

# AN EFFICIENT FEATURE EXTRACTION METHOD WITH LOCAL REGION ZERNIKE MOMENT FOR FACIAL RECOGNITION OF IDENTICAL TWINS

Zahra Ahmadi-Dastjerdi<sup>1</sup> and Karim Faez<sup>2</sup>

<sup>1</sup>Department of Electrical, Computer and Biomedical Engineering, Qazvin branch, Islamic Azad University, Qazvin, Iran

<sup>2</sup>Department of Electrical Engineering, Amirkabir University of Technology, Tehran, Iran

## ABSTRACT

*Face recognition is one of the most challenging problems in the domain of image processing and machine vision. The face recognition system is critical when individuals have very similar biometric signature such as identical twins. In this paper, the facial area in an image is detected using AdaBoost approach. After that the facial area is divided into some local regions. Finally, new efficient facial-based identical twins feature extractor based on the geometric moment is applied into local regions of face image. The utilized geometric moment is Zernike Moment (ZM) as a feature extractor inside the local regions of facial area of identical twins images. The proposed method is evaluated on two datasets, Twins Days Festival and Iranian Twin Society which contain scaled and rotated facial images of identical twins in different illuminations. The results prove the ability of proposed method to recognize a pair of identical twins. Also, results show that the proposed method is robust to rotation, scaling and changing illumination.*

## KEYWORDS

*Face Recognition, Identical Twins, Invariant Moment, Zernike Moment*

## 1. INTRODUCTION

Human face is considered as a suitable property to identify people from his (her) image. Along with this property, recognition of facial of identical twin is one of the most challenging problems in pattern recognition applications because of the similarity between the pair of twin.

In the domain of facial identical twins recognition, previous works are listed as: in [12], Klare and Jain introduced a face detection algorithm which includes three levels. In the first level, an overall appearance of the face is constructed; in the second level, exact geometric and structural embedment of face with differentiating between two similar faces are performed; and finally, the third level consists of process of skin disorders such as wounds, and so on. Sun et al. [16] utilized Cognitec FaceVACS system to recognize identical twins from CASIA Multimodal Biometrics Database and they obtained the true accept rate of approximately 90% at a false accept rate greater than 10%. Park et al. [14] proposed an identical twins recognition algorithm that consists of three steps: in first step, the proposed method consists of face images which are marked using normal geometric methods; in the second step, the Euclidean distance between a pair of markers are measured and compared; and the final step involves finding the strong similarity on the

marked regions. Srinivas et al. [15] studied on distinguishing of twins using marks on the face image. Martin et al. [3] employed DNA approach to recognize identical twins.

In this paper, we study on a pair of facial images in order to determine whether the images belong to the same person or to a pair of identical twin. For this purpose, we propose the geometric moments to extract feature vector from facial images of twins to recognize identical twins.

This paper is organized as follow: feature extraction step of a face recognition system is introduced in Section 2. The proposed method is presented in Section 3. Experimental results are described in Section 4 and the paper will be concluded in Section 5.

## **2. FEATURE EXTRACTION**

Each face detection system contains four steps: pre-processing, face localization, feature extraction and classification. Feature extraction refers to the extraction of useful information from raw data so that they are suitable for the classification process. The feature extraction stage is characterized by a series of input patterns. The major problem of feature extraction is that it depends on application and feature extraction methods are not public.

Feature extraction methods can be divided into two majors: structural features and statistical features [11][19]. The first group is based on local structure of image. In other words, the structural features deals with local data. Facial change or change in environmental conditions is the major problem for the structural features [7].

In the statistics-based feature extraction techniques, global data is employed to create a set of feature vector elements in order to perform recognition. A mixture of irrelevant data, which are usually part of a facial image, may result in an incorrect set of feature vector elements. Therefore, data that are irrelevant to facial portion such as hair, shoulders, and background should be regarded in the feature extraction phase [10]. The statistics-based feature extraction techniques are Principle Component Analysis (PCA), Legendre Moment (LM) [13] and Zernike Moments (ZM) [20]. Legendre functions are Legendre differential equation. The main advantage is that Legendre moments like Legendre basis functions are orthogonal. Legendre moments are independent of each other and are free of data redundancy. In this study, we use ZM to recognize identical twins that are presented in the next Section.

## **3. PROPOSED METHOD**

The main goal of this paper is to distinguish the identical twins by face recognition. For this purpose, AdaBoost [18] technique is used for face localization step and subimage creation. In the next step, the subimage will be divided into regions. After that the ZM technique is employed in each region to extract the feature vector from the region in the subimage of test image. After that the feature vectors inside the subimages of all images in dataset are obtained using ZM approach. Finally, comparison between the feature vector of test image and the feature vectors of all images of dataset is done to select the closest image from dataset as the pair of test image. In the next Section, the AdaBoost face detection, ZM and its task of feature vector creation are described.

