Biometrics Security: Facial Marks Detection from the Low Quality Images

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ABSTRACT
Face recognition indeed plays a major rule in the biometrics security environment. Facial marks as for example freckles, moles, scars etc that are soft biometric traits have played a crucial role in identifying the human face. To provide secure authentication, we require robust methodology for recognizing and authentication of the human face. However, there are numbers of difficulties in recognizing the human face and authentication of the person perfectly. The difficulty includes low quality of images due to sparse dark or light disturbances. To overcome such kind of problems, powerful algorithms are required to filter the images and detect the face and facial marks. This technique comprise extensively of detecting the different facial marks from that of low quality images which have salt and pepper noise in them. Initially we applied (AMF) Adaptive Median Filter to filter the images. The filtered images are then extracted to detect the primary facial feature using a powerful algorithm like Active Shape Model (ASM) into Active Appearance Model (AAM). Finally, the features are extracted using feature extractor algorithm Gradient Location Orientation Histogram (GLOH).

Keywords
Face recognition, Facial marks, Soft biometrics, Active Shape Model, Active Appearance Model, Adaptive Median Filter, GLOH.

1. INTRODUCTION
The term "Biometrics" is derived from the Greek words "bio" (life) and "metrics" (to measure). Automated biometric systems have become available only over the last few decades due to significant advances in the field of computer science. These automated techniques are based on ideas that were originally proposed hundreds years ago. One of the most basic examples of a characteristic that is used very often for recognition is the human face. Since the beginning of civilization, humans have used faces to distinguish between known individuals and unknown individuals. This simple task became increasingly more challenging as the human population. As a result, a new techniques and concepts to automate the facial recognition process have proliferated. A number of studies were examined to improve the face recognition by developing features representation schemes. These features include the salient skin regions, which appear on the human face such as scars, moles, freckles, wrinkles, etc [13]. Previous studies illustrate that facial marks are primarily focused upon in evaluating facial recognition performance using standard face image data set. Park and Jain [7] expressed that facial marks are very essential in identifying twins using semi automatic concept. They also labelled the demographic information such as ethnicity and gender. To detect the facial features the authors applied AAM manually and facial marks are detected using LoG with morphological operator. This method though was not enough to detect the facial marks from the low quality images [7]. But, facial marks have been used to speed up the retrieval process in order to differentiate the human faces [15].

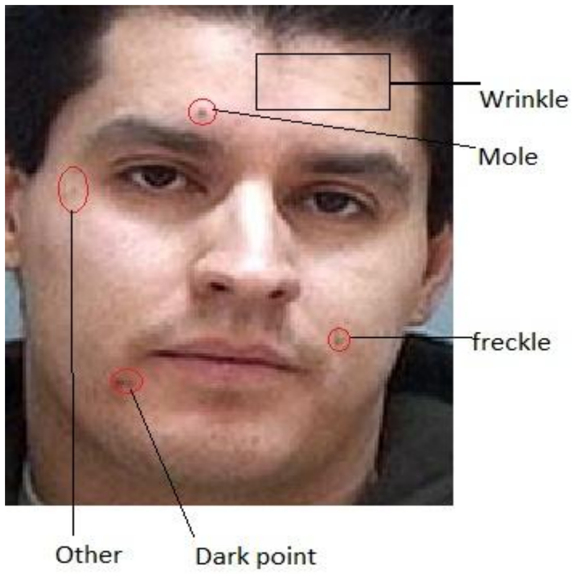


Fig. 1. Example of low quality image with different facial marks.

