International Journal of the Physical Sciences Vol. 6(5), pp. 1233-1243, 4 March, 2011
Available online at http://www.academicjournals.org/IJPS
DOI: 10.5897/IJPS11.067
ISSN 1992 - 1950 ©2011 Academic Journals

Full Length Research Paper

Pupil tracking method based on particle filtering in gaze tracking system

Chi Jian-nan*, Zhang Chuang, Qin Yan-jun, Li Ying and Yang Li

Information Engineering School, University of Science and Technology Beijing, Beijing, 100083, China.

Accepted 03 March, 2011

In this paper we proposed a pupil tracking method based on particle filtering in active infrared source gaze tracking system. We constructed a pupil target model with the combination of gray characteristic and shape characteristic so that the target and the background can be distinguished easily. Pupil motion model which can predict pupil location and shape feature in the next frame was built. Gray histogram similarity and geometrical shape similarity were combined to build pupil observation model, which can improve the credibility of particles. In this paper we also showed the experiment results. The applications in interactive graphical system had verified that our method was effective and feasible.

Key words: Gaze tracking, eye characters, particle filtering, face location, pupil detection, Purkinje segment.

INTRODUCTION

Gaze tracking is defined as "the line of sight", which represents a persons focus of attention (http://www. eyegaze.com). Gaze tracking is the technology of getting gaze direction that make use of mechanical, electronic, optical and other methods and has been an active topic and explored for many decades because it is widely used in various applications such as "human computer interaction" for the disabled, "human behavior study", "virtual reality", "vehicle driver assistance", etc. There are many technologies available for eye tracking, which can be called the intrusive and the non-intrusive. Video-oculography (VOG) (http://www. eyegaze.com) which is based on analysis of digital video is a minimally intrusive or completely noncontact technique commonly used for tracking and recording eye movements. VOG gaze tracking technology commonly used the pupil-corneal reflex method controled by an active infrared light. That is, forming reflex points in the corneal (purkinje) by setting up the infrared light away from the optical axis. In a complete VOG system that determines where a user is looking at, there are two basic task. As shown in Figure 1, the first task is to detect the features of eye in each image and extract parameters of the line of sight used by tracking model, such as 2D or 3D pupil and glint center locations. The second task is to acquire a specific gaze mapping function that will map the extracted gaze direction parameters such as pupil-glint vector to the user's line of sight or fixation point in the screen.

VOG system based on pupil-corneal reflex method in eye features detection needs segment pupil in image firstly, then locate purkinje in the neighbour of pupil. In existing paper, in order to make it easy to detect and segment pupil, the method of differencing bright and dark pupil images is employed extensively. That is, set a illuminator which is consist of two concentric rings of IR LEDS and the center of the rings coincide with the camera optical axis. When the inner ring is on, an even frame is grabved and produce a bright pupil image, and alternately, when the outer ring is on, an odd frame is grabbed and produce a dark pupil image. Then eliminate the background effects via differencing the bright and dark pupil images in adjacent even and odd frames (http://www. eyegaze.com; http: //www.eyetechds.com; http: //www.tobii.se; http://www.a-s-l.com), which will make it convenience to find the eye and pupil on a whole face. This bright and dark pupil differencing is generally followed by thresholding technique in pupil segmentation (Morimoto; 2000). In VOG system, the extraction of LOS

*Corresponding author. E-mail: sy_jnchi@126.com.

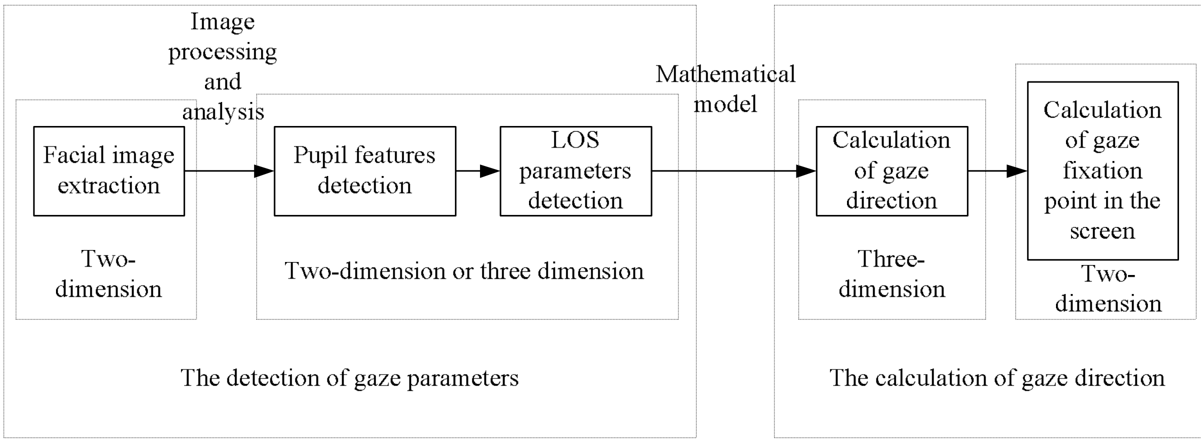


Figure 1. The flow chart of gaze tracking technology.

parameters largely depends on pupil location and is accomplished in two adjacent frames. In order to get the real-time LOS parameters, we must repeat pupil location step in every video sequence because of pupil motion.

