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aZIBO. A new descriptor based in shape moments and rotational invariant features

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***Abstract*—In this work, a descriptor called aZIBO (absolute Zernike moments with Invariant Boundary Orientation) that describes the shape of objects using the module of Zernike moments and the edge features obtained from an almost rotational invariant version of the Edge Gradient Co-occurrence Matrix (EGCM) is proposed. The two descriptors obtained, the Zernike module as global descriptor and the new version of EGCM as local one, are used to characterize images from three different datasets, Kimia99, MPEG2 and MPEG7. Later on, the concatenation of both local and global descriptors was evaluated using kNN with Cityblock and Chi-square distance metrics. Also, the descriptors are assessed separately with a weight-based method, being the results obtained compared with the ones reached by the baseline method, ZMEG (Zernike Moment Edge Gradient). Using MPEG7, which is the most challenging dataset, and the weight-based classifier, this proposal obtained a success rate of 78.29%, outperforming the 75.86% achieved by ZMEG method. With the MPEG2 dataset, results were even better with an 81.00% of success rate against 77.25% of ZMEG.**

***Keywords*—shape retrieval, descriptor, rotational invariant, ZMEG, aZIBO**

I. INTRODUCTION

Nowadays, the proliferation of high quality digital cameras and capturing devices since some years ago, is one of the reasons image processing techniques are becoming more and more popular. Among them, shape description and recognition methods are widely used in multiple fields (i.e. medicine, biometric identification, document retrieval, trademark image retrieval, etc.).

Under specific circumstances, two different objects can have the same shape so object recognition based solely in their shape is not possible. Although the human brain recognizes objects taking into account the context, shape recognition methods are very useful for automatic recognition purposes. There are three main ways to describe a shape: contour extraction, image based and skeleton based techniques and there are also methods combining these three ways. In [1], a perceptual shape descriptor was developed based on the beam angle statistics: the angle between a pair of beams is calculated at each contour point to extract the topological structure of the boundary. In [2], two descriptors are proposed, multiscale fractal dimension and contour saliences using a graph based approach called image foresting transform which returns a root map, a cost map and a label map containing the relevant information of the contour points and its relationship with its influence area points using contour and skeleton based techniques. Later, this method was improved exploiting the resemblance between content-based image retrieval and image analysis in order to develop two new descriptors: both contour and segment saliences testing their retrieval system with a fish dataset [3].

The concept of tensor scale, which is a morphometric parameter that unifies the representation of local structure thickness, orientation and anisotropic, is exploited by Andaló et al. [4]. The authors proposed a shape salience detector and descriptor which, as the previous method, used the Image Foresting Transform. Another method which use the information of the boundary points is the one proposed by García-Ordás [5] in which the minimum circumscribed circumference to the shape is constructed. Then, this region is divided into several bins and finally the descriptor is composed taking into account the number of points corresponding to each bin. Another example is the work developed by Zagoris et al. [6] in which an MPEG-like descriptor that contains conventional contour and region shape features is proposed. They use it in many applications using Support Vector Machines. Zhiyang Li et al. [7] proposed a geometry-based shape descriptor called ROMS which is a multi-scale descriptor defined by the ratio of a triangle middle and side line in each scale.

All these methods are applied to binary images but there are other ones which deal with colour images. One example is the work carried out by Zhu et al. [8] in which a new operator called the orthogonal combination of local binary pattern (OC-LBP) and six new local descriptors based on it enhanced with color information are proposed for the description of the image region.

Another method based on color histograms is the one proposed by Heng Qi et al. [9] in which they proposed an effective solution for trademark image retrieval by combining shape descriptors. Their proposal, not only represents the features of each point of the boundary but also consider the relationship between two adjacent boundary points and the centroid. The work carried out by Proen et al. [10] is other example of retrieval system using colour images.

All these methods can be used in multiple applications. For example, in the medical field, Hao et al. [11] proposed a method to automatically classify the invertebral disks as

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healthy or degenerated using an active learning and saving much human effort by avoiding labelling all training data manually. In the way, Proen et al. in [10] are focused on iris recognition technologies used in the biometric field.

