Automatic Eye State Recognition and Closed-eye Photo Correction

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Abstract

In this paper, we present an approach for eye state recognition and closed-eye photo correction. For eye state recognition, AdaBoosted cascade open-eye detectors of different scales are trained. For closed-eye photo correction, a PCA generative model of concatenated corresponding closed-eye and open-eye texture patterns is built, and given a closed-eye texture pattern, an algorithm is proposed to recover its corresponding open-eye one for closed-eye replacement. Experiments on popular consumer images show our open-eye detectors achieved 94.71% correct recognition rate, and the closed-eye photo correction looks very natural.

1. Introduction

With the state-of-the-art face detection techniques, new ways are open for the management of photo albums among which automatic eye state recognition is an important problem since a closed-eye in a photo greatly affects its quality. In fact, eye state recognition could be used in many applications including fatigue detection and anti-blink system in cameras.

In the literature, eye state recognition has been researched for different applications. Tian et al.'s [4] try to classify eye states into open, very narrow and closed defined in FACS (Face action coding system), in which Gabor features in two eye corners and their center are fed into a neural-network-based eye-state AU detector and an average recognition rate of 83% is achieved in a dataset of 112 images. Hong et al.'s [7] build a real-time embedded eye state (closed/open) detection system to identify driver's drowsy state. Binary images of eyes and a complexity function are used to identify eye state. Their system achieves average accuracy of 90% with an average speed of 10 frames per second in a 600MHz embedded platform.

Although eye state recognition has long been researched, few of researchers directly consider recovering an open-eye image from a closed-eye image. Closed-eye in a photo can be caused by flashlight, strong illumination, fatigue or just wrong occasion. It always makes a beautiful, artistic personal photo become useless. A related work, Lin et al.'s [1], deals with the problem of human faces occluded by other pictures through occlusion detection and occlusion recovery, in which a quality assessment model is used to evaluate each part and then each part is iteratively optimized. However, in their test images, two eyes aren't completely occluded and local information of the same person near eye area can be easily acquired to help rebuild the occluded part.

In this paper, we present a framework to automatically classify eye state and correct closed-eye photo for personal consumer images. The framework of our system is shown in Figure 1. Given a face image, a normalized eye image is extracted after face detection and facial feature point (eye corner) detection to remove changes due to scale and in-plane rotation pose. Then open-eye detectors are applied to the normalized two-eye image region to recognize the eye state. When a closed-eye is found, closed-eye correction will be applied.

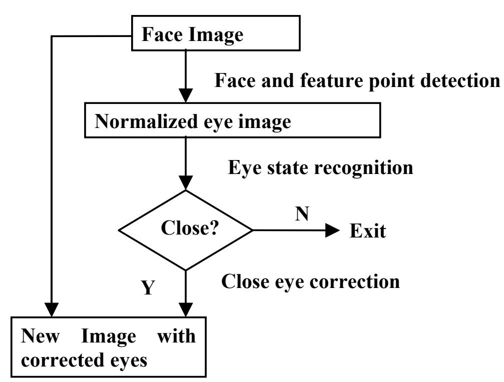

Figure 1. Framework of our system

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2. Eye state recognition

Although previous methods achieve good accuracy in their dataset [4] [7], they're not fit for our problem. In previous works, due to their special application areas faces in their images are in similar resolutions and illumination condition. In fact they need precise positions of eye corners to initialize the eye state recognition. In our case of consumer images, faces vary greatly in both resolutions and illumination conditions, and we can only localize eye corners within an error bound. Therefore we need an eye state recognizer that is tolerable to eye location errors. Inspired by the great success of Haar feature based cascade AdaBoosted detectors on face detection [5] and eye detection [6], we do not directly make a decision on a candidate eye patch which is very sensitive to the localization error of eye corners. Instead, we use an open-eye detector to seek for open-eye pattern within two-eye regions and consider the eye is open only when open-eye pattern is detected.

We pick about 10000 frontal face images from a set of consumer images crawled online. We notice that eyes in different resolutions are very different, especially in open state. Eye images in high resolution contain white and iris parts, but they blur in low resolution images and only iris parts can be distinguished (Shown in Figure 2 where all eye images are scaled to the same size). As a result, a classifier trained in high resolution can't classify eyes well in low resolution images.

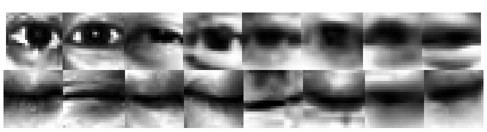

Figure 2. Eye images in different resolutions (First row: open-eye images; Second row: closed-eye images. The left halves are images in the high resolution and the right halves are in the low resolution.)

A histogram statistics of sizes of about 11500 eyes in our dataset is shown in Figure 3. We can notice that the sizes are centralized between 12~26. In high resolution, we find that eyes in size of 24x24 are clear enough for recognition. As far as eye state is concerned, those in larger size than 24x24 can be reduced into 24x24 without losing too much information. In low resolution, we choose 16x16 to balance the concentration of low resolution data and the low information losing rate.

