Fast Eye Tracking and Feature Measurement using a Multi-stage Particle Filter

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Abstract: Eye trackers – systems that measure the activity of the eyes – are nowadays used in creative ways into a variety of domains: medicine, psychology, automotive industry, marketing etc. This paper presents a real time method for tracking and measuring eye features (iris position, eye contour, blinks) in video frames based on particle filters. We propose a coarse-to-fine approach to solve the eye tracking problem: a first particle filter is used to roughly estimate the position of the iris centers. Next, this estimate is analysed to decide the state of the eyes: opened or half-opened/closed. If the eyes are opened, two independent particles filters are used to determine the contour of each eye. Our algorithm takes less than 11 milliseconds on a regular PC.

1 INTRODUCTION

Eye trackers measure the eye positions and movements and are currently being used in a wide variety of disciplines, including medicine, psychology, marketing research and human computer interaction (HCI).

Over the past decades active research studies were conducted in order to detect and track the eyes, but, despite their apparent simplicity, as humans can detect them with no effort, this proved to be a difficult task. It is quite challenging trying to group the proposed eye tracking methodologies into a single and unitary taxonomy. In (Hansen, 2010) the authors present a detailed survey of the eye models used in recently published eye tracking systems. Eye tracking systems are classified as: *shape* based, *appearance* based and *hybrid* methods.

Shape based methods use a prior geometrical model of the eye and a similarity measure. Such methods often impose a circularity constraint (for the iris or pupil) (Daugman, 2002) and therefore they are only suitable for near-frontal images. Other methods use more complicated models, by also modelling the eyelids ((Yuille, 1989), (Borza, 2016)). Appearance based methods (Sirohey, 2001) use information about the colour distribution and/or filter responses near the eye region to detect and track the eyes. Their main drawback is that they require large amount of training data under different conditions (illumination, pose, occlusions etc.). Finally, hybrid methods combine the previous two approaches in order to overcome their drawbacks (Cristinacce, 2008).

Based on the light source used to track the eyes, the proposed models can be split into *active light models* (Morimoto, 2000) – that use infrared (IR) illuminators and rely on a physical property of the pupil that modifies its appearance in the captured image depending on the position of the IR light source – and *passive light models* – that use the ambient light, in the visible spectrum. A lot of research works have been focusing on active light methods, but their main drawback is that outdoor use of such systems can be problematic because of environmental (extreme light, etc.) conditions.

More recently, particle filters (Isard, 1998) emerged as an efficient method for eye tracking systems, due to their improved performance and adaptability. The approach proposed in (Campos, 2013) relies on a chain of Haar classifiers that enable a fast recognition of the eye regions and on particle filtering for tracking the eyes. The system uses the physical properties and the dynamics of pupils to detect the eye regions. However, this approach only roughly tracks the eye positions, and no information about the eye shape, blinking or iris position is computed.

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Wu (Wu, 2007) proposed a system for simultaneous eye tracking and blink detection. They used two interactive particle filters for modelling the dynamics of open-eye and closed-eye separately: one of them is used for tracking the eye localization by exploiting auto-regression models for describing the state transition and a classification-based model in tensor subspace for measuring the observation. One particle filter tracks the closed eyes and the other one tracks the open eyes. A second-order auto-regression model describes the eye's movement, while a first-order auto-regression model describes the scale transition. The system integrates tensor subspace analysis for feature extraction, while logistic regression is applied for evaluating the posterior probabilities. A more elaborated version of this work was published in (Wu, 2010): the system was integrated into a smart environment that also includes facial features detection and localization.

In (Li, 2010) the eyes are tracked using a deformable eye template which can describe both open and closed eye states that is integrated into a particle filtering framework. The measurement model is based on the contour tracking method that was first proposed in (Isard, 1998), but which was adapted for eye tracking. The main drawback of this work is that the eye corners and the eyelid apexes must be manually marked in the initial frames.

In this paper, we propose a fast method for tracking and measuring the eyes features using a two stage particle filter. Our method robustly detects the iris centers as well as the eye contours. In the first stage, the iris center positions and the eyes orientation are roughly estimated, and in the second stage the eye contours are determined.

The remainder of this paper is organized as follows: in Section 2 we show the outline of the proposed solution and in Section 3 we provide its detailed description. In Section 4 we present and discuss the experimental results. Section 5 shows the conclusions and the proposed future improvements of this work.

