Linking Face Images Captured from the Optical Phenomenon in the Wild for Forensic Science

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Abstract

This paper discusses the possibility of use of some challenging face images scenario captured from optical phenomenon in the wild for forensic purpose towards individual identification. Occluded and under cover face images in surveillance scenario can be collected from its reflection on a surrounding glass or on a smooth wall that is under the coverage of the surveillance camera and such scenario of face images can be linked for forensic purposes. Another similar scenario that can also be used for forensic is the face images of an individual standing behind a transparent glass wall. To investigate the capability of these images for personal identification this study is conducted. This work investigated different types of features employed in the literature to establish individual identification by such degraded face images. Among them, local region based featured worked best. To achieve higher accuracy and better facial features face image were cropped manually along its close bounding box and noise removal was performed (reflection, etc.). In order to experiment we have developed a database considering the above mentioned scenario, which will be publicly available for academic research. Initial investigation substantiates the possibility of using such face images for forensic purpose.

1.Introduction

Face recognition is a topic of research which has received substantial attention from the researchers in biometrics, pattern recognition and computer vision communities [1-4]. The face is also a vital interesting subject for forensic community. Nowadays the face images from the video of a closed circuit camera are used for detecting individual in security zones and crime investigations. The applications of face recognition technology in forensic cover a wide field of automated crowd surveillance, access control, mugshot identification (e.g. for issuing driver licenses), facial reconstruction, the design of human-computer interface (HCI), multimedia communication (e.g. Generation of faces), content-based image database management, etc. Furthermore, a number of commercial face recognition systems have been deployed, such that Cognitec [5], Eyematic [6], Viisage [7], Identix [8] etc. Regardless of the overwhelming success of face trait, there are cases of real life applications where face recognition is still a big challenge especially in surveillance scenario.

In some surveillance scenario due to occlusion and blockage, the face images cannot be covered by the camera installed as shown in Figure 1. Such scenario can also be happened for an individual who is not facing towards the camera and for an individual who is behind the camera.

(a) (b)

Figure 1: (a) an individual not facing towards the camera. (b) an individual behind a camera.

In such scenario, we can obtain the face images of the individual from the reflection of the face on the wall or glass or shiny surface etc. It can be assumed that the quality of face images capture from this reflection might be poorer. Another face image scenario where we can obtain the poor quality of face image but can be very relevant for use in forensic is the face images of individually collected while they are behind a transparent glass. In this work, we propose to use such images for forensic porous. Further, we will discuss challenges in collecting and processing face images from such scenarios. We also try to study the viability of using these images and linking them to forensic purpose.

To fulfil the aforementioned aims the present work is done. The specific contributions of the work are:

1. Proposing the use of face images from reflection on the shiny surface and behind the glass and linking them for forensic use.
2. Identifying challenge and address solutions for the aforementioned face images
3) Propose a database with a wide variety of face images acquired in aforementioned scenario, which is made publicly available to the researchers for their research. Rest of the paper is organised as follows. Proposed face recognition protocol is described in Section 2. Section 3 deals with experiment result and discussions. Finally, future work and conclusion are provided in Section 4.

2. Proposed Protocol for Face Recognition

Face features are usually considered to be colour, texture, or component properties, i.e. eye, nose. Many different methods for face recognition have been used during in last few decades [9]. Among this featuring technique seminal work were done with holistic matching methods like Principal Component Analysis (PCA) [10], Eigenfaces, Probabilistic Eigenfaces [11, 14], Fisher faces/subspace LDA [12, 13, 15], SVM [16], Evolution pursuit [17], Feature lines, IC [18] etc. Next category of featuring technique used was Feature-based methods like pure geometry methods [19], Dynamic link architecture [20], and Hidden Markov model [21], Convolution Neural Network [22]. Other category of featuring technique used was Modular Hybrid LFA [22], Shape-normalized [23], component-based [24] etc. Some other category of featuring technique used was LDA/FLD [25, 26], PDBNN [27] etc.