The following two drawbacks are shared in this approach: first, locating pupil in the whole image each time after head movement badly affects system efficiency and real-time quality; secondly, for the influences of eye blinking and external light, it is difficult to build a more robust system without using the historical information of pupil. So after located pupil in the initial frame, pupil tracking should be carried out in the following video suquences to handle these two issues. Various techniques are proposed to do pupil tracking, such as Kalman filtering (Ji and Yang, 2001), mean shift (Zhiwei et al., 2002), combination of Kalman filtering and “mean shift” (Zhiwei and Qiang, 2005). Pupil movement has the following characteristics: first, it occurs randomly and involuntarily, so it’s hard to build an accurate pupil motion model; secondly, the target pupil disappears inherently due to eye blinking. For the above two factors, both Kalman filtering and “mean shift” can not track the pupil accurately. To handle these, we applied particle filtering in pupil tracking to build a more accurate system. Particle filtering is one of the effective mathematical tools to study the optimal estimation of nonlinear and non-Gaussian dynamical system. Dan Witzner Hansen used particle filtering for pupil tracking in his paper, (Hansen and Pece, 2005) used particle filtering for iris tracking in his paper, but the following disadvantages exist in these two experiments: first, they didn’t consider the pupil elliptical shape feature, the foreground and background can not be distinguished with rectangular model; secondly, they didn’t consider the geometric similarity of the target pupil ellipse, and the particle weight credibility would drop only using the similarity of histogram.

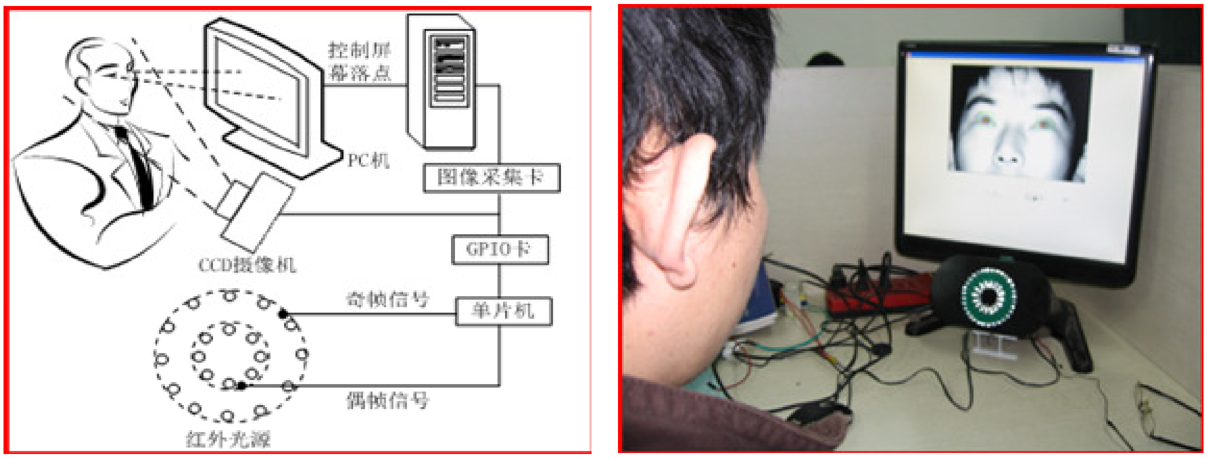
To achieve a real-time pupil tracking in VOG system, we summarized the following requirements as guidelines: first, choose a target model that can distinguish foreground and background to reduce the interferences caused by the background; secondly, build a pupil observation model with high reliability; thirdly, the state transition equation should represent the law of pupil motion as much as possible; fourthly, be sure to hold a long-time tracking and can recapture the pupil after it is lost.

On the basis of developing a low cost and widely used gaze tracking system, pupil-corneal reflex technique for detecting gaze direction is reported in this paper by using a camera and an active infrared light source. A VOG system based on particle filtering is proposed to meet the mentioned requirements of pupil tracking. Major includes the following steps:

1) Considering the morphological characteristics and rectangular block model of pupils, we will build a target model corresponding to its morphological characteristics and change regularity to minimize the interferences from background.
2) Build a pupil observation model which combines the histogram similarity with the geometric similarity to improve the creditability of particle weight.
3) We will also introduce the idea of phase tracking in allusion to meet the requirement of long time tracking, deal with the problem of target state drift and particle dilution, and finally build a more robust tracking system.

Gaze tracking system

The gaze tracking system proposed in this paper is composed of infrared light source with two concentric rings, filters, camera lens, image grabbing cards, CCD, GPIO cards, single-chip computer, the mainframe computer and the display screen. The inner ring of the



(a) (b)

Figure 2. Gaze tracking system. (a) The figure of gaze tracking system. (b) The physical map of gaze tracking system.