We choose 4500 images of open eyes from image dataset. Each image is overturned horizontally to get another sample, so we get 9000 images as positive samples. And 7400 images of closed eyes and other non-eye images derived from upper face areas are chosen as negative samples. We train two 14-layers cascade detectors (Cascade structure [5] is shown in Figure 4) in the two sizes respectively. In the training procedure, 30% false alarm rate and 99.99% pass rate are set for each layer of the classifier. The numbers of weak classifiers in each layer are 3, 6, 8, 13, 20, 30, 45, 60, 75, 90, 100, 110, 110, and 110, respectively.

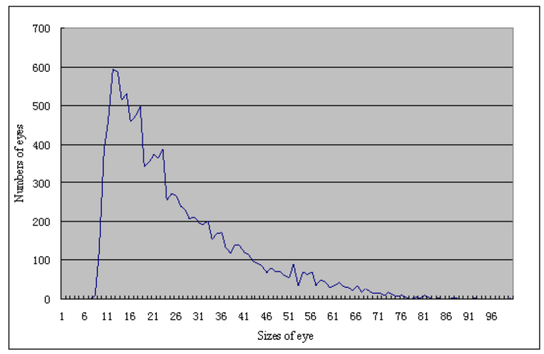

Figure 3. Histogram statistics of sizes of 11500 eyes

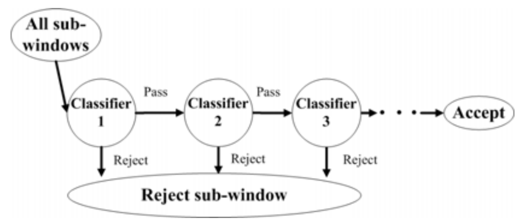

Figure 4. Cascade Structure

Given the eye area, we choose the detector size that is closer to the size of given eyes. Eye state is confirmed by detection results. (Shown in Figure 5)

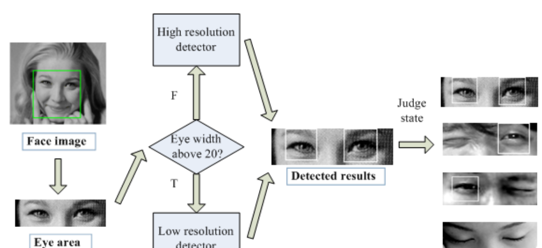

Figure 5. Eye state recognition by open eye detector

3. Closed-eye photo correction

When a closed-eye image is found, an interesting work is to transform it into an open-eye image. To achieve this, we need to find the relationship between open and closed eyes. We collect a number of the same person's corresponding open and closed eye image pairs for training. We concatenate normalized eye images in both closed and open state of the same person into a larger image as shown in Figure 6. It can be written into a vector form by concatenating RGB value of each pixel in the photo. We build a PCA model to acquire the relation between open and closed eyes since it has long been proved an effective model for face recognition and face synthesis in the literature [2] [3]. Because all the constructed vectors contain the relationship between closed and open eyes, we assume that the reconstructed images by this PCA model will maintain the relationship between the two states.

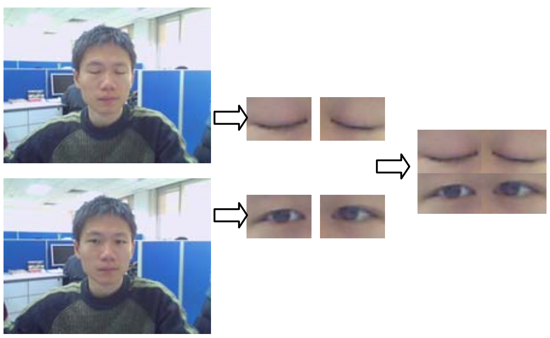

Figure 6. Concatenate both closed-eye and open-eye images of the same person into a larger image.

When a new closed-eye image is found, we concatenate it with the average open-eye image to get an initialized vector I_1. Then we reconstruct it by the PCA model and keep only the reconstructed open-eye part. And the closed-eye will be concatenated with this reconstructed open-eye as I_2 to start next iteration. The above procedure repeats until it converges as I_n of which the open-eye image pattern will be regarded as the final recovered open-eye. The algorithm is shown in Figure 7. We choose the largest k principle components containing 95% energy in the algorithm.

When the image of open eyes is recovered, we warp it to the closed-eye face based on facial alignment points around eyes. The average skin color of the original face is maintained to have smooth effects. Also, transparency is set smoothly increasing from eye center to the edge.

4. Experiments

In eye state recognition, we achieve a 94.71% recognition rate on 5754 facial images that is independent from the training set. Some results are shown in Figure 8. In Table 1, we compare our results with other methods including LDA, SVM and AdaBoosted classifier that are directly applied on detected eye patterns (eye patches) corresponding to automatically detected eye-corner points, and also with the methods only using single detector to seek for open-eye pattern within two-eye regions for eye state recognition. The method of two scale AdaBoosted detectors are better than single scale one, and their combined results are even better than using only the detector with a closer resolution.