Leaving behind the general face recognition challenges additional challenges can be faced in the scenario of face image capture from reflection on the wall/glass. Face images captured from behind the glass may contain blurring due to specular and other, geometrical distortion and other optical phenomena that may produce noise. Texture and marks on the glass can also be additional challenges. These face images can also contain reflections of the other adjacent objects. Illumination factor can also affect the acquiring process like the brightness of the light and dimness of light. Similar phenomenon and noise can occur in the scenarios, of face images acquired from the reflection on the wall. Therefore, a detailed study is required to find the feasibility of using such images. In general human face image appearance has potentially very large intra-subject variations due to 3D pose, illumination (including indoor/outdoor), facial expression, occlusion due to other objects or accessories (e.g., sunglasses, scarf, etc.), facial hair and ageing. These types of inter-subject variance are dealt in the literature with robust feature and classification technique. Excluding these challenges, in the scenario where face images are acquired from its reflection on the wall/glass or image of a face capture which is behind the glass, the intra-subject variance is potentially is very high. Substantial impact on the texture, colour and shape of the face can occur depending on the surface of the wall/glass. Therefore we need to experiment traditional face feature and study the impact. The various challenges that were identified are enumerated next.

a) Challenges in face images capture from reflection on the wall: Main challenges of using the face images captured from the reflection on the wall for individual identification are the impact of the texture of the wall on the face image, low contrast of the reflection and impact of the colour of the wall. Additionally, the specular reflection and other optical phenomenon including occlusion affect the face images in this scenario. Examples of face images of such scenario are shown in Figure 2.

Figure 2: Examples of face images capture from the reflection on the wall.

b) Challenges in face images capture from reflection on the glass: Similar to the scenario of face images captured from the reflection on the wall, main challenges of the face recognition with these images capture from the reflection on the glass are the impact of the texture of the glass on the face image, contrast of the reflection and impact of the colour of the glass. The specular reflection and other optical phenomenon have found to heavily impact as noise in this scenario. Including occlusion and other obstruction reflection of an object in the close proximity also affects the face images in this scenario heavily. An example of the face image of such scenario is shown in Figure 3.

Figure 3: Examples of face images capture from the reflection on the glass.

c) Challenges in face images capture from behind glass: In this scenario, main challenges are the impact of the texture of the glass on the face image, reflecting and shades of other object and, the impact of the colour of the glass. The specular reflection and other optical phenomenon are additional challenges that cannot be handled while acquiring. An example of the face image of such scenario is given in Figure 4.

Figure 4: Example of face images capture from behind the glass.

d)Pre-processing: Other challenges that can exist in individual face recognition for the above mentioned scenario in the wild is automatic segmentation of the face images from the scenes in the wild and pre-processing them.(noise removal, etc.). In this work, we employed manual segmentation and noise masking (automatic pre-processing is beyond the aim of the present work, it will be investigated in future work). The face images are manually segmented and then cropped along its closer bounding box of the face and then noise in the images are masked manually. Examples of these images are shown in Figure 5. In some scenario like Fig.5 (g and h) the noise masking could not be performed as the noise is distributed all over the image and masking might reduce the feature.

e) Featuring and classification technique:

The featuring techniques employed in this work are explained below.

Dense-LDP- A local descriptor method applied in this paper for featuring the traits we considered is Multi-Scale Local Derivative Pattern (SPMS-LDP). We found from our observation that the traits are rich in both global and local feature. The feature SPMS-LDP is both reach in the local and the global feature as the total image and the image divided into different plane are considered for the scenario. Multi-scale of the fourth and third order of the LDP is employed here. Ten different spatial planes are considered for featuring. Each histogram distribution of bin size of 256 is calculated for each plane, order and spatial plane and concatenated to get the total feature of dimension 30720. This can be calculated as below.

$$FD= Ns * No* 256* Nsp \qquad (1)$$

Where, FD= feature dimension; Ns= number of scale, No= number of order, Nsp= number of spatial plane. The Spatial plane division of the image which divides the image into dense sampling plane is explained in the following Figure 6. The various level of the spatial division incorporates the local and the global feature of the traits.

