ARABIC HAND PRINT CHARACTER RECOGNITION USING NEW HYBRID DESCRIPTOR

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Abstract: The matching and retrieval of the 2D shapes are challenging issues in object recognition and computer vision. The principal idea in this paper focus to propose an robust descriptor for indexing and retrieval Arabic hand print character. If we make an observation, we can show that some Arabic letters are completely similar with small deferent is represented by a dots. In this paper, we propose new hybrid descriptor based on Fourier coefficients. The proposed vector descriptor is constructed with Fourier coefficients and tow scalars parameters, the first parameter given by Euler number and the second represent the number of objects in the shape on the binary image. The choice of Fourier descriptor as part in the combination of proposed descriptor is based on studies of four well known descriptors based on, Zernike moments, Invariants Hu moments, Elliptic Fourier coefficients and Fourier coefficients. The comparative studies show that the hybrid descriptor gives good results using a test database constructed by Arabic Hand print letters. The results given by the proposed descriptor show the perfection and robustness of our method.

AMS Subject Classification: 62H30, 68T10

1. Introduction

Shape is one of the important visual features for image representation. During the past decades, a variety of shape descriptors and matching methods have been proposed in the literature Zhang [3]. Shape descriptors can be divided into two main categories: region based and contour based approaches.

Region-based methods use the whole area of an object for shape description. This approach exploits all boundary and interior of the shape. For this reason they are applicable to generic shapes and are more robust to noise and shape distortions. We find for this approach, geometric invariant moments Hu [10], Legendre moments Chiang [1] and Zernike moments, Jin [14].

Contour-based shape descriptors make use of only the boundary information, ignoring the shape interior content. In general, their computational complexity is low. However because they using the boundary shape only, these descriptors cannot represent shapes for which the complete boundary information is not available such as objects with holes, partially occluded objects. Some of the contour-based methods are Fourier descriptors Areni [8], distance interior ratio Kaothanthong [12], Invariant multi-scale descriptor Yang [9], Elliptic Contour Points Distribution Histogram ECPDH Shu [15] and Affine Length Parameterization descriptor Lakehal [2].

In this paper we present a new method for indexing and retrieval an Arabic hand print characters. As well known, the first goal is to search between the two approach, region based-descriptor and contour-based descriptor the convenient descriptor of the Arabic character as images test database, the second goal the hybrid this chosen descriptor with two scalars parameters to generate an hybrid descriptor. Some Arabic letters are completely similar, just a small deferent between them are the dots. This problem is resolved as we show in this paper.

After all, we make comparative studies between four descriptors (Section 2), the descriptor witch give a good result is chosen to become the hybrid descriptor using tow scalars parameters calculated from a shape representing an Arabic letter image as given in Section 3. The proposed hybrid descriptor shows the robustness in terms of response to the query provided by the user.

This paper will be organized as follows: in the second part we present

a related research review. After, we explain the proposed method in section three. The experiments and results of our method will be shown in the fourth part and finally the conclusion of our work.

2. Related work

In this section we give a brief description of each method used in the comparative studies to choice the good descriptor to construct the hybrid descriptor.

2.1. Invariant Moments Descriptor (IMD)

Hu [10] proposed Invariants Moment for two-dimensional pattern recognition applications. Two-dimensional moments of order $(p+q)$ for digital image $f(x, y)$ is defined as follows:

$$m_{pq} = \sum_x \sum_y x^p y^q f(x, y), \tag{1}$$

where $p, q = 0, 1, 2, ...$

The summations are over the values of spatial co-ordinates x and y spanning the entire image. The moments in (1) are not in general invariant under translation, rotation or scale changes in the image $f(x, y)$. Translation invariance can be achieved using central moment defined as follows:

$$\mu_{pq} = \sum_x \sum_y (x - \bar{x})^p (y - \bar{y})^q f(x, y),$$

where $\bar{x} = \frac{m_{10}}{m_{00}}$ and $\bar{y} = \frac{m_{01}}{m_{00}}$.

The normalized central moment of ordre $(p + q)$ is defined as :

$$\eta_{pq} = \frac{\mu_{pq}}{\mu_{pq}^r},$$

where $r = \frac{p+q}{2} + 1$.

