FACE RECOGNITION AND ITS APPLICATION

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This presentation covers...

- Introduction
- Face image acquisition
- Pre-processing
  - -Filters/Image enhancement
  - -others (cropping, resizing, contrast, etc.)
- Feature extractors
  - -PCA (eigen face)
  - -Continuous Orthogonal Moments:
    - Zernike moments (ZMs)
      - *Direct method
      - *Prata's method
      - *Coefficiect method
      - *Modified Kintner's method
      - *q-recursive method (used in the experiment proposed by Chong Chee Way)
    - Legendre moments

Continue...

- -Discrete orthogonal moments
  - *Krawchouk moments (KMs)
  - *Tchebichef moments (TMs)
- Classifiers
  - -Nearest neighbor classifier (NN)
  - -ANN
  - -SVM
- Examples of Experimental results
- Applications
  - - Security System using Face Recognition
  - - Safety Box Access System using Face Recognition
  - - Document Access System using Face Recognition
  - -Others
- Conclusion

Introduction

- The face recognition systems have wide range of applications such as access control systems, content-based video browsing, building or office security, criminal identification, authentication in secure systems like computers or bank teller machines and many others.
- Main problem of Face recognition is to achieve high classification accuracy with constraints such as pose, illumination condition, facial expression, aging and many others .
- A successful face recognition system depends heavily on the particular choice of feature extraction methods.
- Regardless of the method used, extracted features must minimize the within-class face variability and maximize between-class face variability in order to provide sufficient discrimination among different faces

Introduction ...Continue

- The basic flow of the face recognition system is shown in Figure 1 which consists of Face image, Preprocessing, Feature extraction and Face classification.

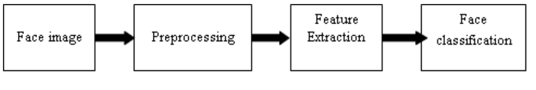

Figure 1

Face image acquisition

- Acquired from the website to name a few;

2D face images
- Cambridge university ,Olivetti Research Laboratory (ORL) database
- Yale university database
- Massachusettes University database
- Ohio state University database
- Others

- Own creation (using good high resolution digital camera)-may requires highly control surrounding intensity
- Acquired real time, involves using camera that is attached to the microcontroller linked to PC.

Pre-processing

- Filters/Image enhancement

  Spatial filters (Linear and Nonlinear) involves creating a mask filter centered at arbitrary point with neighborhood.

  -Linear:

  Examples;

  Average, LOG, Prewitt, Sobel and etc

  -Non-Linear, respond based on ranking among neighbors and center value will be based on the ranking result.

  -Frequency domain filters

  Examples;

  Low pass, High pass, Band pass etc.

  -Image Equalization

  -Others (cropping/resizing)

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Feature extractors

- Principal Component Analysis (PCA)

  -PCA or eigenface was first studied and investigated by Matthew Turk and Pentland .

  -The eigenface approach utilizes the idea of PCA and decomposes face images into small set of characteristic feature images .

  -The recognition is performed by projecting a new face into a low-dimensional linear face space defined as eigenfaces.

  -This technique of face recognition has been claimed to be quite robust.

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Feature extractors...continue

- Continuous orthogonal moments

  Zernike moments (ZMs)

  - First introduced by Teague M.R.

  - Are based on orthogonal functions called Zernike polynomials

  - Computationally more complex compared to geometric moments (regular moments) but superior in terms of:

  -Better feature representation (represent image by a set of mutually independent descriptors).
  - Low noise sensitivity.
  - Features are invariant to rotation and can easily be constructed to an arbitrary high order.
  - Simply reconstruct image by taking its inverse (outstanding property).

*Q-recursive is used in the experiment due to fast computation

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Zernike moments continue...

-The kernel of Zernike moments is orthogonal Zernike polynomials defined over the polar co-ordinates inside a unit circle. The Zernike moment of order p is defined as

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

-where $V_{pq}(r,\theta)$ denote Zernike polynomials of order p and repetition q and is written as

$$V_{pq}(r,\theta) = R_{pq}(r) e^{jq\theta} \qquad (2)$$

-while $*$ denotes complex conjugate

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Zernike moments...continue

- **Radial polynomial**

  -The radial polynomial, $R_{pq}(r)$ is expressed as

$$R_{pq} = \sum_{s=0}^{(p-|q|)/2} (-1)^s \frac{(p-s)!}{s!\left(\frac{p-2s+|q|}{2}\right)!\left(\frac{p-2s-|q|}{2}\right)!} r^{n-2s} \qquad (3)$$

  -where p is a non-negative integer, and q is an integer such that p-$|q|$ is even, and $|q|<=p$.

