An Accurate Eye Detection Method Using Elliptical Separability Filter and Combined Features

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Summary
This paper presents an accurate eye detection algorithm using elliptical separability filter and combined features of eyes. First, a histogram back-projection method is utilized to extract the rough face region, and then iris candidates are detected by using elliptical separability filter developed based on Fukui et al.'s separability filter. By calculating the similarities of pairs of iris candidates, we determine the pair of iris, which has the largest similarity among others. The similarity of a pair of iris candidates consists of the separability of the pair of iris candidates, the similarity between VQ histograms and normalized correlation coefficient between the region including the pair of iris candidates and eye template. Experimental results show the iris detection rate of the proposed algorithm of 95.2% for 516 images of 86 persons without spectacles in the AR database.

Key words:
Eye detection, Back-projection, Elliptical separability filter, Vector quantization (VQ)

1. Introduction

Detection of face and facial features has many applications in a variety of fields such as speech reading [1][2], facial expression analysis [3][4] and face detection and recognition [5][6][7], etc. Recently, rapid development of multimedia applications, such as image and video indexing and retrieval, video scene classification and video/news summarization, face detection has become a valuable tool [8][9].

It can be considered that both the position of the eyes and the inter-ocular distance are relatively constant on the face for most people. So in an automated face detection system, eye detection is usually the first important pretreatment for normalizing the size, location and image-plane rotation of the human face [10][11].

Lots of researches have been published in the last decade on this subject [10]-[18]. Eye detection algorithms can be roughly categorized into two classes [11]. The first class is the holistic approach, which attempts to locate the eyes using global representations. Modular eigenspaces is a representative [15] which utilized an Eigenspace method for eye detection. The second class is the abstractive approach, which extracts and measure discrete local feature, and then locate the eyes using these features. The representative is deformable template proposed by Yuille et al. [16]. But the computation is complicated and computational-power hungry.

Using the same essence of Yuille et al.'s, Fukui et al. [17] also proposed another deformable template-based approach, which is simpler than the former. They first detected circular regions of intensity valleys as the candidates for the eyes using a method called separability filter. Next, a pair of iris candidates corresponding to the irises of both eyes was selected using the Eigenspace method. However, when the variations in size and orientation of the face in the image are not small, template matching and Eigenspace method require the normalization of the face in its size and orientation because these algorithms use sample eye images as eye models.

Kawaguchi et al. [18] proposed an advanced algorithm using separability filter to detect the irises of both eyes. The algorithm extracts iris candidates from the valleys using the feature template and the separability filter proposed by Fukui et al. [17]. Using the costs for pairs of iris candidates, the algorithm selects a pair of iris candidates corresponding to the irises. The costs are computed by using Hough transform, separability filter and template matching. Hough transform is frequently used in eye detection approaches indeed. However, when the eyes of human are in a downward direction, the eyelids will shade the irises. Hough transform will be ineffectual in such a case.

For most people, the shape of eye is reasonably similar to elliptical. When using a circular eye template, its upper and lower parts may be not necessary for calculating the separeability, which will affect the accuracy of irises detection. In this paper, instead of circular deformable eye template, we utilize an elliptical eye template that is more similar to the shape of human eye for detecting the iris candidates more robustly. We call it elliptical separeability filter (ESF) [23]. We present a novel approach for accurate eye detection based on ESF. First, a histogram back-projection method [20] is utilized to extract the

Manuscript received August 5, 2009
Manuscript revised August 20, 2009

rough face region, and then iris candidates are detected by using the elliptical separability filter (ESF). By calculating the total similarities of pairs of iris candidates, we determine the pair of iris, which has the largest similarity among others. The total similarity of a pair of iris candidates consists of the separability of the pair of iris candidates, the VQ similarity which we previously proposed [19], and normalized correlation coefficient between the region including the pair of iris candidates and eye template.

