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Forensic Sketches matching

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Abstract— In this paper we are going to address the problem of matching a forensic sketch to a gallery of mug shot images .In the Previous research in sketch matching they only offered solutions of matching highly accurate sketches but in reality Forensic sketches differ from viewed sketches that have been drawn by artist describe by the police witness. To identify forensic sketches, we present a framework called local feature-based discriminant analysis (LFDA). In today's world automatic face sketch recognition plays a very important role in law enforcement. Recently, various methods have been proposed to address the problem of face sketch recognition by matching face photos and sketches, which are of different modalities .The SIFT feature description and multiscale local binary patterns is applied on sketched images and photos.

Keywords —Face recognition, forensic sketch, viewed sketch, local feature discriminant analysis, feature selection

I.INTRODUCTION

Due to a vital role in law enforcement Face sketch recognition has received significant attention. The only suspect in crime scenes is the verbal information or description provide by the eye witness which can be later be used to draw sketch which is used to identify the suspect. Later this face sketch can be used as query for matching the sketch against the gallery of face photo with the known identities .However, many crimes occur where none of this information is present, but instead an eyewitness account of the crime is available. In these circumstances, a forensic artist is often used to work with the witness in order to draw a sketch that depicts the facial appearance of the culprit according to the verbal description. The major challenge of face sketch recognition is matching images of different modalities [1]

Two different types of face sketches are discussed in this paper: viewed sketches and forensic sketches (see Fig. 1). 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. Published research on sketch to photo matching to this point has primarily focused on matching viewed sketches [1], [2], [3], [4], [5], despite the fact that real-world scenarios only involve forensic sketches. Both forensic sketches and viewed sketches pose challenges to face recognition due to the fact that probe sketch images contain different textures compared to the gallery photographs they are being matched against. However, 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. We highlight two key difficulties in matching forensic sketches:

1) Matching across image modalities and 2) performing face recognition despite possibly inaccurate depictions of the face. Inorder to solve the first problem, we use local feature-based discriminant analysis (LFDA) to perform minimum distance matching between sketches and photos, which is described in Section 3 and summarized in Fig. 2. The second problem is considered in Section 5, where analysis and improvements are offered for matching forensic sketches against large mug shot galleries.

The contributions of the paper are summarized as follows:

1. We observe a substantial improvement in matching viewed sketches over published algorithms using the proposed local feature-based discriminant analysis.

2. We present the first large-scale published experiment on matching real forensic sketches.

3. Using a mug shot gallery of 10,159 images, we perform race and gender filtering to improve the matching results.

4. All experiments are validated by comparing the proposed method against a leading commercial face recognition engine.

The last point is significant since earlier studies on viewed sketches used PCA (eigenface) matcher as the baseline. It is now well known that the performance of PCA matcher can be easily surpassed by other face matchers.

II.RELATED WORKS

Most of the existing works synthesize pseudo photos (sketches) form input sketches (photos) into a same modality which is followed by intra-modality face recognition. Tang and Wang [2,3] proposed a face sketch synthesize and recognition method by applying Eigen-transformation on the entire image of a given face. Similarly, Liu et al. [4] proposed a patch based nonlinear face sketch synthesis and recognition method inspired by local linear embedding. This approach performs Eigen-transformation on local patches instead of the entire image. Later, Wang and Tang [5] improved the method of [4] by modeling the spatial relation of local patches using multi scale Markov random filed (MRF). As another approach based on Markov model, Zhong et al. [6] proposed a method based on embedded hidden Markov model (E-HMM) and selective ensemble strategy to model the nonlinear relationship between photos and sketches. A major limitation of the above methods is that the accuracy of these works is highly dependent on the results of photo-sketch synthesis, i.e. imperfect synthesis results can lead to poor recognition. Therefore, some recent works have focused to reduce the modality difference in feature extraction stage instead of transforming into same modality. The first feature based method was proposed by Klare and Jain [7]. In this approach, dense SIFT descriptors [8] are directly extracted from local patches to reconstruct a holistic image representation. For each local patch, a 128-dimentional SIFT descriptor is calculated. The holistic image representation is obtained by accumulating the local SIFT descriptors. Direct sketch-photo matching was performed by a simple 1-NN classifier. Moreover, Klare et al. [9] proposed local feature based discriminant analysis (LFDA) to match forensic sketches to mug shot photos. Photos and sketches are represented by two different types of features: SIFT descriptors and multi local binary patterns (MLBP). Then, multiple discriminant projections on partitioned vectors of the features are used to extract discriminative features. Despite the high accuracy achieved by this method, the modality difference between sketches and photos has not been solved by LFDA. Since, the SIFT and MLBP are not robust against modality difference in face sketch recognition problem [1]. Recently, Zhang et al. [1] presented a new face descriptor based on coupled information-theoretic encoding to extract modality-invariant descriptor. In this work, coupled information-theoretic projection was introduced to maximize the mutual information between the encoded photo and sketch of same subject. This method is the state-of-the-art in face sketch recognition

III PROPOSED APPROACH

3.1 Preprocessing

A novel preprocessing method is discussed in this section. This preprocessing is different from the conventional face recognition preprocessing techniques where the face is preprocessed so that the region only from forehead to chin and cheek to cheek is visible (internal features of the face).

