Single Object Shape Based Image Retrieval using Zernike Moments

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ABSTRACT: *An important issue to be solved in object recognition is how to represent an object so that a computer vision system is able to recognize it regardless of their shapes, sizes, position and orientation. In this paper we propose a shape based image retrieval based on Zernike Moments as shape descriptor for retrieval of single binary object from image database. To test the robustness of Zernike Moments, MPEG-7 image database is used. Our experimental investigations confirm that Zernike Moment properties are invariant to rotation, and translation with low sensitivity to noise, however is not invariant to scale.*

Keywords: Image Retrieval, Shape-based Image Retrieval, Zernike Moments

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1. Introduction

The advancement of internet technology has lead to tremendous increase of digital image collection. Therefore, the need for efficient search and retrieval of relevant images from large image database is becoming more critical. In the 1970s, a text-based approach was used where images were manually annotated by using keywords. With the availability of huge amount of digital images, this approach was no longer relevant because annotating images involve labor intensive, time consuming as well as highly subjective in nature due to different perception of human annotator. Content Based Image Retrieval (CBIR) was proposed to overcome the manual annotation process where low-level image contents such as color, texture and shape, were used to automatically retrieve the image from the image database [1].

A few papers combined text-based image retrieval with CBIR for efficient image retrieval [2], [3]. Others combines a few low level image features such color and texture features for solving a specific image retrieval problem [4]. Depending on the nature problem to be solved, researchers have proposed various other methods in the past. Similarly, shape based image retrieval has been implemented by using various methods such as Smallest Univalue Segment Assimilating Nucleus (SUSAN) operator [5], the moment invariants [5] and Pseudo-Zernike Moment (PZM) [6]. SUSAN operator and moment invariants have been proven to be rather simple to implement and could provide very good description shape feature of remote sensing images [5]. PZM [6] has been proven to be successfully applied to identify and retrieve human faces. Nevertheless of the introduction of these methods in the past, a universal shape descriptor that is able to model an object under various transformations and disturbances has not been found to date.

Zernike Moments method [7], [8], [18] and [19] has received extensive attentions among the research community in image retrieval applications in recent years. The efficiency and accuracy of Zernike Moments in retrieving an image from a large image database had been compared an analyzed by Kim and Kim [7]. They claimed that the Zernike Moments can be used as an effective global shape descriptor of an image in a large image database. Fu and colleagues [8] had proposed a combination of texture based features, i.e. Gabor filters (GF) and shape based features, i.e. Zernike Moments (ZM) method for image retrieval. They found out that the hybrid of GF and ZM method could provide robust texture and shape features for image retrieval while the retrieval performance of this method is limited for certain database where three different databases were investigated.

This paper presents the design and implementation of shape based image retrieval (SBIR) solely using Zernike Moments method. Its properties for efficient single object retrieval under various transformations such as rotation, translation, scaling and noise disturbances were investigated. The rest of this paper is organized as follows. Section 2 briefly presents the available shape representation and description techniques available in the literature. The details of Zernike Moments method will be elaborated in Section 3. The SBIR architecture is elaborated in Section 4. Section 5 summarizes the popular shape databases and performance measurement used by different researches. In Section 6 we present our experimental findings on using Zernike Moments method 6. Finally, Section 7 concludes this paper.

2. Shape-Based Image Retrieval (SBIR)

A shape representation should satisfy several properties such as affine invariance, robustness, compactness, low computation complexity and perceptual similarity measurement. Depending on the type of application in image retrieval, some applications require the shape representation to be invariant to certain object transformations such as translation, scaling and rotation. By combining both the magnitude and phase coefficients to form a new shape descriptor known as Invariant Zernike Moment Descriptor (IZMD), Li et al. [9] showed that IZMD are robust to changes caused by image shape rotation, translation and scaling. Zhang and Lu [10] proposed that SBIR methods could be classified into two main categories; contour-based and region-based.

2.1 Contour-based technique

Contour-based methods only exploit shape boundary information without explicitly describing the interior of shape. Generally, there are two approaches for contour-based; structural and global. Chain code is one of the structural approaches that had high dimensions and is sensitive to noise. Perimeter, shape signature, Fourier descriptors and scale space are an example of global approach. Fourier Descriptors was first introduced by Zahn and Roskies [11] in 1972. Several shape descriptors were then been studied and compared by Zhang *et al* [12]. They analyzed the strength and limitations of Fourier descriptors (FD), curvature scale space (CSS) descriptors (CSSD), Zernike moment descriptors (ZMD) and grid descriptors (GD). Later, they proposed Generic Fourier Descriptor (GFD) [13] which showed that it satisfies 6 requirements set by MPEG-7 for shape representation; such as good retrieval, accuracy, compact features, general application, low computation complexity, robust retrieval performance and hierarchical coarse to fine representation.