The proposed algorithm has many merits compared with other conventional algorithms. First, for eye detection, only rough face region detection is required, so the simple and fast color-based approach is sufficient for it. Secondly, the calculation of the total similarity of a pair of iris candidates uses three different types of features, thus it may exclude more false candidates.

This paper is organized as follows. First, we describe our whole algorithm of eye detection in detail in section 2. Experimental results compared with other conventional detection approaches will be discussed in section 3. Finally, we make a conclusion in section 4.

2. Proposed algorithm

Our strategy of eye detection is roughly divided into 3 steps. The summary is given as follows.

STEP 1: Localization of the face region.
A histogram back-projection method [20] is utilized to extract the rough face region.

STEP 2: Detection of the iris candidates.
Iris candidates are detected by using the elliptical separeability filter (ESF).

STEP 3: Selection of the pair of irises.
By calculating the total similarities of pairs of iris candidates, we determine the pair of iris, which has the largest similarity among others. The similarity of a pair of iris candidates consists of the separability of the pair of iris candidates, the VQ similarity and normalized correlation coefficient between the region including the pair of iris candidates and eye template.

2.1 Extraction of the rough face region

Advantages of using skin color are that it is orientation invariant, and one of the fastest facial feature detection methods. It is therefore suitable for real time systems. But a problem in robust skin color detection arises under varying lighting conditions. The skin color appearance depends on the brightness of the light source. It can be resolved by transforming RGB into an HSI color space.

In this paper, we utilize a back-projection method proposed by Swain et al. [21] and applied to localization of face region by Yoo et al. [20]. For reducing the dimension of histogram, *I* component is removed. Each of the *H* and *S* axes is quantized into 32 levels, so the total number of bins in a histogram is 1024. To create a chromatic histogram, each pixel in the input color image computes *(h, s)* values and increments the bin corresponding to the *(h, s)*.

A face model histogram (*F*) is computed by an average of the face histograms, which constructed from facial images. The back-projected image *b* is obtained by back-projecting the face model histogram (*F*) onto the input facial image.

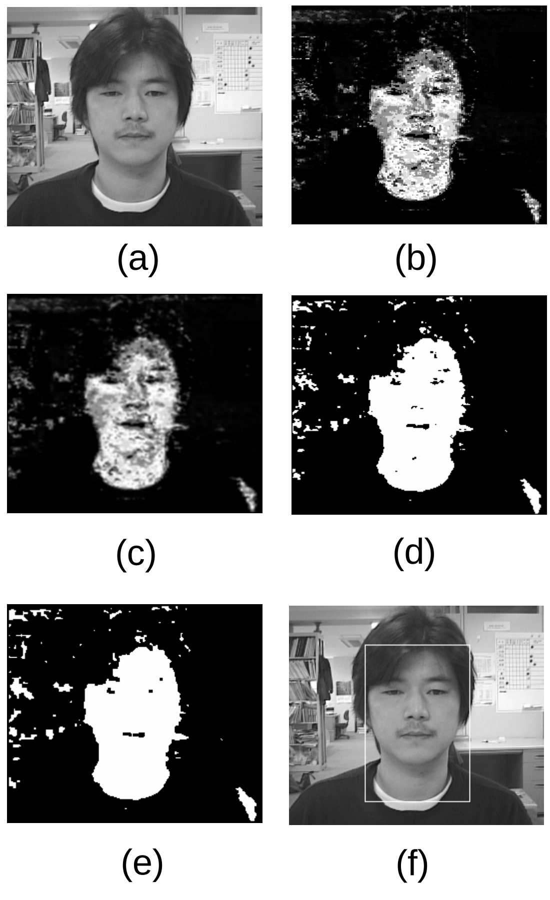


Fig.1 Localization of face region. (a) input image (displayed in gray scale) (b) back-projected image (c) smoothed image by a Gussian filter (d) binarized image (e) dilation and contraction (f) detected face region

The transformation is shown as

$$b_{x,y} = F_{h(C_{x,y})} \tag{2}$$

where $C_{x,y}$ is color value at *(x, y)* of the input image and $h(C_{x,y})$ is the bin corresponding to $C_{x,y}$.

