A face recognition approach using Zernike Moments for video surveillance

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ABSTRACT: In this paper, a face recognition approach using Zernike moments is presented for the main purpose of detecting faces in surveillance cameras. Zernike moments are invariant to rotation and scale and these properties make them an appropriate feature for automatic face recognition. A Viola-Jones detector based on the Adaboost algorithm is employed for detecting the face within an image sequence. Pre-processing is carried out wherever it is needed. A fuzzy enhancement algorithm is also applied to achieve uniform illumination. Zernike moments are then computed from each detected facial image. The final classification is achieved using a kNN classifier. The performance of the proposed methodology is compared on three different benchmark datasets. The results illustrate the efficacy of Zernike moments for the face recognition problem in video surveillance.

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1. Introduction

In recent years, face recognition research has gained prominence owing to the heightened security situation across the western world. Face recognition software has been incorporated in a wide variety of biometrics based security systems for the purposes of identification, authentication and tracking. Unlike humans who have an outstanding capability of recognizing different patterns and faces in varying conditions, machines are still dependent on ideal face images and their performance suffers when there are variations in illumination, background, pose angle, obstacles, etc. Therefore, the problem of automatic face recognition is a very complex and challenging task.

Face recognition methods can be classified into two broad classes: structural and statistical approaches. The structural approaches are based on extracting structural or geometrical features of a face, for example, the shapes of the eyes, nose, lips and mouth. These methods deal with local data instead of global data and suffer from the unpredictability of face appearance and environmental conditions as they are heavily dependent on local facial features. An example of this type of approach is Elastic Bunch Graph Matching [14]. On the other hand, the statistical-based approaches extract features from the whole image. Since the global data of an image is used to determine the feature vectors, irrelevant data pertaining to facial region such as hair, shoulders and background may contribute to these thus adversely affecting the recognition results. The most important examples of statistical approach are Principal Component Analysis [12] and Linear Discriminant Analysis [10]. Other examples include Gabor filters [16], wavelets, Independent Component Analysis [8].

Statistical approaches for feature extraction based on moment invariants have been utilised for classification and recognition applications because of their invariance properties [5]. An image feature is considered invariant if it remains neutral to changes in size (scale), position (translation), orientation (rotation), or/and reflection in an image. Haddadnia *et al* [6] and Pang *et al* [7] were one of the first researchers who explored the use of Pseudo Zernike moment invariants as facial features for face recognition. Pseudo Zernike moments are a good feature representation and provide more information about facial image and reduce the dimension of the feature vector leading to improved results. This is in start contrast to LDA, the most dominant method in face recognition, which is computationally intensive and requires high-speed processing and a large memory.

Face-recognition cameras have been successfully employed in various places for diverse applications but one area where face recognition has failed to make an impact is: surveillance. Face recognition for surveillance is considered extremely difficult because CCTV cameras photograph people at tilted angles or in weak light, both of which create poor images. The goal of this paper is to develop a face recognition system for recognizing facial images obtained from surveillance cameras by comparing them with a database of digital photographs. In the proposed system, a pre-processing step is used to detect and normalize the static face image obtained from the noisy video camera feed. Feature extraction is carried out via Zernike moments and final classification is achieved using a simple Nearest Neighbour classifier. The proposed method has advantages of geometrical invariance, robustness to noise, optimal feature representation, fast convergence and high recognition rates.

2. Pre-processing

Pre-processing of a facial image consists of face detection and normalization. Face detection [3] is a process of localizing and extracting the face region from the background. Face detection and normalization is crucial for the success of a face recognition system as features can only be computed from a face only when it has been detected properly and segmented from all other irrelevant data. The detected faces vary in scale, rotation, brightness, size, etc. in different images even for the same individual. Since the features extracted from images are dependent on detected faces, it is pertinent that there should be some kind of uniformity within the detected images. One way of solving this problem is by normalizing the detected faces. The objective of face normalization is to reduce the effect of the extraneous and redundant information, such as background, hair, caps, scarves, etc so as to enhance the recognition. The different sample images of an individual's face are normalized to a uniform face orientation, size, rotation and illumination. Hence, to ensure a more robust and accurate face recognition performance, the exact location of the face is extracted from the two dimensional video image and then normalized.

