A Discriminant Pseudo Zernike Moments in Face Recognition

Ying-Han Pang, Andrew B.J. Teoh and David C.L. Ngo
Faculty of Information Science and Technology, Multimedia University
Jalan Ayer Keroh Lama, 75450 Melaka, Malaysia
Email: {yhpang, bjteoh, david.ngo}@mmu.edu.my

This paper introduces a novel discriminant moment-based method as a feature extraction technique for face recognition. In this method, pseudo Zernike moments are performed before the application of Fisher’s Linear Discriminant to achieve a stable numerical computation and good generalization in small-sample-size problems. Fisher’s Linear Discriminant uses pseudo Zernike moments to derive an enhanced subset of moment features by maximizing the between-class scatter, while minimizing the within-class scatter, which leads to a better discrimination and classification performance. Experimental results show that the proposed method achieves superior performance with a recognition rate of 97.51% in noise free environment and 97.12% in noise induced environment for the Essex Face94 database. For the Essex Face95 database, the recognition rates obtained are 91.73% and 90.30% in noise free and noise induced environments, respectively.

ACM Classification: I.5.4. (Computer Methodologies-Pattern Recognition – Applications)

1. INTRODUCTION

The face is one of the physiological biometrics. Faces share a common structure in which facial features are always formed in a similar respect. Given this universality, faces possess a unique class of features for face representation. Thus, we can distinguish between different people based upon their facial appearance. Face based recognition systems require significantly less interaction than the other biometric systems because of their adaptability. Individuals are identified actively, by standing in front of a camera, or passively, when they walk past a camera. Thus, the benefit of face authentication has been appreciated in a wide range of applications such as banking services, immigration, computer networks, as well as restricted area and forensic applications. Typically, there are two classes of face recognition methods: structural- and statistical-based approaches. Structural-based approaches utilize priori information or local features of the face (such as eyes, nose, mouth and facial outline) for recognition. An example of this type of approach is Elastic Bunch Graph Matching (Wiskott et al., 1999). On the other hand, statistical-based approaches employ global information, which is fundamentally represented by underlying statistical regularities derived from the image pixels. Bartlett et al. (2002), Chellappa et al. (1995), Er et al. (2002), Hjelmas and Low (2001), Kruger and Sommer (2002), Pentland (2000) and Samal and Iyengar (1992) reported that statistical techniques play a very important role in developing face recognition methods. Some examples are Eigenfaces, Fisherfaces, Gabor wavelet, Independent
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Component Analysis etc. Besides that, pseudo Zernike moments, a statistical-based method, was introduced by Javal et al. (2002) and Pang et al. (2004) as a facial feature descriptor in their face recognition system and a superior recognition performance was obtained. This method possesses advantages of geometrical invariance, robustness to noise, optimal feature representation and nearly zero information redundancy (Teh and Chin, 1988).

A good facial feature extractor should consider representation as well as classification issues (Liu and Wechsler, 2002). Pseudo Zernike moments, hereinafter abbreviated as PZMs, are optimal for image reconstruction from their moment basis (known as weighting kernel). In other words, PZM is a good feature representation, but it may not be an optimal classifier as its discrimination power mainly depends on the image intensity value. On the other hand, Fisher’s Linear Discriminant, hereinafter denoted as FLD, (Swets and Weng, 1996; Belhumeur et al., 1997; Zhao et al., 1998) is one of the most dominant algorithms in face recognition. However, it met some difficulties at the beginning. Since the dimension of faces is tremendously high and the face samples are usually inadequate in face recognition, the intra-class scatter matrix degenerates to be singular (Qiong Yang et al., 2003).

In view of the abovementioned limitations, a novel Discriminant Moment feature extraction technique is introduced in this paper. In this method, PZM is performed before FLD to avoid such matrix degeneration and achieve a stable numerical computation and good generalization in small-sample-size problems. PZM compacts the original tremendously-high-dimensional image space into a considerably-low-dimensional feature space. Therefore, this renders the non-singularity of the intra-class scatter matrix. The introduction of FLD into moment analysis derives an enhanced subset of moment features by maximizing the between-class scatter, while minimizing the within-class scatter, which leads to a better discrimination and classification performance.