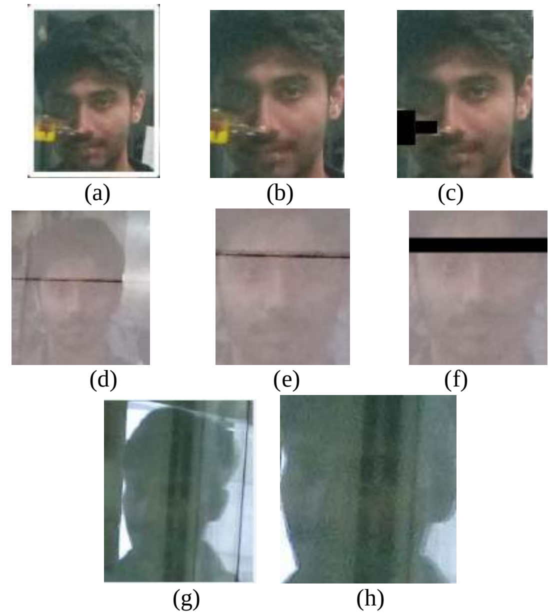

Figure 5: Face images of a user from the database (a) capture behind the glass, (b) the image in (a) cropped around the face feature, (c) noise masked image of (b), (d) image capture from the reflection on the wall, (e) the image in (d) cropped around the face feature, (f) noise masked image of (e), (g) image capture from the reflection on the glass, (h) the image in (g) cropped around the face feature.

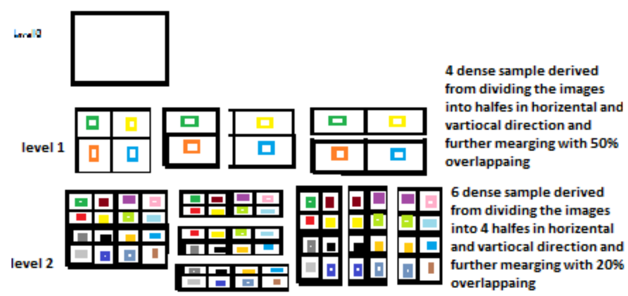

Figure 6: Example of the spatial plane division of the image into dense sampling.

Dense-LBP- Another local descriptor method applied in this paper for featuring the traits we considered Multi-Scale Local Binary Pattern (SPMS-LDP). Similar to D-LDP an image in D-LBP is divided and the feature is extracted which is of 10240 dimensions.

For both local descriptors, Support Vector Machines (SVMs) was employed in this experiment for classification purpose. The Library for Support Vector Machines (LIBSVM) is used here for the SVM implementation. SVM or LIB-SVM makes a binary decision and multi-class classification for personal identification has been made in this study by adopting the one-against-all techniques. This study uses the Linear kernel with SVM type-- C-SVC, kernel type – linear and cost function - 0.07. We carried out grid-search on the hyperparameters in the 5-fold cross-validation for selecting the parameters of the training sequence.

3. Experimental Results

The database employed, experimental results, discussion and observation of the experiments are summarised in this section.

a) Database

To experiment the proposed methodology of face recognition a dataset is prepared. It consists of 631 images from 10 individuals. For training purpose, 20 images of individuals were collected in different pose, illumination, expression and background. Some examples of such images are shown in Figure 7.

Figure 7: Some examples of training images.

All the training images are captured in ideal condition so that all the facial features can be present. Testing images were captured in the wild: 184 face images captured in the glass, 74 face images from the reflection on the wall, and 153 face images from the reflection on the glass. Face images from the reflection from different types of the glass wall, shiny wall and glasses were considered while developing the database. All test images are captured in the wild and in sparse crowd. Four experiments were conducted with the database.