2.1 Face detection

Several methods are given in literature for face localization. In this paper, we have employed the most successful of all face detection methods, the Viola-Jones detector which is based on the Adaboost algorithm [18].The Viola-Jones face detector is capable of processing images extremely rapidly while achieving high detection rates. Its inherent strength lies in three critical components. The first is the Integral Image representation which allows the features to be computed rapidly. The second is a simple and efficient classifier based on the AdaBoost learning algorithm [17] which selects a small number of critical visual features from a very large set of potential features. The third and last concept is a cascading combination of several classifiers which allows background regions of the image to be quickly discarded while potentially face like regions are computed. The results of the face detection procedure are illustrated in the below given figure.

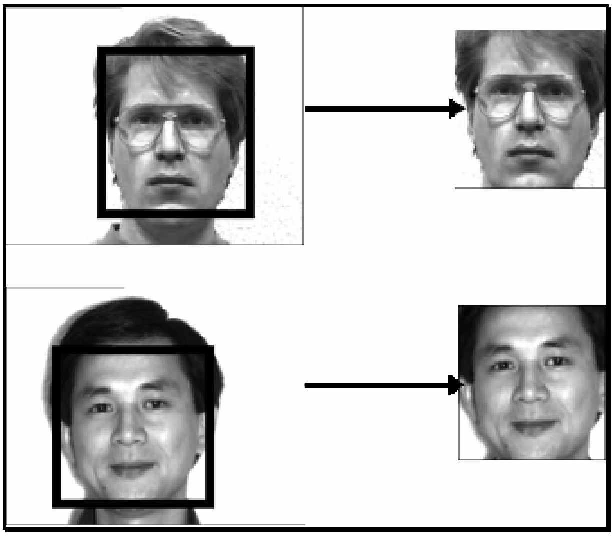

Figure 1: Face detection on two sample images

2.2 Illumination correction

The performance of a face recognition system is severely affected if the facial image is poorly illuminated. Thus, illumination correction is a necessary step before feature extraction. Although, there are many well known image enhancement algorithms such as the histogram equalization method but most of them adopt a global approach and treat the image as a whole and are therefore perform unsatisfactorily over local regions. In this work, we have applied a fuzzy logic-based image enhancement method [15] for illuminating dark regions of a face. The colour intensity property of the image is fuzzified using a Gaussian membership function, which is well suited for under exposed images. The fuzziefied image is then enhanced using a sigmoid type general intensification operator which is dependent on the crossover point and the intensification parameter. The optimum values of these two parameters are obtained by the constrained fuzzy optimization using a modified univariate method which involves learning by gradient descent. The results of face image enhancement using this method are found to be far better than those obtained by histogram equalization and are presented in Figure 2.

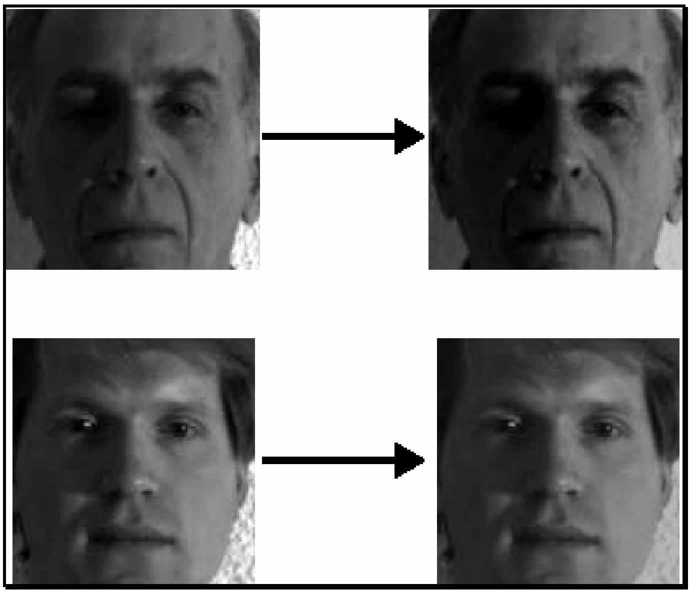

Figure 2: Illumination correction using Fuzzy Image Enhancement

3. Feature extraction using Zernike Moments

Moment features are a set of non-linear functions on the regular, geometric moments of an image. Moment invariants extracted from an image function can be used directly as features and scaled to the appropriate range. The moment features of the compressed image representations describe the shape and geometric properties of the image under consideration which in this case is the detected face image.