Fig. 1, shows the example of different kinds of facial marks on the human face. An existing study found that for face recognition purpose facial marks have been utilized very rarely [7][11]. Also Spaun [13][14] explained that facial examination has to provide identification of "class" and "individual" characteristics. The 'class' involves overall facial shape, presence of hair, hair color, shape of nose, presence of marks etc. Similarly 'individual' characteristics involve the number & location of scars, tattoos, location wrinkles etc on a face. Lin at el [3] first utilized the SIFT operator [5] to extract facial irregularities and fused them with global face matcher. However, the individual types of facial marks are not defined. Therefore their method is not suitable for face database indexing. Krystian Mikolajczyk and Cordelia Schmid et al [21] introduced GLOH is a descriptor which extends SIFT by changing the location grid and using PCA to reduce the size. It also designed to increase its robustness and distinctiveness. Lee *et al.* [30] introduced "scars, marks, and tattoos (SMT)" in their tattoo based image retrieval system. While tattoos can be drawn or made on any point of the body, the study on face recognition with tattoos assumes greater significance. Pierrard et al. [11] proposed a method to extract moles using normalized cross correlation method and a morphable model, they claimed that their method is pose and lighting invariant since it uses a 3D morphable model. They did not consider other types of facial marks besides moles. Eigen faces [27] was one of the first successful face recognition methods. It can handle variations and blur in the images quite well, but it requires a large training set of images. Fig. 2 shows how marks based matcher helps in indexing each face image based on facial marks. These indices enable fast retrieval and also for textual or key word base query.

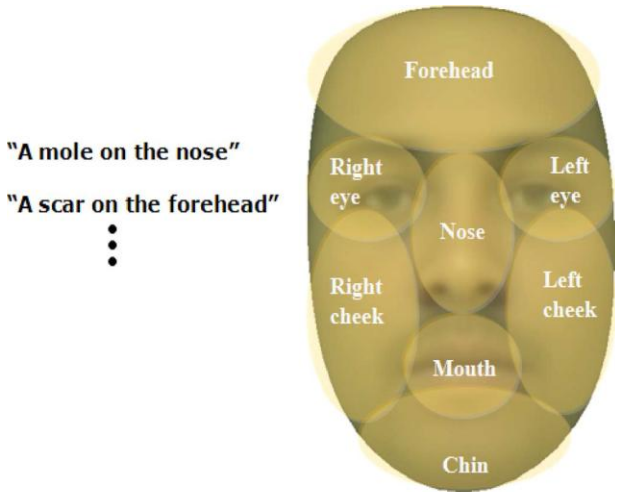


Fig. 2, Example of textual query and a schematic of face region segmentation.

2. PROPOSED METHOD

In existing method they used AAM (Active Appearance Model) using PCA (Principle Component Analysis) to detect the facial land mark from the face image [7]. Also they subtracted unwanted facial features such as eyes, eye brows, nose and mouth from the face image to detect the facial marks. The local irregularities that are facial marks (moles, scars etc) are extracted using LoG or DoG and morphological operators. Their methods are applicable only for normal with high quality images. In the literature we found that their methods are poor to detect the facial marks from the low quality images. We considered the low quality images due to sparse dark or light disturbances known as salt and pepper noise type. Generally these types of marks affect only a small number of image pixels. Typical sources of noise include flecks of dust inside the camera as well as from faulty CCD elements. To overcome these inherent problems, we have proposed a facial marks detection method that can be applied on low quality images. Our proposed method differs significantly from the existing study in determining the facial marks from the low quality images. Fig.4 shows images which contain salt and pepper noise, (i.e. sparse dark or light disturbances). Initially, we filter out those face images containing salt and pepper noise using Adaptive Median Filter (AMF). Therefore to detect the land marks from the face image, we applied powerful techniques ASM (Active Shape Model) into AAM (Active Appearance Model) using PCA (Principle Component Analysis). We also subtract the unwanted facial features such as eye brows, eyes, nose, and mouth are from the face image. Finally, the local irregularities such as scars, moles, freckles etc are extracted using GLOH (Gradient Location Orientation Histogram). Our proposed method showed the best result contrast with existing study. Fig. 3, shows the complete proposed method with necessary steps involved in our research work. Our proposed method differs from the previous works in the following aspects; (i) we concentrate on filtering the face images which contains salt and pepper type. (ii) All the facial marks that are locally salient due to low quality are extracted. (iii) We concentrate on finding semantically meaningful facial marks instead of extracting texture patterns that implicitly include facial marks. These proposed facial marks determination concept can be helpful in forensics and law enforcement agencies as it can supplement existing facial matchers to improve the identification accuracy.

