Spectral Eigenface Representation for Human Identification

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Abstract

Human identification based on face images, as physical biometric means, plays an imperative role in many applications area. The methods for human identification using face image uses either part of the face, all face, or mixture from these methods, in either time domain or frequency domain. This paper investigate the ability to implement the eigenface in frequency domain, the result spectral eigenface is utilize as a feature vector means for human identification. The converting from eigenface implementation in time domain, into spectral eigenface implementation in frequency domain, is based on implemented the correlation by using FFT. The Min-max is invoked as normalization techniques that increase spectral eigenface robustness to variations in facial geometry and illumination. Two face images are contrast in terms of their correlation distance. A threshold (10.50x107) is used to restrict the impostor face image from being identified. The experimental results point up the effectiveness of a new method in either using varying (noisy images, unknown image, face expressions, illumine, and scales), with identification value of 100%.

Keywords: Human Identification, Biometrics, Eigenface, FFT, Correlation, Min-max.

تمثيل محددات الوجه الطيفية لغرض تميز الاشخاص

الخلاصة

تميز الأشخاص بالاعتماد على صورة الوجه كسمة فيزيوبايلوجي تلعب دور مؤثر في العديد من التطبيقات. إن الطرق المستعملة في تمييز الأشخاص بالاعتماد على صور الوجه، تعتمد على أما جزء من الوجه، الوجه كله, أو دمج الطريقتين معا، أما بصورة مباشرة من الصورة أو بعد تحويلها إلى الفضاء الترددي. في هذا البحث، تم استعراض محددات جديدة، وهي سمات الوجه الطيفية في الفضاء الترددي، تم من خلال استخدام الارتباط المبني باستعمال تحويل فورير السريع. وجعل قيمتها سوية باستخدام طريقة الأصغر- الأكبر، تزيد من كفاءة محددة الوجه الطيفية اتجاه التنوع في هندسة الأوجه و الإضاءة. أي صورتان للوجه تعتبر مختلفتين بالاعتماد على المسافة الارتباط. تم استخدام حدا بمقدار (10.5×107) لمنع الصور الدخيلة من أن تميز داخل المنظومة. نتائج الاختبارات عبرت عن مدى فعالية الطريقة الجديدة المطبقة في حالة الأنواع المختلفة ل(أنواع الضوضاء، صور الوجه الدخيلة، تعابير الوجه، الإضاءة، والأحجام) بمقدار 100%.

BP	Backpropagation	MD	Minimum Distance Classification
CN	Convolution Network	MI	Moment Invariant
DCT	Discrete Cosine Transform	NN	Nearest Neighbor Classification
FFT	Fast Fourier Transform	PCA	Principal Component Analysis
HMM	Hidden Markov Model	RBFN	Radial Basis Function Network
LDA	Linear Discriminate Analysis	SOM	Self-Organizing Map

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1. Introduction

Biometrics is fundamentally concerned with digitally encoding physical characteristics of the user's voice, eye, hand or face to a single ID. Biometrics applications require reliable and automatic personal identification for effective application requirements. Traditional, automatic, personal identification can be divided into two categories: token-based, such as a physical key, an ID card and a passport, and knowledge-based, such as a password. However, these approaches have some limitations. In the token-based approach, the "token" can be easily stolen or lost. In the knowledge-based approach, to some extent, the "knowledge" can be guessed or forgotten. Thus, biometric personal identification is emerging as a powerful means for automatically recognizing a person's identity [1]. Identification can be applied in a closed system such as employee positive identification for building access, or in an open system such as a national ID system. Positive biometric identification, a 1-to-many problem, is more challenging than verification, a 1-to-1 problem. As stated in, "positive identification is perhaps the most ambitious use of biometrics technology" [2]. Figure (1) is a simple biometric system has four important components and two phases [1]:

1. Sensor: This captures the biometric data of an individual.
2. Feature Extraction: is the stage in which the acquired data is processed to extract feature values.
3. Matching phase: is carried out when the feature values are compared against those in the template by generating a matching score.
4. Decision-making phase is done when the user's claimed identity is either accepted or rejected based on the matching score generated in the matching module.