2.2 Region-based technique

In region-based technique, all of the neighboring pixels within a shape region are taken into account to obtain the shape representation, rather than only use the boundary information as in contour based methods. Common region based methods use moment descriptors to describe shapes such as Zernike moments, Pseudo-Zernike moments and Legendre moments. Other region based methods include grid method, shape matrix, convex hull and media axis.

3. Zernike Moments

Zernike functions were first introduced in 1934 by Frits Zernike [16]. In 1979, Teague [17] proposed Zernike Moments for image analysis based on the orthogonal functions called Zernike polynomials.

3.1 Definition

The kernels of Zernike Moments are orthogonal Zernike polynomials defined over polar coordinates inside a unit circle. The

Zernike Moments of order p is defined as in (1)

$$Zpq = \frac{(p+1)}{\pi} \int_0^{2\pi} \int_0^1 Vpq * (r, \theta) f(r, \theta) r \, dr \, d\theta \qquad (1)$$

where $r \leq 1$, $p - |q|$ is even and $|q| \leq p$.

3.2 Zernike Polynomials

Zernike polynomials are a set of orthogonal functions with simple rotational properties which forms a complete orthogonal set over the interior of a unit circle. The form of these polynomials can be defined as in Equation (2).

$$Vpq(\rho, \theta) = Rpq(\rho) \exp(-jq\theta) \qquad (2)$$

where

p : positive integer or zero; i.e. $p = 0, 1, 2, \ldots, \infty$.

q : positive integer subject to constraint $p - |q| =$ even, $q \leq p$.

R : length of vector from origin to (x, y) pixel; i.e. $\rho = \sqrt{x^2 + y^2}$

θ : angle between the vector ρ and the x axis is in the counter clockwise direction.

4. SBIR Architecture

The general process of a shape-based image retrieval using Zernike Moments method is shown in Figure 1. Image retrieval process is divided into two phase; offline phase and online phase. In offline phase, a set of shape features of all images were extracted by using Zernike Moments method and stored in the shape feature database. During online phase, a user can select any query image from a list of images from image database and similar set of shape features will be extracted from the query image. This process is followed by computing the distance between the query image features and the respective index features stored in the features database using certain similarity measure. The similarity distance measure value will later be sorted and rank accordingly before it is displayed to the user. In this project, a total of 36 Zernike Moments features of order 0 to 10 were used and Euclidean distance similarity measurement was employed.

