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LOCALIZED REGION BASED FACE RECOGNITION USING DISCRETE KRAWTCHOUK MOMENTS

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Graphical abstract

Abstract

Discrete Krawtchouk moments technique has been discovered as one of the feature extraction technique that is able to extract prominent features from the face and further improve face recognition performance. This technique is less sensitive towards image distortion due to its flexible characteristic in selecting a localized region of interest in face images by varying the value of Krawtchouk polynomial parameter. Therefore, this study intends to analyze the quality of features produced by a different value of Krawtchouk polynomial parameter and quantify using recognition rates produced on two different face databases: ORL and YALE. The study shows that face recognition using discrete Krawtchouk moments results up to 94.7% accuracy on ORL and 81.3% accuracy on Yale. Furthermore, this method outperformed two other classical feature extraction methods, known as Eigenfaces and Fisherfaces.

Keywords: Face recognition, Orthogonal moments, Discrete Krawtchouk Moments

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1.0 INTRODUCTION

Image acquisition, pre-processing, features extraction, and classification are four major components in the development of face recognition algorithm. Feature extraction is among the most important process, as it will extract feature vector, which will represent the image in a compact and distinguishable form. Generally, there are two types of feature extraction technique that are commonly used by the researcher, namely global-based feature and local-based feature [2]. Conventionally, global-based feature, which looks into an image for the overall information, is selected for whole face image due to its simple linear or nonlinear algorithm. However, these global-based features are intolerant to image with obstructions, shadows or illumination [2]. Hence, local-based features have been introduced to overcome this limitation, by focusing on a specific area of a face. To provide distinguishable model identification, local features have the potential to charcaterize an image with its neighboring pixels or regions that is invariant to image deformations.

For a better numerical approximation and modeling, continuous orthogonal moments have been introduced by Teague, who proposed Zernike moment(ZMs) which are orthogonal inside a unit circle [3]. Aside from the ZMs algorithm, Legendre Moment(LMS), Tchebichef Moment(TM) and Gauss-Hermite(GHM) are the most popular continuous moment techniques which have been used for face recognition. These moments based method has a wide range of applications such as character recognition, the direction of arrival estimation and trademark segmentation [2][6]. However, implementation of these continuous moments to discrete images produces an error in computation whereby additional coordinate transformation was required in the area of orthogonality and suited only for discrete estimation of the interval. This estimation interval normally results in an error during numerical computation. Hence, the discrete orthogonal moment was introduced to eliminate to overcome this barrier [4].

Orthogonal moment (OM) of the image been interpreted by equation 1:

$$\Phi_{pq} = \iint_c f(x,y)\Phi_{pq}(x,y)dxdy \quad (1)$$

where Φ_{pq} represent moment order *(p+q)* of an image *f(x,y)* of the localize region.

Moment function with orthogonal polynomial extracts the overall characteristics of an image shape and generates a lot of information especially variance in geometrical features of the images. Hence, the orthogonal characteristics offer modest and precise indicator reconstruction from the produced moments. Moments of orthogonal polynomials have demonstrated to be less sensitive to noise, are naturally invariant to linear transformations and can be effectively used for image representation [8]. There are two types of OM, known as continuous OM and discrete OM. Krawtchouk polynomials are one of discrete OM suitable for extracting features for face recognition applications with less sensitivity to image distortion. Discover by Mikhail Krawtchouk, Krawtchouk polynomials derived from binomial distribution to form a set of polynomials that varies with its order [4]. The lower order of the polynomials will produce higher dimensional characteristic, hence able to detect local deviations of edges in the image [5]. As for higher order Krawtchouk polynomials, it will represent global characteristics due to wider support coverage [5]. The capabilities of selection higher or lower order of the Krawtchouk parametric, allow the user to freely highlight on the localized region of the images. This can be achieved by changing the value of the binomial distribution parameter of the Krawtchouk polynomial function.

This research provides an analysis of the recognition rate for full face and localizes region image produced by varying the value of Krawtchouk moment parameters. The results of the recognition rate via the proposed method will be compared with eigenfaces and fisher faces based feature extraction methods.

