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Facial Marks Soft Biometric for Identification of Identical Twins ,Similar Faces, Sibblings in Face Recognition

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ABSTRACT

We propose to utilize micro features, namely facial marks (e.g., freckles, moles, and scars) to improve face recogni-tion and retrieval performance. This Facial marks are used to differentiate the identical twins and similar face and siblings. Facial marks can be used in three ways: i) to supplement the features in an existing face matcher, ii) to enable fast retrieval from a large database us-ing facial mark based queries, and iii) to enable matching or retrieval from a partial or profile face image with marks. We use Active Appearance Model (AAM) to locate and segment the local or primary facial features (e.g., eyes, nose, and mouth). Then, Laplacian-of-Gaussian (LoG) and morphological operators are used to detect facial marks. Experimental results based on FERET and Mugshot databases show that the use of facial marks improves the identification accuracy of a state-of-the-art face recognition system from 92.96% to 93.90% and from 91.88% to 93.14%, respectively.

Keywords: Face Recognition System, Facial Marks, Soft Bio-Metrics, Local Features, Active Appearance Model

I. INTRODUCTION

E2D Face recognition systems typically encode the human face by utilizing either local or global texture features. Local tech-niques first detect the individual components of the human face (viz., eyes, nose, mouth, chin, ears), prior to encoding the textural content of each of these components (e.g., EBGM and LFA) [12] [9]. Global (or holistic) techniques, on the other hand, consider the entire face as a single entity during encoding (e.g., PCA and LDA) [2]. However, both these tech-niques do not explicitly extract micro-features such as wrin-kles, scars, moles, and other distinguishing marks that may be present on the face (see Fig. 1). While many of these features are not permanent, some of them appear to be temporally in-variant, which can be useful for face recognition and index-ing. That is why we define facial marks as a soft biometric; while they cannot uniquely identify an individual, they can narrow down the search for an identity [4].

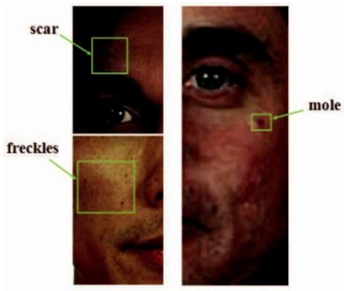


Figure 1. Facial marks: freckles (spots), mole, and scar.

Spaun [11] described the facial examination process car-ried out in the law enforcement agencies. One of the examination steps involves identifying “class” and “individual” characteristics. The class characteristics include overall fa-cial shape, hair color, presence of facial hair, shape of the nose, presence of freckles, etc. The individual characteris-tics include number and location of freckles, scars, tattoos, chipped teeth, lip creases, number and location of wrinkles, etc. in a face or other body parts. While these examinations are currently performed manually by forensic experts, an au-tomatic procedure will not only reduce the manual labor, but is likely to be more consistent and accurate. This has inspired our work on automatic facial mark detection and matching.

There have been only a few studies reported in the lit-erature on utilizing facial marks. Lin et al. [6] first used the SIFT operator [8] to extract facial irregularities and then fused them with a 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 mark were not explicitly defined. Hence, their approach is not suitable for face database indexing. Pierrard et al. [10] proposed a method to extract moles using normal-ized cross correlation method and a morphable model. They claimed that their method is pose and lighting invariant since it uses a 3D morphable model. However, they only explicitly utilized moles - other types of facial marks were ignored or implicitly used. Lee et al. [5] introduced “Scars, Marks, and Tattoos (SMT)” in their tattoo image retrieval system. While tattoos can exist on any body part and are more descriptive, facial marks are defined as marks on the face and they typically show simple morphologies.

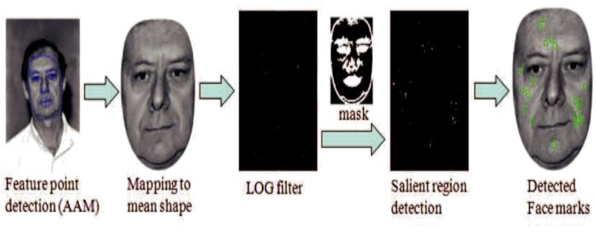


Figure 2. Schematic of automatic facial mark extraction process.

