Optimal Iris Region Matching and Gaze Point Calibration for Real-Time Eye Tracking Systems

Wen-Chung Kao, *Senior Member, IEEE*, Chun-Yi Lin, Chen-Chien Hsu, *Senior Member, IEEE*
Chia-Yi Lee, Bai-Yueh Ke, and Ting-Yi Su
National Taiwan Normal University, Taipei, Taiwan

***Abstract*--Compare with the infra-ray light gaze tracking systems, the visible light gaze tracking (VLGT) design provides new applications to consumer electronics. However, the VLGT suffers from the technical difficulties of accommodating various illumination conditions and unstable image features. These system design issues lead to the problem of low accuracy in estimating iris center location and high computational complexity. Leveraging from our previous work, we further improve the algorithm of ellipse matching for the iris region and the mapping function, whereas the average angular errors are less than 0.45° for both horizontal and vertical directions.**

I. INTRODUCTION

Eye-gaze tracking function has become an important human computer interface. Although the technology of infra-ray (IR) gaze tracking system has been well studied, it is not applicable in outdoor environments illuminated by strong sunlight. The visible light gaze tracking (VLGT) system would be more suitable for consumer electronics to be operated in various lighting conditions [1], [2]. The performance of a VLGT system highly depends on the algorithms of iris center calculation and the mapping function design from iris center to the gaze point location on the screen. This paper enhances the performance of the VLGT system we developed [3] by advancing the eyeball matching algorithm as well as the calibration function for gaze point mapping on the screen. The experimental results show that the performance as well as the accuracy has been significantly improved.

II. ALGORITHM OF GAZE POINT EVALUATION

This work leverages the same signal processing flow presented in our previous work [3], which begins estimating the iris center as well as the radius of limbus circle based on a direct gaze eye image. Then, it determines the optimal matchings of the iris regions from the remaining eye images. As the shape of iris region may vary from a circle to any ellipses depending on the yaw/roll angles (θ,φ) of the eyeball rotation, the problem of gaze point estimation can be formulated as finding the optimal match for the iris region with an ellipse [1]. Finally, the gaze point on the screen is determined through the calibration function which maps the ellipse center coordinate to the gaze point on the viewing screen.

This research is partially supported by the “Aim for the Top University Project” and “Center of Learning Technology for Chinese” of National Taiwan Normal University (NTNU), sponsored by the Ministry of Education, Taiwan, R.O.C. and the “International Research-Intensive Center of Excellence Program” of NTNU and Ministry of Science and Technology, Taiwan, R.O.C. under Grant no. MOST 104-2911-I-003-301 and MOST 104-2511-S-003 -016 -MY3.

This paper aims at improving the accuracy of ellipse matching for the iris region, minimizing the mapping error of the gaze points on the screen, and reducing the overall execution time.

A. *Find the best match of the iris region and ellipse models*

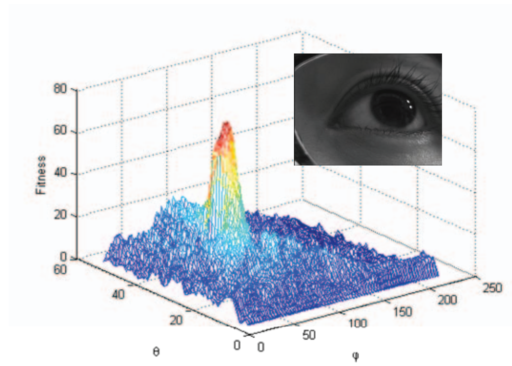

Fig.1 The optimal search plan for an eye image .

The problem of finding the best match of the iris region is formulated as the one of identifying the maximum fitness function f defined in (1) among all possible yaw/roll angles (θ,φ) of the eyeball.