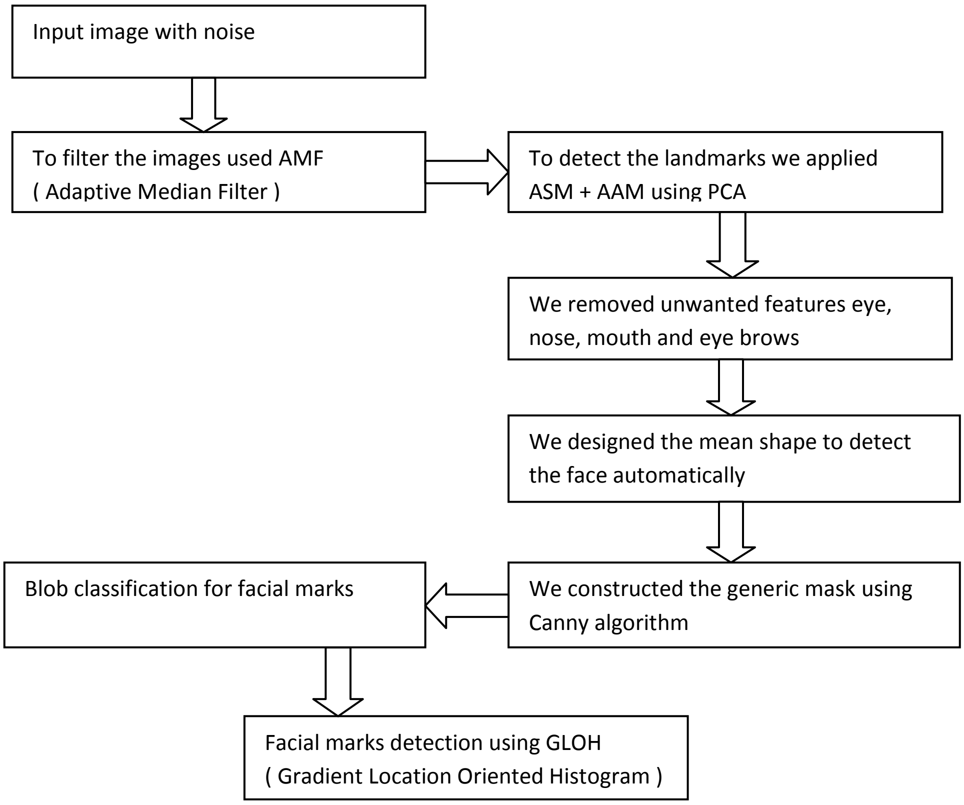


Fig. 3 , Over all structure of our proposed method.

Fig. 4 shows salt and pepper noise images

3. FACIAL MARKS ON THE FACE

Facial marks are located in different regions of face. To know the different categories of facial marks present in face, we need to analyse the categories of marks. Different kinds of facial marks are freckle, mole, scar, pockmark, acne, whitening, dark skin etc. Freckle is a single or a set of dark spots present in the face. Wherever there was a dense set of spots we labelled them in a single bounding box. A mole typically appears large in size and darker in color compared to the other spots. Scar represents the discolored region in the skin due to a cut or injury. Acne is a red region caused due to a pimple and is stable for few days to several months. Whitening represents a skin region that appears brighter in contrast with the surrounding region. We took into consideration the wrinkles that are larger and omitted the smaller wrinkles near the eyes and mouth. We also ignored the beard and facial hair in constructing the ground truth. All other kinds of marks which are not mentioned above are labelled under the “others” group. Fig. 5, shows the different facial marks in a facial image. The average number of marks observed in our database is 9 per subject. All the images in the database showed at least 2 marks per subject.