2 SOLUTION OUTLINE

The proposed solution uses a coarse-to-fine approach to detect and track multiple features of the eyes: iris centers, eye contour and eye-blinks. The outline of the solution is depicted in Figure 1. The solution uses three particle filters in parallel to track the eyes: the first particle filter is used to coarsely determine the iris positions. Two other particle filters are used to determine and track the contour of each eye based on the estimate obtained from the first one.

The first stage uses a particle filter to roughly estimate the position of the iris centers and the eyes' orientation (angle between the line connecting the two eyes and the horizontal axis). On the first video frame, the particle filter is initialized: the face is detected in the input image and the search space is uniformly covered by randomly generating particles to the entire input space.

The particle filtering algorithm is iteratively run on each frame in order to obtain the rough position of the eyes.

Periodically, the obtained estimate undergoes a validity check: the face is detected in the current frame and we check if the estimated eye positions are located in the approximate area of the eyes (the upper half region of the face). If the estimate is no longer valid, then the tracking is re-initialized from the current frame.

If the estimate is valid, it is analysed in order to determine if it corresponds to an open or to a closed eye.

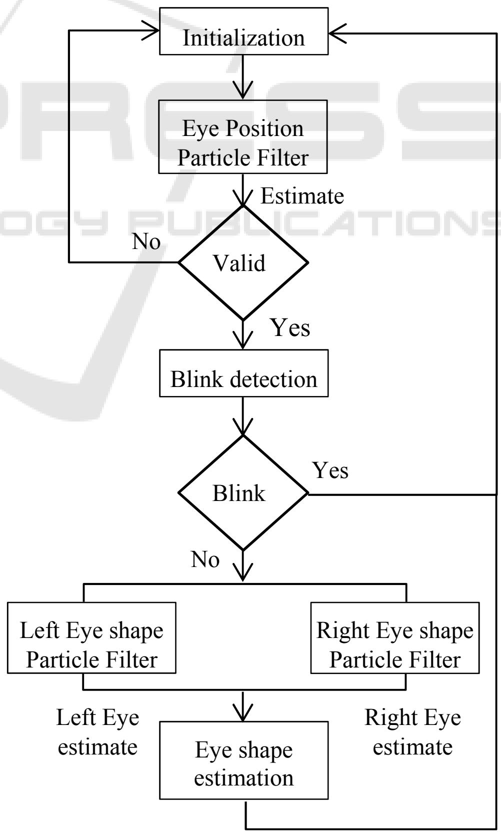


Figure 1: Multistage particle filter.

3 SOLUTION DESCRIPTION

3.1 Particle Filters

Particle filters (bootstrap filters or condensation algorithm) are state estimation techniques usually used for non-Gaussian and multimodal probability distribution functions (*pdf*). Particle filters are applied in object tracking problems, where the state of the systems changes over time and information about the new state are obtained via noisy measurements at each iteration.

The main idea of a particle filter is to represent the posterior probability function by a set of N weighted particles, $P(X) = \{X_i, \pi_i, i = \overline{1, N}\}$, where each particle represents an hypothesis of the object that is being tracked. All the weights are normalized so that they sum up to one.

The filter is an iterative process and it involves the following three steps: *resample*, *predict* and *measure / update*. The particle filter flow is illustrated in Algorithm 1:

```
   BEGIN PARTICLE FILTER ITERATION (P –
particle set)
   RESAMPLE
   -   Compute cumulative sum of
       particle weights CDF
   -   P` ← []
   -   FOR I ← 0: N
       o   r ← rand(0, 1)
       o   k ← 0
       o   WHILE r > CDF[k]
           ▪   k ← k + 1
       o   END WHILE
       o   Insert P[K] into P`
   -   END FOR
   -   Return new weightless particle
       set P`
   PREDICT likelihood of each possible
particle (deterministic drift and
stochastic diffusion)
   MEASURE against the image features
and assign weights to the particles
   END.
```

For the *resampling* step, we perform N random draws with replacement based on the particle weights. Therefore, a particle with a higher weight is likely to be selected multiple times, while a lower weight particle might not be selected at all. After this step, a new set of weightless particles is obtained, with an uneven concentration, which approximates the same *pdf*. In addition, at each iteration, R% of the N particles will be randomly selected by sampling from the uniform probability distribution function in order to ensure that the current estimate does not fall into a local minimum.