3.1 Geometric moments

Geometric (or regular) moments map the image function $f(x, y)$ onto the monomial $x^p\, y^q$. The $(p + q)^{th}$ order of a geometric moment for an $N \times M$ image function, $f(x, y)$, is defined as,

$$m_{pq} = \sum_{x=1}^{M} \sum_{y=1}^{N} x^p y^q . f(x, y) \tag{1}$$

where, $p, q \in Z$

Furthermore, the $(p + q)^{th}$ central geometric moment is defined so as to normalize regular moment calculations with respect to the image centroid, thus yielding moments invariant to object translation:

$$\mu_{pq} = \sum_{x=1}^{M} \sum_{y=1}^{N} \left(x - \bar{x} \right)^p . \left(y - \bar{y} \right)^q . f(x, y) \tag{2}$$

where, $\bar{x}, \bar{y}$ are coordinates of the image centroid.

3.2 Zernike moments

Unfortunately the basis set for geometric moments is not orthogonal and the resulting moments, therefore, lack many desirable properties in the context of feature selection. The complex-valued Zernike polynomials, however, form an orthogonal basis set over the unit circle, $x^2 + y^2 \leq 1$. Orthogonal Zernike moments are defined by the projection of the image function $f(x, y)$ within the unit circle onto the complex Zernike polynomials. The Zernike invariants are the magnitudes (the hypotenuse) of the real and imaginary components of the resulting moments. When images are normalized in terms of scale and translation or in terms of regular low-level central geometric moments, the derived Zernike invariants will be invariant to rotation, translation and scale, given an image function of sufficient resolution within the unit disc. The set of Zernike polynomials is denoted by $\{Z_{nm}(x,y)\}$, or equivalently in their polar form by $\{Z_{nm}(\rho,\theta)\}$.

The general form of the polynomials is:

$$Z_{nm}(x,y) = Z_{nm}(\rho,\theta) = R_{nm}(\rho)e^{jm\theta} \tag{3}$$

where,

x, y and ρ, θ correspond to Cartesian and Polar coordinates respectively ,
$n \in Z^+$ and $m \in Z$; constrained to $n - |m|$ even, $|m| \le n$.

$R_{nm}(\rho)$ is a radial polynomial given by,

$$R_{nm}(\rho) = \sum_{s=0}^{(n-|m|)/2} \frac{(-1)^s[(n-s)!]\rho^{n-2s}}{s!\left(\frac{n+|m|}{2}-s\right)!\left(\frac{n-|m|}{2}-s\right)!} \tag{4}$$

The complex, orthogonal Zernike moments are defined by,

$$A_{nm} = \frac{n+1}{\pi}\sum_{x=1}^{M}\sum_{y=1}^{N} f(x,y).Z^*_{nm}(\rho,\theta)$$

Or, $$A_{nm} = \frac{n+1}{\pi}\iint_{x^2+y^2\le 1} f(x,y)Z^*_{nm}(\rho,\theta)dxdy \tag{5}$$

3.3 Properties of Zernike moments

Among the noteworthy properties, Zernike moments are rotationally invariant and orthogonal, besides being translation invariant. Assume A'_{nm} is the moment of order *n* and repetition *m*, associated with $f'(x,y)$, obtained by rotating the original image $f(x,y)$ by an angle ϕ with respect to the x-axis. Then,

$$A'_{nm} = \iint f'(x,y)Z^*_{nm}(\rho,\theta)dxdy = A_{nm}e^{-jm\theta} \tag{6}$$

This suggests that Zernike Moments merely acquire a phase shift on rotation and magnitude remains constant after rotation. Also it can be shown that

$$\iint_{x^2+y^2\le 1} Z_{nm}(x,y)Z^*_{pq}(x,y)dydx = 0 \tag{7}$$

if, $n \ne p$ or $m \ne q$.

Thus, Zernike moments are orthogonal by definition. Because of their orthogonality, it is expected that a small set of moments can be used to estimate parameters associated with different models. In fact, orthogonality of Zernike moment-form ensures that mutually independent shape-information underlying the intensity surface of an image is captured by Zernike moments of different orders. For example, the zeroth-order moment represents the mean intensity value in an image neighbourhood and first-order moments are related to the centre-of-gravity of the intensity surface, whereas the second-order moment captures the variance of the intensity levels present in the local neighbourhood. Thus, a discontinuity in local intensities results in a high first-order moment, a discontinuity in local gradients results in a high second-order moment, and so on.