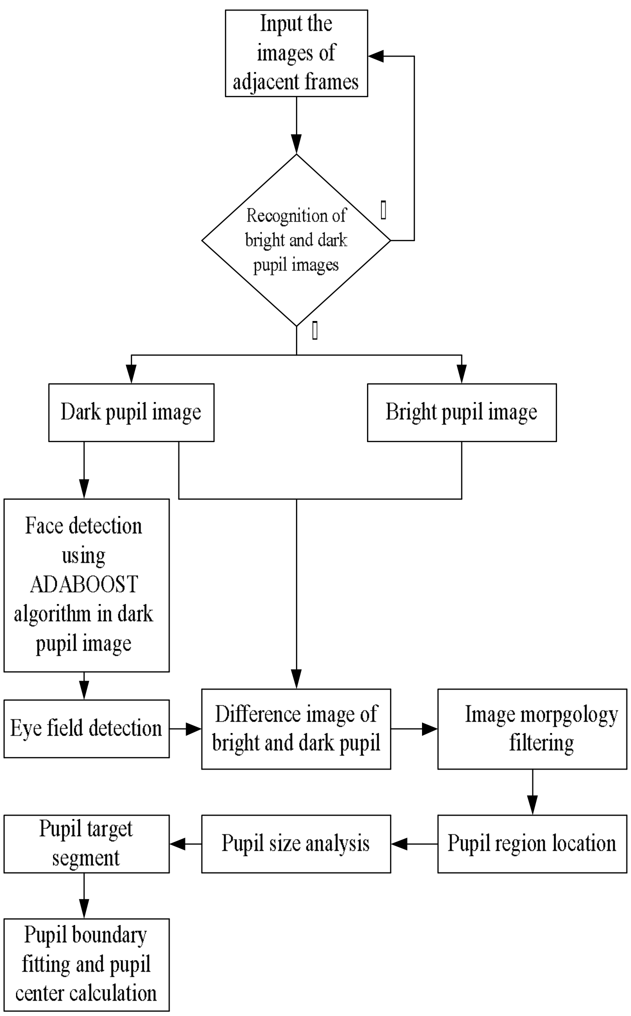


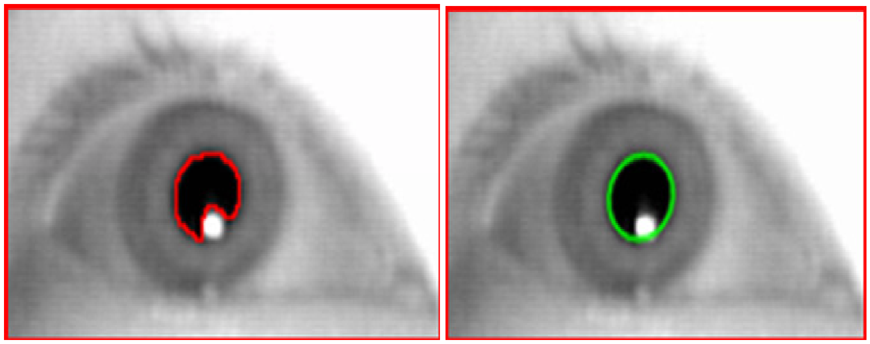
Figure 3. The flow chart of pupil detection.

infrared light source coincides with the optical axis, which can produce bright pupil images when light up. The outer ring can produce purkinje spot. When the user is looking at the display monitor, his face image can be detected by a CCD camera and then sent to the mainframe computer via an image grabbing card. The mainframe computer extracts the characteristic parameters and run gaze mapping function to get the gaze direction. Frame synchronization signals are captured via the GPIO card in the mainframe. The brightness of inner and outer rings of the infrared light source is controlled by the single-chip computer to produce bright and dark pupil images in two adjacent frames. The gaze tracking system was shown in Figure 2.

Pupil detection

To estimate the gaze direction, the first step is to detect planar gaze parameters, and pupil detection is an important content for doing this. The scheme we designed in this paper firstly searches pupil in the initial frame and detects its characteristic parameters, and then tracks it in the following video image sequences. The flow chart is shown in Figure 3 and the result of pupil detection is shown in Figure 4.

1) Collecting the bright and dark pupil images in the two adjacent frames; one subtracts another to get the difference image in which the pupil can be reliably detected.
2) An iteration algorithm called ADABOOST is considered to locate the face-region and detect the facial features.
3) Continue applying the ADABOOST algorithm to locate



(a) (b)

Figure 4. The result of pupil detection. (a) Pupil edge. (b) Pupil fitting.

the eye in face-region with the priori knowledge of facial features distribution.

4) Morphology filtering is used to filter out the stray interferences and correct the boundaries of the located eye.

5) According to the eye-region labeled in the dark pupil image, pupil can be detected in the corresponding region of the difference image by introducing the method of projection.

6) Adopting the morphological method to remove the false objects from the pupil target in pupil field.

7) Performing edge detection and getting the boundary fitted pupil to calculate the center coordinates.

Pupil tracking

The parameters extraction procedure proposed earlier was completed in two adjacent frames. We capture the pupil in the initial frame, and then perform pupil tracking in the following video sequences (Figure 5). We capture the user's face image and sent it into the computer, at each time, a pair of bright and dark pupil images (one-to-one correspondence) will be produced due to the designs of the system light source. And then the tracking process will be performed in the difference of the dark from the bright pupil image, and finally the dark pupil image which shows the tracking results will be displayed on the screen. According to the gray feature and the elliptic shape feature of the pupil detected in the initial frame, we can build the target template. A discrete set of weighted samples called particles will be produced via state transfer function in the subsequent frames. Compare the gray and shape features of these particles with the template, and compute the weight of each particle according to weight algorithm. The particle which is more similar to the template will have a higher weight.