1.1 Discrete Krawtchouk Moment (DKM)

Krawtchouk moments [2] are a series of the group indicated by Krawtchouk Polynomials as the fundamental function set. Krawtchouk polynomials are a group of polynomials related to binomial distribution which able to improved recognition performance due to its capability of having flexibility in highlighting the interest of area from face images. For *N* point one-dimensional signal *f(x)* of the *n*-th order of Krawtchouk moment is defined in equation 2:

$$Q_n = \sum_{x=0}^{N-1} \bar{K}_n(x;p,N-1)f(x) \quad (2)$$

Classical Krawtchouk polynomial order of *n* is interpreted as:

$$K_n(x:p,N) = \sum_{k=0}^{N} ak,n,px^k = 2F_1\,(-n,-x:-N:\frac{1}{p}) \quad (3)$$

where $n = 0,1,2,\ldots, N$, $N > 0$, $p \in (0,1)$ and $2F_1$ function well-defined as :

$$2F_1(a,b:c:z) = \sum_{k=0}^{\infty} \frac{a_k b_k}{c_k}.\frac{z^k}{k!} \quad (4)$$

whereby, a_k, is the Pochhammer symbol :

$$a_k = a(a+1)\ldots(a+k-1) = \frac{\Gamma(\mathrm{a+k})}{\Gamma(a)} \quad (5)$$

A complete set of discrete function is form from the set of (N+1) of Krawtchouk Polynomials { $K_n(x:p,N)$} with given weight function of:

$$w(x:p,N) = \binom{N}{x} p^x (1-p)^{N-x} \quad (6)$$

which fulfill orthogonality condition,

$$\sum_{x=0}^{N} w(x:p,N)K_n(x:p,N)K_m(x:p,N) = \rho(n:p,N)\delta_{nm} \quad (7)$$

where *n, m* = 1, 2…*N* and,

$$\rho(n:p,N) = (-1)^n(\frac{1-p}{p})^n \frac{n!}{(-N)_n} \quad (8)$$

Normalization of Krawtchouk polynomial helps to stabilize the numerical fluctuations for moment computations. The normalized Krawtchouk polynomials, $\tilde{K}_n(x:p,N)$, is defined in Equation 9.

$$\tilde{K}_n(x:p,N) = \frac{K_n(x:p,N)}{\sqrt{\rho(n:p,N)}} \quad (9)$$

Weighted Krawtchouk polynomials $\{\bar{K}_n(x:p,N)\}$ is defined in Equation 11.

$$\bar{K}_n(x:p,N) = \bar{K}_n(x:p,N)\sqrt{\frac{w(x:p,N)}{\rho(n:p,N)}} \quad (10)$$

Hence, the orthogonality condition becomes,

$$\sum_{x=0}^{N} \bar{K}_n(x{:}\,p,N)\,\bar{K}_m(x{:}\,p,N) = \delta_{nm} \qquad (11)$$

Krawtchouk moment able to computed in matrix form Q, as

$$Q = K_b A K_a^T \qquad (12)$$

where *T* is the transpose of the matrix and

$$Q = \{Q_{ij}\}_{i,j=0}^{i,j=N-1} \qquad (13)$$

$$K_v = \{\bar{K}_i(j; p_v, N-1)\}_{i,j=0}^{i,j=N-1} \qquad (14)$$

$$A = \{f(j,i)\}_{i,j=0}^{i,j=N-1} \qquad (15)$$

Hence, the reconstructed image can be defined in a matrix as

$$Q = K_b^T A K_a \qquad (16)$$

1.2 Reconstruction of an image from Krawtchouk moments

Several studies on discrete Krawtchouk moment (DKM) were applied to image reconstruction of normal images and noisy images. Here, the capability of Krawtchouk moments in representing an image can be evaluated. The delta between the reconstructed image and its original image is been interpreted by the normalized root-mean-square error (RMSE).

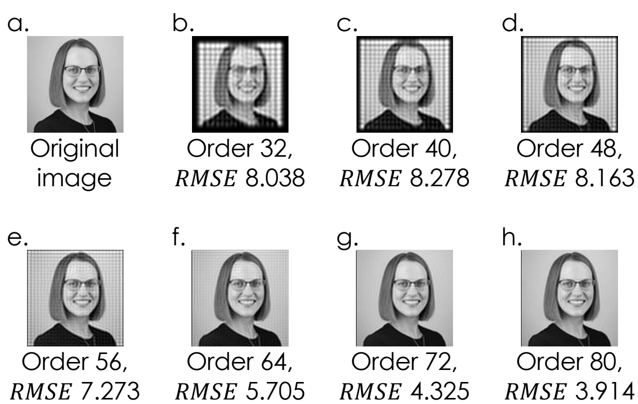


Figure 1 Reconstruction of original image (a) using Krawtchouk moments extracted by varying the number of orders (b)-(h)

Equation 17 defines the RMS error (RMSE) between original image, $f(x,y)$ and reconstructed image, $\bar{f}(x,y)$,

$$RMSE = \sqrt{\sum_{i=0}^{N} \frac{[f(x,y) - \bar{f}(x,y)]^2}{N}} \qquad (17)$$

where *N* represents the total number of pixels.

