Appl. Math. Inf. Sci. 6 No. 2S pp. 323S-329S (2012)

Applied Mathematics & Information Sciences
An International Journal

A Novel Eye Localization Method Based on Log-Gabor Transform and Integral Image

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Received 20 May 2011; Revised 17 Jan 2012 ; Accepted 20 Jan 2012
Published online: April 2012

Abstract: A robust and precise eye localization method plays a critical role in automatic face recognition system. In this paper, a novel eye localization approach using Log-Gabor transform and integral image is proposed. This method mainly involves three steps: firstly, we adopt the Log-Gabor transform with certain scale and orientation to locate the approximate eye-and-brow region. Secondly, in order to detect the coarse region of each eye, the integral image of the Log-Gabor transform result is calculated. Ultimately, we compute the integral image of the original face image within the coarse regions to implement the fine localization. Experimental results on the FERET database show that the method can precisely locate the eyes on both frontal faces and rotated faces in plane within about twenty-five degrees.

Keywords: Eye localization; Log-Gabor; Integral Image

1 Introduction

A practical automatic face recognition system should at least include the following steps: face detection, face normalization, feature extraction and face classification. The face normalization, a crucial process before feature extraction, usually requires the precise localization of the facial landmarks, such as eyes, nose tips and mouth corners. During the recent years, various eye location algorithms have been proposed, but most of them can only be robust and effective in some particular conditions and are sensitive to illumination, rotation and resolution. The general projection function (GPF) is proposed to locate eye centers in [1]. This method is simple and fast, but the accuracy will be seriously impacted by noise and inhomogeneous illumination. It is generally used in coarse localization of eyes, since the results are not precise enough for most eye localization system. Active shape model (ASM) [2], which is based on the statistical model of shape or texture information, is insensitive to the illumination and pose variations, but the accuracy of this method largely depends on the initial coordinate of the shape model. Besides, the massive time consumption makes it unsuitable to the real time automatic face recognition system. A hierarchical-based algorithm is presented in [3], which is robust to the variations of intensity distribution, size and rotation, and partly acceptable in terms of the robustness and accuracy, but there are still no feasible solutions to get rid of some false candidates including eyebrows, nostrils, etc. Tang et. al. [4] performs eye localization by adopting the cascaded Adaboost and support vector machine (SVM) classifiers. This method reduces the computational complexity to some extent, but it requires a complete training set to make the eye detector discriminative enough to separate the true eyes from false detections. Yang et. al. [5] proposed the Gaboreye method to locate the pupil centers. It produces good performance in coarse segmentation of the eye-and-brow region. But the fine segmentation results will be affected if the resolution of the target image is low.

In this paper, we present a novel eye localization method based on the Log-Gabor transform [6] and the integral image [10]. The overall algorithm is a coarse-to-fine procedure. The input of our method is a face image which is the output of Viola-Jones face detector [10]. We firstly select appropriate Gabor kernel to convolve with the face image and then we obtain the highlighted candidate eye-and-brow region (Here, we use the terminology "eye-and-brow region" to describe the region that contains both eyes and brows). Secondly, we use integral projection to simply separate the eye-and-brow region into two parts, i.e., the left eye-and-brow region and the right eye-and-brow region. Then we calculate the integral images for these two parts on the Log-Gabor face respectively. After that, we search the integral image of each part to find the lightest subregion, which is the coarse eye region. Finally, we calculate the integral image of the coarse eye region on the original face image and find out the darkest subregion to finish fine localization. Fig.1 shows the flow chart of the proposed method in this paper.

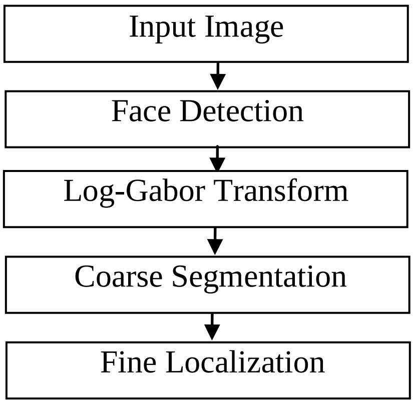


Fig.1. Flow chart of proposed method

The remaining part of this paper is organized as follows: In Section 2, the introduction for the log-Gabor filters, the concept of integral image and how to apply it to region searching will be introduced. Section 3 will present the detailed description of our eye localization method. In Section 4, we will give the experimental results on FERET database and comparisons with other methods. In Section 5, conclusions as well as the future work will be put forward.

