# COMPARISON OF FACE RECOGNITION TECHNIQUES: THE EFFECTS OF FEATURES AND PARAMETERS SETTING

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FERFLETANANN UTTVERSITI MALAYSIA SABAH

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## CERTIFICATION

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Ervin Gubin Moung 31 July 2013



#### ASBTRACT

## Comparison of Face Recognition Techniques: The Effects of Features and Parameters Setting

Face recognition is an important biometric application. In this thesis, a comparison of two common techniques for face recognition is carried out under the same conditions. The first technique is the Principal Component Analysis (PCA) while the second is Linear Discriminant Analysis (LDA). In addition, the performance of PCA and PCA (with Radon) was also carried out. The Euclidean distance is used as the matching criteria. An investigation of the effect of the parameters of PCA on the performance of the face recognition system is carried out. First, it was found that the number of eigenvalues used affects the recognition rates of the system. The maximum number of eigenvalues used is 300. The equal correct rates increases from 1 until 40 to 80 eigenvalues used then become steady afterwards regardless of the image size used. Second, it was found that the higher the number of training images per person the lower the false acceptance rate. Third, the image size used effect the recognition rate when a fixed number of eigenvalues used. However, different image size has their own their optimum number of eigenvalues to achieve highest equal correct rate. When optimum eigenvalues used, their recognition rate did not vary significantly. A comparison of performance, time and resource used by all face recognition system is presented. Four individual systems are compared; PCA, PCA with Radon, LDA, and LDA with Radon. Each individual system gives recognition rate of 89%, 88%, 94%, and 92% respectively with LDA outperform the other three techniques. It was found that no improvement on recognition rate when PCA and LDA use the Radon Transform features as input showing that applying Radon Transform on properly normalized frontal image does not boost the recognition performance. When compared the individual system to the data fusion system, it was found out that data fusion system gives better recognition rate than all the individual face recognition system. Fusion of PCA, LDA, and LDA with Radon give the best recognition performance, giving 98% correct recall and reject rate, and uses 62.8 second process time and 22.2 MB space.



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#### ASBTRAK

Pengesanan wajah adalah satu aplikasi biometrik yang penting. Dalam tesis ini, perbandingan antara dua teknik umum untuk pengesanan wajah dijalankan di bawah keadaan yang sama. Teknik pertama adalah "Principal Component Analysis" (PCA) manakala yang kedua adalah "Linear Discriminant Analysis" (LDA). Di samping itu, perbandingan prestasi PCA dan PCA (dengan Radon) juga telah "Euclidean Distance" digunakan sebagai kriteria perpadanan. dijalankan. Penyiasatan terhadap kesan parameter PCA pada prestasi sistem pengesanan wajah telah dijalankan. Pertama sekali, bilangan "eigenvalues" yang digunakan memberi kesan terhadap kadar pengesanan sistem. Bilangan maksimum "eigenvalues" yang digunakan ialah 300. Kadar pengesanan meningkat dari satu sehingga 40 ke 80 "eigenvalues" yang digunakan dan kemudiannya menjadi stabil tanpa mengira saiz imej. Kedua, semakin tinggi bilangan imej "training" untuk satu orang lebih rendah kadar penerimaan salah. Ketiga, saiz imej yang digunakan memberi kesan terhadap kadar pengesanan apabila bilangan "eigenvalues" yang digunakan adalah tetap. Walau bagaimanapun, saiz imej berlainan mempunyai bilangan "eigenvalues" optimum tersendiri untuk mencapai kadar pengesanan tertinggi. Apabila bilangan "eigenvalues" optimum digunakan, perbezaan kadar pengesanan adalah tidak ketara antara imej saiz yang berlainan. Perbandingan prestasi, masa dan sumber yang digunakan oleh semua sistem pengesanan wajah dibentangkan. Empat sistem individu PCA, PCA (dengan Radon), LDA, dan LDA (dengan Radon) telah dibandingkan. Setiap sistem memberikan kadar pengesanan setinggi 89%, 88%, 94%, dan 92% dengan LDA mengatasi prestasi tiga teknik yang lain. Tiada peningkatan pada kadar pengesanan apabila PCA dan LDA menggunakan "Radon Transform" sebagai input dan ini menunjukkan bahawa aplikasi Radon Transform terhadap imej wajah depan yang "normalized" tidak meningkatkan prestasi pengesanan. Sistem gabungan data memberi kadar pengesanan yang lebih baik apabila dibandingkan dengan sistem individu. Gabungan PCA, LDA, dan LDA (dengan radon) memberi prestasi pengesanan yang terbaik, memberikan 98% peratus kadar penerimaan dan penolakan yang betul, dan menggunakan 62.8 saat masa proses dan 22.2 MB ruang.



