ICIC Express Letters ICIC International ©2016 ISSN 1881-803X
Volume **10**, Number **11**, November **2016** pp. **2685–2694**

COMBINING NSCT AND HIGH DISCRIMINATION FEATURES FOR EYE LOCATION

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Received March 2016; accepted June 2016

Abstract. *Eye location is the prerequisite of face recognition and face analysis, but the accuracy of eye location is vulnerably affected by non-uniform illumination changes and noise. To solve this problem, this paper proposes the algorithm of combining non-subsampled contourlet transform (NSCT) and high discrimination features for eye location. Firstly, illumination changes can be removed by utilizing NSCT. Secondly, the local ternary pattern (LTP) and local phase quantization (LPQ) features are extracted from the eye-candidate regions and then eye probability map is subsequently implemented by calculating the responding classification value of SVR for the eye-candidate point. Lastly, the position of the human eye is accurately determined by Gaussian fitting the eye probability map. Extensive experiments on CMU PIE, Yale B and AR Face Databases demonstrate that our method can effectively overcome the effects of non-uniform illumination changes and noise for the accurate eye location, improve the robustness for illumination changes and outperform the state-of-the-art approaches in terms of the accuracy of eye localization.*
Keywords: NSCT, LTP, LPQ, SVR, Gaussian fitting

1. **Introduction.** As a special case of object recognition, face recognition relates to many other field subjects, such as image processing, pattern recognition and neural networks. Face recognition has received extensive attention during the past decades [1-3]. Face alignment is a prerequisite of the accurate face recognition. The eye is the most important feature of the face images, and occupies a relatively fixed position in the face. The distance between the left and right eye sets the human face size, and is the basis of scale normalization on face recognition.

Common eye location methods mostly have been based on face detection, for example, [4] used an eye detection method based on Hough transform. The rough positions of the left and right eye regions can be established in a small area by using the face binary image and then the corresponding area will undergo the marginalization. Lastly, Hough transform detects the center of the eye and locates the center position of the eye. However, this method requires that the circular features of iris have no much loss and its performance is closely related to the threshold of image binarization and marginalization. [5] automatically separates the eye, other face parts and the background by using the threshold, but the algorithm requests the relatively high quality of face images. Song et al. [1] comprehensively overviews the eye location methods in recent years.

Illumination changes are still the major factor for the accurate eye location. Therefore, in recent years, many experts and scholars have dedicated to the eye localization under the non-uniform illumination. The eye localization algorithm under the non-uniform illumination includes two kinds of modes: 1) The face images undergo the illumination normalization pretreatment for removing the effects of illumination and then eye location will be accomplished; 2) Eye location will be performed through extracting the eye illumination invariant features. Retinex theory [6] based on the retinal cortex theory is the object model of the human visual system on how to adjust to perceive color and brightness. The theory is a representation of illumination normalization methods. Jung et al. [7] proposed eye detection under varying illumination using the retinex theory. This method performs the face illumination regulation by using the retinex theory and then extracts the edge histogram features. Lastly, the method accomplishes eye location by using support vector machine (SVM). However, the proposed method demands to have a high quality of face image. [8] applies the self-quotient image (SQI) to rectifying illumination and then accomplishes eye location. However, in SQI, the image is normalized by division over its smoothed version, which depends on the kernel size of the weighed Gaussian filter to a great extent. [9] applies the fast logarithmic total variation (FLTV) to illumination normalization before eye location. The eye detection method by using the binary edge and intensity information has been reported in [10]. The efficiencies of [9,10] are relatively low. Firstly, the face images carry out illumination normalization; secondly, this method detects the eye-candidate point. Lastly, eye will be located by non-negative matrix factorization (NMF) in [11]. [11] can improve the candidate detection part. Wavelet-based illumination normalization [12] attempts to normalize varying illumination by modifying wavelet coefficients. However, illumination effect cannot be completely removed and Gibbs phenomena are serious.

