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The Fusion Approaches of Matching Forensic Sketch – Photo to Apprehend Criminals by using LFDA framework

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Abstract: Today in modern society forensic face Recognition and matching has gained much attention in the progression of biometric technology. After the 26/11 tragedy in Mumbai, the need for technologies for identification, detection and recognition of suspects has increased. Matching forensic sketches to mug shot photos is one of the important cues in solving crimes and apprehending criminals since face is the convenient way used by the people to identify. Matching sketch with gallery of mugshot images is addressed here using robust framework called Local Feature-based Discriminant Analysis (LFDA). Since forensic sketches or images can be of poor quality, a pre-processing technique is used to enhance the quality of images and improve the identification performance. In LFDA framework, Multiscale Local Binary Pattern (MLBP), Scale Invariant Feature Transform (SIFT) and Discrete Wavelet Transform (DWT) are individually represent sketches and photos. In MLBP, the face image is divided into several regions and features distributions are extracted and concatenated into an enhanced feature vector to be used as face descriptor. SIFT is used to detect or describe local features in images. DWT is used to enhance the quality of forensic sketch- image pairs. After that these recognition methods are combined to enhance matching accuracy, thereby overcoming the performance limitations of single face recognition methods. The results showed that the accuracy of proposed method is better than that of uni-modal face recognition methods

I. INTRODUCTION

In recent years, there is much attention to attract the applications about security issues such as individual identification, access control security appliance, credit card verification, criminal identification etc. For the ease of users, a face recognition and matching system is suitable rather than a traditional personal password or an ID card, and has better communication between human beings and machines and thus used in *LAW ENFORCEMENT*. Therefore, forensic face matching applications become more and more popular [6].

Because of surveillance camera captures the face image which needs to be matched against million of mug shot across country. Automatic retrieval of photos of suspects from police mug-shot database can help the police narrow down potential suspects quickly. However, in most cases, the photo image of a suspect is not available.

Since the forensic sketch is not an exact portrayal of the culprit so it becomes more difficult to match real time sketches exactly against photos. The main key objective for sketch-face photo recognition is to reduce the difference between the two modalities. It can also be used in many other fields where photo is not available but we can illustrate the details of the photo. This method drastically reduces the variation between photo and sketch. To achieve the Rank-I Identification in matching the given probe image with the Database set is very tricky job. Due to the tremendous growth in the law enforcement agencies, the main inspiration of the project is when the photo of the suspect is not available. The proposed system is designed based on the following interpretations

- High discriminating power is required when information present in local facial regions.
- Local facial patterns in sketches and face images can be powerfully represented by local descriptors.

In this research, three different types of sketches are used for performance evaluation.

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1. ***Viewed sketches:*** These sketches are drawn by a sketch artist while looking at the digital image of a person.

2. ***Semi-forensic sketches:*** These sketches are drawn by a sketch artist based on his recollection from the digital image of a person.

3. ***Forensic sketches:*** These sketches are drawn based on the description of an eyewitness from his recollection of the crime scene.

II. RELATED WORK

In traditional forensic face matching technique, accuracy of sketch recognition is very low therefore research in sketch matching started only a decade ago. 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 eigen transformation 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].

In this paper, we extend our previous feature-based approach to sketch matching [7]. This is achieved by using local binary patterns (LBP) in addition to the SIFT feature descriptor, which is motivated by LBP’s success in a similar heterogeneous matching application by Liao et al. [8]. Additionally, we extend our feature-based matching to learn discriminant projections on “slices” of feature patches, which is similar to the method proposed by Lei and Li [9].

III. METHODOLOGY

In this paper [10], our goal is to develop a system that can recognize faces whose appearance changes according to different factors such as pose, expression, sketches where the treatment of face may fail to produce correct recognition. One of the images is taken as test image and consider rest as training image. The important features of face are extracted and similarity measure between training image and test image is taken. Finally, the person who receives minimum distance is chosen as the best match. To provide a perspective on the angle of our region-division approach that uses majority voting, compare the recognition performance of three techniques, namely the Scale Invariant Feature Transform (SIFT), Multiscale Local Binary Pattern (MLBP) and Linear Feature Discriminant Analysis (LFDA) are compared. To provide the perfect match for forensic sketches Scale Invariant Feature Transform (SIFT) can also be used.