It is known seven non-linear functions $\varphi_1, \varphi_2, ..., \varphi_7$ of normalized invariant Hus invariants moments calculating by (2). The vector descriptor is obtained

using seven scalars $\varphi_1, \varphi_2, ..., \varphi_7$:

$$
\begin{cases}
\varphi_1 = \eta_{20} + \eta_{02}; \\
\varphi_2 = (\eta_{20} - \eta_{02})^2 + 4\eta_{11}^2; \\
\varphi_3 = (\eta_{30} - 3\eta_{12})^2 + 3(\eta_{21} - 3\eta_{03})^2; \\
\varphi_4 = (\eta_{30} + \eta_{12})^2 + (\eta_{21} - \eta_{03})^2; \\
\varphi_5 = (\eta_{30} - 3\eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2]; \\
\quad + (3\eta_{21} - \eta_{03})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 + (\eta_{21} + \eta_{03})^2]; \\
\varphi_6 = (\eta_{20} - \eta_{02})[(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] \\
\quad + 4\eta_{11}(\eta_{30} + \eta_{12})(\eta_{21} + \eta_{03}); \\
\varphi_7 = (3\eta_{21} - \eta_{03})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] \\
\quad + (\eta_{30} - 3\eta_{12})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2].
\end{cases}
\tag{2}
$$

2.2. Zernike Moments (ZMD)

Teague [11] has suggested the use of continuous orthogonal moments to overcome the problems associated with the geometric and invariant moments. He introduced two different continuous-orthogonal moments, Zernike and Legendre moments, based on the orthogonal Zernike and Legendre polynomials, respectively. Several studies have shown the superiority of Zernike moments over Legendre moments due to their better feature representation capability and low noise-sensitivity. Therefore, we choose Zernike moments as our second shape descriptor.

The complex ZM are derived by projecting the image function onto an orthogonal polynomial over the interior of a unit circle $x^2 + y^2 = 1$ as follows:

$$
V_{nm} = V(x, y) = V(\rho, \theta) = R_{nm}(\rho)e^{jm\theta},
$$

$$
R_{nm}(\rho) = \sum_{s=0}^{\frac{n-|m|)}{2}} (-1)^s \frac{(n-s)!}{s!(\frac{n+|m|)}{2}-s)!(\frac{n-|m|}{2}+s)!} \rho^{n-2s},
$$

where $n = 0, 1, 2, ...,$ $0 \le |m| \le n$, $n - |m|$ is even , $\rho = \sqrt{x^2 + y^2}$ and $\theta = tan^{-1}(\frac{x}{y})$.

Projecting the image function onto the basis set, results Zernike moments of order n with repetition m are given by :

$$
Z_{nm} = \frac{n+1}{\pi} \sum_x \sum_y f(x, y) V_{nm}^*(\rho, \theta), \quad x^2 + y^2 \le 1.
\tag{3}
$$

If the image is rotated by an angle α, the transformed Zernike moment functions Z'_{nm} are given by:

$$Z'_{nm} = Z_{nm}e^{-jm\alpha}.$$

This means that the magnitude of the moments stays the same after the rotation. Hence, the magnitudes of the Zernike moments of the image $|Z_{nm}|$ could be taken as rotation invariant features, Jin [14]. The vector descriptor is taken as a magnitude of the moments.

2.3. Fourier Descriptors (FD)

Zhang [4] have compared different Fourier descriptors, which use centroid distance, complex coordinates and curvature function as shape signature, respectively. Centroid distance Fourier descriptors are testified to have better performance as a whole. So, modified Fourier descriptors would use the above idea for centroid distance Fourier descriptors.