3.4 Computation of Zernike moments

Zernike Moments provide substantial mutually independent shape information along with the facial image intensity information which are important cues for automatic face recognition. The system diagram (Figure 3) below illustrates all the pre-processing and feature extraction steps leading up to the computation of circular Zernike moments from each detected face.

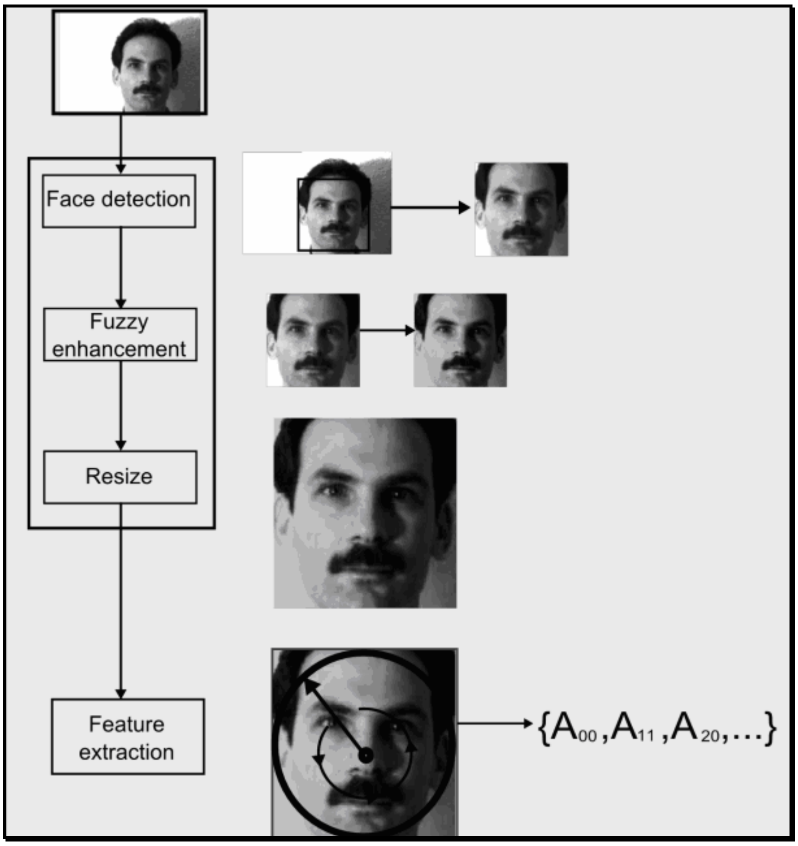

Figure 3: Pre-processing and feature extraction

We calculated Zernike moments up to 12th order which gave rise to 49 moments in total. Table 2 depicts the first 12 orders of the moments with their repetitions. The size of the circular disc size for the calculation of Zernike moments is set to the image size and the centre of the circle is taken as the origin. The moments are computed using Equations 3 & 4.

Table 1: List of the first 12 order Zernike moments

Order	Dimensionality	Zernike moments
0	1	$A_{0,0}$
1	2	$A_{1,1}$
2	4	$A_{2,0}$, $A_{2,2}$
3	6	$A_{3,1}$, $A_{3,3}$
4	9	$A_{4,0}$, $A_{4,2}$, $A_{4,4}$
5	12	$A_{5,1}$, $A_{5,3}$, $A_{5,5}$
6	16	$A_{6,0}$, $A_{6,2}$, $A_{6,4}$, $A_{6,6}$
7	20	$A_{7,1}$, $A_{7,3}$, $A_{7,5}$, $A_{7,7}$
8	25	$A_{8,0}$, $A_{8,2}$, $A_{8,4}$, $A_{8,6}$, $A_{8,8}$
9	30	$A_{9,1}$, $A_{9,3}$, $A_{9,5}$, $A_{9,7}$, $A_{9,9}$
10	36	$A_{10,0}$, $A_{10,2}$, $A_{10,4}$, $A_{10,6}$, $A_{10,8}$, $A_{10,10}$
11	42	$A_{11,1}$, $A_{11,3}$, $A_{11,5}$, $A_{11,7}$, $A_{11,9}$, $A_{11,11}$
12	49	$A_{12,0}$, $A_{12,2}$, $A_{12,4}$, $A_{12,6}$, $A_{12,8}$, $A_{12,10}$, $A_{12,12}$

4. Implementation & Results

This section presents the implementation of the proposed face recognition methodology and documents the results obtained. A brief comparative study is also given to show the superiority of the proposed method over those given in the literature.

