ROBUST COLOR OBJECT DETECTION AND RECOGNITION

Choubeila MAAOUI, Christophe ROSENBERGER and Bruno EMILE

Laboratoire Vision et Robotique – UPRES EA 2078
ENSI de Bourges - Université d'Orléans
10 boulevard de Lahitolle , 18020 Bourges Cedex, France
phone: + (33) 248484000, fax: + (33) 248484040,
email: choubeila.maaoui@.ensi-bourges.

ABSTRACT

In this paper, we propose a new method for the detection and the recognition of objects in color images. The developed method processes in two steps. The first one concerns the object detection by a color segmentation method and a labeling algorithm. The second step deals with the recognition of extracted objects. Each object is described by color Zernike moments. In order to recognize each object, we use a support vector machine. We illustrate the efficiency of the proposed method on color images embedding some objects from the COIL-100 database.

1. INTRODUCTION

Image understanding is a great challenge in image processing. The main problem is the detection and the recognition of objects in an image. Object recognition with complete shapes has been studied for a long time, and can be handled with many existing techniques, such as shape signature, moments and Fourier descriptors [6][11]. However, problems arise when the objects are, for example, partially occluded. This problem has a significant importance in real applications. Many structural methods have been reported. Interest points based recognition methods have been proposed [5]. However, interest points alone are insufficient to form a complete integrated representation of an object. Polygon representation [9] is another technique. However, this method has the drawback to be unstable in finding break points for non-polygon objects. Finally, one or the combination of some basic geometric features, such as a line, arc, corner and contour can be used [8][14], but some complex objects may not be fully represented only by the basic geometric features, practically when the objects are occluded.

We propose here an approach exploiting the color information for the detection and the recognition of objects in an image. An object is described by the combination of two features including color and object shape information.

The paper is organized as follows : section 2 presents the proposed method composed on two stages : object detection and object recognition. Color segmentation and connected component labeling algorithm are used for object detection. To recognize each object, we use the Zernike moments applied on color images and a supervised classification based on a support vector machine. The efficiency of the proposed method is illustrated with some experimental results in section 3 using images containing some objects from the Columbia Object Image Library (COIL-100) [16].

2. DEVELOPING METHOD

The scheme of the proposed method includes the following steps (see figure 1):

- Color segmentation in order to detect the complex background,
- Image binarisation in order to separate the objects from the background,
- Labeling approach to distinguish each object,
- Description of each object using Zernike moments,
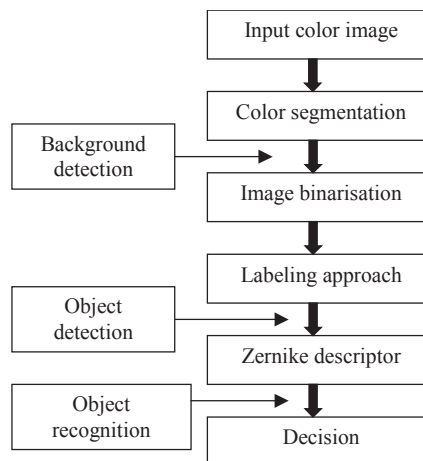- Recognition by a support vector machine.

Fig. 1. Block diagram of the proposed method

2.1 Object detection

2.1.1 Color segmentation

Color image segmentation is useful in many applications. Image segmentation allows to identify objects in the image. Recent works include a variety of techniques : for example, stochastic model based approaches [2], energy diffusion [10], and graph partitioning [13]. However, due to the problem complexity, there are few automatic algorithms that can work well on a large variety of data.

Image segmentation is still a difficult problem because of the presence of texture. Most of natural images are rich in color and texture. The approach used in this work is based on the mean shift algorithm [3]. The technique is a simple non-parametric procedure for estimating density gradients.

2.1.2 Labeling approach

In order to differentiate each object present in the scene, we have used the connected component labeling algorithm [4]. This algorithm uses the binary image for the detection of potential objects.

2.2 Object recognition

Object representation is an important stage for pattern recognition. The representation should be invariant to object position (rotation, translation and scale factor) and robust (presence of noise, occlusion, etc.). The proposed object representation is based on Zernike moments applied on color image.