Although this work is focused on bidimensional methods, there are also three dimensional image description methods such as the one developed by Blenkinsopp et al. [12] in which a digital image correlation system to measure dynamic foot shape during running is developed. Their system use a set of scanning lines that rotate around the shape centroid to collect information. Other example of a three dimensional image description method is the work developed by Smeets et al. [13] in which the geodesic distance matrix is used as an isometry-invariant shape representation. They described two approaches to compute a sampling order invariant shape descriptor: the histogram of geodesic distance matrix values and the set of largest singular values of the geodesic distance matrix and finally, the shape comparison is performed by comparison of the shape descriptors using the χ^2 distance as dissimilarity measure.

Nowadays, more and more methods are trying to improve the efficiency of the characterization by combining two or more shape descriptors. One example is the proposal developed by Singh et. al. [14] which is an effective descriptor based on angular radial transform (ART) and polar Hough transform (PHT). ART is used as a region based shape descriptor which represents the global aspects of the image and PHT is used as a local shape descriptor for detecting linear edges in an edge image. A similar approach is used in [15]. It is an innovative trademark retrieval technique with improved retrieval performance due to the integration of global and local descriptors. Zernike moments coefficients are used as global descriptor and the edge gradient coocurrence matrix derived from the contour information as the local one.

We propose a new shape descriptor called aZIBO (absolute Zernike moment with Invariant Boundary Orientation) and we have compared its performance with ZMEG, the one developed by Anuar et. al. in [15]. The rest of the paper is organized as follows. In section II, our proposed descriptor and two matching methods are explained. In section III, the experiments carried out along with the employed image datasets and the obtained results are explained. Finally, conclusions are discussed in section IV.

II. METHODOLOGY

A. Description

1) Global descriptor: We have used Zernike moments as a global shape descriptor employing the module of the first 36 coefficients up to the 10^{th} order.

Let (x, y) be a point on the euclidean coordinate system, represented in the complex plane by $x + iy = \rho e^{i\theta}$. Zernike polinomials are funcions $V_{nm}: \mathbb{R}^2 \to \mathbb{C}$ defined as:

$$V_{nm}(x, y) = R_{nm}(\rho) \cdot e^{im\theta} \tag{1}$$

Where $R_{nm}(\rho)$ is defined as:

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

where $0 \leq n$, $|m| \leq n$, $n - |m|$ is even.

Taking into account these polynomials, we can define one Zernike moment of an image as:

$$Z_{mn} = \frac{n+1}{\pi} \int \int_{x^2+y^2 \leq 1} f(x, y) V_{nm}^*(x, y) dx dy \tag{3}$$

where V_{nm}^* is the Zernike polynomial complex conjugate evaluated in (x, y) and the continuous function $f : \mathbb{R}^2 \to \mathbb{C}$ represents the image.

We used the module of the Zernike moments as global descriptor because of its invariance to rotation. As ρ is constant if we rotate the image, it seems that the Zernike moments module is invariant to rotation too. The Zernike Moments given a function f are represented in 4:

$$Z_{mn}^f = \frac{n+1}{\pi} \int_0^{2\pi} \int_0^1 f(\rho, \theta) V_{mn}(x, y)^* d\rho d\theta \tag{4}$$

Now, replacing V_{nm} for its definition (see equation (1)), we obtain:

$$Z_{nm}^f = \frac{n+1}{\pi} \int_0^{2\pi} \int_0^1 f(\rho, \theta) R_{nm}(\rho) \cdot e^{(im\theta)^*} d\rho d\theta \tag{5}$$

where $R_{nm}(\rho) \cdot e^{(im\theta)^*} = R_{nm}(\rho) \cdot e^{(-im\theta)}$ and finally, we obtain:

$$Z_{nm}^f = \frac{n+1}{\pi} \int_0^{2\pi} \int_0^1 f(\rho, \theta) R_{nm}(\rho) \cdot e^{(-im\theta)} d\rho d\theta \tag{6}$$

Now, let f^α be a rotation of f in α:

$$f^\alpha(\rho, \theta) = f(\rho, \theta - \alpha) \tag{7}$$

The Zernike moments of f^α are represented, following the equation (6) in the following way:

$$Z_{nm}^{f^\alpha} = \frac{n+1}{\pi} \int_0^{2\pi} \int_0^1 f^\alpha(\rho, \theta) R_{nm}(\rho) \cdot e^{(-im\theta)} d\rho d\theta \tag{8}$$