Figure 1(a) shows an image with an original size of 128 by 128 used for computation Krawtchouk moments with Krawtchouk polynomial parameters, p_1 *and* p_2 = 0.5, where p_1 and p_2 are binomial polynomial parameter used in the calculation of K_a and K_b. Krawtchouk moments were calculated up to a maximum order of 32, 40, 48, 56, 64, 72 and 80 for the image shown in Figure 1(a). The reconstructed images are shown in Figure 1(b) to 1(h), with its respective order.

1.3 Localize Feature Extraction

In order to extract localized features from an image, the binomial parameters, p_1 and p_2, can be varied with $p_1, p_2 \in (0,1)$ whereby parameter p_1 will shift the area of interest in x-axis and parameter p_2 will shifted the focal area in *y*-axis [4][7]. Table 1 summarizes the relationship of parametric value with the focal position of the image.

Table 1 Summary of local feature extraction

Parameter Value	Location
$p_1 < 0.5$	offset to left
$p_1 > 0.5$	offset to right
$p_2 < 0.5$	offset to top
$p_2 > 0.5$	offset to bottom

By varying the value of parameter p, the region of interest (ROI) of the weighted Krawtchouk polynomials changes accordingly. When p_1= p_2= 0.5, the ROI will be located in in the centre of the x-axis, which is referred to full face recognition as shown in Figure 2.

$p_1 = p_2 = 0.5$
Order 60

Figure 2 Full face recognition

Figure 3 demonstrates the results of image reconstruction using Krawtchouk moments by varying the p_1 and p_2 value for different number of orders of 8, 16, 32 and 64. Here, it is can be observed that for higher orders, the localized feature extraction method performs poorly. Thus, localized feature method should be only used for a limited range of orders and must be determined through experiments.

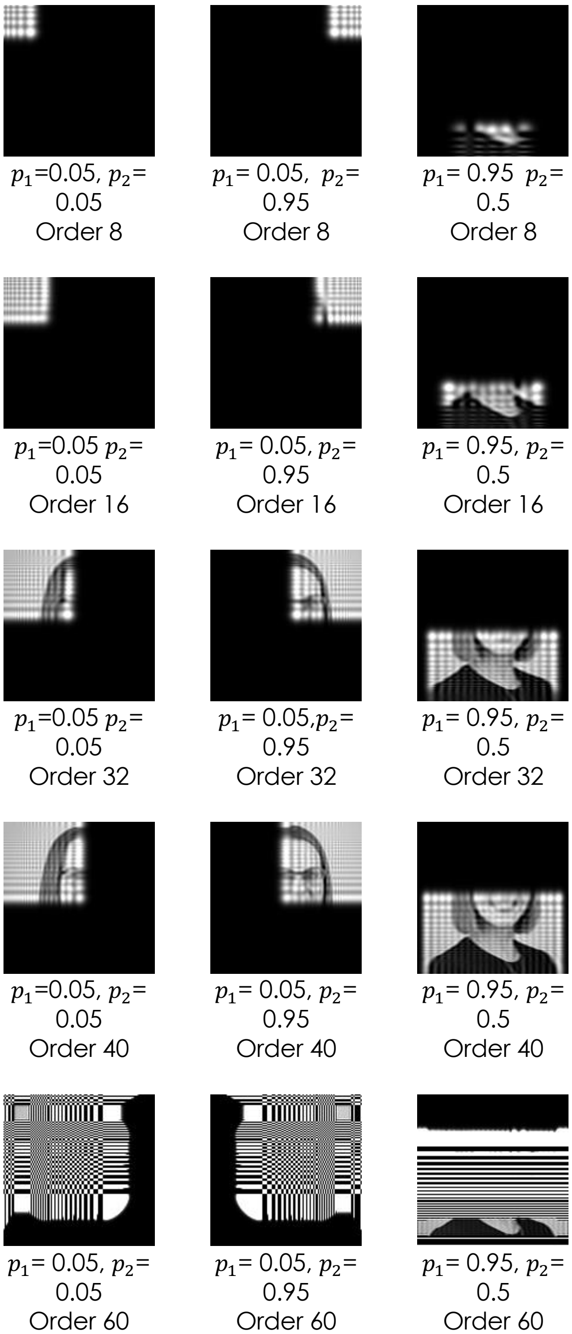


Figure 3 ROI extraction with different orders of P_1 and P_2 value

2.0 METHODOLOGY

The algorithm for localized feature extraction is composed of four major steps which is illustrated in Figure 4.