While there have many great contributions for accurate eye location under non-illumination, the non-illumination is still the major obstacle for large application of face recognition. Based on the motivation of combining the two leading methods for eye location, one is illumination normalization, the other is high discrimination feature descriptors, this paper proposes eye location method by combining local ternary patterns (LTP) and local phase quantization (LPQ) texture descriptors under non-uniform illumination. Firstly, this method will be used to remove the illumination changes by using the advantages of the non-subsampled contourlet transform (NSCT) [13], which can better preserve edges due to NSCT with multi-scale, multi-direction analysis and shift-invariance and can directly detect multi-scale contour structure that is illumination invariant in the logarithm domain of a single face image. Secondly, LTP and LPQ which are the illumination invariant features were extracted from the eye-candidate regions of the processed face images and then eye probability map is subsequently implemented by calculating the responding classification value of support vector regression (SVR) for each eye-candidate point. Lastly, the eye location is accomplished by Gaussian fitting the eye probability map. In order to overcome the effects of illumination changes, the proposed method takes advantage of NSCT for removing the illumination changes of face images and combines the advantages of illumination invariance and noise invariance of LTP and LPQ. The main contribution of this method is that it was combined the illumination normalization method based on NSCT and illumination invariance and noise invariance feature descriptors of LTP and LPQ. The test results show that our method has better accuracy than the other state-of-the-art approaches.

The rest of this paper is organized as follows. Section 2 briefly reviews the removing illumination changes based on NSCT and basic knowledge of LTP and LPQ. Section 3 thoroughly describes the proposed eye location method in detail. Section 4 describes the measure validation criteria. Simulation results in Section 5 will be dedicated to the description of a variety of simulation experiments. Finally, conclusions and future work are presented in Section 6.

2. Preliminary Knowledge.

2.1. Removing the illumination changes based on NSCT.

2.1.1. *Retinex theory.* Based on the retinex theory [6,7,14,15], the perceived scene image is a multiplication between the illumination on the object and their respective reflectance of the surface. That is

$$I(x,y) = R(x,y) \cdot L(x,y), \tag{1}$$

where $R(x,y)$ and $L(x,y)$ are the reflectance and illumination at a point (x,y) of an image $I(x,y)$, respectively. The retinex theory aims to efficiently and simply extract or estimate $R(x,y)$, the illumination invariant part of an input image by using the various mathematical methods. To facilitate processing, the function can be represented and approximated by the logarithm of the intensity of pixels in an image. Equation (1) will be converted into the following:

$$\log(R(x,y)) = \log(I(x,y)) - \log(L(x,y)). \tag{2}$$

2.1.2. *Nonsubsampled contourlet transform (NSCT).* The NSCT can be divided into two shift-invariant parts. Part 1: A non-subsampled pyramid structure that ensures the multiscale property. This is achieved by using two-channel non-subsampled 2-D filter banks. Part 2: A non-subsampled directional filter bank (DFB) structure that gives directionality. This is done by switching off the downsamplers/upsamplers in each two-channel filter bank in the DFB tree structure and upsampling the filters accordingly.

2.1.3. *Removing the illumination changes based on NSCT.* Based on the retinex theory, the illumination can be considered as the low frequency component of image. Besides, NSCT-based denoising technique can better preserve texture information in low frequency illumination fields than others. So NSCT-based image denoising technique can be used to estimate low frequency part $L(x,y)$, and then we can obtain the denoised image by (2). The initial value of $L(x,y)$ should be same as the input image $I(x,y)$. That is, first, decompose an image by NSCT, and then apply denoising model to the high frequency subbands of NSCT; finally, we reconstruct illumination $\log(L(x,y))$ by inverse NSCT.

