MVA2000 IAPR Workshop on Machine Vision Applications, Nov. 28-30, 2000, The University of Tokyo, Japan

5—2

Shape Based Segmentation and Color Distribution Analysis with Application to Bread Recognition

Davar Pishva, Atsuo Kawai and Tsutomu Shiino
Department of Information Science , Faculty of Engineering, Mie University
Address: 1515 Kamihama-cho, Tsu City, Mie Prefecture 514-8507, Japan.
E-mail: davar@photal.co.jp

Abstract

We describe a unique shape based segmentation and color distribution analysis approach that can be used in a machine vision based cash register system for commodity pricing of hand made breads. Systematic sorting and classification of bread samples according to their shapes, sizes, textures and surface color distribution is explored.

Key words: Machine vision; Bread; Color distribution; Texture; Cluster analysis.

1. Introduction

Bar coding is one of the most commonly used techniques for commodity pricing of packed items. Machine vision have been used for commodity pricing of unpacked items, but, the approach has concentrated on product qualities such as size, uniformity, and defects[1][2], rather than product variety.

Machine vision is maturing as a technology as imagery and image processing is being utilized in many applications. In food industry, machine vision inspection system has been used for chocolate chip cookie and orange processing[3][4]. In baking industry, internal textural structure of loaf bread have been cited for flavor analysis[5] and color analysis has been utilized for quality control of hamburger buns[6]. As a new application in the field, we propose a machine vision based cash register system to automatically display commodity prices of various bread types that are placed on a shopping tray in front of it.

Most machine vision problems involve the analysis of images resulting from the reflection of light. Objects surface color is one of the most important pieces of information for computer vision. Colors recorded as images, however, do not specify the true color of object surfaces. Factors such as background color reflection, specular reflection and camera characteristic affect the process.

Humans usually recognize an object through its shape, size, color and texture. Human eyes can visualize underlying color and texture of a moderately hilighted section of an image by associating it with the neighboring matte area.

In this paper, we extracted true object color from bread sample images and developed our analytical approach based on how humans usually distinguish one object from another. We also considered the similarities and differences that exist between this application and other image analysis applications such as hand written Chinese character recognition and human face detection methods.

Because of the diversity of our samples, some identification procedures were just shape and size analyses while other samples required textural analysis, color and surface color distribution analyses.

2. Experimental

2.1 Apparatus An 8-bit 1.4M pixels Fujifilm digital color camera (FUJIX DS-330) was used for data acquisition. The camera was placed normal to the sample stage and was fixed at 46.3 cm height. Two pairs of special 20 watts florescent lamps, incident at 45° to the sample were used as light source. (TURE LITE, Color Rendering Index = 91 and Color Temperature = 5500°K)

2.2 Experiment Setup Camera was set to auto focus, manual exposure and manual aperture mode. An exposure time of 15 msec with an aperture setting of F5.6, were experimentally determined to be optimal for the sample set and its lighting environment. Camera height and zoom-in factor were chosen in such a way that the largest bread in the sample set would perfectly be visible in the image. A uniform blue background was used for easy background elimination. At this setting, reflectance of a white diffuser sample was about 80% of the camera's dynamic range.

2.3 Image Acquisition 73 different types of hand made breads were used in the experiment and image of each type was taken at three different orientations, one at a time. Dark signal and reference signal were also measured. A white diffuser sample, having a 90% reflectivity in the visible range, was used as a reference sample. Figure 1 shows ten sample images.

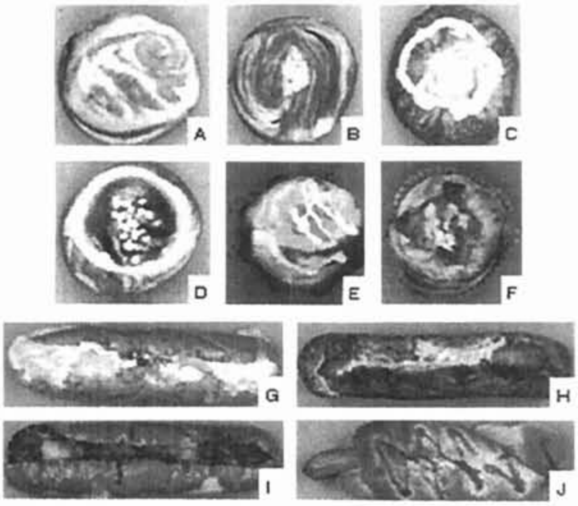

Figure 1: Images of 10 typical breads

3. Bread Classification

Our general analysis approach was to classify breads according to their shapes and sizes, perform textural and color analyses on the remaining unidentified members of each group, and carry out detail surface color distribution analysis for identification of every other remaining bread in the group.

