Face Matching and Retrieval in Forensics Applications

Article *in* IEEE Multimedia · January 2012

DOI: 10.1109/MMUL.2012.4 · Source: DBLP

3 authors, including:

Brendan Klare
Rank One Computing

Unsang Park
Sogang University

To appear, IEEE Multimedia

Face Matching & Retrieval: Applications in Forensics

Anil K. Jain, *Fellow, IEEE*, Brendan Klare, and Unsang Park, *Member, IEEE*

Abstract:

This article distinguishes the forensic face recognition paradigm from typical portrait (2D frontal image) face recognition scenarios, and summarizes recent progress and approaches to some of these difficult problems. We separate forensic face recognition approaches into: (i) preprocessing methods that enhance the quality of an input face image prior to submission to a face recognition system, and (ii) specialized face recognition systems that have been designed to solve a specific matching task. The proposed solutions address the following forensic matching scenarios: (i) utilizing facial marks and scars to improve matching performance, (ii) forensic sketch to photo matching, (iii) face recognition in the presence of aging, (iv) compensating for pose and illumination variations, and (v) matching low resolution images.

Keywords - Face recognition, face retrieval, forensics, facial aging, 3D face model, forensic sketches, facial mark, image enhancement.

A latent fingerprint left on the counter. A drop of blood found on the floor. These forensic clues have been successfully used for decades to catch criminals. But, consider a face image captured by a surveillance camera that needs to be matched against millions of mug shots across the country. With the rapid increase in the number of surveillance cameras[1] and mobile devices with built-in cameras, the world of forensics is changing, and the progress in face recognition is helping to lead the way. Through recent research advances, the foundations for realizing the aforementioned face matching scenarios have been laid, however face recognition in the forensics arena still poses a number of challenges.

In this article we highlight the challenges in applying face recognition technology to forensics applications. We explain why forensic face recognition differs from typical portrait face recognition scenarios, and that a human examiner is often needed to carefully interpret and verify the matching results. Further, we address three specific research problems that pose challenges to commercial-of-the-shelf (COTS) face recognition systems (FRS): (i) robustness to facial aging; (ii) retrieval using facial scars and marks; and (iii) matching forensic (composite) sketches to face photograph databases. Solutions to these three problems are necessary to provide accurate de-duplication of various government face databases, including mug shot, passport and driver license photos (aging invariant FRS), searching a large face database when only partial or low quality face images are available (scar and mark matching), and apprehending criminals when no photo is available of the suspect (sketch to photo matching). Additionally, methods that can augment existing COTS face recognition systems by improving the quality of a face image prior to submission are discussed.

Face Recognition Overview

[1] There are an estimated 30 million surveillance cameras now deployed in the United States shooting 4 billion hours of footage a week. (2009) [2] Americans are being watched, all of us, almost everywhere.

Face recognition is the task of recognizing a person using digital face images. A face recognition system is typically designed to output a measure of similarity between two face images. The design of automated face recognition systems typically involves finding key facial landmarks (e.g. center of the eyes) for alignment, normalizing the appearance of the face, choosing a suitable feature representation, learning discriminative feature combinations, and developing accurate and scalable matching schemes [1] (see Fig. 1).

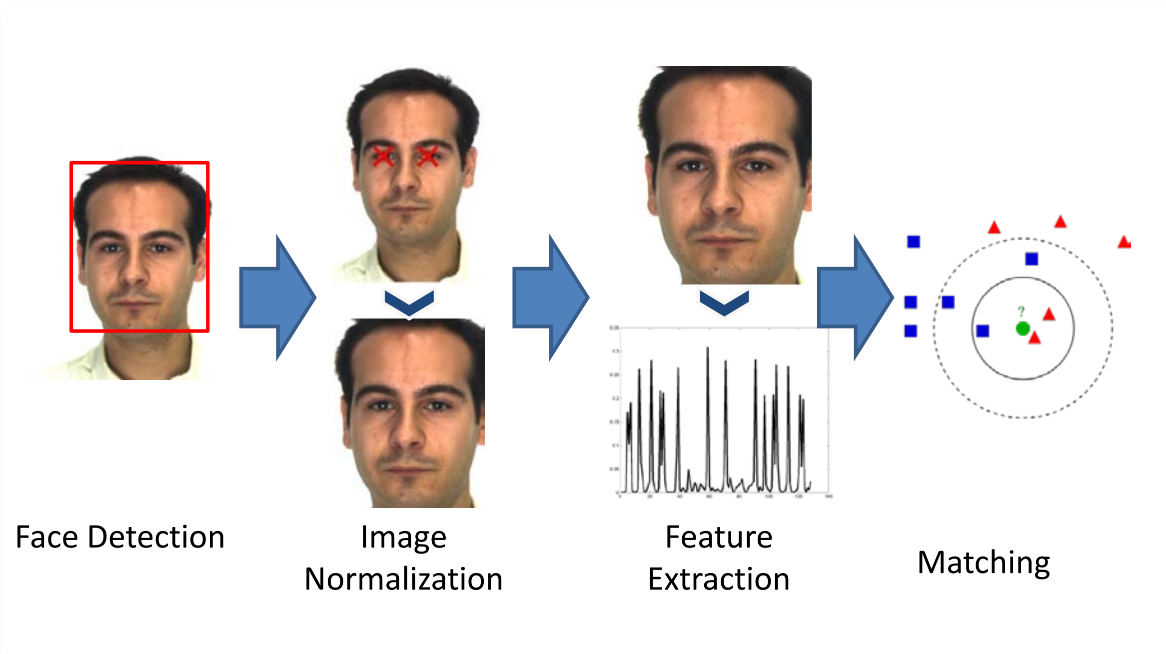


Figure 1: Major steps in automatic face recognition.