All the NSCT subands are $\{C_{i_o}, C_{i,j}\}$, $i, i_o = 1, 2, \cdots, n$; $i \le i_o$; $j = 2, 4, 8, \cdots, m$; $n \in N$, $m \in 2^N$, where i is the scale of decomposition, j is the direction of decomposition, C_{i_o} is the low frequency coefficient, and $C_{i,j}$ is the high frequency coefficient at the j-th directional subband of the i-th scale. In our experiment, the scale of decomposition is 3, and directions of decomposition in each scale are 2, 4 and 8 respectively.

This paper selects the soft-threshold denoising algorithm based on Normalshrink which considers the texture of an image. The detail information can be seen in [16,17].

2.2. **Local ternary pattern.** In this paper, local ternary pattern (LTP) [18] can be applied for extracting local neighborhood relations mode from each image region. Then histogram formed by these features will describe the human eye. Similar to the local binary pattern (LBP) texture descriptor [19,20], the LTP texture descriptor performs the 8 neighborhood samples for each pixel i_c. Then we take the 3-valued mathematical operation between the gray value of the sampling point u and the center pixel i_c:

$$s(u, i_c, t) = \begin{cases} 1, & u \ge i_c + t \\ 0, & |u - i_c| < t \\ -1, & u \le i_c - t \end{cases}, \tag{3}$$

where, $s(u, i_c, t)$ is a 3-valued function; t is the threshold.

2.3. **Local phase quantization.** Local phase quantization (LPQ) [21,22] is the feature extraction method in frequency domain based on discrete fourier transform (DFT). The LPQ operator is highly insensitive to image blurring caused by motion, out of focus or atmospheric turbulence.

It applies the local phase information extracted for computing over a rectangular $M \times M$ neighborhood N_x at each pixel position of the image $f(x)$ defined by:

$$F(u,x) = \sum_{y \in N_x} f(x-y) e^{-j2\pi u^T y} = w_u^T f_x, \tag{4}$$

where, w_u is the basis vector of the 2-D DFT at frequency u, and f_x is a vector containing all the M^2 gray-scale values from N_x. Only four complex coefficients are considered in LPQ, corresponding to 2-D frequencies $u_1 = [a, 0]^T$, $u_2 = [0, a]^T$, $u_3 = [a, a]^T$ and $u_4 = [a, -a]^T$, where, a is a scalar frequency. Let

$$F_x^c = [F(u_1, x), F(u_2, x), F(u_3, x), F(u_4, x)], \tag{5}$$

$$F_x = [Re\{F_x^c\}, Im\{F_x^c\}]^T, \tag{6}$$

where, $Re\{\cdot\}$ and $Im\{\cdot\}$ are real and imaginary parts of a complex number, respectively. Therefore, the corresponding $8 \times M^2$ transformation matrix is

$$W = [Re\{w_{u_1}, w_{u_2}, w_{u_3}, w_{u_4}\}, Im\{w_{u_1}, w_{u_2}, w_{u_3}, w_{u_4}\}]^T, \tag{7}$$

so that

$$F_x = W f_x. \tag{8}$$

The resulting vectors are quantized by a simple scalar quantizer:

$$q_j = \begin{cases} 1, & \text{if } f_j \geq 0 \\ 0, & \text{otherwise} \end{cases}, \tag{9}$$

where, f_j represents the j-th component of F_x. After quantized, F_x will become the 8-bit binary vector. According to the weight 2^{j-1} that is shown in (10), the corresponding LPQ value can be calculated from each component. At last, the corresponding LPQ value can generate the 256-dimendional histogram.