Intermediate data analyses included transformation of RGB data to its HSI[7] components, binarization, size and shape analyses, textural analysis, color and surface color distribution analyses. Cluster analysis was performed on mean centered color data of texturally undeterminable similar shape and size bread to identify each individual bread type.

3.1 Preprocessing Prior to image analysis, various data corrections such as Dark Correction (Image – Dark), Background Correction ((Image – Dark) / (Reference – Dark)) * K, Highlight Correction, Color Balancing and γ Correction were performed on measured image data.

3.2 Binarization Initial analysis stage was to binarize image data so as to extract its shape and size. Despite the fact that a uniform blue background was used for its easy elimination, none of the standard binarization algorithm perfectly worked with all the 73 samples. Although there was no bread with explicit blue color or toppings, any arbitrary threshold setting eliminated parts of some breads during background elimination. This is because, none uniform boundary shadows and strong surface reflectance of some breads greatly affected the process. The following equation was used to successfully binarize image data using its HSI components:

```
if (H[i,j] >= 135 && H[i,j] <= 165 &&
     (S[i,j] * I[i,j] / 255)>= 10)
   B [i,j] = 0;
else
   B[i,j] = 1;
```

where HSI are hue, saturation and intensity components, normalized to 255, and B is the resultant binary image.

3.3 Size and Shape Useful size and shape analyses included Area (pixel counts), Elongation (ratio of the difference between major and minor axes to their sum) and MBR Fill (ratio of pixel counts to minimum bounding rectangle).

As observed in Figure 2, the largest bread, type 31, had an area of 161201 pixels and the smallest one, type 53, had 14393 pixels. Bread types 31 and 38 were considered identified at this stage because of their unique sizes.

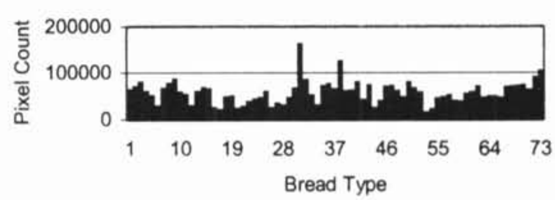

Figure 2: Area histogram of 73 breads

With the aid of elongation analysis (Figure 3), data were subdivided into circular or square group and rectangular or elliptical group. They were then further sub-grouped into their respective shapes using Bound Rect Fill analysis. The final output of shape analysis were bread samples that were grouped into square, rectangular, circular, elliptical and other shapes.

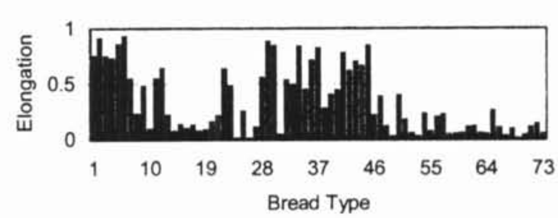

Figure 3: Elongation chart

Unique bread size of each shape region were also considered identified at this stage. The rest were grouped into area regions of 20000 pixels multiples (0-20000, 20000-40000, 40000- 60000, 60000-80000, and so on).

Since most of our bread were either circular or elliptical, as evident from Figure 3, we concentrated our further investigation on circular and elliptical shape breads and tried to immune our analysis method to sample orientation.

3.4 Textural Analysis Dependency matrix method [8] was used for textural analysis. In particular we used the below indicated inertia equation for textural feature extraction:

$$T(j,k,r,\theta) = \sum_{a=0}^{L-1} \sum_{b=0}^{L-1} (a - b)^2 P(a, b, j, k, r, \theta)$$

For a fixed central region of each similar shape and size bread, we computed energy values at four different directions by setting r to 1 and varying θ from 0, 45, 90 to 135. Breads with smoother patterns resulted in higher energy values while those with sesame seeds and sugar toppings had much lower energy values. Furthermore, a higher energy value at a specific angle implied existence of a pattern along that axis. For example, energy values of breads with horizontal stripes were much higher at $\theta=0°$ than other angles while those with vertical stripes yielded higher energy values at $\theta=90°$. Breads of definitive textural structure of each group were considered identified at this stage.

