IMAGE SEGMENTATION FOR OBJECT DETECTION ON A DEEPLY EMBEDDED MINIATURE ROBOT

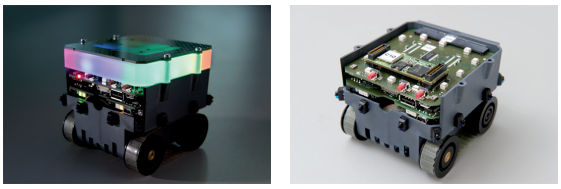
Alexander Jungmann[1], Thomas Schierbaum[2] and Bernd Kleinjohann[1]
[1]*Cooperative Computing & Communication Laboratory, University of Paderborn, Paderborn, Germany*
[2]*Product Engineering, Heinz Nixdorf Institute, University of Paderborn, Paderborn, Germany*

Keywords: Image Segmentation, Run-length Encoding, Moments, Robotics.

Abstract: In this paper, an image segmentation approach for object detection on the miniature robot BeBot - a deeply embedded system - is presented. In order to enable the robot to detect and identify objects in its environment by means of its camera, an efficient image segmentation approach was developed. The fundamental algorithm bases on the region growing and region merging concept and identifies homogeneous regions consisting of adjacent pixels with similar color. By internally representing a contiguous block of pixels in terms of run-lengths, the computational effort of both the region growing and the region merging operation is minimized. Finally, for subsequent object detection processes, a region is efficiently translated into a statistically feature representation based on discretized moments.

1 INTRODUCTION

Embedded systems are usually very restricted with respect to their memory and computational power. The miniature robot BeBot (see Figure 1), which combines an ARM Cortex-A8 600MHz processor, 256MB main memory and a small camera in a 9x9cm chassis (Herbrechtsmeier et al., 2009), is a mobile representative of an embedded system with such restrictions. In addition, it is able to explore its surroundings by means of its differential chain drive. However, for being able to act autonomously, the robot has to perceive its environment by means of its camera. For this purpose, an efficient image segmentation approach that takes the mentioned restrictions into account was developed and is presented within the scope of this paper. Object detection mechanisms are not content of this particular work though.



(a) (b)

Figure 1: Miniature robot BeBot, (a) with and (b) without light guide, enabling the robot to express its internal state.

This paper is organized as follows. The fundamental principles of the realized segmentation process are described in Section 2. Section 3 deals with the external feature representation for subsequent object detection processes. Results of the segmentation algorithm running on a BeBot are content of Section 4. The paper finally concludes with Section 5.

2 SEGMENTATION APPROACH

The basic idea of image segmentation is the identification of contiguous blocks of pixels, that are homogeneous with respect to a pre-defined criterion. By doing so, the pixel-based visual information is abstracted in order to get a reduced data representation, which is more convenient on the one hand and less computational expensive on the other hand. Regarding the computational power of the BeBots, object detection based on raw pixel data is not feasible at all.

2.1 Color as Criterion of Homogeneity

In the context of this paper, the criterion for constructing homogeneous regions is based on color information. Since the camera of the BeBot delivers YUV images, a simple but very efficient heuristic H_{yuv}, which is based on the Manhattan distance, is applied in or-

Jungmann A., Schierbaum T. and Kleinjohann B..
IMAGE SEGMENTATION FOR OBJECT DETECTION ON A DEEPLY EMBEDDED MINIATURE ROBOT.
DOI: 10.5220/0003852104410444
In *Proceedings of the International Conference on Computer Vision Theory and Applications* (VISAPP-2012), pages 441-444
ISBN: 978-989-8565-03-7

der to decide, whether two color tuples (y_1,u_1,v_1) and (y_2,u_2,v_2) reside in a pre-defined neighborhood within the three dimensional YUV color space:

$$H_{yuv} = H((y_1,u_1,v_1),(y_2,u_2,v_2)) = \begin{cases} 1 & \text{if } \begin{array}{c} |y_1-y_2| \le c_1 \\ \wedge \\ |u_1-u_2|+|v_1-v_2| \le c_2, \end{array} \\ 0 & \text{else.} \end{cases} \quad (1)$$

By separating the luma value Y from the chrominance values U and V, the different components can be independently weighted by means of the two parameters c_1 and c_2.

