Robust Facial Marks Detection Method Using AAM And SURF

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Abstract

In face recognition technology, facial marks identification method is one of the unique facial identification tasks using soft biometrics. Also facial marks information can enhance the face matching score to improve the face recognition performance. As numbers of folk apply their face with cosmetic items, some of the facial marks are invisible or hidden from their faces. In the literature, they used AAM (Active Appearance Model) and LoG (Laplacian of Gaussian) method to detect the facial marks. However, to the best of our knowledge, the methods related to the detection of facial marks are poor in performance in cosmetic applied faces. In this paper, we propose robust method to detect the facial marks such as tattoos, scars, freckles and moles etc. Initially we apply active appearance model (AAM) for facial feature detection purpose. In addition to this prior model we apply Canny edge detector method to detect the facial mark edges. Finally SURF is used to detect the hidden facial marks which are covered by cosmetic items. Hence we argue that the choice of this method gives high accuracy in facial marks detection of the cosmetic applied faces. In fact the use of robust marks detection method with soft biometrics traits performed the best facial recognition technology.

Keywords — **face recognition, facial marks, soft biometrics, Active Appearance Model, Canny edge detection, SURF.**

I. INTRODUCTION

Facial marks detection provides a significant role in face recognition and matching in biometrics environment. Face recognition still remains a challenging problem to recognize the face. A number of studies are carried out to improve the face recognition performance by developing feature representation schemes. These features include the salient skin regions, which appear on the human face such as (eg. scars, moles, freckles, wrinkles, etc)[13]. Due to improvement in image processing and computer vision algorithms, the use of facial feature has played a significant role. Local feature have a unique capability to investigate face images in forensic application by enhancing image accuracy. The above information is very essential to provide identification of the suspected folks for forensic experts to provide testimony [14]. Formal face recognition systems encode the face images by applying either local or global texture features. Local techniques initially detects the individual components of the human face such as mouth, chin, nose, eyes etc and prior to encoding the textural content of each of these components (e.g., EBGM and LFA) [12] [9]. In global techniques, during the face recognition process, the entire face is considered as a single entity (e.g., PCA, LDA,

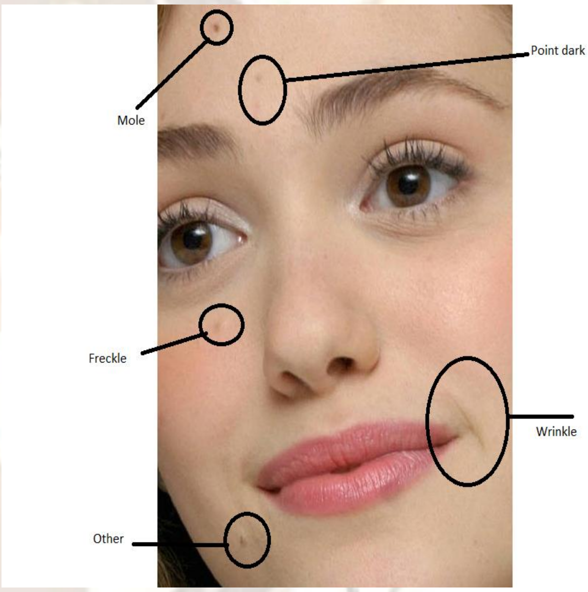


Fig. 1, Examples of facial marks Scar, mole, and freckles etc.

Laplacianfaces etc.) [1]. Example of facial marks are given in fig. 1. Therefore, the given method has a small classifiable marks on the human faces which are considered as noisy. Hence it is not used in the matching process. However, it shown in the Face Recognition Vendor Test (FRVT 2006) [10], the face skin details such as facial marks are highly significant to attain the face recognition accuracy. Hence, facial marks can be used to filter the database to speed up the retrieval process or differentiate identical twins. Facial marks belong to a more general term, Scars, Marks, and Tattoo (SMT), which is gaining increasing attention for its utility of subject identification under non-ideal conditions for forensic investigation [15]. There have been only few studies utilizing facial marks for face recognition purpose [7][11]. Previous studies illustrate that facial marks are primarily focused on facial recognition performance using standard face image data set. Park and Jain [7] expressed that facial marks are very essential for identifying twins using semi automatic concept. Also Spaun [13][14] explained that facial examination process carried out in the low enforcement agencies. One of the major examination steps involves identifying "class" and "individual" characteristics. The 'class' characteristics involve overall facial shape, presence of hair, hair color, shape of nose, presence of marks etc. Similarly 'individual' characteristics include number and location of scars, tattoos, location wrinkles etc in a faces. Lin at el [3] first utilized the SIFT operator [5] to extract facial irregularities and fused them with global face matcher. Facial irregularities and skin texture were used as additional means of distinctiveness to achieve performance improvement. However, the individual types of facial marks not defined. Therefore the method is not suitable for face database indexing. 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. Therefore, besides moles they did not consider other types of facial marks. Lee *et al.* [21] introduced "scars, marks, and tattoos (SMT)" in their tattoo image retrieval system. While tattoos can exist on any body part and are more descriptive, we are interested in marks appearing exclusively on the face which typically show simple morphologies. Pamudurthy *et al.* [18] used distribution of fine-scale skin marks pattern. The correlation coefficients calculated between registered skin patches are aggregated to obtain a matching score.