Now, we can replace f^α by its expression (equation (7)):

$$Z_{nm}^{f^\alpha} = \frac{n+1}{\pi} \int_0^{2\pi} \int_0^1 f(\rho, \theta - \alpha) R_{nm}(\rho) \cdot e^{(-im\theta)} d\rho d\theta \tag{9}$$

and making the change $\theta^\alpha = \theta - \alpha$, we obtain:

$$Z_{nm}^{f^\alpha} = \frac{n+1}{\pi} \int_0^{2\pi} \int_0^1 f(\rho, \theta^\alpha) R_{nm}(\rho) \cdot e^{(-im(\theta^\alpha + \alpha))} d\rho d\theta^\alpha \tag{10}$$

As we have that $e^{(-im(\theta^\alpha + \alpha))}$ is equivalent to $e^{(-im\alpha)} e^{(-im\theta^\alpha)}$ where $e^{(-im\alpha)}$ is a constant given a particular function f', we can define Z_{nm}^f as:

$$Z_{nm}^{f^\alpha} = e^{(-im\alpha)} \frac{n+1}{\pi} \int_0^{2\pi} \int_0^1 f(\rho, \theta^\alpha) R_{nm}(\rho) \cdot e^{(-im\theta^\alpha)} d\rho d\theta^\alpha \tag{11}$$

Combining this with equation (6), we obtain:

$$Z_{nm}^{f^\alpha} = Z_{nm}^f e^{-im\alpha} \tag{12}$$

Taking the module in both side of the previous expression, we have:

$$|Z^{f^{\alpha}}_{nm}| = |Z^{f}_{nm} e^{-im\alpha}| \tag{13}$$

We know that $|e^{-im\alpha}| = 1$, so

$$|Z^{f^{\alpha}}_{nm}| = |Z^{f}_{nm}| \tag{14}$$

Therefore, we have that Zernike moments module is rotationally invariant, which makes the global descriptor robust no matter what the image orientation is. Zernike is applied using binary images resized to 128×128 pixels.

2) Local descriptor: We use EGCM (Edge Gradient Coocurrence Matrix), proposed in [15] as a local descriptor but with several changes in order to improve the results and make it partially invariant to rotation. The first step is to obtain the boundary points of the image. In this case, we have used a Canny edge detector (see figure 1).

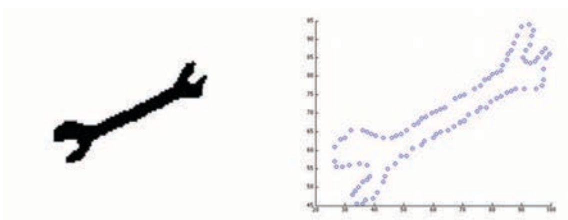

Fig. 1. Image boundary points

For each of these boundary points, the gradient is calculated following the expression 15.

$$\phi(x,y) = \tan^{-1} \frac{I(x+1,y) - I(x-1,y)}{I(x,y+1) - I(x,y-1)} \tag{15}$$

These gradient orientations are quantized to the 8 ones shown in figure 3. Once we have obtained the orientation gradient of each point (see figure 2) we take into account its eight neighbours (only those which are boundary points) and construct the ECGM as shown in figure 3.

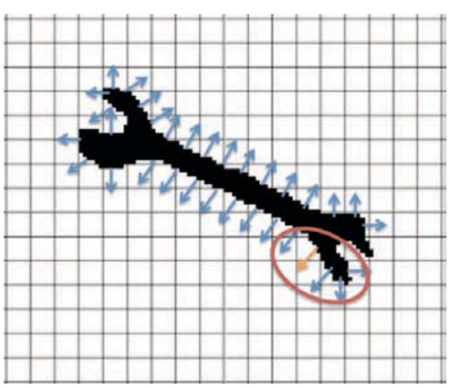

Fig. 2. For each boundary point, its gradient orientation is calculated.