Figure 1 demonstrates the overview of our proposed system. From the figure, we can see that the dimensionality of the original cropped face image ($N^2$) is reduced drastically into a feature vector with length $l$ (where $l << N^2$) via PZM. This feature vector contains the dominant and significant image features, but the redundant information of the image is excluded. The dimensionality reduction is to achieve good generalization. Then, FLD is conducted on the moment features to increase the discrimination between classes. In other words, the dimensionality of the moment feature vector is further reduced into a discriminant moment feature vector with length $f$ (where $f < l$) under Eigenvectors selectivity scheme of FLD. The objective is to derive a lower-dimensional feature representation with enriched distinguishability by maximizing the between-class scatter, while minimizing the within-class scatter. In other words, the proposed method not only enhances the discrimination power, but also performs dimensionality reduction task.

![Figure 1: Overview of our proposed feature extraction method.](Image)

Original image with dimensionality $N^2$  
Moment feature vector with length $l, l << N^2$  
Discriminant moment feature vector with length $f, f < l$
To test the effectiveness of Discriminant Moment (DM) representation, we experiment on two databases: the Essex Face94 and Face95 databases assembled by the Computer Vision Group of Essex University. Experimental results show that the DM method achieves superior performance with a recognition rate of 97.51% in a noise-free environment and 97.12% in a noise-induced environment for the tests on the Essex Face94 database with significant facial expression variations. However, the proposed method shows recognition rates of 91.73% and 90.30% in noise-free and noise-induced environments, respectively, in Essex Face95 database with significant illumination variations.

2. PSEUDO ZERNIKE MOMENTS

In 1934, Zernike introduced a set of complex polynomials which form a complete orthogonal set over the interior of the unit circle, i.e., $x^2 + y^2 = 1$. The proposed polynomials, known as Zernike polynomials, are denoted by $\{V_{pq}(r, \theta)\}$ in polar coordinates (Mukundan and Ramakrishnan, 1998):

$$V_{pq}(x, y) = V_p(r, \theta) = R_{pq}(r)e^{-j\theta} = R_{pq}(r)(\cos q\theta - j\sin q\theta)$$  \hspace{1cm} (2-1)

where $p$ positive integer or zero, $q$ positive and negative integers subject to constraints of $|q| \leq p$ and $p - |q|$ is even

$r$ length of vector from the origin of unit circle to $(x, y)$ pixel

$\theta$ angle between vector $r$ and $x$ axis in counterclockwise direction

$R_{pq}(r)$ is a set of real-valued radial polynomials with definition:

$$R_{pq}(r) = \sum_{k=|q|}^{p+q} (-1)^k \frac{(p-k)!}{k!(p+q)|q| - k(p+q)|q| + p+q+1-s)!} p^{p-r}$$  \hspace{1cm} (2-2)

Note that $R_{-p,q}(r) = R_{p,q}(r)$ and $R_{pq}(r)$ also subject to the constraints in Eq (2-1).

The moment formulation from these Zernike polynomials, Zernike moment, appears to be one of the most popular feature representatives, which outperforms the others in terms of noise resilience, information redundancy and reconstruction capability (Teh and Chin, 1988). However, the constraints in Eq (2-1) limit Zernike polynomials to only containing $\frac{1}{2}(p+1)(p+2)$ linearly independent polynomials (Teh and Chin, 1988), in which fewer features are generated by Zernike moments to represent the image. This causes Zernike moments to achieve inferior feature representation performance.

Therefore, an improved version of Zernike polynomials, denoted as pseudo Zernike polynomials, was proposed by Bhatia and Wolf (1954). This set of polynomials differs from that of Zernike in that the real-valued radial polynomials are defined as:

$$\hat{R}_{pq}(r) = \sum_{s=0}^{p+q} (-1)^s \frac{(2p+1-s)!}{s!(p-|q|-s)(p+q+1-s)!} p^{p-s}$$  \hspace{1cm} (2-3)

where now $p$ positive integer or zero, $q$ positive and negative integers subject to constraint of $|q| \leq p$ only.
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Thus, pseudo Zernike moments, formed by pseudo Zernike polynomials, contain more features \((p+1)^2\) linearly independent polynomials), leading to a better feature representation.