We completely focused to detect the facial marks from the face image and the hidden facial marks that are covered by cosmetic items. We use different powerful algorithms to find the facial marks from the cosmetic applied faces. Our method shows better performance contrast with the existing study. Fig. 2, shows the mark based matcher helps in indexing each face image based on facial marks, these indices will enable fast retrieval as well as for textual or key word based query. Fig. 3, shows the detected facial marks in different types of faces.

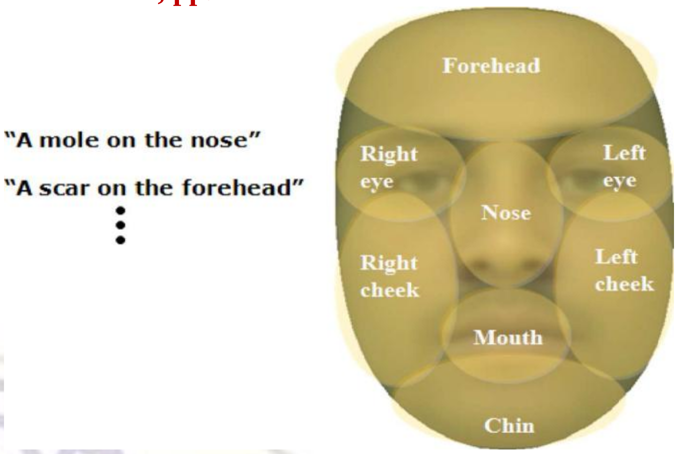


Fig. 2, Examples of textual query and a schematic of face region segmentation.

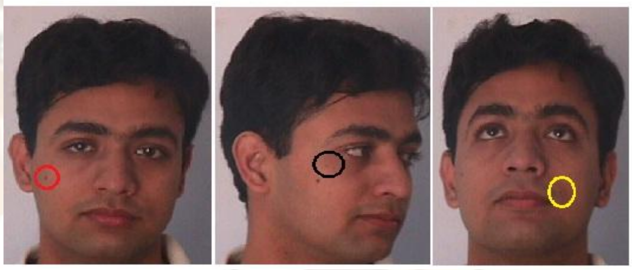


Fig. 3, Three different types of example of facial marks results. Full face, partial face, and off-frontal face

Our method differ from the existing work, we completely focused to determine the facial marks which are covered by cosmetic items using global and local texture analysis methods. Therefore, to overcome such problems, we initially apply the (AAM) Active Appearance Model using PCA to detect the facial features. Some facial features such as eye brows, eyes, nose, and mouth are subtracted from the detected face image. We create a mean shape to detect the face automatically and also construct a mask for the face image. Finally, we apply canny algorithm to identify local irregularities by detecting the edges in the image and Speed Up Robust Feature (SURF) to extract the facial features. Therefore the detected facial marks were combined to enhance the face matching accuracy. Our technique completely differs significantly from the previous studies in the following aspects: (1) initially we extract all the facial marks that are locally salient and covered by cosmetic items. (2) We concentrate on finding semantically meaningful facial marks instead of extracting texture patterns that are implicitly based on facial marks. The proposed facial marks determination concept will be helpful to forensics and law enforcement agencies because it will supplement existing facial matchers to improve the identification accuracy.

II. FACIAL MARK FINDER

The proposed facial mark detection method is based on the appearance of salient localized regions on the face image which are covered by cosmetic items. Therefore, a feature detector SURF [22] has been applied to detect the hidden facial marks. Hence, to detect the direct facial feature on the face image it will increase the number of false positives facial marks due to presence of facial features such as eyes, eye brows, nose, and mouth. Therefore, we initially detected the facial features from the face image and subtracted the unwanted regions to find the accurate marks present in the face, after that we extracted different facial marks present in the face image. The complete process involves different steps; the complete facial mark detection process is illustrated in Fig. 4. We will elaborate with the following steps 1) facial feature detection 2) mean shape mapping 3) face mask construction 4) facial marks blob detection and 5) facial marks blob classification.