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## LIST OF ABBREVIATIONS

1D	One Dimension
1IPP	One image per person
2D	Two Dimension
2DPCA+SVD-U	Two-Dimensional Principal Component Analysis and Singular
	Value Decomposition
2IPP	Two images per person
3D	Three dimension
3IPP	Three images per person
AdaBoost	Adaptive Boosting
ANN	Artificial Neural Network
AR	Aleix Martinez and Robert Benavente
ARENA	Memory-based algorithm for face recognition
AT&T	American Telephone & Telegraph
BIC	Bayesian intra/extrapersonal classifier
CAS-PEAL	Chinese Academy of Sciences-Pose, Expression, Accessories
	and Lighting
CBCL	and Lighting Center for Biological and Computational Learning
CBCL CC	
	Center for Biological and Computational Learning
сс	Center for Biological and Computational Learning Correct Classification
CC CCTV	Center for Biological and Computational Learning Correct Classification Closed Circuit Television
CC CCTV CMU	Center for Biological and Computational Learning Correct Classification Closed Circuit Television Carnegie Mellon University
CC CCTV CMU CPU	Center for Biological and Computational Learning Correct Classification Closed Circuit Television Carnegie Mellon University Central Processing Unit
CC CCTV CMU CPU CVL	Center for Biological and Computational Learning Correct Classification Closed Circuit Television Carnegie Mellon University Central Processing Unit Computer Vision Laboratory
CC CCTV CMU CPU CVL DCT	Center for Biological and Computational Learning Correct Classification Closed Circuit Television Carnegie Mellon University Central Processing Unit Computer Vision Laboratory Discrete Cosine Transform
CC CCTV CMU CPU CVL DCT DNWT	Center for Biological and Computational Learning Correct Classification Closed Circuit Television Carnegie Mellon University Central Processing Unit Computer Vision Laboratory Discrete Cosine Transform Discerete NonSeparable Wavelet Transform
CC CCTV CMU CPU CVL DCT DNWT EBGM	Center for Biological and Computational Learning Correct Classification Closed Circuit Television Carnegie Mellon University Central Processing Unit Computer Vision Laboratory Discrete Cosine Transform Discerete NonSeparable Wavelet Transform Elastic Bunch Graph Method
CC CCTV CMU CPU CVL DCT DNWT EBGM ECR	Center for Biological and Computational Learning Correct Classification Closed Circuit Television Carnegie Mellon University Central Processing Unit Computer Vision Laboratory Discrete Cosine Transform Discerete NonSeparable Wavelet Transform Elastic Bunch Graph Method Equal Correct Rate
CC CCTV CMU CPU CVL DCT DNWT EBGM ECR ESSEX	Center for Biological and Computational Learning Correct Classification Closed Circuit Television Carnegie Mellon University Central Processing Unit Computer Vision Laboratory Discrete Cosine Transform Discerete NonSeparable Wavelet Transform Elastic Bunch Graph Method Equal Correct Rate University of Essex face database