The enrolment phase: is responsible for enrolling an individual into the biometric system. During the enrolment phase, biometric characteristics of an individual are first scanned to produce a raw digital representation of the characteristics. In order to facilitate matching, a feature extract to generate a compact but expressive representation, called a template, further processes the raw digital representation of the template may then be stored in a central database or recorded on a magnetic card or smart card (and issued to an individual) depending on the nature of the application. The identification phase: is responsible for identifying individuals at the point of access. During the operation phase, the biometric reader captures the characteristics of individuals to be identified and converts it to a digital format, which is further processed by the extractor to produce the same representation. The ensuing image is fed to the feature matcher who compares it against the templates to establish the identity [1].

The following factors are needed to have a successful biometric identification method [1]:

1. The physical characteristic should not change over the course of the person's lifetime
2. The physical characteristic must identify the individual person uniquely
3. The physical characteristic needs to be easily scanned or read in the field, preferably with inexpensive equipment, with an immediate result
4. The data must be easily checked against the actual person in a simple, automated way. Other characteristics that may be helpful in creating a biometric identification scheme are[1]:

1. Ease of use by individuals and system operators,
2. The willing (or knowing) participation of the subject is not required

Face identifications fill into three categories: holistic methods, which use the whole face image for recognition, feature-based methods, which use local regions such as eyes or mouth, and hybrid methods, which use both local regions and the whole face. In spite of this, face identification technology seems to be a difficult task to develop since the appearance of a face varies dramatically because of illumination. Facial expression, head pose, and image quality determine the recognition rate. In addition, the number of the same face in the database with different facial expression should be sufficient so that the person can be identified in all possible situations [3]. Many reserch on face identification based on Principal Component Analysis (PCA). However, any system in this world has its limitations and can be improved. To overcome the disadvantages of PCA, such as large computational load and low discriminatory power it can be combined with other techniques. Table (1) illustrates the recent research on face identifications based on PCA feature vector, with varying types of similarity methods, result in varying recognition rates. . Mao, use PCA, and Nearest Neighbor Classification (NN) with 85% recognition rate or Minimum Distance Classification (MD) with 77% recognition rate. Sim, use PCA and Convolution Network (CN) with 78% recognition rate, while Lawrence, and find it 83%. Su use PCA, FFT, and Linear Discriminate Analysis (LDA), and Radial Basis Function Network (RBFN) with 97% recognition rate. Zhao use PCA, and Linear Discriminate Anal (LDA), with recognition rate of 92%. Phrasal, use PCA with recognition rate of 95%. Huang use PCA, and Back propagation (BP), with recognition rate of 92%.

The objective of this paper is to present a novel spectral eigenface implementation, as proposed means for human identification. A threshold is used to restrict the impostor face image from being identified. The experimental results point up the effectiveness of a new method in either using different) noisy images, unknown image, face expressions, illumine, and scales) .

In the following subsections, background knowledge is presented in section 2. Secondly, the purposed spectral eigenface is in Sections 3. In Section 4, Excrement results, followed by a conclusions in Section 5.

2. Background

2.1 Discrete Time Fourier Transform

Once the signal has been acquired and digitized, it can be converted to the frequency domain by using Fast-Fourier-Transformed (FFT). The FFT results can be either real and imaginary, or magnitude and phase, functions of frequency. The choice of output format belongs to the user. the transform and inverse transform pair given for vectors of length N by [4]:

$$X(k) = \sum_{j=1}^{N} x(j) y_N^{(j-1)(k-1)} \quad ,\ldots\ldots (1)$$

$$x(j) = 1/N \sum_{k=1}^{N} X(k) y_N^{-(j-1)(k-1)} \quad ,\ldots.. (2)$$

Where

$y_N = e^{(-2pi)/N}$ is the Nth root of unity.

