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Sketch Matching for Crime Investigation using LFDA Framework

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***Abstract*— Here we are taking database of 264 sketch-photo pairs consisting of 50 forensic images. we are proposing a forensic sketch recognition system in which we are going to use SIFT and MLBP algorithms for feature extraction with an LFDA framework for dimensionality reduction. SIFT and MLBP are used for feature extraction. Training is applied to all sketches and photos in database. We will calculate the accuracy of matched sketch and photo pair by its rank. Rank 1 will be the maximum matched features and Rank 50 will be least matched sketch**

***Index Terms*— Forensic sketches, LFDA (Local Feature Discriminant Analysis), SIFT (Scale Invariant Feature Transform), MLBP (Multiscale Local Binary pattern).**

I. Introduction

Today, advances in biometric technology have provided criminal investigators additional tools to help determine the identity of criminals. In addition to the 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 finding the suspect using biometric identification techniques. However, many crimes occur where not a single 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 , many a times, an eyewitness account of the crime is available who had seen the criminal. The Police patrol deploys a forensic artist to work with the witness in order to draw a sketch that sketches the facial appearance of the culprit. These sketches are known as forensic sketches. At Once the sketch is ready, it is sent to the law enforcement officers and media outlets with the hope of catch holding the suspect. Here, two different conditions may arise for the culprit:

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.

Here we deal with the first type of the scenario. If the criminal has been convicted at-least once, a mug shot photo (photo taken, while the person is being sent to jail) is available. Using an efficient forensic sketch matching system, the police can narrow down the potential suspects which will reduce the future crimes by the same criminal drastically.
We are using 2 types of sketches; Viewed sketches are sketches that are drawn while viewing a photograph of the person or the person himself. Forensic sketches are drawn by interviewing a witness to gain a description of the suspect.

II. Literature Survey

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. Since researchers struggled to get good results.
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. Once projected into the same image subspace, they were matched using a PCA-based matcher. 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. Belief propagation was used to minimize the energy between the selected patches and their corresponding sketch or photo mates as well as their selected neighboring patches. 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 .Principal Component Analysis method which is also called Eigen faces is appearance based technique used widely for the dimensionality reduction and recorded a greater performance in face recognition. Thus they discussed about principle component analysis (PCA) followed by Feed Forward Neural Network called principal component analysis-neural network (PCA-NN).
. In paper [4] which presents a novel and efficient facial image representation base6d on local binary pattern (LBP) texture features. The face image is divided into several regions from which the LBP feature distributions are extracted and concatenated into an enhanced feature vector to be used as a face descriptor. 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 corresponding (SIFT). The goal is to build a system that accurately matches forensic sketches with their photo images using feature based approach
The authors in paper [6] discussed recent developments in automated face recognition that impact the forensic face recognition community. Improvements in forensic face recognition through research in facial aging, facial marks, forensic sketch recognition, face recognition in video,

near-infrared face recognition, and use of soft biometrics are discussed In the paper [7], authors compared the performances of humans and a principle component analysis (PCA)-based algorithm in recognizing face sketches. The experiments were carried out by matching sketches in a probe set to photographs in a gallery set.

III. PROBLEM STATEMENT

The rapid development in computer graphics, realistic animations, human computer interaction and biometric technology has provided law enforcement agencies with additional tools to determine the identity of the suspects. In most of the cases, the photo image of a suspect is not available. The best substitute available is always an artist drawing based on the recollection of an eyewitness. These sketches are called as forensic sketches which can effectively help investigators to locate or narrow down the potential suspects.

The major challenge of face sketch recognition is matching images of different modalities. Basically, a face photo is captured by a digital camera, while a face sketch is drawn by artist with different level of information. Even for the same human subject, the face photo and its sketch might be different. The face shape might be exaggerated by artist or texture might be lost or replaced by some artistic rendering. This problem will be more exacerbated for forensic investigations, when the eye-witness cannot exactly remember the detail of suspect's face.

Earlier mentioned approaches in the literature are mainly based on matching viewed sketches that are highly accurate sketches which are drawn while looking at the subject. So, forensic sketches differ from viewed sketches. Hence, the proposed work focuses on matching forensic sketches to a large gallery of mugshot image database.

IV. PROPOSED SYSTEM

Most previously discussed methods from literature survey for matching viewed sketches and photos are based on either performing a global conversion from one domain to the other, or by using a patch-based conversion that replaces each sketch image patch by a photo patch in a training set. These methods have over published algorithms using the proposed the advantage of being able to generate a synthetic photograph of a sketch or vice-versa, which can then be matched using existing face recognition algorithms. However, the performance of these methods is limited because they are dependent on the amount of training data. When removing the constraints provided by a closed data set, these methods are subject to errors in estimating the synthetic images due to the large dimensionality and range of pixel values in the synthetic image. We observe a substantial improvement in matching viewed sketches local feature-based discriminant analysis. We present a robust method on matching real forensic sketches. Using a mug shot gallery of images, we can perform race and gender filtering to improve the matching results. The results can be then validated by comparing the proposed method against existing methods.