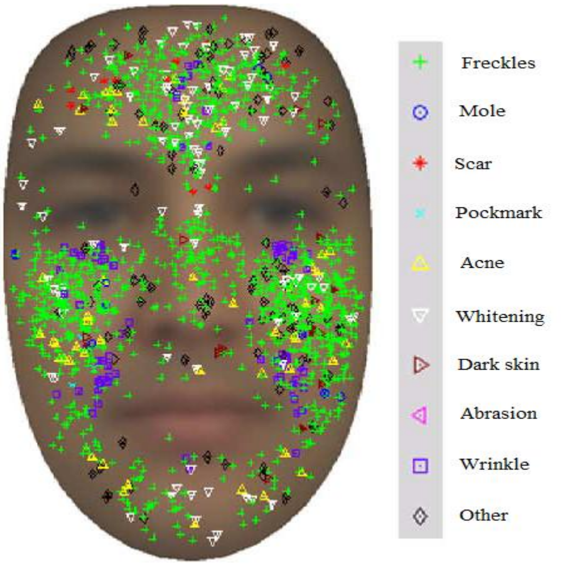


Fig. 5. Different facial marks on the mean face image

4. FACIAL MARKS DETECTION METHOD

The proposed mark detection method is based on the Gradient Location Orientation Histogram (GLOH) [21] that detects local silent points of a low quality input image or noisy image. Therefore, to detect the facial feature, it will increase the local extrema of facial features such as eyes, eye brows, nose, and mouth. To avoid detecting unwanted local facial features we subtracted eyes, eyebrows, nose, and mouth from the face image using ASM in AAM using PCA also detects the facial landmark and we provide masking process using [28]. The complete facial mark detection process is illustrated in Fig. 6 with the following steps 4.1) Noise removal 4.2) Facial feature detection 4.3) Designing mean shape and mask construction 4.4) Gradient Location Orientation Histogram and 4.5) Blob classification for facial marks.

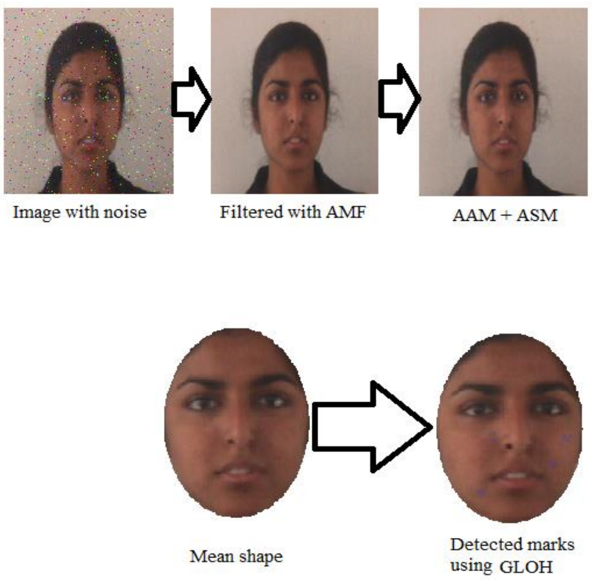


Fig.6, Schematic of Automatic Facial Mark Extraction process

4.1 Noise Removal

Adaptive Median Filter (AMF) [2] is applied to remove the noises (salt and pepper noise) from the face image and performs spatial processing to find out the pixels that have been affected by impulse noise in an image. Moreover, it groups pixels as noise by comparing each pixel in the image to its neighbouring pixels. A pixel which is different from a majority of its neighbours, as well as being not structurally aligned with those pixels to which it is similar, is defined as impulse noise. The median pixel value of the pixels in the neighbourhood that have passed the noise labelling test are then replaced these noise pixels. The filtered image from salt and pepper noise type using AMF is shown in Fig. 7. Fig. 8, 9 shows the histogram of an image. The purpose of applying the AMF is

1). Removing impulse noise from the image.

2). Smoothing of other noises from the image.

3). Reducing distortion, like excessive thinning or thickening of object boundaries.