In the last step, we calculate the weighted average of all the particles to get the pupil state estimation. Implement the aforementioned steps to estimate the state of pupil in each frame, and then pupil tracking will be achieved (Figure 6).

Pupil tracking based on particle filtering

Pupil parameters extraction

The approaches have been elaborated in this study, and the pupil tracking system will not be initialized until the extraction step is success.

Pupil target model

The target model of pupil can be represented by a space vector:

$$State = \{C_x, C_y, C_l, C_s, X, Y, V_x, V_y, H_x, H_y, ad\}$$

where C_x and C_y respectively are the coordinates of pupil center of x and y axes in the image; C_l and C_s respectively are the lengths of major axis and minor axis of the pupil ellipse; X and Y are the coordinates of the rectangular target window center of x and y axes; V_x and V_y are the motion velocity of pupil target along x and y axes; H_x and H_y respectively are the width and height of the rectangular target window; ad is the disturbing amplitude of the aim window.

According to the initial state of the target, select a Gaussian function with appropriate variance for sampling, and then we will get a set of particle states of tracking initial-time.

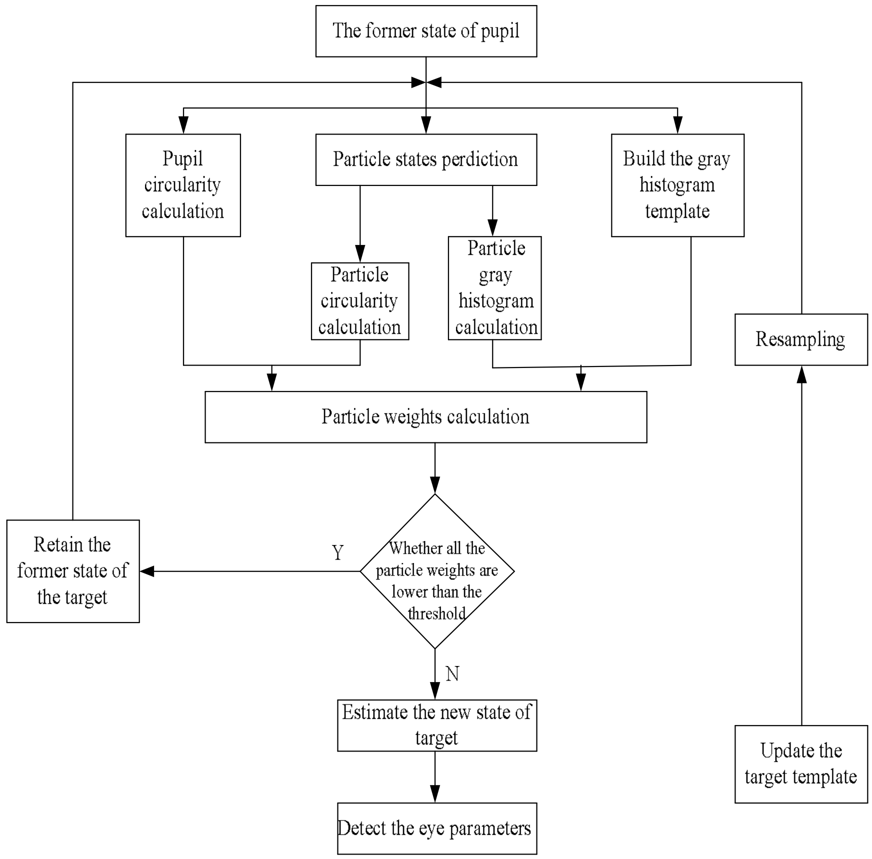


Figure 5. The tracking flow chart of particle filter.

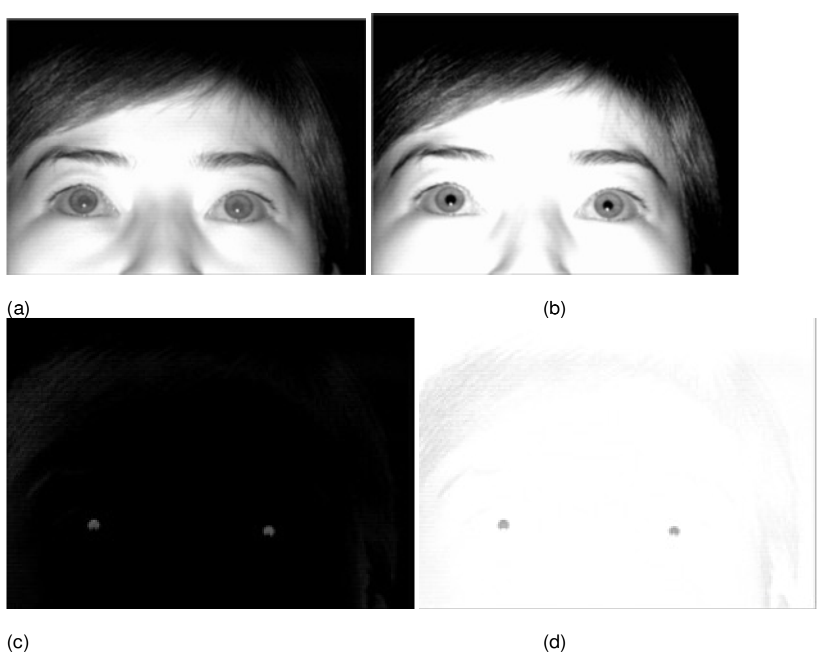


Figure 6. Bright, dark pupil image and difference image. (a) Bright pupils. (b) Dark pupils. (c) Difference result (d) Contrary to the difference.