$$f_{LPQ}(x) = \sum_{j=1}^{8} q_j 2^{j-1}. \tag{10}$$

3. **Eye Location Method.** This paper couples NSCT with LTP texture descriptor and LPQ operator to perform eye location. Firstly, the face regions will be detected from the original illumination image and then the face region can be normalized to I, and the size is 100×100. Secondly, I will be removed the illumination effects by applying NSCT and then we gain I_{rex}. These are displayed in Figure 1. Thirdly, the portion of I_{rex} used to become the training set, and the rest will be tested. As illustrated in Figure 2, the paper manually select positive and negative samples I_g with a fixed size of 10×20 from the training sample set. Contrary to I_g, in this paper, two LTP texture descriptors were selected to extract the eye feature by varying the parameter setting: the number of sampling points P and the search radius R were set to $(P = 8, R = 1)$ in LTP8 and to $(P = 16, R = 2)$ in LTP16. The threshold τ was set to 3 in our paper. Meanwhile, in order to better representation of the human eye, this paper also applies LPQ operator (here, the parameter was selected Gaussian derivative quadrature filters) to extracting the eye feature. In the processing of extracting feature, the eye feature coefficients are divided into four equal parts and then we extract the feature histogram. At last, we obtain the needed eye feature F_e by concatenating the histograms which are shown in Figure 3.

After completing the feature extraction, eye detector can be trained and produced through the training data. Then the eye will be located in the test face image. In the

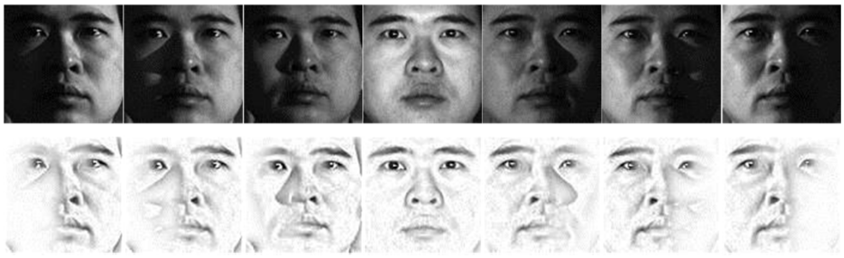

Figure 1. Some illumination normalization results. Top: original facial images. Bottom: illumination normalization results.

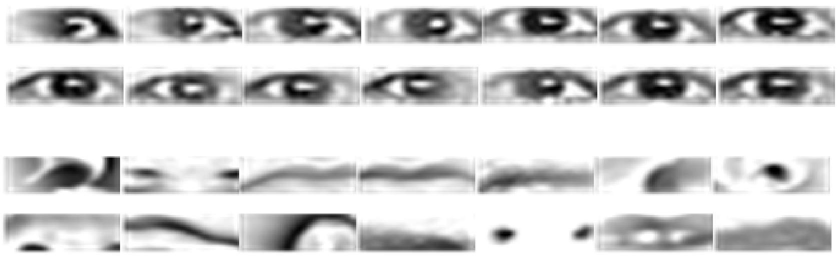

Figure 2. Training data sets. Top: positive samples. Bottom: negative samples.