1. Training followed by testing with images capture behind the glass.
2. Training followed by testing with images captured from the reflection on the glass.
3. Training followed by testing with images captured from the reflection on the wall.
4. Training followed by testing with images captured from the reflection on the glass and wall, and images capture behind the glass (experimented as it can occur in real life scenario).

b) Experimental details

To analyse the effectiveness of the proposed method, recognition and verification scenario are used. For recognition accuracy in percentage is employed as the performance measure and for verification scenario also accuracy in percentage was used as the performance measure. For further performance examination, we calculated the Cumulative Matching/ top choice/ the rank (1^{st} three ranks of the recognition is reflected in the result table). As this study is proposed for the forensic purpose we used Log Likelihood Ratio measure (LR) [27]. We employed min LR measure as well as average LR measure.

c) Experimental performance and discussion

The performance of the above mention experiment is summarised in Table 1. It can be concluded from the result in Table 1 that the overall verification performance is better than the recognition performance. Verification performance for all the cases was close to ~90%, whereas the recognition performance was around ~75%, The verification and recognition result of face images captured from the reflection on the wall improves when they were cropped around the face boundary (~1% for verification for DLDP and ~4% for DLBP, for recognition for ~ 2.5% for both DLBP and DLDP). Whereas, when the noisy part in images was masked the result of the verification improved with respect to original face images (~0.6% for both DLBP and DLDP) but not with respect to cropped face images (reduced by ~2 5 for both DLBP and DLDP). In construct for the recognition scenario, the result improved after masking the noises by ~6% for DLBP. The reason of such performance during verification might because masking the noise. In some images, the noise was present in majority portion of the image as a result masking reduced the face feature. The implication from the LR measures was also very similar to the pattern of recognition and verification. Both LR and Min LR for DLBP reduces (~0.1) from original to crop face image to noisy masked face image taken from on the wall. The top choice/ rank of this scenario found to improve by ~4.5% for each scenario from rank/top choice 1 to 2 to 3. Therefore, DLBP found to be a more effective feature in this scenario.

A similar pattern of performance is found in the experiments performed with images captured from behind the glass. Although in this scenario the performance of DLDP found to be more promising. The improvement of the result occurred by ~2% from original to crop face image to noisy masked face image for verification scenario. For recognition scenario, the improvement was much better by ~6%. The top choice rank also improves for the DLDP scenario by ~5%. A similar tendency of performance was found from the LR measures.

For the scenario of images captured from the reflection on the glass, the performance result improves for cropped images in comparison to the original face images. It further improved while the noisy region was masked (~3% for verification and ~4% for recognition using DLDP). The implication from the LR measures of these experiments was also very similar to verification and recognition performance.

This random behaviour of the results and their performance value achieved in a different category (i.e. face images captured from the reflection on the glass, on the wall, and images captured behind the glass) is due to the number of samples in each category and the quality of the images. Images taken from the reflection on the wall has less number of samples. That is why the performance is better than the images capture behind the glass. Whereas, due to the better quality of images on the glass, although the number of samples were more result is better in contrast to any other scenario.