The two-dimensional pseudo Zernike moments of order \(p\) with repetition \(q\) of an image intensity function \(f(r,\theta)\) are defined as (Mukundan and Ramakrishnan, 1998; Teh and Chin, 1988):

\[
P_{p}^{q} = \frac{p+1}{\pi} \int_{0}^{2\pi} \hat{V}_{pq}(r,\theta) f(r,\theta) r dr d\theta
\]  

(2-4)

where pseudo Zernike polynomials \(\hat{V}_{pq}(r,\theta)\) are defined as:

\[
\hat{V}_{pq}(r,\theta) = \hat{R}_{pq}(r) e^{-j\theta} ; \quad j = \sqrt{-1}
\]  

(2-5)

where \(\hat{R}_{pq}(r)\) is the real-valued radial polynomials of pseudo Zernike moments, as defined in Eq (2-3).

For a digital image, the integrals in Eq (2-4) are replaced by summations to get

\[
P_{p}^{q} = \frac{p+1}{\pi} \sum_{x} \sum_{y} f(x,y) \hat{V}_{pq}(x,y), \quad x^2 + y^2 \leq 1
\]  

(2-6)

To compute pseudo Zernike moments of a given image, the centre of the image is normally taken as the origin and the pixel coordinates are mapped to the range of the unit circle, i.e. \(x^2 + y^2 = 1\). Those pixels failing outside the unit circle are not used in the computation and this might cause important information to be lost. To avoid this, we apply linear transformation technique proposed by Chong et al (2003), see Figure 2. Using this linear transformation, the discrete version pseudo Zernike moments are defined as:

\[
P_{p}^{q} = \lambda(p,N) \sum_{x=0}^{N-1} \sum_{y=0}^{N-1} \hat{R}_{pq}(r) e^{-j\theta} f(i,j)
\]  

(2-7)

where

\[
\begin{align*}
    r_0 &= \sqrt{x_i^2 + y_j^2}, \\
    \theta_0 &= \tan^{-1} \left( \frac{y_j}{x_i} \right), \\
    x_i &= c_1 x + c_2, \\
    y_j &= c_1 y + c_2
\end{align*}
\]

(2-8)

\[
\lambda(p,N) = \frac{2(p+1)}{\pi (N-1)^2}, \quad c_1 = \frac{\sqrt{2}}{N-1}, \quad c_2 = \frac{-1}{\sqrt{2}}
\]  

(2-8)

Figure 2: Coordinate normalization scheme for moments. (a) Discrete image coordinate space of size \((N \times N)\). (b) Image coordinate normalization using the mapping \((0, N-1) \rightarrow (\frac{-1}{\sqrt{2}}, \frac{1}{\sqrt{2}})\).
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3. DISCRIMINANT MOMENT METHOD

In the Discriminant Moment (DM) method, a pseudo Zernike moment (PZM) is performed before the computation of Fisher’s Linear Discriminant (FLD) for discriminatory enhancement. Through this method, the dimensionality of the original image is dramatically reduced via PZM and FLD computations in order to derive a lower-dimensional feature vector with enhanced discrimination power. This proposed method not only achieves a stable numerical computation and good generalization in small-sample-size problems, but also provides effective low-dimensional representation of signals.

FLD is a popular discriminant criterion that measures the between-class scatter normalized by the within-class scatter (Fukunaga, 1991). FLD focuses on the underlying class structure of the image and “shapes” the class scatter by maximizing the between-class scatter and minimizing the within-class scatter in order to acquire an enhanced feature vector with high separability. In our proposed method, the input of FLD is the moment feature vector (vector consists of moment components), instead of the intensity value of image pixels. Let us consider a set of Q moment facial representations \( \{x_j = PZ_{pq,j}, j = 1,2,3, \ldots, Q \} \) having \( l \) dimension and assume there are \( C \) face classes \( \{w_1, w_2, \ldots, w_C\} \) and the number of face images within each face class is \( Q' \), \( \{x_{1i}, x_{2i}, \ldots, x_{Qi}, i \ is \ ith \ class \} \). Let \( M_i \) and \( M_g \) and be the mean of the \( i \)th class and the grand mean, respectively. The within- and between-class scatter matrices, \( S_w \) and \( S_b \), are defined as follows (McLachlan, 1992):

\[
S_w = \sum_{i=1}^{C} \sum_{x_{ik} \in w_i} (x_{ik} - M_i)(x_{ik} - M_i)' 
\]
\[
S_b = \sum_{i=1}^{C} Q (M_i - M_g)(M_i - M_g)'
\]
\[
M_i = \frac{1}{Q_i} \sum_{x_{ik} \in w_i} x_{ik}
\]
\[
M_g = \frac{1}{Q} \sum_{i=1}^{C} M_i
\]

