Face Sketch to Photo Matching Using LFDA

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Abstract: ***The progression of biometric technology has provided criminal investigators additional tools to determine the criminal's identity. In addition to DNA and circumstantial evidence, if a dormant fingerprint is found at an investigative sight or a surveillance camera captures an image of a suspect's face, then these cues may be used to determine the identity of culprit's, using automated biometric identification. However, many crimes occur when none of such information is present, but instead an eye-witness of the crime is available. In such situation 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; such sketch drawn depending on the description given by an eye witness is called forensic sketch. Using feature based approach how to match a forensic sketch to a gallery of mugshot images described here. To match forensic sketches against mugshot images a robust framework called local feature-based discriminant analysis (LFDA) is used. In this paper experiments are carried out using 45 forensic sketches for matching against a gallery of 150 photo images. In this framework, both sketch and photo images are considered for extracting feature descriptors using scale invariant feature transform (SIFT) and multiscale local binary pattern (MLBP) method. The experimental results demonstrate the matching performance using the presented feature based approach.***

Keywords: Mugshot, forensic sketch, Local feature-based discriminant analysis, Feature-based approach, Texture descriptors, Feature descriptors

1. Introduction

Developments in biometric technology have provided criminal investigators additional tools to help determine the identity of criminals. Besides incidental evidence, if a latent 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 times a crime occur when such type of above information is not present. There is a lack of technology to efficiently capture the biometric data like finger prints within a short period 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 so that he can draw sketch that portrays the facial appearance of the criminal. Sketches drawn by using such process is called as forensic sketches. When 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 situations may occur 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.

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

1.1 Viewed Sketches

The sketches which are drawn by an artist, directly looking at the subject or the photograph of the subject.

1.2 Forensic Sketches

The sketches which are drawn by specially trained artists based on the description of subject by an eye witness.

Following are the key difficulties in matching forensic sketches:

1) Matching across image modalities
2) Performing face recognition despite possibly inaccurate depictions of the face.

2. Related Work

Due to the accuracy of sketch recognition is very low, compared to traditional face recognition techniques, research in this area of 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]. 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.

3. Process of Sketch to Photo Matching

The following block diagram shows the proposed feature-based method used for sketch to photo matching:

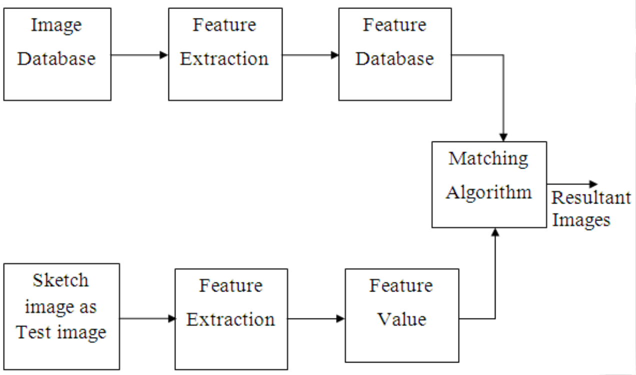

Figure 1: Representation of the sketch matching system

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. 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) and intensity.

3.1 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.

3.2 Matching algorithm

Matching algorithm is used to find a proper match between the probe sketch images with the mugshot images. "Nearest neighbor matching" method is used to match sketch to photo. In this method the minimum distance between the calculated values of the mugshot images and the probe sketch is found out.

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

4. 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) ||. *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).

4.1 Scale Invariant Feature Transform *(SIFT):*

The algorithm for SIFT is as follows:

Step 1: Scale-Space Extrema Detection: The function: $L(x, y, \zeta) = G(x, y, \zeta) * I(x, y)$ is used to define scale space where * is the convolution operator, $G(x, y, \zeta)$ is a variable-scale Gaussian and $I(x, y)$ is the input image. Difference of Gaussians technique is used for locating scale-space extrema, $D(x, y, \zeta)$ by computing the difference between two images, one with scale k times the other. $D(x, y, \zeta) = L(x, y, k\zeta) - L(x, y, \zeta)$

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.

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 accurate 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.

4.2 Multiscale Local Binary Pattern (MLBP)

The novel 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, and 7}.

5. Local Feature-Based Discriminant Analysis (LFDA)

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 below in Figure 2.

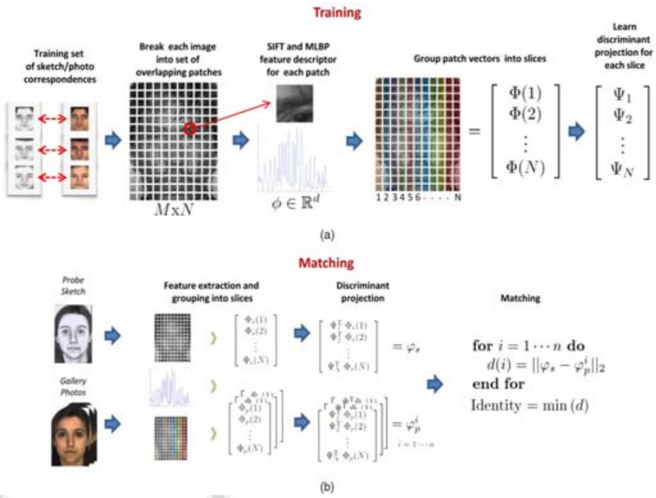

Figure 2: An overview of the (a) training and (b) recognition using the LFDA framework

6. Experimental Results

We conduct experiments using the grouping of viewed sketches and forensic sketches to increase the size of dataset. The database consists of 28 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 45 forensic sketches were used to match against a gallery of 150 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 or top-50 retrieved images. Rank-50 accuracies obtained for matching 45 forensic sketches to 150 gallery images using LFDA method is 55.76%. Example of the forensic sketches correctly identified at rank-1 is as shown in Figure 3.These sketches were good quality sketches resembling perfectly with the suspects photo. In figure 4. A good quality sketch is shown which LFDA failed to recognize at rank-1 top position.

Figure 3: Good quality forensic sketch with best matches at Rank-1

Figure 4: Good sketch, LFDA failed to recognize at top position

7. Conclusion

Using a robust feature based method LFDA; we have performed experiments for matching forensic sketches to mugshot photos. 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 cause additional challenges because of 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. Using a collection of 45 forensic sketches, we performed matching against a gallery of 150 images. There is an incessant research taking place for matching forensic sketches. In future a larger collection of forensic sketches needs to be collected to further understand the difficulty of the problem.

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