2.2.1 Shape descriptor based on Zernike moments

In 1934, Zernike introduced a set of complex polynomials which forms a complete orthogonal set over the interior of the unit circle, i.e., $x^2 + y^2 \leq 1$. Let $\{V_{nm}(x,y)\}$ be the set of polynomials. The form of these polynomials is :

$$ZP = \{V_{nm}(x,y)|x^2+y^2 \leq 1\}$$
$$V_{nm}(x,y) = V(\rho,\theta) = R_{nm}(\rho)\exp(jm\theta) \tag{1}$$

Where n is a positive integer or zero, m is a positive or negative integer subject to constraints $n-|m|$ even, $|m| \leq n$, ρ is the length of vector from origin to (x , y) pixel, θ is the angle between vector ρ and x axis in counter clockwise direction. $R_{nm}(\rho)$ is the radial polynomial defined as:

$$R_{nm}(x,y) = \sum_{s=0}^{(n-|m|)/2} (-1)^s \frac{(n-s)!}{s!\left(\frac{n+|m|}{2}-s\right)!\left(\frac{n+|m|}{2}-s\right)!}(x^2+y^2)^{(n-2s)/2} \tag{2}$$

Note that $R_{n,-m}(\rho) = R_{n,m}(\rho)$.

Zernike moments are the projection of the image function on this orthogonal basis. The expression of Zernike moments of order n with repetition m is given below :

$$A_{nm} = \frac{n+1}{\pi} \sum_{x=0}^{N-1} \sum_{y=0}^{M-1} f(x,y)\left[V_{nm}(x,y)\right]^* \tag{3}$$

Where * denotes conjugate complex number.

To compute the Zernike moments of a given image, the center of the image is taken as the origin and pixel coordinates are mapped to the range of unit circle, i.e., $x^2 + y^2 \leq 1$. The pixels falling outside the unit circle are not used in the computation. Also note $A_{nm}^* = A_{n,-m}$.

Zernike moments are well known to be rotation invariant. In order to obtain the translation and scale invariances, a shape is normalized by obtaining the smallest circle centered at the center of mass, covering all the shape pixels [1], [7]. The obtained circle is then adjusted to match the radius of Zernike moment basis functions.

Classical methods for object recognition based on Zernike moments use function $f(x,y)$ equal to 1 or 0 (binary image). So, for two objects with a similar shape, we have a similar binary image (see figure 2), in other words a close value of the function $f(x,y)$ (equation (3)).

Fig. 2. Binary images of two objects from COIL-100 database with a similar shape : (left) original image (right) binary image.

Figure 3 plots the 12 components of the 10th and 11th Zernike moments applied on binary image of the objects (Obj1, Obj2) from the COIL-100 database. We can notice that we obtain quite similar values for both objects.
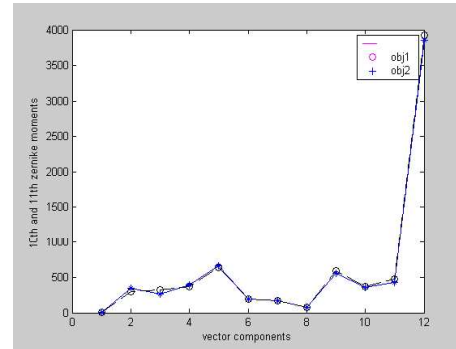

Fig. 3. Zernike moments values applied on binary images from figure 2.

In order to differentiate objects with a similar shape, we use Zernike moments applied on color images. We use the function $f(x,y)$ gray-level image and we add the average value of the three color components RGB (Red, Green, Blue). The function $f(x,y)$ is defined by:

$$f(x,y) = 0.3R + 0.6G + 0.1B \tag{4}$$

Figure 4 shows the Zernike moments values (10th and 11th order) applied on the two objects in Fig. 2 by taking into account the color information.
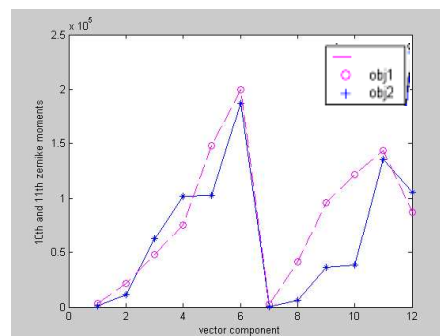

Fig. 4. Zernike moments values applied on the two objects in Fig. 2 with the color information.