Let $f(x, y)$ the Binary image, the canny edge detection operator and boundary tracing algorithm are used to compute the boundary pixel set of the object in $f(x, y)$. Suppose that PBS denote the pixel boundary set. The centroid of the object (x_c, y_c) can be calculated as:

$$x_c = \frac{1}{N}\sum_{k=1}^{N} x(k), \quad y_c = \frac{1}{N}\sum_{k=1}^{N} y(k), \qquad (4)$$

where N denotes the number of boundary pixels and $(x(k), y(k))$ denotes the location of the $k - th$ pixel of the set PBS in $f(x, y)$. Let $r(k)$ the distance of the $k - th$ pixel of the PBS to the c point, we calculate $r(k)$ as following:

$$r(k) = ([x(k) - x_c]^2 + [y(k) - y_c]^2)^{\frac{1}{2}}, \quad k = 1, 2, ..., N.$$

The Fourier coeffients a_n can be denoted as:

$$a_n = \sum_{k=1}^{N} r(k)e^{\frac{-2j\pi nk}{N}}, \quad n = 1, ..., N - 1. \qquad (5)$$

To normalize the coefficients, the first coefficient is used as follows

$$f_k = \left|\frac{a_k}{a_0}\right|, \quad k = 0, ..., N - 1. \qquad (6)$$

The vector f is invariant to translation. By referring to Granluns approach Granlund [6]. For a_n from (5), let a'_n denotes its transformed through translation, rotation, scaling and change of initial point given by:

$$a'_n = s.a_n.e^{jn\theta}e^{j\varphi},$$

where θ and φ denotes the angles incurred by the change of initial point and the rotation respectively, s denotes the scale factor.

The first coefficient a_0' is used to normalize all a_n',

$$\frac{a_n'}{a_0'} = \frac{s.a_n.e^{jn\theta}e^{j\varphi}}{s.a_0.e^{j\varphi}} = \frac{a_n}{a_0}e^{jn\theta}, \tag{7}$$

the magnitude is only used $f_k = \left|\frac{a_k'}{a_0'}\right| = \left|\frac{a_k}{a_0}\right|$, then to vector descriptor is given by:

$$V = (f_1, f_2, \cdot, f_p). \tag{8}$$

The vector V is invariant to translation, rotation, scaling and change of initial point Zhang [7].

2.4. Elliptic Fourier Descriptors (EFD)

The main aim of the elliptical Fourier analysis step consists to approximate a closed edge as a sum of elliptic harmonics. Considering the contour which represent a shape on binary image (Fig. 1), with freeman encode a closed contour can be describe by a chain:

$$C = u_1 u_2 ... u_n,$$

where $u_i \in \{0, 1, 2, 3, 4, 5, 6, 7\}$ is an oriented vector on the $(\frac{\pi}{4})u_i$ direction. The module of each u_i will be equal to 1 or $\sqrt{2}$ when each u_i will be even or odd respectively Jin [14].

$$|u_i| = \Delta t_i = 1 + \frac{\sqrt{2}-1}{2}(1 - (-1)^{u_i}). \tag{9}$$

For example the Freeman encoding of the edge shown in (Fig. 1) will be given by the following chain:

$$0000006667066644444442201344222,$$

therefore, if p is the number of elements in the chain of the whole contour, the length of the chain will be given by:

$$t_p = \sum_{i=1}^{p} \delta t_i,$$

and the following $T = t_k$ will identify such length.

Let Δx_i and Δy_i the changes of the x and y projections of u_i are given by:

$$\Delta x_i = sign(6 - u_i).sign(2 - u_i),$$
$$\Delta y_i = sign(4 - u_i).sign(u_i),$$

where

$$sign(k) = \begin{cases} 1, & if \quad k > 0, \\ 0, & if \quad k = 0, \\ -1, & if \quad k < 0, \end{cases}$$

the projections on x and y the first p links of the chain are respectively:

$$x_p = \sum_{i=1}^{p} \Delta x_i, \quad y_p = \sum_{i=1}^{p} \Delta y_i.$$

Kuhl [5] uses four Fourier coefficients a_n, b_n, c_n, d_n for each harmonic, and to identify the closed contour of K elements they consider N harmonics. These coefficients are given by:

$$\begin{cases} a_n = \dfrac{T}{2n^2\pi^2} \sum_{p=1}^{K} \dfrac{\Delta x_p}{\Delta t_p}(\cos(\dfrac{2n\pi t_p}{T}) - \cos(\dfrac{2n\pi t_{p-1}}{T})); \\[2mm] b_n = \dfrac{T}{2n^2\pi^2} \sum_{p=1}^{K} \dfrac{\Delta x_p}{\Delta t_p}(\sin(\dfrac{2n\pi t_p}{T}) - \sin(\dfrac{2n\pi t_{p-1}}{T})); \\[2mm] c_n = \dfrac{T}{2n^2\pi^2} \sum_{p=1}^{K} \dfrac{\Delta y_p}{\Delta t_p}(\cos(\dfrac{2n\pi t_p}{T}) - \cos(\dfrac{2n\pi t_{p-1}}{T})); \\[2mm] d_n = \dfrac{T}{2n^2\pi^2} \sum_{p=1}^{K} \dfrac{\Delta y_p}{\Delta t_p}(\sin(\dfrac{2n\pi t_p}{T}) - \sin(\dfrac{2n\pi t_{p-1}}{T})). \end{cases} \quad (10)$$

The coefficients a_n, b_n, c_n, d_n are used for constructing the vector descriptor.

3. Proposed hybrid descriptor

Create a recognition system able to retrieve similar hand print characters in the test database is one of the CBIR problems. The main question is how to create convenient descriptor of these kinds of characters. Some Arabic letters are identical except a small difference is a dot as shown in (Fig. 2). If we negligee the dots, the letters in the same column appear similar, but they are
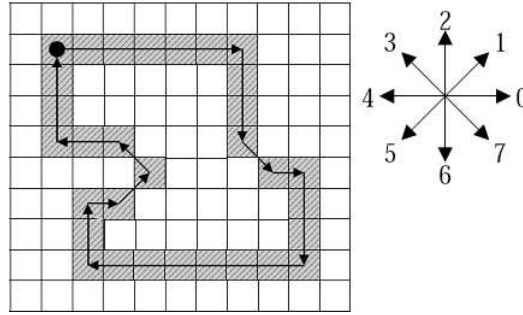
Figure 1: Example of binary image contour and vectorial representation of Freeman encode.

completely different. So, the goal of this study, to find a discriminate descriptor, able to retrieve similar images of query and make a large deference between a letters in the same column (Fig. 2). The first step consists to choice one off the descriptors that presented in section 2, this descriptor must give a good result between these four descriptors using our test database, second step consist to construct our hybrid descriptor based on combination of this chosen descriptor and tow scalars parameters extracted from a shape character as mentioned by following. So in the first follow sub section we give a comparative study and the second we present a proposed hybrid descriptor.

Figure 2: Some Arabic letters in the database.

3.1. Comparative studies between four descriptors

In this section we compare four descriptors using a test database where representative classes are shown in (Fig. 3 (1)). The compared descriptors are, Invariant moment descriptor (IMD), Zernike moment descriptor (ZMD) which represents a region-based descriptors and Fourier descriptor (FD) and Elliptic Fourier descriptor (EFD) to represent contour-based descriptors. From each

binary image we extract the following vectors descriptors:

- Invariant moments vector descriptor (IMD) given by :

$$V_{IMD} = (\varphi_1, \varphi_2, \varphi_3, \varphi_4, \varphi_5, \varphi_6, \varphi_7), \tag{11}$$

where φ_i are calculated by : (2)

- Zernike moment vector descriptor (ZMD) given by :

$$V_{ZMD} = (z_1, z_2, ..., z_p), \tag{12}$$

where $z_p = |Z_{nm}|$ and $p = n + m$.

- Fourier vector descriptor given by :

$$V_{FD} = (f_1, f_2, ..., f_n). \tag{13}$$

- Elliptic Fourier vector descriptor given by :

$$V_{EFD} = (a_1, ..., a_n, b_1, ..., b_n, c_1, ..., c_n, d_1, ..., d_n), \tag{14}$$

where a_n, b_n, c_n, d_n the vectors with n component for each one given by (10).

The vector descriptor length is chosen under tow conditions: the first, the length vector must be long enough to give a discriminate descriptor able to retrieve many similar images to the query and the second condition we consider a complexity computation, for this raison the vector must take small length as possible. The choice of vector descriptor length for each descriptor is based on experimental results using the test database as mentioned in Section 4.

As mentioned in Section 4, Fourier descriptor (FD) is the best of these compared descriptors. As shown in (Fig. 4) the retrieval rates of the images database is less than 50%, this problem caused by the Arabic letters whose are appear similar except the dots between them as shown in (Fig. 4). The follow sub-section gives a resolution of this problem.