We propose a fully automatic facial mark extraction sys-tem using global and local texture analysis methods. We first apply the Active Appearance Model (AAM) to detect and re-move primary facial features such as eye brows, eyes, nose, and mouth. These primary facial features are subtracted from the face image. Then, the local irregularities are detected us-ing the Laplacian-of-Gaussian (LoG) operator. Finally, we combine these distinguishing marks with a commercial face matcher in order to enhance the face matching accuracy. Our method differs significantly from the previous studies in the following aspects: (a) we extract all types of facial marks that are locally salient and (b) we focus on detecting seman-tically meaningful facial marks rather than extracting texture patterns that implicitly include facial marks. The proposed facial mark extraction system will be useful to forensics and law enforcement agencies because it will (a) supplement ex-isting facial matchers to improve the identification accuracy,(b) enable fast face image retrieval, and (c) enable matching or retrieval from occluded, partial, or severely damaged face images.

II. FACIAL MARK DETECTION SYSTEM

The major categories of facial marks are defined as freckle, mole, scar, pockmark, acne, whitening, dark skin, abrasion, wrinkle, and others. All these facial marks appear as salient lo-calized regions on the face. Therefore, a blob detector based on Difference of Gaussian or Laplacian of Gaussian operator [7] can be used to detect the facial marks. However, a direct application of a blob detector on a face image will result in a large number of false positives because of the pri-mary facial features (e.g., eyes, eye brows, nose, and mouth). Currently, we do not distinguish between the individual mark categories. Instead, our focus is to automatically detect as many of these marks as possible. This facial marks used to distinguish between identical twins .The overall facial mark de-tection process is shown in Figure 2.

2.1. Local Facial Feature Detection

We have used Active Appearance Model (AAM) [3] to au-tomatically detect 133 landmarks that delineate the local or primary facial features: eyes, eye brows, nose, mouth, and face bound-ary (Figure 2). These primary facial features will be disregarded in the subsequent facial mark detection process.

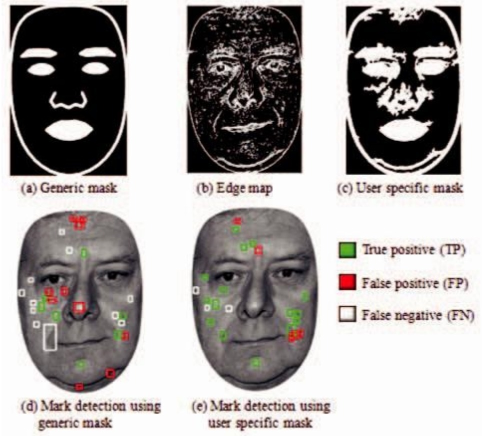


Figure 3. Effects of generic and user specific masks on facial mark detection. Both false negatives and false positives are decreased by using a user specific mask.

2.2. Mapping to Mean Image

Using the landmarks detected by AAM, we tightly crop each face image and map it to the mean shape to sim-plify the mark detection and matching process. Let S_i, $i = 1, 2, \ldots, N$ represent the shape of each face image based on the 133 landmarks. Then, the mean shape is simply $S_\mu = (1/N) \sum_{i=1}^{N} S_i$. Each face image, S_i, is mapped to the mean shape, S_μ, by using Barycentric coordinate based texture mapping process. In this way, all face images are nor-malized in terms of scale and rotation and allows us to use the Euclidean distance based matcher in facial mark matching.

2.3. Mask Construction

We construct a mask from the mean image, S_μ, to suppress false positives due to primary facial features in the blob de-tection process. The blob detection operator is applied to the face image mapped into the mean shape. A mask constructed from S_μ is used to suppress blob detection on the primary fa-cial features. Let the mask constructed from the mean shape be M_g, namely, a generic mask. Since the generic mask does not cover the user specific facial features such as beards or small winkles around eyes or mouth that increase the false positives, we build a user specific mask, M_s, using the edge image. The user specific mask M_s is constructed as a sum of M_g and edges that are connected to M_g. The effect of generic mask and user specific mask on mark detection is shown in Fig. 3. The user specific mask helps in removing most of the false positives appearing around the beard or small wrinkles around eyes or mouth.

2.4. Blob Detection Method

Facial marks mostly appear as isolated blobs. Therefore, we use the well-known blob detector, LoG operator, to detect fa-cial mark candidates. A 3×3 LoG kernel with $\sigma = \sqrt{2}$ is used. The LoG operator is usually applied at multiple scales to detect blobs of different sizes. However, we used a sin-gle scale LoG filter followed by a morphological operator (e.g., closing) to reduce the computation time. The LoG fil-tered image subtracted with the user specific mask under-goes a binarization process with a series of threshold values c_i, $i = 1, \ldots, K$ in a decreasing order. The threshold value c_0 is selected such that the resulting number of connected com-ponents is larger than n_0. A brightness constraint ($\geq b_0$) is also applied on each of the connected components to suppress false positives from weak blob responses. When the user spe-cific mask does not effectively remove sources of false pos-itives, true marks with lower contrast will be missed in the mark detection process. The overall procedure of facial mark detection is enumerated below.[1]