*The q-recursive method proposed by Chong Chee Way utilizes recurrence relation whereby it employs Zernike radial polynomial of fixed order p with higher index q to derive the polynomial of the lower index q without computing the polynomial coefficients and the power series of the radius.

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Zernike moments-continue...

-The discrete approximation of the continuous Zernike integral of equation (1) is written as follows

$$Z_{pq} = \lambda(p,N) \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} R_{pq}(r_{ij}) e^{-jq\hat{\theta}_{ij}} f(i,j),$$

$$\text{for } 0 < r_{ij} < 1 \qquad (4)$$

-where, $\lambda(p,N)$ is the normalizing constant based on the mapping transformation.

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Continuous moments -continue

- Legendre moments (LMs)

  - Introduced by Teague M.R.

  - LMs have a form of projection of the image intensity function onto the Legendre polynomials

  - coordinate representation does not easily produce translational, scale and or rotation invariant functions since it is difficult to extract a common displacement, scale or orientation factor from Legendre polynomials

  - The invariant functions are than derived by Chong Chee Way for translation, scale and rotation invariants

Legendre moments-continue...

The LMs of order *(p+q)* with image function *f(x,y)* are defined as

$$L_{pq} = \frac{(2p+1)(2q+1)}{4} \int_{-1}^{1}\int_{-1}^{1} P_p(x)P_q(y)\, f(x,y)\,dxdy \qquad (5)$$

where, *p, q =1, 2, 3, …∞* and *Pp(x)* denote Legendre polynomial of order *p*.

To evaluate the LMs, the square image of *N x N* pixels with intensity function *f(i,j)* where, *0≤i, j≤N*, has to be scaled in the region of [*-1<x, y<1*] and equation (5) can be written in discrete form as

$$L_{pq} = \lambda_{pq} \sum_{i=1}^{N}\sum_{j=1}^{N} P_p(x_i)P_q(y_j)\, f(i,j) \qquad (6)$$

Legendre moments-continue...

where the normalizing constant is $\lambda_{pq}=(2p+1)(2q+1)/(N-1)^2$ and x_i and y_i denote the normalized pixel coordinates in the range of [-1,1] which are given by,

$$x_i = \left(\frac{2i}{N-1}\right) - 1,\; y_j = \left(\frac{2j}{N-1}\right) - 1 \qquad (7)$$

$P_p(x)$ is Legendre polynomial of order *p* defined as

$$P_p(x) = \sum_{k=0}^{p} (-1)^{(p-k)/2} \frac{1}{2^n} \frac{(p+k)!\,x^k}{\left(\frac{p-k}{2}\right)!\left(\frac{p+k}{2}\right)!\,k!} \qquad (8)$$

where, $|x| \le 1$ and *(p-k)* is even.

Obtained from the equation,

$$P_p(x) = \frac{1}{2^p\, p!} \frac{d^p (x^2-1)^p}{dx^p}$$

Legendre moments-continue

The recurrence relation of Legendre polynomials, *Pp(x)* is given as follows;

$$P_p(x) = \frac{(2p-1)P_{p-1}(x) - (p-1)P_{p-2}(x)}{p} \qquad (9)$$

where, $P_0(x)=1$, $P_1(x)=x$, $|x|\le 1$ and $p>1$

The recurrence relation of LMs helps to reduce the computation time thus fast computation is achieved.

Feature extractors-Continue...

- Discrete orthogonal moments

  Krawtchouk moments (KMs)

  - Introduced by a Ukrainian mathematician Mikhailo Pylypovych Kravchuk

  - KMs are derived from the weighted Krawtchouk polynomials and can be used to form the basis of a set of discrete orthogonal moments

  - Since it is orthogonal, it ensures minimal information redundancy. With this property, KMs are well suited as pattern features in the analysis of two-dimensional images.

  - Unlike other moments KMs have the ability to extract local features from any region of interest (ROI)

Discrete orthogonal moments

- Krawtchouk moments

-The KMs of order *(n+m)* in term of weighted Krawtchouk polynomials for an image intensity function, *f(x,y)* is defined as

$$Q_{nm} = \sum_{x=0}^{N-1}\sum_{y=0}^{M-1} \overline{K}_n(x:p_1,N-1)\overline{K}_m(y;p_2,M-1)\, f(x,y) \qquad (10)$$

-Substituting *N* with *N-1* and *M* with *M-1* able to match *N x M* pixel points of an image. The KMs corresponding to *n=m=0* is the weighted mass of the image that is

$$Q_{nm} = \sum_{x=0}^{N-1}\sum_{y=0}^{M-1} \sqrt{w(x:p_1,N-1)w(y;p_2 M-1)}\, f(x,y) \qquad (11)$$

-Since the orthogonality of weighted Krawtchouk polynomial is

$$\sum_{x=0}^{N} \overline{K}_n(x;p,N)\overline{K}_m(x;p,N) = \delta_{nm} \qquad (12)$$

Krawtchouk moments-continue...

