AUTOMATIC SEGMENTATION OF EYEBROWS FOR BIOMETRIC RECOGNITION USING MODIFIED LEVEL SET

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ABSTRACT

Recent research results have suggested the effectiveness of eyebrow features for the tasks of biometric recognition and soft biometric (gender) classification. To date, the problem of eyebrow segmentation has been investigated by few. In this paper, a novel method of eyebrow segmentation based upon a modified level set method is presented. The algorithm first employs adaptive image enhancement methods to detect the dark regions and eye from facial images. Then an estimated region is obtained for the initialization of a modified level set method. The output of the algorithm is a mask of the detected eyebrow. The effectiveness of the proposed approach is demonstrated utilizing a large, challenging set of images from the Facial Recognition Technology (FERET) Database which contain instances of various skin colors, illumination, and partial occlusions.

***Index Terms*—** Eyebrow segmentation, biometrics recognition, level set

1. INTRODUCTION

In the field of biometrics, researchers have typically focused on the detection and segmentation of salient feature [5]. Recently, periocular biometric features, which are defined as the region surrounding the eye which may or may not include the eyebrow, has been suggested as a potential modality for biometric recognition [3]. The motivation for the use of periocular features is its potential uses in non-ideal scenarios, for instance recognition under partial occlusion. The use of periocular features also has the potential to improve the biometric recognition performance of an iris-based system when the input images are of poor quality [4]. Within the periocular region may be more robust to varying illumination and motion blur than texture based features [1]. According to the results shown in [1], the shape of an eyebrow provides useful information in biometric recognition and gender classification. Thus, how to accurately segment the eyebrow from a facial image becomes a significant issue. Usually, the contour of the eyebrow from a facial image is difficult to detect because of the low contrast of the image, texture of the eyebrow, shade in periocular region, and occlusions by hair. Few researchers have investigated the problem of eyebrow segmentation. Radeva and Marti [8] proposed a model-based snake to segment eyebrow from a single facial image which requires symmetric information from complete facial images. Other research efforts in eyebrow detection/segmentation include the work by Sohail and Bhattacharya [9]; Ding and Martinez [12]; and Batista [13] require the accurate detection of other biometric features such as the nose and eye midpoints which may not be possible under non-ideal operating scenarios. The only requirement of the proposed approach is that the eyebrow be visible within the image representing a significant improvement over previous approaches.

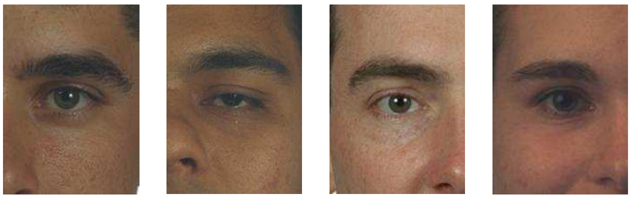

Fig. 1. Examples of test images from Facial Recognition Technology (FERET) Database.

In the following sections, the proposed algorithm is described. Section 2 describes the pre-processing while section 3 discusses the eyebrow segmentation using a modified level set method. Experimental results of the algorithm applied to 1,000 images from the Facial Recognition Technology (FERET) Database [2] are provided in section 4. Sample test images are shown in Figure 1. Section 5 provides suggestions for future work.

2. INITIALIZATION OF CONTOUR

2.1. Preprocessing

Since biometrics systems focus on the automatic identification or verification of an individual, the segmentation of eyebrow features should not require human intervention. This capability would allow for the integration of the algorithm within a biometric system. To remove noise and have the capability of accommodating various image sizes and properties (color or gray scale), all images are preprocessed using the following steps:

1. Crop the top and the bottom of input images.
2. Smooth images by applying a Gaussian kernel.
3. Convert color images into gray scale.
4. Resize input images to a resolution of 200x200 pixels.

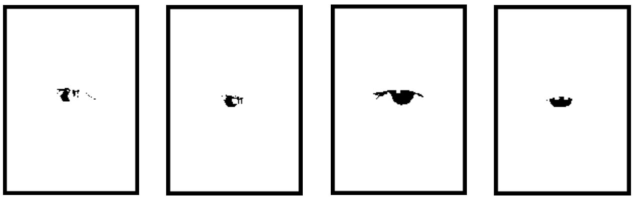

Fig. 2. Sample results of eye position detection.

2.2. Eye Detection

Empirically, the eye is usually located near the center of the preprocessed image, with the iris and eyelid indicated as darker regions as compared to other parts of the eye. This information along with the fact that the eyebrow is always located above the eye is used to obtain the eye position using the following method:

1. Select the lower two thirds of the input image I in which eye locates, denoted as I_{bottom}. This will remove most of the eyebrow region so that the eye will be the only feature in the image with lower intensity.