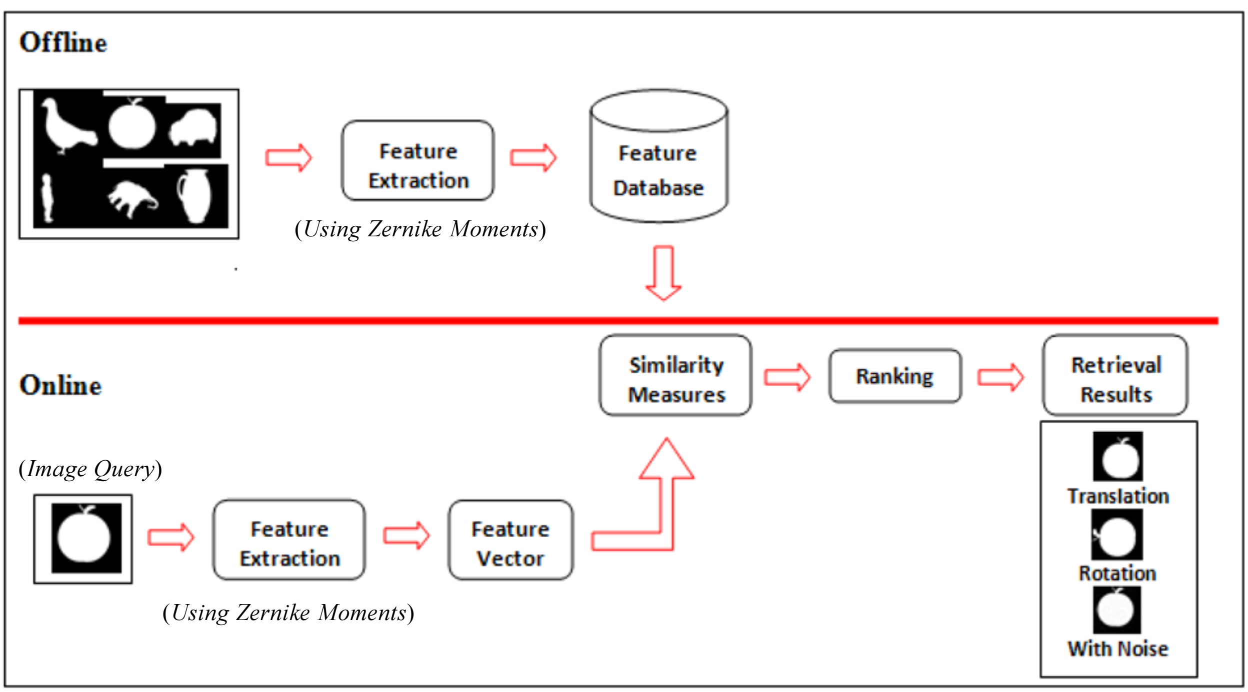


Figure 1. SBIR architecture using Zernike Moments method

5. Dataset For Shape Image Retrieval

Today, some of image databases for image processing research are sharable in the Internet. Summary of the shape database source and performance measurement by different authors is shown in Table 1. Based on this review, it is found that the MPEG-7 shape database is among the most popular shape image database used by many researchers. Therefore, in this paper, the MPEG-7 Core Experiment Shape-1 Part B has been selected to be used in this paper.

In this paper, a precision and recall performance indicator is used to evaluate the proposed method. The precision and recall rates are defined as follows:

$$\text{Precision rate} = \frac{\textit{number of relevant image selected}}{\textit{total number of retrieved images}} \tag{3}$$

$$\text{Precision rate} = \frac{\textit{number of relevant image selected}}{\textit{total number of similar images in the database}} \tag{4}$$

Authors / *Year*	**Database Source**	**Database catagories**	**Types of Data**	**Algorithm/ Method**	**Performance Measurement**
Latecki et. al., 2000 [14]	▪ MPEG-7 Core Experiment Shape-1 http://www.imageprocessingplace.com/root_files_V3/image_databases.htm ▪ Short video clip with a bream fish swimming and marine animals databa	1400 images: 70 classes 200 frames and 1100 shapes	Binary Binary	Correspondence of visual parts (P298) Curvature scalespace (P320) Zernike moment (P687) Wavelet contour descriptor (P567) Multilayer eigenvectors (P517) Directed acyclic graph (DAG)	P298 and P320 significantly outperformed the other four methods.
Belongie et. al., 2002 [15]	▪ Columbia University Image Library (COIL-20) http://www1.cs.columbia.edu/CAVE/software/softlib/coil-20.php ▪ MPEG-7 Core Experiment Shape-1 part B ▪ Kimia25	1440 images: 20 objects 1400 images: 70 classes 25 images	Grayscale Binary Binary	New approach based on Novel descriptor, Shape context	Greatly improved point set registration, shape matching and shape recognition.
Fu et. al., 2006 [8]	▪ MPEG-7 Core Experiment Shape-1 part B	1400 images: 70 classes	Binary	Gabor filters (GF) & Zernike moment (ZM)	GF and ZM are robust for texture & shape retrieval
Li et. al., 2009 [9]	▪ MPEG-7 Region Shape DB CE-2 ▪ Columbia University Image Library (COIL-100) http://www1.cs.columbia.edu/CAVE/software/softlib/coil-100.php	3621 trademarks 100 objects	Binary Color	Invariant Zernike Moment Descriptor (IZMD)	Robustness under various image transformations as compared with magnitude-only ZMD

Table 1. Summary of shape dataset and performance measurement

6. Results and Discussion

An experimental investigation were conducted using Zernike Moments method to test its capability in retrieving similar images under rotation different, translation different, scaling difference as well as noise difference. This method is coded using MATLAB® and implemented on Intel (R) CPU 2.00GHz with 3.0GB RAM and Windows XP. The experiment involves the use of MPEG-7 Core