4.1 Databases

The performance of our method was evaluated on three different sets of face recognition databases. CMU AMP and Essex Faces94 databases are chosen for their significant facial expression variations whereas the Yale database has considerable illumination variations. The details of these databases are as follows:

- *CMU AMP face expression database* [2] consists of 13 individuals with 75 images of each subject showing different expression. These samples were taken in the same lighting condition using CCD camera. All of them have been well registered by eye locations.

- *Essex Faces94 database* [1] contains face images from 153 subjects (20 females and 133 males) in total. 20 colour photographs are obtained from each subject using an S-VHS camcorder. The database has considerable variations in expressions but very minor variations in head turn, tilt and slant. Each subject sits at fixed distance from the camera and is asked to speak, whilst a sequence of images is taken. In this experiment, the samples were transformed into grayscale images first before they were processed.

- *Yale Face Database* [19] consists of 15 individual sets, each containing 11 grayscale image samples. The samples have variations in lighting condition (left-light, center-light, right-light), facial expression (normal, happy, sad, sleepy, surprised and wink), and with/without glasses. If a subject is using glasses, then there is at least one sample image of that subject without glasses.

Table 1 summarises the key points of the three face datasets used in this study. Sample images are presented in Figure 3.

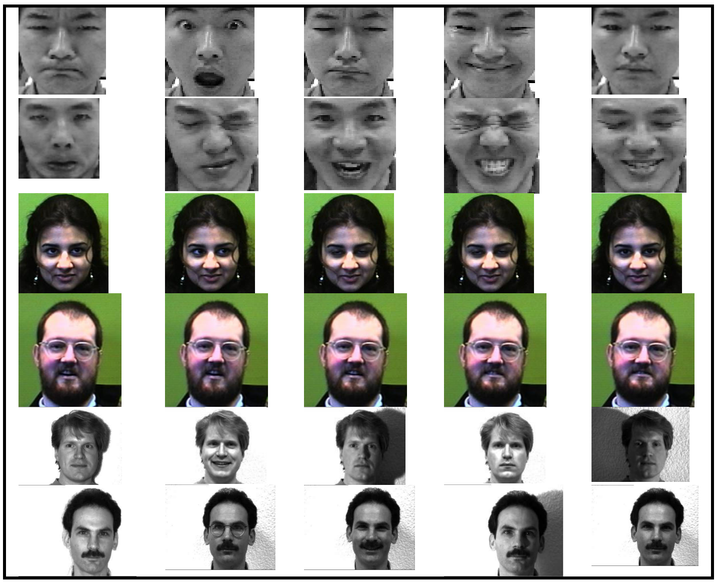

Figure 3: Sample images from CMU, ESSEX Face94 and Yale face databases

Table 1: Face Recognition Databases

Database name	Image size	Number of subjects	Number of samples per subject
CMU AMP face expression	64 × 64	13	75
Essex Faces94 Database	180 × 200	153	20
Yale Database	320 × 243	15	11

4.2 Implementation

We carried out extensive experiments to test the effectiveness of Zernike moments for the face recognition problem. It would be safe to say that Zernike moments perform well over facial images with uniform pose angles. Pre-processing steps were applied wherever it was needed. No pre-processing steps were applied for CMU AMP face database because the samples in this are well-registered and do not have any lighting variations. Face detection and resizing step were applied in both Essex and Yale face database. Resizing step is important because the size of detected faces is not always the same. All images were resized to the smallest sized facial image in the database. Illumination correction was applied in Yale database using the Fuzzy enhancement method described in Section 2. Parameters of fuzzy enhancement t, μ_c were set to 5 and 0.50 respectively after optimisation. In each experiment we randomly select *k* images for training with the remaining constituting the testing set. This process was repeated 50 times till we achieved convergence with the best possible training set.