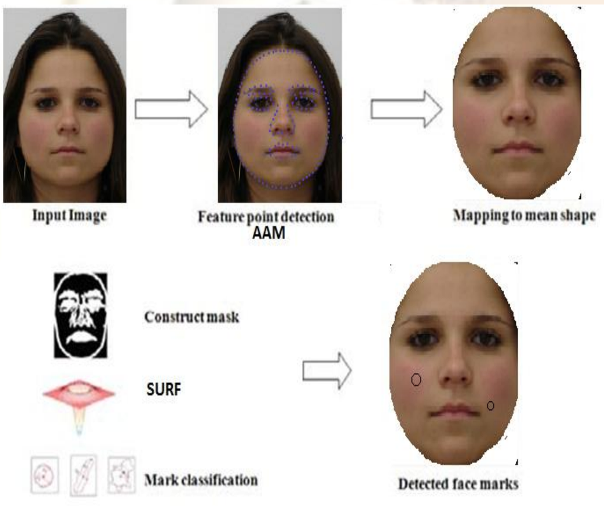


Fig. 4, Schematic of automatic facial mark extraction process.

1. Facial Feature Detection

We applied Active Appearance Model (AAM) using PCA [16], [17] to detect automatically facial features with 120 landmarks that delineate the facial features such as eyes, eye brows, nose, mouth, and face boundary (Fig. 4). Therefore the facial features detection process will be disregarded in the sequence of facial mark detection process which provides easy identification of the marks. Active Appearance Models both the shape and texture of face images using the Principal Component Analysis (PCA). We labeled a set of landmark points in training data using manually:

1.1, A set of shapes information $X=\{x_1,\dots x_N\}$ and corresponding textures $G = \{g_1,\dots\dots g_N\}$ are obtained.

1.2, Applying to get eigen value using PCA both On X and G, principal components of shape and texture, P_x and P_G are obtained.

1.3, The image shape and texture, $\mathcal{X}_{new}$ and $\mathcal{G}_{new}$, of a new face can be expressed as $\mathcal{X}_{new} = \mathcal{X}_{\mu} + P_x b_x$ and $\mathcal{G}_{new} = g_{\mu} + P_G b_G$, where $\mathcal{X}_{\mu}$ and g_{μ} (b_X and b_G) are means (weight vectors) of X and G, respectively. The 120 landmark points were labeled on a subset of database images for training.

2.Mean Shape Mapping

Active Appearance Model has applied to detect the landmarks, therefore to simplify the mark detection we map each face image to the mean shape. Consider S_i, i=1,…,N represent the shape of each of the N face images in the database (gallery) based on the 120 landmarks. Hence the mean shape is calculated using the equation $S_{\mu}=\sum_{i=1}^{N} Si$.

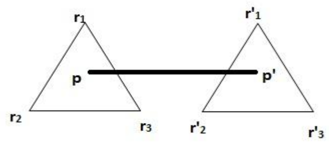


Fig.5, Schematic of texture mapping process using the triangular Barycentric coordinate system.

Each face image S_i is mapped to the mean shape S_{μ} by using the Barycentric coordinate-based [2] with texture mapping process. Initially, both S_i and S_{μ} are subdivided into a set of triangles. 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. 5 using the schematic of the Barycentric mapping process. This mapping process has repeated for all the points which is present inside all the triangle, the texture in Si is mapped to S_{μ} . Hence, after this mapping process, all face images are normalized in terms of scale and rotation and it facilitated us to represent each facial mark in a face-centered common coordinate system. Fig. 6 shows the schematic of mean face construction.

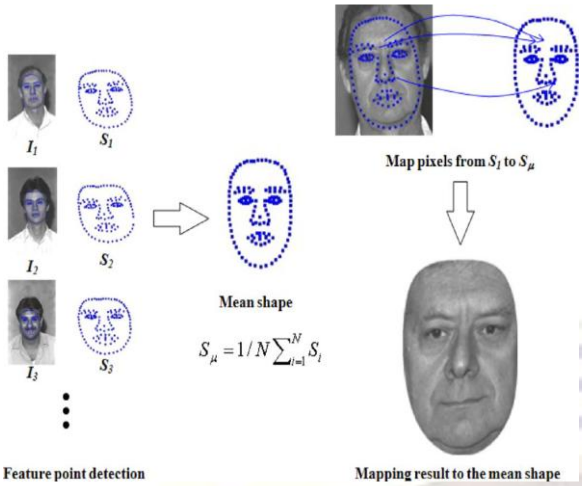


Fig. 6, Schematic of the mean face construction.