2.2 Correlation Implementation Using FFT

Let X, and Y be data sets such that, correlations based FFT is defend as: take FFT of X, and FFT of Y, multiply one resulting transform by the complex conjugate of the other, and inverse transform the result product such as [5]:

$$Corr(X,Y) = IFFt(FFT(X) * FFT(Y)) \quad ,\ldots (3)$$

2.3 Eigenface

Eigenface or the Principle Component Analysis (PCA) is a statistical measurement method, which operates in the linear domain and can be used to reduce the dimensionality of an image. A face image can be viewed as vectors and represented in matrix form. This method can be described as follows [4]:

Let I denote a $n_1 \times n_2$ gray scale image. We then can represent it by means of a vector, $x = n_1 \times n_2$, which can be seen as a point in Rn. When performing PCA on these vectors, the eigenvectors obtained from the sample covariance matrix are called Eigenfaces. Here are the steps to computing these Eigenfaces [4]:

1. Obtain face images I1, I2,..., I M (training faces).
2. Represent every image Ii as a vector xi.
3. Compute the average face

$$y = \frac{1}{M} \sum_{i=1}^{M} x_i \quad , \qquad \ldots\ldots.(4)$$

4. Subtract the mean face

$$j_i = x_i - y_i , \qquad \ldots\ldots\ldots(5)$$

5. Compute the covariance matrix

$$C = \frac{1}{M} \sum_{n=1}^{M} j_n j_n^T = AA^T \quad , \qquad \ldots\ldots(6)$$

6. Compute the eigenvectors ui of AAT :

6.1 Consider matrix AAT as an MxM matrix.
6.2 Compute the eigenvectors vi of AAT such that

$$A^T A v_i \Rightarrow m_i v_i \Rightarrow AA^T A v_i = m_i A v_i \Rightarrow C u_i = m_i u_i$$

$$m_i = A v_i, \qquad \text{……….(7)}$$

where 6.3 Compute the M best eigenvectors of AAT:

$$m_i = A v_i, \qquad \text{………..(8)}$$

7. Keep only K eigenvectors.

2.4 Normalization

A feature is normalized by scaling its values so that they fall within a small-specified range, such as 0.0 to 1.0. For distanced-based methods, normalization helps prevent features with initially large ranges from outweighing features with initially smaller ranges. Min-max normalization performs a linear transformation on the original data. Suppose that mina and max are the minimum and the maximum values for feature A. Min-max normalization maps a value v of A to v' in the range [newmin, newmax] by computing:

$$v' = ((v - mina)/(max - mina)) \times (new_{max} - new_{min}) + new_{min}, \qquad \text{… …. (9)}$$

2.5 Eigenface Matching

Let X and Y be two spectral eigenface feature vectors where, xi$\in$ X, yi $\in$ Y, i=1,…,n. to calculate the degree of association, a correlation distance is defined as[5]:

$$R = 1 - r, \qquad \text{…… (10)}$$

where r is the linear correlation coefficient which is given by the formula [5]:

$$r(X,Y) = \frac{\sum_{i=1} (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1} (x_i - \bar{x})^2} \sqrt{\sum_{i=1} (y_i - \bar{y})^2}} \qquad \text{…..(11)}$$

where $\bar{x}$ is the mean of the vector X, $\bar{y}$ is the mean of the vector Y.
the correlation distance determines the genuine or forged query sample, it is easy to verify the input pattern by a pre-defined threshold value T. If the value R is smaller than threshold T, then the owner of query sample is claimed to be individual X. Otherwise, the query sample is classified as a forged pattern.

2.6 Threshold Selection

In any face identification system, it is essential to pike a suitable threshold (T), for a good performers results. To this end, an approach based on intra-class and inter-class information collected from the Enrolment database. The intra-class (D) measures the distances between images of the same individual, therefore it gives an indication of how similar the images of the same individual are. The intra- distance is defined as:

$$d_{ik}^{ik'} = (1 - r(\Omega_{ik}, \Omega_{ik'})), \text{ Where } i \in I \text{ I}, k' \in K, \text{ and } K \neq K', \qquad \text{… ….(12)}$$

The inter-class (P): The distances between the images of an individual are measured against the images of other individuals in the Enrolment database, therefore it gives an indicates how different each image of an individual is when compared to images of other individuals in the Enrolment database. The inter-distance is defined as:

$p_{ik}^{ik'} = (1 - r(\Omega_{ik}, \Omega_{jl}))$, Where $j \in I$, $i \neq j$, and $l, k \in K$,………....(13)

