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Matching different sketches to photographs from database using LFDA

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Abstract
The advancement of biometric technology have provided criminal investigators additional tools to determine the identity of criminals. In many crimes where biometric information is not present but instead an eye-witness of crime is available. In these circumstances a forensic artist is draw a sketch that depicts the facial information of the culprit according to verbal description. This problem of matching a forensic sketch to mug shot photographs is addressed here using a local feature-based discriminant analysis (LFDA). 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. 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 sketches, Mug shots, Feature-based approach, Local feature-based discriminant analysis, Feature descriptors.

Introduction

Today, numbers of biometric techniques have provided criminal investigators additional tools determine the identity of criminals. In many crimes biometrics information is not present but with the help of eye-witness we can find the criminal.

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.

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 byan 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


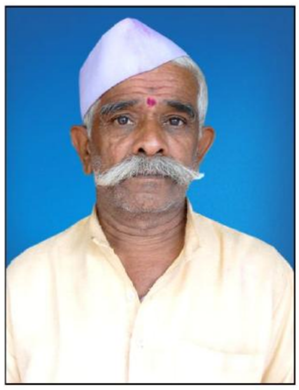

Fig. 2 Forensic sketch and its corresponding photograph

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:

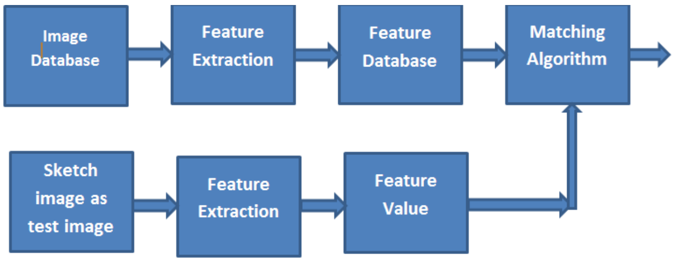

Fig. 3 Representation of the sketch matching system

Here we have a set of sketches (Probe images) and a set of Mug shot 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 mug shot 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 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 images with the mug shot images. We can match sketch to photos using nearest neighbor matching' method in which the minimum distance between the calculated values of the mug shot 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.

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 frameworks are as shown above in Fig.

B. Feature descriptors:

In LFDA framework [7], the following feature descriptors are used i.e. scale invariant feature transform (SIFT) and multi scale 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

$L(a, b, \sigma) = G(a, b, \sigma) * I(a, b)$

Where * is the convolution operator, $G(a, b, \sigma)$ is a variable scale Gaussian and $I(a, b)$ is the input image.

Difference of Gaussians technique is used for locating scale space extreme, $D(a, b, \sigma)$ by computing the difference between two images, one with scale k times the other.

$D(a, b \sigma) = L(a, b, k\sigma) - L(a, b, \sigma)$

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.

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 key point. If there are multiple peaks above the 80% mark, they are all converted into a new key point (with their respective orientations).

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

Step 4: Key point Descriptor:

Key point descriptors typically use a set of 16 histograms, aligned in a 4x4 grid, each with 8 orientation bins, one for

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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-neighbors 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.

Multistage 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 anduses 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 neighborhoods 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 a multiple scales by combining the LBP descriptors computed with radii r ε {1, 3, 5, and 7}.

Results:

The data to be analyzed consist of set of number of sketch and related photographs .In this way five sets will undergo SIFT and MLBP based image matching process. Apply LFDA method to each sketch and available database. In this paper we have to calculate key point of forensic sketch by using LFDA similarly apply same procedure to available database and calculate keypoints of each photographs and match sketch and photographs.

The experiments are performed on different sketches by using LFDA.

sketch	Key point of original sketch	Key point of match photograph
Sketch 1	786	658
Sketch 2	456	396
Sketch 3	536	485
Sketch 4	892	802
Sketch 5	298	250

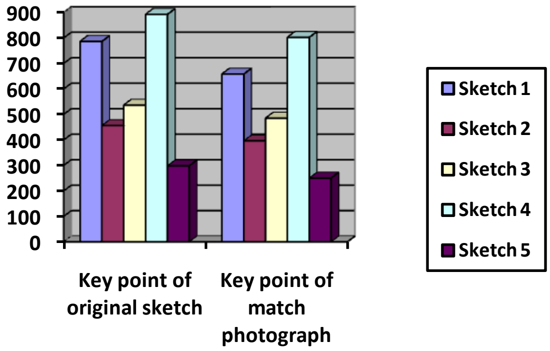
Sketch 1

Sketch2

Sketch 3

Sketch 4

Sketch 5



Conclusion :

By using this method we can match any different sketch to its relative photograph with only available database. If photo is not available then result shows sketch is not matching.

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 anensemble of discriminant classifiers, and termed this frameworklocal feature discriminant analysis

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