Forensic Sketch-Photo Matching using LFDA

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Abstract— The advancement of biometric technology has provided criminal investigators additional tools to determine the identity of criminals. In addition to DNA and circumstantial evidence, if a latent fingerprint is found at an investigative scene or a surveillance camera captures an image of a suspect's face, then these cues may be used to determine the culprit's identity using automated biometric identification. However, many crimes occur where none of this information is present, but instead an eye-witness of the crime is available. In these circumstances a forensic artist is often used to work with the witness or the victim in order to draw a sketch that depicts the facial appearance of the culprit according to the verbal description. These sketches are known as forensic sketches. This problem of matching a forensic sketch to a gallery of mugshot images is addressed here using a robust framework called local feature-based discriminant analysis (LFDA). Since, forensic sketches or digital face images can be of poor quality, a pre -processing technique is used to enhance the quality of images and improve the identification performance.In this paper experiments are carried out using 52 forensic sketches for matching against a gallery of 264 photo images. The experimental results demonstrate the matching performance of the proposed algorithm with the use of preprocessing approach yields better identification accuracy compared to other methods.

Keywords—Forensic sketch, Mugshots, Feature-based approach, Local feature-based discriminant analysis, Feature descriptors.

I. INTRODUCTION

Today, advances in biometric technology have provided criminal investigators additional tools to help determine the identity of criminals. In addition to the incidental evidence, if a dormant fingerprint is found at the scene of crime or a surveillance camera captures an image of the face of a suspect, then these clues are used in determining the suspect using biometric identification techniques. However, many crimes occur where none of the above discussed information is present.

Also, the lack of technology to effectively capture the biometric data like finger prints within a short span after the scene of crime is a routine problem in remote areas. Despite these repercussions, many a times, an eyewitness account of the crime is available who had seen the criminal. The Police department deploys a forensic artist to work with the witness in order to draw a sketch that depicts the facial appearance of the culprit. These sketches are known as forensic sketches. Once the sketch is ready, it is sent to the law enforcement officers and media outlets with the hope of catching the suspect. Here, two different scenarios may arise for the culprit:

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1. The person may have already been convicted once or
2. The person has not been convicted even once or this is the first time, he may be committing crime.

In general, sketches are classified into two categories: viewed sketches and forensic sketches

- Viewed Sketches: These are the sketches drawn by an artist, directly looking at the subject or the photograph of the subject as shown in fig. 1.
- Forensic Sketches: These are the sketches drawn by specially trained artists based on the description of subject by an eye witness as shown in fig. 2.

Two key difficulties highlighted in matching forensic sketches are: (1) Matching across image modalities, and (2) performing face recognition despite possibly inaccurate depictions of the face.

Fig. 1 Example of viewed sketch and its corresponding photograph

Fig. 2 Forensic sketch and its corresponding photograph

II. RELATED WORK

Research in sketch matching started only a decade ago. This is because the accuracy of sketch recognition is very low, compared to traditional face recognition techniques. This is in turn due to a large texture difference, between a sketch and a photo. Even though all the methods that are applicable to viewed sketches, are also applicable to forensic sketches, the unavailability of a public database for forensic sketches led to a lack of standard test procedure on the latter one. That is why most of the early work consists of tests on viewed sketches only.

Most of the work in matching viewed sketches was performed by Tang and Wang [1] [2]. Tang and Wang first approached the problem using an eigentransformation method [1] to either project a sketch image into a photo subspace, or to project a photo image into a sketch subspace. An improvement to this method was offered by Wang and Tang [2], where the relationship between sketch and photo image patches was modeled with a Markov random field. Here, the synthetic sketches generated were matched to a gallery of photographs using a variety of standard face recognition algorithms.

In the paper [3] the authors discussed a method for representing face which is based on the features which uses geometric relationship among the facial features like mouth, nose and eyes. Feature based face representation is done by independently matching templates of three facial regions i.e. eyes, mouth and nose. In paper [4] which presents a novel and efficient facial image representation based on local binary pattern (LBP) texture features.

To identify forensic sketches much efficient algorithm is presented here in [5]. Both sketches and photos are considered for extracting feature descriptors using Scale Invariant Feature Transform (SIFT).

A feature-based method for matching sketches was presented by Klare and Jain [6], which serves as the motivation for the sketch matching method presented in this project. In this feature-based sketch matching approach uniformly samples both sketch and photo images using SIFT feature descriptors at different scales. From this A.K.Jain in [7] proposed a system which used SIFT and multiscale local binary pattern (MLBP) as feature descriptors with a new framework called as LFDA i.e. local feature based discriminant analysis.