3.2. Proposed hybrid descriptor

The descriptor suppose that the letters are similar but there arent because the dots make a big different between letters as shown in (Fig. 4), in this figure the query represent the class 4 and several retrieval images are in the class 25, the small difference between them is a dots.
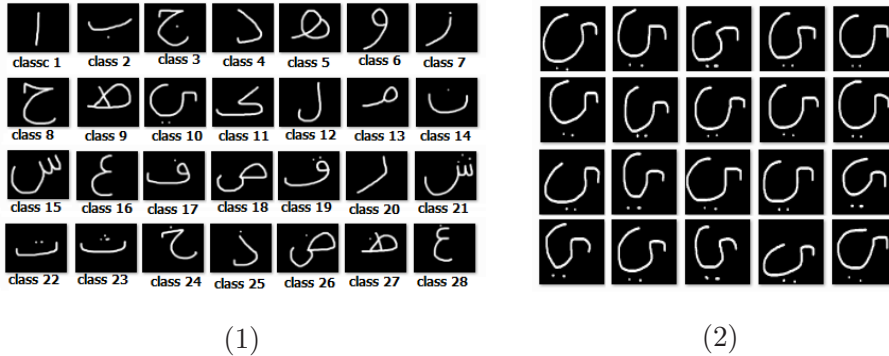
(1)   (2)

Figure 3: (1): The representatives of the classes of the test database, (2): Class number 10 of the test database.

To solve this problem, we introduce for each descriptor tow scalars parameters, the first parameter is the Image Euler Number IEN extracted from the big object of the shape of the binary image and the second is Image Object Number ION of the shape binary image. To extract this tow scalars from a shape that represent Arabic letter (Fig. 5 (1)(a)), the segmentation of the objects in image is necessary (Fig. 5(1)(b)) before extraction of these scalars. So we calculate the ION that represents the number of segmented objects in the image then we calculate the IEN from a big segmented object in this image.

For more explanation, as shown in (Fig. 5 (2)) we have in (a),(d) and (f) three letters have a same IEN and ION (Table 1) but they have a vectors descriptors completely different, otherwise, in (b) and (e) tow letters appear that similar with small difference with a dot, they have a small perturbation in the vectors descriptors, but they are completely different, the IEN and ION make a large different between them, the same thing for a letter in (c) and (f).
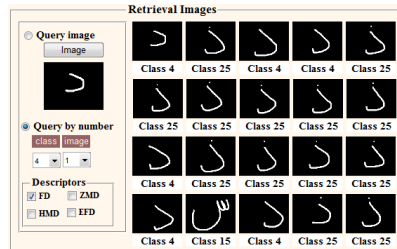

Figure 4: Query image in left and 20 images retrievals using FD.

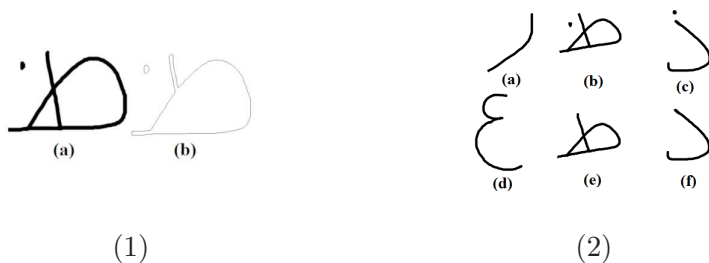The hybrid vector descriptor is constructed from one of the best mentioned

(1)   (2)

Figure 5: (1):The image in (a) represent an letter and its segmented objects in (b), (2): Some letters of the test database.

image	(a)	(b)	(c)	(d)	(e)	(f)
IEN	1	0	2	1	-1	1
ION	1	2	2	1	1	1

Table 1: Some Character Arabic letters and their IEN and ION numbers.

vector descriptor in Section 2 with combination by the two numbers: IEN and ION.