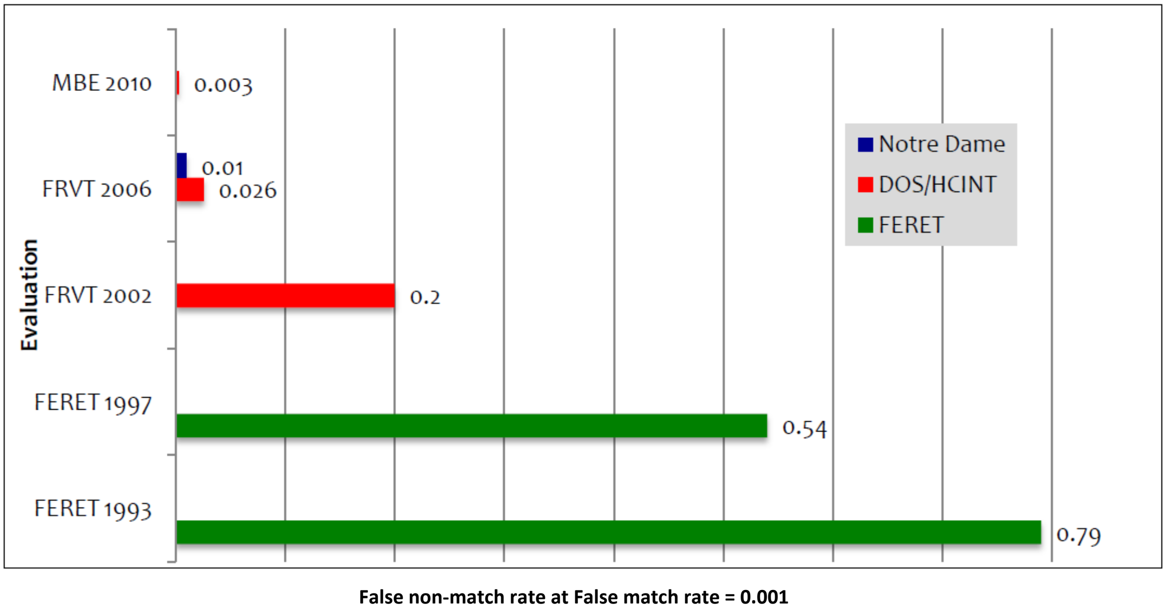


Figure 2. The reduction in error rate for state-of-the-art face recognition algorithms as documented through the FERET, FRVT 2002, FRVT 2006, and MBE 2010 face evaluations conducted by NIST. Performance is shown separately for the FERET, DOS/HCINT, and the Notre Dame FRVT 2006 data sets [14].

Two decades of vigorous research has yielded face recognition systems that are highly accurate in controlled environments (see Fig. 2). However, within the face recognition community, four key factors are known to significantly compromise recognition accuracy: pose, expression, illumination and aging (Fig. 3). Fig. 4 shows the impact of facial aging on face recognition performance. Thus, deployments of **fully automated face recognition** systems are largely limited to scenarios in which these factors can be largely constrained. Face images in government issued identification documents (e.g. driver's license, passport) and mug shots are two scenarios that offer such constraints, which has lead to success in the de-duplication[2] of identification cards and prevention of false prisoner releases.

Paradigm for Forensic Face Recognition

[2] De-duplication is a 1:N matching process to detect ID cards enrolled under different names but belonging to the same subject.

In forensic identification, investigators must make use of any available information to facilitate subject identification. Typically, the sources of face images are surveillance cameras, mobile device cameras, forensic sketches, and images from social media sites. These sources of face images are difficult to match because the images are often captured under non-ideal conditions (see Fig. 5).

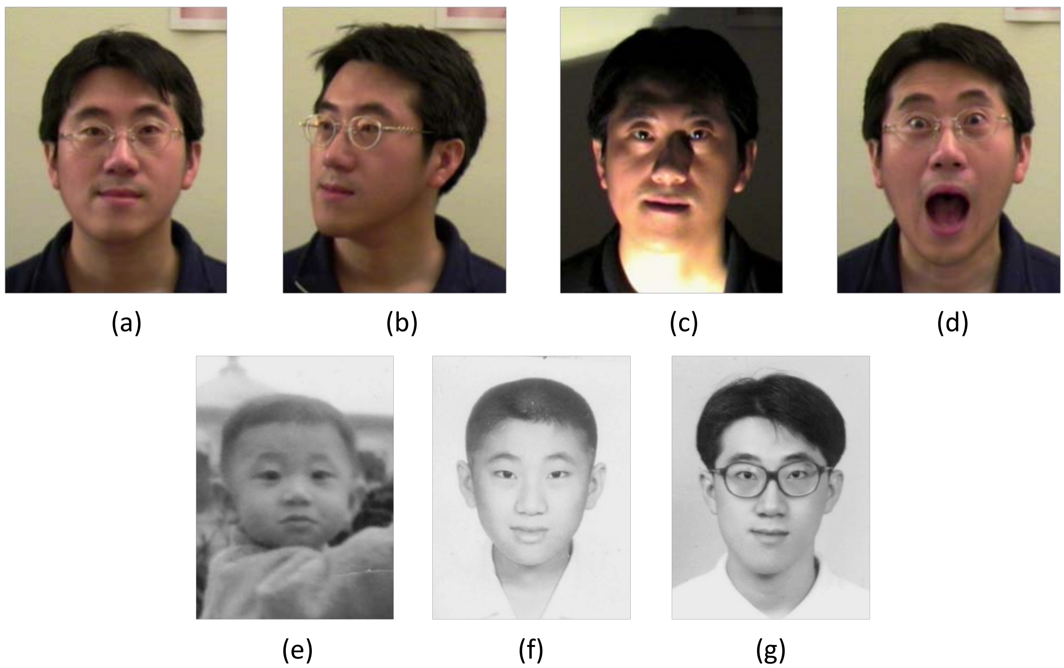


Figure 3. Four key factors compromising the face recognition accuracy are pose, illumination, expression, and aging variations. Face images of one subject are shown under (a) ideal capture condition, and with (b) pose, (c) illumination, (d) expression, and (e), (f), (g) aging variations (32, 21, and 15 years younger than (a)). Often, these factors do not occur in isolation, further compounding the face recognition problem.