The paper [8] surveys about forensic face recognition approaches and the challenges they face in improving the matching and retrieval results as well as processing the low-quality images.

III. PRE-PROCESSING ALGORITHM

The digital images may be noisy and of sub-optimal quality because of the printing and scanning of images. Forensic sketch-digital image pairs of lower visual quality may lead to reduced matching performance as compared to good quality sketch-digital image pairs. Forensic sketches may also contain distortions and noise introduced due to the excessive use of charcoal pencil, paper quality, and scanning (device noise/errors).

In this paper, following pre-processing technique [9] is used that enhances the quality of forensic sketch-digital image pairs.

1. Let f be the color face image to be enhanced. Let f^r and f^y be the red and luma channels respectively. These two channels are processed using the multi-scale retinex (MSR) algorithm. MSR is applied on both red and luma channels to obtain f^{rm} and f^{ym}.

2. Image denoising is applied to get $f^{rm'}$ and $f^{ym'}$ respectively.

3. Noise removal may lead to burring of edges. Hence Weiner filter is applied to obtain f^1 and f^2.

4. After computing globally enhanced red and luma channels, DWT fusion algorithm is applied on f^1 and f^2 to compute a feature rich and enhanced face image, F. Single level DWT is applied on f1 and f2 to obtain the detail and approximation bands of these images. Let $f^j{}_{LL}$, $f^j{}_{LH}$, $f^j{}_{HL}$, $f^j{}_{HH}$ be the four bands and j = 1, 2. To preserve features of both the channels, coefficients from the approximation band of f^1 and f^2 are averaged.

$$f^e{}_{LL} = \text{mean}\,(f^1{}_{LL}, f^2{}_{LL})$$

Where $f^e{}_{LL}$ is the approximation band of enhanced image. All three detailed subbands are divided into windows of size 3×3 and the sum of absolute pixels in each window is calculated. For the i^{th} window in HL subband of the two images, the window with maximum absolute value is selected to be used for enhanced subband $f^e{}_{HL}$. Similarly, enhanced subbands $f^e{}_{LH}$ and $f^e{}_{HH}$ are obtained. Finally, inverse DWT is applied on the four subbands to generate a high quality face image.

$$F = \text{IDWT}\,(f^e{}_{LL}, f^e{}_{LH}, f^e{}_{HL}, f^e{}_{HH})$$

This DWT fusion algorithm is applied on both forensic sketches and digital face images.

IV. PROCESS OF SKETCH TO PHOTO MATCHING

The proposed feature-based method for sketch to photo matching system is shown in the following given block diagram:

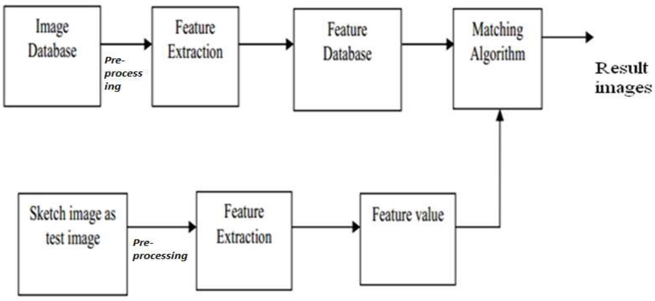

Fig. 3 Representation of the sketch matching system

Here we have a set of sketches (Probe images) and a set of mugshot photographs.

The steps involved in sketch to photo matching are as follows:

1. For the input sketch image and the corresponding photo, apply feature extraction techniques on each of them and store results in the database.
2. Store this feature extraction results for every image into a feature database.
3. For every probe image, the corresponding match is that with the minimum distance calculated with the nearest neighbor matching method.
4. The final top retrieved images from the database are then displayed.

From the above figure, we can say that the image database represents the gallery of images of the culprits. These images are called as the mugshot images. A mug shot is a photographic portrait taken after one is arrested. Sketch image is the probe sketch which is the input given to the matching system that is to be identified against the available mugshot images.

- *Feature extraction:* Feature extraction represents any feature-based sketch matching technique. For example there are different types of feature (image) descriptors which can be used, that are SIFT, MLBP, SURF (Speeded up Robust Features), Haar, Gabor, and intensity.
- *Feature database:* Feature database is the database maintained where all the results or values obtained from

the feature extraction method are stored. These are afterwards used for matching purpose with the probe sketch.

- *Matching algorithm:* Matching algorithm is used to find a proper match between the probe sketch image with the mugshot images. We can match sketch to photos using 'nearest neighbor matching' method in which the minimum distance between the calculated values of the mugshot images and the probe sketch is found out.