Noise with salt & pepper   Filtered with AMF

Fig. 7. Salt and pepper noise filtered with AMF

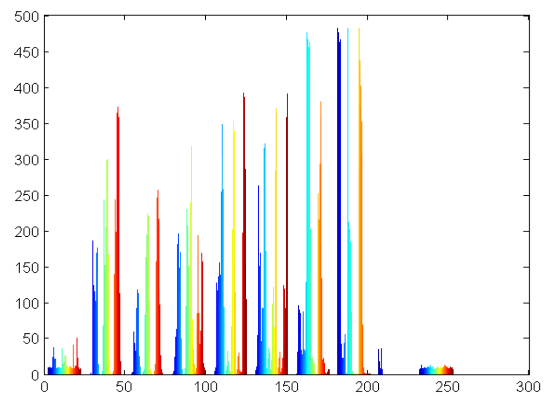


Fig. 8 shows histogram for noisy color image

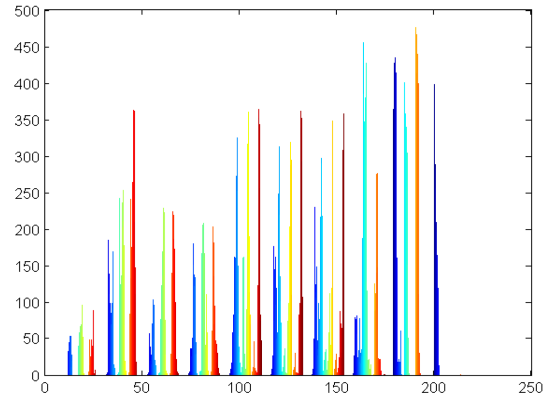


Fig. 9 shows histogram for noiseless color image

4.2 Facial Feature Detection

The integrated Active Shape Model (ASM) into Active Appearance Model (AAM) [28] to detect automatically 80 landmarks that delineate the facial features such as mouth, nose, eyes, eyebrows and face boundary. For reliability, we first detect the landmarks of two eyes, nose and mouth. These facial features will be disregarded in the subsequent facial mark detection process. ASM into AAM identifies both the shape and texture of face images using the Principle Component Analysis (PCA). ASM finds the shape parameters so that the profile at each model is similar to the pre-learned profile. It is another way of keeping the shape parameter within the learned range in the parameter space. Similarly, AAM finds the shape and appearance model parameters such that the model instance is most similar to the input image. Models that are obtained from the current model parameter are as similar as the input image. ASM and AAM are hence combined to reduce the error rate and detect the face with perfect landmark points.

4.3 Designing Mean Shape and mask construction

(4.3.1) Active Shape Model in Active Appearance Model has been applied to detect the landmarks, thereby to simplify the mark detection. We then map each face image to the mean shape. Consider that S_i where i=1, 2…,N represents the shape of each of the N face images in the database (gallery) based on the 120 landmarks. The mean shape is calculated using the equation $S_\mu = \sum_{i=1}^{N} Si$.

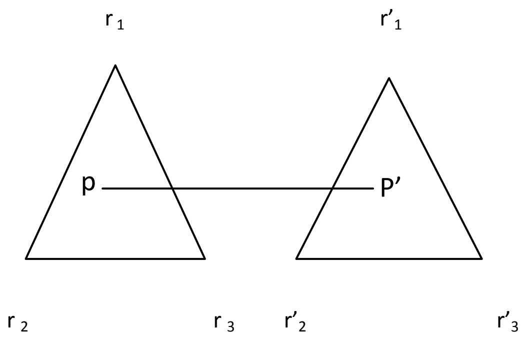


Fig.10 Schematic of texture mapping process using the triangular Barycentric coordinate system.

Fig. 10 shows the schematic of mean face construction system. Each face image S_i is mapped to the mean shape S_μ by using the Barycentric coordinate-based [2] texture mapping process. Initially, both S_i and S_μ are subdivided into a set of triangles in such a way that given a triangle T in S_i, its corresponding triangle T' is found in S_μ . Let r_1,r_2 , and r_3(r'_1 ,r'_2 and r'_3) be the three vertices of T(T'). Then, any point p inside T is expressed as $p=\alpha r_1 + \beta r_2 + \gamma r_3$, and the corresponding point p' in T' is similarly expressed as $p'=\alpha r'_1 + \beta r'_2 + \gamma r'_3$, where $\alpha + \beta + \gamma = 1$. In this way, the pixel value is mapped and shown in Fig. 10 using the schematic of the Barycentric mapping process.

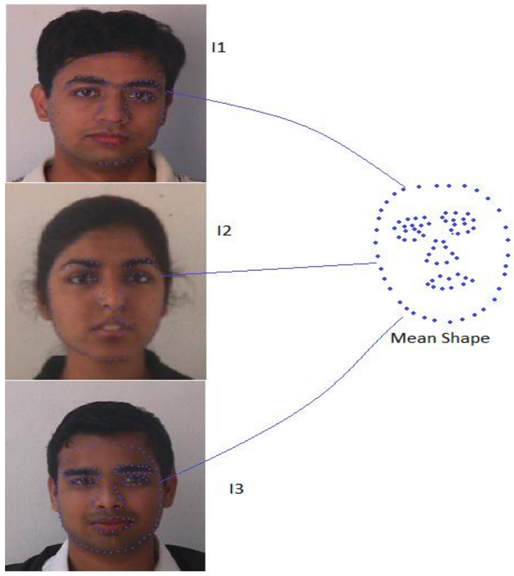


Fig. 11 Schematic of the mean face construction.