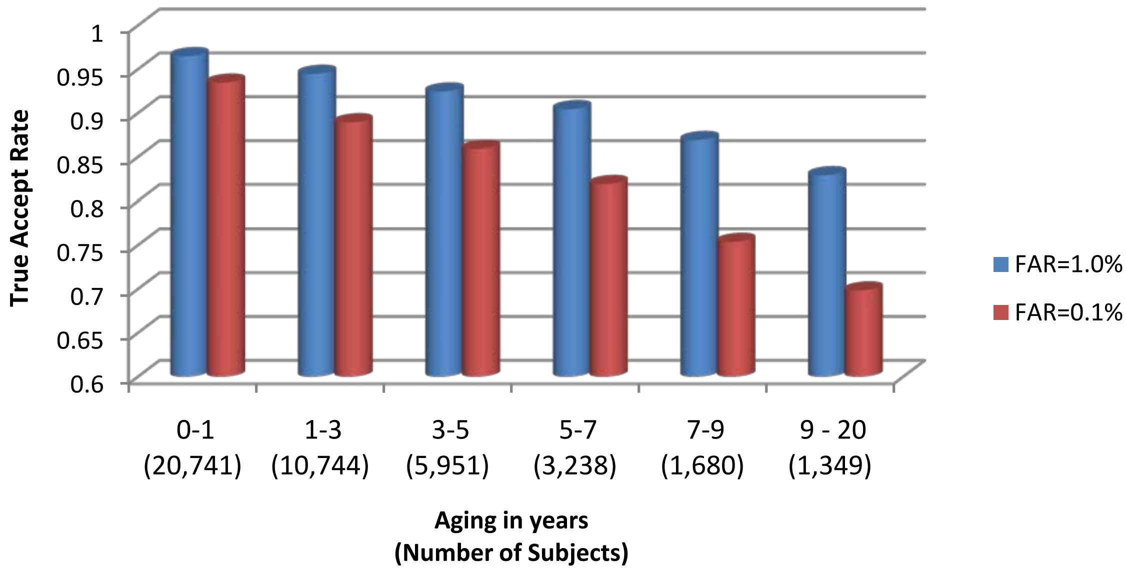
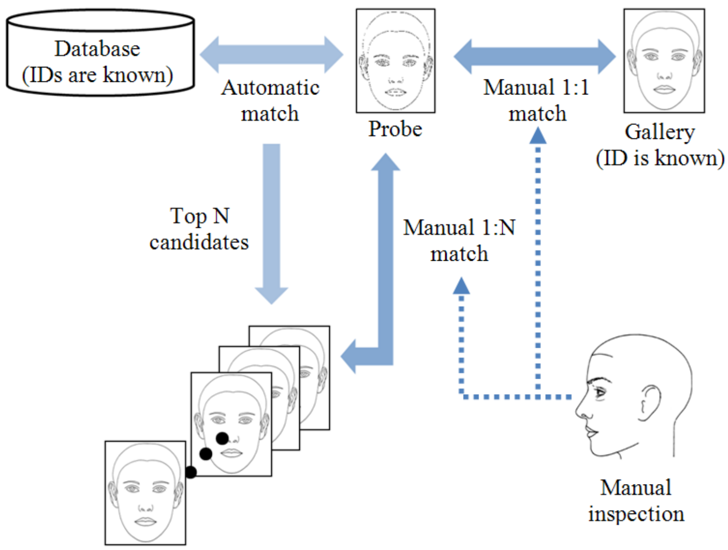


Figure 4. Accuracy of a leading COTS FRS as a function of the time lapse between the probe and gallery images across a mug shot database containing 94,631 face images of 28,031 subjects. The degradation in recognition accuracy suggests that face recognition systems may need to be specially designed to match across large age variations.

	Pose	Illumination	Expression	Aging	Heterogeneous
Non-forensic					
Access control		✓			
De-duplication				✓	
Border control		✓			
Forensic					
Missing person	✓		✓	✓	
Child trafficking	✓	✓	✓	✓	
Surveillance	✓	✓	✓		
Forensic sketch					✓

Figure 5. Challenges in forensic face recognition range from pose, illumination, expression, and aging variations, as well heterogeneous images. Non-forensic, fully automated scenarios are not severely impacted by these performance degrading factors. As a result, forensic face recognition often requires a preprocessing stage of image enhancement or a specialized matcher to perform recognition.

Another important aspect in face recognition in forensics is the continuously increasing size of face databases or galleries. For example, the mug shot database at the Pinellas County Sheriff's Office (PCSO) in Florida contains over 7.5 million face images. Most Departments of Motor Vehicles (DMV) in the United States (34 states) utilize face recognition systems [15]. The U.S. Department of State hosts one of the largest face databases in the world, with a gallery size in the order of 100 million images which is being used for de-duplication of passport and visa applicants.



(a)

(b)

Figure 6. Forensic face recognition. (a) schematic; note that in many forensic scenarios, face recognition is not yet fully automatic and requires manual intervention during preprocessing and an examination of top-K retrieved faces from a large gallery (b) typical face images encountered in forensic face recognition: mug shot, deceased subject, sketch, video frame, and near-infrared (NIR) image from left to right.

The problem of forensic face recognition can be stated as follows. A low quality query (or probe) image of an unidentified subject is available from a source such as a surveillance camera or a forensic sketch. An expansive database (or gallery) of high quality face images (e.g. mug shots) exists in which the subject may or may not reside. To boost the recognition accuracy in this difficult matching scenario, a modified matching paradigm with a human in the loop is considered. While this semi-automated face recognition is not often considered in mainstream face recognition research, it is indeed necessary to include a human in the recognition loop to boost the accuracy and confidence in forensic scenarios [3]. The role of man and machine may vary in this scenario, with two expectations: (i) the machine is used to return a similarly score from some probe image to each image in the gallery, and (ii) the human is used to examine the top-K matches (as opposed to only returning the closest match) (see Fig. 6).

