, 45	:	47, 413
346, 45	744, 138	:
445, 45	47, 229	:
544, 45	:	744, 413
644, 45	:	47, 506
744, 45	744, 229	:
:	47, 322	:
:	:	744, 506]

Figure 6: Coordinates of center of area gravity in reference image with 8*6 symbols.

In our case, a grid with 8*6 symbols is detected. Since the identification of the symbols by comparison the shape of the extracted contours with the shape of the reference symbol is the key to a reliable detection of all symbols, it is necessary to use a reference symbol whose shape (represented through its FDs) differs greatly from those of other occurring objects or possible noise. To choose the reference symbol as a circle, for example, would result in confusion with all circular contours that arise due to lighting errors. Such a reference symbol is not suited for the present application.

For this reason, the following strategy to select a suitable reference symbol was used in this work.

3 SELECTION OF A SUITABLE REFERENCE SYMBOL

Within this work, a total of 30 symbols were investigated in order to select the most suitable symbol for generating the grid structure. Figure 7 shows 10 of those symbols.

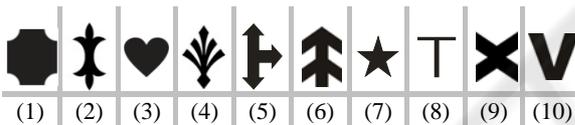


Figure 7: Some representatives of the symbols considered for the generation of a symbol pattern.

The goal here is to find a symbol which gives the smallest confusion risk with other contours that may occur. For this reason, the FDs of all considered symbols were calculated and compared using the minimum distance method (Nabout, 1993). Figure 8 shows for example the first 20 FDs of the above given symbols in a graphical comparison.

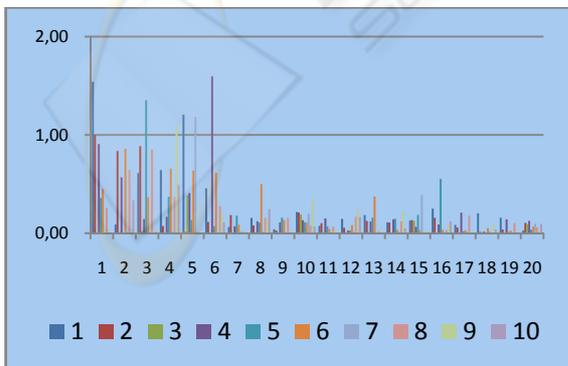


Figure 8: The first 20 FDs for the symbols of Fig.7.

The Euclidean distances d_i between every two symbols were calculated, according to Eq. (2).

$$d_{ij} = \sqrt{\sum_{k=1}^n (A_{ik} - A_{jk})^2}; \quad i, j = 1, \dots, 30 \quad (2)$$

d_{ij} : Euclidean distance between object i and j

n : Number of Fourier descriptors

A_{ik}, A_{jk} : Amplitude spectrum of object contour i, j

The most suitable symbol, with the smallest confusion risk, is that one which fulfills the following three conditions:

1. The chosen symbol must have big distances to all other symbols. This is fulfilled for that symbol i with the maximum mean value \bar{d}_i of the Euclidean distances $d_{ij}, j: 1, \dots, 30$.
2. The symbol must have approximately equal distances to all other symbols. This is fulfilled for that symbol i with the minimum variance v_i of the Euclidean distances.
3. The chosen symbol must have partially regular contour rather than irregular to contrast to noise contours.

The means \bar{d}_i and the variance v_i are determined for every symbol i according to Eq. (3).

$$\bar{d}_i = \frac{1}{M} \sum_{j=1}^M d_{ij} \quad (3)$$

$$v_i = \frac{1}{M-1} \sum_{j=1}^M (d_{ij} - \bar{d}_i)^2$$

Here, M is the number of considered symbols.

Finally, the symbol i with the maximum mean value and the minimum variance is selected according to Eq. (4).

$$i_{opt} = \operatorname{argmin} \left(\frac{v_i}{\bar{d}_i} \right) \quad (4)$$

To fulfill the third condition we calculated all values $\frac{v_i}{\bar{d}_i}$ and sorted them according to their values from small to large in a list (L). Then we chose the first symbol in the list (symbol 2) which shows partially regular contour shape. The following two Figures show the mean value and the variance for the objects of Fig.7.