2. Compute an initial global threshold G_I using Otsu's method [11] to generate a binary image. In Otsu's method, a threshold that minimizes the intra-class variance is calculated, defined as a weighted sum of variances of the two classes using equation 1

$$\sigma_{\omega}^2(t) = \omega_1(t)\sigma_1^2(t) + \omega_2(t)\sigma_2^2(t) \quad (1)$$

where, ω_i are the probabilities of the two classes separated by a threshold t and σ_i^2 are the sum of the variances of these classes.

3. Adjust the initial global threshold G_I by multiply a threshold factor F to compute a modified global threshold G_M because the intensity of the eye is always darker than the computed threshold G_I due to shadow of nose bridge and eye socket. The image is converted into a binary image where all the pixels greater than the G_M are set to 1, and all the other pixels are set to 0. This step generates a binary mark called M.

4. Calculate the mean of intensity M_{eye} of I_{bottom} where the pixel has the value one using the mask M. And set two parameters $EYE_{lowrange}$ and $EYE_{highrange}$ based on the value of M_{eye}. The pixel values between the range are stretched along a full range from 0 to 255. This results in the determination of the position of the eye as illustrated in Figure 2.

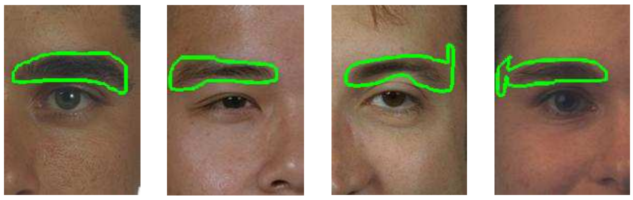

Fig. 3. Sample results of initial contour of the eyebrow.

2.3. Image enhancement

After the detection of the eye, the area around the eyebrow is enhanced and an eyebrow contour is obtained for initialization of the level set method.

1. Construct a mask I_{mask} of the detected eye shown in the Figure 2, where the eye pixels are labeled one, and the other pixels are zero.

2. Dilate the mask such it includes pixels lying on the eyelids and eyelash areas of the image.

3. Using the same methods described in the previous section, define two parameters $MASK_{lowrange}$ and $MASK_{highrange}$ using the top half of the image I_{mask}. Only retain the pixels with intensity within this range and scale them to 0 to 255.

4. Initialize a contour according to I_{mark} by subtracting eye pixels, which only contains the region of the eyebrow. Sample results are shown in Figure 3.

3. EYEBROW SEGMENTATION

As discussed in section 2, after the detection of eye and image enhancement, a region of interest (ROI) around the eyebrow region which is slightly larger than the eyebrow region is generated. The problem of eyebrow segmentation can then be defined as the finding the intensity edge of the image. There are many well known methods of finding the image intensity edge, including graph cuts, active contour / snakes, and level sets. The level set method is utilized by our approach due to its abilities to account for sharp corners and cusps in the propagating solution as well as topological variations. To take full advantages of these abilities, one must carefully construct suitable velocities during function evolutions.

3.1. Chan-Vese Level Set Model

The level set method was first introduced by Osher, and Sethian [10]. Shortly thereafter many have built upon this work, including Chan-Vese who proposed the Chan-Vese model [6]. This model segments the image using interior and exterior models along with a level set function for curve representation. For simplicity, the Chan-Vese model assumes interior and exterior energies both have approximately constant intensity. The energy functional is defined as:

$$E(c_i, c_o, \Gamma) = \mu \cdot L(\Gamma) + \nu \cdot S(\omega) + \lambda_i E_i(c_i, \Gamma) + \lambda_o E_o(c_o, \Gamma) \quad (2)$$

where, μ, ν, λ_i, and λ_o are constants. Γ is the contour. ω is the inner region bounded by Γ. $L(\Gamma)$ is the length of the contour and $S(\omega)$ is the area inside the contour. c_i and c_o are average intensities inside and outside teh contour Γ, respectively.

As the implicit function ϕ evolves, it can generate kinks. In order to alleviate this problem, periodical re-initialization of ϕ is considered by the signed distance to the contour. The Chamfer distance is usually employed for the signed distance computation. However, re-initialization has its limitation during evolution. For example, if ϕ is not smooth or ϕ is steeper on one side of the interface than the other, the evolution of the curve may move incorrectly. Moreover, if the level set function itself is far away from the signed distance function, re-initialization is probably not able to relocate the level set function to a signed distance function.