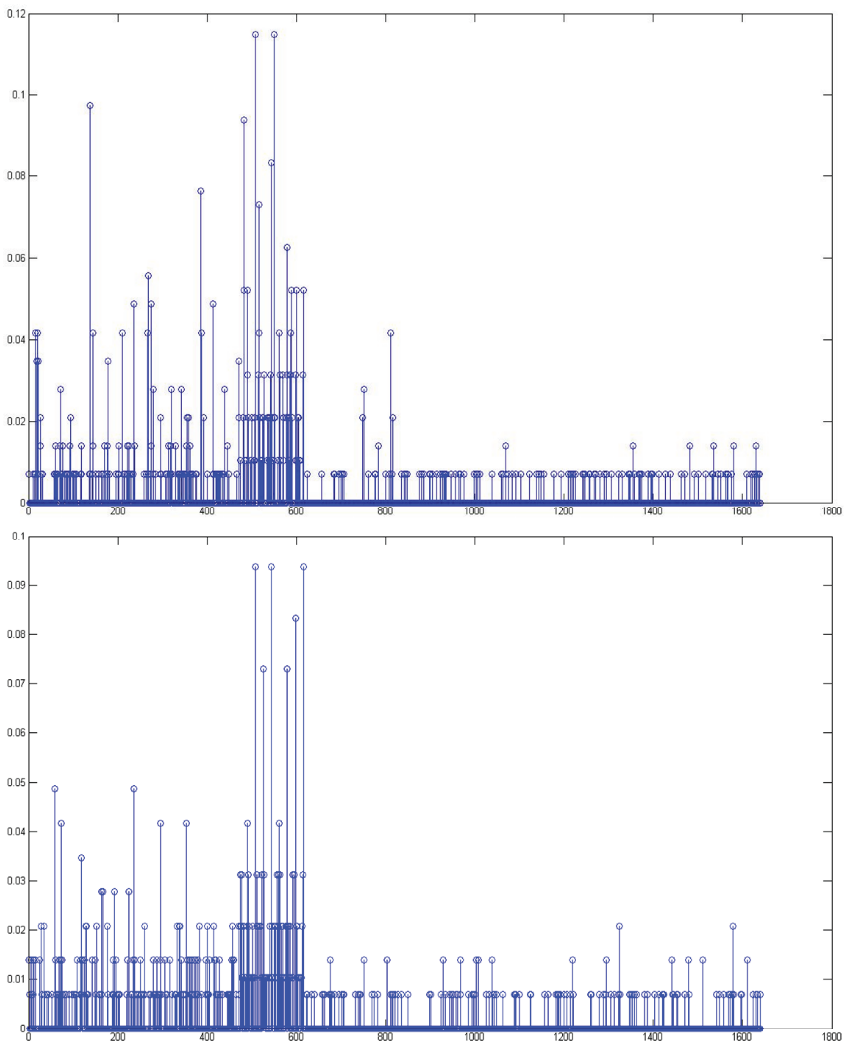

Figure 3. The histogram sets of training data character. Top: positive samples. Bottom: negative samples.

processing of the above mentioned, we use SVR to complete of the human eye detection and location.

SVR is an important branch of SVM. SVM is the classical binary classifier introduced by Vapnik [23]. The purpose of SVM is to calculate the optimal separating hyper-plane which can separate two class samples in the feature space. The decision function can be described as follows:

$$f(\mathbf{X}) = \sum_{i=1}^{n} \alpha_i y_i \left(\mathbf{X}_i^T \bullet \mathbf{X}\right) + b. \tag{11}$$

where, f is the distance function between the testing samples and the decision hyper-plane; $y_i \in \{1(self), -1(non-self)\}$ denotes a class label; $\mathbf{X}$ is the input feature vector; $\mathbf{X}_i$ is the i-th support vector; n, α_i and b represent the number of support vectors, the Lagrange multiplier and a bias, respectively. Because of the nonlinear condition, the feature space is converted to the high-dimensional space by the nonlinear kernel function [24]. Equation (11) can be written as follows:

$$f(\mathbf{X}) = \sum_{i=1}^{n} \alpha_i y_i K\left(\mathbf{X}_i, \mathbf{X}\right) + b, \tag{12}$$

where, K is the kernel function.

The paper carries out eye location from the produced image through illumination normalization. Firstly, our method crops a rectangular window with the size of 10×20 from the upper left corner of the face image for right eye location. The region covered with the rectangular window can be regarded as eye-candidate regions. Secondly, the eye feature F_e is extracted from eye-candidate regions and then the responding classification value can be obtained by SVR. Each responding classification value of eye-candidate regions constructs the eye probability map. Lastly, the position of the human eye is accurately determined by 2-D Gaussian fitting. Figure 4 shows that the center of 2-D Gaussian will