In the Anuar's work [15], the local descriptor is composed by all the EGCM rows concatenated in one vector yielding a 64-element descriptor and then it is normalized in the range

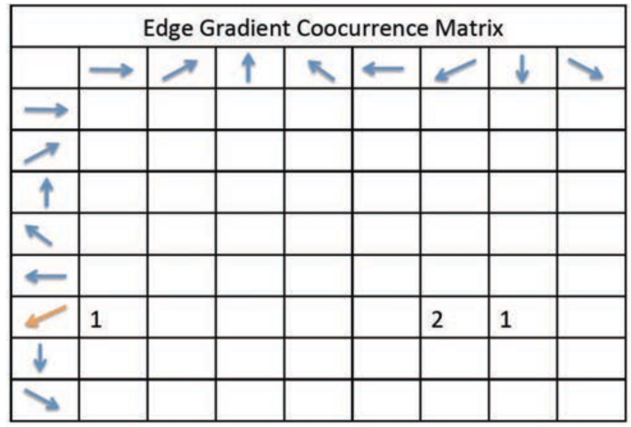

Fig. 3. Edge gradient coocurrence matrix construction

of 0 to 1. On the contrary, in this work, we preserve the real values in order to obtain as much information as possible.

Furthermore, we make this local descriptor partially rotational invariant which is considered an important issue in the shape retrieval field avoiding the previous step of rotating all the images of the dataset as Anuar et al. done in their work. First of all, we obtain the dominant orientation ϕ_d of the image. Let $p_1 = (x_1, y_1)$ and $p_2 = (x_2, y_2)$ be the most distant points on the contour. ϕ_d is considered as orientation of the vector $\overrightarrow{p_1 p_2}$:

$$\phi_d = \arctan \frac{y_2 - y_1}{x_2 - x_1} \tag{16}$$

where p_1 and p_2 are the furthest points of the boundary.

So we shifted the eight orientations in the EGCM placing this dominant orientation in the first position in the matrix obtaining partially invariant EGCM (IEGCM).

$$IEGCM = EGCM(\phi_d, ..., \phi_8, \phi_1, ..., \phi_{d-1}) \tag{17}$$

Then, following equation (17), for several spins, we obtain the same description for one image wherever it orientation is, as we can see in the example on figure 4. Concatenating the matrix rows, we obtain the 64 element invariant local descriptor.

B. Shape Retrieval

Many retrieval methods exist but most of them are very expensive in terms of computational cost. In this paper, two fast and efficient retrieval methods have been used: A concatenation of the global and local descriptor classified using Chi-square and Cityblock distances and the matching proposed in [15], a weight based solution.

1) k-Nearest neighbours (kNN): We used kNN with k equals 1, 3, 5, 7 and 9 with two distances, Chi-square and Cityblock to classify the concatenation of the global and local shape descriptor explained in the previous sections. Therefore, we are proposing a descriptor composed by the module of the first 36 Zernike moments extracted from the original binary images and the Invariant Edge Gradient Co-occurrence Matrix concatenated by rows and with not normalised values.

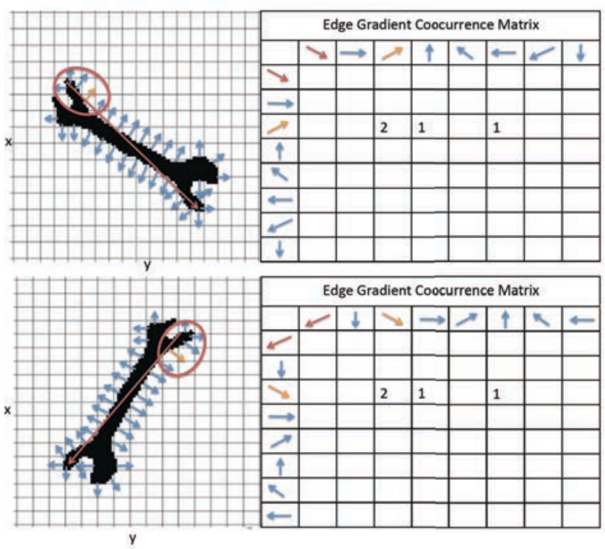

Fig. 4. Invariant Edge gradient co-occurrence matrix construction example

2) Weight based solution: This weight based solution was proposed by Anuar et al [15] with the aim of enabling the system to retrieve images with local and global similarities. First of all, a filtering step using only a global descriptor (such as Zernike) is carried out using the Euclidean distance to construct the dissimilarity matrix. After that, an average global dissimilarity value is computed and set as the threshold value. All images with a global dissimilarity value D_g higher than the threshold value are not further considered. In the second stage, the dissimilarity value D_l is computed. The total dissimilarity D_t value is given by the expression 18. Finally, this dissimilarity matrix is classified with kNN and Euclidean distance.