2.2 Internal Data Representation

For the internal representation of the regions during the segmentation process, the *Run-Length Encoding* concept is incorporated: sequences of adjacent pixels are compactly encoded as so called run-lengths (or runs), whereas a single run is defined in terms of three integer values:

$$run_i = \langle (x_i,y_i), l_i \rangle, \quad (2)$$

with (x_i,y_i) being the coordinates of the starting pixel, whereas l_i represents the number of adjacent pixels within the same row and therefore denotes the length of a single run. Furthermore, an entire region R may consist of a sequence of n adjacent runs:

$$R = \langle \langle (x_1,y_1), l_1 \rangle, \langle (x_2,y_2), l_2 \rangle, \ldots, \langle (x_n,y_n), l_n \rangle \rangle. \quad (3)$$

The computational effort for both the *region growing* as well as the *region merging* operation (cf. Section 2.3) is minimal. While adding a pixel to a region is nothing but incrementing the length l_i of the associated run run_i, merging of two regions is realized by simply appending the sequence of runs of the first region to the sequence of runs of the second region.

2.3 Basic Algorithm

The basic segmentation process is depicted in Algorithm 1. The main loop (lines 3-25) iterates row by row over the whole *image*, starting at the topmost row. The inner iteration loop (lines 4-24) processes each pixel within a row once, starting at the leftmost pixel position. After identifying the left adjacent run run_{left} as well as its associated region R_{left}, heuristic H_{yuv} (1) is applied in order to check if the colors of the current pixel and R_{left} are similar (line 7). If so, the region growing step takes place by adding the current pixel

Algorithm 1: Image Segmentation Algorithm.

```
 1: image = latest camera image
 2: regions = {∅} // set of identified regions
 3: for all row ∈ image do
 4:   for all pixel ∈ row do
 5:     run_left = left adjacent run
 6:     R_left = region(run_left)
 7:     if H(yuv(pixel), yuv(R_left)) then
 8:       // region growing
 9:       add(run_left, pixel)
10:       continue with next pixel
11:     else
12:       regions_top = top adjacent regions
13:       for all R_top ∈ regions_top do
14:         if H(yuv(R_left), yuv(R_top)) then
15:           // region merging
16:           merge(R_left, R_top)
17:           remove(regions, R_top)
18:         end if
19:       end for
20:       run_new = new_run(pixel)
21:       R_new = new_region(run_new)
22:       add(regions, R_new)
23:     end if
24:   end for
25: end for
26: return regions
```

pixel to the left adjacent run run_{left} (length of run_{left} is incremented by value 1) and updating the associated region R_{left} with respect to its average color. Afterwards, the algorithm continues with the next pixel of the row (line 10).

If heuristic H_{yuv} fails, the left adjacent run run_{left} is considered to be completed. The algorithm proceeds with its region merging mechanism. For this purpose, all regions bordering run run_{left} at the top are identified. Subsequently, another iteration loop tries to identify every region R_{top} within $Regions_{top}$ that can be merged with the run_{left} associated region R_{left} (lines 13-19) by again applying heuristic H_{yuv}. If H_{yuv} succeeds for two regions R_{top} and R_{left}, the regions are merged by appending all runs of R_{top} to R_{left}. Furthermore, region R_{left} is updated with respect to its average color, whereas region R_{top} is completely discarded by removing it from the set of heretofore identified regions.

Independent of the region merging step, a new run run_{new} with length 1 and with the current pixel as its starting position as well as a new region R_{new} with run_{new} as its first run are allocated. Finally, R_{new} is added to the set of heretofore identified regions.

3 FEATURE DESCRIPTION

By interpreting a region's associated pixels as a two-dimensional Gaussian distribution in the image plane, a region can be implicitly described by means of statistical parameters, namely the two mean values m_x and m_y, the two variances σ_x^2 and σ_y^2, and the covariance σ_{xy}. A generalization of these specific parameters are the statistical moments, which can be directly applied in our context in discretized form (Hu, 1962): the two mean values correspond to the two moments of first order (m_{10} and m_{01}), whereas the two variances and the covariance correspond to the centralized (or central) moments of second order (μ_{20}, μ_{02} and μ_{11}). In addition, the mass of a region is equivalent to the moment of zeroth order (m_{00}).