This mapping process is repeated for all the points which are present inside the triangle and the texture in S_i is mapped to S_μ. Hence, after the mapping process, all face images are normalized in terms of scale and rotation and hence this facilitates us to represent each facial mark in a face-centered common coordinate system. Fig. 11 shows the schematic of mean face construction. (4.3.2) We construct a generic mask and derive a user specific mask to suppress false positive value detection around the facial feature. The user specific mask covers small unusual landmarks around the facial feature. We suppress the false positives of small wrinkles or beard that are connected to the facial feature. We then build a user specific mask from the edge image obtained using the canny edge detector [23].

4.4 Gradient location and orientation histogram (GLOH)

Gradient location and orientation histogram (GLOH) is a descriptor which extends SIFT by changing the location grid and using PCA to reduce the size. [21], it also designed to increase its robustness and distinctiveness. The SIFT descriptor is computed for a log-polar location grid with 3 bins in radial direction i.e. the radius set to 6, 11 and 15 and 8 in angular direction, which results 17 location bins. It is to be mentioned that the central bin is not divided in angular directions and the gradient orientations are quantized in 16 bins. It provides a 272 bin histogram and the size of this descriptor is reduced using PCA. The 128 largest eigenvectors are used for description. Shape context is similar to the SIFT descriptor, but it is based on edges. Shape context is a 3D histogram of edge point locations and orientations. Edges are extracted by using the Canny [22][23] detector. Location is quantized into 9 bins of a log-polar coordinate system. The radius set to 6, 11 and 15 and orientation quantized into 4 bins (horizontal, vertical and two diagonals). This leads to a 36 dimensional descriptor and it has shown to give better results than using the same weight for all edge points, as proposed in [31]. Therefore the original shape context was computed only for edge point locations and not for orientations.

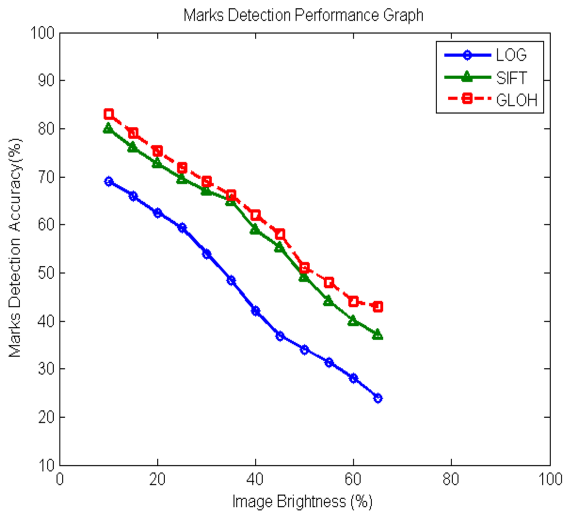
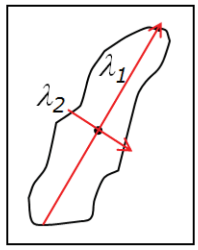


Fig. 12. Marks detection performance graph

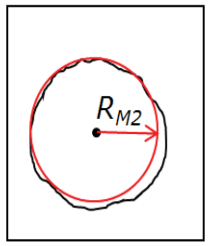
LOG, SIFT -- the existing mark detection performance.

GLOH -- the proposed mark detection performance.

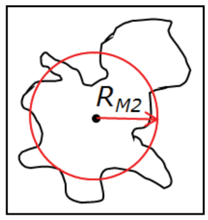
Mark detection performance is evaluated in terms of mark detection accuracy and image brightness, as shown in fig. 12. In Y axis carried out the mark detection accuracy in percentage and X axis carried out the image brightness label in percentage. In Y axis the number of marks which are detected from the face image with the adjustment of image brightness increments. The brightness contrast increased up to 0 to 65 percentages. According to brightness percentage the marks detection has been changed. The marks have been detected 69% when the contrast level 10% and 26% for the contrast level 65% in LoG. For SIFT, marks are detected 80% to 37% with image brightness level 10% to 65% in existing work and in our proposed work it detects 83% to 43% with image brightness level 10% to 65%. The mark detection performance graph in fig. 12, shows that marks detection accuracy by our method is better than existing marks detection accuracy. This helps to improve the face recognition accuracy.