The procedure of face region detection is as follows. First, the input color image (RGB) is transformed into an HSI color space, and then back-projection is applied using formula (2). An example of the back-projected image is shown as Fig. 1(b). Then the back-projected image is smoothed using a Gaussian filter and the smoothed image (Fig. 1(c)) is binarized using a fixed threshold (of 50 got by experiments). The binary image as shown in Fig. 1(d), and then dilation and contraction processing are be implemented to connect facial skin components (Fig. 1 (e)). Connected components are identified and small ones are deleted as noises. The face shape of a human is close to ellipse, so other shapes are unsuitable, for example, extremely long and narrow connected components are excluded. By geometrical constraints processing [25], the possible face region is extracted (as shown in Fig. 1(f)).

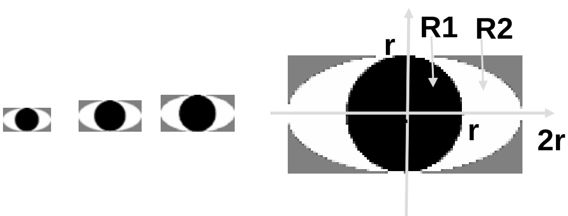


Fig.2 Eye templates of elliptical separability filter.

Fig.3 Detection of the iris candidates ((a) face region (b) elliptical masking (c) valley detection and (d) iris candidates).

2.2 Detection of the iris candidates

Elliptical separability filter (ESF) is utilized to detect the centers and radii of iris candidates. At first, the algorithm extracts the darker subregion of the face region by threshold. After that, the algorithm generates circles in the darker subregion by changing their centers and radii and gives the separability η between each circle R_1 and its surrounding R_2 by formula (3). Parameter r is named filter size, which refers to the radii of iris candidates. Elliptical eye templates similar to the shape of human eye for calculating separeability are shown in Fig. 2.

$$\begin{aligned} \eta &= \frac{\delta_b^2}{\delta_T^2} \\ \delta_b^2 &= n_1(\overline{P_1} - \overline{P_m})^2 + n_2(\overline{P_2} - \overline{P_m})^2 \\ \delta_T^2 &= \sum_{i=1}^{N} \left(P_i - \overline{P_m}\right)^2 \end{aligned} \quad (3)$$

where n_k (k = 1, 2) is the number of pixels in R_k, N = n_1+n_2; $\overline{P_k}$ (k = 1, 2) is the average intensity in R_k, $\overline{P_m}$ is the average intensity in the union of R_1 and R_2, and I (x_i, y_i) the intensity values of pixels (x_i, y_i) in the union of R_1 and R_2. And, the circles that give the local maxima of the separability η are selected as iris candidates.

Before extracting the darker sub-region of the face region, an ellipse which best fits the face region localized by back-projection method is used to mask the greater part of the hair. The center of the ellipse is determined to be the center of the face region. The masked face region is shown in Fig. 3(b). It can reduce the computational amount of separability filtering and exclude possible false iris candidates. Then valleys are determined by threshold. The threshold value was set to the smallest value T satisfying the inequality (4).

$$\frac{1}{N}\sum_{i=0}^{T} h(i) \geq \frac{p}{100} \quad (4)$$

where N is the number of pixels in the face region. $h(i)$ is the number of pixels (x, y) in the face region and p is a parameter given as input. We used p=20 for all images used in our experiments and the valleys are the white part shown in Fig. 3(c).

Then separability filtering is implemented in the valleys. The radius of eye template is changed from 4 to 6 in our experiments. Detected iris candidates are shown in Fig. 3(d).