Solving equations 11 and 12 for *f(x,y)* the image intensity function can be rewritten in terms of KMs and given by

$$f(x,y)=\sum_{x=0}^{N-1}\sum_{y=0}^{M-1}Q_{nm}\bar{K}(x;p_1,N-1)\bar{K}_m(y;p_2,M-1) \quad (13)$$

-Interpreting the above equation where the image intensity function as representing a series of weighted Krawtchouk polynomials weighted by KMs and if the moments are limited to *order ≤ P < 2N-2*, the series is truncated to

$$f(x,y)=\sum_{x=0}^{p}\sum_{y=0}^{m}\phi(n-m,m,x,y) \quad (14)$$

Krawtchouk moments-continue

then, if S_N = {0, 1, 2, ...,N-1}

$$\phi(k,l,x,y)=\begin{cases}Q_{nm}\bar{K}_n(x;p_1,N-1)\bar{K}_m(y;p_2,M-1), & k\in S_N,\ l\in S_M\\ 0 & others\end{cases} \quad (15)$$

-From equation (10) the KMs are seen as an inner product of *f(x,y)* and .

$$\bar{K}_n(x:p_1,N-1)\bar{K}_m(y;p_2,M-1)$$

-A proper selection of *p1* and *p2* allows the local features at different positions of the image to be extracted.

Discrete orthogonal moments...continue

- Tchebichef or Chebyshev moments (TMs)

  - Belongs to the class of discrete orthogonal moments and based on discrete Tchebichef polynomials.

  - It can be effectively used as pattern features in the analysis of two-dimensional images.

  - The implementation of these moments does not involve any numerical approximation and its polynomials do not require coordinate space transformations.

Tchebichef moments...continue

The mathematical basis of TMs is the discrete orthogonal Tchebichef polynomials satisfying the condition

$$\sum_{x=0}^{N-1}t_m(x)t_n(x)=\rho(p,N)\delta_{mn},\quad 0\le m,n\le N-1 \quad (16)$$

-Where the set of discrete classical Tchebichef polynomials

tn(x) is defined as

$$t_n(x)=n!\sum_{k=0}^{n}(-1)^{n-k}\binom{N-1-k}{n-k}\binom{n+k}{n}\binom{x}{k} \quad (17)$$

-and the square norm as

$$\rho(n,N)=\frac{N(N^2-1)(N^2-2^2)...(N^2-n^2)}{2n+1} \quad (18)$$
$$=(2n!)\binom{N+n)}{2n+1},\quad n=0,1,...,N-1$$

- Other Methods:

  -Frequency domain technique namely DFT, DWT, ST etc.

Classifiers

- Nearest neighbor classifier ;

  -Wide applications classification method. Use to compare the feature vector of the prototype image and the feature vectors stored in the database.

  -Obtained by calculating the min square distance between the prototype image and the database. For instance let C_1, C_2, C_3 ... C_k be the *K* clusters in the database. The class is found by measuring the distance *d(x(q), k)* between *x(q)* and the *K th* cluster C_k.

  -The feature vector with minimum difference is found to be the nearest matching vector. The expression for the minimum distance is given by

$$d(x^{(q)},C_k)=\min\{\|x^{(q)}-x\|: x\in C_k\} \quad (25)$$

Classifiers...continue

- Artificial Neural Network (ANN)

  -ANN is one of the popular approaches in computational models that are inspired from the concepts of biological neurons in the brain and has been used in pattern recognition and computer vision.

  -Multi-Layer Perceptron (MLP) consists of multiple layers and normally the network consists of three layers. First layer is called input layer, next is hidden layer and the output layer as in Figure 2 .

  -The hidden computation units are determined as hidden neurons.

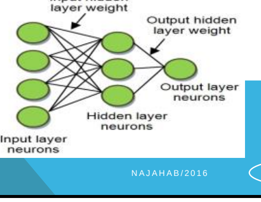

Figure 2

ANN...continue

MLP Activation Function (TANSIG) used in hidden layer and also used in output layer for solving problem in pattern classification.