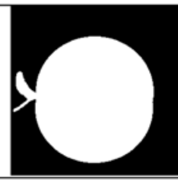
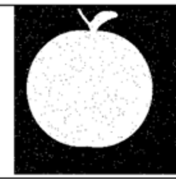
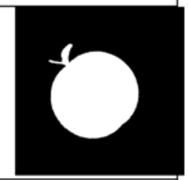
Type of Image	1st: Original Image	2nd: Rotation	3rd: Translation	4th: Noise	5th: Scaling & Rotation
Image					
Order of Zernike Moments	Zpq = 1.0e+016 *	Zpq = 1.0e+016 *	Zpq = 1.0e+016 *	Zpq = 1.0e+016 *	Zpq = 1.0e+017 *
	Z_{00} 0.9782	**0.9782**	**0.9782**	0.9818	0.4051
	Z_{11} 0.1474	0.1587	0.1625	0.1478	0.0545
	Z_{20} 2.4232	**2.4232**	**2.4232**	2.4322	1.0043
	Z_{22} 0.2364	0.2545	0.2604	0.2371	0.0879
Processing Speed (seconds)	0.852706	2.775829	3.806255	1.331837	2.275362

Table 2. Examples of Zernike Moments features

Image Query	Retrieval Results									
	Rank 1	Rank 2	Rank 3	Rank 4	Rank 5	Rank 6	Rank 7	Rank 8	Rank 9	Rank 10

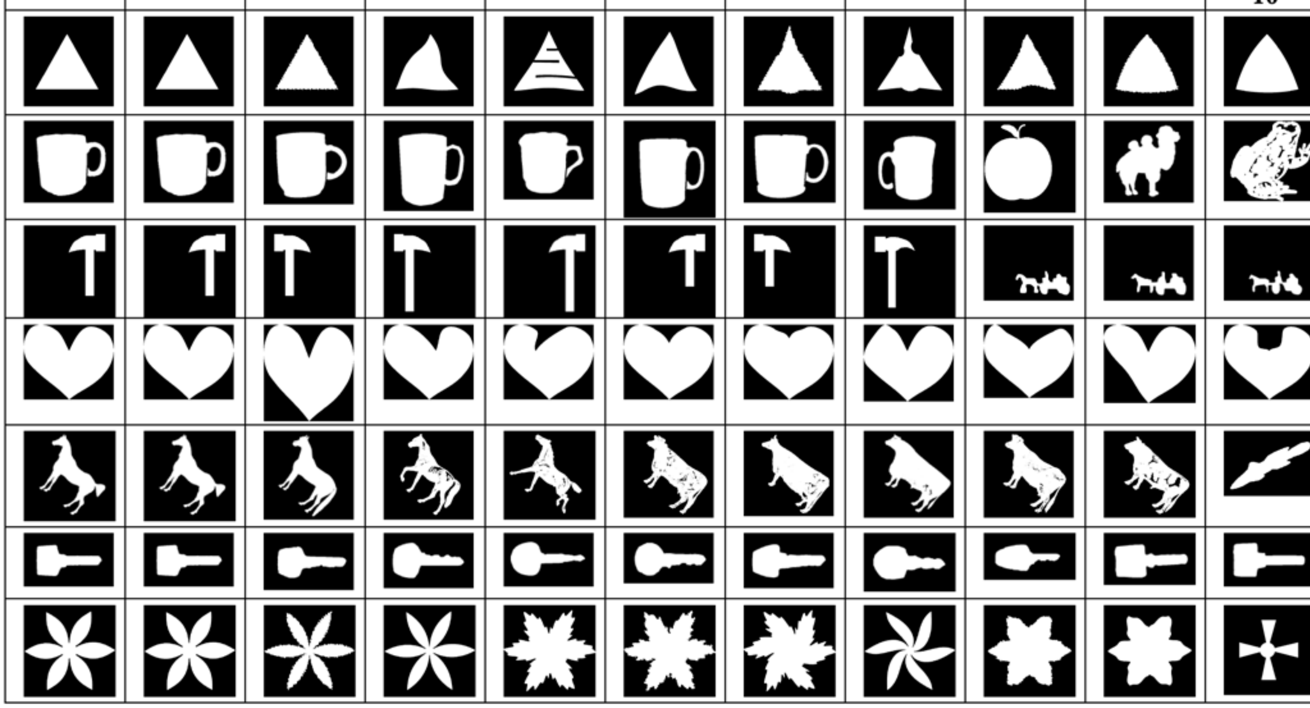


Table 3. Sample of the top-10 image retrieval results

Experiment CE Shape-1 Part B and a variety of MPEG-7 images that have been modified under different points of view such as rotation, translation, scaling and noise for testing purposes. In the case of noise disturbances, the original image were corrupted with salt and pepper noise and the image was rotated at 90 degrees. Table 2 shows the selected Zernike moments properties of an apple image that have been modified. The total image in the shape image database is 1,450 images including 1,400 original MPEG-7 images and 50 images that have been corrupted with noise and under 90 degrees rotation.

