Classification of Bottles in Range Images

Ragnar Bang Huseby[1], Rama Chellappa[2]
[1] Norwegian Computing Center, P.O. Box 114 Blindern, N-0314 Oslo 3, Norway
[2] Center for Automation Research, University of Maryland,
College Park, MD 20742–3275, U.S.A.
email: Ragnar.Huseby@nr.no (corresponding author)

Abstract

In this paper, we present an investigation of methods for locating and identifying bottles in crates based on height information obtained by a laser range finder.
Four bottle types have been used in this study. The bottles are of equal size but their shapes are slightly different. The bottles are made of plastic and are without caps.
The bottles are isolated by a region-based segmentation procedure and the center of a bottle is determined approximately by the centroid of the convex hull of the corresponding top region. We evaluate several features for classification of bottles. We obtain perfect recognition for three different classes when the classification is based on the average distance from the center of a bottle to a pixel in the top region.
We also present a successful method for detecting a sticker on the slanting part of the surface of a bottle made of transparent plastic. The approach utilizes that the measured height is higher in regions where a sticker is present, than in regions where there is no sticker.

1 Introduction

The goal of the research reported in this paper was to examine some methods that might be used in a system that can locate and identify bottles in crates automatically. Such a system is developed to handle empty bottles that are returned from customers at grocery stores. Before the bottles are sorted and sent to the appropriate manufacturer to be washed and refilled, the type of each bottle must be identified. Classification of bottles is also necessary when the amount reimbursed for a bottle depends on its type.

In [5], a method for classification of bottles using computerized image analysis is presented. Their method is based on features extracted from the caps of the bottles. However, one cannot expect that caps are always present. It is therefore necessary to develop alternative methods.

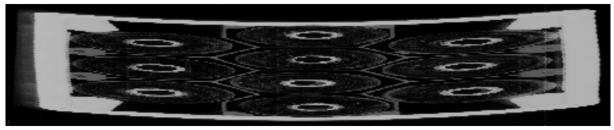

Figure 1: *A range image is displayed as a gray-level image such that low height corresponds to dark gray. Each horizontal line corresponds to a scan. The geometric distortion is due to the scan-pattern. The image shows a crate containing ten bottles viewed from above.*

In this paper, we will consider plastic bottles without caps. Since the bottles to be classified are placed in crates, the bottles are to be viewed from above in order to avoid that bottles are occluded. The analysis is based on range images. In the recent years there has been a growing interest in 3D object recognition using range images [1][6].

Descriptions of the images and the bottles are given in section 2. In section 3, the analysis of the images is described. The analysis consists of segmentation, detection of stickers, feature extraction, and classification. Results are presented at the end of each subsection. Summary and conclusion are given in section 4.

2 Data

The data used in this study are acquired by a laser range camera [2] generating scans while moving above a crate placed on a conveyor belt. An image consists of measurements from 140 scans containing 876 samples each. In a cartesian coordinate system the xy-coordinates of the ith sample point from the jth scan are given by

$$x = a\,(1.0 + \cos\theta), \quad y = b\,(1.0 - \sin\theta) + c\,i + d\,j,$$

where $\theta = \alpha\,i + \beta$, and a, b, c, d, α, and β are constants. The resolution of the height measurements is 2mm, the distance along the y-axis between two neighboring scans is 5mm, and the distance between two neighboring samples at a scan-line is between 0.68mm and 0.71mm. The resolution is quite coarse because only a limited amount of data can be stored. A depth map of a crate is shown in Fig. 1. The scan-pattern is shown in Fig. 2.

Four bottle types have been used in this study. Only bottles without caps have been considered. Samples of each type are shown in Fig. 3. The bottles are made of plastic and designed to contain 1.5 liters of liquid. The true heights are between 33 and 34cm while the true widths are between 8 and 9cm. For each bottle the collar is approximately 2 cm below the top, and the true widths of the collars are between 3cm and 4cm. *Pepsi* is the tallest. *Coke* and *Sprite* have wider collar than *Pepsi* while *Pepsi* has wider collar than *Hero*. The shape of the upper part of *Coke* and the shape of the upper part of *Sprite* are virtually indistinguishable. Fig. 4 shows the upper part of one sample of each bottle type. Fig. 5 shows scans passing through the central part of one sample of each bottle type.