Figure 2.1: Example of the image preprocessing, done with our proposed method. The external features of the face are not lost in the preprocessed image

Here, we preprocess the images, so that the hairline and neck region along with the ears are also visible (as shown in Figure 2.1). This is due to two reasons:

1. Experiments conducted by Frowd et al. [10] showed that human beings remember the familiar with the help of internal features and unfamiliar faces with the help of external features of the face. Since a culprit is essentially unfamiliar and you don't come across him in your everyday life, the external features of the face region are very important and hence need not be removed.

2. Forensic Sketch artists not only draw the internal parts of the face, but also the External ones. Moreover, logically from the first point, it is clear that external features are more saliently remembered and hence drawn with a good accuracy. Also, Jain et al. [11] reported that when doing the matching of forensic sketches, using only the external features(Chin,hairline,ears) of the face gave better accuracies compared to using only the internal features(eyes, nose ,mouth etc.,). Further in their experiments, they found out that using both internal and external features gave better accuracies compared to using only external features. Since SURF is both rotation and scale invariant, we did not preprocess the images further.

3.2 Feature based matching

The true identity of an individual is invaluable information. While the average person has no qualms with their identity being known, a collection of individuals would prefer to keep such knowledge hidden despite the negative impact it may cause on the population at large. Typically, the sole motivation for an individual to hide his identity is to evade detection by law enforcement agencies for some type of criminal activity. Ongoing progress in biometric recognition has offered a crucial method to help ascertain who a person truly is. The three most popular biometric traits in use are the fingerprint, face, and iris. Though fingerprint and iris are generally considered more mature and accurate biometric technologies, face recognition is now receiving a significant amount of interest in the research community. The two main reasons for a growing interest in face biometrics are: (i) unlike fingerprint and iris, faces can be captured in a covert way, so it is an extremely valuable biometric for surveillance applications. With the rapidly growing number of digital cameras capturing data in public areas, having a robust and accurate face recognition method is critical to apprehend suspects and prevent crimes. (ii) Solving unconstrained face recognition requires a significant amount of research in face modeling, feature extraction and matching. The past two decades have witnessed a tremendous progress in face

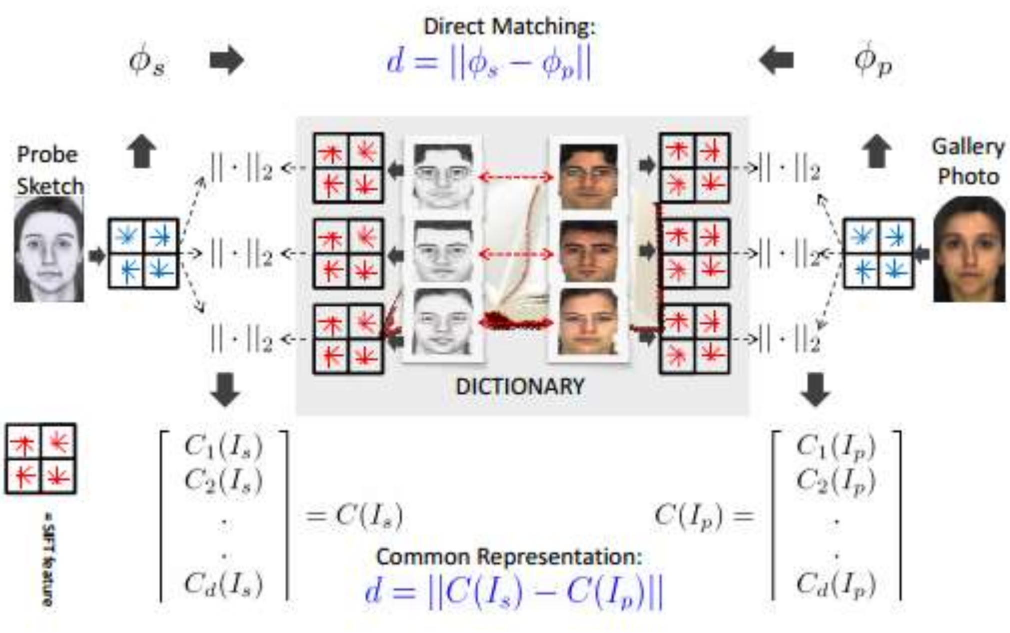

Figure1. The process of comparing a face sketch to a face photo using both the common representation and the direct matching method is illustrated here. The first step is to compute the SIFT representation for each image (Section 3.3). Direct matching (top) proceeds by computing the distance of the SIFT representation between the sketch and photo. For the common representation (bottom), we describe the probe sketch image as a d-dimensional vector, where d is the product of the number of subjects in the dictionary (n) and the number of patches sampled to generate the SIFT features (p). The d vector components are the L2 distances from the p sampled SIFT descriptors of the sketch to the same descriptors for each of the n sketches in the training set. The same process is then applied to the gallery photos, this time comparing them to the training set photos. The sketches and photos can then be directly compared in this common representation