3.5 Color Analysis Color analysis was carried out in two stages. The first included histogram analysis of hue component of the entire sample. Breads of different and unique color of each group were considered identified at this point.

In the second stage, histogram analysis was performed on segmented sections of similar color breads of each group to segregate those that had different color distribution. To clearly explain our point, let us consider breads A and B of Figure 1. Although to human eyes their colors look different, their color histogram are surprisingly similar as indicated in Figures 4 and 5.

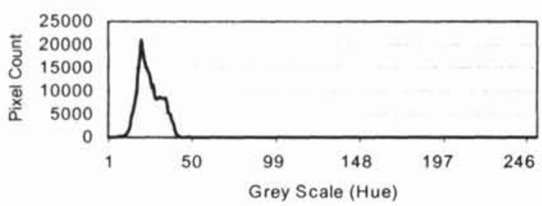

Figure 4: Color of bread A

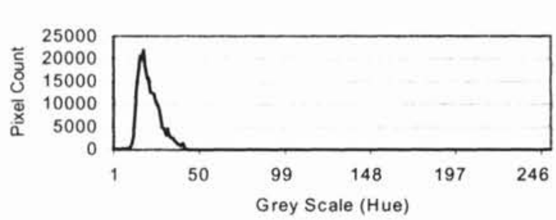

Figure 5: Color of bread B

When their segmented color histograms were compared at circular sections, their color greatly differed within the inner most circular sections as bread B had almond topping (yellowish) at the center and the other did not have. This can be clearly seen in Figures 6 and 7.

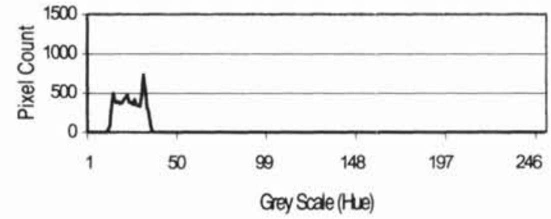

Figure 6: Inner color of bread A

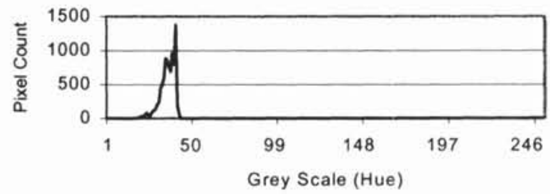

Figure 7: Inner color of bread B

3.5.1 Color Distribution Analysis of Circular Breads For a comprehensive color distribution analysis, we segmented each similar size circular bread into five circular regions (Figure 8) and computed hue histogram of each region.

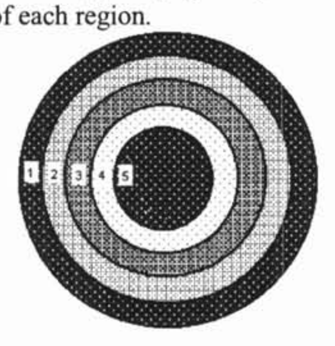

Figure 8: Five typical circular regions

The choice of circular regions for round breads was very important for our purpose since breads could be placed at any orientation and it would be difficult to correctly align round breads

3.5.2 Color Distribution Analysis of Elliptical Breads Since elliptical breads could be aligned along their major axis, only a shift of 180° in the orientation would be possible. To be able to cover the entire bread, we chose nine rectangular regions. To make our analysis' results immune to a 180° shift in orientation, we reduced the nine regions into five regions by combining each symmetrical rectangular pairs and considering their average values instead. Figure 9 and below indicated equations explain the idea:

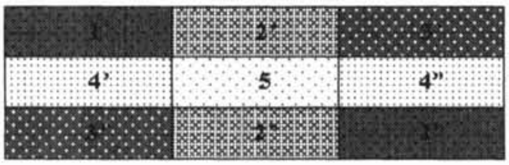

Figure 9: Nine typical rectangular regions

We reduced them into five by using the following equations:

$1 = (1' + 1") / 2$
$2 = (2' + 2") / 2$
$3 = (3' + 3") / 2$
$4 = (4' + 4") / 2$ and
$5 = 5$

3.5 Cluster Analysis For a complete identification process, we subdivided useful range of the above mentioned hue histograms into fourteen color regions (Figure 10) and computed area of each color region.