2. Log-Gabor Filters and Integral Image

2.1 Log-Gabor Filters

Gabor filters, maximally compact in both space and frequency, have been extensively used for image analysis and computer vision [6-9]. Log-Gabor filter [6], an alternative to the ordinary Gabor filter, has Gaussian transfer functions when viewed on the logarithmic frequency scale, and this attribute is consistent with measurements on mammalian visual systems which indicate we have cell responses that are symmetric on the log frequency scale. In [7] the excellent performance of Log-Gabor wavelets is analyzed from the viewpoint of characteristics of human visual system (HVS), and its superiority over ordinary Gabor wavelets in image feature detection is also demonstrated.

The Log-Gabor filters have Gaussian transfer functions when viewed on the logarithmic frequency scale. They have extended tails at high frequency end and they have no DC component, which means the variations in illumination on input images can be compensated. According to [6], The Log-Gabor transfer function on the linear frequency scale can be described as follows:

$$G(x) = e^{\frac{-\log(\frac{x}{x_0})^2}{2(\log\frac{k}{x_0})^2}} \qquad (2.1)$$

The x denotes the radius from centre, x_0 denotes the centre frequency of filter, k is a scaling factor of the bandwidth and k/x_0 is the ratio of the standard deviation of the Gaussian, which determine the bandwidth of the filter. In our experiments, k/x_0 was selected such that each filter had a bandwidth of approximately 2 octaves.

As to the angular component, we can obtain it through the following equation:

$$A_{cop} = e^{\frac{-\theta^2}{2\delta^2}} \qquad (2.2)$$

Where, θ denotes the absolute angular distance, and δ denotes the standard deviation of the angular Gaussian function. The δ can be calculated as:

$$\delta = \frac{\pi}{N_{ori}\theta_\delta} \qquad (2.3)$$

N is the number of wavelet scales and θ_δ is the ratio of angular interval between filter orientations and the standard deviation of the angular Gaussian function.

2.2 Integral Image

Integral image is an intermediate representation for images introduced in [10]. It is designed to accelerate the speed of computing rectangular features applied in object detectors. Viola and Jones utilized it to calculate the various Haar features in [10]. Based on the integral image representation of the input image, we can compute the sum of gray values within any rectangles on that image in constant time. In our experiments, we employ this representation to rapidly obtain the lightest subregion on the Log-Gabor face and the darkest subregion on the input face image. It greatly accelerates the computation speed of our localization algorithm.

The value of the integral image at point (x, y) is the sum of all the pixels above and to the left of (x, y), it can be described as:

$$ii(x, y) = \sum_{x' \le x, y' \le y} i(x', y') \qquad (2.4)$$

$ii(x, y)$ denotes the value of integral image at location (x, y), $i(x', y')$ denotes the original gray value of the location (x', y'). Through the integral image we can calculate any rectangular gray value sum in four array references. For instance, the sum of pixels within rectangle D in Fig.2 can be computed as follows:

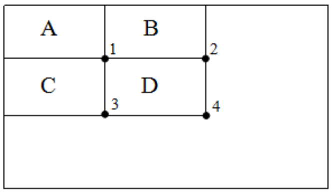


Fig.2. The sum within D can be computed as 4+1-2-3

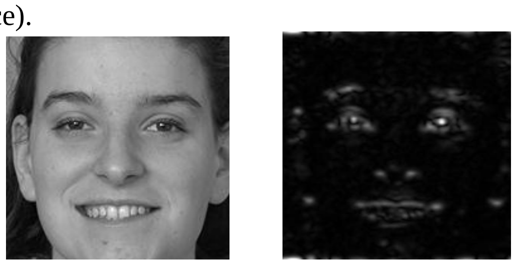
$$Sum(D) = ii(4) - ii(2) - ii(3) + ii(1) \qquad (2.5)$$

Where, $Sum(D)$ denotes the sum of pixels in region D, $ii(n)$ denotes the value of integral image at location n. After computing the integral image of the input image, we can rapidly calculate the sum of pixels in any rectangles.

