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A Survey on Face-Sketch Matching Techniques

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Abstract— Face recognition is a well-studied problem in many application domains. Matching sketches with digital face images is a very important law enforcement application. One of the important clues in solving crimes and apprehending criminals is matching sketches with digital face images. Since, 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. This paper presents different algorithms that extract discriminating information from local regions of both sketches and digital face images. Face recognition technique become easier.

Keywords— Face recognition, Scale Invariant Feature Transform, Local Feature-Based Discriminant Analysis, Extended Uniform Circular Local Binary Pattern, Webers Local Descriptor, Facial Self Similarity, Memetically Optimized Multi Scale WLD

I. INTRODUCTION

Developments in biometric technology have provided additional tools to criminal investigators that help to determine the identity of criminals. If a fingerprint is found at the scene of crime or a surveillance camera captures an image of the face of a suspect, then these are used in determining the suspect using biometric identification techniques. In many times such type of above information is not present. The technology to efficiently capture the biometric data like finger prints within a short period of time is impractical. So in many cases an eyewitness account of the crime is available who had seen the criminal. A forensic artist draw sketch that portrays the facial appearance of the criminal. Sketches drawn by using such process is called as forensic sketches. When sketch is ready, it is sent to the law enforcement officers and media outlets with the hope of catching the suspect. Generally, forensic sketches are manually matched with the database comprising digital face images of known individuals.

There are three different types of sketches are used. 1) Viewed sketches, drawn by a sketch artist while looking at the digital image of a person. 2) Semi-forensic sketches, drawn by a sketch artist based on his recollection from the digital image of a person. 3) Forensic sketches, drawn based on the description of an eyewitness from his recollection of the crime scene.

Forensic sketches are drawn based on the recollection of an eye-witness and the expertise of a sketch artist. The most difficult problem is that the process of identifying a person from facial appearance has to be performed differently for each image in database, because there are so many conflicting factors altering facial appearance.

This paper deals with a review on various face recognition techniques such as SIFT, LFDA, WLD, MCWLD etc. The paper is organized as follows. Section 2 describes the different techniques used for matching sketches with digital images. Section 3 concludes the paper.

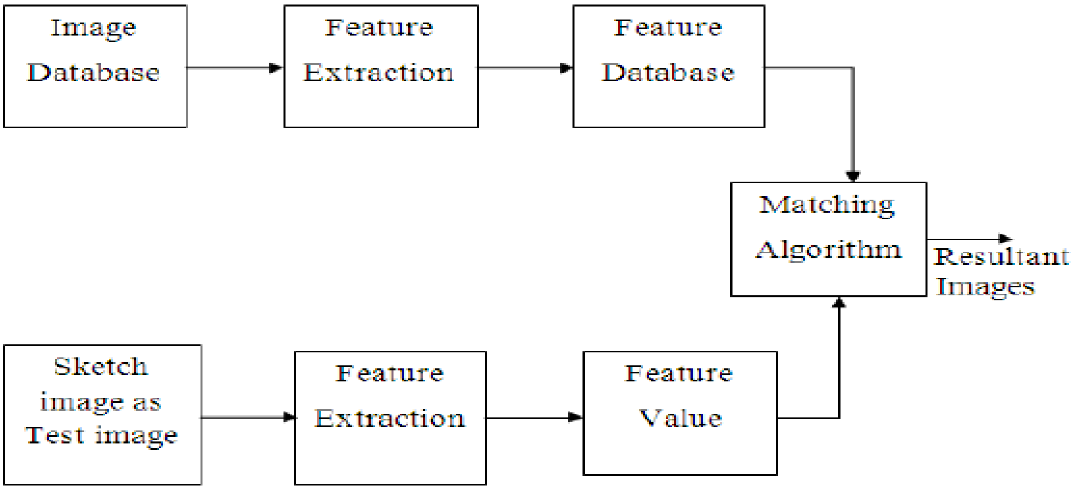

Figure1: Representation of the sketch matching system

II. TECHNIQUES FOR MATCHING SKETCH TO IMAGE

2.1. Scale Invariant Feature Transform (SIFT)

Jiang, et al. [1] proposed Scale Invariant Feature Transform (SIFT) feature based face recognition. SIFT features are features extracted from images to help in reliable matching between different views of the same object. That extracted features are invariant to scale and orientation. The algorithm for SIFT is as follows[7]:

- Scale-Space Extrema Detection: Scale-Space extrema function is used to define scale space using convolution operator of variable-scale Gaussian and the input image. Difference of Gaussians (DoG) technique is used for locating scale-space extrema by computing the difference between two images, one image with scale k times the other.
- Extrema Detection: This stage is to find the extrema points in the DoG pyramid. To detect the local maxima and minima of difference each point is compared with the pixels of all its 26 neighbors. If its value is the minimum or maximum this point is an extrema.
- Keypoint Elimination: Keypoint Localization Elimination of more points by finding those that have low contrast or are poorly localized on an edge. It is achieved by calculating the Laplacian.
- Orientation Assignment: The most prominent gradient orientations are identified using the histogram. If there is only one peak, it is assigned to the keypoint. If there are multiple peaks above 80% mark, they are all converted into a new keypoint. Then a highly distinctive feature vector, having 128 different numbers for each keypoint is generated.
- Descriptor Computation: A descriptor is computed for the local image region that is as distinctive as possible at each candidate keypoint. The orientations and image gradient magnitudes are sampled around the keypoint location.
- Transformation: Some matching tests are running to test the repeatability and stability of the SIFT features. The features of the two images are computed separately. Each keypoint in the original image is then compared to every keypoints in the transformed image using the descriptors computed in the previous stage. One feature is picked in each image for each comparison.

After computing the SIFT features for each sampled patch of the gallery, and probe sketches, the common representation for sketch image and for photo is found out. To compare the similarity between photo and sketch, directly compare the distance between the two common representation vectors.

The SIFT features described in this implementation are computed at the edges and they are invariant to image scaling, rotation, addition of noise. Noise adjustment is a very essential part for this approach which could result in inefficient or false matching. The major disadvantage is that the average number of SIFT features extracted decreases with decreasing the resolution of the image. SIFT computes only for the regions of interest that have usually already been normalized with respect to scale and rotation.

2.2. Local Feature-Based Discriminant Analysis (LFDA)

Ambhore et al. [2] proposed face sketch to photo matching using LFDA. In LFDA framework [7], scale invariant feature transform (SIFT) and multiscale local binary pattern (MLBP) feature descriptors are used. First feature based representation of both sketch and photograph is found out. For both, SIFT feature descriptor is computed. The SIFT feature descriptor quantizes both the spatial locations and gradient orientations within an s×s-sized image patch, and computes a histogram in which each bin corresponds to a combination of a particular spatial location and orientation. The descriptors are computed over a set of uniformly distributed sub-regions of the face. The feature vectors at each sampled regions are then concatenated together. Minimum distance sketch matching can be performed directly using this feature-based representation by computing the normed vector distance.

The local binary patterns (LBP) operator takes a local neighborhood around each pixel, thresholds neighborhood pixels of the central pixel and uses the resulting binary-valued image patch as a local image descriptor. The limitation of the LBP operator is that its small 3 × 3 neighborhood cannot capture the dominant features with large scale structures. To deal with texture at different scales, the operator was extended to use neighborhoods of different sizes called as MLBP.

LFDA is more effective in handling large feature vectors. When dealing with the smaller sized slices, the LFDA algorithm is able to extract a larger number of meaningful features.

2.3. Extended Uniform Circular Local Binary Pattern (EUCLBP)

Balaji et al. [3] Extended Uniform Circular Local Binary Pattern (EUCLBP) Matching Algorithm. It extracts discriminating information present in local facial regions at different levels of granularity. Digital face images and sketches are decomposed into multi resolution pyramid which forms the discriminating facial patterns. EUCLBP use these patterns to form a unique signature of the face. For matching, a memetic optimization based approach is used to find the optimum weights corresponding to each facial region. Steps involved in matching sketches with digital face images are:

- Preprocessing technique is used to enhance the quality of both the digital and sketch face images.
- Both the digital face images and sketch are tessellated into non overlapping local facial regions (6x7).
- For each local facial region EUCLBP descriptors are computed.
- Memetic algorithm was uesd for weights optimization for matching two EUCLBP descriptor.
- The top matches are obtained by applying this procedure for each gallery probe image pair.

