Eyebrow Modeling For Knowledge Representation

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Abstract. Eyebrow is a new biometric and effective feature for personal identification as evidenced in recent existing literature. In this paper, we propose a new model of eyebrow representation based on both the shape and the texture features of eyebrows. We will integrate the existing Li et al.'s model with a pseudo-sphere-based edge detector, and this integration can improve segmentation performance significantly. Experimental results show that the proposed integration method can extract the eyebrow more accurately than the original Li et al.'s model. Also the proposed eyebrow representation can be used for personal identification via a simple experiment.

Introduction

Biometrics is a useful technology for people identification, and valuable biometric characteristics have received much attention in computer vision community, especially the eyebrow, which could be served as a novel biometric feature for personal recognition due to its stable shapes [1-3]. Implicit eyebrow models can be obtained by 2DPCA [4] or wavelet transform [5], which are difficult to understand and have poor tailor-ability for manually adjusting. The main goal of this paper is to present an explicit eyebrow model with an aim of obtaining semantic features.

In order to construct an eyebrow model, the most important preparatory work is to extract face eyebrows. Extraction is performed mainly on pure eyebrow images which involve only eyebrows and skin background. Currently, the pure eyebrow images are produced generally by manually cropping [1], [3]-[6] or automatic segmentation [7]. Broadly speaking, the level set method (LSM) has been applied extensively in extracting objects due to its abilities to account for topological variations and convergence stability [8]-[12], [14], [16]. In process of implementing LSM, the initial-curve is a key factor for level set evolution, and it highly depends on the appropriate manual initialization [12]. Li et al. proposed a model in [10] which can segment images with intensity inhomogeneity specifically, but sometimes it has a long evolving time because of the unreasonable initial-curve. In fact, edge detection techniques could be used to estimate an initial contour on the pure eyebrow image, and in fact the pseudo-sphere-based edge detector has been proved its effectiveness with which one can achieve a better precision for edge location than the canny operator with the same condition [13]. Therefore, we hope in this paper the pseudo-sphere-based edge detector can play an important role on edge detection, which can give a better initial condition for LSM.

In order to compare the proposed idea with Li's approach fairly, we first adopt a manual segmentation to obtain pure eyebrow images. Secondly, in order to extract eyebrows, we incorporate the pseudo-sphere operator into the Li et al.'s model to obtain the level set initial contour for further evolving with expectation of fewer iterations. More importantly, the explicit eyebrows model as knowledge representation is constructed based on both features of the shape and the texture with expectation for better personal identification.

The organization of this paper is as follows. First, Li's model is reviewed; Second, the proposed model is presented; Third, some experiments are conducted and comparison with Li's model is analyzed; Finally the conclusion is given.

Eyebrow Extraction

In this section, we briefly review Li *et al.*'s model, and show how to extract eyebrows by the LSM.

Li et al.'s Model for Eyebrow Extraction. The model [10] can simultaneously segment the image and estimate the bias field for intensity inhomogeneity correction. The total energy function is defined as:

$$F(\phi,c,b)=\varepsilon(\phi,c,b)+vL(\phi)+\mu R_p(\phi) \tag{1}$$

where the level set function ϕ, constant vector c and the bias field b are the variables, $v>0$, $c>0$, $\mu>0$ are all constants, ε is the area term; L is the length term; and R_p is the distance regularization term [14]. The area term is defined by

$$\varepsilon(\phi,c,b)=\int\sum_{i=1}^{N}e_i(x)M_i(\phi(x))dx \tag{2}$$

where M is determined by the Heaviside function, e_i is the function given by

$$e_i(x)=\int K(y-x)|I(x)-b(y)c_i|^2 dy \tag{3}$$

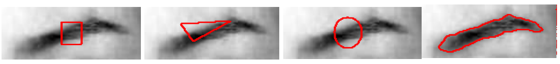
where $I(x)$ is the image defined over the domain Ω and K is introduced as a nonnegative window function also called kernel function.

By calculus of variations [15], one can obtain a gradient flow equation expressed by

$$\frac{\partial\phi}{\partial t}=-\delta(\phi)(e_1-e_2)+v\delta(\phi)div\left[\frac{\nabla\phi}{|\nabla\phi|}\right]+\mu div(d_p(|\nabla\phi|)\nabla\phi) \tag{4}$$

where d_p is derived from a potential function $p(s)$ defined by $d_p(s)=p'(s)/s$, δ is the Dirac delta function, ∇ is the gradient operator, $div(\cdot)$ is the divergence operator.