(1) Linear



(2) Circular



(3) Irregular

Fig.13. Mark classification using morphology.

Figure 14. Examples of facial marks which are detected from face image.

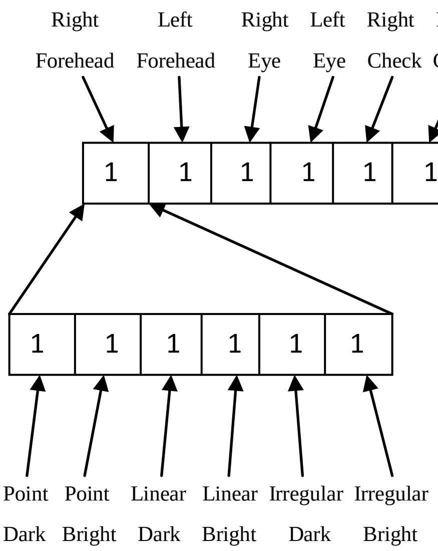
4.5 Blob Classification for Facial Marks

The classification of blobs is shown in the fig. 13. Each detected local extrema such as Marks, Moles, freckles etc are assigned that bounding box. Pixels in the bounding box are binarized with a threshold value selected from the mean value of the surrounding pixels. Local extrema is brighter or darker than its surrounding region, so the average value of the surrounding area can serve effectively for fixing the bounding box. Then a mark is classified in hierarchical fashion: linear versus all, followed by circular point versus irregular. In linearity classification of a blob, λ_1 and λ_2 are the two eigen value that we obtained from the eigen decomposition on the x and y coordinates of blob pixels. When λ_1 is larger than λ_2, the mark is considered as a linear blob. Then the second moment of the blob pixels M_2 for the circularity detection is calculated. A circle RM_2 with radius M_2 will enclose most of the blob pixels. In view of this, a decision can be made based on the ratio of the number of pixels within and outside of RM_2.

Fig. 14 elaborates facial marks detection results using our new method.

5. FACE BASED MATCHING FOR FACIAL MARKS

We then encoded the detected facial marks into a 48 bins histogram representing the morphology, color, and location of facial marks. For encoding, the face image is subdivided in to eight different regions in the mean shape space. Each mark is encoded by six digit binary number representing its morphology and color. If more than one facial mark is found in the same region, a bit by bit summation is applied. The six bin values are concatenated for the eight different regions in the order as shown in Fig.15, to generate the 48 bin histogram. If a mark is obtained on the borderline of the face segments, it is included into both regions considering the variation of the segments across multiple face images of the same subject. Given the indices obtained from face images, the histogram intersection method is used to calculate the matching scores or filter the candidate face image.



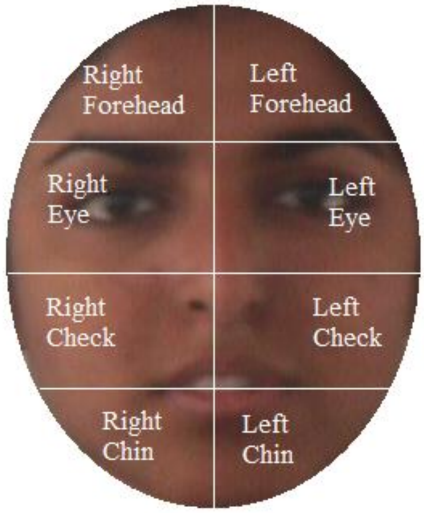


Fig.15 Schematic of the mark based indexing scheme.

6. EXPERIMENTAL RESULTS

6.1 Database

The face images data set which contains low quality images are named as DB1 and DB2 which are collected from Indian face database. DB1 and DB2 are used to evaluate the proposed mark-based matcher. We gathered 1000 images to demonstrate the proposed facial mark detection method. The image size in our database is 640*480 (width * height) with 96 dpi resolution. We manually labeled different types of facial marks as defined at section III as ground truth. This process allows us to evaluate the proposed facial marks extraction method. DB1 is used to evaluate the effectiveness of the indexing scheme to improve the facial individuality. The soft biometric traits based matcher is used to retrieve the data from the data base. It can be combined with any face matcher to improve the overall accuracy [20]. Weights are chosen to obtain the best face recognition accuracy.

