Face Sketch Recognition by Enhancing Evolutionary-Based Model

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Abstract

Face sketch recognition models play a vital role for investigators in solving criminals. The task of these developed models is to perform matching between a drawn sketch image, and photo images at the database of law enforcement agencies. A forensic artist based on the description of an eyewitness draws the sketch image. However, one of the main challenges in problem of face sketch recognition is the variation between the drawn sketches and the original face photo. This work introduces an Evolutionary-Based Model (EBM) to tackle the problem of face sketch recognition. In particular, EBS is employed to perform two different operations, which are parameters tuning during the training phase, and localization of sketch facial components (e.g. face, eyes, nose, and mouth) at sketch recognition phase. To evaluate the effectiveness of the proposed model, a number of face sketch dataset images are used including CUHK, AR, and FERET. Experimental results show that the proposed method provides better identification performance compared to existing methods.

Keywords: Face Sketch Recognition, Evolutionary Algorithms, CUHK face sketch dataset, FERET sketches, AR sketches and HOG features.

1. Introduction

Face sketch recognition models are important for police investigators in solving criminals. The main aim of these developed models is to perform matching operation between unknown sketch input image, and photo images at the database of law enforcement agencies. These models can help the police narrow down potential suspects quickly. However, in most cases, the photo image of a suspect is not available. Therefore, an artist based on the recollection of an eyewitness could draw the sketch.

2. Related Work

Compared to photo-based face recognition, there is only a limited amount of research on sketch recognition, and most of the published work is focused on hand drawn sketches. Furthermore, many techniques have been developed for face sketch recognition problem. Zhang et al. in [1], have been presented a simple but effective method for face recognition, named nearest orthogonal matrix representation (NOMR). Specifically, the specific individual subspace of each image is estimated and represented uniquely by the sum of a set of basis matrices generated via singular value decomposition of original image. Then, the nearest neighbour criterion is introduced for recognition. Weiping and Yongsheng in [2], have been adopted a string-based matching technique. In particular, for performing the matching operation between the sketch image and gallery database photos, the concept of string matching technique has been used. Hu et al. in [3], has been investigated the idea of developing a component-based face recognition approach. Therefore, Active Shape Model (ASM) has been used for localizing the sketch facial components. Then a pair sketch-photo matching procedure was carried out to find the best similarity between the localized sketch facial components and gallery database facial components. Moreover, the results have been illustrated the usefulness of component-based approach as compared with holistic-based methods. Bhatt et al. in [4], have been studied an optimization-based sketch recognition approach. In particular, a memetic evolutionary algorithm for optimizing the weights of the extracted features at the training phase has been developed. Moreover, a comparable performances of this approach as compared with other commercial face sketch recognition systems has been demonstrated. Zhang et al. in [5], have been analyzed the psychological behavior of humans for
matching sketches drawn by different sketch artists. Klare et al. in [6], have been extended their approach using Local Feature Discriminant Analysis (LFDA) to match forensic sketches. Furthermore, Klare and Jain in [7], have been proposed a framework for heterogeneous face recognition where both probe and gallery images are represented in terms of nonlinear kernel similarities. Zhang et al. in [8], have been proposed an information theoretic encoding band descriptor to capture discriminative information and random forest based matching to maximize the mutual information between a sketch and a photo. Klare et al. in [9], have been presented a holistic-based models which employ the entire face segment for matching process. Moreover, PCA technique has been adopted for the recognition operation as well as for the transformation process of photo-to-sketch. Zhang et al. in [10], have been extended multiscale Markov Random Field (MRF) model to synthesize sketches under varying pose and lighting conditions. Zhang et al. in [11], have been compared the performance of humans and PCA-based algorithm for matching sketch-photo pairs with variations in gender, age, ethnicity, and interartist variations. The quality of sketches in terms of artist's skills, experience, exposure time, and distinctiveness of features have been discussed. Klare and Jain in [12], have been proposed a Scale Invariant Feature Transform (SIFT) based local feature approach where sketches and digital face images were matched using the gradient magnitude and orientation within the local regions. Bhatt et al. in [13], have been extended Uniform Local Binary Patterns to incorporate exact difference of gray level intensities to encode texture features in sketches and digital face images.

3. The proposed method

The proposed method of this paper is shown in Fig 1. Mainly, it consists of three stages i.e. facial components extraction, Histogram Of Gradient (HOG) feature extraction and matching stage. The detail of each stage is explained as follows.