Table 1: Detail performances of the experiments conducted

Type of image	Feature	Verification in %	Rank1/ Recognition in %	Rank2	Rank3	Min LR	Average LR
Face images captured from the reflection on the wall	DLBP	94.11	80.50	85.69	89.05	0.4790	0.4813
	Cropped face image-DLBP	97.37	82.50	87.72	91.23	0.3906	0.3929
	Noise masked Cropped face image- DLBP	**94.41**	**88.40**	**90.70**	**95.35**	**0.3681**	**0.3699**
	DLDP	90.25	77.60	81.18	87.06	0.3583	0.3598
	Cropped face image-DLDP	91.54	80.70	84.21	85.96	0.3378	0.3394
	Noise masked Cropped face image- DLDP	89.94	79.10	81.40	83.72	0.3833	0.3849
Face images captured while individual is present behind a glass	DLBP	91.87	69.30	71.23	73.89	0.5244	0.5265
	Cropped face image-DLBP	90.05	70.70	76.19	80.95	0.5220	0.5240
	Noise masked Cropped face image- DLBP	86.97	74.80	88.66	90.23	0.4711	0.4725
	DLDP	90.62	66.72	78.31	82.54	0.5194	0.5213
	Cropped face image-DLDP	91.53	74.10	79.59	85.71	0.4323	0.4337
	Noise masked Cropped face image- DLDP	**95.63**	**80.00**	**89.57**	**91.30**	**0.4288**	**0.4305**
Face images captured from the reflection On the glass	DLBP	88.12	68.80	76.55	80.36	0.5997	0.6009
	Cropped face image-DLBP	92.31	71.30	81.74	85.22	0.5043	0.5062
	Noise masked Cropped face image- DLBP	95.53	83.30	88.56	91.25	0.3272	0.3295
	DLDP	90.96	68.60	7143	77.14	0.4262	0.4268
	Cropped face image-DLDP	91.56	73.04	77.39	81.74	0.4633	0.4646
	Noise masked Cropped face image- DLDP	**97.23**	**84.80**	**87.88**	**90.91**	**0.2959**	**0.2980**
All	DLBP	80.21	49.00	57.45	64.90	0.7761	0.7767
	Cropped face image-DLBP	79.68	49.20	57.78	65.08	0.7791	0.7803
	Noise masked Cropped face image- DLBP	**88.27**	**60.50**	**72.50**	**79.00**	**0.6361**	**0.6373**
	DLDP	81.09	51.70	63.46	72.60	0.7182	0.7177
	Cropped face image-DLDP	80.05	48.30	61.90	70.16	0.7344	0.7355
	Noise masked Cropped face image- DLDP	82.80	55.00	68.00	73.50	0.5963	0.5976