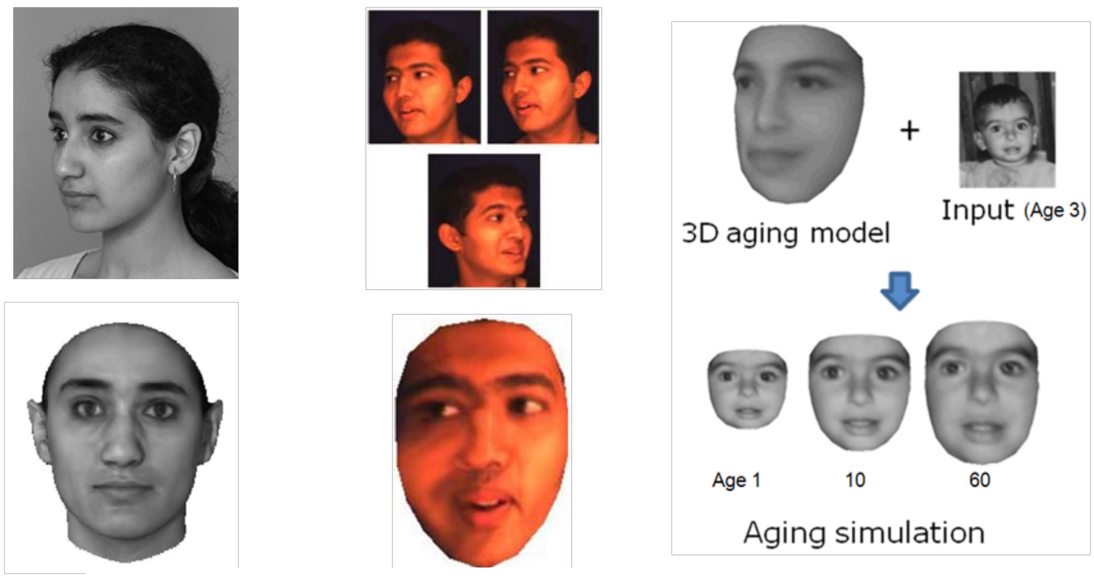
Below we will discuss additional scenarios in which man or machine may be used to improve the prospects of successful face identification. We separate such methods into two main categories. The first approach uses preprocessing methods that seek to improve the quality of a face image prior to submission to a COTS FRS. These methods do not require any changes to existing systems, but are limited in that they can only modify the input face image itself and not the features that will be extracted from the face images. Preprocessing methods have been developed with the ability to improve the pose [4][5] and illumination of the image [4], alter the subject's age [6], and improve the image resolution [16]. The second approach is to design special purpose face recognition systems for a specific matching problem. These methods allow any of the modules of the face recognition process (e.g. feature representation) to be appropriately modified. Special purpose face recognition systems are discussed for problems where preprocessing is not feasible, such as forensic sketch recognition [9], and matching and retrieval using soft biometrics such as facial marks, scars, and demographics [11]. A special purpose face recognition system for facial aging [8] is also discussed for augmenting the aging preprocessing approach. The four specific problems addressed below (sketch recognition, aging, facial scars and marks, pose and illumination correction, and matching low resolution images) reflect a body of research that has been directly motivated by recent research progress and which have been the most difficult for law enforcement agencies to overcome.

Preprocessing approach to Forensic FR

Preprocessing methods in forensic face recognition receive a face image as input, and output an enhanced quality face image. The key benefit to such methods is they are compatible with the COTS FRS already in use by law enforcement agencies.

When a face image is off pose and suffers from poor illumination, using the 3D morphable model proposed by Blanz and Vetter [4] allows a user to correct the facial pose and compensate for adverse illumination conditions. 3D morphable models use a training set of face images to learn the distribution of 3D facial shape and texture in a parameterized feature space. Variations in the feature space alter the face texture, shape, pose, and the 3D illumination model. Given a 2D face image, gradient descent is performed on the difference between the 2D face image and the texture of the 3D morphable model. At convergence, the 2D face image is parameterized, and thus controlled, in a 3D graphics environment. This allows a user to adjust the pose of the 3D face to frontal, and set the illumination to ideal ambient conditions. The accuracy of morphable models is generally improved by manually adjusting the initial alignment between the input 2D image and 3D morphable model.

Instead of a single off pose face image, often many off pose and low quality face images are available from surveillance video frames. These multiple image frames can be inspected manually to find the highest quality frame, which can then be fed into the COTS FRS. Alternatively, Park and Jain [5] used a structure from motion algorithm that utilizes facial landmarks obtained from video sequences to infer the 3D face shape. The factorization method factorizes a set of 2D landmark points, W, to initially estimate the rotation matrix, M', and 3D shape, S'. These initial estimates of M' and S' are adjusted by a correction matrix, A, obtained from the orthogonal constraint on the true rotation matrix $M=M' \cdot A$. The true 3D shape is obtained as $S=A^{-1} \cdot S'$. The reconstructed 3D model can be used to generate the pose corrected frontal face images for improved identification accuracy [5] (see Fig. 7).



(a) (b) (c)

Figure 7. Preprocessing methods. (a) A 3D morphable model [4] allows a single off-pose face image to be fit to a 3D model, where the pose can be corrected to a frontal view for improved face recognition performance. (b) Given multiple off pose face images of a subject, a structure from motion algorithm [5] is able to infer the 3D shape of the face to generate frontal pose face image. Tools such as these offer forensic investigators methods for normalizing a face image prior to submitting for a match against large face databases. (c) Aging simulation methods allow investigators to use the age progressed (or regressed) output from the aging model to improve face recognition accuracies across existing COTS FRS configurations.

In addition to correcting variations in pose and illumination, face preprocessing algorithms can also simulate the facial aging process. Park et al. [6] proposed a generative 3D aging modeling method where the input image is projected into the parametric 3D aging pattern space and simulated face images are generated at target ages (see Fig. 7). The ability to take face images and simulate aging (or de-aging) is useful in cold case investigations, missing children cases and de-duplication of government issued documents.

Another problem often encountered in forensic face recognition involves low resolution face images. A common source of low resolution face images in law enforcement units is face images that have been faxed, printed, or heavily compressed (see Fig. 8). Bourlai et al. [16] proposed a method that applies image filtering, linear denoising, and thresholding-based nonlinear denoising method to enhance the quality of the low resolution images for improved matching accuracy.

Original (a) | *JPEG Compressed* (b) | *Interpolated from 10% down-sampled image* (c) | *Half-toning* (d) | *Scanned passport* (e)

Figure 8. Degraded and low-resolution probe face images. (a) Original image. (b) JPEG compressed (medium quality). (c) Resized to 10% and up-scaled to the original spatial resolution (d) Half-toning. (e) Scanned passport.