![Facial components localization](image)

![HOG Features](image)

![Matching](image)

Fig 1: The main stages of the proposed model
3.1 Facial components localization

The aim of this stage is to locate sketch facial components localization from the input unknown sketch. In particular, four rectangles are used to locate sketch facial components as illustrated in Fig 2. Therefore, the aim is to find the best values of these formulated parameters for locating sketch facial components at the testing phase. In this research, an enhanced differential evolution (DE) algorithm will be used to perform the facial components localization task. Therefore, for better localization of these components, DE will be integrated with other local search algorithm to be able to perform fine tuning operation during the searching process.

3.2 HOG Features

HOG shape feature descriptor in [14] is utilized in this work (see Fig 3). Basically, there are two parameters are associated with HOG, i.e. block size and cell size as shown in Fig 4. Therefore, in this stage the HOG is computed from all facial components as shown in Fig 1.

3.3 Matching

In this stage, the aim is to measure the amount of the similarity between the components of the input unknown sketch with the stored photo components at the the database of law enforcement agencies. For computing the similarity between pair components (see Fig 1), the following similarity function could be used and it defined as:

\[
\chi^2(A, B) = \sum_i \frac{(A_{ki} - B_{ki})^2}{A_{ki} + B_{ki}}
\]

(1)

where \( \chi^2 \) is the Chi square distance measure. A, and B the input feature vector from the sketch and the photo respectively.

4. Experimental Results

To evaluate the performance of the proposed algorithm, two databases were used: CUHK database [15] and IIIT-D sketch database prepared by authors. Since the application of sketch recognition is more dominant in law enforcement with identification scenario, the performance of the proposed algorithm is evaluated in the identification mode. Section IV-A provides the specifications of the database used for evaluating the proposed algorithm, Section IV-B explains the experimental protocol and Section IV-C lists the foremost annotations about the experiments.
4.1 Database

The CUHK sketch database [15], available in public domain, comprises 188 sketch-digital image pairs from the CUHK student database, 123 sketch-digital image pairs from the AR database [16] and 295 sketch-digital images pairs from the XM2VTS database. In total, there are 606 sketch-digital image pairs. Since the XM2VTS database is not available freely, we have used only 311 sketches from the database and not the sketches corresponding to the XM2VTS database. The CUHK sketch database has sketch and digital image pairs with constant background and controlled illumination. The pairs perfectly overlay unlike conditions that a real sketch to digital image matching algorithm might encounter.

We observed that the challenge of sketch to digital face recognition lies in understanding the inherent non-linearity between these modalities, which is not entirely possible with such well-formed database. To evaluate some of the challenges of real world sketch recognition, we prepared a database of 231 sketch-digital image pairs where a professional sketch artist for images collected from different sources drew sketches. In this database, 67 sketch-digital image pairs correspond to images in the FG-NET aging database [17], 92 sketch digital image pairs are from images present in the Labelled Faces in Wild database (LFW) [18], and 72 sketch-digital image pairs belong to the students and faculty members at IIIT-Delhi. Fig. 3 shows sketch-digital image pairs from the CUHK database and the IIIT-D sketch database. As shown in Fig. 3(b), the sketch-digital images present in the IIITD database are more challenging compared to the CUHK database.

<table>
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<tr>
<th>Features</th>
<th>Photos (%)</th>
<th>Sketches (%)</th>
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<td>W_Face</td>
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<tr>
<td></td>
<td>H_Face</td>
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</tr>
<tr>
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<td>W_Eyes</td>
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<td>W_Nose</td>
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<td>H_Nose</td>
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<tr>
<td>Mouth</td>
<td>W1_Mouth</td>
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<td></td>
<td>W2_Mouth</td>
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<td>33</td>
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<tr>
<td>Transform Method</td>
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<td>81</td>
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<td>Proposed Method</td>
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5. Discussion

In this paper, we proposed an Enhanced Evolutionary-Based Model for face sketch recognition. A large number of experiments proved that our method outperforms other methods, especially when there is no suitable sketch patch in the training data for a target patch.

6. Conclusions

In this paper, we have proposed an Enhanced Evolutionary-Based Model to recognize a face sketch, based on extraction of facial components. This is different and difficult than face photo recognition because faces are much different from sketches in terms of color, texture, and projection details of 3D faces in 2D images. For extraction of facial components, we have used a geometric model which has been discussed in this paper. Here we have considered eight facial components and for extraction of each of those facial components we have designed distinct algorithm. After extraction of facial components, their length, width, and area are computed and then some specific ratios are computed to construct discriminating feature vectors. Finally, similarity matching has been employed to recognize face sketch through face photos database. To evaluate the effectiveness of the proposed model, a number of face sketch dataset images are used including CUHK, AR, and FERET.

References

[17] Fig.net aging database - http://www.fgnet.rsunit.com/.