The above LSM performs image segmentation by minimizing the energy function $F(\phi,c,b)$. But different initial curves may lead to different convergence speeds and final result. For example, the pure eyebrow image is marked as A, three different initial-contours evolve into the final contour at various iterations on the image A, as shown in Fig.1.



(a) (b) (c) (d)

Figure 1. Three different initial-contours (a,b,c) and their completed segmentation result (d), with number of iterations, 50, 80 and 60.

Selection of the Initial Contour. If the initial curve is close to the true contour, it can improve the convergence speed undoubtedly. The curve can be obtained by edge detectors. The pseudo-sphere-based edge detector [13] has been proved to have better location precision than the canny operator with the same condition. Therefore, in the following, we will introduce the pseudo-sphere operator briefly, and then describe how to use it to obtain an initial contour.

Pseudo-sphere-based Edge Detector: This detector is built by replacing the Gaussian filter in the classic canny edge detector with the pseudo-sphere filter. The steps are as follows [13]:

a) Using a template (discrete pseudo-sphere filter) PSF_{ij} in (5) to smooth the image;

b) Computing amplitude and direction of the gradient by two pseudo-sphere operators of PSX_{ij} in (6) and PSY_{ij} in (7);

c) Non-maximum suppression, double threshold detection and connection.

$$PSF_{ij}=PSF(\sigma(i-N-1)/N,\sigma(j-1-N)/N) \tag{5}$$

$$PSX_{ij} = PSX\left(\sigma(i-N-1)/N, \sigma(j-N-1)/N\right) \tag{6}$$

$$PSY_{ij} = PSY(\sigma(i-N-1)/N, \sigma(j-N-1)/N) \tag{7}$$

where σ is a scale parameter and $i, j = 1,2,...,2N+1$ in (5), (6), and (7).

The Initial-curve: The binary edge image *Q* can be obtained by using the pseudo-sphere-based edge detector on image *A*. But the edge isn't always a closed curve. Therefore, the full eyebrow contour image *P* as coarse segmentation can be gained by using general morphological operations. The closed contour in *P* serves as the initial-curve for level set evolution on image *A*. And then, A with the final contour of eyebrows is marked as A'.

Knowledge Representation via Eyebrow Modelling

In this section, we mainly discuss how to quantify eyebrows and construct an explicit eyebrow knowledge representation.

Shape Features of Eyebrow. The shape features of eyebrow refer to numerical and directional parameters, and they are defined as follows:

1)*Numerical parameters* : The pixels inside contour is set to 1 and that outside is set to 0 on image *A'*, then, the final binary eyebrow image can be marked as *B*. Numerical parameters can be computed by using built-in *Regionprops* function from Matlab on the image *B*. The feature vector R_1 in (8) includes the eyebrow's perimeter *L*, area *S*, width *W*, height *H* and eccentricity E, where eccentricity is one of the important parameters of an ellipse.

$$R_1 = (L, S, W, H, E) \tag{8}$$

Directional Parameters: Image *C* with only the eyebrow contour and a shape fitting curve as l_f is from A', as shown in Fig.2. The fitting curve can avoid noise from some small jiggers on contour of eyebrows, which can be gained by using the relative functions from Matlab in (9) and (10). The feature vector R_2 in (12) includes five special direction angles θ_1, θ_2, θ_3, θ_4 and θ_5 respectively corresponding to points such as h_1, h_2, h_3, h_4 and h_5. These parameters can directly reflect the tortuosity of eyebrows.

$$p = polyfit\,(c\_x, c\_y, n) \tag{9}$$

$$y = polyval(p, c\_x) \tag{10}$$

In (9), p is a row vector containing the polynomial fitting coefficients in descending powers, c_x, c_y are respectively the abscissa and ordinate values of the eyebrow contour line in image C. n is the fitting order and the value is set to be 6 in this paper; in (10), y is the value of a polynomial p evaluated at c_x. l_f is obtained by the abscissa values c_x and the ordinate values y.