Next, in the *prediction* step, the new particle set is modified according to the system's transition. A stochastic diffusion is also applied in order to consider the random events that might influence the system state. In the *measurement / update* state, the posterior probability density function is obtained by simply weighting the distribution of weightless particles (the prior state probability distribution) according to the likelihood of observation.

The estimation $\tilde{S}$ of the tracked object at each time step t can be obtained by simply combining the particles (or a subset of particles) according to their weights:

$$\tilde{S} = \sum_{i=1}^{M} \pi_i s(X_i) \tag{1}$$

, where $s(X_i)$ is the state vector that describes the particle X_i and π_i is the particle weight.

3.2 Eye Position Estimation

In the first stage of the algorithm the eye position is roughly estimated: only the iris centers and the eyes' orientation are determined.

The eye position is fully described by the following state vector (2):

$$\begin{vmatrix} (x_l, y_l) & \text{left iris center} \\ ipd & \text{pupillary distance} \\ \theta & \text{eye orientation} \end{vmatrix} \tag{2}$$

, where (x_l, y_l) is the center of the left eye position, *ipd* is the distance between the left and the right pupil centers and θ is the rotation of the eyes in the frontal plane.

By using this feature vector instead of two simultaneous independent iris trackers, we also include the relationship between the two eyes in the feature vector and we reduce the computational costs.

The particle used model the eye pair is depicted in Figure 2.

3.2.1 Symmetry Transformation

To evaluate the circular symmetry of the irises we used Fast Radial Symmetry Transform (FRST) (Loy, 2003), a simple and fast image transformation which uses image gradients to detect regions of high radial symmetry.

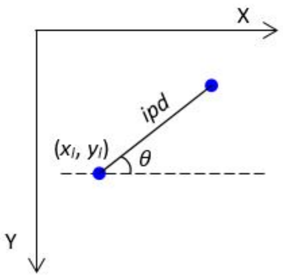


Figure 2: Eye position particle. The iris centers are depicted in blue circles: (x_l, y_l) are the coordinates of the left iris center, *ipd* is the inter-pupillary distance and θ is the rotation angle between eyes.

For each pixel p under consideration, two neighbouring pixels at a distance r away from p are determined: p_+ (the positively affected pixel) or the pixel the gradient is pointing to, and p_- (the negatively affected pixel) or the pixel the gradient $g(p)$ is pointing away from.

$$p_{\pm} = p \pm \mathrm{round}\left(\frac{g(p)}{|g(p)|} r\right) \tag{3}$$

Based on these neighbouring pixels the magnitude projection image M_r and the orientation projection image O_r are formed iteratively (4).

$$\begin{aligned} M_r(p_{\pm}) &= M_r(p_{\pm}) \pm g(p) \\ O_r(p_{\pm}) &= O_r(p_{\pm}) \pm 1 \end{aligned} \tag{4}$$

The radial symmetry transform at radius r is defined by the convolution:

$$S_r = F_r * A_r \tag{5}$$

, where

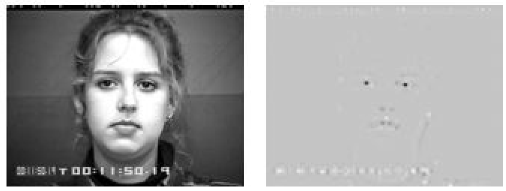
$$F_r = \|\widetilde{O_r}(p)\|^{(\alpha)} \widetilde{M}_r(p) \tag{6}$$

A_r is an isotropic Gaussian smoothing kernel used to spread the symmetry contribution, and $\widetilde{O_r}$ and $\widetilde{M_r}$ are the normalized orientation and magnitude projection images.

The full transform S is computed over a set of radii:

$$S = \sum_r S_r \tag{7}$$

The radial symmetry was tuned so that only dark symmetrical regions are found, as the iris and pupil area are darker that the surrounding neighbourhood: only the negatively affected pixels (p-) were used to update the images O_r and M_r. The search radii for the iris were determined based on the canonical facial proportions. Figure 3 shows the symmetry transformation for a grayscale input image.



(a) (b)

Figure 3: Symmetry transform image. (a) Grayscale image; (b) Corresponding symmetry transformation. Darker regions correspond to areas that have a high circular symmetry.