3. Face Mask Construction

From the mean shape we constructed a mask known as S_μ to suppress false positives values, after applying the facial feature detection for blob detection. Applying the blob detection operator to the face image mapped into the mean shape S_μ is used to suppress blob detection on the facial features detection process. Consider the mask constructed from the mean shape to be denoted as M_g , namely, a generic mask. However, the generic mask does not cover the user-specific facial features, eg. beard or small winkles around eyes or mouth, that are likely to increase the false positives. Therefore we also build M_s known as a user-specific mask using the edge image. Hence the conventional Canny edge detector [23][24] is applied to obtain the edge from the face image. The user specific mask Ms, constructed as a sum of M_g and edges that are connected to M_g, it aid to removing most of the false positives present around the beard or small wrinkles around eyes or mouth.

4. Facial Marks Blob Detection

Our facial marks are mostly appeared and present in isolated blobs. To detect the facial marks which is covered such as cosmetic items, we use a familiar algorithm canny edge detector [23][24] and SURF [22] is applied to extract the facial marks appeared on the face. The algorithms are illustrated given below:

4.1, Canny edge detector: It was developed by John F Canny in 1986. It allows to detect the blob, motivated by this algorithm we detect the hidden facial marks which is covered with cosmetic items. It uses the Gaussian filter, and it introduces a two-dimensional Gaussian function, and it uses first order derivation to filter the image. The two-dimensional Gauss function is given follows:

$$G(x, y, \sigma) = \frac{1}{2\pi\sigma^2}\exp\left(-\frac{1}{2\sigma^2}(x^2+y^2)\right)$$

Where σ is known as variance of Gaussian function to control the length of Gaussian windows. Consider the origin image as T(x, y), and it filtered by Gaussian filter and the result is given below:

$$F(x,y) = T(x,y) * G'(x,y,\sigma)$$

For the G(x, y, σ) having two variables, the partial derivation along x and y direction are given :

$$G_x(x,y,\sigma) = \frac{\partial G(x,y,\sigma)}{\partial x}$$
$$G_y(x,y,\sigma) = \frac{\partial G(x,y,\sigma)}{\partial y}$$

The filtered image can be described as convolution of T(x,
y) and partial derivation of G(x, y, σ) along x, y:

$$\begin{vmatrix} F_x(x,y) \\ F_y(x,y) \end{vmatrix} = T(x,y) * \begin{vmatrix} G_x(x,y,\sigma) \\ G_y(x,y,\sigma) \end{vmatrix}$$

One of the pixels (x, y)'s gradient magnitude in image is

$$\sqrt{F_x^{\,2}(x,y) + F_y^{\,2}(x,y)}$$

and the direction angle is arctan is given as :

$$\frac{F_y(x,y)}{F_x(x,y)}.$$

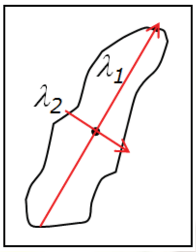
Canny edge detection can detect all the edges which is present in the skin in silent region.

4.2, SURF: We use SURF (Speed Up Robust Feature) [22] as a feature detector to extract the facial marks. We also applied Hessian matrix base detector because of its good performance in computation time and accuracy. Therefore, we apply Hessian-Laplace detector [25] rather than using a different measure for selecting the location and the scale and we rely on the determinant of the Hessian for both. The Hessian matrix H(**x**, σ) in **x** at scale σ is defined as follows:

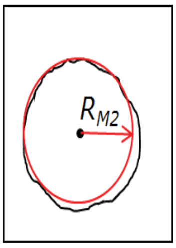
$$\mathcal{H}(\mathrm{x},\sigma) = \begin{bmatrix} L_{xx}(\mathrm{x},\sigma) & L_{xy}(\mathrm{x},\sigma) \\ L_{xy}(\mathrm{x},\sigma) & L_{yy}(\mathrm{x},\sigma) \end{bmatrix},$$

Where L_{xx} (**x**, σ) is the convolution of the Gaussian second order derivative $\partial^2/\partial x^2$ g(σ) with the image I in point **x**, and similarly for L_{xy} (**x**, σ) and L_{yy} ($\mathbf{x}$, σ). To complete the procedure of facial mark detection process is enumerated below:

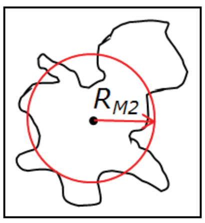
a) Landmark detection from the face using AAM.
b) Mapping to mean shape S_{μ}.
c) Mask construction.
d) Apply Canny edge detector to detect the edges.
e) SURF is applied to extract the features.
f) Represent the marks with bounding box.