$$f(\theta,\varphi)=\sum_{\alpha} g_{\theta,\varphi}(x_\alpha,y_\alpha) \quad (1)$$

where the function g denotes the matching score of a rotational model (θ,φ) on the starburst trace with angle α. Let $p(\alpha,\theta,\varphi)$ represent the pixel value on the ray with angle α crossing the ellipse defined by the rotational model (θ,φ) as shown in Fig. 2. The function g is formulated as

$$g_{\theta,\varphi}(x_\alpha,y_\alpha)=\begin{cases}1 & \text{if } \Delta p(\alpha,\theta,\varphi)>0\\ 0 & \text{otherwise}\end{cases} \quad (2)$$

where the condition $\Delta p(\alpha,\theta,\varphi)>0$ is used to examine whether the point $p(\alpha,\theta,\varphi)$ possibly locates on the limbus circle or not. Based on (1) and (2), the fitness function scores for each possible rotational angle (θ,φ) can be evaluated. Fig.1 shows an example of eye image and its corresponding fitness values on the search space. Thus, the best match problem is formulated as finding the maximum fitness score $f(\hat{\theta},\hat{\varphi})$ on the search space (θ,φ). The search ranges for raw/roll angles are set as $\theta\in[0,\theta_{\max}], \varphi\in[0,\varphi_{\max}]$, while the search ranges $\theta_{\max}$ and $\varphi_{\max}$ are set as 50 and 210 in the current system, respectively.

The search for the best match on the solution space (θ,φ) is done by a powerful stochastic optimization tool called particle swarm optimization (PSO) algorithm [4], [5]. The search process is executed by first randomly produce a set of initial particles on the solution space, and each possible solution (θ_i,φ_i) is modelled as a particle i on the space. Then, the

978-1-4673-8364-6/16/$31.00 ©2016 IEEE

algorithm adjusts the locations of the particles according to their current fitness values among companions and their own flying experiences.

We assume there are n particles $(P_i, i = 1 \ldots n)$ and their locations at time t are denoted as $P_i(t) = \left(\theta_i(t), \varphi_i(t)\right)$. Based on particle moving scheme of PSO, the new location of a particle i can be determined as

$$\theta_i(t+1) = \theta_i(t) + v_{i,\theta}(t+1) \quad (3)$$

$$\varphi_i(t+1) = \varphi_i(t) + v_{i,\varphi}(t+1) \quad (4)$$

where $v_{i,\theta}(t)$ and $v_{i,\varphi}$ denote the velocity components in θ and φ directions at time t, respectively. With PSO, each particle tends to move to the location that has the highest fitness based on the travelling history of the particle itself and others. This idea can be formulated as

$$v_{i,\theta}(t+1) = w \times v_{i,\theta}(t) + \delta_1 \times \left(\hat{\theta}_i(t) - \theta_i(t)\right) + \delta_2 \times \left(\hat{\theta}(t) - \theta_i(t)\right) \quad (5)$$

$$v_{i,\varphi}(t+1) = w \times v_{i,\varphi}(t) + \delta_1 \times \left(\hat{\varphi}_i(t) - \varphi_i(t)\right) + \delta_2 \times \left(\hat{\varphi}(t) - \varphi_i(t)\right) \quad (6)$$

where $(\hat{\theta}_i(t), \hat{\varphi}_i(t))$ denote the best match location whose fitness value is the highest for particle i from time 0 to t. The best match location for all particles from time 0 to t is denoted as $(\hat{\theta}(t),\ \hat{\varphi}(t))$. The parameter w, is set as 0.9, while δ_1, and δ_2 are randomly selected from[0,2.1]in our current implementation, respectively.

If the location of a particle is over the range of the solution space, a new location is reproduced as

$$\theta_i(t+1) = \hat{\theta}(t) \times \alpha + \theta_{\max} \times rand \times \beta \quad (7)$$

$$\varphi_i(t+1) = \hat{\varphi}(t) \times \alpha + \varphi_{\max} \times rand \times \beta \quad (8)$$

Note that the initial positions of the particles also affect the entire search performance. By observing the data correlations among the successive frames, their best match solutions are usually very close. This heuristic rule can be realized by incorporating a special particle whose initial location is the same as the final result of the previous frame. From the experimental result, this scheme significantly improves the performance of the best match solution. Once the best match angles (θ,φ) for a frame are determined, the gaze direction as well as the gaze point on the screen can be estimated.