Note that \( x \) and \( \hat{x} \) are pseudo Zernike moment-based features, \( PZ_{pq} \), defined in Eq (2-7). FLD in DM method derives a projection matrix \( \psi \) which maximizes the ratio of the determinant of the between-class scatter matrix to the determinant of the within-class scatter matrix, i.e.,

\[
\psi = \arg \max_{\psi} \left| \psi^T S_b \psi \right| \left| \psi^T S_w \psi \right|
\]

where \( \{\psi_i | i = 1,2,3, \ldots, m\} \) is a set of generalized eigenvectors of \( S_b \) and \( S_w \) corresponding to the \( m \) largest generalized eigenvalues \( \{\lambda_i | i = 1,2,3, \ldots, m\} \). In other words, the ratio is maximized when \( \psi \) consists of the eigenvectors of the matrix \( S_b^{-1} S_w \) (Swets and Weng, 1996):

\[
S_b^{-1} S_w \psi = \lambda \psi
\]

\[
S_w \psi = \lambda S_w \psi
\]
There are at most \( c-1 \) non-zero generalized eigenvalues (Duda and Hart, 1973), thus the upper bound of \( m \) is \( c-1 \) where \( c \) is the number of face classes. In this paper, \( m = c-1 \) is set in all the experiments.

Since we have fixed the value of \( m \) for eigenvectors generation in FLD, the only factor that influences the recognition performance of DM is moment length \((l)\). In order to observe the influence of moment length on the recognition performance, a seven classes data set is considered.

![Figure 3: A comparison with Discriminant Moment method of moment length, (a) \( l=100 \) and (b) \( l=300 \), respectively for a seven classes data.](image)

Figure 3: A comparison with Discriminant Moment method of moment length, (a) \( l=100 \) and (b) \( l=300 \), respectively for a seven classes data.
of moment length in DM, a low dimensional analogue to the classification problem is illustrated, in which the face representations represented by discriminant moment features lie on a linear feature subspace. Figure 3(a) and 3(b) show the discriminant moment feature distributions of seven face classes for $l = 100$ and $l = 300$, respectively. For this example, 500 face images are transformed into their corresponding discriminant moment feature vector via the proposed method with $m = c-1$. Then, we randomly select 35 discriminant moment feature vectors formed by 35 face images from seven face classes where each class consists of five images. The samples from each class lie on a two-dimensional feature space because only the first two features with largest eigenvalues are taken into account. Comparing the two feature distributions in the figure, the DM method with lower moment length, e.g. $l = 100$, achieves greater between-class scatter and smaller within-class scatter, and, thus, a perfect classification is achieved. However, the proposed method with higher moment length, e.g. $l = 300$, obtains poorer classification performance, in which the method with $l = 300$ actually smears the classes together. The reason is a moment vector with larger length, e.g. $l = 300$, comprises redundant and unwanted information, such as noise, and this information may degrade the discriminability of FLD in the proposed method. On the other hand, a moment vector with suitable length, e.g. $l = 100$, provides significant and expressive image information to FLD to construct a powerful vector basis for linear subspace in order to learn which features are significant for recognition.

4. OUR FACE RECOGNITION SYSTEM

Our face based recognition system is divided into two phases, namely the enrolment phase and the recognition phase. During enrolment, users are requested to register by providing their facial data, called a training image, and personal identity information. Training images are input into PZM analysis to be transformed into a feature vector consisting of expressive features, $P_{Zpq}$. These moment features are then input into FLD for Fisherspace generation. Then, the training moment features are projected onto the Fisherspace to output a compact but expressive representation domain, denoted as a discriminant moment feature/template. The template is then stored in a centralized database. A private password and/or username are granted to the user as a key to retrieve the template from the database during recognition phase. During recognition, the system validates the user’s identity by comparing the generated testing discriminant moment features, obtained from his testing face image, with his own template stored in a database. Figure 4 illustrates the block diagram of our proposed face recognition system.