The height is not measured properly on the slanting part of a transparent plastic bottle. Consequently, it is very difficult to determine the width of the bottles

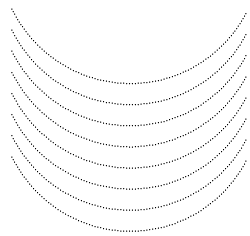

Figure 2: *The pattern of pixels is indicated.*

Figure 3: *Plastic bottles*

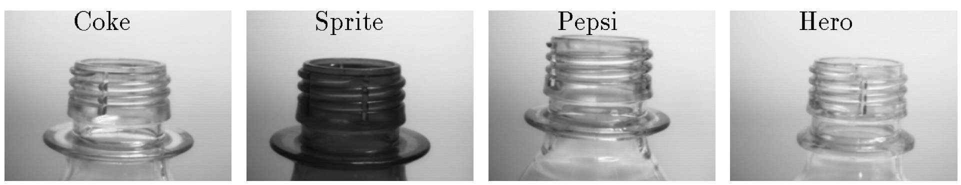

Figure 4: *The upper part of various bottles.*

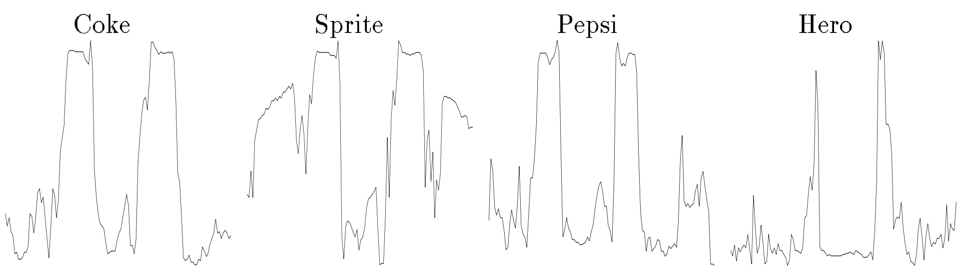

Figure 5: Scans passing through the central part of a sample of each bottle type

Figure 6: *A range image showing a bottle of Sprite viewed from above*

from the range images. Mainly the upper part consisting of top and collar is used as a basis for identification of a bottle. However, since stickers are not transparent, the height measurements from the slanting part are reasonable if a sticker is present. Fig. 6 shows a bottle having a sticker on the slanting portion of the surface.

3 Image Analysis

3.1 Segmentation

In the initial stage, regions containing a single bottle are segmented from the rest of the image. When viewed from above a bottle corresponds to a circular disk in the plane. The segmentation procedure is as follows:

A threshold for the input image is selected and a binary image is produced. Connected regions corresponding to the upper part of the scene are collected. For each region a bounding box is determined. The region having the largest bounding box is identified to be the crate. The crate and the regions outside the crate are not analyzed further. Remaining regions are merged if their union fits into a bounding disk not larger than the expected size of a bottle top. The resulting regions, not necessarily connected, are identified as bottle tops.

In order to compute some of the features described in section 3.3, the center of each bottle must be determined. Several algorithms for estimating a disk center from its digital image have been proposed [4], achieving subpixel accuracy, among which the most popular is the centroid algorithm. Using this method, the disk center is taken to be the centroid of a representative set of pixels.

In our case, a representative set is the union of an extracted bottle top region and the corresponding set of bottom pixels. A reasonable approximation of this set is the convex hull of the top region. Because the samples are not uniformly spaced we will not take the average of the sample coordinates to be the center. Instead we use the centroid of the convex hull regarded as a continuous region. Then the center estimate is given by

$$x_c = \frac{1}{A}\iint_\Omega x\,dx\,dy, \quad y_c = \frac{1}{A}\iint_\Omega y\,dx\,dy$$

where Ω is the convex hull and A is its area which is equal to $\iint_\Omega dx\,dy$. Hence

$$x_c = \frac{1}{A}\sum_{i=1}^{n} W_i\,(x_i - x_{i+1}), \quad y_c = \frac{1}{A}\sum_{i=1}^{n} W_i\,(y_{i+1} - y_i),$$

where $A = \frac{1}{2}\sum_{i=1}^{n}(x_i\,y_{i+1} - x_{i+1}\,y_i)$, $W_i = \frac{1}{3}(x_i\,y_i + x_{i+1}\,y_{i+1}) + \frac{1}{6}(x_i\,y_{i+1} + x_{i+1}\,y_i)$, and $(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)$ are the vertices named in counterclockwise order around the region.