3 Proposed Eye Localization Method

3.1 Preprocessing

At the beginning, a standard Viola-Jones face detector [10] gives the face bounding box of the input image and the face image is normalized into 300×300. Then we apply the Log-Gabor transform to the face image. The scale of Log-Gabor filter is 2, the angle is $4/5\pi$, and the ratio of the standard deviation of the Gaussian transfer function is 0.65. The selection of these parameters is based on experiments. Fig.3 shows an input face image and its Log-Gabor transform result (i.e. Log-Gabor face).

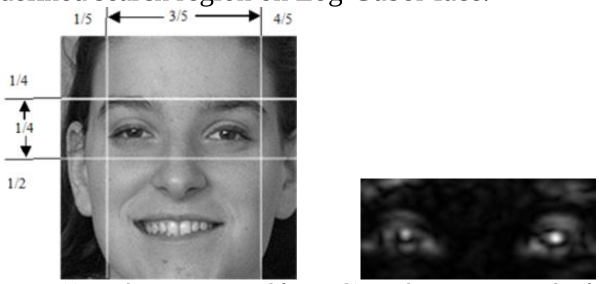


(a) An input face image (b) The result of Log-Gabor transform for (a)

Fig.3. Log-Gabor transform of an input face image

As the two eyes are the most salient features on human face, they contain rich edges and drastic intensity variations, which make them distinctive from other parts of human face. The eyebrows have similar characteristics but the intensity variations are not as intense as the eyes. After convolving the input face image with the Log-Gabor filter of suitable scale and orientation, the eye-and-brow region is highlighted.

According to prior knowledge about the human face, we define the search region as follows: The width of the region ranges from 1/4 to 1/2 of the face width, and the length ranges from 1/5 to 4/5 of the face length. Which can help us separate the mouth region (that is also salient on human face) from the eye regions, and therefore make the search procedure more effective and faster. We will perform coarse eye segmentation based on this defined search region on Log-Gabor face.



(a) Search region on original face (b) Search region on Log-Gabor face

Fig.4. Search region on original face and on Log-Gabor face

Such preprocessing can not only decrease the computation time, but also lower the probability of search error, since some noise regions have been filtered out. In addition, the illumination and orientation variations will make less influence on the precise of segmentation due to the characteristic of Log-Gabor filters.

3.2 Coarse segmentation

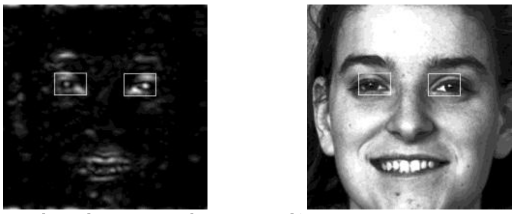
After obtaining the Log-Gabor image of the eye-and-brow region, shown in Fig.4 (b), we apply the histogram equalization on this region to enhance the contrast. We use the general projection function [1] to split the eye-and brow region into two parts (the left region and the right region). Then we calculate the integral image of the separated eye-and-brow region on the Log-Gabor image. The lightest subregion of the eye-and-brow region always contains the major part of the eyes and little part of the eyebrows. If the size of the search rectangle for the lightest subregion is appropriate, the major part of the eyebrows will be ruled out in the search result, only the eyes remain.

If we directly employ the integral image to find the darkest rectangle region within the eye-and-brow region on the original face image, the accuracy will be greatly affected by the illumination and pose variations. For some people, brows are dark enough to be selected as the candidate region, which may also affect the accuracy of the localization. However, the Log-Gabor results are not that sensitive to the illumination changes and the face orientations, thus by using integral image on Log-Gabor face we can get more accurate eye localization.