The measurement probability of the i[th] particle X_i is defined as:

$$\pi_i = \frac{1}{(\sqrt{2\pi}\,\sigma)^2} e^{-\frac{S(xl,\,yl)+S(xr,\,yr)}{2\sigma^2}} \tag{8}$$

where $S(x_l, y_l)$ is the value of the symmetry transform image in the hypothetical left iris center and $S(x_r, y_r)$ is the value of the symmetry transform image in the hypothetical right iris center. This weight indicates how much the current estimate matches the ground truth location of the eyes.

The particle filter iterations, resample, predict and measure are iteratively applied on each frame.

The eye position at each frame is estimated by splitting the particle set into several disjoint-set data sets (Cormen, 2001) based on the iris positions and orientation. The set that contains the particles with the highest average score is selected, and the estimate is computed by taking the weighted average of all the particles that belong to this set (1). We preferred this approach, rather than a simple weighted average of the best particles, because the orientations of the eye hypotheses can have different signs and by adding positive and negative numbers the orientation contributions can be lost.

Next, the current estimate is analysed to determine whether the eye is closed or not. To make this decision, we used the following constraint: we presume that the eyes are opened in the first frames of the video sequence and we "learn" a threshold for the open eyes by averaging the weights of the first $L = 7$ frame estimates. As the first particle filter, roughly estimates the iris centers, we argue that the symmetry of the iris is not observable when the eye is (semi-)closed.

After learning this threshold (from the $(L + 1)^{th}$ frame) we compare the estimate score with this threshold; if its score is lower than this threshold we assume that the eye is closed. Otherwise, the eye is considered to be opened.

Figure 4 shows the tracking result in some blink and half-closed eyes cases.

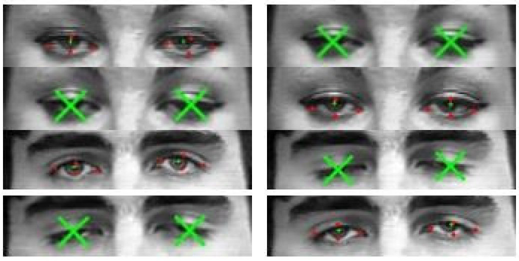


Figure 4: Tracking results in case of blinking and eye closure. The iris centers are marked with green crosses and the eye landmarks (eye corners and eyelid apexes) are marked in red circles. In the case of blinking, two green Xs are drawn over the eye area.

The main drawback of this simple procedure is that it is sensitive to illumination changes and it is based on a constraint (the image sequence must begin with the eyes open) that cannot always be fulfilled.

3.3 Eye Shape Estimation

Following the approximation of the iris position, if the eye is open, we proceed to the estimation of the eye contour.

The eye contour particle (Figure 5) is defined by the following state vector (8):

$$\left|\begin{array}{cc} (x\,,y) & \text{eye center} \\ w & \text{eye width} \\ h & \text{eye height} \\ \alpha & \text{eye orientation} \\ d_{corners} & \text{corners y distance} \end{array}\right| \quad (9)$$

(x, y) are the coordinate of the center of the eye, w and h are the eye width and height respectively, α is the eye orientation and $d_{corners}$ determines the vertical position of the eye corners (as a percent of the eye height h) starting from the lower eyelid apex. Using this deformable template model we can model the eyes in both open and closed states (the eye is closed or half closed if the height of the eye is close to 0).

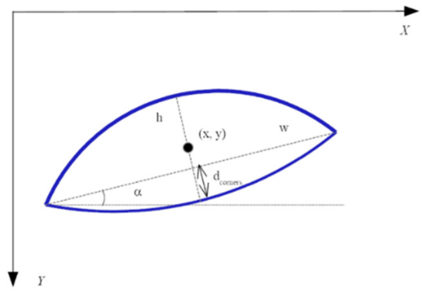


Figure 5: Eye shape particle visual representation. The eye contour is represented by the blue parabola. The point (x, y) is the centroid of the eye shape, α is the orientation of the eye, $d_{corners}$ is the vertical position of the eye corners, and w and h are the eye width and height, respectively.

By using a two stage approach (first we determine the approximate eye position and then we use independent trackers for the eye contour) we reduce the computational cost of the algorithm. The main bottleneck of the particle filter is the measurement/update phase; by using a simplified eye model to find the position of the eyes and two independent particle filters to determine the shape of the eyes the measurement function can also be significantly simplified.

3.2.1 Distance Transformation

Distance transform or distance map is a representation of a binary image, in which each pixel indicates the distance to the nearest object/obstacle point. Figure 6 shows the Canny edge map for an eye image and the corresponding distance transformation.