Manual or interactive enhancement techniques may also be used for preprocessing. For example, Fig. 9 shows the result of forensic artists inferring accurate facial appearances from low quality videos in a recent case in Los Angeles [7]. Two of the suspects shown were manually identified after the sketches were posted in public places. As shown below, using a specialized sketch recognition further improves the ability to perform identification from the original low quality images.

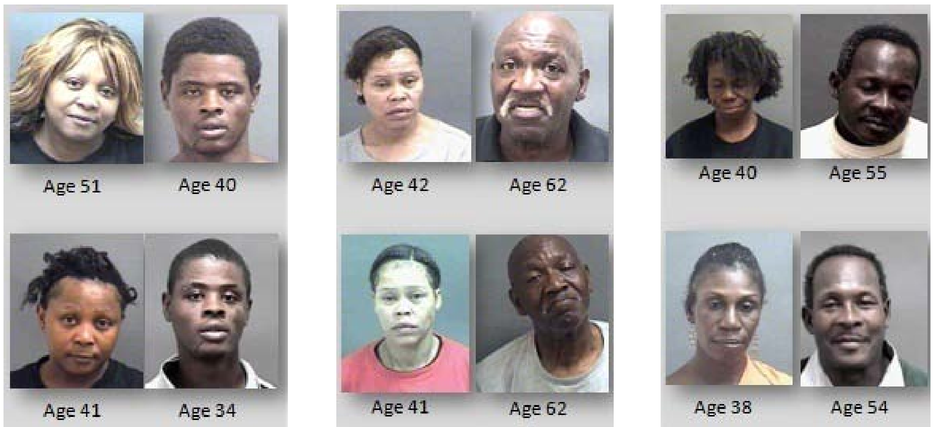
Figure 9. The detailed sketches of the four suspects above were drawn from low resolution surveillance video in a high profile LAPD case [7]. An example of the highest quality frame available for each subject is also shown. This manual enhancement technique is useful for both human-based identification, as well as recognition using a specially designed sketch recognition system.

Special-purpose Face Recognition Systems

There are certain face recognition scenarios where image enhancement alone is insufficient for automated identification. Instead, specially designed face recognition algorithms are needed in place of the COTS FRS. These systems allow any aspect of the face recognition process (e.g. feature representation, statistical learning) to be tailored to the given scenario.

Facial aging:

In addition to simulating the face aging process to improve any generic COTS FRS [6], Li et al. developed a specialized face recognition system to compensate for aging [8]. Their approach uses a discriminative aging model to learn a robust face representation. The discriminative model is trained on a set of age separated image pairs using Scale Invariant Feature Transformation (SIFT) and Multi-scale Local Binary Pattern (MLBP) descriptors and random sampling Linear Discriminant Analysis (LDA) subspace analysis. Combining the discriminative aging modeling method with the generative preprocessing method discussed above offered significant improvements in identification accuracy over a leading COTS FRS (see Fig. 10).



(a) (b) (c)

Figure 10. Some examples of successful face retrieval at rank-1. The first row shows the probe images and the second row shows the successfully retrieved or matched images from the gallery. (a) Two examples where COTS FRS and the generative method fail, while the discriminative method succeeds. (b) Two examples where the discriminative method fails, while the COTS FRS and the generative method succeed. (c) Two examples where all the three methods (COTS FRS, generative model, and discriminative model) fail, but the score-level fusion of the generative model and the discriminative model succeeds. Both probe and gallery contain 10,000 (different) images of 10,000 different subjects.

Forensic sketch recognition: Automated identification of a subject based on a composite sketch query expands face recognition capabilities to situations where a face image of a suspect is not available from the crime scene. In such situations, only a verbal description of a subject, provided by witnesses or victims, is available for use by a forensic sketch artist or a composite software tool to generate a depiction of the subject's facial appearance. Forensic sketches have been successfully used for over a century in criminal identification; however, the paradigm for using a forensic sketch has been limited to dissemination of the sketch to the media and law enforcement agencies with the hopes that citizens will provide tips to enable arrest of the suspect.

Despite the strengths of COTS FRS in matching photographs, their ability to match forensic sketches to face photographs is severely limited. To fill this void, Klare et al. developed a face recognition system specifically designed for this task, called local feature-based discriminant analysis (LFDA) [9]. LFDA operates by representing both forensic sketches and photographs using SIFT and local binary pattern (LBP) feature descriptors. A column-wise concatenation of these descriptors are used to learn discriminant subspace projections that attempt to maximize the Fisher criterion, where the within-class feature spaces consist of both a sketch and photo from the same subject.

Forensic sketch recognition is an example of a problem known as heterogeneous face recognition (HFR), where the probe and gallery images are from different imaging modalities. As the number of imaging devices continues to increase (such as near-infrared, thermal infrared, and LIDAR sensors), situations are being encountered where a lack of sensor interoperability can impact the face recognition performance. To fill this void, Klare and Jain proposed a generic HFR framework using kernel prototype similarities [10].

In addition to the aforementioned LDA-based method [8][9], a gradient orientation pyramid (GOP) based method has also been proposed by Ling et al. for age invariant face recognition [17]. To handle the sketch recognition problem, Wang and Tang proposed a Markov random field approach to synthesize a photograph from a facial sketch [18].

Face Mark Based Matching and Retrieval: Facial marks consist of temporarily persistent skin irregularities, such as scars, moles, and freckles. Different scenarios exist where this information can be explicitly leveraged by a specially designed system. The first such use is to supplement the similarity score from a COTS FRS, which Park and Jain demonstrated to offer improvements in recognition accuracy [11]. Another scenario is a face retrieval system, where face mark information in the probe image, along with demographic information, can filter a large gallery database. The use of facial marks also enables verbal description based retrieval, such as "Find all faces with large dark scar on right cheek." Facial marks can also help to individualize identical twins. In fact, in surveillance videos, where often the face image is not frontal and of low resolution were, face marks are the only source of information to identify the suspect. Face images identified based on marks also serve as valuable evidence in legal testimony.