The images need to be preprocessed first as given below and then matching can be performed on them.

V. FEATURE-BASED SKETCH MATCHING

In feature-based technique [7], feature descriptors describe an image or image region using a feature vector that captures the distinct characteristics of the image. Here we find out feature based representation of both sketch and photograph. For both, we compute a SIFT feature descriptor. Because most image descriptors are not sufficiently verbose to fully describe a face image, the descriptors are computed over a set of uniformly distributed sub-regions of the face. The feature vectors at sampled regions are then concatenated together to describe the entire face. The feature sampling points are chosen by setting two parameters: a region (or patch) size s and a displacement size δ. The region size s defines the size of the square window over which the image feature is computed. The displacement size δ states the number of pixels the patch is displaced for each sample; thus, (s- δ) is the number of overlapping pixels in two adjacent patches. For an H × W image, the number of horizontal (N) and vertical (M) sampling locations is given by N= (W – s) / δ+1 and M = (H – s)/ δ +1. At each of the M × N patches, we compute the d-dimensional image feature vector φ. These image feature vectors are concatenated into one single (M * N * d)-dimensional image vector Φ. Minimum distance sketch matching can be performed directly using this feature-based representation of subjects i and j by computing the normed vector distance || F (Ii) – F (Ij) ||.

A. Local Feature-Based Discriminant Analysis:

In the LFDA framework [7], each image feature vector is first divided into "slices" of smaller dimensionality, where slices
correspond to the concatenation of feature descriptor vectors from each column of image patches. Next, discriminant analysis is performed separately on each slice by performing the
following three steps: PCA, within class whitening, and between class discriminant analysis.
Finally, PCA is applied to the new feature vector to remove redundant information among the feature slices to extract the final feature vector. The training and matching phases of LFDA framework are as shown above in Fig. 4.

B. Feature descriptors:

In LFDA framework [7], the following feature descriptors are used i.e. scale invariant feature transform (SIFT) and multiscale local binary pattern (MLBP).

- Scale Invariant Feature Transform (SIFT):
  The algorithm for SIFT is as follows:

Step 1: Scale-Space Extrema Detection: The scale space is defined by the function:

$$L(x, y, \sigma) = G(x, y, \sigma) * I(x, y)$$

Where * is the convolution operator, G(*x*, *y*, σ) is a variable-scale Gaussian and I(*x*, *y*) is the input image.
Difference of Gaussians technique is used for locating scale-space extrema, D(*x*, *y*, σ) by computing the difference between two images, one with scale *k* times the other.

$$D(x, y, \sigma) = L(x, y, k\sigma) - L(x, y, \sigma)$$

Step 2: Keypoint Localization

Elimination of more points by finding those that have low contrast or are poorly localized on an edge. This is achieved by calculating the Laplacian.

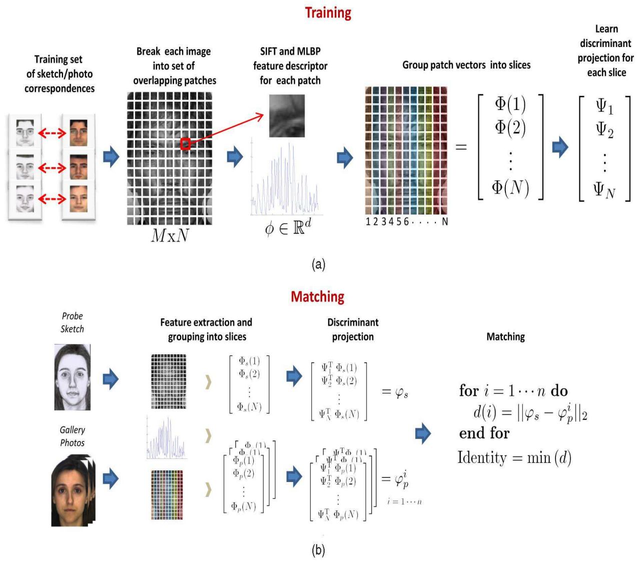

Fig. 4. An overview of the (a) training and (b) recognition using the LFDA framework

Step 3: Orientation Assignment

To assign an orientation we use a histogram and a small region around it. Using the histogram, the most prominent gradient orientation(s) are identified. If there is only one peak, it is assigned to the keypoint. If there are multiple peaks above the 80% mark, they are all converted into a new keypoint (with their respective orientations).

Next, we generate a highly distinctive "fingerprint" or "feature vector", having 128 different numbers for each keypoint.