We can notice, in this case, that the Zernike moments values discriminate both objects.

2.2.2 Supervised classification

In this section, we describe the supervised classification method based on support vector machines (SVM). SVM was proposed by Vapnik [15]. This method creates functions from set of labeled training data [12]. The function can be a classification function with binary outputs or it can be a general regression function. For the classification, SVMs operate by finding a hypersurface in the space of possible inputs. This hypersurface attempts to split the positive examples from the negative examples. The split will be chosen to have the largest distance from the hypersurface to the nearest of the positive and negative examples. Intuitively, this makes the classification correct for testing data that are near, but not identical to the training data.

3. EXPERIMENTAL RESULTS

This section describes experimental results obtained with of the proposed method. The COIL-100 database is used. This database contains color images of 100 different objects. 72 views of each object are taken at pose interval of 5° [16].

Figure 5 presents some examples of objects of the database, while figure 6 presents one object of the COIL-100 database for different rotations.

Fig. 5.   Several objects from the COIL-100 database.

Fig. 6.   Example of one object in the COIL-100 with different rotations

3.1 Object detection results

Figure 7 shows an example of object detection from the COIL-100 database with textured background using color segmentation and connected component labeling. We first, compute the histogram of the color segmentation result. If the background represents the dominant region of the scene, this step allows to easily detect it. However, the background can be considered as an object which will not be recognized in the final stage.
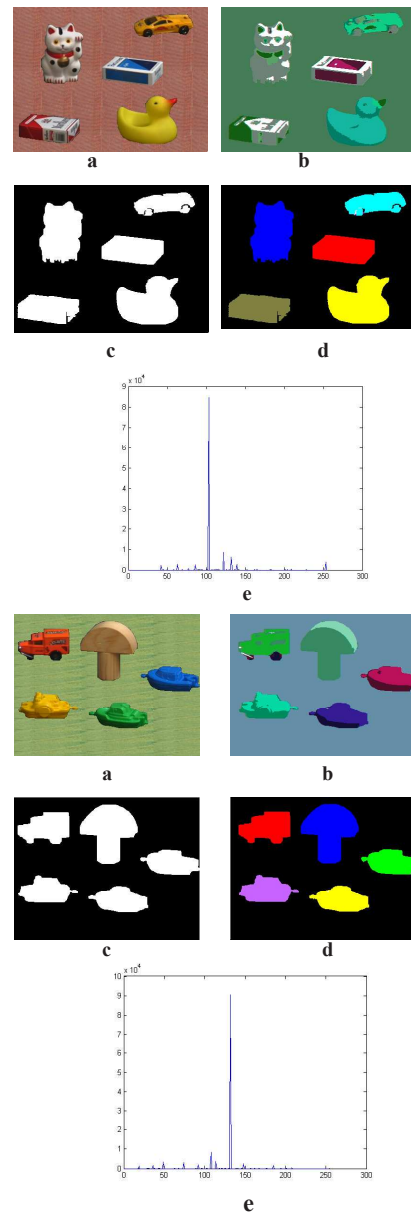

Fig. 7.   Object detection results : (a) original image, (b) color segmentation result, (c) background result, (d) labeling result, (e) histogram of image (b).

3.2 Object recognition results

For the object recognition part, we have tested different sizes of input patterns for the learning process. Each training vector is formed by 73 components of Zernike moments of order 0 to 15th applied on color images. The COIL-100 database is composed of 7200 images. We create a learning database containing some views of each object. The test database corresponds to the last views of each object.

Figure 8 shows the recognition rate for the objects of COIL-100 database. It can be seen that the recognition rate increases when color information is used.
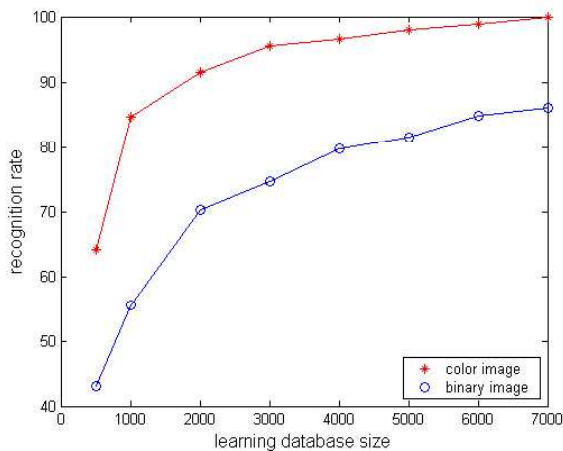
Fig. 8. Evaluation of the recognition rate with the number of images in the learning database.