3.2. Modified Level Set Method

Li, et. al. introduced the level set method which does not require re-initialization [7]. In this work, a variational energy functional containing two terms: internal energy and external energy is proposed. The internal energy term penalizes the deviation of the level set function from a signed distance while the external energy term drives the motion of the zero level set to the desired image features such as the boundary. As a result of using this approach, the level set function ϕ no longer requires re-initialization as a signed distance function. In other words, if the ROI (region of interest) is roughly and automatically obtained through preprocessing as described in section 2, then the initialized contour can be used as the region Ω mentioned in section 2. Futhermore, the initialized curve will evolve stably according to the evolution function, with its zero level curve converging to the exact boundary of ROI.

The variational formulation is defined as:

$$E(\phi) = \mu P(\phi) + \lambda L(\phi) + \nu S(\phi) \quad (3)$$

where,

$$P(\phi) = \int_{\Omega} \frac{1}{2}(|\nabla \phi| - 1)^2 dxdy$$

$$L(\phi) = \int_{\Omega} \frac{1}{1 + |\nabla G_\sigma * I|^2} \delta(\phi) \, |\nabla \phi| \, dxdy$$

$$S(\phi) = \int_{\Omega} \frac{1}{1 + |\nabla G_\sigma * I|^2} H(-\phi) dxdy$$

G_σ is a Guassian kernel with standard deviation σ.

4. EXPERIMENTAL RESULTS

To demonstrate the performance of the proposed approach, 1,000 images were randomly chosen from the Facial Recognition Technology (FERET) Database for testing [2]. The images were collected from subjects with different skin colors under varying lighting conditions. In addition, there were numbers of images with occluded eyebrows and/or captured under low illumination which resulted in instances of poor eyebrow segmentation. The parameters mentioned in section 2 were: $F = 0.8$, the weight and parameters for each term in section 3 are: $\mu = 0.0125$, $\lambda = 3$, $\nu = 5$, $\sigma = 1.5$, and time step = 5.

Figure 4 depicts examples of successful eyebrow segmentation. These examples include subjects with different skin colors, varying illumination, and instances of hair occlusion and illustrate the robustness of the proposed algorithm. By comparing Figure 3 with Figure 4, in can be seen that the initialized contours are similar but not complete accurate because their location is based only on the local intensity. However, by applying modified level set method, the contour converges to an accurate eyebrow segmentation result.

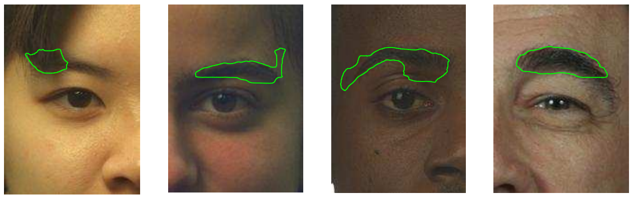

Fig. 5. Sample failure examples of FERET images from Facial Recognition Technology (FERET) Database.

Examples of failed eyebrow segmentation are provided in figure 5. In the first image from left, the subject's hair, which is the same color as the eyebrow, occludes part of the eyebrow which results in a false detection. In the second image, due the poor illumination, there are shadows in the image that generate dark areas similar to the eyebrow that causes a false detection. In the third image, the subject's skin has a similar intensity of the eyebrow so it is difficult to locate the correct position of the eyebrow. In the last example, part of the eyebrow has similar intensity as adjacent skin. Since the proposed algorithm focuses on the intensity edge, it is difficult to obtain an accurate contour.

5. CONCLUSION AND FUTURE WORK

This work presents a novel method for the automatic segmentation of eyebrows from intensity images using a modified level set method. The robustness of the approach under partial occlusion as well as varying illumination conditions and skin tones has been demonstrated using a large set of images from the Facial Recognition Technology (FERET) Database.