FaceVideoDB	Video based face database
FAR	False Acceptance Rate
FERET	Face Recognition Technology
FLD	Fisher Linear Discriminant
FRR	False Rejection Rate
GP	Genetic Programming
GTFD	Georgia Tech Face Database
нмм	Hidden Markov Model
HP	Hewlett-Packard
HSV	Hue Saturation Value
I(2D) <sup>2</sup> PCA	Incremental Two-Dimensional Two-Directional Principal
	Component Analysis
ICA	Independent Component Analysis
ID	Identification
IDU	A real time face detection, tracking and identification system
jpeg	Join Photographic Experts Group
KFDB	Korea Face Database
KLT	Karhunen-Loève transform
КРСА	Kernel Principal Component Analysis
ктр	Known testing database
LBP	Local Binary Patterns
LDA	Linear Discriminant Analysis
LFA	Local Feature Analysis
LLE	Locally Linear Embedding
LPCA	Linear Principal Component Analysis
LS-SVM	Least Square Support Vector Machine
MLPCA	Multilinear Principal Component Analysis
MID	Mugshot Identification Database
MIT	Massachusetts Institute of Technology
МоВо	Motion of Body
MPEG	Moving Picture Experts Group
MRTD	Machine Readable Travel Documents



ND HID	Notre Dame Human Identification Database
NFL	Nearest Feature Line
NIST	National Institute of Standard and Technology
OCPCA	Orthogonal Component Principal Component Analysis
OS	Operating system
PC	Personal computer
PCA-SIFT	Principal Component Analysis and Scale Invariant Feature
	Transform
PCA	Principal Component Analysis
PCAW	Principal Component Analysis based whitening transform
PDA	Personal digital assistant
PIE	Pose, Illumination and Expression
ppm	Portable PixMap
RAM	Random-access memory
RGB	Red Green Blue
RT&KPCA	Radon transform plus Kernel Principal Component Analysis
RT&LPCA	Radon transform plus Linear Principal Component Analysis
SFFS	Sequential Floating Forward Selection
SPCA	Statistical Principal Component Analysis
SVM	Support Vector Machine
Tcpara	Threshold tuning parameter
τν	Television
UCSD	University of California San Diego
ULLELDA	Unified Locally Linear Embedding and Linear Discriminant
	Analysis Algorithm
UMIST	University of Manchester Institute of Science and Technology
UTD	Unknown testing database
XM2VTS	Multi modal face database
YCbCr	Luminance; Chroma Blue; Chroma Red



<u>,</u>

## LIST OF SYMBOLS

- *I* In PCA algorithm, this is the N<sup>2</sup>-dimensional vector representation of an image
- ∞ Infinite
- $\lambda$  In PCA algorithm, this is the eigenvalue of  $A^{T}A$
- λ In LDA algorithm, this is the eigenvalue
- μ In LDA algorithm, it denote the mean face of each person P<sub>i</sub>
- Ω In PCA algorithm, this is the low dimension vector, a new representation of a training image
- $\rho$  In Radon Transform,  $\rho$  is defined as the distance of the line from the origin
- $\Psi$  In PCA algorithm, this is the mean face vector obtained from the training database set
- $\theta$  In Radon Transform,  $\theta$  is the angle from the horizontal x axis
- $\theta_{tc}$  Distance threshold value
- A In PCA algorithm, this is the collection of *Φ* obtained from the training database set
- C In PCA algorithm, this is the covariance matrix of  $AA^{T}$
- $E_{largest}$  The largest distance threshold value,  $\theta_{tc}$ , boundary
- $E_{min}$  The minimum value from matrix  $\mathbf{E}_{\mathbf{r}}$
- **E**<sub>r</sub> A set of Euclidean distance scores
- $E_{smallest}$  The smallest distance threshold value,  $\theta_{tc}$ , boundary
- I An N by N dimension image
- *i* In PCA algorithm, the maximum number of *i* is the total number of training images which is M
- *i* In LDA algorithm, the maximum number of *i* is the total number of images per person have which is n



- *j* In PCA algorithm, the maximum number of *j* is the total number of eigenvectors obtained. For the matrix  $AA^{T}$ , the maximum number of *j* is N<sup>2</sup>. For the matrix  $A^{T}A$ , the maximum number of j is M.
- **K** In PCA algorithm, this is the number of eigenvector used in face recognition system with  $K \leq M$
- **k** In LDA algorithm, the maximum number of k is the total number of eigenvectors obtained, *m*
- M The total number of images in the training database
- *m* In LDA algorithm, this is the total number of eigenvectors obtained.
- N The width or height of a square image in pixel unit
- *n* In LDA algorithm, it denote the total number of images per person
- Pc In LDA algorithm, it denote the person in the training database where C
  denote total number of persons in the training database
- *S* In Radon Transform, *S* is defined as line integral in the image
- S<sub>B</sub> In LDA algorithm, this is the between-class scatter matrix
- **S**<sub>w</sub> In LDA algorithm, this is the within-class scatter matrix
- u, In PCA algorithm, this is the eigenvector of covariance matrix C
- $v_j$  In PCA algorithm, this is the eigenvector of  $A^T A$
- v<sub>k</sub> In LDA algorithm, this is the eigenvector
- $w_j$  In PCA algorithm, this is the weight value of  $\phi_{I_i}$  when multiplying  $u_j^T$  with  $\Phi_i$