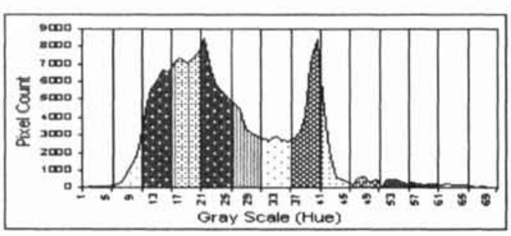

Figure 10: Fourteen color regions

We formulated a color distribution matrix with these area information and autoscaled the data for unity standard deviation. Figure 11 indicates the result of cluster analysis that was carried out for six similar size circular breads (breads A-F of Figure 1). Correct identification were verified with both validation and prediction samples. (Subscripts 1, 2, 3 correspond to calibration, validation and prediction sample of the same bread type.)

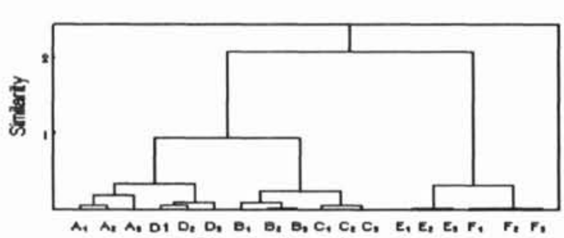

Figure 11: Dendogram of six similar size bread

The result of cluster analysis for four elliptical breads (breads G-J of Figure 1) are shown in Figure 12. Correct identification were also verified with both validation and prediction samples. (Similarly, subscripts 1, 2, 3 correspond to calibration, validation and prediction sample of the same bread type.)

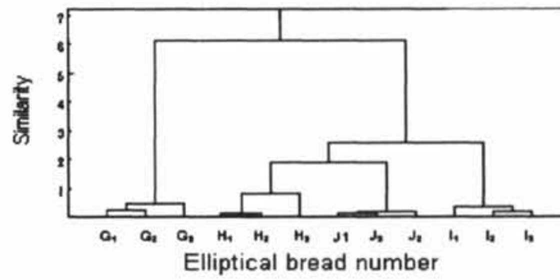

Figure 12: Dendogram of four similar size bread

4. Conclusions

This paper explored a new application of image analysis. It utilized solid and proven image analysis and pattern recognition techniques with a unique approach and sequence to ensure correct identification of each sample. To make our analysis approach invulnerable to orientation, we carried out textural analysis in four directions, used circular segmentation analysis on round breads and performed symmetrically mapped rectangular segmentation on elliptical shape breads.

References

[1] K.Fukuda et.al, "Agricultural Product Sorting System By Using High Speed Image Pipelined Processor and FA Components", MVA'p2, IAPR Workshop on Machine Vision Application, pp.553-556 (1992)

[2] John Pilkington, "Identifying and Inspecting Pumpkin Seeds", Advanced Imaging, pp.22-24 (1998)

[3] Daniel C. McCarthy, "The Perfect Chocolate Chip Cookie", Photonics Spectra, pp. 105-111 (2000)

[4] Daniel C. McCarthy, "The Perfect Orange", Photonics Spectra, pp. 113-117 (2000)

[5] Koshimizu, "Machine Vision Technology for Visual Inspection", Techno System, pp. 249-267 (1995)

[6] Peter Locht and Kund Thomsen, "Advanced Color Image Analysis for the Food Industry", Advanced Imaging, pp. 12-16 (1996)

[7] S.J. Sangwine and R.E.N. Horne, "The Color Image Processing Handbook", Chapman & Hall, pp.76-82 (1998)

[8] R. M. Haralic, "Textural Feature for Image Classification", IEEE Trans. On SMC, Vol. SMC-3, No.6,pp.610-621 (1973)