1. Facial landmark detection (AAM)
2. Mapping to the mean shape, S_μ
3. Construct user specific mask M_s
4. Apply LoG operator

5. Using threshold c_i , $i = 1, \ldots, K$, binarize and detect blobs (m_j) such that m_j does not overlap with M_s and the average brightness of $m_j \geq b_0$; stop if total #blobs$\geq n_0$
6. Encode each mark with a bounding box

2.5. Facial Mark Based MatchingTechnique

Given the facial marks, we compare their (x, y) coordinates in the mean shape space. A pair of marks, m_1 and m_2, is considered to match when $d(m_1, m_2) \leq t_0$, where $d(.,.)$ is the Euclidean distance. The number of matching marks is used as the matching score between two face images.

III. EXPERIMENTAL RESULTS

We used FERET and a Mugshot face database for evaluat-ing the proposed mark based matcher. FERET (Mugshot) database consists of 426 (1,225) images belonging to 213(671) different subjects, where 213 (554) of the subjects in the database have duplicate images[1]. The image size varies from 215×323 to 384×480 (width×height) for Mugshot and 512×768 for FERET both with 96 dpi resolution. We manu-ally labeled the ten facial mark types as defined in Sec. 2 in all the images to create the ground truth. This allows us to evaluate the proposed facial mark extraction method.

For the mark based matching, three different matching schemes are tested based on whether the ground truth or auto-matic method was used to extract the marks in the probe and gallery: i) ground truth (probe) to ground truth (gallery), ii) automatic (probe) to automatic (gallery), and iii) ground truth (probe) to automatic (gallery). Constructing ground truth for a large gallery database with millions of images is very time consuming and not feasible in practice. Therefore, using au-tomatically detected marks on the gallery database and the automatic or manually labeled marks on the individual probe image is more practical. The score-level fusion of a commer-cial face matcher, FaceVACS [1] and mark-based matcher is carried out using the weighted sum technique after min-max normalization of scores. The weights of the two matchers were selected empirically as 0.6 for FaceVACS and 0.4 for facial mark matcher.

Table 1. Face recognition accuracy using FaceVACS matcher, proposed facial mark matcher and their fusion.

Matcher	FERET (Rank-1)	Mugshot (Rank-1)
FaceVACS only	92.96%	91.88%
FaceVACS + Ground truth mark	93.90%	93.14%
FaceVACS + Automatic mark	93.43%	92.78%
FaceVACS + Ground truth (probe) & Automatic mark (gallery)	93.43%	93.14%

The precision and recall values for the mark detector with a range of brightness contrast thresholds b_0 (see Sec. 2.4) varies from (32%, 41%) to (38%, 16%) and from (30%, 60%) to (54%, 16%) for FERET and Mugshot, respectively. The rank-1 identification accuracies from FaceVACS only and the fusion of FaceVACS and marks are shown in Table 1 using b_0=200 and t_0=30. The range of parameter values tried are 200, 400, 600, 800, and 1,000 for b_0 and 10, 30, and 50 for t_0 to obtain the best recognition accuracy. Among the 213 (554) probe images, there are 15 (45) cases that fail to match at rank-1 using FaceVACS for FERET (Mugshot). Af-ter fusion, three (seven) out of these 15 (45) failed probes are correctly matched at rank-1 for the ground truth (probe) to ground truth (gallery) matching in FERET (Mugshot). There is one case that was successfully matched before fusion but failed after fusion. Only one out of the 15 failed probes are correctly matched at rank-1 for the ground truth (probe) to automatic marks (gallery) matching. Example matching re-sults for FERET database are shown in Fig. 5. The 15 image pairs where FaceVACS failed to match at rank-1 contain rela-tively large pose variations. The examples in Fig. 5 that failed before fusion but succeeded after fusion contain at least four matching marks, which increases the final matching score af-ter fusion to successfully match the true image pairs at rank-1.The proposed mark extraction method is implemented in Matlab and takes about 15 sec. per face image. Mark based matching time is negligible.