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:

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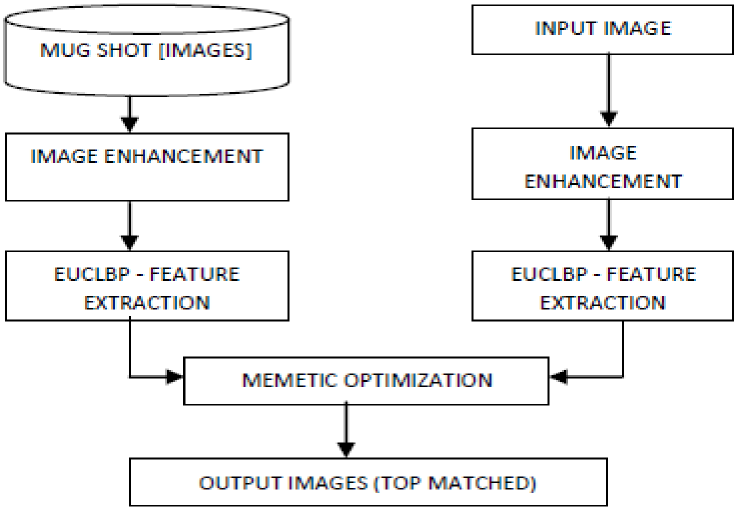

Fig 1. Architecture Diagram for matching sketches with photos

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

Step 1: Here, the witness gives his description about the criminal to the artist

Step 2: The Artist draws the sketch as per the witness description.

Step 3: The Sketch obtained is compared with the photos present in the police database.

Step 4: Average of all photos matching with the sketch is taken out.

a) Acquiring the image of individual face using photograph or live picture of the individual.
b) Location the face in the image
c) Apply feature extraction techniques on image and store results in the database
d) Store this feature extraction results for every image into a feature database
e) Analysis of facial image according different feature extraction techniques
f) Comparison of face by average calculated with the nearest neighbour matching method
g) Declaration of match or no match

Step 5: If match, those matched photos are given to witness so that he/she can help to criminal detection agencies/ Law Enforcement agencies for exactly find out the criminal.

From the above figure 1, 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. The purpose of the mug shot is to allow law enforcement to have a photographic record of the arrested individual to allow for identification by victims and investigators. 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. The acquisition module of forensic face matching system captured images with a digital or surveillance camera or any image capturing devices. These captured images are sent through the Pre-processing module to meet the standards required by the given recognition system. The pre-processing module convert color to gray scale image, resizing and illumination and background removal in order to normalize the input image. Then the normalized images are added to the face database. Some of the databases are taken as training database and one of the face

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databases is taken as test database. Acquisition The Feature Extraction module takes the normalized image as input and outputs only the important features of input image, thereby reducing its dimensionality [11][12]. Finally the classifier module performs the comparison between the test image and training image and further it decides the closest match and retrieves it.

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. 2.