Pupil motion model

Predict the particle states of the next frame via the state transfer model, that is:

$$State_t^n = A \cdot State_{t-1}^n + V_{t-1}^n \tag{1}$$

$$A = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & \Delta t & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & \Delta t & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & C_l \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & C_s \\ 0 & 0 & 0 & 0 & 1 & 0 & \Delta t & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & \Delta t & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & H_x \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & H_y \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

Where the noise vector V in this formula is: $\eta(\text{t-1}) \sim N(0,\sigma^2)$ 。

Pupil observation model

The information of color, texture and shape features is steady in target tracking and these descriptors have their own characteristics in tracking calculation (Feris, 2001; Hui, 2007; HyungSoo and Daijin, 2007). Gray feature is generally recorded by histogram while shape feature is generally described by circularity. In this paper, we combined these two features together to provide a steadier and more robust pupil tracking system.

Gray feature and gray histogram

Assume that the center of the designated rectangular area is $(x_{0,}y_0)$, the quantity of the pixels in this area is N, the width and the height are W and H, then they can be represented as follows:

$$a^2 = W^2 + H^2 \tag{2}$$

$$r^2 = \frac{(x - x_0)^2 + (y - y_0)^2}{a^2} \tag{3}$$

$$k_j(r) = \begin{cases} 1 - r^2 & |r| < 1 \\ 0 & others \end{cases} \tag{4}$$

$k_j(r)$ is the kernel function.

The kernel density weighted histogram can be represented as follow:

$$q_u = g \bullet \sum_{j=0}^{N} k_j(r)\delta(h(x_j) - u) \tag{5}$$

Where $g = \left(\sum_{i=0}^{N} k(r)\right)^{-1}$, $h(x_j)$ is the gray-scale of each pixel, $u = 1, \cdots, bins$ are the gray levels.

Gray-scale observation model

Assume that the gray histogram of the template is p_u and of the particle $state_t^i$ is q_t^i, the gray observation value of this particle is computed as follows:

$$E_t^i = e^{-d_i^2/\sigma^2} \tag{6}$$

The monomial d_i is the Euclidean distance:

$$d_i = \sqrt{\sum_{u=1}^{bins}(q_u - p_u)^2} \tag{7}$$

The shape feature-circularity

Converted the image into binary image, and then compute the circularity of the object from particle field in this binary image. Let R be the circularity and $R = 4\pi S / L^2$. Here, S is the area of the object in particle field while L is the perimeter. Both of them are described by pixels. The range of value R is $[0,1]$, and this value will increase as the object becomes rounder. In an optimal situation, the R value of a standard circle is 1. The shape feature of the pupil ellipse can be described by circularity quantitatively.

Shape observation model

With the calculated circularity of the object, the shape observation value can be computed as follows:

$$F_t^i = e^{-(1-R)^2/\sigma^2} \tag{8}$$

Where R is pupil circularity at the current time. The

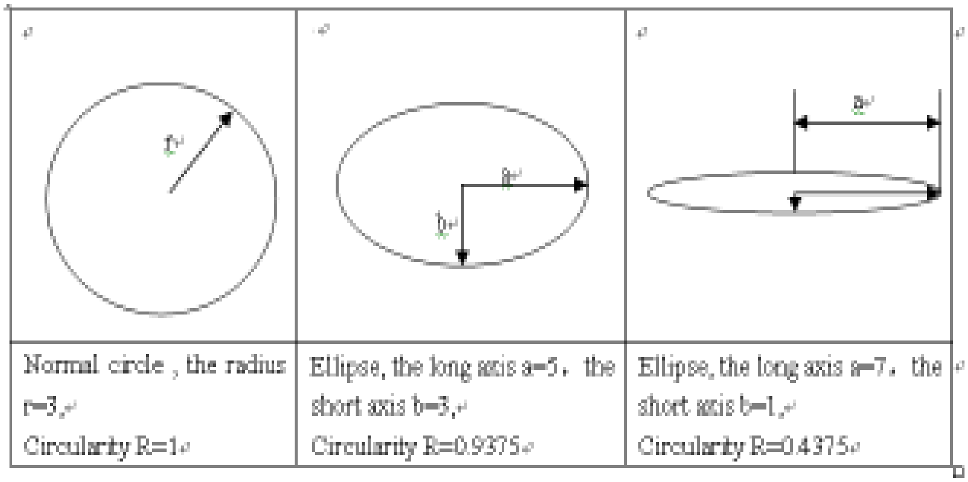


Figure 7. The sketch map of circularity.

sketch map of circularity is shown in Figure 7.

Integrate the gray feature with the shape feature to calculate the weight of each particle via the following formula:

$$\omega_t^i = \alpha \cdot E_t^i + (1\text{-}\alpha)\, F^i \tag{9}$$

α is a decimal range from 0 to 1.