A threshold (T) is then calculated from intra-class and inter-class information as described in [2]. The estimation of threshold (T) depends mainly on the number of images per individual in Enrolment, therefore as in [3], every individual should have at least 4 images for Enrolment database. The algorithm for the maximum intra-class and the minimum inter-class calculation is described as:

Input: $I = \{1, ... I'\}$, where I' = number of individuals, $K = \{1, ..., K'\}$, where K' = number of images per individual, Fik= normalized Face image feature vector i∈ I and k ∈ K

Ω = feature matrices of training images for each image

Output: Dmax=Maximum intra-class , and Pmin=minimum inter-class

Process:

Step1: Do while the $(\text{Fik} \neq 0)$

Step2: Compute the intra distances, and the inter distances

Step3: End of while

Step4: Store the intra-class (D), and the inter-class (P) in ascending order

Step5: Compute Dmax, and Pmin .

Step6: End.

2.7. Eigenface Identification Process

An unknown query face image can be represented as a linear combination of the best K Eigenfaces of the obtaining eigenvectors for a given dataset. In face identification, the eigenfaces are used once again in order to compute a distance from the query image in the face space, as presented in Figure (2). The algorithm is summarized below:

Input: an unknown image vector x

Output: matching result

Process:

Step1.

Compute $j = \text{x} - \text{y}$,………..………(14)

Step2. Compute

$j^{\wedge} = \sum_{i=1}^{k} \text{w}_i u_i$ where $w_i = u_i^T j$,…..(15)

Step3. Compute $\text{D}_e = \left\| j - j^{\wedge} \right\|$,…… (16)

Step4. If $\text{De} < \text{T}$, then x is a face. De is the distance from face space.

3. The proposed Spectral Based Eigenface Feature

The new proposed idea of applying the FFT in the implementation for Eigenface is by use FFT in the implementation of the correlation, as an alternative of conventional ideas of converting the intensity of the image face data into the spectral domain, followed by applying the Eigenface. The new proposed idea is named as the spectral based eigenface feature.

The correlations can be computed by using the FFT as follows: FFT the two data sets, multiply one resulting transform by the complex conjugate of the other, and inverse transform the product.

Hence, by evaluating this cross correlation, a speed up ratio can be obtained comparable to conventional Eigenface. Let I denote a $n_1 \times n_2$ gray scale image. We then can represent it by means of a vector, $x = n_1 \times n_2$, which can be seen as a point in Rn . Here are the steps to computing these Eigenfaces:

1. Obtain face images I1 , I2 ,..., I M (training faces).
2. Represent every image Ii as a vector xi .
3. Compute the average face $y = \frac{1}{M}\sum_{i=1}^{M} x_i$
4. Subtract the mean face $j_i = x_i - y_i$
5. Compute the covariance matrix $C = IFF(FF(j)FF(j^T)) = AA^T$
6. Compute the eigenvectors ui of AAT :

6.1 Consider matrix AAT as an $\mathrm{M} \times \mathrm{M}$ matrix.

6.2 Compute the eigenvectors vi of AAT such that:

$$A^T A v_i \Rightarrow m_i v_i \Rightarrow AA^T A v_i = m_i A v_i \Rightarrow C u_i = m_i u_i$$

where $m_i = Av_i$

6.3 Compute the M best eigenvectors of AAT: $m_i = Av_i$

7. Keep only K eigenvectors.

4. Experiment Results

A set of faces full between April 1992 and April 1994 at the Olivetti Research Laboratory (ORL) in Cambridge, UK. There is 10 different images of 40 distinct individuals. The images were taken at different times, varying illuminance, facial expressions "open/closed eyes, smiling/non-smiling " and facial details "glasses/no-glasses,"", a sample of the used images is in Figure(3). All the images are taken against a dark homogeneous background and the individuals are in up-right, frontal position "with acceptance for some side movement". The files are in PGM format, with a size of each image is 92x112, 8-bit grey levels. The Enrolment Database consists of 160 normalized spectral eigenfaces, 4 for each individual. A threshold T is calculated for the enrolment database, to prevent unknown individual from being identified and found to be equal to 10.50×10^7.