Since the central moments can be directly derived from the moments through second order (Hu, 1962), the basic feature descriptor for representing an extracted region is given by the following set M of moments:

$$\begin{aligned} M &= \{m_{pq} | p+q \leq 2\} \\ &= \{m_{00}, m_{10}, m_{01}, m_{11}, m_{20}, m_{02}\} \end{aligned} \tag{4}$$

For efficiently computing the required five moments, the runs of a region can be directly used by applying the *Delta "δ" Method* (Zakaria et al., 1987). In this context, $S1_i$ and $S2_i$ are defined as follows:

$$\begin{aligned} S1_i &= \sum_{k=0}^{\delta_i - 1} k = \frac{(\delta_i^2 - \delta_i)}{2} \\ S2_i &= \sum_{k=0}^{\delta_i - 1} k^2 = \frac{\delta_i^3}{3} - \frac{\delta_i^2}{2} + \frac{\delta_i}{6}, \end{aligned} \tag{5}$$

with δ_i corresponding to the length l_i of a single run run_i. The required geometric moments m_{00_i}, m_{10_i}, m_{01_i}, m_{11_i}, m_{20_i} and m_{02_i} of run_i can then be computed in the following way:

$$\begin{aligned} m_{00_i} &= \delta_i \\ m_{01_i} &= \delta_i \cdot y_i \\ m_{02_i} &= \delta_i \cdot y_i^2, \\ m_{10_i} &= \delta_i \cdot x_i + S1_i \\ m_{11_i} &= y_i \cdot [\delta_i \cdot x_i + S1_i] = y_i \cdot m_{10_i} \\ m_{20_i} &= \delta_i \cdot x_i^2 + 2 \cdot S1_i \cdot x_i + S2_i \end{aligned} \tag{6}$$

Finally, the moments of an entire region R correspond to the sums of the particular moments of all associated n runs:

$$M = \{m_{pq} | m_{pq} = \sum_{i=1}^{n} m_{pq_i} \wedge p+q \leq 2\} \tag{7}$$

For representing a feature in a more explicit manner, additional geometric attributes can be derived from M and the associated central moments (Teague, 1980; Prokop and Reeves, 1992). In this context, the coordinates $(\bar{x}, \bar{y})$ of the *center of mass* of an extracted feature in the image plane are defined by the moments of zeroth and first order:

$$\bar{x} = \frac{m_{10}}{m_{00}} \quad \text{and} \quad \bar{y} = \frac{m_{01}}{m_{00}} \tag{8}$$

Furthermore, due to the statistical interpretation in terms of a Gaussian distribution, a feature is equivalent to a *elliptical disk* with constant intensity, having definite size, orientation and eccentricity and being centered at the origin of the image plane. The lengths of its major and minor axes as well as its angle of inclination can be computed with the use of the associated central moments (Teague, 1980). By combining both the center of mass and the elliptical disk, a feature can be geometrically described in terms of an ellipse that is located at the center of mass of the respective feature (cf. Figure 3).

4 RESULTS

The image segmentation approach was implemented in C/C++ and successfully applied to the BeBot. While capturing a YUV image of size 320x240 pixels, the algorithm enables us to process at least 10 entire images per second. Regarding the load factor of the BeBot during our experiments, the overall performance of the segmentation algorithm heavily depends on the number of different regions that are constructed, which in turn depends on the values of the calibration parameters in combination with the homogeneity of the original image.

Figure 2 shows different segmentation results with respect to different values of the calibration parameters c_1 and c_2 of heuristic H_{yuv}. Whereas the goal of the algorithm was to clearly extract the colored objects (four balls and one rectangular block), we constructed the background (the horizon) as inhomogeneous as possible (see Figure 2(a)). From Figure 2(c) to Figure 2(d), only parameter c_1 for modifying the influence of the luma component Y was changed. By increasing c_1, the segmented image becomes more and more homogeneous in comparison to Figure 2(b). The same holds true when the second parameter c_2 of heuristic H_{yuv} is exclusively modified (Figure 2(e) to Figure 2(f)). However, when comparing Figure 2(c) and Figure 2(f), changing the allowed range of luma similarity (c_1) seems to have a greater influence than changing the allowed range of chrominance similarity (c_2). Keeping that in mind, Figure 2(g) shows a great overall result with respect to the homogeneity of the