(1) Linear

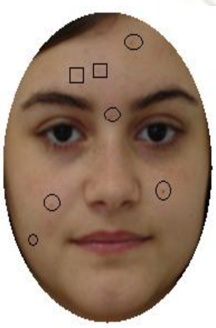


(2) Circular

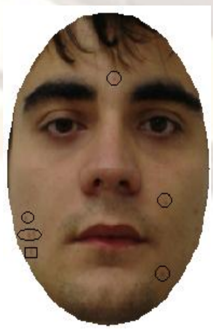


(3) Irregular

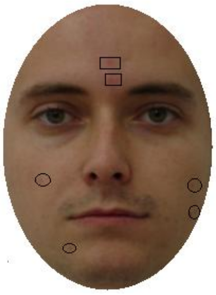
Fig.7 Mark classification using morphology.



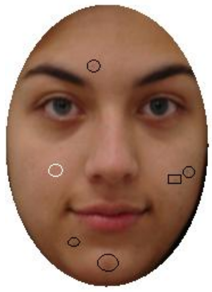
(1)



(2)

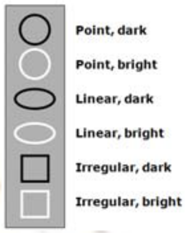


(3)



(4)

(5)



(6)

Figure 8. Examples of mark detection and classification results. (1),(2), (3), (4), (5) and (6) Symbols are used to denote six different classes of marks.

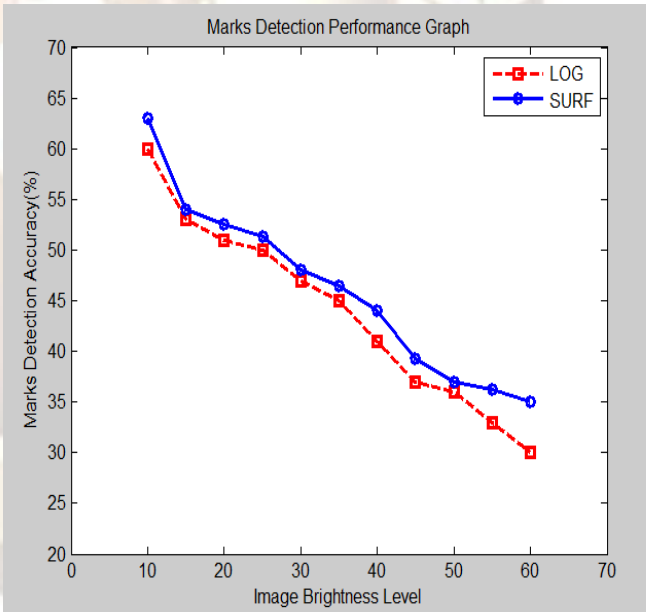


Fig. 9. Mark detection graph

LOG is the existing mark detection performance. SURF is the our proposed mark detection performance.

Mark detection is evaluated in terms of mark detection accuracy and image brightness, shown in fig. 9. The mark detection accuracy of mark detection with the range of brightness contrast varies from (30% , 60%) to (60%, 10%) in existing work and our proposed work varies from (35%, 64%) to (60%, 10%) from the face image. These results showed the automatic mark detection accuracy and performance. Our mark detection performance graph shows that marks detection accuracy is better than the existing marks detection accuracy. We evaluated the automatic mark detection process which helps us to improve the face recognition accuracy.

5. Facial Marks Blob Classification

Each detected blob such as Marks, Moles etc are assigned a bounding box tightly enclosing the blob. Then we classify a mark in a hierarchical fashion: linear versus all, followed by circular point versus irregular. Therefore linearity classification of a blob such as λ_1 and λ_2 known as two eigen values are obtained from the eigen decomposition on x and y coordinates of blob pixels. When λ_1 is larger than λ_2, the mark is considered as a linear blob. We calculate the second moment of the blob pixels M_2 for the circularity detection. A circle RM_2 with radius M_2 will enclose most of the blob pixels if they are circularly distributed. Therefore, a decision can be made based on the ratio of the number of pixels within and outside of RM_2. The color of the blob can be decided based on the ratio of the mean intensity of the pixels inside and outside of the blob (e_{in}/e_{out}).