4.3 Recognition Results

Face recognition is carried out using the Nearest-Neighbour classifier (kNN). This classifier relies on a metric or 'distance' function between different patterns. The distances between a test set and all the training sets are computed and the *k* nearest distances set is selected. The decision as to which class a particular test element belongs is taken by choosing the class having more vectors in *k* nearest distances set. In our experiments, *k* is set to 1. Probabilistic Neural Network (PNN) and Linear Discriminant Analysis (LDA) were also employed for comparison purposes. PNN is an extension from *Parzen-window* classifier. One of the advantages of using PNN is that their learning speed which the training vectors only need to be processed once. The Gaussian width for PNN was set to 0.1 based on experimentation.

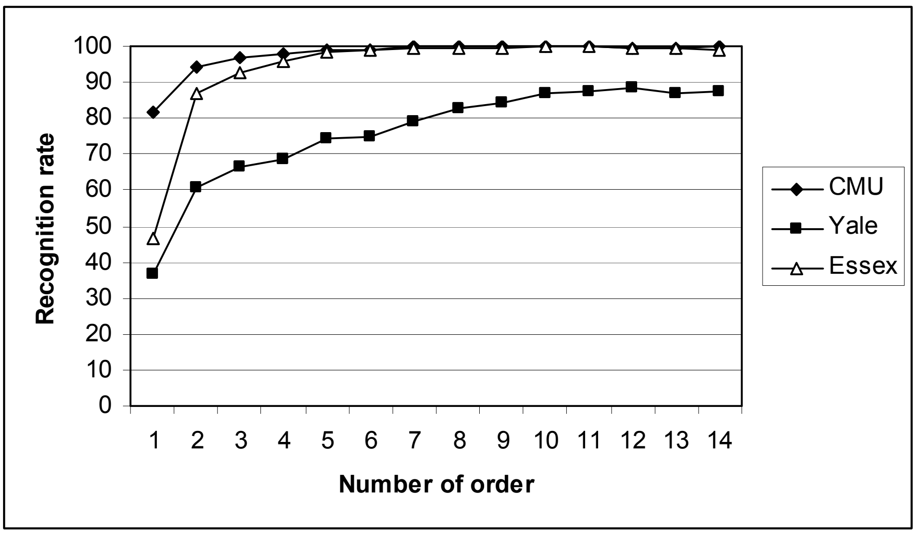

Figure 4: Recognition rate graph for different orders

Figure 4 depicts the graph showing the best recognition rate for all orders of Zernike moments which are being used. Pre-processing steps were applied in this experiment. It is observed that Yale database has a lower recognition rate in comparison with other two databases. This is because that Yale database possesses more variations in the image samples. Table 3 quantifies the recognition rates obtained on the three databases. Yale database gets the highest increase in recognition rate after pre-processing steps have been applied. In addition, since we have not dealt with pose variations in detail, the recognition accuracy is lower than expected. The relationship between number of training sets and recognition rate is illustrated in figure 6. This confirms the accepted fact that the more training sets we have, the better the recognition rate.

Table 3: Best recognition accuracy on different databases

		Recognition rate	
Database	**Order**	**No Pre-processing**	**Pre-processing**
CMU AMP	9	100.00 %	N/A
Essex Faces94	11	99.08 %	99.80 %
Yale	12	80.83 %	88.33 %

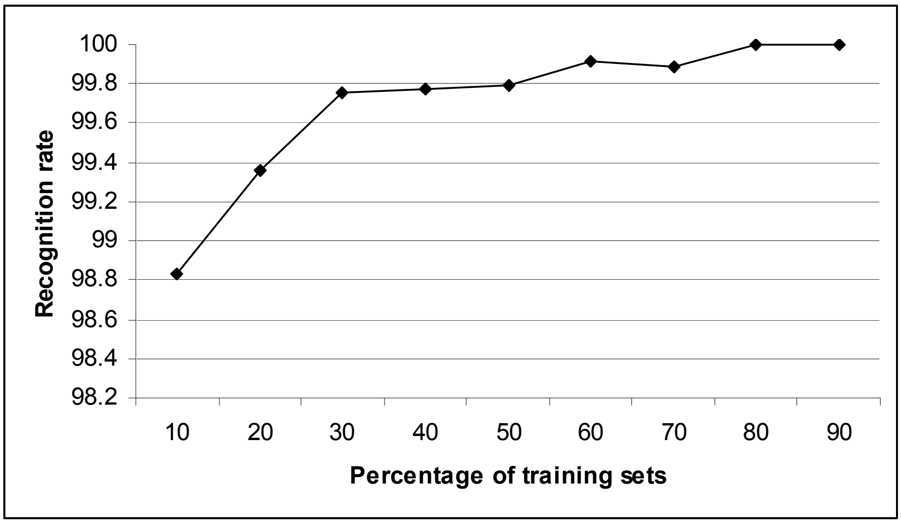

Figure 6: Recognition accuracy on different number of training sets.