5. EXPERIMENTAL RESULTS AND DISCUSSIONS

We evaluate the performance of our proposed Discriminant Moment method in face recognition by using two sets of face databases, Essex Face94 with significant facial expression variations and Essex Face95 with significant illumination variations. The details of these databases can be obtained on the web page with URL http://cswww.essex.ac.uk/mv/allfaces/index.html. Comparative analysis is mainly carried out mainly between the original solely-PZM method and the proposed Discriminant Moment method. Besides, a comparative performance is also carried out against the other popular face recognition schemes, such as the Eigenfaces and Fisherfaces methods, in both noise free and noise induced cases. For all experiments, classification is performed by using a simple classifier- Euclidean distance metric, instead of more complex classifiers (such as neural network or SVM). This is because we are more concerned about the performance of the proposed method as feature extractor rather than the classification task.
5.1 Essex Face94 Database
In this experiment, the Essex Face94 database, which contains 100 face classes with 20 images per class, is used. Ten face images from each face class are used to construct a vector basis for linear subspace, known as Fisherspace. The other ten images are used as testing images for recognition. Figure 5 shows the recognition performance of Discriminant Moment (DM) and PZM methods in a noise free environment. This result vindicates the effectiveness of FLD in the proposed method, in which the method achieves superior performance to the PZM method. The best recognition rates obtained by DM and PZM methods are 97.51% and 95.80%, respectively, when $l = 120$.

Although the recognition rate shown in Figure 5 indicates that discriminant moment features carry discriminating information, leading to the better recognition, it does not necessarily mean that the DM method also possesses good representation and classification capabilities in a noise induced database. Thus, a comparative analysis is repeated by adding white Gaussian noise, $n_\sigma$, where $\sigma$ is a parameter that controls the noise intensity to face images. Figure 6 illustrates the face images with induced Gaussian noise of different $\sigma$. From Figure 7, we can see that the DM method again obtains a high recognition rate in the noise induced environment. This means that the DM method retains the property of pseudo Zernike moments, which is robustness to noise (Teh and Chin, 1988). This method attains 97.46% and 97.12% when $\sigma = 0.005$ and 0.01, respectively. The PZM method obtains 95.76% and 94.74% when $\sigma = 0.005$ and 0.01, respectively.
In order to make a fair comparison between the DM method and the other popular recognition schemes, all these methods have the same parameter settings, where the FLD length, \( m = c - 1 = 99 \) for the DM and Fisherfaces methods, and moment length, \( l = 120 \) for the DM and PZM methods, as well as principal component length = 120 for the Fisherfaces and Eigenfaces methods. The comparative face recognition performance of these methods is shown in Table 1 and we can see from the table that the DM method attains the highest recognition rate in both noise free and noise induced cases, followed by the Fisherfaces, Eigenfaces and PZM methods. This shows that discriminant moment facial representation, generated from the proposed method with the introduction of FLD, possesses improved discriminability that is a factor to achieve optimal recognition.

![Figure 5: Recognition performance of DM and PZM methods in noise free environment.](image)

![Figure 6: Face images with induced white Gaussian noise of different level of \( \sigma \).](image)
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Figure 7: Error and recognition rates of DM and PZM methods in noise induced environment.

(a) noise induced, $\sigma = 0.005$, environment

(b) noise induced, $\sigma = 0.01$, environment
5.2 Essex Face95 Database

Next, we design the experiments to access our proposed method under various illumination conditions by using the Essex Face95 database. In this database, there are 72 face classes and 20 face images per class. As in the previous experiments, ten face images from each face class are used to construct a Fisherspace. The other ten images are used as testing images for recognition. In Figure 8, the DM method with moment length, $l < 240$, performs better than the PZM method, but the former with $l > 240$ shows inferior performance. This justifies the statement in Section 3 that

![Figure 8: Recognition performance of DM and PZM methods in noise free environment.](image)

<table>
<thead>
<tr>
<th>Method</th>
<th>Noise level, $\sigma$</th>
<th>FAR (%)</th>
<th>FRR (%)</th>
<th>TSR (%)</th>
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<tbody>
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<td></td>
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<td>0.01</td>
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<td>Fisherfaces method</td>
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<td>95.8796</td>
</tr>
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</table>

Table 1: Comparative analysis among various face recognition schemes
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(a) noise induced, $\sigma = 0.005$, environment
(b) noise induced, $\sigma = 0.01$, environment