New state estimation and target template update

New state estimation:

$$E\left(X_{t}\right) = \frac{\sum_{i=1}^{N} \omega_t^i state_t^i}{\sum_{n=1}^{N} \omega_t^i} \tag{10}$$

Where N is the quantity of the particles.

New estimated state will be considered as the tracking output and be brought into the template matching process to update the template to prepare for calculating particle weights in the next step.

Re-sampling: Re-sample each element from the array $\left\{state_t^i, \omega_t^i\right\}_{i=1}^{N}$ in order to arrive at a new array $\left\{state_t^M, \omega_t^j\right\}_{j=1}^{N}$, assume that u_i is a sampling value uniformly distributed within the area [0 1]. The sampling results from the collection $state_t^M$ which can meet the requirement $\sum_{j=1}^{M-1} \omega_t^j < u_i < \sum_{j=1}^{M} \omega_t^j$ will be chosen as the elements of the new re-sampling array. And repeat the re-sampling step for N times, we will get a set of new particles in this array. Because some of the particles weight will become lower after a few times iteration, the tracking precision will be badly affected. The purpose of re-sampling is to discard the particles with lower weight (Zhiwei and Qiang, 2005) while pick the particles with higher weight for the next computational step. In this way, almost all the particles used in iterative calculation and target estimation will have high weights to ensure a more accurate system.

Template update: Considering the changes in user's head orientation, the pupil characteristic parameters between true state and the template will have a great difference. If we still use the primary template in particles similarity calculation to estimate the current pupil state, gross errors will be produced, and the validity of the tracking process will be badly affected. So template matching is a necessary step, and we should update the template appropriately on the basis of new estimated state to decrease the differences between two adjacent frame images.

Treatment for eye blinking

When involuntary blinking occurs, the pattern of the eye region changes abruptly, and the system might lose the tracking pattern, even the highest particle weight calculated by the previous particle state will be smaller than a threshold. When detect this, particle space will not remove the last particle state that is calculated before blinking until the next frame image is put in. And then the system uses the state transfer function to push out the reserved particle state, and repeats the particle tracking steps to get a new estimation. At this moment, the interference of eye blinking will be generally reduced.

The flow chart of particle filter

Assume that the state of particle i at time t is $state_t^i$, the corresponding observation value is ω_t^i ,the particle states collection at time t is $STATE_t$。

Tracking initialization

1) Calculate the gray histogram of the initial target:

$$Q_X = \left\{ q_X^u \middle| q_X^u = f \sum_{x \in X} k(r) \delta\big(h(x) - u\big) \right\}$$

2) Initialize the state of each particle:

$$STATES_{t-1} = \left\{ \left(state_{t-1}^i, \omega_{t-1}^i\right) \middle| state_{t-1}^i = X_{t-1} + V_{t-1}, \omega_{t-1}^i = 1/N \right\}$$

Particle states prediction

Build the target motion model (the state transfer model):

$$STATES_t = \left\{ state_t^i \middle| state_t^i = Astate_{t-1}^i + V_{t-1}^i \right\}$$

Predict the particle states via this state transfer model to arrive at a collection $STATES_t$ of the new time point.

Particle states observation

1) Calculate the gray histogram of each particle:

$$Q_{state_t^n} = \left\{ q_{state_t^n}^u \middle| q_{state_t^n}^u = f \bullet \sum_{i=0}^{N} k(r) \delta(h(x_i) - u) \right\}$$

2) Calculate the Euclidean distance between each particle and the template. Suppose that the template histogram is q , the gray histogram of particle i at time t is $q_{state_t^i}$:

$$d_{state_t^i} = \sqrt{\sum_{j=1}^{bins} (q^j - q_{state_t^i}^j)^2}$$

3) Compute the gray observation value of each particle at time t as follows:

$$E_t^i = e^{-\frac{d_{state_t^i}^2}{\sigma^2}}$$

4) Evaluate the particles circularity, that is:

$$R_t^i = \frac{4\pi S_t^i}{L_t^{i\,2}}$$

5) Compute the shape observation value of each particle as follows:

$$F_t^i = e^{\frac{-(1-R)^2}{\sigma^2}}$$

6) Integrate the gray and the shape observation value to get the particles weight:

$$\omega_t^i = \alpha \cdot E_t^i + (1 - \alpha) \cdot F_t^i$$

Pupil state estimation

1) Estimate the state of pupil target, which is:

$$E(X_t) = \frac{\sum_{i=1}^{N} \omega_t^i state_t^i}{\sum_{n=1}^{N} \omega_t^i}$$

2) Assume that ω_t^E is the probability weight of the estimated target state, Euclidean distance between the state and the template is d_t^E , and the circularity is R_t^E at time t , we can get the following equation:

$$\omega_t^E = \alpha \cdot e^{-\frac{(d_t^E)^2}{\sigma^2}} + (1 - \alpha) \cdot \mathrm{e}^{-\frac{(1-R_t^E)^2}{\sigma^2}}$$

Re-sampling

Suppose the particle collection array is $\{state_t^i, \omega_t^i\}_{i=1}^{N}$, and