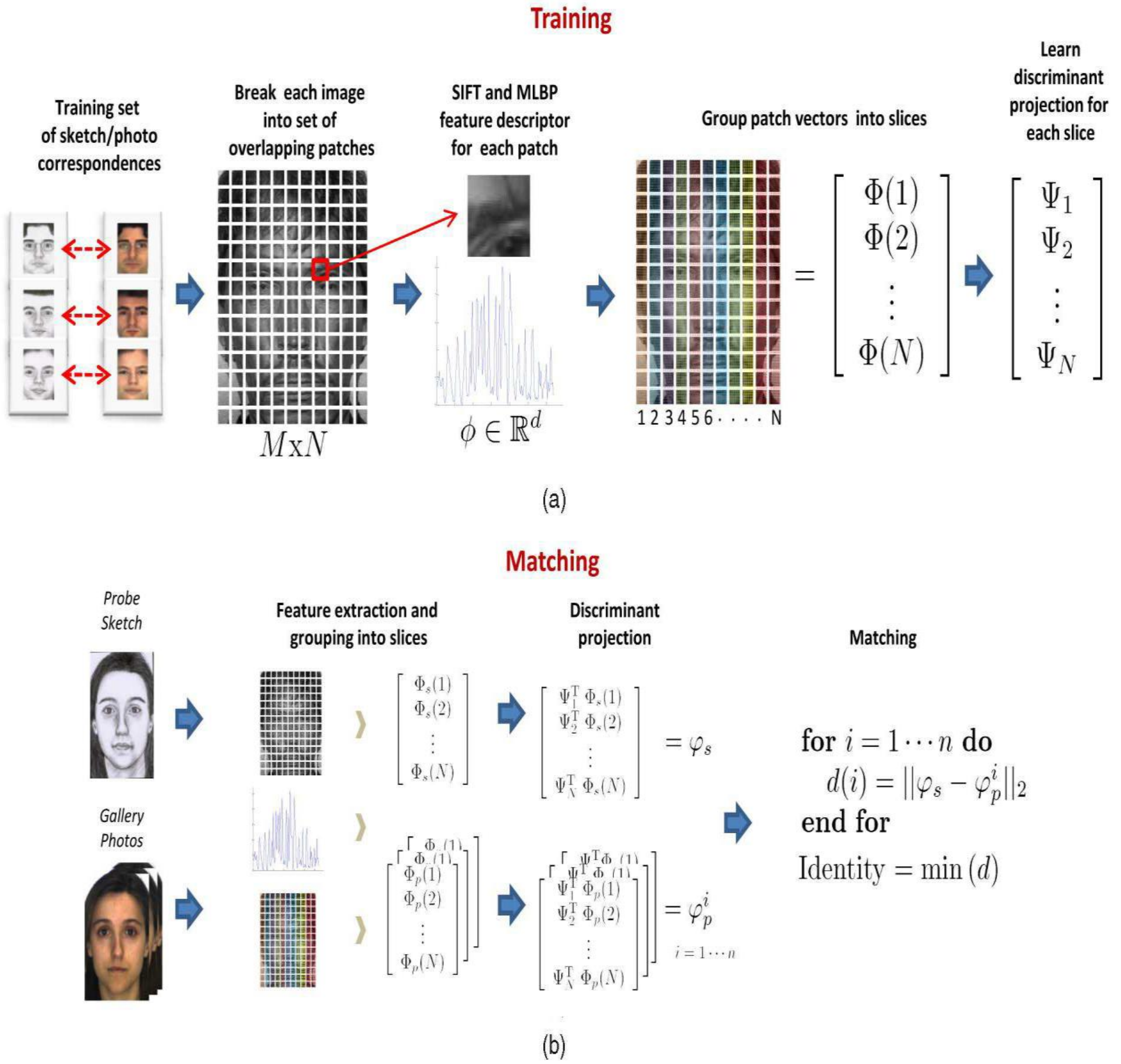

Fig. 2. An overview of the (a) training and (b) recognition using the LFDA framework

In LFDA framework In LFDA framework [7], the scale invariant feature transform (SIFT) and multiscale local binary pattern (MLBP), Discrete wavelet transform (DWT) are used.

- Scale invariant feature Transform (SIFT) :
  The flowchart for SIFT is as follows

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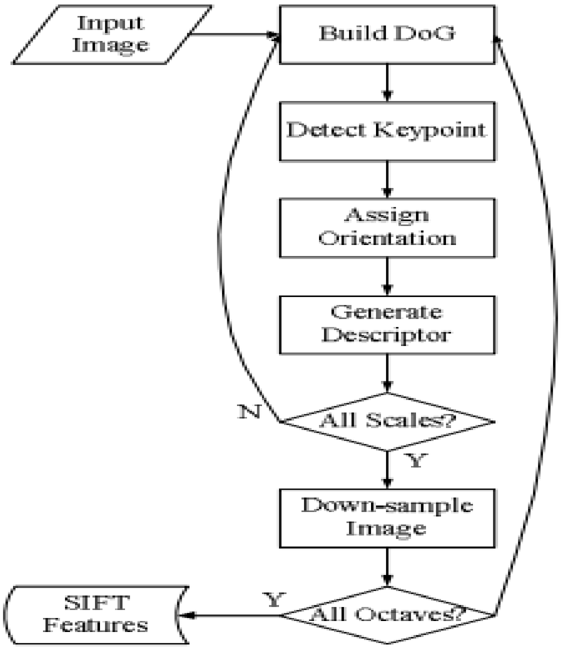

