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A PATH FOR HORIZING YOUR INNOVATIVE WORK

FORENSIC SKETCH-PHOTO MATCHING USING SIFT- MLBP- LFDA

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Abstract: The problem that is dealt in the project is to match a forensic sketch against a gallery of mug shot photos. Research in past decade offered solutions for matching sketches that were drawn while looking at the subject (viewed sketches). In this thesis, emphasis is made on matching the forensic sketches, which are the sketches drawn by specially trained artists in police department based on the description of subject by an eyewitness. Recently, a method for forensic sketch matching using using LFDA (Local Feature based Discriminant Analysis) was published. In LFDA, we individually represent both sketches and photos using SIFT feature descriptors and multiscale local binary patterns (MLBP)SIFT descriptor has also been applied at dense grids (dense SIFT) which have been shown to lead to better performance for tasks such as object categorization, texture classification, image alignment and biometrics. 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, pre-processing technique is used that enhances the quality of forensic sketch-digital image pairs.

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

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INTRODUCTION

Today, advances in biometric technology have provided law enforcement agencies additional tools in the identification 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 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 limns 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:

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 felony.

Sketches

Sketches are the figures, drawn by trained artists on a piece of white paper with a single pencil or a bunch of pencils. In general, sketches are classified into two categories: viewed sketches (Figure 1.1) and forensic sketches (Figure 1.2)

1.1) Viewed Sketches: These are the sketches drawn by an artist, directly looking at the subject or the photograph of the subject

1.2) Forensic Sketches: These are the sketches drawn by specially trained artists based on the description of subject by an eye witness.

Since viewed sketches are drawn, by directly looking at the subject or the photograph of the subject, they carry a very good detail of the original subject in terms of accuracy. On the other hand, since forensic sketches are drawn, just based on the verbal description, their accuracy is considerably low. It is succinct to say that the accuracy of forensic sketches is directly proportional to the remembrance capability of the eye witness.

Sketch recognition

Even though there existed multiple face recognition schemes since the past two decades, research on sketch to photo matching started only a decade ago. This is because of the difficulty in the problem compared to traditional recognition.

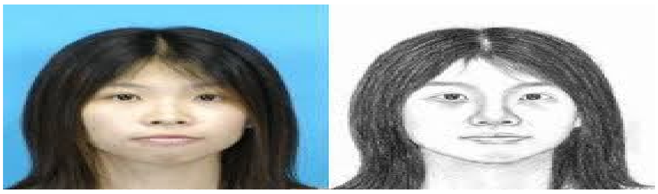


Figure 1.1: Example of viewed sketch and its corresponding photograph

Figure 1.2: Example of forensic sketch and its corresponding photograph

And also, the best recognition levels in photo matching came only at the onset of past decade. The sketches are mainly drawn using pencils and for a sketch, atmost 4-5 pencils are used pertaining to different darkness levels. So a sketch has atmost 4-5 grey levels. The photographs on the other hand are taken with a camera that can capture 256 grey levels (If a colour image is present, it could be easily converted to a 256 grey level image). So to match 4-5 grey levels against 256 grey levels is a near impossible problem. Contrast stretching, in which we convert the 256 grey levels into 3-4 grey levels is tried by various researchers, but proven to be in effective to solve the problem. Throughout the past decade, scientists have been trying various methods like synthetic photograph generation, spectral regression, using feature based descriptors etc., out of which some have proven to be fruitful. Based on the past research in sketch recognition, and the research done on the cognitive ability of human mind, a new method is proposed by us, that could effectively solve the problem of sketch recognition to a great extent. Experiments were conducted on the two kinds of sketches that are available (viewed and forensic sketches). But we emphasize on matching of forensic sketches, since it has a practical purpose in apprehending criminals [1]. Nevertheless, viewed sketches acted as a baseline for forensic sketches and helped us perform continuous experiments on them, before proceeding to experiment with forensic sketches.