Step 4: Keypoint Descriptor:

Keypoint descriptors typically uses a set of 16 histograms, aligned in a 4x4 grid, each with 8 orientation bins, one for each of the main compass directions and one for each of the mid-points of these directions. This result in a feature vector containing 128 elements. These resulting vectors are known as SIFT keys and are used in a nearest-neigbours approach for sketch to photo matching.
The nearest neighbors are defined as the keypoints with minimum Euclidean distance from the given descriptor vector. The probability that a match is correct can be determined by taking the ratio of distance from the closest neighbor to the distance of the second closest. All matches are rejected in which the distance ratio is greater than 0.8, which eliminates 90% of the false matches while discarding less than 5% of the correct matches.

- Multiscale Local Binary Pattern (MLBP):

The original local binary patterns (LBP) operator takes a local neighborhood around each pixel, thresholds the pixels of the neighborhood at the value of the central pixel and

uses the resulting binary-valued image patch as a local image descriptor. It was originally defined for 3 × 3 neighborhoods, giving 8 bit codes based on the 8 pixels around the central one. The operator labels the pixels of an image by thresholding a 3 × 3 neighborhood of each pixel with the centre value and considering the results as a binary number, and the 256-bin histogram of the LBP labels computed over a region is used as a texture descriptor.
The limitation of the basic LBP operator is that its small 3 × 3 neighborhood cannot capture the dominant features with large scale structures. As a result, to deal with the texture at different scales, the operator was later extended to use neighborhoods of different sizes called as MLBP. It describes the face at multiple scales by combining the LBP descriptors computed with radii r ε {1, 3, 5, 7}.

V. EXPERIMENTAL RESULTS

The experiments are performed using the combination of viewed sketches and forensic sketches to increase the size of dataset.
The database consists of 142 viewed sketch-photo pairs from CUHK database [2] and 70 viewed sketch-photo pairs from IIIT- D database [9]. Forensic pairs are collected as 25 pairs from Forensic composite sketch database [10], which contains sketch photo pairs from L. Gibson [11] and 27 pairs are taken from IIIT-D forensic database. Initially training was performed on all the sketches with its corresponding photographs. And the probe set consisting of 52 forensic sketches were used to match against a gallery of 264 gallery images.Matching forensic sketches to large mug shot galleries is different in several respects from traditional face identification techniques. Hence, when matching forensic sketches we are generally concerned with the accuracy at rank-50 i.e. whether or not the true subject is present within the top-50 images that were near (Euclidean distance between descriptors) or top-50 retrieved images. Hence with 52 probe set of forensic sketches, the results obtained are shown in the following Table 1.

Table 1
Rank-10 and Rank-50 accuracies obtained for matching 52 forensic sketches to 264 gallery images.

Methods	Rank-10 Accuracy (%)	Rank-50 Accuracy (%)
LFDA	23.07%	55.76%
LFDA with Pre-Processing	26.92%	57.69

Examples of the forensic sketches correctly identified at rank-1 with both methods are as shown in Fig. 5(a).These two sketches were good quality sketches resembling perfectly with the suspects photo. In Fig 5(b) one more good quality sketch is

shown which LFDA failed to recognize at rank-1 top position, but with preprocessing it is identified at top position.

(a) LFDA and LFDA with preprocessing correctly recognizes

(b) LFDA with preprocessing correctly recognizes at Rank-1

Fig.5 Examples of Recognition at Rank-1 position

Comparison of all the other methods with the proposed method at Rank-50 accuracy is shown as follows in Table 2.

Table 2
Comparison of Rank-50 Accuracy

Methods	Rank-50 Accuracy (%)
LFDA with Pre-Processing	57.69%
LFDA	55.76%
SIFT	51.92%
LBP	50.00%

The CMC curves in Fig.6 (a) and (b) show that the pre-processing technique used along with the LFDA method i.e. proposed approach enhances the quality of images and also helps to improve the rank-50 accuracy of the system by atleast 2%.