Fig 3. Flowchart of SIFT feature

- Four main stages of SIFT are introduced in the following:

1. *Scale-space extrema detection:* This stage detects local extrema in the scale space as interest points. Gaussian blur functions with different scales are firstly applied to the original image to produce Gaussian images. Then the scale space is constructed by difference-of-Gaussian (DOG) images that are the differences of every two Gaussian images with nearby scales. The interest points are defined as the local extrema in the scale space. Each sample point of the DOG image will be compared with the neighbors in the current, bigger and smaller scales. If the sample point is the local extremum among these neighbors, it is the interest point with the scale invariant property as well as the candidate of the key point.

2. *Keypoint localization.* At each position of the interest point, a 3D quadratic Taylor expansion function is used for modeling the variation around it and determining the accurate location and scale of the extremum. If the extremum is localized neither in the low contrast region nor along the edge, it will be chosen as a key point.

3. *Orientation assignment.* According to the statistics of the gradient orientations which are calculated within the local region centered on the keypoint, one or more dominant orientations are assigned to each location of the keypoint. For the locations with multiple dominant orientations, there will be multiple keypoints constructed at the same location and scale but different orientations. In order to achieve the rotation invariant property, the local region centered on the keypoint will be rotated relative to the keypoint dominant orientation before the local descriptor is constructed.

4. *Keypoint descriptor.* For each keypoint, a 16 x16 local region centered on it is extracted and divided into 4 x 4 blocks. Then, the gradient magnitude and orientation at each position in these blocks are calculated. For each block, the gradient magnitude of each position is accumulated by the gradient orientation to the orientation histogram with 8 directions. The accumulated gradient magnitude values of 8 directions form a sub-descriptor for each 4 x 4 block, and then 4 x 4 = 16 sub-descriptors are merged to a SIFT local descriptor. Each SIFT local descriptor is a vector with 16 x 8 = 128 elements.

- 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

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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}.

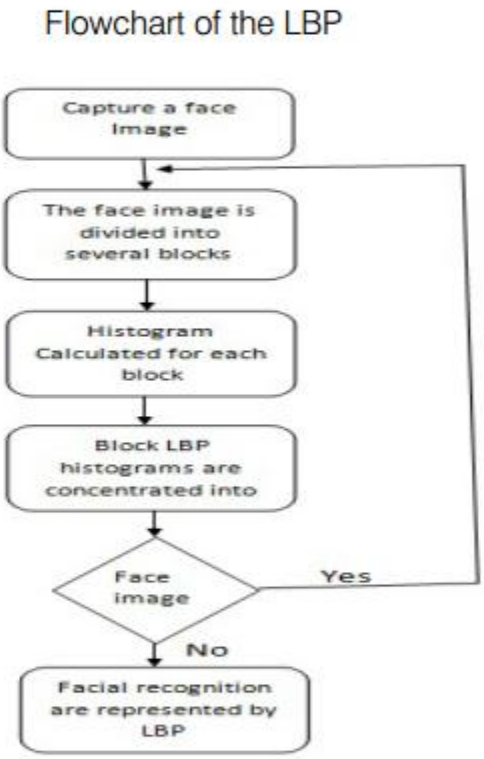

Fig. 4 – flowchart of LBP

- Discrete Wavelet Transform (DWT):