Figure 7: *A thresholded image.*

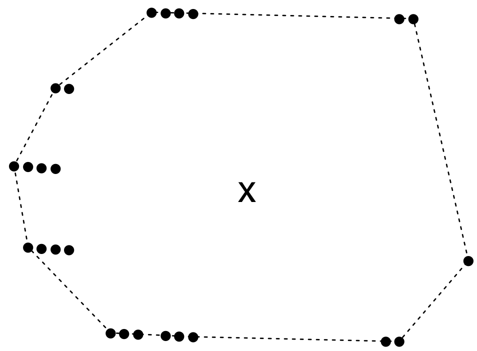

Figure 8: *A bottle top region, its convex hull, and the estimated center are shown.*

Results: The segmentation procedure was tested on 66 images of crates containing bottles. For each image the number of bottles in the crate was correctly determined, and each estimated center was found to be in the central part of the bottle region. The accuracy of the estimates has not been evaluated since classification is the goal of the work described in this paper.

Based on knowledge about the height of the bottles the threshold was set to 30cm. Similar results were achieved when the threshold was changed moderately. Fig. 7 and Fig. 8 show two of the steps in the segmentation procedure.

3.2 Detection of Stickers

Some of the bottles have stickers on the slanting part of the surface which is called shoulder. Those stickers are visible in the images since the measured height is higher in regions where a sticker is present, than in regions where there is no sticker, see Fig. 5 and Fig. 6. We want to determine whether there is a sticker on the shoulder of a bottle. For the bottles considered in this paper, the shoulder corresponds roughly to the annular region between two circles of radii, 25mm and 37.5mm, respectively, centered at the bottle center. If the sticker is present it may not cover the whole shoulder.

In order to detect stickers, we divide the shoulder into several annular rings which are examined separately. We assume that each ring is narrow so that the boundary of the sticker is radial if present. Since there is a jump edge between a sticker region and a non-sticker region, the ring may be segmented into regions of approximately constant height by using an appropriate edge operator. After the ring has been divided into homogenous segments each segment is classified.

Let f_1 and f_0 be the probability densities of the height measurements from a sticker region and a non-sticker region, respectively. Assume that the height measurements from the segment of consideration, $Y_1, Y_2, \ldots, Y_n$, are independent, and assume that the prior probabilities of *sticker* and *non-sticker* are equal. Using Bayes' classification rule [3], a segment is classified to *sticker* if

$$\prod_{j=1}^{n} f_1(Y_j) > \prod_{j=1}^{n} f_0(Y_j),$$

and to *non-sticker* otherwise.

It is assumed that f_i can be approximated by a normal density with expectation μ_i and standard deviation σ_i. By using knowledge about the height of the shoulder μ_1 and σ_1 can be determined. Since the measurements are spurious on the shoulder if the sticker is not present, we use estimates of μ_0 and σ_0 based on image data. Bottles without sticker on the shoulder are used as training samples.

Results: The performance of the method was investigated on two data sets generated by two different scanners. The sets contained a total of 330 and 329 samples, respectively, of which 100 had sticker. One set was used as training set and the other set was used as training set. All the bottles having sticker were detected, and 3% of bottles without sticker were wrongly declared to have a sticker. When interchanging the sets we got similar results.

3.3 Feature Extraction

In order to classify the bottles, features are extracted from the regions representing the bottles. In this paper, we examine the following features:

- v_1 = the maximum height.
- $v_2(h)$ = the most frequent height above h.
- $v_3(h)$ = the maximum distance from the bottle center to a pixel above h.
- $v_4(h)$ = the average distance from the bottle center to a pixel above h.
- $v_5(r_1, r_2)$ = the average height of a pixel in the region between two circles of radii, r_1 and r_2, respectively, centered at the bottle center.

We may expect that v_1 can discriminate between bottles of unequal height, and that $v_2(h)$, by choosing h larger than the measurements from the bottoms, can discriminate between bottles having collar of unequal height. Furthermore, $v_3(h)$ and $v_4(h)$ characterize the width of the collar for an appropriate choice of h. Finally, $v_5(r_1, r_2)$ may have the discriminatory properties of v_1, $v_2(h)$, $v_3(h)$, and $v_4(h)$ for selected pairs of (r_1, r_2).

Results: Several features were computed for each sample in the data set. A summary of the results is shown in Table 1.

Note that v_1 and $v_2(300)$ do not discriminate between any two of the classes considered in this paper. However, v_1 and v_2 might be used in other classification tasks provided that the height difference between two bottle types is sufficiently large.

