Shape Descriptor for Binary Image Retrieval

Moe Zet Pwint[1], Thi Thi Zin[2], Mitsuhiro YOKOTA[2]
[1]Dept. of Electrical and Electronic Eng., University of Miyazaki
[2]Faculty of Engineering, University of Miyazaki, Japan
[1]smithmoezet01@gmail.com, [2]thithi@cc.miyazaki-u.ac.jp

Mie Mie Tin[3]
[3]Dept. of Computer Science and Engineering
University of Computer Studies, Mandalay, Myanmar
miemietin1983@gmail.com

***Abstract*—Content-based Image Retrieval (CBIR) system search the images according to the image content such as color, texture, shape and others prominent features from the image. Among these features, shape can give visual structure and appearance of the image. In this paper, we propose a system for binary image retrieval, using Zernike moment, angular radial histogram together with horizontal and vertical histogram of the image. We focus on region-based shape approach and features are extracted from the image. And then, similarity matching process between query image and images in the database is carried out. As a result, the extracted images are shown to the user according with the rank value. Some experimental results by using MPEG-7 CE Shape-1 Part-B dataset are presented.**

Keywords—shape descriptor; Content-based Image Retrieval; binary image; angular radial histogram; region-based approach; Zernike moment

I. Introduction

Due to the increasing numbers of digital act such as photographs and videos, the efficient and effective computerized retrieval system is always demanding. The Content-based Image Retrieval (CBIR) systems are addressed to solve this problem. The CBIR systems extract features from image according to its contents. Basically, low-level features such as color, texture, shape and others distinctive features are extracted from the image. Among these features, shape feature can give appearance and outline of the image.

Shape features can be divided into contour-based and region-based approaches. Contour-based approach deals with boundary or outline of the image while region-based operates on the interior part of the image. A robust shape descriptor should have the following properties such as translation, scaling and rotation invariant of geometric transformations.

In this paper, we proposed a region-based shape descriptor that operates directly on object image pixels. The rest of the paper is organized in following sections. In section II, we describe our proposed system. In section III, performance evaluation and some experimental results are shown. Conclusion and future work are described in section IV.

II. Proposed Method

We propose a region-based shape descriptor to apply in binary image retrieval. Our shape descriptor is combination of three features such as angular radial histogram, horizontal and vertical histogram count of the object region and Zernike moment. Zernike moment has the properties of rotational invariance. Translation and scaling can also be done by applying normalization procedure [1]. Zernike moment have been studied and applied in different field of research areas [2-4].The proposed system is composed of three modules namely, preprocessing module, feature extraction module and similarity matching module. These modules are discussed in details in the following.

A. Preprocessing Module

Image preprocessing is the foremost and important step in image retrieval systems. Image preprocessing can enhance and support to other modules. In our system, the object region is cropped and then the image are resize into N x N pixel width and height for standardizing the image format. When resizing the image, some images do not fit into N x N format due to the much differ in width and height. For that condition, we pad with zero values to the required space in the resize image.

B. Feature Extraction Module

For feature extraction, we extract three features, especially region-based features such as angular radial histogram, horizontal and vertical histogram and Zernike moment.

1) Angular Radial Histogram Feature: Before extracting angular radial features from the image, first we create a binary mask relating with each angle and radius. Fig.1 shows example of binary mask operation on the image. In our system, there are k radius: r_1, r_2 to r_k and θ_1, θ_2 to θ_n for n number of θ respectively. Let $H_{R,\theta}$ represents the histogram count of pixel that fall in radial R and θ,

$$H_{R,\theta}(i) = H_{R,\theta}(i) + 1 \quad (1)$$

where $R = r_1, r_2, \ldots, r_k$, $\theta = \theta_1, \theta_2, \ldots, \theta_n$ and $i = 1, 2, \ldots, k \times n$. In our system, we set $k = 3$ and n = 8 for three radial parts and eight angular bins.