-The equation for MLP Activation function (TANSIG) is defined as,

$$tansig(n) = \frac{e^{cn} - e^{-cn}}{e^{cn} + e^{-cn}} \qquad (1)$$

where, c=1 and n=output value

-The calculation value of units in hidden layer,

$$H_1 = tansig(b_I * W_{I_0 \to H_1} + \textstyle\sum_{i+1}^{N} I_i * W_{I_i \to H_1}) \qquad (2)$$

Where,

bI = Bias of input layer

WIo = Weight of output layer

WII = Weight of input layer

The value of unit in output layer is determined by ,

$$O_1 = tansig(b_H * W_{H_0 \to O_1} + \textstyle\sum_{i+1}^{M} H_i * W_{H_i \to O_1}) \qquad (3)$$

Where,

bh = Bias of hidden nodes layer

WHo = Weight between hidden and output layer

WHI = Weight between input and hidden layer

Others

- **SVM and etc.**

Experimental Results

- Example:

-Experiments were conducted on various numbers of subjects from ORL database of 40 subjects, where each subject consists of 10 different orientations of the images and non of them are identical.

-Each image of size 92x112 is resized to 64x64 to reduce complexity in computation. Figure 3 shows some of the train images from Cambridge University database (ORL database), with different orientation used in the experiments

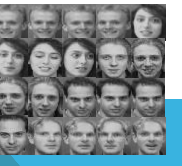

Figure 3: Some of the train images

Results-continue...

The number of subjects considered in these experiments is 5, 20, 25, 30 and 40. Experiments conducted on 5, 20 and 25 subjects do not include those wearing spectacles while 30 and 40 subjects include those with spectacles and subjected to constraints as mentioned earlier.

The number of subjects wearing spectacles in the experiment of 30 subjects is 5 and increased to 15 when 40 subjects are considered.

Classifier used is Nearest Neighbour

Results-continue...

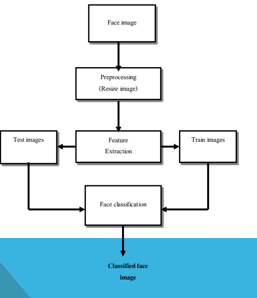

Figure 4: Block diagram of face recognition system using NN

RESULTS (ZMS)

- <u>Using original image</u>

First experiment utilizes ZM of order 2 to12 and the extracted feature vector is of size 47.

Reasons for choosing order 2 to 12 because

- experiments on 5 and 20 subjects show high classification accuracies at this range of orders

- lower orders ie. 0 and 1 contain less information since during reconstruction only gross shape characteristic of the image is obtain while more detail and finer information content is achieved at higher order.

-Tables 1, shows the classification accuracies of ZMs at various number of subjects

RESULTS (ZMS)-CONTINUE...

					Classification. accuracy (%)		
		Train images	Image1-image4	image5-image8	image9,10,1,2	image3-image6	image7-image10
No. of subjects/images	No. of train images	No. of test images					
5(50images) w/o spects.	20	30	100.00	100.00	100.00	100.00	100.00
20(200image) w/o spects.	80	120	91.67	95.83	95.83	90.83	96.67
25(250images) w/o spects.	100	150	89.33	94.67	96.00	90.67	94.67
30(300images) with spects.	120	180	89.44	95.00	96.11	90.00	94.44
40(400images) with spects.	160	240	84.17	91.25	92.50	87.08	83.75

Table 1. Percentage classification accuracy using ZM order 2 to 12 (47 features)

RESULTS (LMS)-CONTINUE...

-Second experiment utilizes LMs of order 4 feature vector of size 25

Reasons for selecting order 4 after going through the experiments on 5 and 20 subjects because

-test on 5 subjects including orders 0 and 1shows similar classification accuracies while excluding 0 and 1shows reduction in classification accuracies .

-test on 20 subjects shows classification accuracies are very much reduced.

Tables 2, shows the classification accuracies of LMs at various number of subjects

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RESULTS (LMS)-CONTINUE...

					Classification accuracy (%)		
		Train images	image1-image4	image5-image8	image9,10,1,2	image3-image6	image7-image10
No of subjects/ images	No of train images	No of test images					
5(50images) w/o spectacles.	20	30	83.33	100.00	80.00	90.00	96.67
20(200images) w/o spectacles.	80	120	77.50	81.67	81.67	80.00	85.00
25(250images) w/o spectacles	100	150	72.67	77.33	80.67	76.67	77.33
30(300images) with spectacles.	120	180	70.00	74.44	78.89	75.56	75.00
40(400images) with spectacles	160	240	64.17	68.33	72.92	66.67	68.75

Table 2: **Percentage classification accuracy of LMs order 4 feature vector 25**

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Results (KMs)-continue...

Third experiment utilizes KMs of order 34 parameter *p1=p2*=0.5 and order 25, *p1* =0.9 and *p2* =0.5.