The relationship between the order of Zernike moment and the recognition rate is explored in Table 4. This table shows the relationship between the first nine orders and recognition rate. It is noted that the rise in the order, the recognition also improves. Furthermore, the computation time (including pre-processing steps, feature extractions and recognition step) also increases as the number of dimensions increase.

Table 4: Recognition rate with nine first orders

Order	Dimensionality	Recognition rate	Computation time (in seconds)
1	2	36.67 %	33.60
2	4	60.83 %	37.47
3	6	66.67 %	46.91
4	9	68.33 %	58.69
5	12	74.17 %	75.67
6	16	75.00 %	97.50
7	20	79.17 %	125.28
8	25	82.50 %	157.64
9	30	86.67 %	194.08
10	36	87.50 %	243.47

4.4 Comparative Analysis

The performance of Zernike moments as a feature descriptor is evaluated via three different classifiers on the Yale database and the results obtained are enumerated in Table 5. It is quite apparent that the difference in recognition rates between classifiers is negligible after pre-processing steps are applied. PNN gets the highest recognition rate before and after pre-processing steps are applied. However, for PNN we have used a higher order of Zernike moments which implies that PNN uses more dimensions and hence takes more time to converge. Before pre-processing is applied, kNN is the lowest among the others. This is because the decision in kNN depends on each of the training vectors. Pre-processing steps change the vectors and groups them differently leading to the distance between vectors from the same subject being minimised.

Table 5: Best recognition accuracy on Yale database using different classifiers

Classifier	Order	Recognition Rate	
		No Pre-processing	**Pre-processing**
kNN	12	80.83 %	88.33 %
LDA	12	81.67 %	88.33 %
PNN	15	88.33 %	89.17 %

We have also compared the Zernike moments with other statistical approaches such as the Eigenfaces and Fischerfaces. Principal Component Analysis (PCA) or Eigenfaces technique is a popular unsupervised method which has aim to extract a subspace where the variance of the projected data is maximized. Eigenvectors and eigenvalues of all training sets in each subject are calculated. Then, all test sets are projected to the subspaces. Within these subspaces the distance are calculated to determine test vector membership. Fisherface, or so-called Linear Discriminant Analysis (LDA), on the other hand, aims to maximize variance between classes while minimize variance data within class. LDA-based algorithms often perform better than PCA-based ones. However, LDA suffers from the *small-sample-size* problem which is problematic in face recognition application (Wang et al. 2007). It is clearly noticeable from Table 6 that Zernike moments outperform the other two popular face recognition methods although it has fewer dimensions than them.

Table 6: Comparison between Zernike moment and other methods on Yale database

Method	Dimensionality	Recognition Result
Eigenfaces	35	78.56 %
Fisherface	14	83.22 %
Zernike moments	49	88.33 %

5. Conclusions

This paper presents an efficient statistical approach based on Zernike moments for obtaining an optimum feature vector set for the purpose of face recognition in video surveillance. The face within each 2D digital image captured from a video sequence is first detected using the Adaboost detector and then normalized to take care of variations in scale, size and illumination. Zernike moments are computed from the detected face image by enclosing a circular disc within the image. We show that higher order moments carry more information but the use of an optimum number of Zernike Moments feature vector set gives better accuracy. The validity of the proposed method is demonstrated by means of several experiments.

The results show that by the use of Zernike moments as a face feature, a face image could be represented using fewer dimensions as compared to other popular approaches. In addition, recognition rate is higher, processing is faster and less memory is required. Pre-processing using fuzzy enhancement method further improves the recognition rate. Finally, a comparative study with other approaches demonstrates the superiority of the proposed approach. The proposed face recognition approach incorporates robustness to rotational, scale, pose and illumination variance.

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