3.3 SIFT Representation

For each sketch query, gallery photograph, and each sketch/photo correspondence in our dictionary, we compute a SIFT feature representation. SIFT based object matching is a popular method for finding correspondences between images. Introduced by Lower[12] SIFT object matching consists of both a scale invariant interest point detector as well as a feature-based similarity measure. Our method is not concerned with the interest point A SIFT image feature is a compact vector representation of an image patch based on the magnitude, orientation, and spatial vicinity of the image gradients. For an s x s sized patch of image pixels, the SIFT feature vector is computed as follows. First, the intensity image is used to compute the gradient image, which is weighted by a Gaussian kernel using $\sigma = s/2$. The spatial coordinates in the gradient image are then coarsely quantized into m x n values (generally such that $m = n$). With each gradient image pixel containing a gradient orientation ranging from $[0, \pi)$, the values are then quantized into one of k orientations. At each of the $m \cdot n$ spatial coordinates, the sum of the Gaussian weighted gradient magnitude values for each of the k orientations is computed. This yields a $(m \cdot n \cdot k)$-dimensional feature descriptor, where each component contains the sum of weighted gradient magnitudes at the given location and orientation. The final step is to normalize the feature vector to unit length. A second normalization step is performed by suppressing any component larger than 0.2 down to 0.2 and re-normalizing the vector to unit length. Typical parameters used in this process are $m = 4$, $n = 4$, and $k = 8$, which results in a 128-dimensional vector. These are also the parameter values used in our algorithm.

3.2 Sketch/Photo Direct Matching

We initially believed that direct matching between sketches and photos using the SIFT descriptors would not be successful because the gradient images generated from each image domain are not the same. This initial (and incorrect) belief motivated our development of the common representation vector. However, further investigation demonstrated that directly matching sketches and photos described by SIFT descriptors was highly successful

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If acknowledgement is there wishing thanks to the people who helped in work than it must come before the conclusion and must be same as other section like introduction and other sub section.

CONCLUSION

We have presented methods and experiments in matching forensic face sketches to photographs. Matching forensic sketches is a very difficult problem for two main reasons: 1) Forensic sketches are often an incomplete and poor 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 representation 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. While previous research efforts have focused on viewed sketches, most real-world problems only involve matching forensic sketches. Using a collection of 159 forensic sketches, we performed matching against a gallery populated with 10,159 mug shot images. Further improvements to the LFDA method were achieved by utilizing ancillary information such as race and gender to filter the 10,159 member gallery. For an unbiased evaluation of our methods, we used a state-of-the-art face recognition system, FaceVACS [26]. Continued efforts on matching forensic sketches are critical for assisting law enforcement agencies in apprehending suspects. A larger data set of forensic sketches and matching photographs needs to be collected to further understand the nature and complexity of the problem

We have proposed an effective method for matching facial sketch images to face photographs. Our method uses local image features to describe both sketch and photo images in a common representation framework. Many opportunities for future research stem from the results shown in this work. fusion between our local feature-based method and Wang and Tang's global matching framework.8 We believe that such a method of hybrid sketch/photo matching should improve recognition accuracy even further due to the complementary nature of the two approaches (i.e. one method harnesses local differences between two faces, while the other considers global differences). The use of alternate image features is also a fruitful direction of research. In our experimentation we have observed that simple image features such as image intensity, Haar features, and Gabor images do not yield successful matching results, though there likely exists other descriptors with the same (or better) discriminative capabilities as the SIFT descriptor. Finally, the effectiveness of our matching algorithm across other image domains (e.g. NIR and visible light images) should be investigated. The next phase in sketch to photo matching is to begin using description-based sketches. While sketch matching has already been shown to be a difficult problem, the method presented in this paper and in prior publications5–8,11 have only dealt with sketches that were drawn by an artist who viewed each person's photograph.

However, real world uses of sketch matching are with forensic sketches that are only drawn from eye witness description. Figure 6 shows a description-based sketch drawn by famed forensic sketch artist Lois Gibson.18 Larger discrepancies between the sketch and photo are observed in the description based sketch than sketches shown in Figure 2. Future sketch matching will need to account for not only the difference between sketches and photos, but also the further appearance changes introduced by only a description being used to draw the sketch.

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