The rest 360 normalized spectral eigenfaces, 6 for each individual, is used in the identification phase, the results are depicted in Table (2). The result of any identification goes in one of four situations. A correct identification: identify an individual already registered in the enrollment database. A correct refusal: refuse an individual not registered in the enrolment database. A wrong acceptance: accept an imposter not registered in the enrolment database, or to identify imposter as someone in the database incorrectly. Wrong refusal: refuse a genuine user registered in the enrolment database, or to identify the genuine users as unknown incorrectly.

The performance of the spectral eigenfaces approach is study under different conditions either from the 360 rest images or out of it, as depicted in bellow subsections.

Identification With Different Head Tilts: The robustness of the spectral eigenfaces identification algorithm to head tilt is studied, with different head tilts either left-oriented or right-oriented, top-orientation, and down-orientation as shown in Figure (4(a-e)).

Identification with Varying Illuminance: The robustness of the spectral eigenfaces identification algorithm to head tilt is studied, as depicted in Figure (5(a-c)) with face images moved by 45 degrees and the other with light moved by 90 degrees.

Identification with Varying Head Scale: The robustness of the spectral eigenfaces identification algorithm studied, with a medium head scale and the other with a small one, as shown in Figure (6(a-c)).

Identification With Different Face Expression: The robustness of the spectral eigenfaces identification algorithm is studied, with different head face expression either smiling, eye move, with glasses, and smiling with glasses as shown in Figure (7(a-e)).

Identification with Different Noise Type and Level: The robustness of the spectral eigenfaces identification algorithm over noise image, with different noise types as shown in Figure (8(a-c)). Table (3) represents the parameters of the used varying types of noise. Table (3) represents the result of the identification.

Identification with Unknown Face Images: The robustness of the spectral eigenfaces identification algorithm is studied, with different unknown face images for boys and girls with glass and without, with varying faces expressions, as shown in Figure (9(a-d)). The result of the identification is depicted in Table (5).

5. Conclusions

this paper investigate the ability of implementing the eigenfces in the frequency domain by using the FFT as a means for Human identification. The ORL face images are used to evaluate the performance of new proposed algorithm, which is implemented by using Matlab 7 as programming language. The proposed eigenface based FFT system is investigated and it found that:

1. the used of min-max approch as a normalization method for the result feature vector is to remove the outliner in the enrolment database.
2. The benefit of using a threshold is to prevents the impostor from being identified.
3. One of the major advantages of spectral eigenfaces recognation approch is the ease of implementation. Futhermore, no knowledge of geometry or specific feature of the face is required, and only a small amount of work is needed regarding preprocessing for any type of face images.

4. The robustness of the spectral eigenfaces identification algorithm to head tilt is studied, using images depicted in Figure(4(a-e)).
5. The robustness of the spectral eigenfaces identification algorithm to varying luminance is studied using images as depicted in Figure(5(a-c)).
6. The roubustness of the spectral eigenfaces identification algorithm studied with varying head scale as depicted in Figure (6(a-c)).
7. The robustness of the spectral eigenfaces identification algorithm studied with different face expression as depicted in Figure (7(a-e)).
8. A different noise types as in depected in Table (3) are used to investigate the application of spectum eigenface in different noise levels, and the method gives a success of spectrum eigenface in different noise levels, and the method gives a succes identification of 100%. Table(4) depicts the effectiveness of the proposed method.
9. The robustness of the spectral eigenfaces identification algorithm is studied, with different unknown face images for boys and girls with glass and without , with varying faces expressions as in Table(5), with identification of 100%

6. References

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Table (1): Success Face Recognition Rates for Various Algorithms. [8]

Author	Algorithm	Average Rate of Success Face Recognition	Recognition Time
Mao	PCA + NN	85%	n.a.
	PCA + MD	77%	n.a.
	LDA + NN	89%	n.a.
	LDA + MD	84%	n.a.
Sim	PCA + CN	78%	n.a.
	SOM + CN	85%	n.a.
Su	FFT + PCA + LDA + RBFN	97%	n.a.
Zhao	PCA + LDA	92%	n.a.
Phiasai	PCA + MI	95%	n.a.
Lawrence	PCA + CN	83%	n.a.
Eickeler	HMM + DCT	100%	1.5s (PII/400 Mhz)
Huang	PCA + BP	99%	n.a.