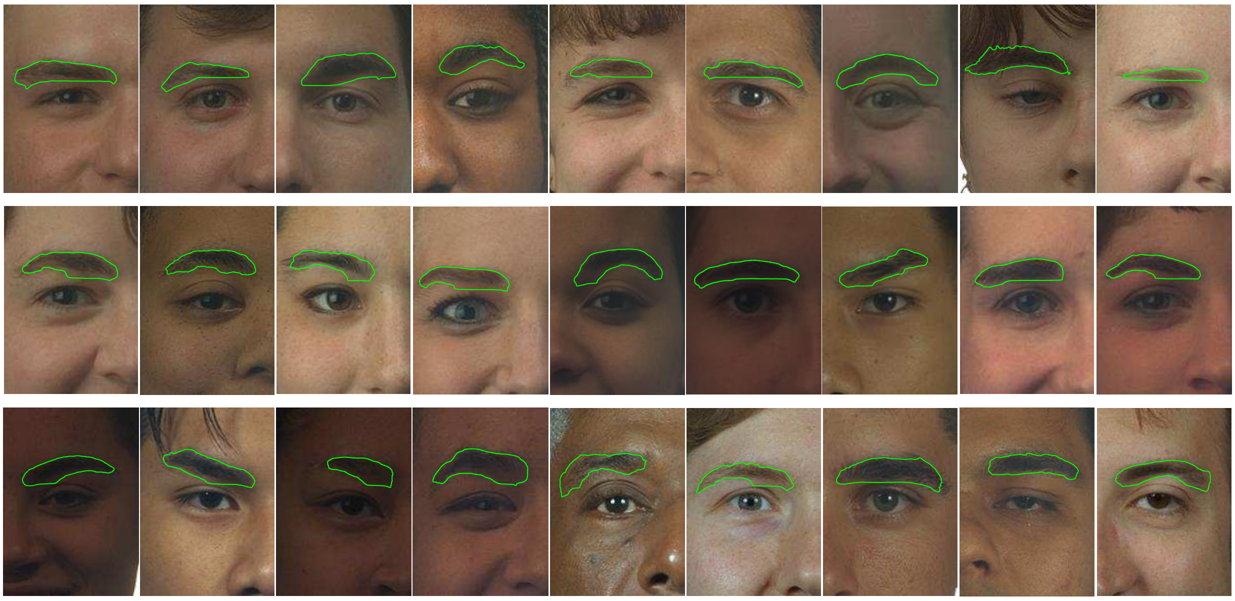

Fig. 4. Examples of successful segmentation results.

Future work would involve the use of a much larger set of images, which consist of exhibit more challenging conditions such as non-frontal subject pose, poor image focus, and low resolution. Methods for algorithm optimization which would allow for real-time operation will also be explored.

6. REFERENCES

[1] Y. Dong and D. L. Woodard. “Eyebrow Shape-Based Features for Biometric Recognition and Gender Classification: A Feasibility Study ”. In *Proceedings of International Joint Conference on Biometrics*, 2011

[2] P. J. Phillips, H. Moon, P. J. Rauss, and S. Rizvi, “The FERET Evaluation Methodology for Face Recognition Algorithms”. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 2000

[3] U. Park, A. Ross, and A. K. Jane, “Periocular Biometrics in the Visible Spectrum: A Feasibility Study”. *Biometrics: Theory, Applications and Systems*, 2009

[4] D. L. Woodard, S. Pundlik, P. E. Miller, R. Jillela, and A. Ross, “On the Fusion of Periocular and Iris Biometrics in Non-ideal Imagery”. *Proceedings of the 2010 20th International Conference on Pattern Recognition*, 2010

[5] A. K. Jain, L. Hong, and R. Bolle. “On-Line Fingerprint Verfication”. *IEEE Transactions on Pattern analysis and machine intelligence*, 19(4):302-314, 1997

[6] T. F. Chan, and L. A. Vese. “Active Contours Without Edges”. *IEEE Transactions on Image Processing*, 10(2):266-277, 2001

[7] C. Li, C. Xu, C. Gui, and M. D. Fox. “Level Set Evolution Without Re-initialization: A New Variational Formulation”. In *IEEE Conference on Computer Vision and Pattern Recognition*, 2005

[8] P. Radeva and E. Marti. “Facial Features Segmentation by Model-Based Snakes”. *IIIA, Bellaterra (Barcelona),* , Spain, September, 1995.

[9] A. S. Md. Sohail and P. Bhattacharya. “Detection of Facial Feature Points using Anthropometric Face Model”. *Multimedia Systems and Applications*, 31(3):189-200, 2008

[10] S. Osher, and J. A. Sethian, “Fronts Propagating with Curvature-Dependent Speed: Algorithms Based on Hamilton-Jacobi Formulations”. *Journal of Computational Physics*, 91:12-49, 1988.

[11] N. Otsu, “A Threshold Selection Method from Gray-Level Histograms”. *IEEE Transactions on Systems, Man and Cybernetics*, 9(1): 62-66,1979.

[12] L. Ding and A. M. Martinez. “Precise Detailed Detection of Faces and Facial Features”. In *IEEE Conference on Computer Vision and Pattern Recognition*, 2008

[13] J. Batista. “A Drowsiness and Point of Attention Monitoring System for Driver Vigilance”. In *Proceedings of the 2007 IEEE Intelligent Transportation Systems Conference*, 2007