Figure 9: Error and recognition rates of DM and PZM methods in noise induced environment.
moments with larger length bring in high frequency information (e.g. noise) and redundant data that affect the separability of the DM method. The same circumstance also occurs when the face database is induced with Gaussian noise, as shown in Figure 9. From this figure, we can see that the proposed method obtains recognition rates of 91.73%, 91.23% and 90.30% in noise free and noise induced \((\sigma = 0.005 \text{ and } 0.01)\) cases, respectively; while, the PZM method possesses recognition rates of 88.02%, 87.73% and 86.54% in noise free and noise induced \((\sigma = 0.005 \text{ and } 0.01)\) cases, respectively.

Table 2 presents the error and recognition rates of the DM, PZM, Eigenfaces and Fisherfaces methods in the noise free and noise induced environments. From the table, the DM method shows slightly inferior performance than the Fisherfaces method. It seems that the Fisherfaces method selects optimal projections which can perform well over a range of lighting variations (Belhumeur et al., 1997); but, the DM method possesses better recognition rate compared to the PZM method. This means that the FLD in our proposed method improves the limitation of pseudo Zernike moments, which is sensitive and not invariant to the changes of contrast (Maitra, 1979). In the moment analysis of both the PZM and DM methods, image representation is a function of image intensity. This means that image intensity, is the main factor that causes the moment polynomials, varies among different images providing that the images have the same size. Therefore, illumination variation provides different moment-based features representing face images from the same class if the images are taken under various lighting condition. These inaccurate features result in large intra-class variations and then degrade the discrimination power of pseudo Zernike moments in the DM and PZM methods.

6. CONCLUSION
In this paper, we have introduced a novel Discriminant Moment (DM) method feature extraction technique for face recognition. This DM method firstly derives a moment-based feature vector produced from the pseudo Zernike moment (PZM) computation. Then Fisher’s Linear Discriminant (FLD) operates on the feature vector by maximizing the between-class scatter and minimizing the within-class scatter in order to derive a set of enhanced discriminant moment features. The proposed

<table>
<thead>
<tr>
<th>Method</th>
<th>Noise level, (\sigma)</th>
<th>FAR (%)</th>
<th>FRR (%)</th>
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Table 2: Comparative analysis among various face recognition schemes
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method appears to be the best at handling variation in facial expression as the FLD component in this method greatly improves the classification capability of PZM. The feasibility of the proposed method under facial expression variation condition has been successfully tested on face recognition using Essex Face 94 database. The recognition rates obtained are 97.51% in noise free case, as well as 97.46% and 97.12% when noise with $\sigma = 0.005$ and $\sigma = 0.01$ is induced, respectively. However, this method achieves inferior performance to the Fisherfaces method under significant illumination variation condition, tested using Essex Face 95 database. But, the DM method possesses a better recognition rate compared to the PZM method. In other words, the FLD in the DM method improves the limitation of pseudo Zernike moments, which are sensitive and not invariant to the changes of contrast (Maitra, 1979). Thus, our next goal is to further enhance our proposed method to develop the capability of robustness to noise.

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BIOGRAPHICAL NOTES

Pang Ying Han received her BEng (Electronics) with first class Honors from Multimedia University, Malaysia, in 2002. In 2005, she obtained her Master in Science from Multimedia University, Malaysia. She is currently working as a lecturer at the Faculty of Information Science and Technology, Multimedia University. Pang’s current research interests include biometrics, computer vision, and image understandings.

Andrew Teoh Beng Jin obtained his BEng (Electronics) in 1999 and PhD degree in 2003 from the National University of Malaysia. He is the Associate Dean of the Faculty of Information Science and Technology, Multimedia University, Malaysia. Teoh’s research interests are multimodal biometrics, pattern recognition, multimedia signal processing and Internet security.

David Ngo Chek Ling is an Associate Professor and the Dean of the Faculty of Information Science and Technology, Multimedia University, Malaysia. David was awarded a BAI in Microelectronics & Electrical Engineering and PhD in Computer Science from Trinity College, Ireland. Ngo is also a member of the Review Committee of Displays and Multimedia Cyberscape and is the chairman of Center of Biometrics and Bioinformatics (CBB) at Multimedia University.