Let V the original vector descriptor extracted from binary image writing as:

$$V_D = (v_1, ..., v_p), \tag{15}$$

where p denotes the length of vector. To complete this vector we added IEN and ION scalar parameters noted k_1 and k_2 respectively, by this combination we have the hybrid vector descriptor given by:

$$V_{HD} = (v_1, ..., v_p, k_1, k_2). \tag{16}$$

Let I_1 and I_2 tow image of the test database, to measure the similarity between them, considering the similarity measurement as follows:

$$Sm : IS^2 \to [0, 1]$$
$$(I_1, I_2) \to Sm(I_1, I_2).$$

If the value of $Sm(I_1, I_2)$ is near the 0 the images supposed not similar and if this value is near the 1 the images supposed similar. This application is defined by:

$$Sm(I_1, I_2) = \frac{1}{1 + d(V^{I_1}, V^{I_2})},$$

where V^{I_1} and V^{I_2} are the vectors descriptors of the images I_1 and I_2 respectively. The Euclidian distance d is defined as:

$$d(V_{HD}^{I_1}, V_{HD}^{I_2}) = \sqrt{\sum_{i=1}^{p}(v_i^{I^1} - v_i^{I^2})^2 + \alpha \sum_{i=1}^{2}(k_j^{I_1} - k_j^{I_2})^2}, \qquad (17)$$

where $V_{HD}^{I_1}$ and $V_{HD}^{I_2}$ denote hybrid Fourier vector descriptor of image I_1 an I_2 respectively. This distance can be rewritten as:

$$d = \sqrt{l + \alpha k},$$

where

$$l = \sum_{i=1}^{p}(v_i^{I^1} - v_i^{I^2})^2,$$

and

$$k = \sum_{i=1}^{2}(k_j^{I_1} - k_j^{I_2})^2.$$

The parameter α is introduced to give a good influence of the vector k in the calculus of the distance d between tow vectors descriptors of images. If the images compared are identical except dots between them, we must have a big value of the distance d, for this raison the parameter α must take a big value. So we have the following system:

$$\begin{cases} l << \alpha k; \\ \quad \alpha > 1. \end{cases}$$

Switch the value of l and k we can separate three cases:

1. First case, the characters letters which would compare are identical, but just the dot is making a difference as shown in (c) and (f) in (Fig. 5 (2)). If when we using the original descriptor these images supposed similar (Fig. 4) but there are completely deferent. As they have deferent values of IEN and ION numbers, the distance d is very big and this makes binary images not similar. In this case we have $k > 1$.

2. Second case, if not similar as shown in (Fig. 5 (2)) (a) and (d), these images are not similar but they have a same IEN and ION number. As their shapes are completely deferent the distance d is big as distance between to vectors descriptor completely deferent. In this case we have $k = 0$.

3. Third case, the binary images are similar, in this case we have $k = 0$ and the distance between their vectors descriptor is small, that men the binary images are supposed similar by system.

4. Experimental results

In this section we give the experimental results. First, we represent the results of experimental comparative studies of four descriptors that represented in section 2 to choice the descriptor that gives good results. Second we test the hybrid descriptor.

4.1. Test Database

In this section we evaluate the capability of the proposed method. Concerning the experimental side we constructed a test database by Arabic Hand print character. The test database contains 28 classes, and each class that represent an Arabic Hand print letter. For each letter we take 20 variant that writing randomly as shown in (Fig. 3 (2)). The test database contains 560 binary images.

4.2. Experimental studies of four descriptors

Each image in the database is taken as query image than we calculate the retrieval rate of each class of database given by (Table 2(1)). A global result is given by (Fig. 6(1)) when we represent a retrieval rate of each descriptor using all images database. The statistical results in this figure permits to conclude that the Fourier descriptor can be used to construct the hybrid descriptor because that gives good results between all others. We can remark that the retrieval rate of these descriptors is less than 50% using all images of database as query.

4.3. Experimental results of hybrid descriptor

In the figure (Fig. 6(2)) a query image in left and 20 retrieval images using Hybrid Fourier Descriptor (HFD) in the right of figure.

A simple comparison we show that Hybrid Fourier descriptor used in (Fig. 6(2)) give many similar images of query than its original version in (Fig. 4)

using a same query.