## CHAPTER 1

## INTRODUCTION

## 1.1 Overview of Face Recognition

Face recognition is one of the biometric methods used to identify a person by the features of his/her face. Face recognition has received a considerable attention in recent years both from the industry and research communities (International Biometric Group, 2009). The importance of face recognition arises from the fact that a face recognition system does not require the cooperation of an individual while most biometric system needs such cooperation. Among the popular biometric technologies, facial features and face recognition scored the highest compatibility in a machine readable travel documents (MRTD) system based on a number of evaluation factors (see Figure 1.1) and is the most successful form of human surveillance (Lu, 2003).

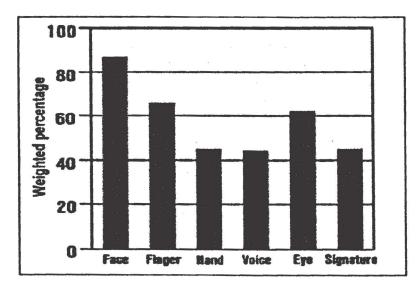


Figure 1.1: Comparison of various biometric features based on MRTD Source: (Lu, 2003)

Facial recognition technology is one of the fastest growing fields in the biometrics industry. Interest in face recognition is being fueled by the availability



and the low cost of video hardware, the ever-increasing number of video cameras being placed in the workspace and the noninvasive aspect of facial recognition systems.

The goal of the face recognition is to identify or verify the persons present in the shots based on their facial features, despite of wide variations in pose, facial expressions and illumination changes (Zhao, 2003). But automatic face recognition systems need to overcome various problems like pose invariance, illumination invariance, facial expression changes etc. Many methods of face recognition have been proposed during the past 30 years (Zhao, 2003). As a result, the current status of face recognition technology is well advanced. Various novel techniques have been proposed ranging from the traditional template matching to the latest three-dimensional techniques. Although over 30 years of extensive research has been conducted in this area, there still exist open research issues, the performance of the current algorithms being still far from that of human perception.

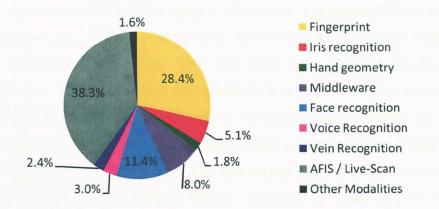
## **1.2** Applications of Face Recognition

Face recognition has received considerable interest as a widely accepted biometric because of the ease in collecting face images of persons. Although very reliable methods of biometric personal identification exist, for example, fingerprint analysis and retinal or iris scans, these methods rely on the cooperation of the participants, whereas a personal identification system based on analysis of frontal or profile images of the face is often effective without the participant's cooperation or knowledge (Zhao, 2003).

Face recognition is being used in various applications like crowd surveillance, criminal identification, and criminal record, access to restricted area etc. Nowadays, the necessity for personal identification in the fields of private and secure system make face recognition one of the main fields among other biometric technology, such as fingerprint identification, hand geometry identification, iris identification etc. Figure 1.2 shows that facial recognition takes 11.4% of the total biometric market. Table 1.1 shows the typical applications of face recognition.