Park and Jain [11] developed an automatic facial mark detection method based on the Laplacian of Gaussian operator, $\nabla^2 G(x, y, \sigma)$ in scale space. A scale space representation, $D(x, y, \sigma)$, is obtained by convolving the normalized Laplacian of Gaussian operator, $\sigma^2\nabla^2 G(x, y, \sigma)$ with the input image, $I(x,y)$:$D(x, y, \sigma) = \sigma^2\nabla^2 G(x, y, \sigma) * I(x, y)$. From a multi scale space representation with scales or standard deviations $(\sigma_1, ..., \sigma_k)$, local maxima and minima are extracted depending on whether $D(x,y,\sigma)$ is greater or smaller than pixels in a neighborhood. Fig. 11 shows examples of automatic mark detection results. The size of each circle, ellipse, and rectangles represents the scale (σ) at which a mark is detected, which is proportional to the size of each mark.

Forensic experts often use facial marks to verify a suspect against a candidate face image. Park et al.'s face image matching and retrieval system provides tools such as, manual/automatic mark labeling, image retrieval using facial marks and demographic information, and an interactive interface for the Analyze, Compare, Evaluate, and Verify (ACE-V) operation practiced in forensics [12]. Fig. 12 shows the retrieval system and two example retrieval results from 100,000 gallery images, where correct mates were found at rank-1 by using facial marks and demographic information in addition to a COTS FRS. In Fig. 12(b), the use of gender and ethnicity successfully filtered 99.7% of the database, which improved the matching accuracy with reduced computation time. The rank-1 matching accuracy using COTS FRS only, COTS FRS + facial marks, and COTS FRS + facial marks + demographic information (i.e., gender and ethnicity) are 56.3%, 57.1%, and 57.7%, respectively, using 1,000 probe images and 100,000 images in gallery.

A face mark retrieval system is a prime example of how forensic face recognition differs from other “lights out” (fully automatic) face recognition applications. The use of a human operator is necessary to first verify and then utilize the results of the retrieval system. The system is not intended to replace forensic experts, but instead is meant to augment their capabilities, particulary for difficult probe face images.