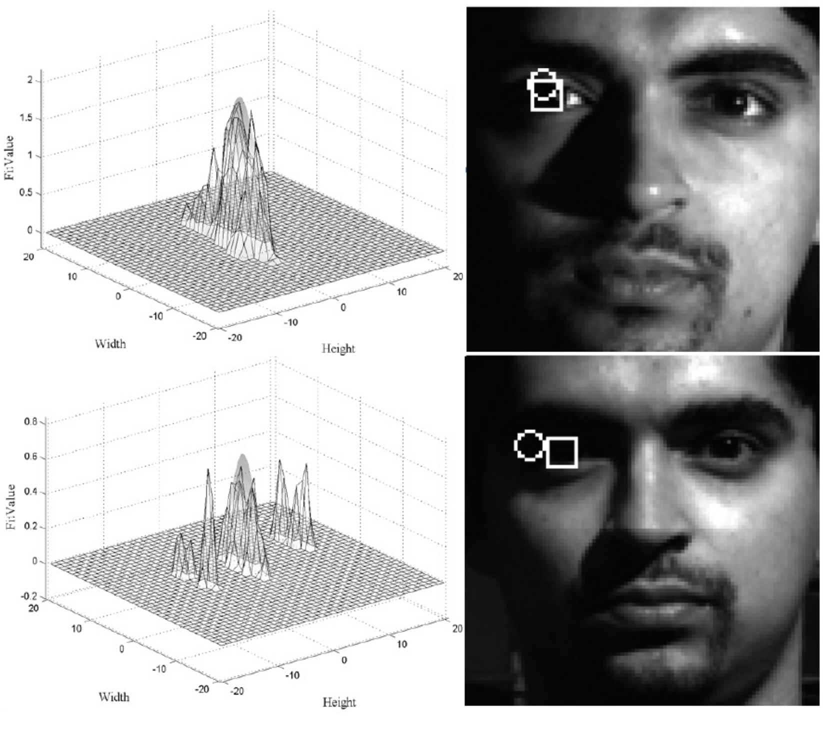

FIGURE 4. Eye location results by Gaussian fitting. Left: the schematic diagram of Gaussian fitting. Right: the result of Gaussian fitting (the white square is the Gaussian fitting result while the white circle is the maximum positioning results).

be regarded as the final position of the human eye. For locating the left eye, the produced face image through the symmetrical transformation utilizes the right eye-location method. For the parameter of SVM, we select the radial basis function (RBF, where $t = 2$) as the kernel function. To find the optimal RBF kernel parameter g and the trade-off C, our experiment conduct 10-fold cross validation. Finally, g and C are set to 2^{-12} and 10, respectively. The distance function f is calculated by [25].

4. **Measure Validation.** In order to verify the accuracy of the human eye location, a common algorithm is Hausdorff distances measure proposed by Jesorskey et al. [26] and is defined as: $e = \frac{\max(d_l, d_r)}{d}$, where d_l and d_r are the Euclidean distances between the automatically and manually located eye centers, left and right respectively. d is the Euclidean distance between the two manually located eye positions. Meanwhile, a large number of experiments proved that e is selected to 0.25 (a quarter of the interocular distance). If $e \leq 0.25$, the result will be considered correct. At this moment, d roughly equals double of an eye width. In our experiment, we utilize the following method:

$$abs(d_x - p_x) \leq disparity \quad \&\& \quad abs(d_y - p_y) \leq disparity. \tag{13}$$

where, (d_x, d_y) is automatically located eye center, (p_x, p_y) is manually located eye center, and *disparity* is set to 0.25R, 0.3R, 0.35R, 0.4R, 0.45R and 0.5R, respectively. R equals an eye width.

5. **Experimental Results.** To systematically evaluate the robustness of the proposed method, three publicly available subsets of CMU PIE, Yale B and AR are used. The CMU PIE database contains 41368 images of 68 subjects with 13 different poses, 43 different illumination conditions, and 4 different expressions. We select the frontal faces with 21 different illumination conditions and then the total number of face images is 1428. The Yale B database contains 5760 gray images of 10 subjects each seen under 576 viewing conditions (9 poses $*$ 64 illuminations). We test the system on frontal faces under changing illumination (10 subjects $*$ 64 illuminations). The AR database consists of over 4000 frontal images from 126 individuals. For each individual, 26 pictures were taken in two separate sessions. We select the images with 6 different illumination conditions for 120 subjects and then the total number of images is 720. Among them, we select 500 images for training from each database, and the rest are used for testing.