Representation of Sketch to Photo Matching

The schematic representation of the sketch to photo matching system is shown in the following given block diagram i.e. figure 1 as follows.

Here we have a set of sketches (Probe images) and a set of gallery photographs to be matched against i.e. mug shot photos.
The steps involved in sketch to photo matching are as follows:
1. Store this feature extraction results for every image into a feature database.

2. For every probe image, the corresponding match is that with the minimum distance calculated with the nearest neighbor matching method.
3. The final top retrieved images from the database are then displayed.

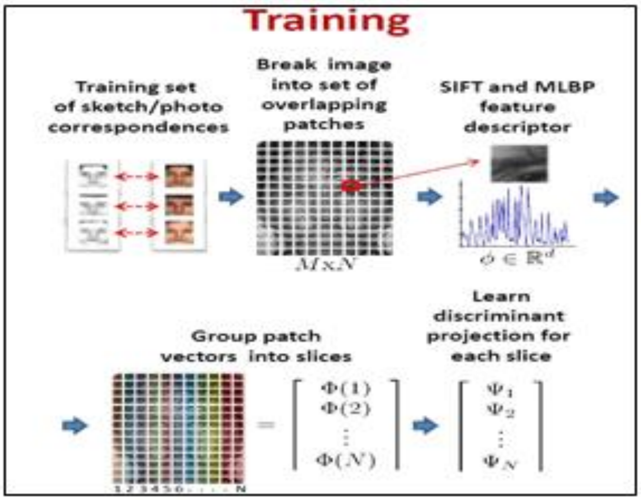

Figure 1 Schematic representation of the sketch matching system

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. Feature value is the calculated feature vector of the given input probe sketch image which is to be matched against the gallery of mugshot database i.e. the values stored in the feature database.
Matching algorithm is used to find a proper match between the probe sketch image with the mugshot images. For example, 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. So, this can be used to select the gallery photo with the minimum distance to the probe sketch.

The two phases of the LFDA framework having Training phase in the figure 1 and matching phase in figure 2 are shown as follows:
In figure 2 each sketch and photo is represented by SIFT & MLBP feature descriptors extracted from overlapping patches. After grouping "slices" of patches together into feature vectors Φ (k) where k=1….N. Then we take a discriminant projection Ψk for each slice.

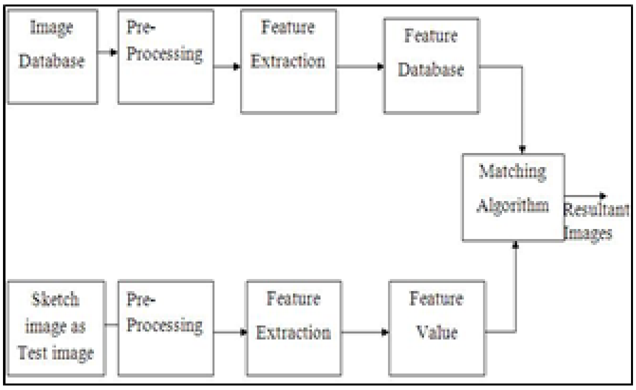

Fig 2. Overview of Training using the LFDA Framework

In figure 2 each sketch and photo is represented by SIFT & MLBP feature descriptors extracted from overlapping patches. After grouping "slices" of patches together into feature vectors Φ (k) where k=1….N. Then we take a discriminant projection Ψk for each slice.

Recognition is performed after combining each projected vector slice into a single vector φ and measuring the normed distance between a probe sketch and gallery photo. In this sketch matching framework, two feature descriptors are used: SIFT and LBP.

The SIFT feature descriptor quantizes both the spatial location and gradient orientations within a sxs sized image patch, and computes a histogram in which each bin corresponds to a combination of a particular spatial location and orientation. For each image pixel, the histogram bin corresponding to its quantized orientation and location are incremented by the product of:

(i)The magnitude of the image gradient at that pixel . (ii)The value of a Gaussian function centered on the patch with a standard deviation of s/2.

Tri-linear interpolation is used on the quantized location of the pixel, which addresses image translation noise. The final vector of histogram values is normalized to sum to one. It is important to reiterate that because we are sampling SIFT feature descriptors from a fixed grid, we do not use SIFT keypoint detection; the SIFT feature descriptor is computed at predetermined locations.

For the local binary pattern feature descriptor, we can extend the LBP to describe the face at multiple scales, by combining the LBP descriptors computed with radii r Є {1, 3, 5, 7}. This is called as the multi-scale local binary pattern (MLBP).

Local Feature-based Discriminant Analysis

With both sketches and photos processed using SIFT and MLBP image descriptors, we further refine this feature space using discriminant analysis. This is done to reduce the large dimensionality of the feature vector Φ. We apply classical subspace analysis (such as LDA) directly on Φ, and extract discriminant features for classification. However, there are problems with this approach. First, the feature dimensionality is too high for direct subspace analysis. Here each image is divided into either 154 overlapping patches (for s = 32) or 720 overlapping patches (for s = 16), with each patch producing a 128-dimensional SIFT descriptor or a 236-dimensional MLBP descriptor. The second problem is the possibility of overffitting due to the small sample size (SSS) problem.