The proposed recognition system is tested in the following perspectives: robustness to texture background, occlusion, illumination, and noise. Figure 9 presents some examples of occluded objects.

Obj58   Obj93   Obj99

Fig. 9. Examples of occluded objects from COIL-100 database

Table. 1 presents the recognition rate by learning the 72 views of the COIL-100 database and testing 10 altered views of objects. In the case of the uniform background, we have used gray level background (in the original database, the background is black).

We have tested different Gaussian noise with variance equal 5,10 and 20.

uniform background	noised background	textured background	occlusion with gray level background	occlusion with black background	illumination	noise
89.42	86.46	88.17	87.80	87.82	87.82	93.5

Table. 1. Recognition rate (%) for different alterations

It can be noted, that our recognition system is robust to these different alterations.

4. CONCLUSION

In this paper, an object detection and recognition algorithm using Zernike moments applied on color images is presented. The combination of color segmentation method and connecting component labeling is first used to detect objects.

Experimental results showed that the proposed Zernike descriptors using color information significantly increase the recognition rate of objects having the same shape. The rec-

ognition method is also robust against different alterations: occlusion, illumination and noise.

REFERENCES

[1] S. M. Abdallah, E.M. Nebot, et D.C. Rye " Object Recognition and Orientation via Zernike moments". In Chin, and Pong, T .C. editors, Proc. Computer Vision ACCV'98, volume 1 of LNCS 1351, pages 386-393. Springer Verlag, 1998.

[2] S. Belongie, Chad Carson, Hayit Greenspan, and Jitendra Malik, "Color and texture based image segmentation using EM and its application to content-based image retrieval", Proc. of ICCV, pp. 675-682, 1998.

[3] D. Comaniciu and P. Meer, "Robust analysis of feature spaces: color image segmentation", Conference on computer vision and pattern recognition, pp. 750-755, 1997.

[4] L. Di Stefano, A. Bulgarelli, "A simple and efficient connected components labeling algorithm". Image Analysis and Processing, Proceedings. International Conference, 27-29 Sept. 1999 pp : 322 – 327.

[5] M. H. Han and D. S. Jang, "The use of Maximum curvature points for the recognition of partially occluded objects", Pattern Recognition, vol. 23,21-33, 1990.

[6] M. Hu, "Visual pattern recognition by moment inavarints", IRE Trans. On Information Theory, vol. IT-8, pp. 179-167, 1962.

[7] A. Khotanzad, Y.H. Hong, "Invariant image recognition by Zernike moments", Pattern Analysis and Machine Intelligence, Volume: 12, Issue: 5 pp. 489-497, May 1990.

[8] K. B. Lim, K. Xin, G. S. Hong, "Detection and Estimation of Circular arc Segments", Pattern Recognition Letters 16, pp. 627-636,1995.

[9] H. C. Liu and M. D. Srinath, "Partial Shape Classification using Contour Matching in Distance Transformation", IEEE Trans. Pattern Anal. Mach. Intell. PAMI-12(11), pp. 1072-1079,1990.

[10] W. Y. Ma and B. S. Manjunath, " Edge flow: a framework of boundary detection and image segmentation", Proc. of CVPR, pp. 744-749,1997.

[11] E. Person and K. S. Fu, " Shape Discrimination using Fourier Descriptors", IEEE Trans. Syst. Man Cybern. 7, pp, 170-179, 1997.

[12] J. Platt, "Support Vector Machines", http://research.microsoft.com/users/jplatt/svm.html, 2003.

[13] J. Shi and J. Malik, "Normalized cuts and image segmentation", Proc. of CVPR, pp. 731.737, 1997.

[14] P. W. M. Tsang, P.C. Yuen and F. K. Lam, "Recognition of Occluded Objects", Pattern Recognition 25, pp. 1107-1117, 1992.

[15] V. Vapnik, "Suppport-Vector Network", Machine Learning, vol. 20, issue 3, September 1995, pp. 273-397.

[16] http://www1.cs.columbia.edu/CAVE/research/softlib/coil-100.html