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Implementation of Partial Face Recognition using Directional Binary Code

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Abstract— In many real-world scenarios especially some unconstrained environments, human faces are occluded by other objects, therefore it is difficult to obtain fully holistic face images for recognition. Most ancient face recognition algorithms have faith in face alignment and face standardization, which is highly infeasible. To address this, a effective partial face recognition approach is required to recognize persons of interest from their partial faces A new partial face recognition approach based on Directional Binary Code is proposed. It is used for automatic conversion of partial faces to gallery faces by aligning partial face patches to gallery faces automatically. DBC is applied on image to encode the directional edge information. It captures the spatial relationship between any pair of neighborhood pixels in a local region along a given direction. The extracted features from the given image are used for face recognition. It reflects the image local feature. It is robust to occlusions as well as illumination changes.

Keywords— Face recognition, partial face recognition, feature set matching, feature alignment, image matching, bio metrics.

1. Introduction

Facial recognition is a biometric method of identifying an individual by comparing live capture or digital image data with the stored record of that corresponding person. Facial recognition systems are commonly used for security purposes but can be used in a variety of other applications. Partial face recognition is one of its fascinating Biometric applications. Partial face recognition is used to develop a face recognition system that Acknowledges partial faces directly without manual alignment and conjointly strong to occlusions in these applications. Due to its wide applications mainly in data security, law enforcement and police investigation, sensible cards, access management, and others, face recognition techniques have received considerably inflated attention from eachthe educational and industrial communities throughout the past many decades [1].

A variety of face recognition approaches are projected over the past 3 decades [6].While most of them have achieved promising performance; they only work well under well-controlled conditions. Moreover, these algorithms use holistic face images to recognize people, where face images in both the gallery and probe sets have to be pre aligned and normalized to the same size before recognition [7].In many real world applications such as smart surveillance systems in crowded scenes, human faces are easily occluded by other objects in such scenarios and it is difficult to obtain fully holistic face image for recognition. Therefore, it is desirable to develop a face recognition system which is able to recognize partial faces directly without manual alignment and also robust to occlusions in these applications.

The Eigen face is the first method considered as successful technique of face recognition but requires manipulation of large database [8]. Various matching techniques such as stereo matching, content based image retrieval can be formulated that can be used in point matching problems. Because point representations are general and easy to extract [5][10].

Both aligned and unaligned images are recognized with face algorithm specifically developed for and trained on hand-labelled face images[8].Accuracy and efficiency can be improved through two level boosted regression, shaped index features and correlation based feature selection method[9][2]. Discriminative learning can be enabled through Multi Manifold Analysis method by learning discriminative features from image patches [3].The face image is divided into several regions from which the Local Binary Pattern (LBP) feature descriptions are extracted and concatenated into an enhanced feature vector to be used as a face descriptor [4].

The major steps involved in a general recognition system are; acquisition of image, pre-processing to obtain feature extraction and comparison. A good quality image is obtained from camera and refinement is done by data pre-processing. In feature extraction, morphological or textual attributes are done, which uniquely represents the input image. Principal Component Analysis (PCA), Discrete Cosine Transform (DCT) , Discrete Wavelet Transform (DWT), and Local Binary Patterns (LBP) are used for feature extraction. The LBP extracts the relation between given pixel with its neighbouring pixels. The major drawback of LBP is that it does not provide any directional information of the image.

2. Architecture diagram

The architecture diagram is given below.

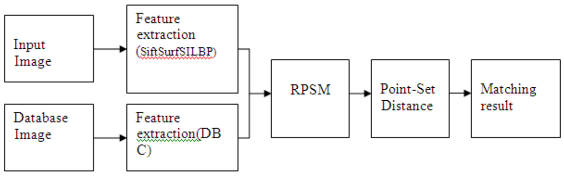

Fig.1: overall architecture diagram

The overall architecture diagram which is shown above describes the methodology of the proposed system. In this method, features of both input image and database image are extracted using sirfsift algorithm and DBC algorithm. Then these images are given to Robust Point Set Matching in which the matching is done using local binary pattern. At last, the results will be displayed.

3. Methodology

- Directional Binary Code.
- SURF & SIFT.
- Matching.