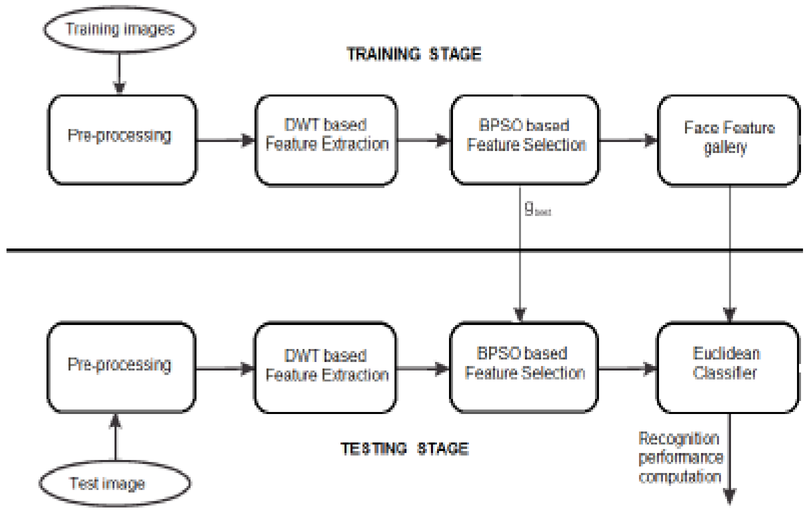

Fig. 5 – block diagram of forensic face matching with DWT

DWT fusion algorithm is applied on both forensic sketches and digital face images. pre-processing technique enhances the quality when there are irregularities and noise in the input image; however, it does not alter good quality face images (i.e. sketch-digital image pairs from the viewed sketch database). Sketches are scanned as three channel color images. Further, the forensic images obtained from different sources are three channel color images. If a gray scale image is obtained, multi-scale retinex and wiener filtering are applied only on the single channel. Along with quality enhancement, face images are also cropped to the image size of 200 by 250 pixels.

V. EXPERIMENTAL RESULTS

Using the combination of viewed sketches semi forensic sketches and forensic sketches, the experiments are performed to increase the size of database. we used a data set consisting of 164 forensic sketches, each with a corresponding photograph of the subject who was later identified by the law enforcement agency. All of these sketches were drawn by forensic sketch artists working with witnesses who provided verbal descriptions after crimes were committed by an unknown culprit. The corresponding photographs (mug shots) are the result of the subject later being identified. The forensic sketch data set used here comes from different sources.

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.

Methods	Rank - 25 Accuracy (%)	Rank – 50 Accuracy (%)
LFDA	45.33%	60.50%
LFDA with pre-processing	50.50%	70.05%

Table 1. – Rank 25 and rank -50 accuracies obtained for matching 52 forensic sketches to 264 database

With the help of pre-processing, 3 of the best matches at rank-1 are shown as below in Fig.6 (a) and in fig 6 (b) 3 of the worst matches which are retrieved at ranks 16, 33, 46 respectively.

Fig 6 (a) – correct match

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Fig 6 (b) – worst match

The performance of matching forensic sketch that were labeled as good and poor against a gallery of 264 mug shot images without using race/gender filtering is shown in below fig.7