Motivation

The main motivation behind the undertaking of this project is that there are a lot of problems in forensic sketch recognition compared to normal face recognition (in which both probe and gallery images are photographs). The textures of sketches, whether they may be viewed or forensic are quite different from that of the gallery of photographs that were being matched against. Previous work in sketch matching is done only on viewed sketches [2], [3], [4], [5], [6], even though most real world scenarios involve forensic sketches only. Forensic sketches have additional problems compared to viewed sketches. Due to the petulant nature of the memory, the exact appearance of the criminal cannot be remembered by the witness. This leads to an incomplete and inaccurate depiction of the sketches which reduces the recognition performance substantially.

Fig: forensic sketch and its corresponding photograph

Related Work

Research on sketch matching started only a decade ago. Due to the unavailability of standard public database for forensic sketches, throughout the past decade, the research is done on viewed sketches only. On viewed sketches; most of the early work is done by Tang *et al*. [3], [4], [6]. A synthetic photograph is generated from the sketch in these works; And then matching is performed with standard face recognition algorithms.

In the recent years, research on sketch matching is done using feature based descriptors. Klare and Jain published a Scale Invariant Feature Transform (SIFT) based approach [2] for the sketch to photo matching. Other methods similar to this such as Coupled Spectral Regression [7], Local Binary Patterns [8], [9], [10] are used for matching near-infrared images (NIR) to visible light images (VIS).Only one paper is published in forensic sketch matching till date. Klare and Jain [11] published a Local Feature based Discriminant Analysis (LFDA) approach for matching forensic sketches to mug shot photos. It is claimed as the first large scale experiment conducted on forensic sketch matching in which 159 forensic sketches are matched against 10159 mug shot photographs. We propose a technique based on pre-processing algorithm that could solve the problem of forensic sketch matching in a much better manner. Our results are compared to LFDA; since it is reported to be the one with highest accuracy till date in forensic sketch matching. We also compare our results to face VACS, a commercially off the shelf system for traditional face recognition.

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 is used that enhances the quality of forensic sketch-digital image pairs.

1. Let f be the color face image to be enhanced. Let fr and fy be the red and luma channels respectively. These two channels are processed using the multi-scale retinex (MSR) algorithm.

2. MSR is applied on both red and luma channels to obtain frm and fym.

3. Image denoising is applied to get frm′ and fym′ respectively.

4. Noise removal may lead to burring of edges. Hence Weiner filter is applied to obtain f1 and f2.

5. After computing globally enhanced red and luma channels, DWT fusion algorithm is applied on f1 and f2 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 fj LL, fj LH, fj HL, fj HH be the four bands and j = 1, 2. To preserve features of both the channels, coefficients from the approximation band of f1 and f2 are averaged.

fe LL = mean (f1LL, f2LL)

Where feLL is the approximation band of enhanced image. All three detailed sub bands are divided into windows of size 3×3 and the sum of absolute pixels in each window is calculated. For the ith window in HL sub band of the two images, the window with maximum absolute value is selected to be used for enhanced sub band fe HL. Similarly, enhanced sub bands fe LH and fe HH are obtained. Finally, inverse DWT is applied on the four sub bands to generate a high quality face image.

F = IDWT (fe LL, fe LH, fe HL, fe HH)

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

Feature-Based Sketch Matching

Image feature descriptors describe an image or image region using a feature vector that captures the distinct characteristics of the image. Image-based features have been shown to be successful in face recognition, most notably with the use of local binary patterns.

LH	**HH**
LL	HL

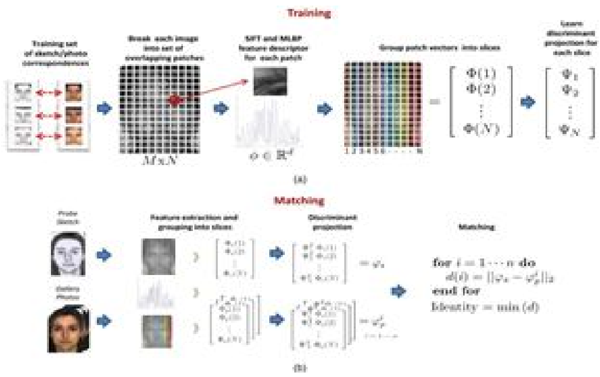


Fig. 2.An overview of the (a) training and (b) recognition using the LFDA framework. Each sketch and photo are represented by SIFT and MLBP feature descriptors extracted from overlapping patches. After grouping “slices” of patches together into feature vectors ϕ(k)(k=1…N), we learn a discriminant projection $\_{k}$ for each slice. Recognition is performed after combining each

projected vector slice into a single vector and measuring the normed distance between a probe sketch and a gallery photo.