B. Calibration of mapping function

A calibration procedure is necessary for computing the mapping function, which converts the center point (x, y) of the limbus circle to the real coordinate (x_s, y_s) of the gaze point. The user looks at nine targets on the screen and the calibration process builds the correspondence between them. The most common mapping function is based on two second-order mapping polynomial functions which contain six parameters for each mapping function [6], [7]. In this paper, we further revise mapping functions as

$$x_s = c_{x,1}x^2y^2 + c_{x,2}x^2y + c_{x,3}x^2 + c_{x,4}xy^2 + c_{x,5}xy + c_{x,6}x + c_{x,7}y^2 + c_{x,8}y + c_{x,9} \quad (9)$$

$$y_s = c_{y,1}x^2y^2 + c_{y,2}x^2y + c_{y,3}x^2 + c_{y,4}xy^2 + c_{y,5}xy + c_{y,6}x + c_{y,7}y^2 + c_{y,8}y + c_{y,9} \quad (10)$$

The new mapping function would be more flexible to represent the nonlinear mapping by using nine parameters. As a result, the average angular errors for both horizontal and vertical directions can also be significantly reduced.

C. Experimental Results

The proposed VLGT system is equipped with a high speed camera (480 frames/s). The average processing speed for each frame is only 5 ms running on a four-core microprocessor. Fig.2 shows average angular errors in horizontal (x) and vertical (y) directions based on the nine gaze points on the screen. The final performance with traditional six parameters calibration function (Old) and the proposed calibration one (New) are analyzed. It is obvious that applying the new calibration function generally receives higher accuracy in both horizontal and vertical directions. The worse cases of the average angular errors found in both directions are less than 1.65° and 0.45° with the old and the new mapping functions, respectively. The overall tracking accuracy is much better than other similar systems and the proposed VLGT system would be appropriate for applying on consumer electronics.

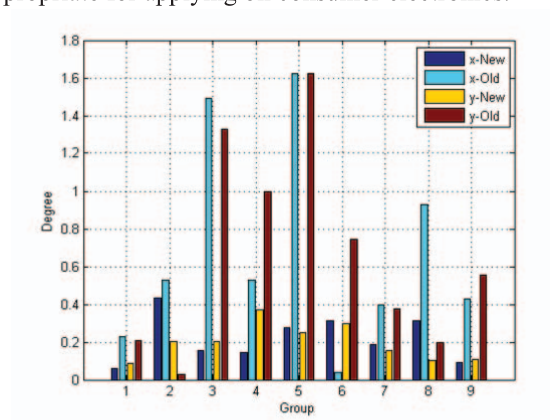

Fig.2 The statistics of angular errors in horizontal (x) and vertical (y) directions with the old and the new mapping functions.

REFERENCE

[1] S J. Baek, K. A. Choi, C. Ma, Y. H. Kim, and S. J. Ko, “Eyeball model-based iris center localization for visible image-based eye-gaze tracking systems” *IEEE Trans. Consumer Electronics*, vol. 59, no. 2, May 2013.

[2] T. Moriyama, T. Kanade, J. Xiao, and J.F. Cohn, “Meticulously detailed eye region model and its application to analysis of facial images” *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. 28, no. 5, pp. 738-752, May 2006.

[3] W. C. Kao, C. Y. Lee, C. Y. Lin, T. Y. Su, B. Y. Ke, and C. Y. Liao, “Gaze tracking with particle swarm optimization,” in *Proc. IEEE International Symposium on Consumer Electronics*, May 2015.

[4] J. Kennedy and R.C. Eberhart, “Particle swarm optimization,” in *Proc. IEEE International Conference on Neural Networks*, vol. 4, Dec. 1995, pp. 1942-1948.

[5] N. J. Li, W. J. Wang, C. C. Hsu, and C. M. Lin, “Global optimization using novel randomly adapting particle swarm optimization approach,” in *Proc. IEEE International Conference on Systems, Man and Cybernetics*, Oct 2011, pp.1783-1787.

[6] J. Sigut and S. A. Sidha, “Iris center corneal reflection method for gaze tracking using visible light” *IEEE Trans. Biomed. Eng.*, vol. 58, no. 2, pp. 411–419, Feb. 2011.

[7] C.H. Morimoto, D. Koons, A. Amit, M. Flickner, and S. Zhai, "Keeping an eye for HCI", *Computer Graphics and Image Processing*, pp. 171-176, Oct 1999.

978-1-4673-8364-6/16/$31.00 ©2016 IEEE