From Table 2, it can be observed that the value of Zernike Moments, Z_{00} is not significantly changed under for rotation and translation; however it changed slightly under the effect of noise. On the contrary, this is not happening under the scaling and rotation. This observation has been observed to have similar trend with all 1,450 test images. Based on these findings, it can be concluded that Zernike Moments properties are invariant to rotation and translation and have a low sensitivity to noise. However, Zernike Moments are not invariant to scale.

Table 3 shows some of the sample shape based image retrieval results obtained for selected image query and its respective retrieved images from the database in that have been sorted in ranking order. Based on these results, the superiority and robustness of Zernike Moments properties under translation and rotation transformations have successfully been proven in this paper. However, it should be noted that image with similar shapes will be rank near to each other as can be observed in the fifth to sixth row in Table 3. This mean that if the object in the database having almost similar shapes in different class, such as horse and cow (fifth row), it might be retrieved in close ranking order. Therefore, it can be concluded that Zernike Moments method will not be able to solve the almost similar shape object problems. To provide, a more detail retrieval performance indicator in term of precision and recall rate, Figure 2 shows the precision and recall graph of the first top 3 rows of query images in Table 3.

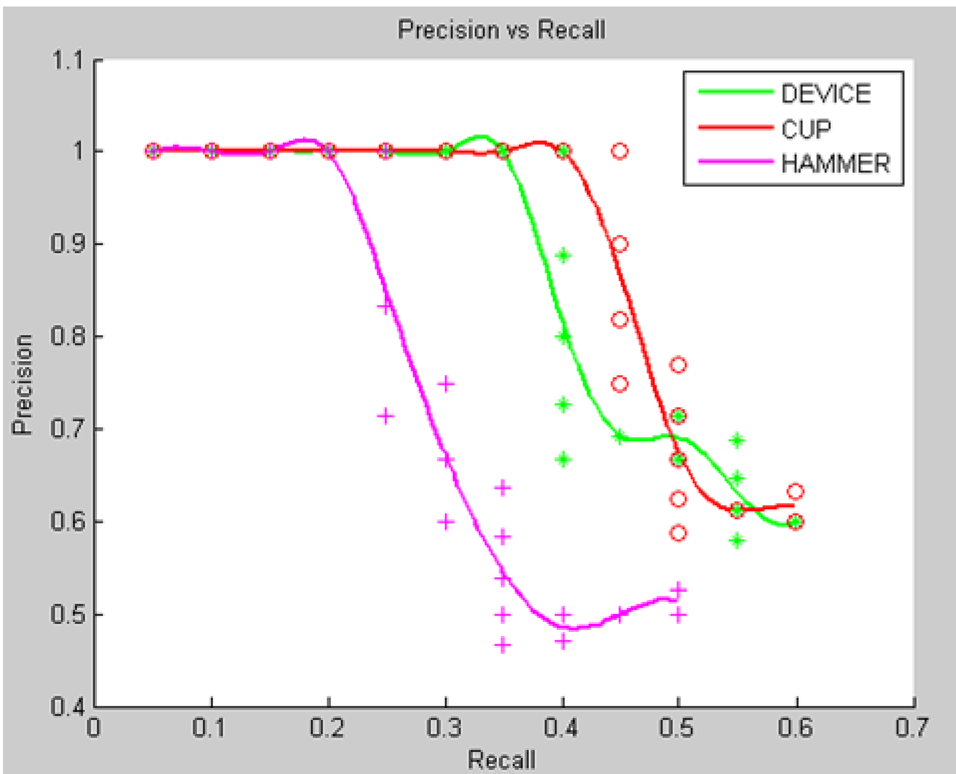


Figure 2. Precision and recall graph of the first top 3 rows of query images in Table 3

7. Conclusions

In this paper we have demonstrated that Zernike Moments properties are rotation and translation invariant. However, it is slightly affected by noise and could not tolerate scaling variation. It is worth noting that the performance of Zernike Moments method for image retrieval is perhaps only suitable for very different object shapes between object classes. If the objects between different classes are looking almost similar to each other, the performance of retrieval results will be degraded. Thus, further research is needed to search for more powerful shape features that could discriminate almost similar look shape's objects.

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