Each step is briefly defined as follows:

Step 1: Train samples
Use discrete Krawtchouk moment (DKM) to compute the feature vector of the train images from the selected database. This algorithm is applied to the whole image and will only accept grey scale images.

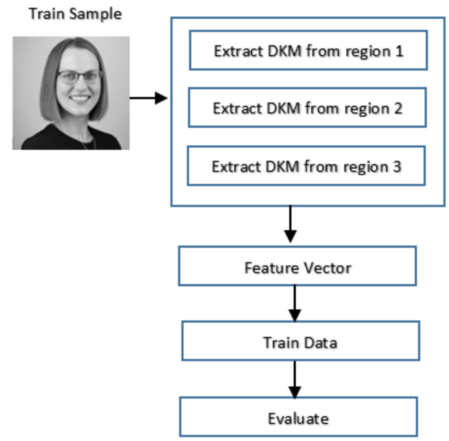


Figure 4 Proposed algorithm

Step 2: Localize region area extraction of Discrete Krawtchouk moment
Define three localize region of interest, by manipulating the Krawtchouk polynomial parameters, p_1 *and* p_2, and compute the feature vectors for respective regions using discrete Krawtchouk Moments at specific order.

Step 3: Feature Vector
Concatenate these localized feature vectors to form a single feature vector.

Step 4: Train and evaluate the image accuracy
The data were trained, classified using similarity measure which uses Euclidean distance function and finally the recognition rate was calculated.

Two different databases, which are ORL and Yale database been used to evaluate the proposed method.

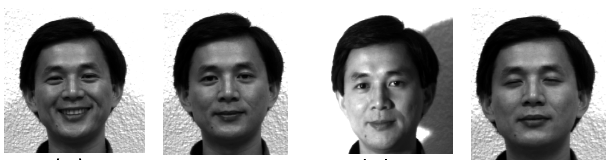
A. ORL Dataset

The ORL (Olivetti Research Laboratory in Cambridge, UK) database consist with 10 different images of 40 different individuals of each image which make a total of 400 images from The face images are stored in PGM format. Images were taken from individuals with a varying source of illumination, facial expressions, and facial details. All face images in ORL have the same longitudinal dimension of 92 x 112 pixels, with 256 grey levels by pixel. Figure 5 shows several samples of image that can be extracted from the ORL database.

Figure 5 Sample image from ORL Database with different individuals

B. Yale Dataset

The Yale Face Database consists of 15 individuals with 11 images per subject, which gives a total of 165 grayscale images in GIF format. Each individual or subject demonstrated with multiple facial expression or structure, which are center-light, with spectacles, happy, left-light, no spectacles, normal, right-light, sad, sleepy, surprised, and wink. Figure 6 shows samples of images that are available in the Yale Database.



(a) (b) (c) (d)

Figure 6: Sample images of one particular subject from Yale Database with 4 different conditions: (a) happy, (b) no spectacles, (c) left light and (d) sleepy

For both databases, experimental data will be prepared based on five different groups, (labeled as Group1, Group2, Group3, Group4 and Group 5) with each group having five different ways of selecting the train and test samples. For example, ORL Database which contains 10 images per subject, 5 images will be selected into train set and 5 images will be selected into test set. The selection of images for train set will be from image number 2, 4, 7, 8 and 9 and selection for test set will be from image number 1, 3, 5, 6 and 10. This selection method will be referred to Group 1, as shown in Table 2(a). The selection method will be applied to all subjects within the same database. Table 2(a) summarizes the selection method for 5 groups in the ORL database. A similar procedure will be used for the Yale database and selection method is summarized in Table 2(b). To evaluate the capability of DKM for full face recognition and localized region recognition, the average recognition rate based on the 5 groups will be calculated. First and foremost, for full face recognition evaluation, Krawtchouk polynomial value, p is fixed to a pair of value: p_1= 0.5 and p_2 = 0.5 and the number of order of Krawtchouk moments will be varied from 1 till 60. This step is repeated for localize region evaluation with three sets of different values of Krawtchouk polynomial p, , which are {p_1= 0.05, p_2=0.05}, {p_1= 0.95, p_2=0.5} and {p_1= 0.05, p_2=0.95}.