Table (2): The results of identification

No. of test images	No. of Correct identifications	No. of Correct Refuse identifications	No. of Rung Acceptance identifications	No. of Range Refuse identifications
360	360	0	0	0

Table (3): Noise tyeps parameters

Solt and Paper	Gaussian	Poisson
Noise Density = 0.01	Mean = 0 Variance = 0.01	-

Table (4): The result of identification

No.of test images	No.of Correct identifications	No.of Correct Refuse identifications	No.of Rong Acceptance identifications	No. of Ronge Refuse identifications
30	30	0	0	0

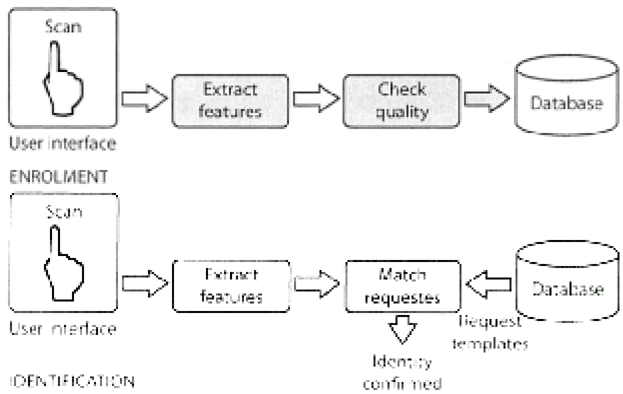

Figure (1): The Identification System.

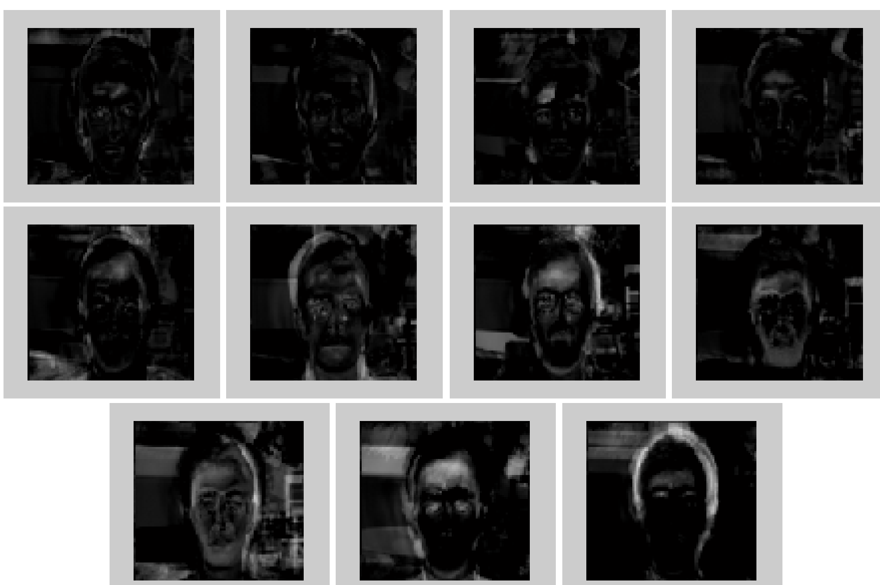

Figure (2) : Sample Eigenfaces for a given database [6].

Figure (3): A sample of the ORL Face Images

a: Original b: Left c: Right d: Down e: Top

Figure (4(a-e)): The Face images with viring head tilts.

a: Original b: light moved by 45 degress c: light moved by 90 degrees

Figure (5(a-c)): Face Image with varying illuminance.

a: Original b: Small scale c: Big scale

Figure (6(a-c)): A face image with varying scales.

a: original b: with glasses c: smiling d: eye moved e: smiling with
Up glasses

Figure (7(a-e)): A face image with varying face expressions

a: Salt and Paper b: Gaussian c: Poissan

Figure (8(a-c)): A face image with varying noise types

a: sample 1 b: sample 2 c: sample 3 d: sample 4

Figure (9(a-d)): A sample of the used unknown individuals face image