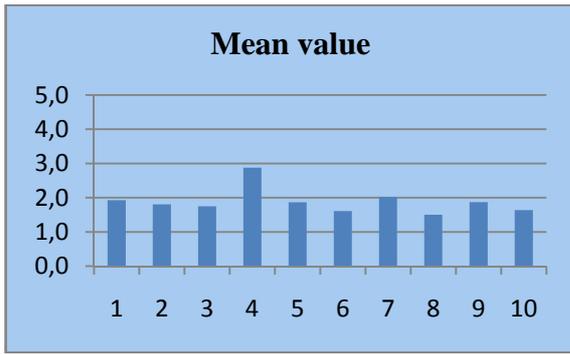


Figure 9: Mean for each symbol (10 symbols).

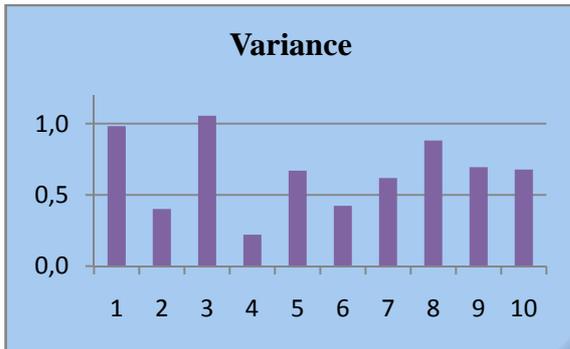


Figure 10: Standard variance for each symbol (10 symbols).

4 DETECTION OF OBSTACLES

To detect the obstacles, first a picture of the workspace is taken. This picture contains the reference symbols on the structured floor, as well as a certain number of obstacles. Figure 11 shows an image with simulated obstacles.

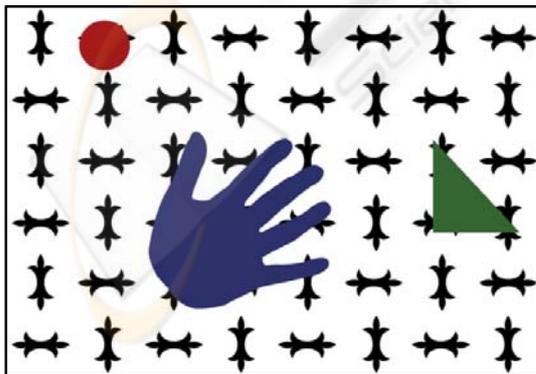


Figure 11: Reference image with obstacles.

To evaluate this image, the following steps were executed:

1. Contour extraction using OKE method
2. Contour approximation using KKA method
3. Computation of FDs
4. Determination of the centers of all detected reference symbols in the image.

After performing these steps and comparing the FDs to those of the reference symbols by the minimum distance method we received for the given example 35 detected reference symbols. The detection occurs, if the computed minimum distance value between a considered object and the reference symbol is smaller than a specified threshold. In our case, the threshold was determined *a priori* and set to the value 0.5.

If the minimum distance is greater than this threshold, the considered object is designated as an obstacle. To locate the positions and sizes of existing obstacles the centers of found symbols in the current image are compared with the centers of the symbols in the reference image. The centers of the detected symbols and the centers of the symbols in the reference image must be identical, within a certain tolerance value. For our example, we obtain the following results (Fig. 12).

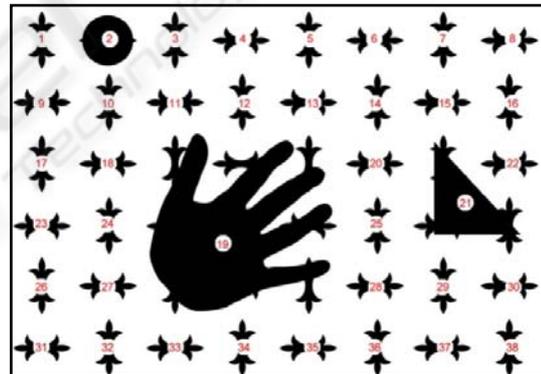


Figure 12: Binary image with numbered objects.