3.1 Directional Binary Code:

DBC is applied on image to encode the directional edge information. It captures the spatial The Directional Binary Codes (DBC) retains all the advantages of LBP by overcoming the disadvantage of th0e same. The database images and a test image is compared by its attributes. The comparison is done directional to give the decision of status of affiliation. Directional Binary Code is applied on LLsub band to encode the directional edgeinformation. Thus it extracts more accurate spatial information than Local Binary Patterns. In this paper DBCFR algorithm is proposed to identify a person. The image is pre-processed and DWT is applied. The Euclidian distance is used for the comparison between test image and database images relationship between any pair of neighbourhood pixels in a local region in the corresponding directions. It reflects the image local feature. It extracts more spatial information than LBP. Let Zi,j be a point in a cell, four directional derivatives at Zi,j are given

d=1,

I ‘0,d(zi,j)=I(zi,j)- I(zi,j-d);

I ‘45,d(zi,j)=I(zi,j)- I(zi-d,j+d);

I ‘90,d(zi,j)=I(zi,j)- I(zi-d,j);

I ‘135,d(zi,j)=I(zi,j)- I(zi-d,j-d);

The resized image of size 50*50 is divided into 100 cells of 5*5 matrixes. Table 1 shows a 3*3 neighbourhood centre on I i,j taken out of 5*5 cell size, where each cell contributes one coefficient.

i) False Acceptance Rate (FAR): It is the probability that unauthorized person is incorrectly accepted as authorized person.

ii) False Rejection Rate (FRR): It is the probability that authorized person is incorrectly rejected as unauthorized person iii) Recognition Rate (RR) : It is the number of persons recognized correctly in the database.

iv) Equal Error Rate (EER) : It is defined as the value at which both FRR and FAR are same.

Algorithm

1. Imageis pre-processed.
2. DWTis applied.
3. LL band of 50*50 is partitioned into 100 cells of 5*5 matrixes for each.
4. For each cell, the directional derivatives along 0, 45, 90 and 135 degrees are computed.
5. Derivatives are converted into binary and read in anticlockwise direction to form 9-bit binary code.
6. 9-bit code generated is then converted into a decimal equivalent value.
7. The decimal values of all directional derivatives of each cell are averaged 8. Euclidean distance between feature vectors of images in database and feature vectors of test image is computed.
8. Image with minimum value of the Euclidean distance is considered as matched image.

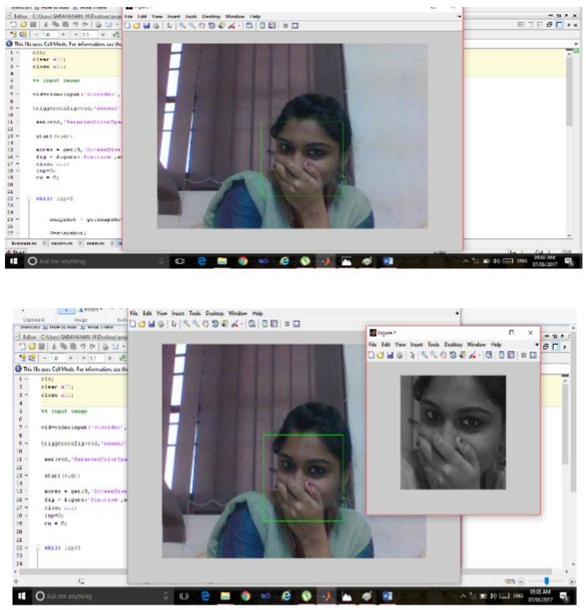

Fig.2: Screenshots of module

The overall module 1 results have been shown in figure 2 which captures the spatial relationship between any pair of neighbourhood pixels in a local region in the corresponding directions.

3.2 Surf and Sift

Speeded Up Robust Features (SURF). SURF descriptors are used to find and acknowledge objects, folk s or faces, to reconstruct 3D scenes, to trace objects and to extract points of interest.

3.2.1 *Scale Invariant Feature Transform (SIFT)*

Scale Invariant Feature Transform (SIFT) includes object recognition,robotic mapping and navigation,image stitching,3D modeling, gesture recognition,video tracking.SURF has gained wide popularity in many computer vision applications. It has been shown to have higher accuracy and speed in comparison to other feature descriptors in the context of object recognition. Input image are taken, this will be given to the SIFT algorithm. This algorithm is used to find the featurepoints.