$$D_t = D_g \cdot w_g + D_l \cdot w_l \tag{18}$$

where D_g is the global descriptor, D_l is the local descriptor and w_g and w_l are their respective weights. The values proposed by Anuar et at. [15] are 0.2 and 0.8 for the global and local descriptors, respectively.

III. Experiments

A. Datasets

Three image datasets have been used in order to test the behaviour of the proposed method with image retrieval systems. Kimia99, MPEG7 and a subset of MPEG7 called MPEG2. Kimia99 is composed of 99 images: 9 classes with 11 images each one (see figure 5).

MPEG 7 contains 1400 images distributed in 70 classes and finally, MPEG2 is a subset of this one containing just 400 images: 20 classes with 20 samples per class. In figure 6 an example of these two datasets is shown.

B. Experiments and results

In this section, results obtained with the baseline method, the ZMEG descriptor [15] and our proposal aZIBO, are compared using two matching methods: the concatenation of global and local descriptor and the weighted based solution.

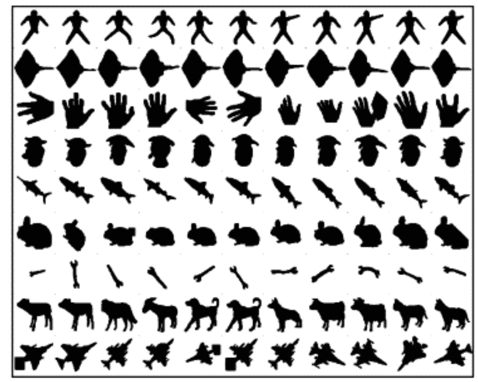

Fig. 5. Kimia99 dataset

TABLE I. Kimia99 classification using our proposal aZIBO (upper side) and ZMEG (lower side) with k equals one, three, five, seven and nine for the concatenation and the weight based solution with Euclidean distance.

Dataset Kimia99					
Classifier	aZIBO				
Distance	k=1	k=3	k=5	k=7	K=9
kNN Chi-square	86.87%	78.79%	74.75%	69.70%	71.72%
kNN Cityblock	87.89%	82.83%	77.78%	67.68%	69.70%
WeightBased	86.87%	81.82%	73.94%	68.25%	63.19%
Classifier	ZMEG				
Distance	k=1	k=3	k=5	k=7	K=9
kNN Chi-square	72.73%	70.71%	66.67%	58.59%	53.54%
kNN Cityblock	83.84%	81.82%	77.78%	75.76%	71.72%
WeightBased	87.88%	82.15%	70.1%	58.00%	48.93%

TABLE II. MPEG2 classification using our proposal aZIBO (upper side) and ZMEG (lower side) with k equals one, three, five, seven and nine for the concatenation and the weight based solution with Euclidean distance.

Dataset MPEG2					
Classifier	aZIBO				
Distance	k=1	k=3	k=5	k=7	K=9
kNN Chi-square	79.25%	76.00%	73.25%	71.75%	69.75%
kNN Cityblock	79.00%	75.00%	72.75%	72.00%	70.25%
WeightBased	81.00%	71.50%	67.85%	65.36%	62.86%
Classifier	ZMEG				
Distance	k=1	k=3	k=5	k=7	K=9
kNN Chi-square	61.25%	56.50%	54.25%	54.50%	53.00%
kNN Cityblock	79.00%	74.50%	71.25%	70.75%	68.75%
WeightBased	77.25%	69.08%	65.10%	61.57%	58.83%

The results, which can be seen on tables I, II and III, show that our descriptor using both classifiers outperforms the baseline ZMEG method in all cases but in Kimia99 dataset classifying with the weight based solution. In table I, we can see that the best hit rate is obtained using cityblock distance with a hit rate of 87.89% against 83.84% obtained using the ZMEG method. The classification using the weighted based method proposed in [15], yields a hit rate of 86.87% when using aZIBO against an 87.88% using the baseline one. This is the only case in which the proposed descriptor has obtained worse results than ZMEG.