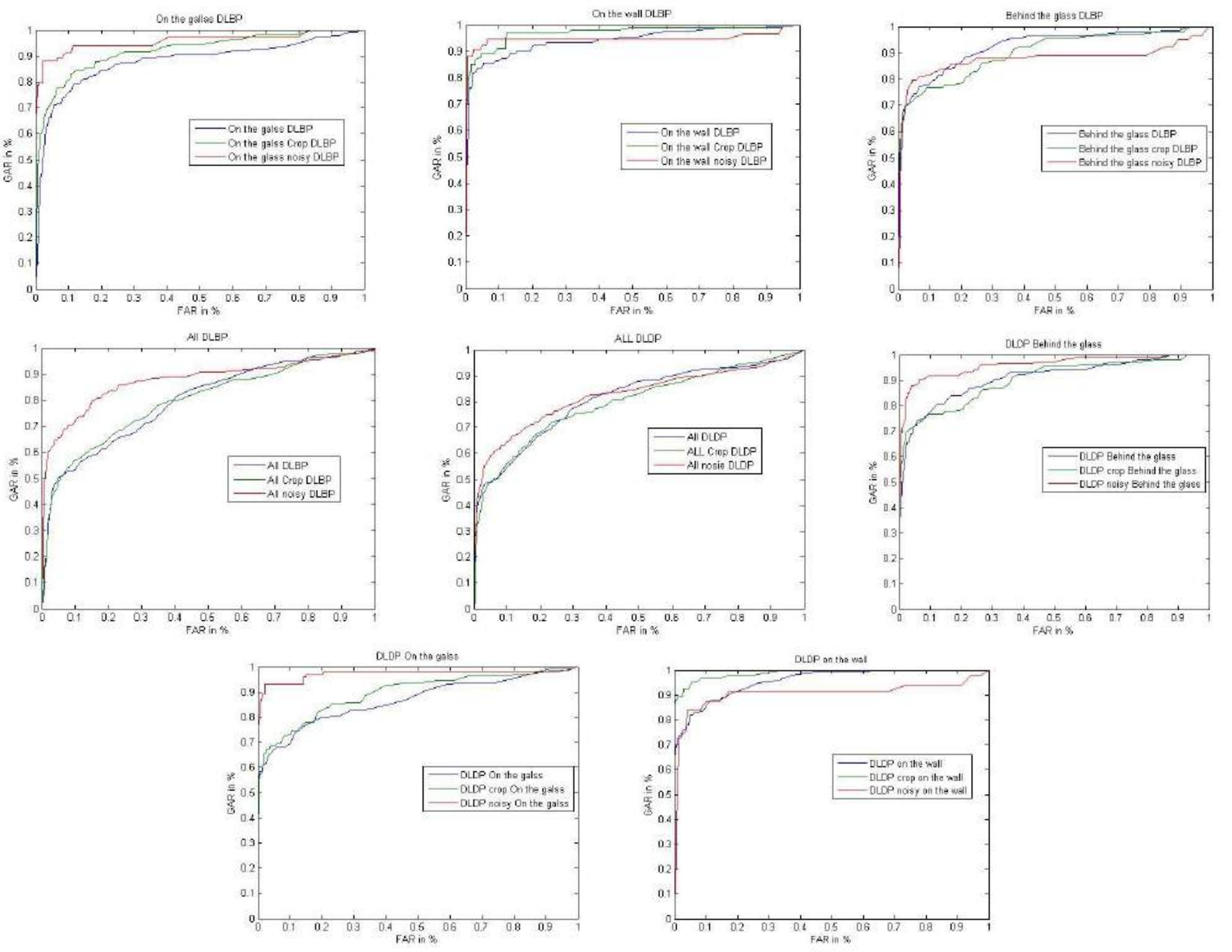

Figure 8: ROC curves of the experiments

The performance of the images captured from the reflection on the glass is quite near to that of the images taken from the reflection on the wall regardless of the more number of samples present.

The performance of the experiments when all types of images were tested together reduced a lot ~10% for verification scenario, ~20% for recognition scenario and top choices. The significant downgrade of the LR measures also observed in this scenario (~0.3% increase). The major reason for the drop in the performance is assumed to be the larger number of testing samples.

Overall, it can be concluded that substantial personal identification can be made employing these types of images. But, the random performance of the experimental scenario and incongruous effectiveness of DLBP and DLDP point further scope of research in this area.

For a state-of-art comparison, we performed all the experiments with PCA, LDA, Fisher face, Eigen's face. They found to attend ~11% for and ~6% less performance than D-LDP and DLBP for recognition and verification scenario respectively.

4. Conclusion and Future Scope

In this work, we propose about the possibility of using face images captured from an optical phenomenon in the wild for forensic purpose. For occluded and under cover face surveillance scenario, we propose to capture face images from the reflection on a glass surface or on a smooth wall in the surrounding. Another such scenario proposes for the forensic scenario is the face images of the individual capture while the individual is behind a transparent glass wall.

The various challenges of this scenario are identified and dataset for such scenario is developed. Different local descriptor based feature extraction techniques were found to be effective. To achieve higher accuracy and get better facial feature face image are cropped manually along the face boundary and noise removal was performed. The developed database will be publicly available for academic research. The initial investigation substantiates the possibility of using these face images in the wild for forensic.

Future work will involve in expanding the database and employing deep CNN to resolve the identified gaps and exploring the possible way to automatically segment the face images for these scenarios.

References

[1] R. Chellappa, C. L. Wilson, and S. Sirohey, Human and machine recognition of faces: A survey, Proc. IEEE, vol. 83, pp. 705–740, 1995.

[2] H. Wechsler, P. Phillips, V. Bruce, F. Soulie, and T. Huang, Face Recognition: From Theory to Applications, Springer-Verlag, 1996.

[3] W. Zhao, R. Chellappa, A. Rosenfeld, P.J. Phillips, Face recognition: A literature survey, CVL Technical Report, University of Maryland, 2000.

[4] S. Gong, S. J. McKenna, A. Psarrou, Dynamic Vision: From Images to Face Recognition, Imperial College Press and World Scientific Publishing, 2000.

[5] Cognitec Systems GmbH .,< http://www.cognitec systems.de/Contact/contact.html>.

[6] Eyematic Interfaces Inc.,<http://www.eyematic.com/>.