2.3 Selection of the pair of iris

2.3.1 Selection of the pairs of iris candidates

For each pair of iris candidates $B_i(x_i,y_i)$ and $B_j(x_j,y_j)$, let d_{ij} and θ_{ij} denote the length and the orientation of the line segment connecting B_i and B_j. The limitations of possible pairs of irises are as follows:

$$\begin{aligned} &8r \leq d_{ij}, \\ &-30^\circ \leq \theta_{ij} \leq +30^\circ, \end{aligned} \quad (5)$$

$$y_i, y_j \le \frac{1}{2}H$$

where r is the radius of iris candidate, H is the height of the masked face region. Then affine transforms are applied to the image so that pairs of irises candidates are normalized to be same size with the eye template and θ_{ij} to be zero by using the coordinates of B_i and B_j (see Fig. 4).

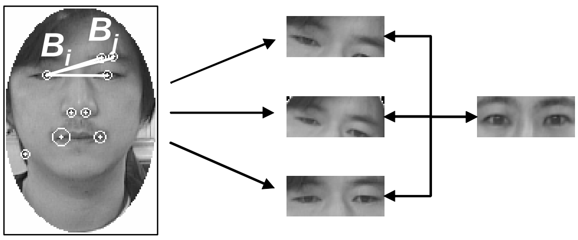


Fig.4 Selection of the pair of irises.

2.3.2 Total similarity for determining the pair of iris

By calculating the similarities of pairs of iris candidates, we determine the pair of iris, which has the largest similarity among others. The similarity S of a pair of iris candidates consists of the separability η of the pair of iris candidates, the VQ similarity S_{VQ} and normalized correlation coefficient R between the region including the pair of iris candidates and eye template.

$$S = \frac{k_0\eta + k_1 R + k_2 S_{VQ}}{\sum_{i=0}^{2} k_i} \qquad (6)$$

where k_i (i= 0, 1, 2) is a weighting coefficient of respective component. The values of k_0, k_1, k_2 are 2, 2, 1 respectively for all images used in our experiments, which determined by actual experiments.

2.3.3 Normalized correlation coefficient

Normalized correlation coefficient R between the region including the pair of iris candidates and the eye template is computed by

$$R = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}\left(\left[f(i,j)-\overline{F}\right]\times\left[g(i,j)-\overline{G}\right]\right)}{\sqrt{\sum_{i=1}^{M}\sum_{j=1}^{N}\left(\left[f(i,j)-\overline{F}\right]^2\right)\times\sum_{i=1}^{M}\sum_{j=1}^{N}\left(\left[g(i,j)-\overline{G}\right]^2\right)}} \qquad (7)$$

$$\overline{F} = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N} f(i,j)}{M \times N}, \quad \overline{G} = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N} g(i,j)}{M \times N}$$

where M, N are width and height of the eye template and $g(i,j)$, $f(i,j)$ are the value of pixels and $\overline{F}$, $\overline{G}$ are the averages of the total pixels in the eye template and the region of a pair of iris candidates, respectively. The true pair of iris candidates is expected a higher value of normalized correlation coefficient R.