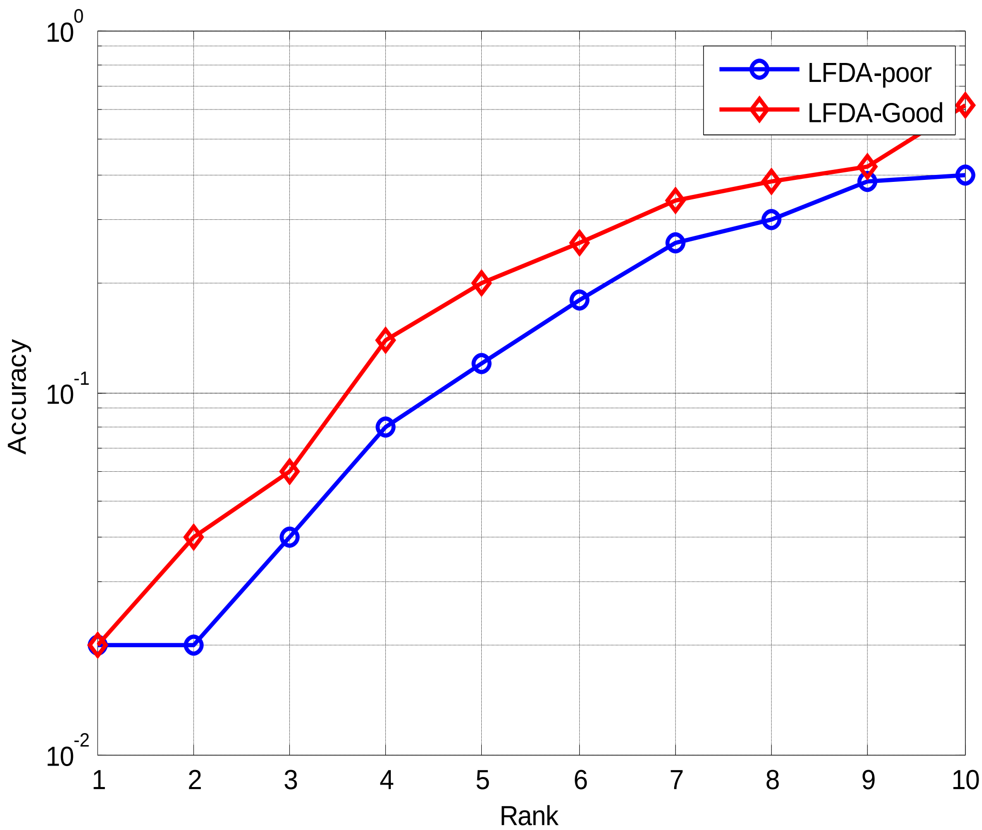

Fig. 7 – Matching performance of LFDA (Good and Poor) against 256 gallery

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Comparison of all the other proposed methods at rank -50 accuracy is shown as following table 2 and fig. 8

Methods	Rank – 50 Accuracy(%)
SIFT	60.50%
MLBP	55%
SIFT + MLBP	62%
DWT (SIFT+MLBP)	62.47%

Table 2 – comparison at rank 50 accuracy

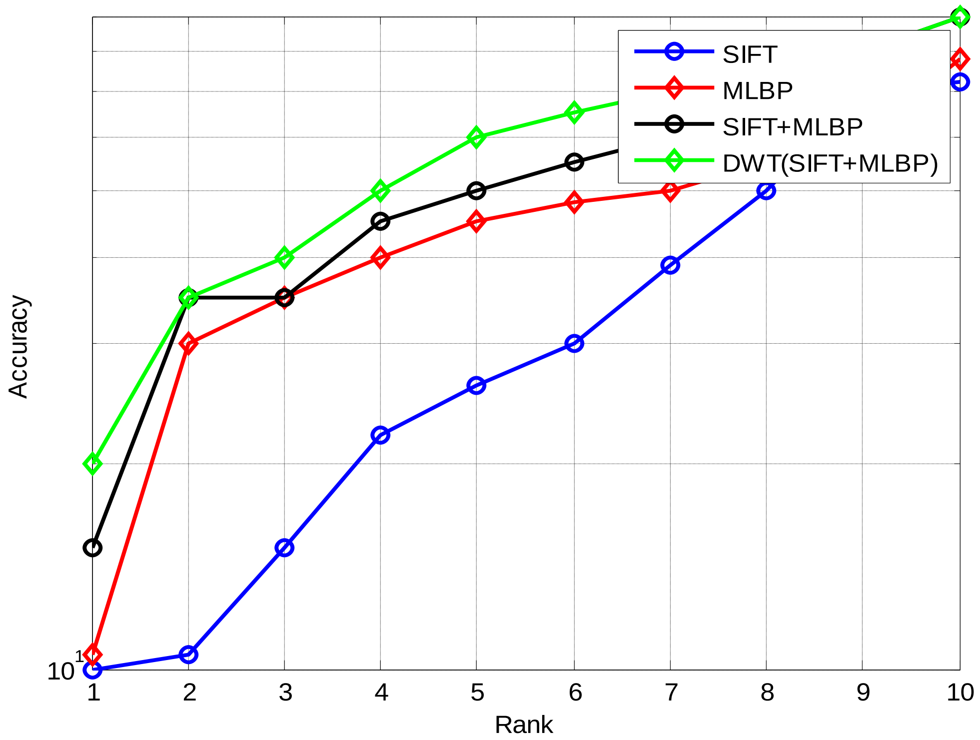

Fig 8 – Rank -50 curve with comparison

VI. CONCLUSION

One of the key contributions of this paper is using SIFT and MLBP feature descriptors to represent both sketches and photos. We improved the accuracy of this representation by applying an ensemble of discriminant classifiers, and termed this framework local feature discriminant analysis. The LFDA feature-based representation of sketches and photos was clearly shown to perform better on a public domain-viewed sketch data set than previously published approaches. This paper also presented an independent, comparative study of different popular face recognition algorithm (SIFT feature, MLBP, SIFT +MLBP, DWT) for problems arises in existing methods. So proposed methods of face recognition in forensic department had their work ease in finding the criminals rather than using conventional methods.

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