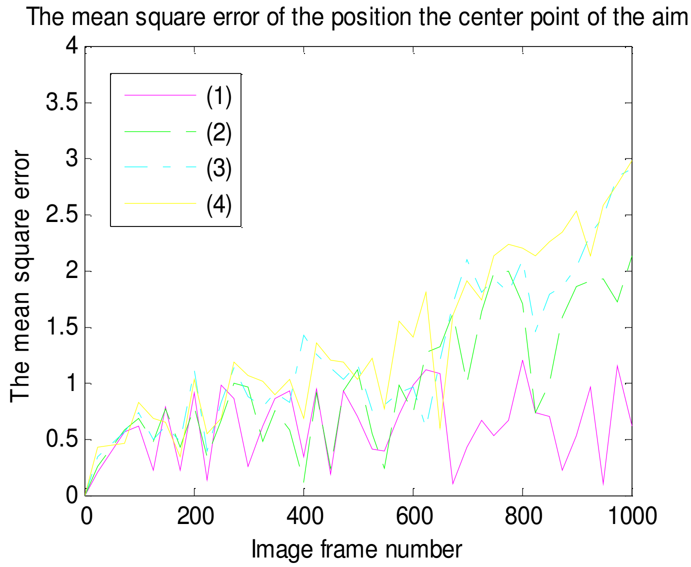


Figure 8. The comparison of these several kinds of tracking results.

the re-sampling results will put into array $\{state_t^M, \omega_t^j\}_{j=1}^N$, where $u_i \sim U(0,1)$. Pick out $state_t^M$ when u_i meet the requirement $\sum_{j=1}^{M-1} \omega_t^j < u_i < \sum_{j=1}^{M} \omega_t^j$ and put it into the array $\{state_t^M, \omega_t^j\}_{j=1}^N$, repeat this step for N times.

Update the template of target model

$$
\begin{aligned}
&\text{if } \omega_t^E > \omega_T \\
&\qquad X_t = (1-\beta) X_{t-1} + \beta E(X_t) \\
&\quad \text{else} \\
&\qquad X_t = X_{t-1} \\
&\quad \text{end}
\end{aligned}
$$

RESULTS AND ANALYSIS

In order to prove the validity of the procedure proposed in this paper, 1051 frame consecutive image sequences offered by 4 users are chosen for our experiments. Figure 8 is the analysis and comparison of these tracking results under the same image sequences condition. The tracking sequences chosen for experiment are consecutive and were collected under normal light conditions. The image resolution is 760 by 576 pixels. The experiment circumstances are indoor, cloudy, normal fluorescent lamp illumination and without strong light interference. In Figure 8, Method 1 is proposed in this paper; Method 2 uses color histogram of the difference images for pupil tracking; Method 3 is reported in Paper 12 (the particle filter tracking method based on color traits); Method 4 is reported in Paper 8 (the method combines Kalman filtering and mean shift for pupil tracking). The result showed that all the approaches can track the target accurately at the beginning of the tracking process. But with the increase of interference factors, after 500 image sequences, the errors of Methods 3 and 4 will grow bigger. Method 2 has some improvements for introducing the difference images to segment pupil, but it also can't satisfy the accuracy of long-time tracking and shows a bad robustness after 700 image sequences. Compared to Methods 2, 3 and 4, Method 1 mentioned in this paper is proved to have better robustness, smaller errors and its precision will not change too much over time.

In the experiment, we finished the real-time test and compared the aforementioned four tracking methods in Core 2 2.1G/2G computer under the software environment of VC++6.0. The data we captured in the image sequences respectively under the condition of gazing, blinking and eye closing. When a user stares at the screen, the range of his eye movement is very small, so his current pupil position won't be far from the position detected the last time. Table 1 shows the experimental parameters of the tracking method proposed in this paper. Table 2 shows the comparison of the four tracking approaches. The average time for target orientation of our approach is 20 MS/frame and the tracking precision is 99.14%. Obviously, applying the observation model which is combined gray features and shape features can largely improve the tracking precision, and by introducing the method of particle filtering, tracking velocity is also improved effectively. Figure 9 has shown the tracking

Table 1. Parameter analysis in the tracking system.

Course of events	Target detection	Particle filtering	
Processing times	**Initial orientation in the first frame**	**Stable condition in 638 frames**	**Blinking condition in 386 frames**
Times of accurate tracking	1+20	637	384
Successful rate (%)	70.08	99.84	99.22
Average execution time (Ms/frame)	29	8	23

Table 2. Comparison of the four tracking methods.