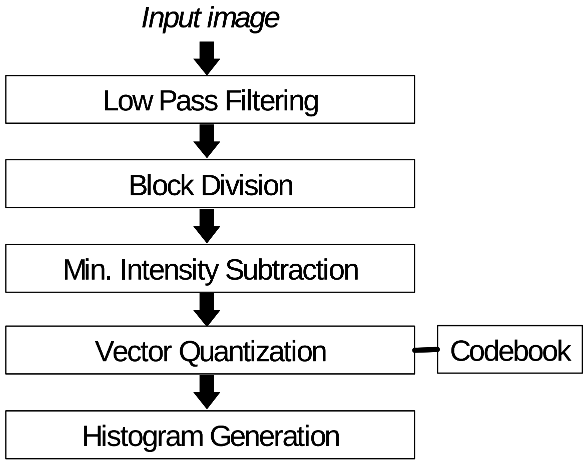


Fig.5 Vector quantization histogram method

2.3.4 Similarity of VQ histogram

In this section, we will describe Vector Quantization (VQ) histogram method [19]. Fig. 5 shows process steps of VQ histogram method. First, low-pass filtering is carried out using simple 2-D moving average filter. This low-pass filtering is essential for reducing high-frequency noise and extracting most effective low frequency component for recognition. Block segmentation step, in which facial image is divided into small image blocks (for example, 2x2) with overlap, namely, by sliding dividing-partition one pixel by one pixel, is the following. Next, minimum intensity in the individual block is searched, and found minimum intensity is subtracted from each pixel in the block. Only the intensity variation in the block is extracted by this process. This is very effective for minimizing the effect of overall brightness variations. Vector quantization is then applied to intensity-variation blocks (vectors) by using a codebook which was prepared in advance. The most similar (matched) codevector to the input block is selected.

After performing VQ for all blocks divided from an input image, matched frequencies for each codevector are counted and histogram is generated. In the image recognition application, this histogram becomes the feature vector of the human face. When this algorithm is applied to the face recognition, experimental results show recognition rate of 95.6 % for 40 persons' 400 images of publicly available database of AT&T Laboratories Cambridge [24] containing variations in lighting, posing, and expressions.

By utilizing the table look-up (TLU) method in the vector quantization (VQ) processing step, the VQ processing time can be shorten to be about 1 msec by running on a conventional PC (Pentium(R)D processor 840 3.2GHz) [26].

The Vector Quantization (VQ) histogram method described above was applied to the eye detection in this study. The similarity of VQ histogram S_{VQ} is calculated by the following equation.

$$S_{VQ} = \frac{2 \times N - \sum_{i=1}^{33} \left| x_i - r_i \right|}{2 \times N} \quad (8)$$

N is effective number of codevector in the image, x_i and r_i are the counts of code for #i.

Fig.6 shows the example of the VQ histogram similarity evaluation. The best match is the one with similar histogram feature between iris candidates and the corresponding eye template.

3. Experimental results and discussions

We evaluated our algorithm on the publicly available AR database [22]. The face images are color images with size of 768x576 in the database. 516 images of 86 persons without spectacles of the AR database are utilized in experiment, which have different expressions under general illumination condition. Fig. 7 shows the example images of the AR database.

To reduce the execution time, we change the image size to 1/4 of original size. The lower bound r_L and the upper bound r_U on the radius of the iris used in the candidate radius detection were set to 4 and 6, respectively.

Firstly, we investigate the parameters of k_i (i= 0, 1, 2), which is a weighting coefficient of respective component for calculating total similarity. The values of k_0, k_1, k_2 are determined by experiments.

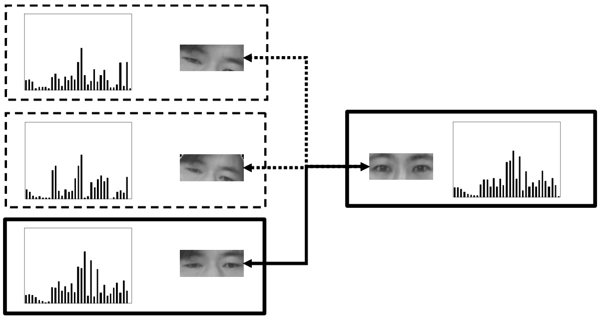


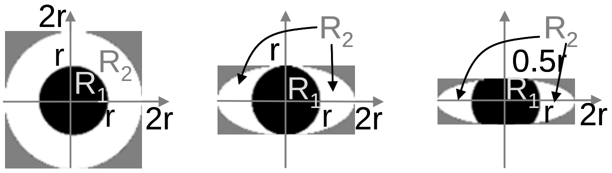
Fig.6 VQ histogram similarity

Fig.7 Example images of AR database.

Table 1. The results of the experiments obtained by changing the weight of parameters k_i (i= 0, 1, 2), where ESF is used.