To illustrate the performance of the original and hybrid descriptor of each one of the four descriptors a comparative experimental studies as given bellow.
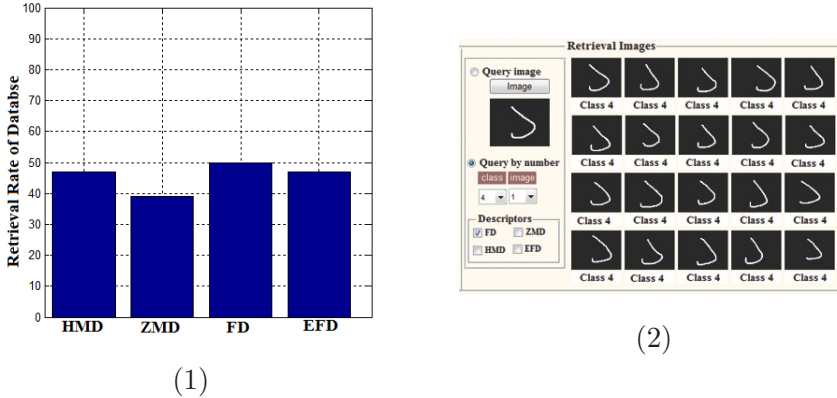

(1)

(2)

Figure 6: (1): Retrieval rates of the images database for each descriptor, (2): Query image in left and 20 images retrievals using HFD.

4.4. Result and performance

In order to evaluate the measurement of retrieval performance, we examine the Recall-Precision graph for the proposed hybrid descriptors. All images in the test database are given as query. For each descriptor we give a Recall-Precision graph of the descriptor used and its hybrid version, the results are shown in the following figures. The figure (Fig. 7(1)) illustrates the Recall-precision graph of Zernike moment descriptor with blue color and his hybrid version in red. The same thing for the three others descriptors shown in (Fig. 7(2)), (Fig. 7(3)) and (Fig. 7(4)).

The Recall-Precision for each descriptor show that the superiority of the hybrid version. We can show if we comparing the results in (Table 2(1)) and (Table 2(2)) the superiority of proposed methods.

To chose a descriptor that able to give a better results than other descriptors of our database, we are make an comparative of Recall-Precision of all hybrid descriptors as shown in (Fig. 8(1)), this study illustrate that the Hybrid Fourier descriptor is a convenient method for this kind of database. Other way to illustrate this capability of retrieval shape with these hybrid descriptor, we give in (Fig. 8(2)) a retrieval rate of all images database for all hybrid descriptors.

| Class	HMD	ZMD	FD	EFD	Class	HMD	ZMD	FD	EFD
1	49%	54%	99%	30%	1	80%	77%	100%	31%
2	66%	35%	32%	40%	2	73%	51%	57%	55%
3	32%	28%	28%	27%	3	40%	39%	42%	31%
4	37%	27%	49%	37%	4	63%	40%	79%	40%
5	45%	51%	49%	73%	5	61%	82%	77%	74%
6	53%	50%	56%	60%	6	62%	58%	91%	85%
7	46%	27%	54%	62%	7	94%	48%	67%	74%
8	30%	37%	31%	28%	8	47%	62%	58%	31%
9	53%	56%	30%	47%	9	70%	86%	81%	86%
10	61%	33%	62%	60%	10	99%	72%	100%	60%
11	63%	42%	84%	37%	11	82%	72%	88%	38%
12	78%	45%	78%	83%	12	81%	61%	91%	88%
13	46%	68%	47%	82%	13	66%	90%	72%	89%
14	47%	38%	94%	41%	14	54%	53%	96%	46%
15	45%	44%	44%	47%	15	83%	61%	64%	52%
16	33%	40%	44%	39%	16	52%	59%	70%	41%
17	61%	37%	46%	49%	17	92%	75%	93%	54%
18	40%	35%	40%	48%	18	87%	61%	65%	81%
19	58%	30%	53%	43%	19	99%	100%	100%	50%
20	60%	43%	57%	41%	20	96%	67%	97%	51%
21	26%	32%	34%	61%	21	99%	80%	99%	86%
22	33%	33%	44%	37%	22	88%	97%	100%	50%
23	48%	34%	40%	36%	23	99%	95%	100%	50%
24	28%	37%	33%	35%	24	44%	46%	48%	38%
25	57%	43%	55%	36%	25	86%	63%	83%	36%
26	41%	47%	49%	55%	26	99%	79%	88%	90%
27	46%	45%	43%	53%	27	100%	100%	100%	82%
28	39%	50%	26%	20%	28	48%	64%	67%	25%

(1)   (2)

Table 2: (1): Retrieval rate of classes by each descriptor, (2): Retrieval rate of classes by each hybrid descriptor.