[7] Viisage, Littleton, MA,<http://www.viisage.com/>.

[8] Identix, Minnetonka, MN,<http://www.identix.com/>.

[9] I. Craw, P. Cameron, Face Recognition By Computer. In Proceedings, British Machine Vi-Sion Conference. 489–507. 1996.

[10] M. Kirby, L Sirovich,. Application Of The Karhunen-Loeve Procedure For The Characteri- Zation Of Human Faces. IEEE Trans. Patt. Anal. Mach. Intell. 1990.

[11] M. Turk , A. Pentland . Eigenfaces For Recognition. Cogn. Neurosci. 3, 72–86, 1991.

[12] B. Moghaddam, A Pentland. Probabilis-Tic Visual Learning For Object Representation.Ieee Trans. Patt. Anal. Mach. Intell. 19, 696–710, 1997.

[13] P. N. Belhumeur, J. P. Hespanha , D. J. Kriegman. Eigenfaces Vs. Fisherfaces: Recogni-Tion Using Class Specific Linear Projection. Ieee Trans. Patt. Anal. Mach. Intell. 19, 711–720. 1997.

[14] D. L. Swets, J. Weng, Using Dis-Criminant Eigenfeatures For Image Retrieval.Ieee Trans. Patt. Anal. Mach. Intell. 18, 831–836. 1996.

[15] W Zhao, R. Chellappa, A, Krishnaswamy,.Discriminant Analysis Of Principal Components For Face Recognition. In Proceedings, International Conference On Automatic Face And Gesture Recognition. 336–341. 1998.

[16] P. J. Phillips, Support Vector Machines Ap- Plied To Face recognition. Adv. Neural Inform. Process. Syst. 11, 803–809. 1998.

[17] C. Liu, H Wechsler, Evolutionary PurSuit And Its Application To Face Recognition. IEEE Trans. Patt. Anal. Mach. Intell. 22, 570–582, 2000.

[18] Z. Lis. J Lu, Face Recognition Using The Nearest Feature Line Method. Ieee Trans. Neu- Ral Netw. 10, 439–443, 1999.

[19] M. S Bartlett, H. M., Lades, T. Sejnowski, Independent Component Representation For Face Recognition. In Proceedings, Spie Sym Posium On Electronic Imaging: Science And Tech-Nology. 528–539, 1998.

[20] K. Etemad, R. Chellappa. Discriminant Analysis For Recognition Of Human Face Images. J. Opt. Soc. Am. A 14, 1724–1733, 1997.

[21] S. H. Lin, S. Y.. Kung, L. J. Lin, Face Recognition/Detection By Probabilistic Decision-Based Neural Network. Ieee Trans. Neural Netw. 8, 114–132. 1997.

[22] T. Kanade, Computer Recognition Of Hu-Man Faces. Birkhauser, Basel, Switzerland, And Stuttgart, Germany. 1973.

[23] M. D. Kelly, 1970. Visual Identification Of Peo-Ple By Computer. Tech. Rep. Ai-130, Stanford Ai Project, Stanford.

[24] I. J. Cox, J. Ghosn, P. N. Yianilos , Feature-Based Face Recognition Using Mixture-Distance. In Proceedings, Ieee Conference On Computer Vision And Pattern Recognition. 209–216, 1996.

[25] B. S. Manjunath. R. Chellappa, C. V. D. Malsburg. A Feature Based Approach To Face Recogni-Tion. In Proceedings, Ieee Conference On Computer Vision And Pattern Recognition. 373–378, 1992.

[26] K. Okada, J. Steffans, T. Maurer, H, E. Hong , E. Lagin , H. Neven, C. V . D. Malsburg, The Bochum/Usc Face Recognition System And How It Fared In The Feret Phase Iii Test. In Face Recognition: From Theory To Applications, 186–205, 1998.

[27] N. Brümmer, J. du Preez, Application-independent evaluation of speaker detection, Computer Speech & Language, Volume 20, Issues 2–3, April–July 2006, Pages 230-275.