(a) (b)

Figure 6: (a) Canny edge map. (b) Distance transformation.

This image representation can be used to determine the degree to which an objects fits an input image by simply superimposing the contour of the object over the distance transformation and adding the pixels values that lies under the contour:

$$D_{edge} = \frac{1}{|\Omega|} \sum_{(x,\,y) \in \Omega} DT(x, y) \quad (10)$$

, where $|\Omega|$ is the length of the contour of the eye Ω and $DT(x, y)$ is the value of the pixel in the distance transform map at coordinates (x, y).

To compute the eye contour estimate, we select the fittest $\varepsilon = 0.3 \times N$ particles (P) and combine them into a weighted average according to their weights:

$$\tilde{S} = \frac{\sum_{X_i \in P} \pi_i s(X_i)}{\sum_{X_i \in P} \pi_i} \tag{11}$$

, where $s(X_i)$ is the state vector of the i^{th} particle X_i and π_i is the weight of that particle.

4 EXPERIMENTAL RESULTS

The proposed solution was tested both on video frames captured in our lab and on image sequences from the publically available Extended Cohn-Kanade database ((Kanade, 2000), (Lucey, 2010)).

The Extended Cohn-Kanade database (ck+) contains 593 image sequences from 123 individuals of different races and ages (18 – 50 years) which perform various facial expressions. The subjects were asked to perform a set of 23 facial displays; each image capturing session begins and ends with a neutral display. The images have 640x480 or 640x490 pixels resolution.

The eye tracking method is implemented in C++ and all the experiments were performed on a PC with a 4th generation Intel Core i7 processor (2.4 GHz).

In our experiments, the particle filter used to determine the iris center and the orientation of the eye uses N = 200 particles, and each one of the two particle filters used to find the shape of the eye uses N = 200 particles.

The average execution time of the proposed solution is, in average, less than 11 milliseconds on 640x480 face images on a 4th Generation Intel i7 CPU.

Several tracking results are shown in Figure 7.

We used two metrics to evaluate the performance of the proposed solution: the Euclidian distance D between the estimated eye landmarks and their real location and normalized Euclidian distance $\widetilde{D}$. By normalizing the errors we obtain a numerical value of the error that is independent of the image resolution.

Table 1 shows the performance results on the Extended Cohn-Kanade database. In the case of eye corners and eyelid apexes the Euclidian distance is normalized with the average width of the eye, and in the case of iris centers the metric is normalized with the inter-pupillary distance.

Table 1: Average errors on the Extended Cohn-Kanade (ck+) database.

Feature	**D (pixels)**	**$\widetilde{D}$ (%)**
Temporal eye corner	4.88	0.11
Nasal eye corner	6.42	0.14
Upper eyelid apex	3.15	0.07
Lower eyelid apex	2.69	0.06
Iris center	5.3	0.05

Figure 8 and 9 show the ROC curves for the eye corners and the eyelids apexes, respectively.