The classification of blobs is shown in the fig. 7 and fig. 8 elaborated facial marks detection results using our new method of facial marks detection which is covered by cosmetic items. We demonstrate that our proposed method detects the facial marks robustly detected.

III. FACIAL-MARK-BASED MATCHING

We encoded the detected facial marks into a 48 bins histogram representing the morphology, color, and location of facial marks. To encode the facial marks, the face image is subdivided in to eight different regions in the mean shape space Fig. 10. Each mark is encoded by six digit binary number representing its morphology and color. If facial marks are more than one 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.10, to generate the 48 bin histogram. If a mark is obtained on the borderline of the face segments, it is consider as a both regions also considering the variations of the segments across multiple face images of the same subject. The soft biometric traits based matcher is used to retrieve the data from the data base. Soft biometrics can be combined with any face matcher to improve the overall accuracy [20]. The weights are chosen to obtain the best face recognition accuracy.

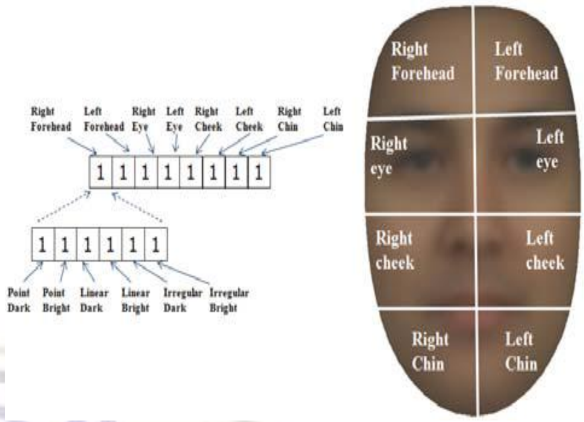


Fig. 10, Schematic of the mark based indexing scheme.

IV. EXPERIMENTAL RESULT

1. Database

We used two different kind of database, CVL database and CMU PIE database to design two separate databases, DB1 and DB2 are used to evaluate the proposed mark-based matcher. DB1 consists of images from CVL and CMU PIE databases with 1000 images, one image per subject, for probe and 2000 images, one per subject for gallery. DB2 consists of CMU PIE face images with 1000 images from 1000 subjects for probe and 2000 images from 2000 subjects for gallery. The image size varies from 384×480 to 640 × 480 (width height) for the CMU PIE and 1000 ×2000 for CVL databases both at 96 dpi resolution. Therefore, we manually labeled the fifteen facial mark types for DB2 and eight facial mark types (e.g., based on color and morphology) for the CVL images in DB1 to create the ground truth. This allows us to evaluate the proposed facial mark extraction method. We used the images from the CVL database in DB1.

2. Face image matching and retrieval

Facial marks play a critical role to recognize the given face. Therefore some of the facial marks are not stabilize in human face for example pimples, acne or zits. To enhance the matching accuracy, we fixed up the permanent marks such as moles, scar, birth marks etc on the face image. It will improve performance of the recognition or identification of the human face. Also we focused those face images that includes facial marks but that are covered by cosmetic items. Our method detects the all kind hidden facial marks on the face image. We simply filter out the unnecessary facial edges and fixe the particular importance of facial marks. It improves the matching accuracy and enhanced the results. We collected small amount of facial images which contains 1000 images. We retrieved the images and it shows 90% of accuracy from the face database. Fig. 11 shows the detected facial marks that are retrieved from the database. Our database contains numerous detected face images. We have two databases DB1 and DB2; DB1 data base contains the facial marks detected images and DB2 data base contains the face matching data. Our proposed mark detection method is implemented using Matlab 7.10.0(R2010a).

Fig. 11. Examples of face image retrieval result.

V. CONCLUSION

We have proposed a new facial mark detection process as well as face matching which are covered by the cosmetic items on each faces. We have shown that the proposed facial based indexing scheme helps us in matching the facial marks and to enhance the security based on biometrics. For marks detection and enhancing purpose, we used powerful canny edge detection method and SURF algorithm for feature extraction purpose. In contrast to the previous studies where the facial marks are presented implicitly and with poor accuracy, we presented the most effective method to detect the facial marks. We are currently working for further improvement with robust mark detection methods and we are also studying image resolution requirements for reliable mark extraction.

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