In our experiment, for simplicity we choose to flip the face image in left-right directions, and thus only the data of the right-eye position is extracted. The human eye and the approximate eye manually extracted from the training data sets will be used to train. Some training samples are shown in Figure 2. For testing samples, firstly, reference position of the eye can be manually extracted. Secondly, our method locates the position of the eye. Lastly, the accuracy of eye location will be measured by (13). As illustrated in Figure 5 and Figure 6, some representative location results used to be displayed. Figure 5 shows the successful location by our method and Figure 6 shows the some false locations.

We compare the accuracy of eye location of our method with some state-of-the-art approaches, such as, illumination normalization-edge histogram descriptor-support vector machine (IN-EHD-SVM) [7], SQI [8] and FLTV [9] approaches. In this paper, the databases of our method are consistent with IN-EHD-SVM. SQI and FLTV used to be applied to Yale B database and the data of Yale B are consistent with our method. Table 1 reports that the location accuracy obtained using different methods, where, the bold numbers represent the best accuracy in each database. As can be seen in Table 1, our method can obtain the best accuracy on CMU PIE and Yale B databases comparing with the state-of-the-art approaches. Meanwhile, the advantage of our method is its accuracy in comparison with others under the complex illumination (The illumination of Yale B

Figure 5. The successful eye location. (The white circle denotes the result of eye location by our method. The white square denotes the manually located position.)

Figure 6. The false eye location. (The white circle denotes the result of eye location by our method. The white square denotes the manually located position.)

Table 1. Location accuracy of different methods on CMU PIE, Yale B and AR databases. (NR: not reported)

Method	CMU PIE	Yale B	AR
Our method	**0.9619**	**0.9750**	0.9977
IN-EHD-SVM	0.9188	0.8976	**1.0000**
SQI	NR	0.8540	NR
FLTV	NR	0.8650	NR

Table 2. Location accuracy of different measure standards

	0.25R	0.3R	0.35R	0.4R	0.45R	0.5R
CMU PIE	0.9167	0.9286	0.9381	0.9476	0.9595	0.9619
Yale B	0.9393	0.9571	0.9643	0.9679	0.9714	0.9750
AR	0.9750	0.9795	0.9864	0.9955	0.9977	0.9977

database is more complex than other databases.). Our method achieves the better location accuracy than SQI, FLTV and IN-EHD-SVM with an average improvement of 11%, 12% and 8% on Yale B database, respectively.

In order to exhibit the effectiveness of our algorithm effectively and visually, the paper measures the accuracy of eye location on the standards of 0.25R, 0.3R, 0.35R, 0.4R, 0.45R and 0.5R which are shown in Table 2. It is obvious that, on the standard of 0.35R, the accuracy of our method can approximately reach 100% on AR database and exceed 93% on CMU PIE and Yale B databases. On the standard of 0.5R, our method can approximately reach 96% on CMU PIE and Yale B databases. The results show that our method can locate the human eye accurately and be of robustness and effectiveness.

6. **Conclusion.** In this paper, the produced images can be extracted the LTP and LPQ features on the basis of the removed illumination changes by utilizing NSCT algorithm. Then we obtain the eye probability map from eye-candidate regions by integrating SVR. Finally, the paper can integrate 2-D Gaussian fitting to locate the human eye under the non-uniform illumination. The results get the better robustness than other state-of-the-art approaches. We believe that the proposed method is acceptable for the human eye location under the non-uniform illumination in the future. At the same time, the proposed method can be used in face recognition, feature point location and salient region detection. Our method is a little time-consuming, so the future work will improve the run-time. Furthermore, how to integrate the structural features of the human eye to further refine the eye location and then accurately locate the position of the eye center is also worthy of the further study.

Acknowledgment. This work was partially supported by the National Natural Science Foundation of China (No. 61372187), Key Fund Project of Sichuan Provincial Department of Education (No. 14ZA0118).

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