### **3.1. Face Detection Method**

As the mentioned before, face detection step is the second step of this algorithm to recognize identical twins. This step is based on the combing of successively more complex classifiers in a

cascade structure using AdaBoost [18]. Furthermore, the AdaBoost technique is used to select a small number of Haar-like features [18].

After finding an object in an image as a face candidate, an ellipse is drawn around the main location of face in an image[8]. For this purpose, an ellipse model is constructed using five parameters:  $X_0$  and  $Y_0$  are the centers of the ellipse,  $\theta$  is the orientation, and  $a$  and  $b$  are the minor and the major axes of the ellipse, respectively. Before the calculation of these parameters, geometric moments are required to describe. The geometric moments of order  $p+q$  of a digital image are defined as

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

where  $p, q = 0, 1, 2, \dots$  and  $f(x, y)$  is the grey-scale value of the digital image at  $x$  and  $y$  location. The translation invariant central moments are obtained by placing origin at the center of the image:

$$\mu_{pq} = \sum_x \sum_y f(x, y) (x - x_0)^p (y - y_0)^q \quad (2)$$

where  $x_0 = \frac{M_{10}}{M_{00}}$  and  $y_0 = \frac{M_{01}}{M_{00}}$  are the centers of the connected components. Thus, center of gravity of the connected components is used as the center of the ellipse. The orientation of the ellipse is computed by determining the least moment of inertia [8].

$$\theta = \frac{1}{2} \arctan\left(\frac{2\mu_{11}}{\mu_{20} - \mu_{02}}\right) \quad (3)$$

where  $\mu_{pq}$  shows the central moment of the connected components as described in (2). The length of the major and the minor axes of the best-fit ellipse can also be computed by evaluating the moment of inertia. With the least and the greatest moments of inertia of an ellipse defined as

$$I_{min} = \sum_x \sum_y [(x - x_0) \cos \theta - (y - y_0) \sin \theta]^2 \quad (4)$$

$$I_{max} = \sum_x \sum_y [(x - x_0) \sin \theta - (y - y_0) \cos \theta]^2 \quad (5)$$

Length of the major and the minor axes are calculated from [8] as

$$\alpha = \frac{1}{\pi [I_{max}^3 / I_{min}]^{\frac{1}{8}}} \quad (6)$$

$$\beta = \frac{1}{\pi [I_{min}^3 / I_{max}]^{\frac{1}{8}}} \quad (7)$$

To determine how well the best-fit ellipse approximates the connected components, a distance measure between the connected components and the best-fit ellipse is calculated as follows [8]

$$\phi_i = \frac{P_{inside}}{\mu_{00}} \quad (8)$$

$$\phi_o = \frac{P_{outside}}{\mu_{00}} \quad (9)$$

where the  $P_{inside}$  is the number of background points inside the ellipse,  $P_{outside}$  is the number of points of the connected components that are outside the ellipse, and  $\mu_{00}$  is the size of the connected components. After drawing of ellipse, a subimage is made according to the ellipse and finally, the ZM is used to extract features inside the subimage.

### 3.2. Zernike Moment (ZM)

ZM is geometric-based moment that is a two dimensional function of orthogonal polynomials on the unit disk. The orthogonal moments of ZM are rotation and scale invariants which are suitable for pattern recognition applications [5][6][8][17]. ZM contains several orthogonal sets of complex-valued polynomials defined as

$$V_{nm}(x, y) = R_{nm}(x, y) \exp\left(jm \tan^{-1}\left(\frac{y}{x}\right)\right) \quad (10)$$

where  $x^2 + y^2 \leq 1$ ,  $n \geq 0$ ,  $|m| \leq n$ , and the radial polynomials  $\{R_{nm}\}$  are defined as

$$R_{nm}(x, y) = \sum_{s=0}^{(n-|m|)/2} S_{n,|m|,s}(x^2 + y^2)^{\frac{n-2s}{2}} \quad (11)$$

where

$$S_{n,|m|,s} = (-1)^s \frac{(n-s)!}{s! \left(\frac{n+|m|}{2} - s\right)! \left(\frac{n-|m|}{2} - s\right)!} \quad (12)$$

The ZM of order  $n$  and repetition  $m$  can be computed as

$$ZM_{nm} = \frac{n+1}{\pi} \sum_x \sum_y f(x, y) V_{nm}^*(x, y) \quad (13)$$

It should be noted that the PZM is computed for positive  $m$  because  $V_{nm}(x, y) = V_{nm}^*(x, y)$ . Center of the unit disk is located on the origin of coordinates and so ZM technique is independent of scaling and rotation. In the next Section, ZM approach will be utilized to extract feature vector elements.