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 any object in an image, interesting points on the object can be extracted to provide a "feature description" of the object. This description, extracted from a training image, can then be used to identify the object when attempting to locate the object in a test image containing many other objects. To perform reliable recognition, it is important that the features extracted from the training image be detectable even under changes in image scale, noise and illumination. Such points usually lie on high-contrast regions of the image, such as object edges.

Another important characteristic of these features is that the relative positions between them in the original scene shouldn't change from one image to another.

Scale Invariant Feature Transform (SIFT) is an image descriptor for image-based matching developed by David Lowe **(1999, 2004).** This descriptors as well as related image descriptors are used for a large number of purposes in computer vision related to point matching between different views of a 3-D scene and view-based object recognition. The SIFT descriptor is invariant to translations, rotations and scaling transformations in the image domain and robust to moderate perspective transformations and illumination variations. Experimentally, the SIFT descriptor has been proven to be very useful in practice for image matching and object recognition under real-world conditions.

A. Local Feature-Based Discriminant Analysis:

In the LFDA framework [7], each image feature vector is first divided into “slices” of smaller dimensionality ty, 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:

1) PCA, within class whitening,

2) Between class discriminant analysis.

3) 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 fig 2.

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).In its original formulation, the SIFT descriptor comprised a method for detecting interest points from a grey-level image at which statistics of local gradient directions of image intensities were accumulated to give a summarizing description of the local image structures in a local neighbourhood around each interest point, with the intention that this descriptor should be used for matching corresponding interest points between different images. Later, the SIFT descriptor has also been applied at dense grids (dense SIFT) which have been shown to lead to better performance for tasks such as object categorization, texture classification, image alignment and biometrics . The SIFT descriptor has also been extended from grey-level to colour images and from 2-D spatial images to 2+1-D spatio-temporal video.

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, $G(x, y, \sigma)$ is a variable-scale Gaussian and $I(x, y)$ is the input image.

Difference of Gaussians technique is used for locating scale-space extrema, $D(x, y, \sigma)$ 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: Key point 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.

Multiscale Local Binary Pattern (MLBP):

Local Binary Pattern (LBP) is a simple yet very efficient texture operator which labels the pixels of an image by thresholding the neighbourhood of each pixel and considers the result as a binary number. Due to its discriminative power and computational simplicity, LBP texture operator has become a popular approach in various applications. It can be seen as a unifying approach to the traditionally divergent statistical and structural models of texture analysis.

Perhaps the most important property of the LBP operator in real-world applications is its robustness to monotonic gray-scale changes caused, for example, by illumination variations. Another important property is its computational simplicity, which makes it possible to analyse images in challenging real-time settings. Fig .Local Binary Pattern

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 156 viewed sketch-photo pairs from CUHK database [2] and 80 viewed sketch-photo pairs from IIIT- D database [9]. Forensic pairs are collected as 35 pairs from Forensic composite sketch database [20], which contains sketch photo pairs from L. Gibson [11] and 37 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 72 forensic sketches were used to match against a gallery of 328 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 72 probe set of forensic sketches, the results obtained are shown in the following Table 1.

Rank-10 and Rank-50 accuracies obtained for matching 72 forensic sketches to 328 gallery images.

Table: I

Methods	Rank-10 Accuracy (%)	Rank-50 Accuracy (%)
LFDA	24.07%	56.76%
LFDA with Pre-Processing	27.92%	58.69

Examples of the forensic sketches correctly identified at rank-1 with both methods are as shown in Fig. (a).These two sketches were good quality sketches resembling perfectly with the suspects photo. In Fig (b) one more good quality sketch is shown which LFDA failed to recognize at rank-1 top position, but with pre-processing it is identified at top position.