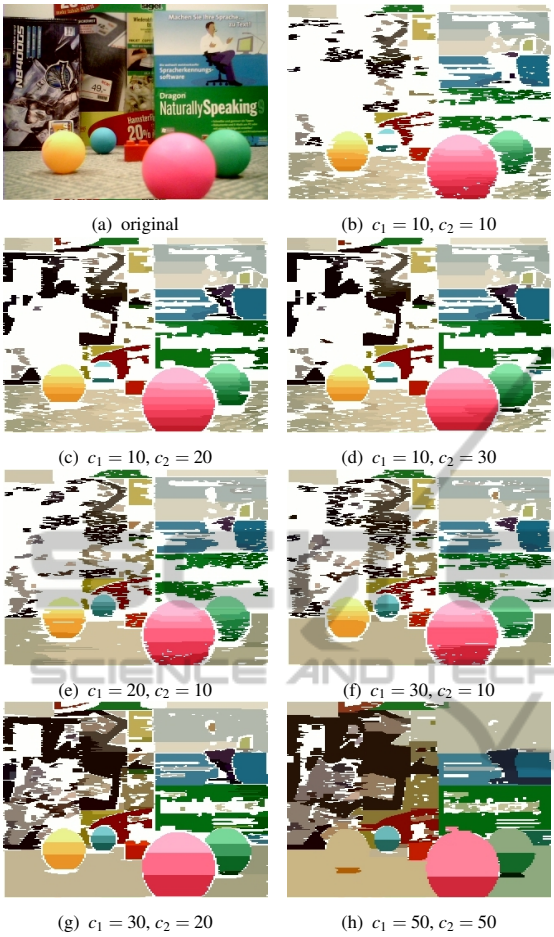


Figure 2: Results of the segmentation algorithm running on the BeBot with different parameters c_1 and c_2. In addition, the minimal length of a run was limited to 5 pixels.

segmented image. In this context, the value of parameter c_1 was set to 30, whereas the value of parameter c_2 was set to a slightly lower value of 20.

We tried to relax the restriction of color similarity even more by simultaneously increasing both parameters c_1 and c_2. At some point, the algorithm begins to merge color values, that obviously are not similar at all, whereas regions, which are of similar color but differ with respect to their intensity (brightness), are not merged (see Figure 2(h)). This issue can be traced back to the characteristics of the YUV color space.

Last but not least, Figure 3 exemplary depicts the external region representation in terms of equivalent ellipses, which are located at the centers of mass of the extracted features.

Figure 3: Feature representation in terms of the associated center of masses and equivalent ellipses.

5 CONCLUSIONS

In this paper, an efficient color-based image segmentation approach for the deeply embedded miniature robot BeBot is presented. In order to minimize the computational effort as well as the memory consumption during the segmentation process, regions are compactly represented in terms of runs while they are constructed. Furthermore, in order to provide a convenient data representation for subsequent object detection processes, the constructed regions are interpreted as a two-dimensional Gaussian distribution in the image plane. Hence, they are efficiently translated into a statistical feature description in terms of discretized moments. Finally, even though the chosen heuristic for deciding whether two color values are similar or not is very simple, it produces sufficient good results with respect to the separation of objects in a realistic environment.

REFERENCES

Herbrechtsmeier, S., Witkowski, U., and Rückert, U. (2009). Bebot: A modular mobile miniature robot platform supporting hardware reconfiguration and multi-standard communication. In *Progress in Robotics*, volume 44, pages 346–356. Springer Berlin Heidelberg.

Hu, M.-K. (1962). Visual pattern recognition by moment invariants. *Information Theory, IEEE Transactions on*, 8(2):179–187.

Prokop, R. J. and Reeves, A. P. (1992). A survey of moment-based techniques for unoccluded object representation and recognition. *CVGIP: Graph. Models Image Process.*, 54(5):438–460.

Teague, M. R. (1980). Image analysis via the general theory of moments. *Journal of the Optical Society of America (1917-1983)*, 70:920–930.

Zakaria, M. F., Vroomen, L. J., Zsombor-Murray, P. J. A., and van Kessel, J. M. H. M. (1987). Fast algorithm for the computation of moment invariants. *Pattern Recogn.*, 20(6):639–643.