### 3.3 Creating feature vector

After face localization and subimage creation, the ZM is computed for each subimage as face features. The feature vector elements are defined according to ZM orders as

$$FV_j = \{ZM_{km} | k = j, j + 1, \dots, N\} \quad (14)$$

where  $j$  is interval  $[1, N-1]$  and so,  $FV_j$  contains all the ZM from order  $j$  to  $N$ . Samples of feature vector elements will be demonstrated in Table 1 for  $j = 3, 5$  and  $9$ , and  $N = 10$ . As Table 1 shows, increasing of  $j$  decreases the number of elements in each feature vector ( $FV_j$ ).

## 4. EXPERIMENTAL RESULTS

The proposed method is evaluated on two datasets: Twins Days Festival [2] and Iranian Twin Society [1] which contain 520 and 600 pairs of identical twins images, respectively. The used datasets contain the scaled and rotated faces with different illuminations. Figure 1 shows the subimages of some twin test images. The results of identical twins recognition using ZM is

compared with the results of LM [13]. Experiments have been carried out in three steps according to order of moment. In the first step, order  $n$  is in interval [1,6], in the second step, order  $n$  is in interval [6,8] and for third step, order  $n$  is in interval [9,10] (Table 2).

In this paper,  $N$  is set 10 ( $N=10$ ) and  $j$  varies from 1 to 9. The misclassification rate of all geometric moments (LM and ZM) is presented in Table 3. The misclassification rate reported in the table are computed as

$$Error\ rate = \frac{No.\ of\ misclassification}{No.\ of\ total\ testing\ patterns} \quad (15)$$

Table 3 shows misclassification rates of LM and ZM. Comparison between geometric moments in Table 3 proves that higher order moments of the ZM have most information for face recognition while low-order moments have no significant effect on the system error. According to the table, LM achieves high misclassification rate on recognition of twins because the rotation of face in an image has bad effect on the performance of LM. As Table 3 shows, the misclassification rate of ZM is lower than the LM because ZM is rotation and scale invariant.

Table 1. Feature vector elements based on the ZM

$j$ value	FV <sub>j</sub> feature elements ( $ZM_{km}$ )		Number of feature element
	K	M	
4	4	0,2,4	30
	5	1,3,5	
	6	0,2,4,6	
	7	1,3,5,7	
	8	0,2,4,6,8	
	9	1,3,5,7,9	
	10	0,2,4,6,8,10	
6	6	0,2,4,6	24
	7	1,3,5,7	
	8	0,2,4,6,8	
	9	1,3,5,7,9	
	10	0,2,4,6,8,10	
9	9	1,3,5,7,9	11
	10	0,2,4,6,8,10	

Table 2. Feature vector elements produced by geometric moments in each experiment.

Cat.	LM feature elements	ZM feature elements
1	$n=1, m=1$	$n=1, m=1$
	$n=2, m=0,2$	$n=2, m=0,2$
	$n=3, m=1,3$	$n=3, m=1,3$
	$n=4, m=0,2,4$	$n=4, m=0,2,4$
	$n=5, m=1,3,5$	$n=5, m=1,3,5$
	$n=6, m=0,2,4,6$	$n=6, m=0,2,4,6$
2	$n=6, m=0,2,4,6$	$n=6, m=0,2,4,6$
	$n=7, m=1,3,5,7$	$n=7, m=1,3,5,7$
	$n=8, m=0,2,4,6,8$	$n=8, m=0,2,4,6,8$
3	$n=9, m=1,3,5,7,9$	$n=9, m=1,3,5,7,9$
	$n=10, m=0,2,4,6,8,10$	$n=10, m=0,2,4,6,8,10$

Visual results of ZM on pair of identical twins are illustrated in Figure 2 which refers to Twins Days Festival [2] and Iranian Twin Society [1] datasets, respectively.

According to numerical and visual results, ZM is able to create informative feature vector inside the subimages of pair of identical twins which is necessary for recognition of identical twins. The results prove that ZM is scale and rotation invariant.

Table 3. Error rate of each geometric moment in different categories. The bold values means the best values

Cat.	LM			ZM		
	No. of Feature Elements	No. of Misclassification	Error rate	No. of Feature Elements	No. of Misclassification	Error rate
$n=1,2,\dots,6$	15	20	10%	15	17	<b>8.5%</b>
$n=6,7,8$	13	18	9.1%	13	13	<b>6.5%</b>
$n=9,10$	11	12	6.1%	11	8	<b>4%</b>



Figure 1. Creating of subimage based on the ellipse formation.