A) LFDA and LFDA with preprocessing correctly recognizes

B) LFDA with pre-processing correctly recognizes at Rank-1

When the matching the forensic sketches is being done, generally we are 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. This is because forensic sketch matching significantly differs a lot from the conventional face recognition. In normal face recognition, human interaction is limited to the cases, only when there is some ambiguity. But 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.

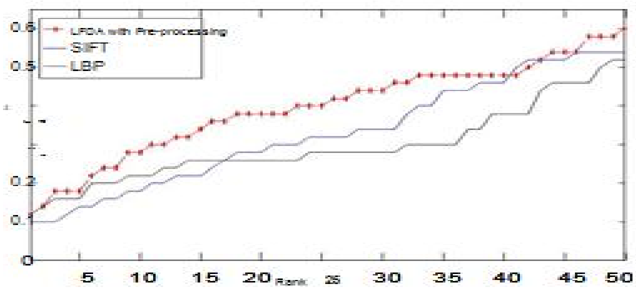
First, all the 72 forensic sketches available with us were used for matching. We achieved a very good accuracy rate of 58.69%. We believe that this is by far, the best recognition rate achieved in forensic sketch matching. The rank curve or the Cumulative Match Curve (CMC) that was generated is shown in Fig. 3.2

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

Comparison of Rank-50 Accuracy

Methods	Rank-50 Accuracy (%)
LFDA with Pre-Processing	58.69%
LFDA	56.76%
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%.



Three of the best matches which were discovered at rank-1

CONCLUSIONS II

We performed experiments for matching forensic sketches to mug shot 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.

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 repre-sentation of sketches and photos was clearly shown to perform better on a public domain-viewed sketch data set than previously published approaches. Another major contribution of the paper is the large-scale experiment on matching forensic sketches.

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, pre-processing technique is used that enhances the quality of forensic sketch-digital image pairs.

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If I have seen a little further it is by standing on the shoulders of Giants.

REFERENCES

1. A.K. Jain and B. Klare. Matching forensic sketches and mug shots to apprehend criminals. *IEEE Computer, IEEE Society*, 44(5):94–96, 2011.

2. B. Klare and A. Jain. Sketch to photo matching: A feature-based approach. *Proceedings of SPIE Conference on Biometric Technology for Human Identification VII*, 2010.

3. X. Wang and X. Tang. Face sketch recognition. *IEEE Transactions on Circuits and Systems for Video Technology*, 14(1):50–57, January 2004.

4. Q. Liu, X. Tang, H. Jin, H. Lu, and S. Ma. A nonlinear approach for face sketch synthesis and recognition. *Proceedings of IEEE Conference on Computer Vision and Pattern Recognition*, pages 1005–1010, 2005.

5. J. Zhong, X. Gao, and C. Tian. Face sketch synthesis using e-hmm and selective ensemble. *Proceedings of IEEE Conference on Acoustics, Speech, and Signal Processing*, 2007.

6. X. Wang and X. Tang. Face photo-sketch synthesis and recognition. *IEEE Transactions on Pattern Analysis and Machine Intelligence (PAMI)*, 31(11):1955–1967, 2009.

7. Z. Lei and S. Li. Coupled spectral regression for matching heterogeneous faces. *Proceedings of IEEE Conference on Computer Vision and Pattern Recognition*, pages 1123–1128, June 2009.

8. S. Liao, D. Yi, Z. Lei, R. Qin, and S. Li. Heterogeneous face recognition from local structures of normalized appearance. *Proceedings of Third International Conference on Biometrics*, 2009.

9. B. Klare and A. Jain. Heterogeneous face recognition: Matching nir to visible light images. *Proceedings of International Conference Pattern Recognition*, 2010.

10. T. Ojala, M. Pietikainen, and T. Maenpaa. Multiresolution gray-scale and rotation invariant texture classification with local binary patterns. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 24(7):971–987, July 2002.

11. B. Klare, Z. Li, and A.K. Jain. Matching forensic sketches to mug shot photos. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, pages 639–646, March 2011.

12. H. Bay, T.Tuytelaars, and L. Van Gool. Surf: speeded up robust features. In *European Conference on Computer Vision*, 2006.