Method	Method 4			Method 3			Method 2			Method 1		
State of eye	**Normal**	**Blinking**	**Closing**	**Normal**	**Blinking**	**Closing**	**Normal**	**Blinking**	**Closing**	**Normal**	**Blinking**	**Closing**
Number of frames	639	386	26	639	386	26	639	386	26	639	386	26
Frames number for accurately tracking	623	357	7	628	364	11	633	378	13	638	384	20
Successful rate (%)	97.50	92.49	26.92	98.28	94.30	42.31	99.06	97.67	50.00	99.84	99.22	73.08
Average successful rate (%)		93.91			95.43			97.43			99.14	
Average time for location (Ms/frame)		28			27			31			20	

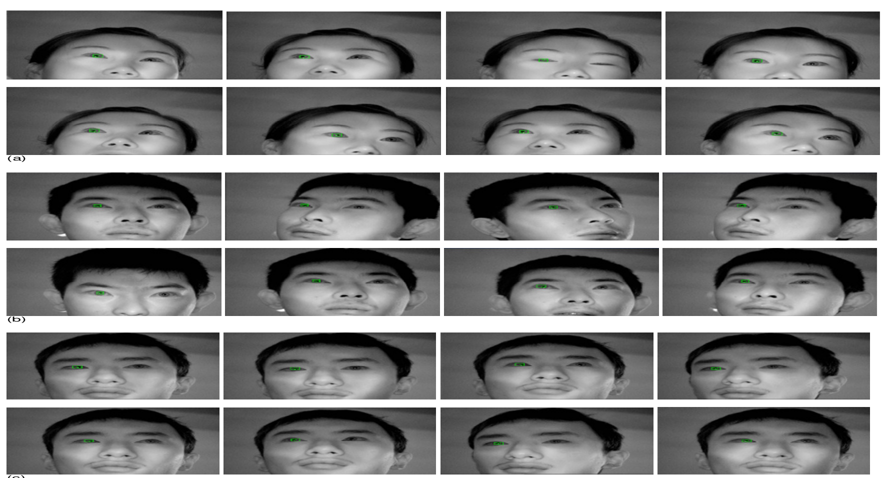


Figure 9. The experiment results of the particle filter tracking method which integrated the gray scale trait and the shape figure. (a) The partial tracking result of the first image sequences. (d) The partial tracking result of the second image sequences. (c) The partial tracking result of the third image sequences. (d) The partial tracking result of the fourth image sequences.

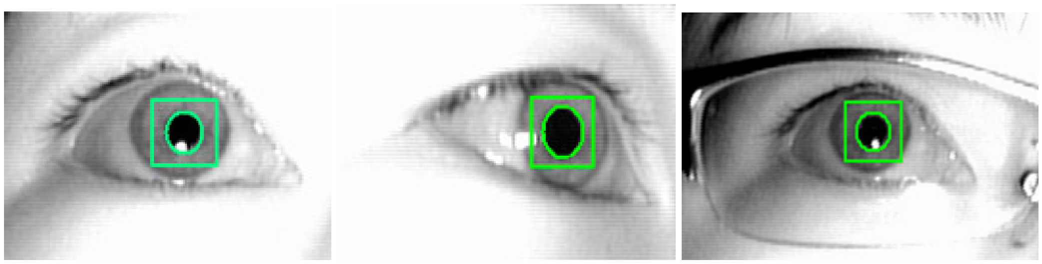


Figure 10. Magnified partial effect of the pupil tracking with our method.

effects of frame 1, 166, 360, 519, 767, 802, 901, and 1000 picked out from the 4 group of image sequences. Figure 10 has shown the magnified partial effect of pupil tracking with the proposed method in this paper.

Conclusion

In this paper, a gaze tracking system is presented based on particle filtering. A single camera and an infrared light source with two concentric rings are used for rapid pupil detection. Target model that can meet the characteristics of the pupil's shape and gray scales, motion function that can effectively predict the pupil's real-time state, observation model that can improve the credibility of the particle weight, are all build in this process. The results achieved by our gaze tracking scheme are promising, and compared with other approaches, our research has been proved to be more validity.

REFERENCES

Eyetech Digital Systems. [Online]. Available: http: //www.eyetechds.com/ Tobii Technology, Danderyd, Sweden. [Online]. Available: http: //www.tobii.se/ LC Technologies Inc., Eye gaze Systems. [Online]. Available: http://www. eyegaze.com/ Applied Science Laboratories [Online]. Available: http://www.a-s-l.com.

Morimoto CH, Koons D, Amir A, Flickner M (2000). Pupil detection and tracking using multiple light sources. Image Vis. Comp., 18: 331–336.

Ji Q, Yang X (2001). Real time visual cues extraction for monitoring driver vigilance. Comput. Vision Syst., 2095/2001: 107-124.

Zhiwei ZHU, Kikuo F, Qiang J (2002). Real-time eye detection and tracking under various light conditions. Eye Tracking Res. Appl., 10: 139-144.

Zhiwei Z, Qiang J (2005). Robust Real-time Eye Detection and Tracking Under Variable Lighting Conditions and Various Face Orientations. Comp. Vision Image Underst., 38(1): 124-154.

Feris RS, Cesar RM, Kruger V (2001). Efficient real-time face tracking in wavelet subspace. IEEE ICCV Workshop Recognit. Anal. Tracking Faces Gestures Real-Time Syst., pp. 113-118.

Hui T, Tuanfa Q, Lin L (2007). Image retrieval based on color texture shape and relevance feedback. Appl. Res. Comp., 24(11): 292-294.

HyungSL, Daijin K (2007). Robust face tracking by integration of two separate trakers Skin color and facial shape. J. Patt. Recognit. Soc., 40(11): 3225-3235.

Dan WH, Riad IH (2007). An improved likelihood model for eye tracking. Comput. Vision Image Underst., 106(2-3): 220-230.

Hansen DW, Pece AEC (2005). Eye tracking in the wild. Comput. Vis. Image Underst. 98(1): 155–181.