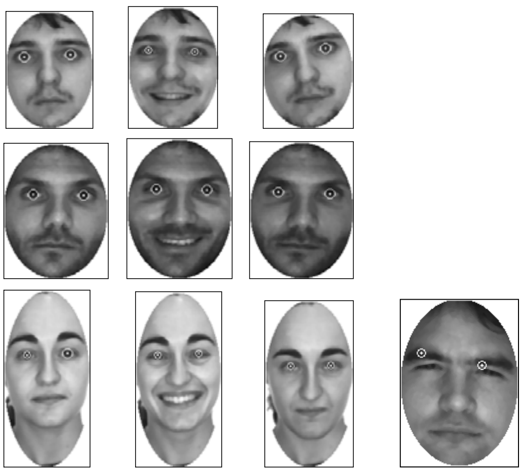
k_0 (η)	k_1 (R)	k_2 (S_{VQ})	Detection rate (%)
1	0	0	71.1%
0	1	0	79.5%
0	0	1	76.2%
1	1	0	84.3%
1	0	1	82%
1	1	1	90.1%
2	2	1	91%

Table 1 gives experimental results of some combinations of k_i (i= 0, 1, 2), where the elliptical separeability filter (ESF) is used as the eye template. The result of Table 1 shows that the best performance is obtained when the values of k_0, k_1, k_2 are set to be 2, 2, 1, respectively, and will be used in later experiments. It indicates that the proposed algorithm using three different types of features can exclude more false candidates than that of each separate feature.



(a) circle (b) ellipse (c) partial ellipse

Fig.8 Types of separability filter.



(a) Successful examples (b) False image

Fig.9 Detection results of AR database.

Table 2. Comparison of experimental results obtained by using different types of separability filter.

Type of SF	Evaluation measure	Detection rate (%)
Circle	Total Similarity	88.4%
ESF	Total Similarity	91%
Partial ESF	Total Similarity	95.2%
Partial ESF	Template Matching	85.2%

Table 2 shows the comparison of the performance of the different types of separability filter shown in Fig. 8. When p=20, the successful detection rate was 88.4% by using circular eye template, 91% by elliptical separeability filter (ESF) and 95.2% by partial ESF, respectively. The maximum detection rate in partial ESF can be explained that this shape is close to the average status of human eye. The result of the template matching after partial ESF is also given with 85.2%.

By utilizing 63 images of 21 persons without spectacles in the first CD-ROM of the AR database, Kawaguchi et al. [18] reported the detection results of 96.8%. In the same case, by using ESF, we got the number of successful images was 62 and the number of failed images was only one. Thus, the success rate was 98.4%.

Fig. 9(a) shows some successful examples of the images and Fig. 9(b) is the false image. It can be said proposed algorithm is very efficient.

Table 3. Running times of the proposed algorithm (msec)

Stage	Execution time (msec)
Face candidate detection	184
Valley detection	75
Iris candidates detection	35
Iris pair selection	59
Total	353

The proposed algorithm is programmed by ANSI C and run on a conventional PC (Pentium(R)D processor 840 3.2GHz). Table 3 shows the running times of the proposed algorithm on each stage. The total execution time of the proposed algorithm was about 353msec on the average, which is composed of 184msec for localization of the rough face region, 110msec for detection of the iris candidates including valley detection and separability calculation, and 59msec for selection of the pair of irises.

4. Conclusion

We present an approach to the accurate eye detection using elliptical separability filter (ESF) developed based on Fukui et al.'s separability filter. Calculation of the total similarity of a pair of iris candidate uses three different types of features, thus it may exclude more false candidates. Experimental results show the iris detection rate of the proposed algorithm of 95.2% for 516 images of 86 persons without spectacles in the AR database. The proposed algorithm is demonstrated to be very efficient and robust.

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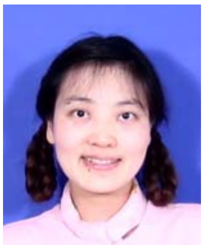

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