5. Conclusion

In this study, we have presented a new hybrid descriptor to indexing and retrieval binary in the test database. Four famous descriptors are used, Zernike moment descriptor, Hu moment descriptor, Fourier descriptor and Elliptic Fourier descriptor. Each one of these descriptors are associated to tow scalars extracted from object in the binary image, the first scalar is Euler number of the big object in binary image and the second is the number of object in this image. We combined each vector descriptor with these scalars to constructing
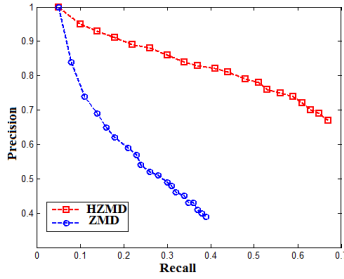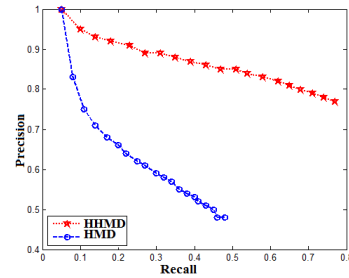
(1)
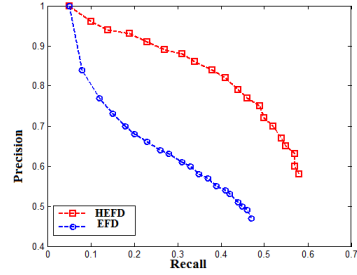
(2)
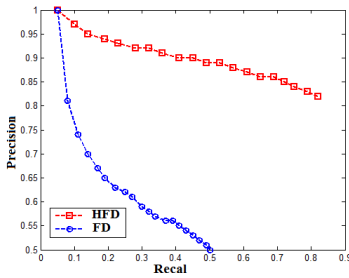
(3)

(4)

Figure 7: (1): Recall-Precision of Zernike moment descriptor (ZMD) and its hybrid version (HZMD), (2): Recall-Precision of Elliptic Fourier descriptor (EFD) and its hybrid version (HEFD), (3): Recall-Precision of Fourier descriptor (FD) and its hybrid version (HFD), (4): Recall-Precision of Hu moments descriptor (HMD) and its hybrid version (HHMD).

the hybrid vector descriptor. The comparative test illustrate that the hybrid descriptor has a good performance and gave a better result than its original version. Finally we concluded that the hybrid Fourier descriptor is good between the all others and its able the retrieve more than 80% similar images retrievals of all database as shown in (Fig. 8(2)).

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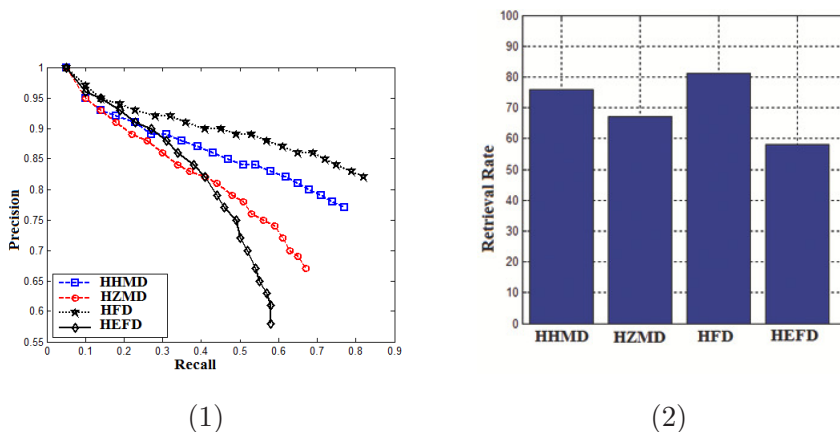
(1)   (2)

Figure 8: (1): Recall-Precision curves of all hybrid descriptorss, (2): Retrieval rates of the all images of database for all hybrid descriptors.

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