2





Area	Specific applications
Entortainmont	Video game, virtual reality, training programs
Entertainment	Human-robot-interaction, human-computer-interaction
	Drivers' licenses, entitlement programs
Smart cards	Immigration, national ID, passports, voter registration
	Welfare fraud
	TV Parental control, personal device logon, desktop logon
Information	Application security, database security, file encryption
security	Intranet security, internet access, medical records
	Secure trading terminals
Law	Advanced video surveillance, CCTV control
enforcements	Portal control, post event analysis
and surveillance	Shoplifting, suspect tracking and investigation

Table 1.1:	Applications	of face	recognition
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Source: (Zhao, 2003)

#### 1.3 Motivation

There are many biometrics methods that can be used to identify a person such as face, fingerprint, hand, voice, eye and signature. Among these biometric methods, the face is the feature which best distinguishes a person and face recognition is a widely accepted biometric because of the ease in collecting face images of persons



and can be use as biometric trait for system where user is unaware that he or she is being subjected (Lu, 2003). Although over than 30 years of extensive research has been conducted in this area, there still exist open research issues, the performance of the current algorithms being still far from that of human perception (Zhao, 2003). Nowadays, there are many research works related to face recognition. Most of the work claimed to have good performance on recognition rate but no benchmark test to compare the face recognition systems, thus making a comparison between the various results reported is hard to be made. Comparison between various face recognition systems is important so that we can know which system performs better than others under the same test condition. This thesis will focus on preparing a benchmark test for evaluating common reported global based face recognition approach. The test bed and test criteria

## **1.4 Problem Statement**

Currently there are many face recognition research reports published. Most of them used different database and different criteria for their experiments, thus a comparison between the various results reported is hard to be made. In addition, from all the face recognition reports published, there are no comparisons made for resources used by the published system.

chosen are based on the literature review of face recognition.

## 1.5 Objectives

The main objectives of the thesis are:

- i. To establish a test bed and test criteria for evaluating common reported global approach. The test bed and test criteria chosen are based on the literature review.
- ii. To investigate fusing strategies for combining several global approaches.

## 1.6 Scope

The scopes of the thesis are:

- i. All the face images used for experiments are still image type.
- ii. There is only one face per image.



#### REFERENCES

- Achermann, B. and Bunke, H. 1996. Combination of Face Classifiers for Person Identification. 13th International Conference on Pattern Recognition. Volume 3. Pp. 416.
- Aleemuddin, M. 2004. A Pose Invariant Face Recognition system using Subspace Techniques. King Fahd University of Petroleum and Minerals, Dhahran, Saudi Arabia.
- Apostoloff, N. and Zisserman, A. 2007. *Who are you? Real-time person identification*. British Machine Vision Conference.
- Arandjelovic, O. and Cipolla, R. 2005. *A Face Recognition System for Access Control using Video*. Department of Engineering, University of Cambridge, Cambridge, UK.
- Arandjelovic, O. and Cipolla, R. 2006. *Face recognition from video using the generic shape-illumination manifold.* The 9th European Conference on Computer Vision 2006, Graz, Austria.
- Balakrishnama, S. and Ganapathiraju, A. 1998. Linear discriminant analysis A brief tutorial. http://www.music.mcgill.ca/~ich/classes/mumt611\_07/ classifiers/lda\_theory.pdf. Retrieved 18 November 2011.
- Balasuriya, L. S. and Kodikara, N. D. 2001. *Frontal View Human Face Detection and Recognition*. Proceedings of the International Information Technology Conference.
- BenAbdelkader, C. and Griffin, P. A. 2004. *Comparing and combining depth and texture cues for face recognition*. Image Vision Computing. Pp. 339-352.