This approach gives better performance even in cases where images are not perfectly aligned.

2.4. Weber's Local Descriptor (WLD)

Chen et al. [4] proposed Weber's Local Descriptor inspired by Weber's law. It states that the change of a stimulus that will be just noticeable is a constant ratio of the original stimulus. WLD is a dense descriptor computed for every pixel and depends on both the local intensity variation and the magnitude of the center pixel's intensity. 2D WLD histogram is used for texture classification. WLD consists of two components: 1) Differential excitation and 2) Orientation. The differential excitation component is a function of the ratio between two terms: First one is the relative intensity differences of a current pixel against its neighbors; the other is the intensity of the current pixel. Next the orientation component is the gradient orientation of the current pixel. The two components are used to construct a concatenated WLD histogram. Corresponding to each dominant orientation, differential excitations are organized as a histogram. Then each histogram is evenly divided into M sub histograms each with S bins. Then these histograms form a histogram matrix, where each column corresponds to a dominant direction. Then each row of this matrix is concatenated as a histogram. Subsequently, then these histograms concatenated into a single histogram. This histogram is referred to as WLD descriptor.

2.5. Facial Self Similarity (FSS)

Mian et al. [5] proposed Facial Self Similarity descriptor (FSS) for sketch to photo matching. Both sketch and photo faces were rotated with respect to the manually located eye coordinates and scaled so that the inter-ocular distance is 25 pixels. Then a region of 100 x 100 pixels was then cropped keeping the eyes fixed at row 48 of the image.

- In Preprocessing stage the Difference-of-Gaussian (DoG) filter is used for reducing the low frequency information and retaining the high frequency information.
- Facial Self Similarity (FSS) Descriptor: The usage of co-occurrence of a higher order image representation and the usage of mean compared to max of correlation surface for pooling in histogram bins in order to make it sensitive to the matching part over a small local region instead of a single pixel makes it more advantageous than Local Self Similarity (LSS) descriptor. There are two steps to compute the FSS descriptor. The first step is to compute a local self-similarity surface at a point. Next step is to convert the similarity surface into a polar histogram.
- FSS Descriptor Matching: Here matching the descriptors using nearest neighbor classification. The minimum distance between probe-gallery pair is obtained by using the Euclidean distance function.

2.6. Memetically Optimized Multi Scale WLD (MCWLD)

Bhatt et al. [6] proposed Memetically Optimized Multi Scale WLD (MCWLD). Multi-scale Circular WLD is one of the most advanced types of image descriptors. WLD is optimized for matching sketches with digital face images by computing multi-scale descriptor in a circular manner. Memetic optimization algorithm is proposed to assign optimal weights to every local facial region to boost the identification performance. This algorithm extracts the discriminating information from local regions of both digital face images and sketches. A pre-processing technique is presented for enhancing the quality of forensic sketch-digital image pairs. MCWLD has two components: 1) differential excitation and 2) gradient orientation. MCWLD representation is constructed by tessellating the face image and computing a descriptor for each region. Multi-scale analysis is performed by varying the radius R and number of neighbors P. Differential excitation is computed as an arctangent function of the ratio of intensity difference between the central pixel and its neighbors to the intensity of central pixel. Orientation component is the gradient orientation of the current pixel. A 2D histogram of circular WLD feature is constructed. And latter is further encoded into1D histograms. Within each orientation, range of differential excitation is evenly divided into M intervals and then reorganized into a histogram matrix. Sub-histogram segments, across all dominant orientations are reorganized into M one dimensional histograms. M sub-histograms are concatenated into a single histogram thus representing the final M × T × S circular WLD histogram. In Multi-scale analysis, CWLD descriptor is extracted with different values of P and R and the histograms obtained at different scales are concatenated to form the facial representation. Memetic algorithm can be effectively used to optimize large number of weights for best performance.

III. CONCLUSION

Sketch to digital face matching is an important research challenge and is very pertinent to law enforcement agencies. The techniques are used for the feature extraction from the local regions. Each technique for matching sketch to digital image has its own benefits. Memetic optimization will enhance the performance by identifying the optimized weight.

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