The initial size of the search windows is 30 pixels in height, 45 pixels in width, which provides best performance in our experiments. The scope of the height ranges from 30 to 40 pixels and the scope of the width ranges from 45 to 60 pixels. The selection of these parameters is based on the approximate size of human eyes in the input face image. The searching direction is from the left-top corner to the right-bottom corner within the region. By computing the average gray value of candidate region we obtain the lightest subregions within the eye-and-brow region. The average gray value can be defined as follows:

$$avg(R) = \frac{1}{height * width} * \big(ii(i,j) + ii(i+height, j+width) - ii(i, j+width) - ii(i+height, j)\big) \tag{3.1}$$

$ii(m,n)$ denotes the integral image value at location (m,n). Figure 5 shows the results of the coarse segmentation.



(a) Search results on Log-Gabor image (b) Coarse segmentation on original image

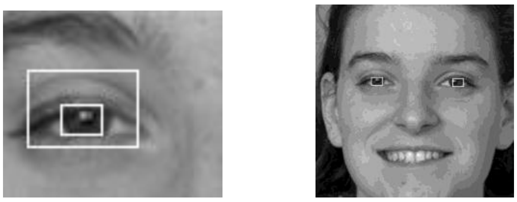
Fig.5. Coarse eye segmentation

Though rough bushy eyebrows on some faces are dark enough to become the darkest region in the eye-and-brow region, the variation of the intensity in these eyebrows still cannot be as drastic as the pupil region and they also do not have as rich edges as the eyes do. Therefore, as we mentioned before, the major part of the eyebrows will be excluded by the search algorithm on Log-Gabor image and the remains will not make crucial influences on the result of fine localization.

Generally speaking, the coarse region can not meet the accuracy requirements of the eye localization system. What we need is the locations of the two pupils, which can provide more precise references for the face normalization. Thus in the next step, the integral image is used again to find the pupils within the coarse regions.

3.3 Pupils localization

Finally, we exploit the integral image information of the coarse eye regions on original face image to locate the pupils. Different from the previous step, here we directly search the darkest subregion within the coarse eye region. The evaluation function is the same as Eq (3.1). Firstly, we calculate the integral image of the coarse eye region on the original image and set the scope of searching parameters. Based on our experiments on a mass of face images, we set the initial height as 16 pixels and the upper bound of height as 22 pixels, the initial width as 20 pixels and the upper bound of width as 26 pixels. These parameters make the size of search rectangle similar to that of human pupils. Fig.6 shows the result of fine localization.



(a) The pupil localization (b) Final results of eye localization

Fig.6. Fine localization

As we can see in the Fig.6(b), the pupil regions are well located by our algorithm. The result of fine localization is adequate to meet the demand of eye localization.

4 Experiments and Analysis

To evaluate the performance of our algorithm, we implement experiments on the FERET face database with MATLAB platform. Three subsets (*ba*, *bj* and *bg*) of the FERET database were chosen. The test faces have different expressions, illuminations and face poses. The images in *ba* are frontal faces with common illuminations, the images in *bj* are frontal faces with smile and the images in *bg* rotate 22.5 degree to left. The input face images are resized to the size of 300×300 and we use the white rectangle to label the pupil regions.

To demonstrate the effectiveness of our eye localization method, we carry out some comparison experiments with other methods. We first compare our method with [5]. We follow the rules in [5] as below:

Coarse segment precision: if the eye is included in the rectangle R_l or R_r, the segmentation result is right. The left eye segmentation is right means that left eye is in R_l, The right eye segmentation is right means that right eye is in R_r.

Fine segment precision: after re-segmentation operation, if both pupils are in R_{sl} and R_{sr} the re-segmentation is right.

As [5] did not perform experiments on *bj*, we only compare the results in *ba* and *bg* with them. The following Table.1 and Table.2 show the comparison results.