- Bolme, D. 2003. *Elastic bunch graph matching*. Master's thesis, Colorado State University.
- Bozorgtabar, B., Noorian, F. and Rad., G. A. R.. 2010. *Comparison of different PCA based Face Recognition Algorithms using Genetic Programming*. Telecommunications (IST), 2010 5<sup>th</sup> International Symposium. Pp. 801-805.
- Cai, D., He, X., Han, J. and Zhang, H. J. 2006. *Orthogonal Laplacianfaces for Face Recognition*. IEEE Transactions on Image Processing, volume 15, pp. 3608-3614.
- Chen, L., Man, H. and Nefian, A.V. 2005. *Face recognition based on multi-class mapping of Fisher scores*. Presented at Pattern Recognition. Pp. 799-811.
- Chen, S., Berglund, E., Bigdeli, A., Sanderson, C. and Lovell, B. C. 2008.
  *Experimental Analysis of Face Recognition on Still and CCTV Images.* Advanced Video and Signal Based Surveillance 2008. IEEE Fifth International Conference. pp. 317-324.
- Choi, Y., Tokumoto, T., Lee, M. and Ozawa, S.. 2011. Incremental Two-Dimensional Two-Directional Principal Component Analysis (I(2D)<sup>2</sup>PCA) for Face Recognition. Proceedings of the IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP'11), 2011. Pp. 1493-1496.
- Duda, R. O., Hart, P. E., Stork, D. H. 2000. *Pattern Classification* (2nd edition). Wiley Interscience.
- Ebied, H. M. 2012. *Feature Extraction using PCA and Kernel-PCA for Face Recognition*. Informatics and Systems (INFOS), 2012 8<sup>th</sup> International Conference. Pp. MM-72 MM-77.



- Ekenel, H. K. and Sankur, B. 2004. *Multiresolution face recognition*. Electrical and Electronic Engineering Department, Bogazici University, Bebek, Istanbul, Turkey.
- Ekenel, H. K. and Stiefelhagen, R. 2006. Analysis of local appearance based face recognition: Effects of feature selection and feature normalization. Computer Vision and Pattern Recognition Workshop 2006. Pp. 34.
- Gross, R., Matthews, I. and Baker, S. 2004. *Appearance-based face recognition and light-fields*. IEEE Transactions on Pattern Analysis and Machine Intelligence. Volume 26, pp. 449.
- Gross, R. 2005. *Face Databases, Handbook of Face Recognition*. S.Li, A.Jain, ed. Springer.
- Gokberk, B., İrfanoğlu, B. O., Akarun, L. and Alpaydın, E. 2007. *Learning the best subset of local features for face recognition*. Pattern Recognition, volume 40, issue 5. Pp. 1520-1532.
- Hadid, A. and Pietikainen, M. 2004. From Still Image to Video-Based Face Recognition: An Experimental Analysis. Proceeding Sixth IEEE International Conference. Automatic Face and Gesture Recognition. Pp. 813-818.
- Hadid, A. 2005. *Learning and Recognizing Faces: From Still Images to Video Sequences.* Ph.D. Dissertation, Oulu University.
- Heisele, B., Ho, P., Wu, J. and Poggio, T. 2003. Face recognition: componentbased versus global approaches. Computer Vision and Image Understanding 2003. Volume 91, number 1, pp. 6-21.
- "International Biometric Group's market report". http://ibgweb.com/products/ reports/ bmir-2009-2014. Retrieved 16 August 2011.



- Jeong, D., Lee, M. and Ban, S.-W.. 2009. (2D)2PCA-ICA: A New Approach for Face Representation and Recognition. Systems, Man and Cybernetics, 2009. SMC 2009. IEEE International Conference. Page(s) 1792 – 1797. Publication Year, 2009.
- Jeong, K., Han, D., Kim, Y. and Moon, H. 2008. Optimization of Face Recognition Algorithms for Ubiquitous Computing Environment. Future Generation Communication and Networking 2008. Second International Conference on volume 2, pp. 298-301.
- Jin, L., Satoh, S., Yamagishi, F., Le, D. D. and Sakauchi, M. 2004. *Person X Detector*. National Institute of Informatics at TERCVID 2004, Tokyo. Pp. 101-8430.
- Jolliffe, I.T. 2002. *Principal Component Analysis*. Springer Series in Statistics, 2nd ed., Volume XXIX. Pp. 487.
- Kamencay, P., Breznan, M., Jelsovka, D. and Zachariasova, M. (2012). Improved Face Recognition Method based on Segmentation Algorithm using SIFT-PCA. Telecommunications and Signal Processing (TSP), 2012 35<sup>th</sup> International Conference. Pp. 758-762.
- Kamencay, P., Jelsovka, D. and Zachariasova, M.. (2011). The Impact of Segmentation on Face Recognition using the Principal Component Analysis (PCA). Signal Processing Algorithms, Architechtures, Arrangements, and Applications Conference Proceedings (SPA), 2011. Pp. 1-4.
- Karibasappa, K. and Patnaik, S. 2004. Face recognition by ANN using wavelet transform coefficients. Institute of Engineering (India). Computer Engeneering. Pp. 17–23.