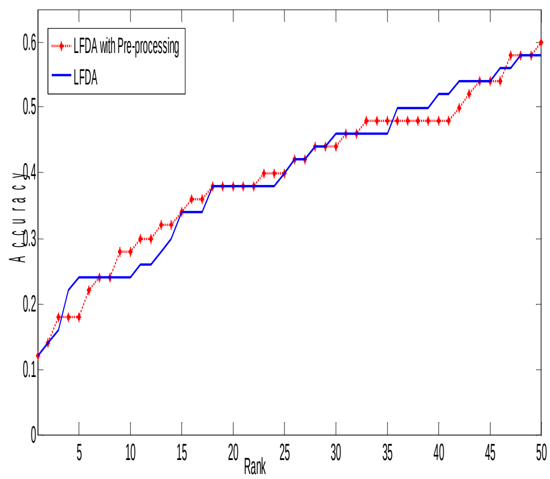

Fig.6(a) Rank curve of LFDA with preprocessing

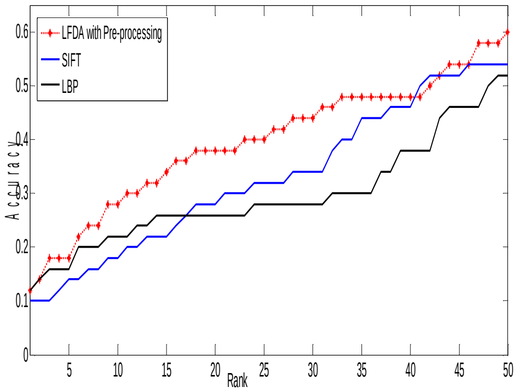

Fig.6(b) Rank curve with comparison

VI. CONCLUSIONS

We performed experiments for matching forensic sketches to mugshot photos using a robust feature based method LFDA with additional pre-processing method. This pre-processing algorithm helps to enhance the forensic images by removing the

irregularities and noise.Matching forensic sketches is a very difficult problem in heterogeneous face recognition for two main reasons. (1)Forensic sketches are often an incomplete portrayal of the subject's face. (2) We must match across image modalities since the gallery images are photographs and the probe images are sketches. Forensic sketches are drawn by interviewing a witness to gain a description of the suspect. Research on sketch to photo matching to this point has primarily focused on matching viewed sketches despite the fact that real-world scenarios only involve forensic sketches. Forensic sketches pose additional challenges due to the inability of a witness to exactly remember the appearance of a suspect and her subjective account of the description, which often results in inaccurate and incomplete forensic sketches. Comprehensive analysis, including comparison with different methods is performed using the viewed, semi-forensic, and forensic sketch databases.Using a collection of 52 forensic sketches, we performed matching against a gallery of 264 images. The results with pre-processing with LFDA method shows the rank 50 accuracy at 57.69%, while the same with only LFDA framework gives accuracy at 55.76%.It helps to improve the accuracy with atleast 2%. Thus, the results show that the proposed approach with the help of pre-processing performs significantly better than other methods. There is a continual research taking place for matching forensic sketches. In future a larger collection of forensic sketches needs to be collected to further understand the complexity of the problem.

REFERENCES

[1] X. Tang and X. Wang, "Face sketch recognition," *IEEE Trans. Circuits and Systems for Video Technology*, vol. 14, no. 1, pp. 50–57, 2004.

[2] X. Wang and X. Tang, "Face photo-sketch synthesis and recognition," *IEEE Trans Pattern Analysis & MachineIntelligence*, vol. 31, no. 11, pp.1955–1967, Nov. 2009.

[3] Amit R. Sharma and Prakash. R. Devale "An Application to Human Face Photo- Sketch Synthesis and Recognition," *International Journal of Advances in Engineering & Technology* May 2012.

[4] Timo Ahonen, Abdenour Hadid and Matti Pietikainen, "FaceDescription with Local Binary Patterns: Application to Face Recognition," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 28, No. 12, December 2006.

[5] Mohd. Ahmed and F. Bobere, "Criminal Photograph Retrieval based on Forensic Face Sketch using Scale Invariant Feature Transform," *International Conference on Technology and Business Management*, Mar 2012.

[6] B. Klare and A. Jain, "Sketch to photo matching: A feature-based approach," in *Proc.SPIE Conference on Biometric Technology for Human Identification*VII, 2010.

[7] Anil K. Jain, Z. Li and Brendan Klare, "Matching ForensicSketches and Mug Shot Photos," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, pages 639–646, March 2011.

[8] Anil K. Jain, B. Klare, and Unsang Park, "Face Matching and Retrieval in Forensics Applications," *Multimedia in Forensics, Security, and Intelligence, Published by the IEEE Computer Society*, 2012.

[9] H. S. Bhatt, S. Bharadwaj, R. Singh, Mayank Vatsa," Memetic Approach for Matching Sketches with Digital Face Images", *Submitted to IEEE transactions on IFS*.

[10] Scott Klum, Hu Han, Anil K. Jain, "Sketch Based Face Recognition: Forensic vs. Composite Sketches", InternationalConference on Biometrics, June 4-7, 2013.

[11] Lois Gibson's website at:http://www.loisgibson.com/sketches.asp

[12] H. Bhatt, S. Bharadwaj, R. Singh, and M. Vatsa, "On matching sketches with digital face images", in *Proceedings of International Conference on Biometrics: Theory Applications and Systems*, 2010.