Table 2 (a) Five different sequence of selecting images from a single subject to form the train and test set in ORL database.

		Subject				
Group 1	Train	2	4	7	8	9
	Test	1	3	5	6	10

		Subject				
Group 2	Train	3	6	8	9	10
	Test	1	2	4	5	7

		Subject				
Group 3	Train	2	4	6	8	10
	Test	1	3	5	7	9

		Subject				
Group 4	Train	2	3	6	8	9
	Test	1	4	5	7	10

		Subject				
Group 5	Train	1	3	8	9	10
	Test	2	4	5	6	7

Table 2 (b): Five different sequences of selecting images from a single subject to form the train and test set in Yale database.

		Subject					
Group 1	Train	2	4	7	8	9	10
	Test	1	3	5	6	11	

		Subject					
Group 2	Train	3	6	7	8	9	10
	Test	1	2	4	5	11	

		Subject					
Group 3	Train	2	4	6	8	9	10
	Test	1	3	5	7	11	

		Subject					
Group 4	Train	2	3	6	8	9	11
	Test	1	4	5	7	10	

		Subject					
Group 5	Train	1	3	7	8	9	10
	Test	2	4	5	6	11	

3.0 RESULTS AND DISCUSSION

The average recognition for 5 groups against the number of order of computation of DKM, for full face and localize region extraction, evaluated on both ORL and Yale database are shown in Figures 7 and 8 respectively.

Figure 7 compares the recognition rate between full face and localize region for ORL images for different number of orders. It can be observed that the recognition increases as the number of order increases, and reach an optimum recognition rate of 94.0% at 36th order for full face and 94.7% at 40th order for localized region. However, for localized region, the recognition rate significantly drops to 52.80% from 44th order onwards.

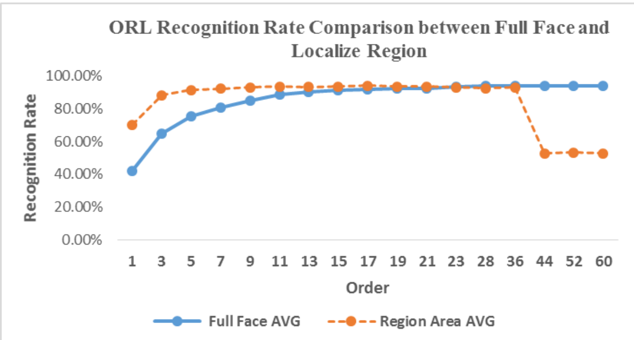


Figure 7 ORL recognition rate for full face and localize region

Results from Yale database shows that average recognition rate for full face reached an optimum rate of 82.67% at 32nd order, and localize region attained optimum recognition rate of 81.33% at 36th order. The recognition of localize region dropped significantly to 31.73% from 44th order onwards.

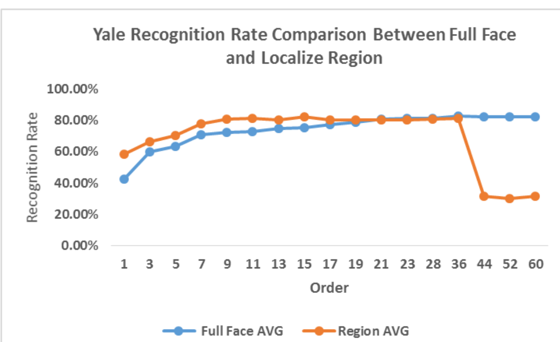


Figure 8 Yale recognition rate for full face and localize region

Table 3 Comparison of recognition rate on ORL Dataset

Method	Recognition Rate
Eigenfaces	94.0%
Fisherface	91.6%
DKM (Full Face)	93.8%
DKM (Localize Region Face)	94.7%

Our recognition rate has been compared with the other methods such as Eigenfaces and Fisherface. The average recognition rate for Eigenfaces and Fisherface were computed based on 5 groups given in Table 2(a) and (b). The overall result, given in Table 3, shows that DKM with localize region gives the best performance when compared to others method.

4.0 CONCLUSION

This study evaluates the performance of localized Krawtchouk moments (DKM) in face recognition tasks. Our study shows that DKM computed on three regions by manipulating the Krawtchouk polynomials parameter yields the highest recognition rate on two face datasets, ORL and Yale, when compared to full face recognition and other popular methods: Eigenfaces and Fisherfaces.

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