In order to handle the combination of a large dimensionality (feature size) and small sample size, an ensemble of linear discriminant classifiers, called local feature- based discriminant analysis (LFDA), is proposed. However, we choose the proposed LFDA method because it is designed to work with a feature descriptor representation as opposed to an image pixel representation.

In LFDA framework each image feature vector Φ 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.

Experiments and results

A database of 264 sketch-photo pairs is made consisting of 52 forensic sketches. These images were collected from different sources. 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 keeping in mind that the proposed approach consisting of pre-processing method which is only used to improve the bad quality of forensic sketches instead of viewed sketches, the results with 52 probe set of forensic sketches are obtained as shown below. The results are compared with LFDA framework and also with SIFT and LBP.

Examples of the forensic sketches correctly identified at rank-1 with both methods are shown in Fig. 3.These sketch does a good quality sketch resemble perfectly with the suspects photo.

Fig 3: Best Match at Rank 1

Fig 4 shows the worst match which is retrieved at rank 142.

Comparison with other methods:

Comparison of all the other methods with the proposed method at Rank-50 accuracy is shown as follows in Table 1.

Methods	Rank-50 (% Accuracy)
LFDA	55.76%
SIFT	51.92%
LBP	50.00%

The CMC curve for comparison between the proposed approach and other two methods i.e. Scale invariant feature transform (SIFT) and Local binary pattern (LBP) is also shown as given below in Fig.5.From the CMC curve it can be shown that how the rank-50 accuracy of proposed system is better than the previous methods i.e. sift and LBP.

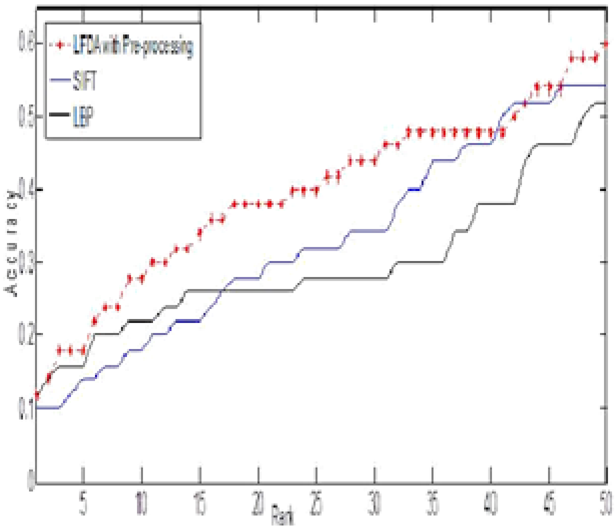

Fig.5 Rank curve showing comparison between different methods

Performance Evaluation

The performance of the sketch to photo matching system can be evaluated on the following basis given as follow:

Accuracy:

Accuracy is calculated as how accurately the correct photo is retrieved at the top-most position when a particular sketch is given as input.

Accuracy is calculated as follows

$$\text{Rank} = \frac{\text{Number of correct matches}}{\text{Total number of input sketches}} * 100$$

In forensic sketch matching, we are matching a sketch to a photo, and that sketch too is drawn just based on the verbal description of an eye-witness; hence, there are a lot of chances for ambiguity. So the law enforcement officers are generally concerned with the top *P* retrieved results. Here, we take *P* to be 50.Hence, number of correct matches is considered from top-50 retrieved images.

Rank 1 Accuracy

Rank-1 accuracy was calculated using a combined database having 264 sketch-photo pairs.264 sketch-photo pairs were used for training purpose. For testing 52 forensic sketch images were used. Rank-1 accuracy is defined as the top retrieved photo image of the suspect at the Rank-1 position. The following are the examples given for the rank-1 retrieved photo for the corresponding sketches in Fig 6

Figure 6. Correct Rank-1 Matches

These are typical cases in which the true subject photo was not retrieved at rank 1, but the impostor subject retrieved at rank 1 looks more similar to the sketch than the true subject as shown in Fig 7.

Probe Sketch

Top Retrieval

True Suspect

Figure 7.:Incorrect Rank-1 match

The top retrieval may sometimes, look visually more similar to sketch rather than the true subject. This gives us another reason to explain why we consider top-50 retrieved images rather than one single image that appears at rank-1.

V. CONCLUSION

We performed experiments for matching forensic sketches to mugshot photos using a robust feature based method LFDA.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 50 forensic sketches, we performed matching against a gallery of 264 images. The results with LFDA method show the rank 50 accuracy at 55.76%. Thus, the results show that the proposed approach is better than other methods such as only using SIFT and MLBP. 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. We observed an improvement in matching viewed sketches over published algorithms using the proposed local feature-based discriminant analysis. We presented a robust method on matching real forensic sketches. Using a gallery of images, we can also perform race and gender filtering to improve the matching results in future. The results can be then validated by comparing the proposed method against existing methods.

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