- Karsili, L. and Acan, A. 2007. A Radon Transform and PCA hybrid for high performance face recognition. IEEE International Symposium on Signal Processing and Information Technology.
- Kim, T. K., Kim, H., Hwang, W. and Kittler, J. 2005. Component-based LDA face description for image retrieval and MPEG-7 standardization. Image Vision Computing. Volume. 23, pp. 631-642.
- Lang, L. and Yue, H. 2008. Study on the Core Algorithm of Access Control System Based on Face Recognition. Computational Intelligence and Security 2008. International Conference on volume 1, pp. 76-79.
- Li, C., Diao, Y., Ma, H. and Li, Y. 2008. A Statistical PCA Method for Face Recognition. Intelligent Information Technology Application 2008. Second International Symposium, volume 3, pp. 376-380.
- Li, C. and Fang, Z.. 2010. Infrared Face Recognition Method Based on Radiative Energy and Block-PCA. International Conference on Multimedia Technology (ICMT). Pp. 1-5.
- Liu, C. J. 2004. *Gabor-Based Kernel PCA with Fractional Power Polynomial Models for Face Recognition*. IEEE Transactions on Pattern Analysis and Machine Intelligence. Volume 26, pp. 572-581.
- Li, J. M., Poulton, G., Guo, Y. and Qiao, R. Y. 2003. Face Recognition Based on Multiple Region Features. Proceeding VIIth Digital Image Computing: Techniques and Applications, Sun, C., Talbot, H., Ourselin, S. and Adriaansen, T. (editors), Sydney.
- Lu, X. 2003. *Image analysis for face recognition*. http://www.cse.msu.edu /lvxiaogu/publications/ImAna4FacRcgJu.pdf. Retrieved 16 August 2011.



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- Moghaddam, B. 2002. *Principal Manifolds and Probabilistic Subspaces for Visual Recognition*. IEEE Transactions on Pattern Analysis and Machine Intelligence.
- National Institute of Standards and Technology. *Face Recognition Technology* (*FERET*). http://www.nist.gov/itl/iad/ig/feret.cfm. Retrieved 10 July 2012.
- Neagoe, V.-E., Mugioiu, A.-C., Stanculescu, I.-A.. 2010. Face Recognition using PCA versus ICA versus LDA cascaded with the Neural Classifier of Concurrent Self-Organizing Maps. Communications (COMM), 2010 8th International Conference. Page(s) 225 – 228. Publication Year, 2010.
- P. N. Belhumeur, J. P. Hespanha, and D. J. Kriegman. 1996. Eigenfaces vs Fisherfaces Recognition Using Class Specific Linear Projection, European Conf. Computer Vision.
- Pearson, K. 1901. On Lines and Planes of Closest Fit to Systems of Points in Space, Philosophical Magazine.
- Perronnin, F., Dugelay, J.-L. and Rose, K. 2003. *Deformable face mapping for person identification. IEEE ICIP*, 2003.
- Puyati, W. and Walairacht, A. 2008. Efficiency Improvement for Unconstrained Face Recognition by Weightening Probability Values of Modular PCA and Wavelet PCA. Advanced Communication Technology 2008. 10th International Conference. Volume 2, pp. 1449-1453.
- Qian, Z. M., Su, P. Y. and Xu, D. 2008. Face Recognition Based on Local Feature Analysis; Computer Science and Computational Technology 2008. International Symposium on Volume 2. Pp. 264-267.