In Fig.2, h_1 and h_5 are the left and right endpoints on l_f, the coordinate value of $h_3$is computed by the following formulas:

$$x3 = (x1 + x5)/2;\ y3 = polyval(p, x3) \tag{11}$$

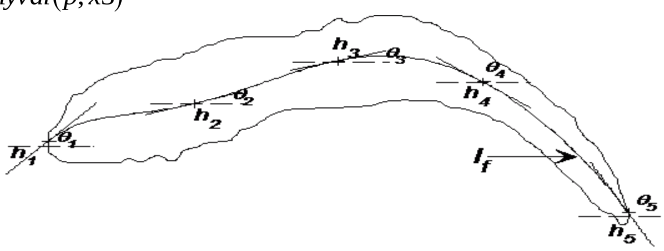


Figure 2. Directional parameters of eyebrow

where $x1,x2$ are the abscissa values of the points h_1 and h_5. Similarly, h_2 is from h_1 and h_3, and h_4 is from h_3 and h_5.

$$R_2 = (\theta_1, \theta_2, \theta_3, \theta_4, \theta_5) \tag{12}$$

Texture Features of Eyebrow. Based on the image B as a mask, we need to compute the intensity information of eyebrow areas on the image A for their texture features. The feature vector R_3 in (13) includes four classic texture feature parameters, i.e., the angular second moment M_1, the contrast M_2, the correlation M_3 and the entropy M_4 [16]. These parameters can be calculated by the Gray level co-occurrence matrix (GLCM) [17] because the GLCM is an image processing technique that has been widely used for measuring textures in images.

$$R_3 = (M_1, M_2, M_3, M_4) \tag{13}$$

Knowledge Representation for Eyebrow. People's eyebrows are intrinsically asymmetric, and such degree of asymmetry varies among people [2]. In this paper, the shape and texture features are fused together to represent features of an eyebrow. Both these two types of eyebrow features merge into a model as knowledge representation for personal identification. The model can be expressed as:

$$R_d = (R_{1l}, R_{2l}, R_{3l}, R_{1r}, R_{2r}, R_{3r}) \tag{14}$$

The feature elements in mode R_d are described as above for right and left eyebrows. Meanwhile, the model [14] can be manually adjusted according to potential applications, i.e., deleting or adding some elements.

Experimental Results and Analysis

To evaluate the effectiveness of the proposed method, we collect 50 individual images with natural light, each person generates 4 facial images as a sample group. We roughly cut out the eyebrow region manually, and obtain a total of 200 pure eyebrow images. All eyebrow pure images are transformed into uniform size of 50×300 by using the bilinear interpolation algorithm for size consistency. Our experiments are conducted on a PC (32 bit) with Windows 7 Enterprise, Intel(R) Pentium(R) 2.13GHz processor, and 2GB RAM, and the programming platform is MATLAB2012b.

Eyebrow Segmentation. To show the performance of our segmentation method, we randomly select three different eyebrow samples of a, b and c from 200 pure eyebrow ones, and these segmentation results are produced from two methods as shown in Fig. 3: one is the proposed approach in this paper and another is Li et al.'s model. In addition to the different iterations, the LSM default parameter values from Li et al. [10] are the Gaussian kernel scale parameter $\sigma = 4.0$, $v = 0.001 \times 255^2$, $\mu = 1.0$ and the time step $\Delta t = 0.1$. The two LSMs are set with same iterations on the same sample image, i.e., a, b and c are respectively at iteration numbers of 80, 50 and 50.

In Fig.3, it is obvious that the proposed method used less iterations and are more accurate segmentation than Li et al.'s method.

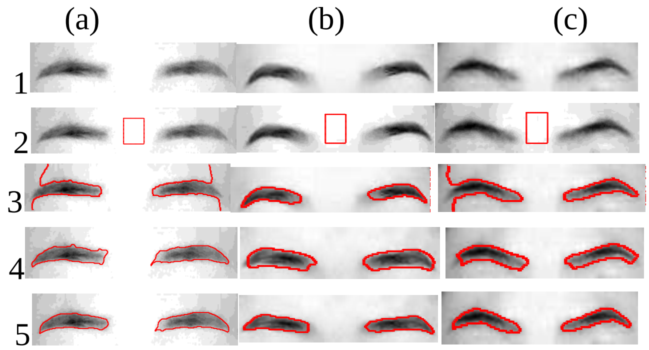


Figure 3. Pure eyebrow images (row 1), rectangular initial contour (row 2), segmentation results of Li et al.'s method (row 3), automatic acquisition for the initial contour (row 4) and segmentation results of the proposed method (row 5)