As it is depicted on tables II and III, the behaviour is similar.

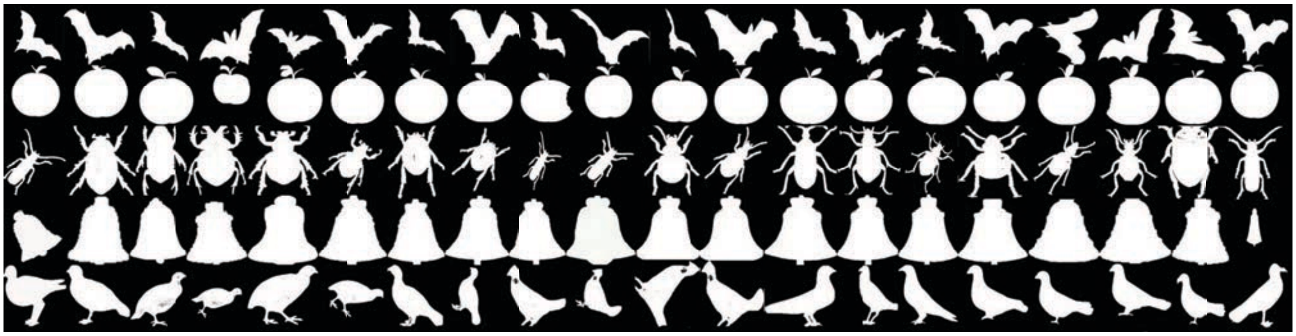

Fig. 6. MPEG7 and MPEG2 dataset example.

TABLE III. MPEG7 CLASSIFICATION USING OUR PROPOSAL AZIBO (UPPER SIDE) AND ZMEG (LOWER SIDE) WITH K ONE, THREE, FIVE, SEVEN AND NINE FOR THE CONCATENATION AND THE WEIGHT BASED SOLUTION WITH EUCLIDEAN DISTANCE.

Dataset MPEG7

Classifier	aZIBO				
Distance	k=1	k=3	k=5	k=7	K=9
kNN Chi-square	76.50%	71.79%	68.86%	66.21%	65.57%
kNN Cityblock	77.07%	71.00%	69.00%	65.79%	64.36%
WeightBased	78.29%	70.36%	65.10%	60.87%	57.52%
Classifier	ZMEG				
Distance	k=1	k=3	k=5	k=7	K=9
kNN Chi-square	56.79%	51.29%	49.36%	46.79%	45.64%
kNN Cityblock	76.57%	71.36%	68.14%	64.57%	62.79%
WeightBased	75.86%	77.33%	60.99%	56.48%	53.05%

In table II, we obtain a 79.25% of hit rate using Chi-square distance against the 61.25% obtained using the baseline descriptor. Once again, using the classification method proposed in [15], our descriptor outperforms the original one with an 81.00% against the 77.25% of success rate obtained with ZMEG. Finally, in table III the results using the most challenging dataset, MPEG7, are shown. They outperform one more time ZMEG descriptor with both classifiers (concatenation with kNN and weight-based) and with all the distances. The best hit rate is achieved using the weight-based solution with a 78.29% against their 75.86% and 77.07% against 76.57% using cityblock distance.

The performance of our descriptor aZIBO using both kNN and the weighted based solution using Euclidean distance in both cases is shown in figures 7, 8 and 9 and it is compared with the original retrieval method in the same conditions.

In [15], Anuar et al. used the MPEG7 dataset with the images rotated. In our proposal, this preprocessing step is not necessary because the aZIBO method is rotationally invariant thus all the experiments have been carried out using the original MPEG7 dataset without modifications.