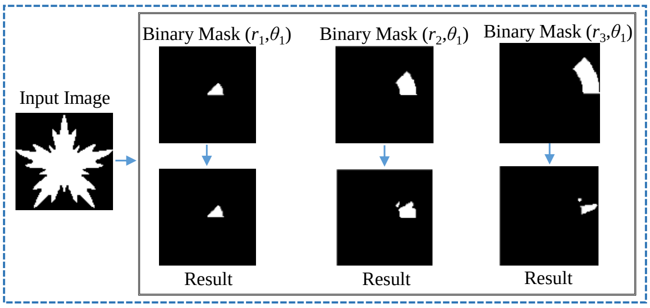

Fig. 1. A sampel binary mask operation with radius of r_1, r_2 and r_3 with 15, 30, 45 pixel each and θ_1 range from 0° to 45°

This work is partially supported by KAKENHI 25330133 Grant-in-Aid for Scientific Research(C).

2) Horizontal and Vertical Histogram Feature: In this feature, we count the pixels of the image row by row and column by column respectively. Let H_H and H_V represent the histogram count of horizontal and vertical of the image,

$$H_H(i) = [h(i,1), h(i,2), \ldots, h(i,n)] , \tag{2}$$

$$H_V(j) = [h(j,1), h(j,2), \ldots, h(j,n)] , \tag{3}$$

where i, j represent row and column and the image size is $n \times n$.

3) Zernike Moment Feature: The Zernike radial polynomials are calculated on polar coordiante by,

$$R_{p,q}(r) = \sum_{s=0}^{\frac{(p-|q|)}{2}} (-1)^s . \frac{(p-s)!}{s!(\frac{p+|q|}{2}-s)!(\frac{p-|q|}{2}-s)!} . r^{p-2s} , \tag{4}$$

where p-$|q|$ is always even and $p \geq |q|$. The Zernike basis function of p order and q repetition of $V_{p,q}(r,\theta)$ is defined by,

$$V_{p,q}(r,\theta) = R_{p,q}(r)\exp(jq\theta) , \tag{5}$$

where $r \leq 1$. Finally, the Zernike moment of the image is,

$$A_{p,q} = \frac{p+1}{\pi} \iint_{x^2+y^2 \leq 1} f(x,y) V^*_{p,q}(r,\theta) dxdy , \tag{6}$$

where $V^*_{p,q}$ is complex conjugate part of $V_{p,q}$ .In our system, we extract the first 4 order Zernike moment for Zernike features.

C. Similarity Matching Module

We apply Euclidean distance measure for calculating similarity measure between query image and images in the database. We use MPEG-7 CE Shape-1 Part-B dataset. This dataset is composed of 70 classes and each class contains 20 images. There are strong variations within each class and therefore having 100% accuracy for shape descriptors are challenging [5]. The Euclidean distance measure is calculated separately on each feature. Let E_{Dist} represents the total of the Euclidean distance value,

$$E_{Dist} = E_A + E_H + E_V + E_{ZM} , \tag{7}$$

where E_A, E_H, E_V, E_{ZM} represent the Euclidean distance value of angular radial histogram, horizontal histogram, vertical histogram and Zernike moment, respectively. The Euclidean distance values are sorted in ascending order and rank results are shown to the user.

III. Experimental Results

We test our system on MPEG-7 CE Shape-1 Part-B dataset. We make performance evaluation by using bulls-eye test [5]. Every image in the dataset is used as query and top 40 images are returned. Fig. 2 show the some retrieval results of top 21 results returned by our system (red square are correct matches) and Fig. 3 and Fig. 4 list the retrieval accuracy of each feature and each class. Overall, our system gets 63.91% of bulls-eye scores.