Table 1 Comparison of segmentation accuracy (%)

No.	1	2	3	4	5	6	7	8
Li's Method	67.52	80.19	79.55	86.49	79.16	77.40	67.85	80.28
Our Method	85.90	87.49	81.46	86.85	82.61	81.42	75.90	83.66

In order to objectively evaluate the superiority of the proposed method, we randomly select eight pure eyebrow images to segment utilizing Li et al.'s method and the proposed method respectively with same number of iterations. We use the index of Jaccard Similarity (JS) [18] to quantity the results of segmentation performance. Let S_1 and S_2 be the segmentation result and the ground truth, respectively, JS is calculated by $|S_1 \cap S_2|/|S_1 \cup S_2|$. JS closer to 1 indicates superior performance. The quantitative performance is shown in Table 1. The results show that segmentation accuracies from manually extracting the initial-contours are less than those from the pseudo-sphere edge detector which can automatically extract contours.

Identification based on Eyebrow Representation. Assume that the eyebrows model is the vector R_d with explicit meaning for all elements. Four pure eyebrow images A from each person are split into training and testing. The former is randomly selected three ones from the four R_d, and the latter is the left one. There are totally testing data set with 50 vectors R_d and other 150 vectors R_d as training data set for 50 people. The *Euclidean Distance* is computed as the similarity criterion to match the test and the training. Two popular indexes of the receiver operating characteristic (ROC) curve and the equal error rate (EER) [19] are used to evaluate the identification performance. The ROC curve reveals the relation of the genuine acceptance rate (GAR) to the corresponding false acceptance rate (FAR). FAR is defined as the percentage of occurrences where a non-authorized user is falsely accepted while GAR is defined as the percentage of occurrences where an authorized user is correctly accepted. The EER is a threshold independent performance measure to indicate the case in which the false rejection rate (FRR=1-GAR) equals the FAR.

By changing the distance threshold, the relation of the GAR to the corresponding FAR using the eyebrow knowledge representation model for feature matching is shown in Fig.4, where EER is calculated by FAR+GAR-1 [20] and we obtain the best performance at a 0.036 EER. In this case, GAR=96.59% while FAR is very small. We find that light eyebrows and a significant illumination variation may affect the identification result in the experiment, but in general, the pair of eyebrows can be recognized as the biometric feature for personal identification, and the eyebrow knowledge representation model is very effective.

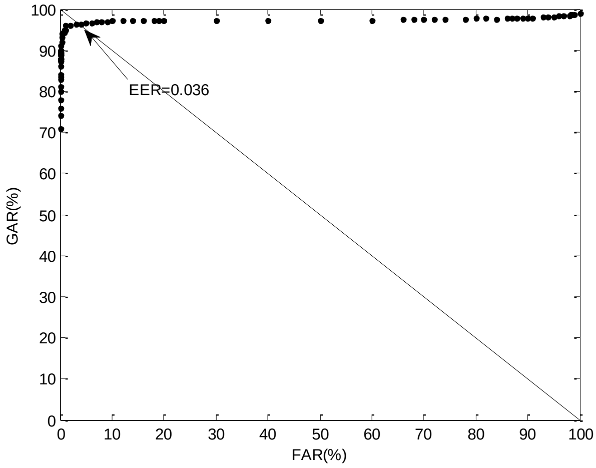


Figure 4. The relationship between FAR and GAR

Summary

This work presents a novel method to model eyebrows for knowledge representation. The proposed method mainly utilizes the pseudo-sphere operator for finding the proper initial curve, and further helps the level set evolution for gaining the accurate eyebrow region. Although it slightly increases computational complexity because some additional parameters such as the edge-preserving parameter and scale parameter are adopted in the pseudo-sphere operator, what we should pay more attention to is that it can improve the positioning accuracy and flexibility. Also the eyebrow models use two quantifiable features of the shape and the texture.

The experiment results are very encouraging and could also provide useful insights in personal identification problem.

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