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- Radon, J. 1986. On the determination of functions from their integral values along certain manifolds. Parks, P.C. (translator). IEEE Transactions on Medical Imaging 5.
- Sigari, M. H. and Fathy, M. 2007. *Best wavelength selection for Gabor wavelet using GA for EBGM algorithm*. Machine Vision, ICMV 2007, Islamabad. Pp. 35-39, pp. 28-29.
- Sim, T., Sukthankar, R., Mullin, M. and Baluja, S. 2000. Memory-based face recognition for visitor identification. Automatic Face and Gesture Recognition Fourth IEEE International Conference. Pp. 214 – 220.
- Smith, L.I.. 2002. *A Tutorial on Principal Component Analysis*. http://www.sccg.sk/~haladova/principal\_components.pdf. Retrieved 18 November 2011.
- Turk, M. and Pentland, A.. 1991. Face Recognition using Eigenfaces. Proceedings of the Computer Society Conference on Computer Vision and Pattern Recognition, Lahaina, Maui, Hawaii. Page(s) 586 – 591.
- Perlibakas, V.. 2004. *Distance measures for PCA-based face recognition*. Pattern Recognition Letters Volume 25, Issue 6, 19 April 2004, Pages 711–724.
- Wang, R., Cui, X., Xiong, M., Peng, H. and Lv, K. 2008. A Highly-Efficient Face Recognition Method Based on Weighted LDA. Proceedings of the 2008 International Symposium on Intelligent Information Technology Application Workshops. Publisher IEEE Computer Society Washington, DC, USA. Pp. 475-478.
- Weyrauch, B. Heisele, B. Huang, J. and Blanz, V. 2004. Component-Based Face Recognition with 3D Morphable Models. Computer Vision and Pattern Recognition Workshop, 2004 Conference 2004. Pp. 85.



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- Wiskott, L., Fellous, J. M., Kruger, N. and Malsburg, C. V. D. 1999. Face Recognition by Elastic Bunch Graph Matching. Intelligent Biometric Techniques in Fingerprint and Face Recognition. Chapter 11, pp. 355-396.
- Xiao, C.. 2010. Two-dimensional Sparse Principal Component Analysis for Face Recognition. Future Computer and Communication (ICFCC), 2010 2nd International Conference. Volume: 2, page(s) V2-561 - V2-565. Publication Year, 2010.
- Xie, J. 2008. KPCA Based on LS-SVM for Face Recognition. Intelligent Information Technology Application 2008. Second International Symposium. Volume 2, pp. 638-641.
- Xu, G., Zhang, S. and Liang, Y.. 2009. Using Linear Regression Analysis for Face Recognition Based on PCA and LDA. Computational Intelligence and Software Engineering, 2009. CiSE 2009. International Conference. Page(s) 1 – 4. Publication Year, 2009.
- Yambor, W., Draper, B., and Beveridge, R. 2002. Analyzing PCA-Based Face Recognition Algorithms: Eigenvector Selection and Distance Measures. Empirical Evaluation Methods in Computer Vision, H. Christensen and J. Phillips (editors).
- Yang, F., Paindavoine, M., Abdi, H. and Arnoult, D. 2006. *Fast panoramic face mosaicing and recognition*. Journal of Multimedia. Pp. 14-20.
- Yokono, J. J. and Poggio, T. 2006. *A Multiview Face Identification Model with No Geometric Constraints*. Sony Intelligence Dynamics Laboratories Inc.
- Yoo, S., Park, R. and Sim, D. 2007. *Investigation of Color Spaces for Face Recognition*. In Proceedings of Machine Vision Application. Pp. 106-109.



- Zhang, D., You, X., Chen, Q. and Tu, J. 2008. *Face Recognition Based on New Non-separable Bivariate Wavelets*.
- Zhao, S. and Rainer, G. R. 2005. *An automatic face recognition system in the near infrared spectrum*. International conference on machine learning and data mining in pattern recognition 2005. Volume 3587, pp. 437-444.
- Zhao, W., Chellappa, R., Phillips, P. J. and Rosenfeld, A. 2003. Face recognition: A literature survey. ACM Computing Surveys (CSUR). Volume 35, issue 4, pp. 399-458.
- Zhang, Y. and Wu. L. 2011. *A Rotation Invariant Image Descriptor based on Radon Transform*. International Journal of Digital Content Technology and its Applications. Volume 5, number 4, April 2011.
- Zhang, Y. B. and Martinez, A. M. 2006. A weighted probabilistic approach to face recognition from multiple images and video sequences. Image and Vision Computing (24). Volume 24, issue 6, pp. 626-638.