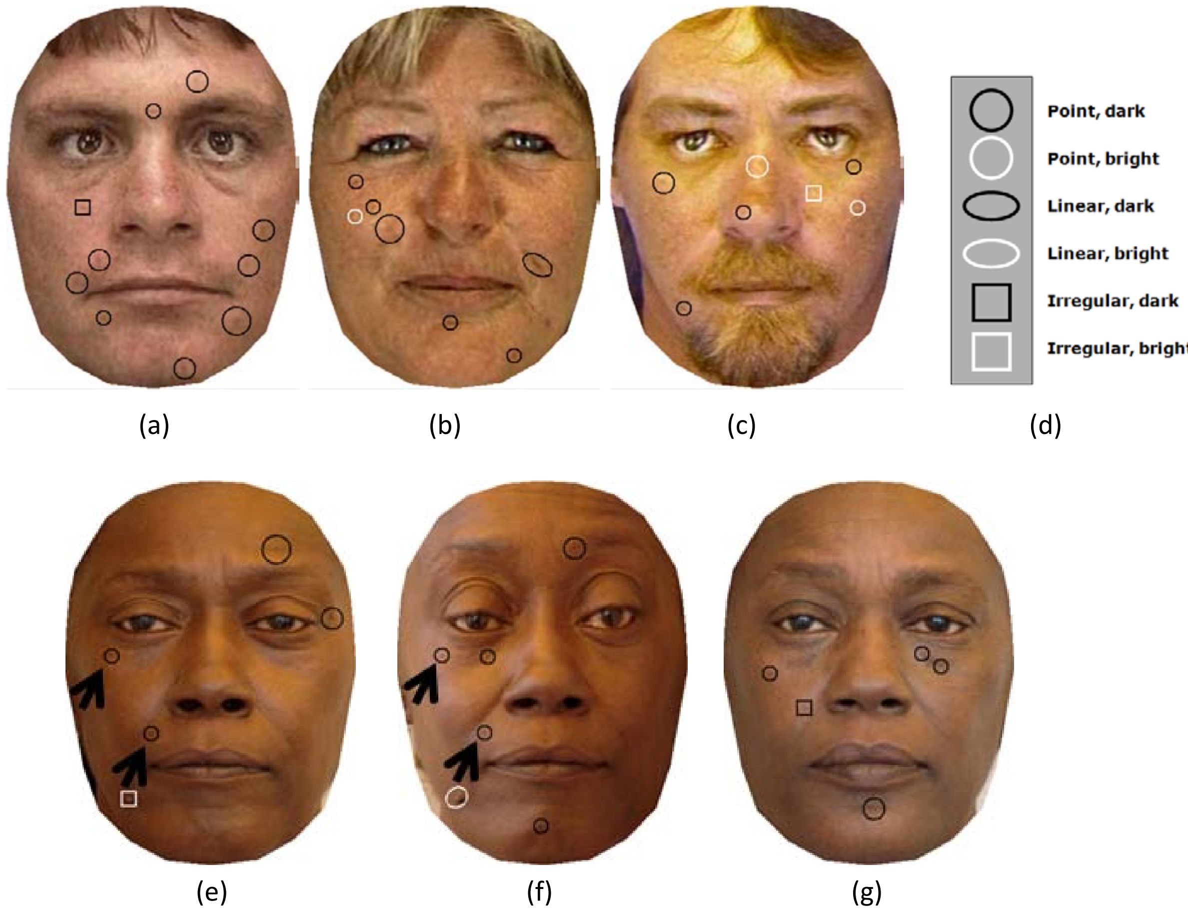
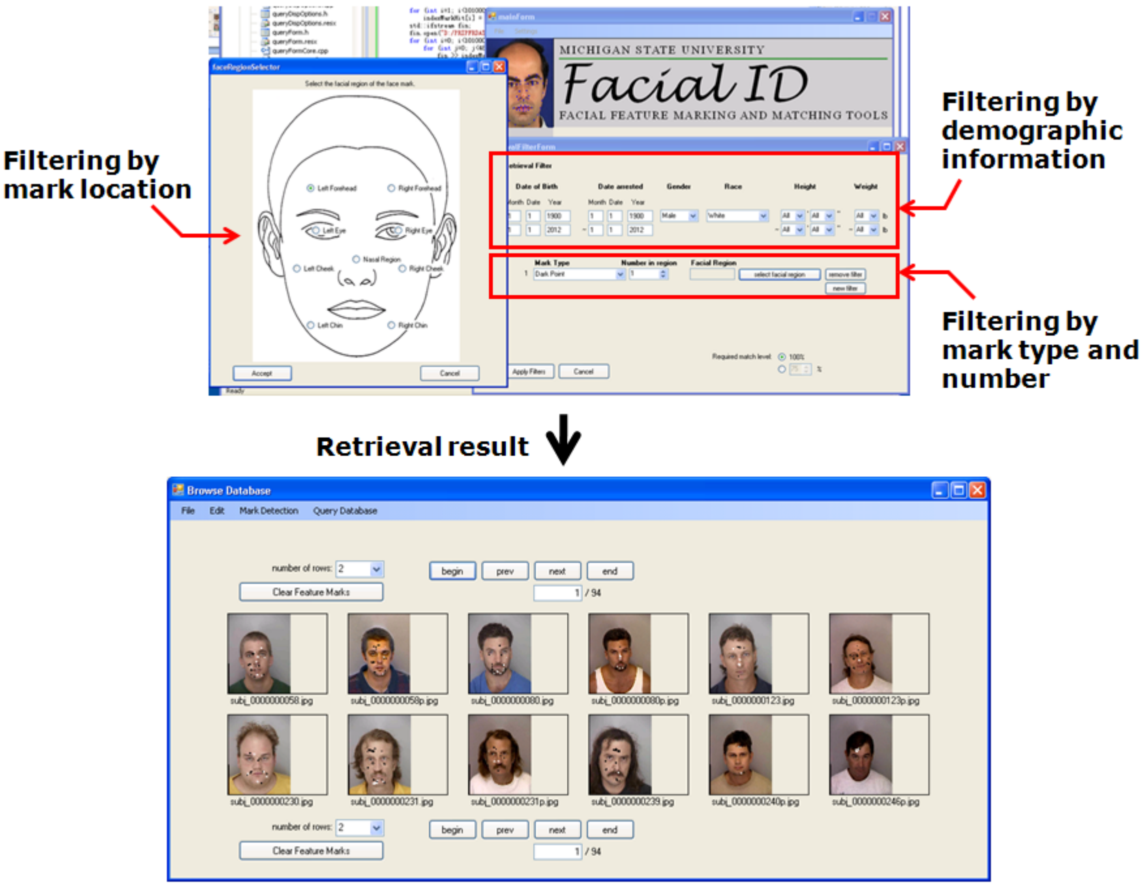
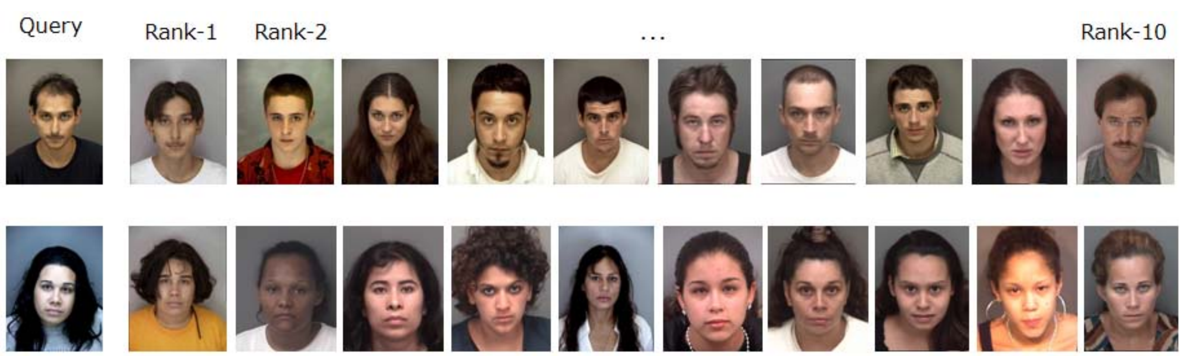


Figure 11. Automatic mark detection results on face images of three different subjects ((a)-(c)) and one pair of identical twins ((e)-(f)). All significant marks have been successfully detected and marked using circles, ellipse, and rectangles. A taxonomy of marks is shown in (d). (e) and (f) show face images of an identical twin pair and (g) is the image of the twin sister of (e) and (f). Face image in (e) was incorrectly matched to (g) at rank-1 using COTS FRS only, but this match was successfully excluded using COTS FRS + facial marks. Black arrows in (e) and (f) show the two marks that contributed to match (e) and (f) rather than (e) and (g).



(a)



(b)

Figure 12. Face image retrieval system that can filter a large database based on facial mark type, number, and locations as well as demographic information. (a) System GUI and retrieval results. (b) Two example queries where the correct mates were not retrieved at rank-1 using COTS FRS only, but correct mates were successfully retrieved at rank-1 using

Discussion

While most researchers consider face recognition from a fully automated perspective, this paper brings to light the forensic face recognition paradigm, which often necessitates the design of special purpose face matchers that require close interaction with forensic experts. We present two different families of solutions for many difficult forensic face matching problems. The first set of solutions is preprocessing methods that transform an input face image prior to submission to a face matcher in order to improve recognition accuracy. These methods were shown to impact the performance of important problems such as pose and illumination correction, aging, and low resolution images. The second set of solutions presented are a number of special-purpose face matchers that offer identification solutions for a range of scenarios where only certain low quality face information is available, such as forensic sketches, an aged image, soft biometric information such as face marks, scars, or demographics.

The need for the systems presented here was realized through close collaboration with the law enforcement community. The end users of such systems (e.g. forensic investigators) are generally the best source to find future avenues of forensic face recognition research that will have the most impact in identifying suspects and victims. Thus, fostering close collaboration between the pattern recognition community and law enforcement is critical to further the state of the art in forensic face recognition.