6.2 Image matching and retrieval for security

We applied our marks based matcher to facial images to identify the human face. The soft biometric matcher successfully retrieves the correct images to probe the face images. The facial feature points are manually labeled with 80 landmarks for the partial face and automatically labeled for the database images. Fig. 16 shows the face matching and retrieval results in which all the marks are detected automatically from the database. As some of the facial marks are not stabilized in our face for example pimples, acne or zits, problems occurred during the matching. To enhance the matching accuracy we fixed up the permanent marks such as moles, scar, birth marks etc on the face image. It improves the recognition or identification of the particular person. Our method detects majority of the facial marks from a low quality face image. We simply filtered out the unnecessary facial edges. It also improved the matching accuracy and enhances the results. The proposed marks detection method is implemented using Matlab 7.10.0(R2010a).

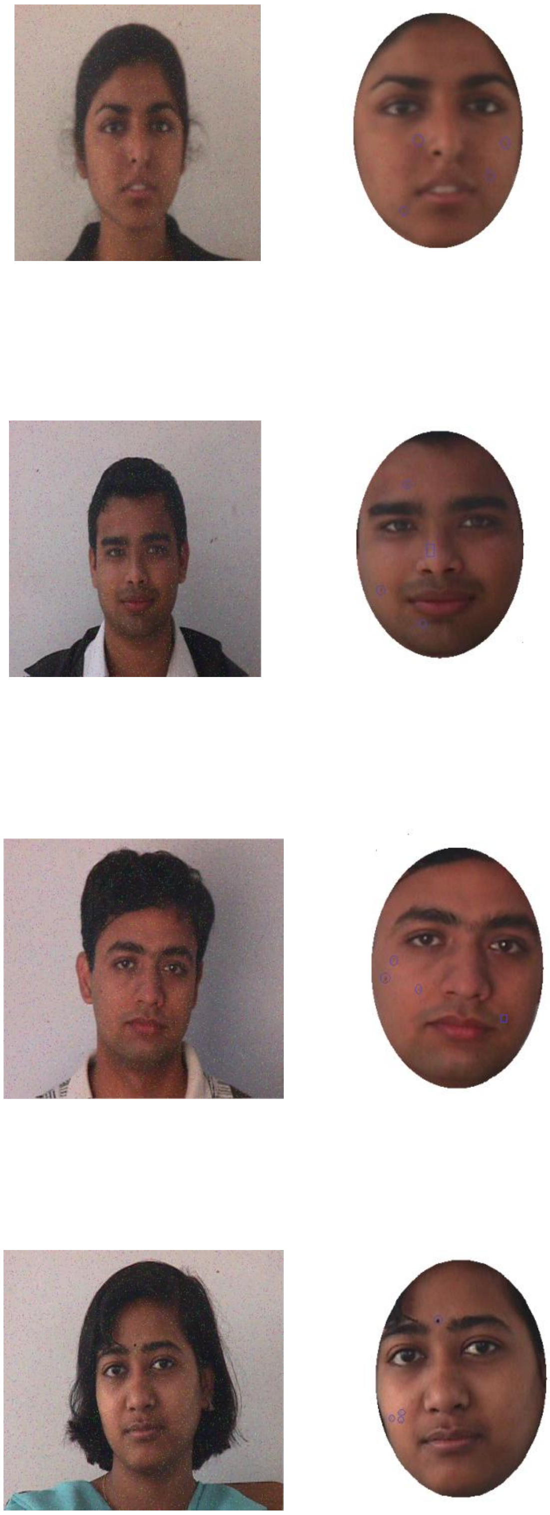


Fig. 16 face matching and retrieval results

7. CONCLUSIONS

We have proposed a new facial mark detection process from the low quality images. The images are filtered using Adaptive Median Filter to improve the quality of images. We have shown that the proposed method is also useful for face matching and retrieval to enhance the security and in biometrics system. GLOH algorithm is used for feature extraction.

In contrast to the previous studies that employed the facial marks implicitly or with poor accuracy, here we present the most effective method to detect the marks. We are currently working for further improvement in the different quality of face images to detect the facial marks. We are also studying image resolution requirements for reliable marks extraction.

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