Table 4 shows the second phase of testing where the two geometric moments are compared on finding a pair of a person as the twin  $ink$ -nearest persons. In the other words for a test image, his (her) pair is found in  $k$ -nearest persons. In Table 4, the above comparison is done in several ranks ( $k$ ),  $k=3, 5, 7$  and  $9$ . Also, visual results of ZM on the second phase of testing are demonstrated in Figure 3. The results reported in Table 4 are the percentage of identical twins that the pair of a person cannot be found in  $k$ -nearest persons (16). According to the results of ZM in Table 4 and Figure 3, pair of input image as the identical twin is detected in 3-nearest persons with the

probability of 95.1% (100%-4.9%) while with LM, the obtained value is with the probability of 91.3% (100%-8.7%). For the other ranks, the ZM approach takes the best error rates. As a result of Table 4, the detected person as the identical twin using the proposed feature extractor is in  $k$ -nearest persons with high probability.

$$Error\ rate\ on\ rank\ k = \frac{No.\ of\ misclassification\ samples\ on\ rank\ k}{No.\ of\ total\ testing\ patterns} \quad (16)$$

## 5. CONCLUSIONS

This paper is focused on the improving of face recognition systems for distinguishing of a pair of identical twins. The proposed method is based on the Zernike Moment (ZM) as a feature extractor to recognize a pair of (identical or non-identical) twins. Also, the location of the face in an image is detected using the AdaBoost method and then the ZM method is utilized to construct feature vector elements. Experimental results on two datasets show that the proposed method is superior to the other geometric moment such as Legendre Moment (LM) and also is robust to rotation and scaling and changing illumination.

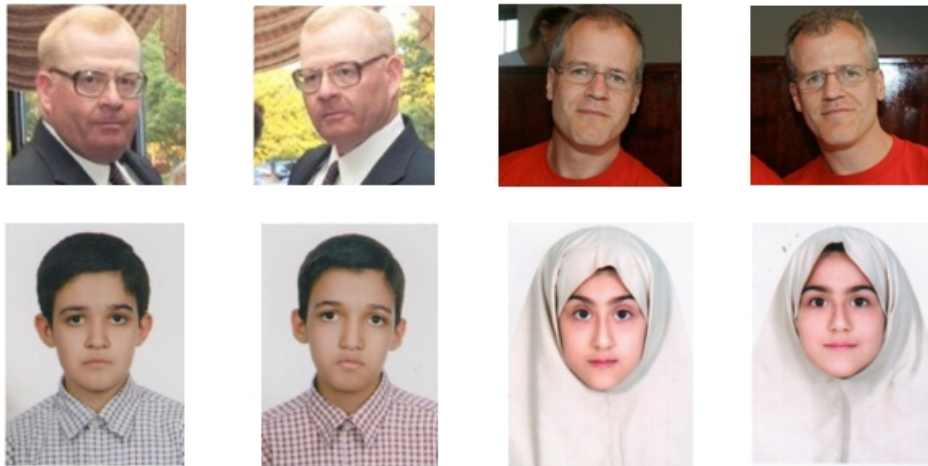


Figure 2. Samples of testing identical twins which were correctly classified by ZM. The first row refers to the results of ZM on the Twins Days Festival dataset [2] and the second row is the results of ZM on the Iranian Twin Society dataset [1].

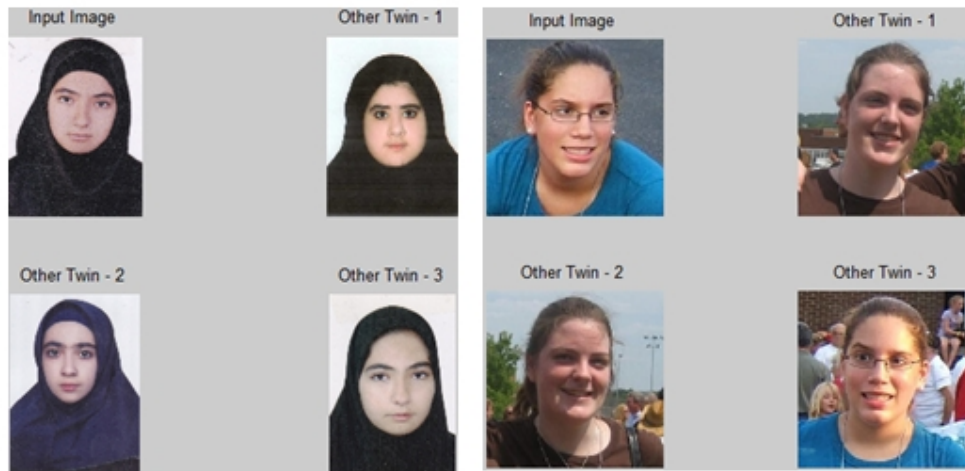


Figure 3. Visual results of ZM on the second phase of testing with rank=3.

Table 4. Results of geometric moments on the second phase of testing with rank=3. Bold values refer to the best scores.

Rank	Feature extractor	
	LM	ZM
3	8.7%	<b>4.9%</b>
5	5.3%	<b>1.2%</b>
7	3.2%	<b>0%</b>
9	0.9%	<b>0%</b>

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