One of the most important aspects of forensic face recognition systems is that they are not always successful in matching faces. This leads to the most critical area of human interaction in the forensic face recognition process, namely interpreting the results. The top (rank-1) match returned should not always be given precedence over (say) the rank-10 match. Instead, the top K retrieved results should be given careful consideration. Forensic experts indicate that they routinely use value of “K” in the range [100, 200], i.e. they examine up to top 200 returned matches for culpability. Often, a majority of these retrievals can be quickly discarded from information such as incarnation status or demographics.

Another reason why face recognition results in a forensic setting must be used with caution is that, despite being designed using elements of statistical decision theory, face matchers are incapable of generating a probability of false match. This deficiency is because no face individuality models have been developed. Klare and Jain proposed an organization of facial features into three distinct levels, which follow the convention used in fingerprint recognition [13]. This feature organization is meant to serve as a precursor to face individuality studies. In the meantime, the use of face recognition results in legal proceedings is severely limited. Instead, forensic face recognition can only point to a suspect, from there additional evidence must be found for a conviction.

Acknowledgment

We thank Shengcai Liao for providing facial mark detection results. The support of Captain Greg Michaud of Michigan State Police and Scott McCallum of the Pinellas County Sheriff's Office in providing operational face databases and their valuable suggestions is greatly appreciated. This research was partially supported by WCU (World Class University) program funded by the Ministry of Education, Science and Technology through the National Research Foundation of Korea (R31-10008). All correspondences should be directed to Unsang Park.

References

[1] S. Z. Li and A. K. Jain (eds.), Handbook of Face Recognition, Second edition, Springer, 2011

[2] J. Vlahos, "Surveillance Society: New High-Tech Cameras are Watching You," Popular Mechanics, October, 2009.

[3] L. Ding, C. Shu, C. Fang, and X. Ding, "Computers do better than experts matching faces in a large population," IEEE International Conference on Cognitive Informatics, pp. 280-284, 2010.

[4] V. Blanz and T. Vetter, "Face Recognition Based on Fitting a 3D Morphable Model," IEEE Trans. on Pattern Analysis and Machine Intelligence, Vol. 25, No. 9, pp. 1063-1074, 2003

[5] U. Park and A. K. Jain, "3D Model-Based Face Recognition in Video," Proc. 2nd International Conference on Biometrics (ICB), pp. 1085 - 1094, 2007.

[6] U. Park, Y. Tong, and A. K. Jain, "Age Invariant Face Recognition," IEEE Trans. on Pattern Analysis and Machine Intelligence, Vol. 32, No. 5, pp. 947-954, May, 2010

[7] "Los Angeles Officials Identify Video Assault Suspects," The New York Times. Jan. 7, 2011. http://www.nytimes.com/2011/01/08/us/08disabled.html

[8] Z. Li, U. Park, and A. K. Jain, "A Discriminative Model for Age Invariant Face Recognition," IEEE Trans. on Information Forensics and Security, Vol. 6, No. 3, 2011 (To Appear)

[9] B. Klare, Z. Li, and A. K. Jain, "Matching Forensic Sketches to Mugshot Photos," IEEE Trans. on Pattern Analysis and Machine Intelligence, Vol. 33, No. 3, pp. 639-646, March, 2011.

[10 B. Klare and A. K. Jain, "Heterogeneous Face Recognition using Kernel Prototype Similarities", IEEE Transactions on Pattern Analysis and Machine Intelligence, 2011 (Under Review).

[11] U. Park and A. K. Jain, "Face Matching and Retrieval Using Soft Biometrics," IEEE Trans. on Information Forensics and Security, Vol. 5, No. 3, pp. 406-415, 2010

[12] H. Tuthill and G. George, Individualization: Principles and Procedures in Criminalistics. Florida: Lightning Powder Company, Inc., 2002.

[13] B. Klare and A. K. Jain, "On a Taxonomy of Facial Features," Proc. Conference on Biometrics: Theory, Applications and Systems (BTAS), 2010.

[14] P. Grother, G. Quinn, and P. J. Phillips, "Multiple Biometric Evaluation 2010: Still Face Report," NISTIR 7709, 2010, http://face.nist.gov

[15] R. Charette, "Here's Looking at You, and You, and You ...," IEEE Spectrum, 2011.

[16] T. Bourlai, A. Ross, and A. K. Jain, "Restoring Degraded Face Images: A Case Study in Matching Faxed, Printed and Scanned Photos," IEEE Trans. on Information Forensics and Security, Vol. 6, No. 2, pp. 371-384, June 2011.

[17] H. Ling, S. Soatto, N. Ramanathan, and D. Jacobs, "Face verification across age progression using discriminative methods," IEEE Trans. on Information Forensic and Security, Vol. 5, No. 1, pp. 82-91, Mar. 2010.

[18] X. Wang and X. Tang, "Face Photo-Sketch Synthesis and Recognition," IEEE Trans. on Pattern Analysis and Machine Intelligence, Vol. 31, No.11, pp.1955-1967, 2009

Anil K. Jain is a university distinguished professor in the Department of Computer Science and Engineering at Michigan State University. He is also a distinguished professor in the Department of Brain and Cognitive Engineering at Korea University, Korea. His research interests include pattern recognition, computer vision, and biometric authentication. Jain has a PhD in electrical engineering from Ohio State University. Contact him at jain@cse.msu.edu. 3115 Engineering Bd. East Lansing, MI 48824, USA. Phone: 517-353-3148, Fax: 517-432-1061

Brendan Klare is a PhD candidate in the Department of Computer Science and Engineering at Michigan State University. His research interests include pattern recognition and computer vision. Klare has a M.S. in computer science and engineering from the University of South Florida. Contact him at klarebre@cse.msu.edu. 3115 Engineering Bd. East Lansing, MI 48824, USA. Phone: 517-353-3148, Fax: 517-432-1061.

Unsang Park is a post doctoral fellow in the Department of Computer Science and Engineering at Michigan State University. His research interests include pattern recognition, image processing, computer vision, and machine learning. Park has a PhD in computer science and engineering from Michigan State University. Contact him at parkunsa@cse.msu.edu. 3115 Engineering Bd. East Lansing, MI 48824, USA. Phone: 517-353-3148, Fax: 517-432-1061.