Figures 3(a) and (b) show the face images at the above setting while Tables 3(a) and (b) show the classification accuracies of KMs at various number of subjects

(a) (b)

Figure 3: Face image using KMs: order 34 parameter p1=p2=0.5 order 25 parameter p1=0.9 p2=0.5

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Results (KMs)-continue...

					Classification accuracy (%)		
		Train images	image1-image4	image5-image8	images 9,10,1, 2	image3-image6	image7-image10
No of subjects/ images	No of train images	No of test images					
5(50images) w/o spectacles.	20	30	93.33	100.00	96.67	100.00	100.00
20(200images) w/o spectacles.	80	120	87.50	93.33	91.67	91.67	90.00
25(250images) w/o spectacles.	100	150	86.00	92.00	86.67	90.67	88.00
30(300images) with spectacles.	120	180	87.78	92.22	87.22	91.67	87.22
40(400images) with spectacles.	160	240	79.58	87.50	86.25	86.67	80.42

Table 3(a): Percentage classification accuracy using KMs order 34 parameter p1=p2=0.5

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Results (KMs)-continue...

					Classification accuracy (%)		
		Train images	image1-image4	image5-image8	Image 9,10, 1, 2	image3-image6	image7-image10
No of subjects/ images	No. of Train images	No. of test images					
5(50images) w/o spectacles	20	30	93.33	96.67	93.33	96.67	100.00
20(200images) w/o spectacles	80	120	92.50	92.50	90.83	90.00	90.00
25(250images) w/o spectacles	100	150	81.33	86.00	86.00	82.67	85.33
30(300images) with spectacles	120	180	83.33	87.78	87.22	85.00	87.22
40(400images) with spectacles	160	240	76.67	84.58	84.58	80.83	80.00

Table 3(b): Classification accuracies of KMs at order 25 where p1=0.9 and p2=0.5

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Results (TMs)-continue...

Fourth experiment utilizes TMs of order 6 feature vector of size 36

Reasons for selecting order 6 because

- tests on both 5 and 20 subjects show high classification accuracies when order is 6 while increasing order shows reduction in classification accuracies.

Table 4, shows the classification accuracies of TMs at various number of subjects

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Results (TMs)-continue

					Classification accuracy(%)		
		Train images	image1-image4	image5-image8	Image 9,10, 1, 2	image3-image6	image7-image10
No. of subjects/ images	No. of train images	No. of test images					
5(50images) w/o spectacles.	20	30	100	100	96.67	100	100
20(200images) w/o spectacles.	80	120	90.83	90.83	87.5	86.67	90.83
25(250images) w/o spectacles.	100	150	86.67	88.67	85.33	82	87.33
30(300images) with spectacles.	120	180	86.67	89.44	85.56	85	88.89
40(400images) with spectacles.	160	240	80.42	83.75	84.17	80	80.42

Table 4: **Percentage classification accuracy using TMs order 6 feature vector of size 36**

Results...continue

Table 5 shows the result of ZM using ANN

				Classification accuracy (%)			
No of subjects/ images	No. of train images	No. of test images	Image 1-4	Image 5-8	Image 9,10,1,2	Image 3-6	Image 7-10
5 (50 images)	20	30	100	100	100	100	100
20 (200 images)	80	120	100	100	100	100	100
25(250 images)	100	150	82	100	100	90.67	94
30(300 images)	120	180	98.33	100	96.33	94.25	97.33
40(400 images)	160	240	91.67	86.67	81.25	92.08	97.08

Table 5: Result of ZM using ANN (Feed forward)

Applications

- Security System using Face Recognition

"A Conceptual Hybrid Security System using Face Recognition
Nurul Husna Muhamad Hassan, Rohani Hassan and Nor'aini Abd. Jalil"

- Safety Box Access System using Face Recognition

"Safety Box Access System Using Face Recognition "
Abdul Mutalib bin Abu Bakar

- Document Access System using Face Recognition

"Smart Document Access System Using Face Recognition "
Ahmad Fahmi Akmal Bin Muhammad Nor

- Others

Conclusions

- Other then the applications mentioned above, face recognition has widely been applied in smart homes, high security organizations such as in banks and in surveillance operations where both applications involve real time face acquisition.
- The techniques of pre-processing the face images require further research in order to acquire precise recognition especially when it involves the complex surroundings.
- The capability of any feature extractors is very much dependent on the face database (i.e. subjected to constraints of the face images such as either they are well controlled in terms of expression, background illumination, orientation or otherwise).
- In the case where direct application of feature extraction does not show good performance hybrid technique can be considered.

THANK YOU FOR YOUR ATTENTION!