Table.1 The results on *ba* subset with 200 face images

Ours	Gabor eye	Algorithm
99% (2 error images)	99.5%	Coarse segmentation in R_l
99% (2 error images)	98.5%	Coarse segmentation in R_r
99% (2 error images)	97%	Coarse segmentation in both
95.5% (9 error images)	96.5%	Fine segmentation

Table.2 The results on *bg* subset with 200 face images (22.5 rotation)

Ours	Gabor eye	Algorithm
98.5% (3 error images)	95%	Coarse segmentation in R_l
99% (2 error images)	100%	Coarse segmentation in R_r
98% (4 error images)	95%	Coarse segmentation in both
96% (8 error images)	95%	Fine segmentation

From comparison we can see that the accuracy is similar between the two methods. In the *ba* subset the fine segmentation accuracy of Gaboreye algorithm is 1% better than ours, while in the *bg* subset, the fine segmentation accuracy of our algorithm is 1% better than that of Gaboreye.

We again change the evaluation rules in order to compare with the result in [11]. The deviation Euclidean distance between the authentic coordinates provided by FERET database and the locations we obtained will be calculated. We evaluate the accuracy within 5 pixels tolerance and 7 pixels tolerance, as shown in Table.3 and Table.4:

Table.3 The results within 7 pixels tolerance

Ours	IIA	Algorithm
98.5%	95%	*ba*
97%	90%	*bj*

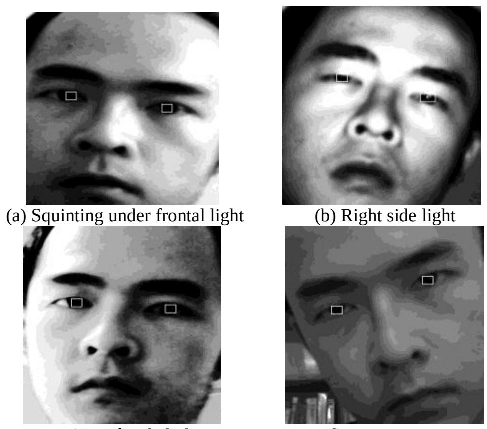
Table.4 The results within 5 pixels tolerance

Ours	IIA	Algorithm
97%	87.5%	*ba*
96.5%	93.4%	*bj*

From the Table.3 and Table.4 we can see that our algorithm has better performance in all of the subsets compared with the IIA in [11].

By analyzing the false localization results in our experiments, we can find the following facts. First of all, faces which have small and dark sclera always lead to the incorrect results as the rectangle may contains the eyelid region, especially under the low image resolution. The canthus will affect localization if the sclera cannot effectively separate the pupil with the canthus. Secondly, the heights of some faces are too long or too short and the eyes on these faces may locate out of the supposed boundaries. Thus the preprocessing will eliminate part or even most of the eyes, which would deviate the eye locations from the true coordinates. Finally, in subset *bj*, some people's eyes are not completely open. These eyes are either open partly or thoroughly closed, which makes it impossible to locate the pupils.

These experimental results show that our algorithm performs well under various face poses, orientations and illuminations. The Fig.7 shows some localization results under different conditions. The Fig.8 shows several localization results based on FERET database.



(a) Squinting under frontal light (b) Right side light

(c) Left side light (d) Face rotation

Fig.7. Eye localization under different conditions

Fig.8. Eye localization results for FERET database

5 Conclusions

In this paper, we proposed a novel method to accurately locate the eyes on a given human face image by combining Log-Gabor filters and integral image effectively. The experiments show that our method can effectively locate the eyes on frontal human faces and faces within 22.5 degree rotation.

The main characteristics of our method is that we not only utilized the gray value information on the original face image, but also exploit useful information on the Log-Gabor face image, which is advantageous to separate the eyes from the brows and reduced the influences caused by the illumination and face rotation. Through combining the integral image with the Log-Gabor face, we simplify the process of the fine localization and reduce the computation time, while still ensure the precision of eye localization. Besides, the time complexity is acceptable in current automatic face recognition system as the integral image can be calculated within constant time.

In future work, the machine learning would be introduced into our method to handle the condition that the rotation of the input face exceeds 30 degree, which our method could not deal with at present. Besides, we will continue to improve the algorithm robustness to the interferences from glasses and low image resolution.

Acknowledgements

This research was supported by the Fundamental Research Funds for the Central Universities (No. 2011121023).

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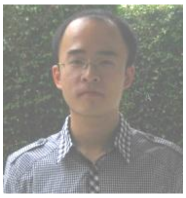

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