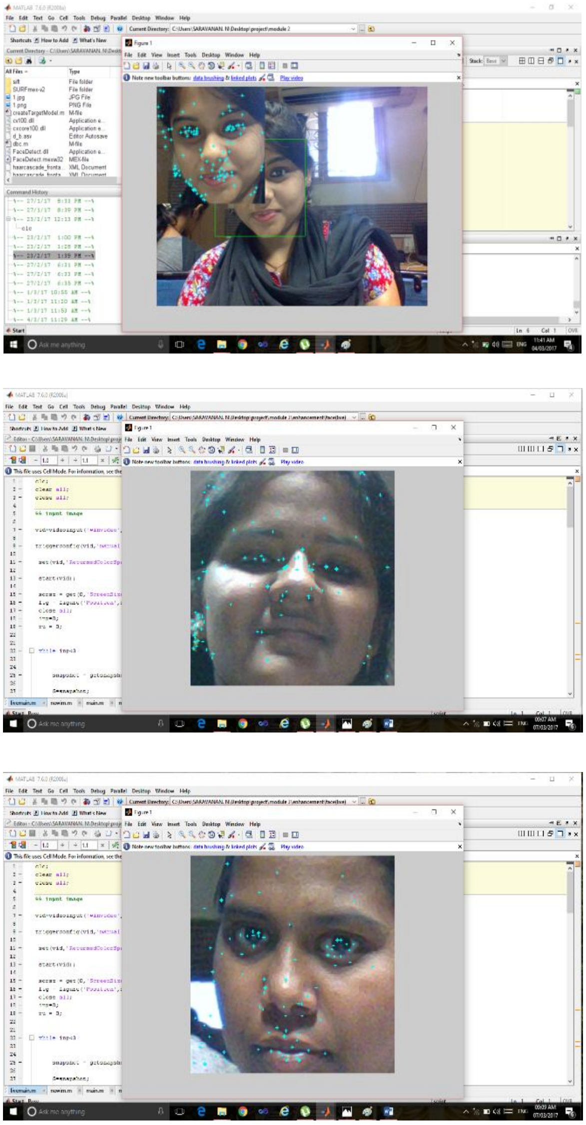

Fig. 3: Screenshot of module 2

The overall module 2 results has been shown in figure 3 which extracts the facial features efficiently.

3.3 *Matching*

3.3.1 *Local Binary Pattern*

LBP is a type of visual descriptor it is a particular case of Texture Spectrum this has benn since found has a powerful feature for texture classification and further been determined that when LBP is combined with Histogram of Oriented Gradients it improves the detection performance on some datasets.

The features generated by each LBP are then sampled into a corresponding LBP histogram. Hence, for each keypoint, we obtain four scale-invariant LBP (SILBP) histograms, one SIFT histogram, and one SURF histogram. These various histograms are concatenated into a single descriptor which is simply coined as “SiftSurfSILBP”. To align a probe partial face patch to a gallery image, we need to match their corresponding geometrical and textural features simultaneously

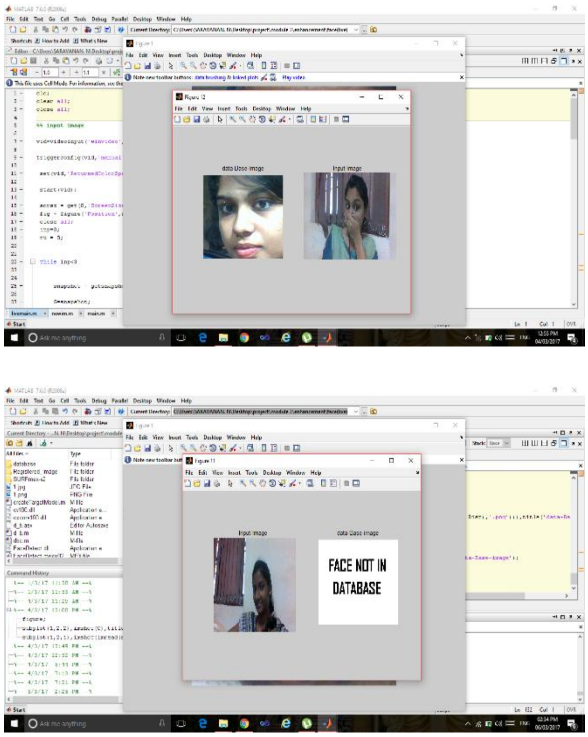

Fig. 3.3.1 Screenshots of module 3

The overall module 3 results has been shown in figure 3.3.1 which compares the images in database and results it as found if it has same image in database and it results in not found if it is not found database.

4. Future enchancement

Here,Directional Binary Codes are used which is efficient and accurate face recognition algorithm for both live and registered images. The algorithm is used effectivey to recognize partial and holistic images effectively. The major consideration of DBC araises when the intensity of light changes.The algorithm recquires effective hue and brightness for accurate face recognition.

5. Conclusion

In many real-world applications such as smart surveillance systems in crowded scenes, human faces are easily occluded by other objects in such scenarios and it is difficult to obtain fully holistic face images for recognition.Thus the euclidean distance is calculated between every pixels,using geometric and texture information matching. Therefore Directional Block Codes ,an efficient partial face recognition is achieved.

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