IV. CONCLUSIONS

In this paper, a new shape descriptor called aZIBO based on the ZMEG method is proposed. Changing the original Zernike moments by their module and shifting the EGCM as it is described previously, we achieved partial invariance to rotation, yielding in a more robust algorithm. Furthermore, the method proposed is able to be classified not only with the weighted dissimilarity method presented in the Anuar et

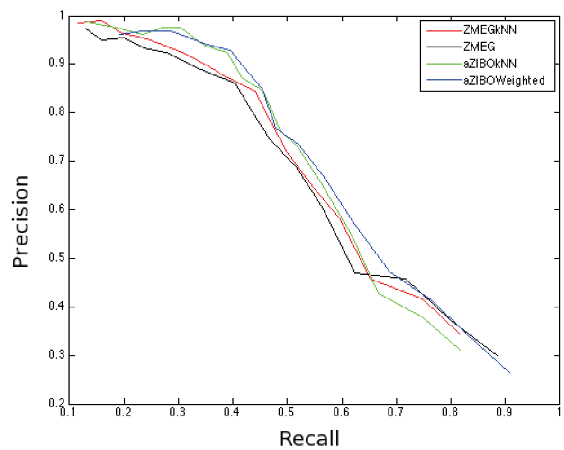

Fig. 7. This figure shows Precision-Recall curves for MPEG7, the most challenging dataset using aZIBO and ZMEG descriptors. They have been classified with the concatenation of the global-local descriptor with kNN and also with the weighted based solution using Euclidean distance in both cases.

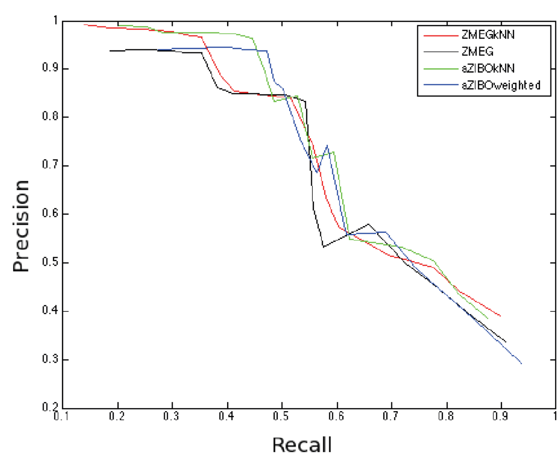

Fig. 8. This figure shows the Precision-Recall curve for MPEG2 dataset using aZIBO and ZMEG descriptors and classifying the concatenation of the global-local descriptor with kNN and also with the weighted based solution using Euclidean distance in both cases.

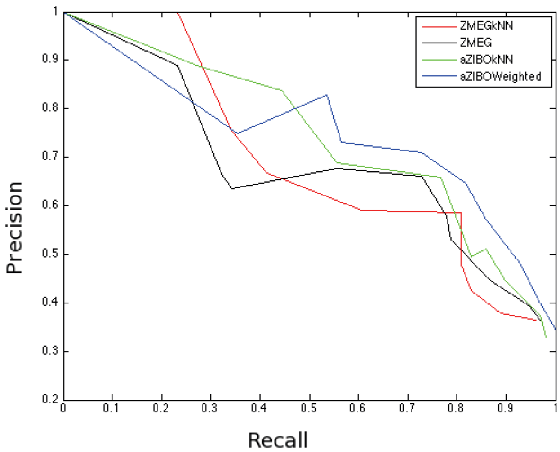

Fig. 9. This figure shows the Precision-Recall curve for Kimia99 dataset using aZIBO and ZMEG descriptors and classifying the concatenation of the global-local descriptor with kNN and also with the weighted based solution using Euclidean distance in both cases.

al. [15] work, but also using classical k-nearest neighbors. Results show that our method outperforms the ZMEG using their weight based classifier in MPEG2 and MPEG7 with a 4.85% and 3.20% of improvement respectively. Furthermore, using the k-nearest neighbors, aZIBO achieved better results with all the datasets evaluated, obtaining the higher difference using kNN Cityblock and Kimia99 dataset with a 4.83% of improvement. In conclusion, the proposal demonstrates the better performance of aZIBO against ZMEG, being evaluated with several datasets which contains rotated images of the same class.

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