1. Assume that $I_{ci}(x,y)$ means RGB information of pixel (x,y) in i^{th} closed-eye image of size m*n; $I_{oi}(x,y)$ means RGB information of pixel (x,y) in i^{th} open-eye image of the same person.

2. Concatenate the data of I_{ci} and I_{oi} , $i \in S_{training}$:

$$I_i = \{I_{ci}(0,0), I_{ci}(1,0), I_{ci}(2,0), ..., I_{ci}(0,1), I_{ci}(1,1), I_{ci}(2,1), ... I_{ci}(m,n), I_{oi}(0,0), I_{oi}(1,0), I_{oi}(2,0), ..., I_{oi}(0,1), I_{oi}(1,1), I_{oi}(2,1), ... I_{oi}(m,n)\}'_{2mn*1}$$

Do PCA transformation on $I_i, i \in S_{training}$, get the transformation matrix W_{t*k}, where k is the reduced dimension, t=2*m*n.

3. Given a new image I_c of closed-eyes, first concatenate it with $\overline{I_o}$ (the mean image of open eyes) to get the vector I_1

4. For j= 2, 3, 4 ….:
   - i. $P = W^T I_{j-1}$
   - ii. $I'_j = WP = \{I_{cj} I_{oj}\}$
   - iii. Update I_j : $I_j = \{I_c I_{oj}\}$
   - iv. Go on until I_j converges.

5. I_{oj} is the open-eye image we need .

Figure 7. Closed-eye image correction

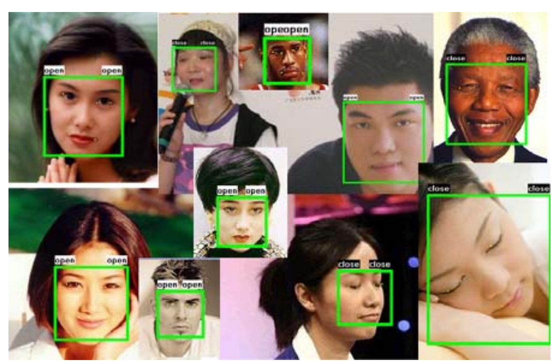

Figure 8. Some results of eye state recognition (Closed states are marked in white characters on black background and open ones are in opposition)

Some error results are shown in Figure 9. Most of them are caused by hair occlusion, narrow eyes when laughing, profile face and bad illumination.

In closed-eye correction, the training set contains 120 image pairs from which a PCA model for closed-eye and open-eye relationship is built. Some results are shown in Figure 10. From the result we can see the correction looks rather natural.

Table 1. Comparisons of different classify methods.

	Correct rate
LDA on detected eye pattern	77.91%
SVM on detected eye pattern	85.18%
AdaBoosted classifier on detected eye pattern	83.07%
AdaBoosted detector in low resolution	92.13%
AdaBoosted detector in high resolution	93.37%
AdaBoosted detector with the closer resolution to low or high	94.71%
AdaBoosted detectors in both resolutions combined	96.05%

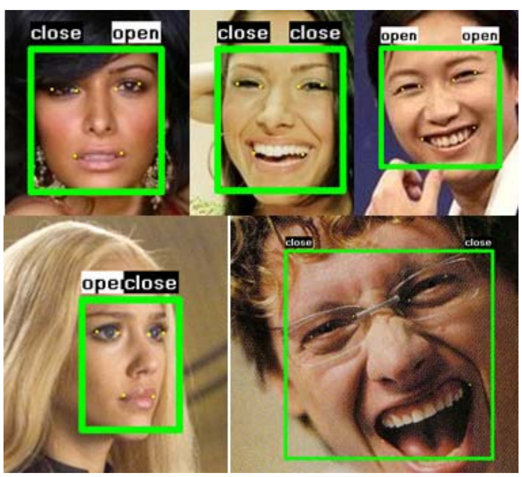

Figure 9. Some error results of eye state recognition step

5. Conclusion

In this paper, we present an automatic eye state recognition method and a closed eye photo correction method. AdaBoosted cascade open-eye detectors are used for eye state recognition and a PCA generative model of concatenated corresponding closed-eye and open-eye texture patterns is used to recover an open-eye from a closed-eye for closed-eye photo correction. Eye state recognition can be used for photo quality evaluation and expression recognition. Closed-eye photo correction can be used as the back-ends for personal image retrieval. It helps to recover an open-eye photo from a less desired close-eye photo. It is especially valuable for group photos because closed eyes occur more often in these situations. Further works remains to make the eye state recognition algorithm more robust and to make the closed-eye correction more natural.

Figure 10. Some results of closed-eye correction step

6. Acknowledgement

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