Feature	*Coke*	*Sprite*	*Pepsi*	*Hero*
v_1	334	336	344	336
	352	358	354	348
$v_2(300)$	316	316	310	302
	332	334	332	344
$v_3(300)$	19.9	20.0	17.9	12.6
	21.9	24.7	19.8	15.7
$v_4(300)$	15.5	15.5	14.1	9.2
	16.4	16.7	15.0	12.4
$v_5(18, 19)$	308	295	147	22
	332	336	289	79

Table 1: *For each bottle type the minimum and the maximum of selected features are indicated. The unit is mm.*

We see that $v_3(300)$ and $v_4(300)$, and $v_5(18, 19)$ split the bottle types into three groups: *Coke/Sprite*, *Pepsi*, and *Hero*. Similar results were achieved for $v_3(h)$ and $v_4(h)$ when h was slightly different from 300. $v_3(h)$ was the more sensitive to the choice of h and tended to have a larger sample range.

$v_5(r_1, r_2)$ was examined for $r_1 = 8, 9, \ldots, 25$, and $r_2 = r_1 + 1$. Only $v_5(18, 19)$ splits the bottle types into three groups. As expected *Coke* and *Sprite* cannot be separated by features extracted from the upper part of the bottles.

3.4 Classification

The results of section 3.3 indicate that it may be possible to classify the bottles into three groups perfectly by using only one feature. Thus we do use only one feature for this task.

Having chosen an appropriate feature, this feature is evaluated for all bottle samples in a training set, that is a set where the class of each bottle is known. Let μ_i and σ_i be the sample mean and the standard deviation, respectively, for class i. Then, if a bottle of unknown class is given, and Z is the value of the feature for this bottle, the bottle is assigned to the class that minimizes $|Z - \mu_i|/\sigma_i$. This classification procedure is derived from Bayes' classification rule [3] in the case of normal class densities and equal prior probabilities.

If we wish to distinguish between *Coke* and *Sprite* the sticker test of section 3.2 may be used. Note that this test fails if the sticker is removed from the shoulder of *Sprite*.

Results: We wanted to classify the bottles into three groups: *Coke/Sprite*, *Pepsi*, and *Hero*. The training set and the test set were as in section 3.2. We obtained 100% correct classification when using the feature $v_4(300)$ of section 3.3, and almost 100% correct classification when using $v_3(300)$ or $v_5(18, 19)$.

4 Discussion

In this paper, we have examined methods for locating and identifying bottles in crates based on height information obtained by a laser range finder. The bottles are isolated by a region-based segmentation procedure and the center of a bottle is determined approximately by the centroid of the convex hull of the corresponding top region. We obtained perfect recognition for three different classes when the classification is based on the average distance from the center of a bottle to a pixel in the top region. The bottles were of equal size but their shapes were slightly different. We conclude that our approach is useful.

We have also presented a successful approach for detecting stickers. Information concerning stickers can provide additional discrimination though a classification system should not solely rely on this.

Classification of bottles from range images should be further investigated on a larger data set containing bottles of different size. Then the segmentation procedure should be modified by successively lowering the threshold instead of keeping the threshold fixed [5]. Alternative features should be extracted too.

Acknowledgements

A major part of this work was performed while Ragnar Bang Huseby was visiting the University of Maryland during the fall of 1993. We are grateful to Dag Bremnes, Andreas Nordbryhn, Gisle Aas, and Kjersti Aas for providing data, useful information and illustrations. This work has been supported by the Research Council of Norway.

References

[1] P.J. Besl: *Surfaces in Range Image Understanding*, New York, NY: Springer-Verlag, 1986.

[2] P.J. Besl: *Active Optical Range Imaging*, in J.L.C. Sanz, editor, Advances in Machine Vision: Architectures and Applications, Springer-Verlag, 1988.

[3] R.O. Duda and P.E. Hart, *Pattern Classification and Scene Analysis*, John Wiley & Sons, New York, 1973.

[4] A. Efrat and C. Gotsman: *Subpixel image registration using circular fiducials*, Proceedings of the 2nd Israel Symposium on Theory and Computing Systems, Natanya, Israel. pp. 49-58, June 1993.

[5] M. Magee, R. Weniger, and D. Wenzel: *Multidimensional Pattern Classification of Bottles using Diffuse and Specular Illumination*, Pattern Recognition, vol. 26, no. 11, pp. 1639-1654, 1993.

[6] M. Suk and S.M. Bhandarkar: *Three-Dimensional Object Recognition from Range Images*, New York, NY: Springer-Verlag, 1992.