IV. Conclusion

In this paper, we proposed a region-based shape descriptor to apply on binary image retrieval. The angular radial, horizontal and vertical histogram, Zernike moments are extracted as features from the image. Our system has good retrieval result, when query image and database images are similar and not too much having difference within each class. Further research will be done on feature extraction and matching to improve the accuracy rate.

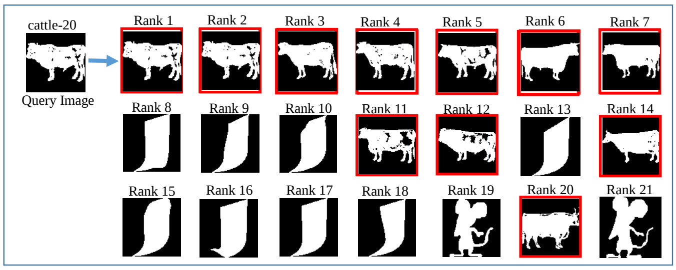

Fig. 2. ‘cattle-20’ query, no. of relevant images = 11

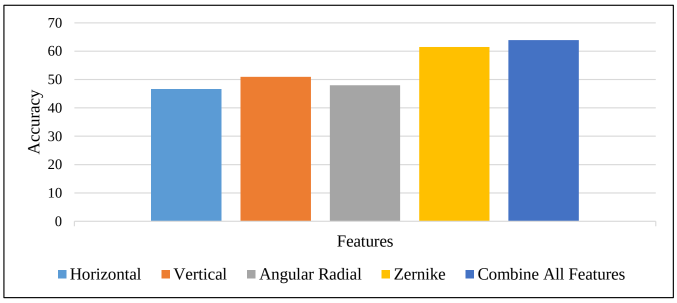

Fig. 3. Retrieval Accuracy of Each Feature and Combine Features

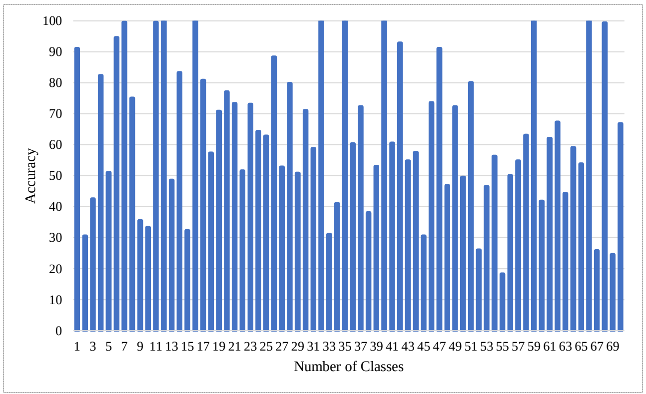

Fig. 4. Retrieval Accuracy of Each Class

References

[1] A. Khotanzad, Y. H. Hong, “Invariant Image Recognition by Zernike Moments”, IEEE Transactions on pattern analysis and machine intelligence 12, no. 5, pp. 489-97, May. 1990.

[2] C. H. Wei, Y. Li, W. Y. Chau, and C. T. Li, “Trademark image retrieval using synthetic features for describing global shape and interior structure”, Pattern Recognition 42, no. 3, pp. 386-394, Mar. 2009.

[3] A. Tahmasbi, F. Saki, S. B. Shokouhi, “Classification of Benign and Malignant Masses Based on Zernike Moments”, Comput. Biol. Med., vol. 41, no.8, pp. 726-735, 2011.

[4] F. Saki, A. Tahmasbi, H. Soltanian-Zadeh, S. B. Shokouhi, “Fast opposite weight learning rules with application in breast cancer diagnosis”, Comput. Biol. Med., vol. 43, no. 1, pp. 32-41, 2013.

[5] L. J. Latecki. R. Lakämper, U. Eckhardt, “Shape Descriptors for Non-rigid Shapes with a Singel Close Contour”. Proc of IEEE Conference on Computer Vision and Pattern Recognition, vol. 1, pp, 424-429, 2000.