Here, there are 13 symbols obscured by obstacles, whose centers are also known.

The calculation of the positions and sizes of the obstacles to determine the region occupancy is illustrated in the following section.

4.1 Mapping the Obstacles into the Workspace

In an X-Y coordinate system, whose origin is situated in the upper left corner of the workspace (cf. Fig.11), each symbol S_i is represented by the position of its center (x_i, y_i) . For two adjacent symbols on a horizontal line, the distance between

the centers of these two symbols is dx . Similarly, for two adjacent symbols, which are arranged vertically, it is dy .

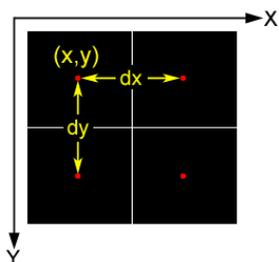


Figure 13: Center of a macro pixel with horizontal and vertical distance to its neighbours.

In order to detect the positions and size of the existing obstacles in the workspace, a binary image with the same resolution as the original grayscale image is generated. The image is then divided into regular $M \times N$ blocks, where M is the number of columns and N is the number of rows in the symbol grid. All pixels within one block are assigned as "0" (black), if the symbol represented by this block is obscured by an obstacle, otherwise, the pixels are assigned the value "1" (white). Figure 14 shows the binary image generated for the example of Figure 11.



Figure 14: Binary image showing occupancy of obstacles.

As the picture shows, there are three black areas, which represent the positions of the obstacles. In order to determine the size of the obstacles, the contours of the areas are described as polygons. For these polygons the Minimum Area Rectangles of the obstacle regions (MAR) are then calculated (Al Zeer, Nabout and Tibken, 2008). These regions represent the workspace area occupied by the present obstacles.

5 CONCLUSIONS

With the obstacle detection method presented here, it is possible to detect existing obstacles in the workspace of mobile robots. This method uses grayscale images and a specially chosen reference symbol. The results show that symbols with irregular contour shape are not qualified to be used as reference symbol, since the recognition process leads to confusion with possible lighting errors and other noise. The paper shows how to choose a good reference symbol using a mathematical formula.

The method was developed for the detection of obstacles in a robot vision system which is part of a fully automated stockkeeping application. In this context the results of the obstacle detection described in this paper were also used for path planning using auxiliary corners.

REFERENCES

- Al Zeer, G., Nabout, A., Tibken, B., Path Planning for Mobile Robots by Means of Approximate Routes, 2007 IEEE International Conference on Control and Automation, Guangzhou, CHINA, May 30 to June 1, 2007, pp. 2468-2473.
- Al Zeer G., Nabout, A., Tibken, B., Hindernisvermeidung für Mobile Roboter mittels Ausweichecken, 52nd Internationales Wissenschaftliches Kolloquium, Technische Universität Ilmenau, 10.-13. Sep. 2007, pp. 437-442.
- Al Zeer, G., Nabout, A., Tibken, B., Extended Method for Path Planning Using Auxiliary Corners, the 3rd IEEE International Conference on Information & Communication Technologies: from Theory to Application, ICTTA'08, 7-11 April 2008, Damascus – Syria.
- Borenstein, J., Koren, Y., Real time obstacle avoidance for fast mobile robots in cluttered environments. IEEE Conf. Robotics and Automation, pp. 572-577, 1990.
- Nabout A., Modulares Konzept und Methodik zur wissensbasierten Erkennung komplexer Objekte in CAQ-Anwendungen, 1993.
- Simmons. R., The Curvature-Velocity Method for Local Obstacle Avoidance. In Proc. IEEE Conf. Robotics and Automation, 1996.
- Sabe, K., Fukuch, M., Gutmann, J., Ohashi, T., Kawamoto K., Yoshigahara, T., Obstacle Avoidance and Path Planning for Humanoid Robots using Stereo Vision. Proceedings of the International Conf. on Robotics and Automation, ICRA'04, New Orleans, April 2004.
- Ulrich, I., Nourbakhsh, I., Appearance-Based Obstacle Detection with Monocular Color Vision, Proceedings of the AAAI National Conference on Artificial Intelligence, Austin, TX, July/August 2000.