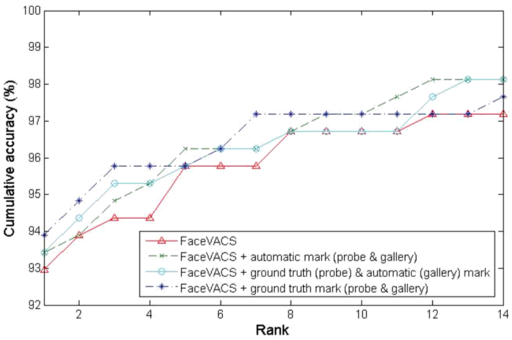
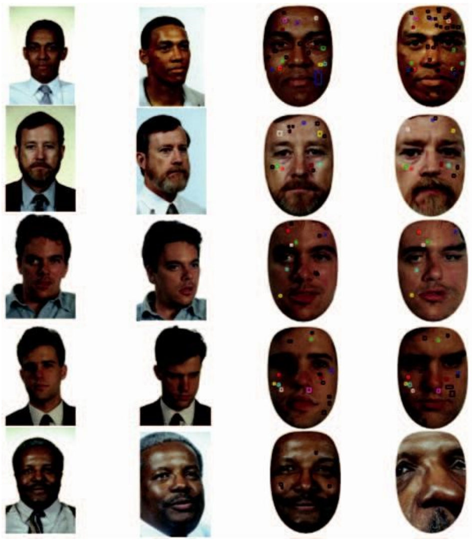


Figure 4. Cumulative Characteristic Matching Curve for FERET database



(a) probe (b) gallery (c) probe (mean shape) (d) gallery (mean shape)

Figure 5. First four rows shows example face image pairs that did not match correctly using FaceVACS but matched correctly after fusion with mark based matcher. Col-ored (black) boxes represent matched (unmatched) marks. The fifth row shows an example that matched correctly with FaceVACS but failed to match after fusion due to errors in facial landmark detection.

IV. SUMMARY AND FUTURE WORK

Facial marks (e.g., freckles, moles and scars) are salient lo-calized regions appearing on the face that have been shown to be useful in face recognition. An automatic facial mark extraction method has been developed that shows promising performance in terms of recall and precision. The fusion of facial marks with a state-of-the-art face matcher (FaceVACS) improves the face recognition performance on a public domain as well as an operational database. This demonstrates that micro-level features such as facial marks do offer some discriminating information. Most of the facial marks detected are semantically meaningful, so users can issue queries to re-trieve images of interest from a large database Future work includes (i) improving the facial mark detection accuracy to enable the face mark based image retrieval, ii) improving the mark based matching accuracy (iii) extending the mark detection process to partial or damaged face images.(iv)improving the distinguish between identical twins and similar faces and siblings

V. REFERENCES

[1]. A. K. Jain and U. Park, "Facial Marks: Soft Biometric For Face Recognition", Proc. International Conference on Image Processing, Nov., 2009

[2]. P. N. Belhumeur, J. P. Hespanha, and D. J. Kriegman. Eigen-faces vs. fsherfaces: recognition using class specific linear pro-jection. IEEE Trans. PAMI, 19(7):711-720, 1997.

[3]. T. F. Cootes, G. J. Edwards, and C. J. Taylor. Active appearance models. In Proc. ECCV, volume 2, pages 484-498, 1998.

[4]. A. K. Jain, S. C. Dass, and K. Nandakumar. Soft biometric traits for personal recognition systems. In Proc. ICBA, pages 731-738, 2004.

[5]. J-E. Lee, A. K. Jain, and R. Jin. Scars, marks and tattoos (SMT): Soft biometric for suspect and victim identification. In Proc. Biometric Symposium, Biometric Consortium Confer-ence, pages 1-8, 2008.

[6]. D. Lin and X. Tang. From macrocosm to microcosm. In Proc. CVPR, pages 1355-1362, 2006.

[7]. T. Lindberg. Feature detection with automatic scale selection. IJCV, 30(2):79-116, 1998.

[8]. D. G. Lowe. Distinctive image features from scale invariant keypoints. IJCV, 60(2):91-110, 2004.

[9]. P. S. Penev and J. J. Atick. Local feature analysis: a general sta-tistical theory for object representation. Computation in Neural Systems, 7:477-500, 1996.

[10]. J. S. Pierrard and T. Vetter. Skin detail analysis for face recog-nition. In Proc. CVPR, pages 1-8, 2007.

[11]. N. A. Spaun. Forensic biometrics from images and video at the Federal Bureau of Investigation. In Proc. BTAS, pages 1-3, 2007.

[12]. L. Wiskott, J.-M. Fellous, N. Kruger, and C. von der Malsburg. Face recognition by elastic bunch graph matching. IEEE Trans. PAMI, 19(7):775-779, 1997.