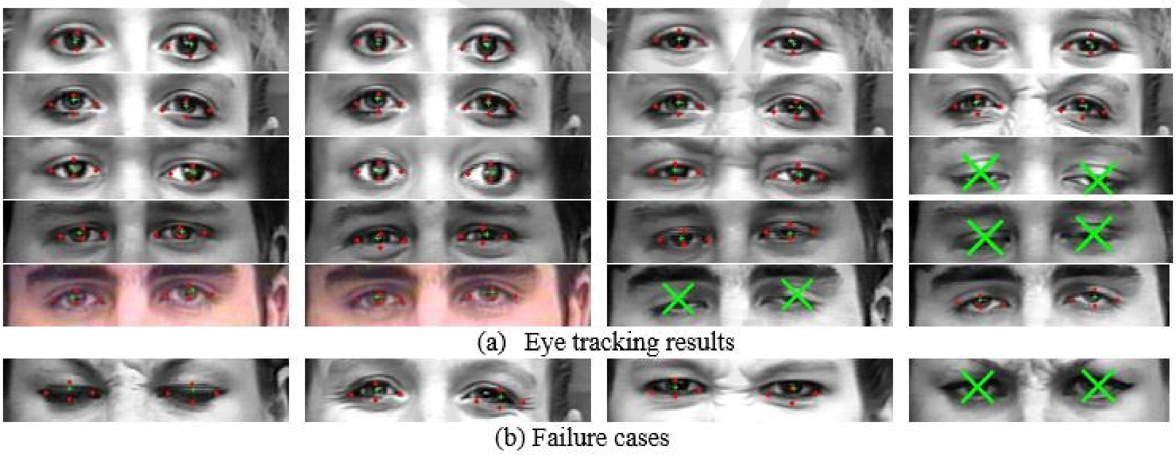


Figure 7: Eye tracking results and failure cases. The eye landmarks (eye corners and eyelid apexes) are depicted in rec circles and the iris center is marked in with a green cross. When the eye is detected as closed, the eyes are marked with a green X sign.

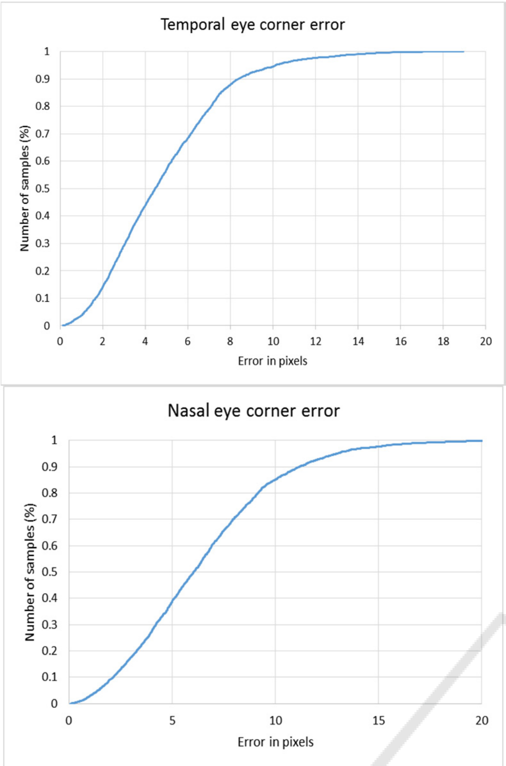


Figure 8: Cumulative error distribution for the eye corners.

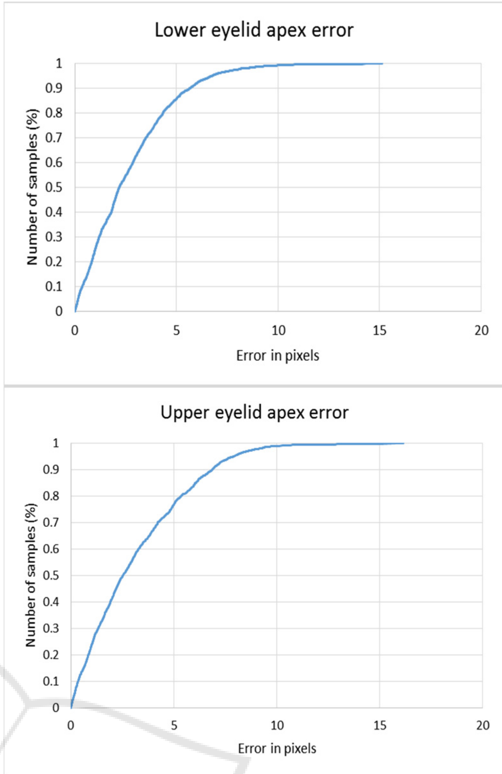


Figure 9: Cumulative error distribution for the eyelid apexes.

In the rest of this section, we will compare the proposed methods with other works published in the specialized literature.

In (Campos, 2013) the eye tracking is performed using two particle filters for each eye, where one particle filter estimates the x position and other one the y position of the eye. However, the algorithm only outputs the location of the eyes as a circle with a (x, y) position; it doesn`t give any information about the iris position, blinks or eye shape. The runtime of the algorithm is not specified in the manuscript, only that "the eyes are detected in real-time video images" (Campos, 2013).

(Wu, 2007) proposed a method to simultaneously track the eyes and detect blinking. Two particle filters are used: one particle filter tracks the closed eyes and the other one the open eyes. The particle set with the highest confidence is used to detect the eyes position and their state (open or closed). This work estimates only the bounding rectangle of each eye.

In (Li, 2010) the eyes are tracked using a deformable model of the eyes and a particle filter. This method outputs information about the eye shape and can track the eyes even when they are closed by including three eye states (open, half-closed and closed) in the eye model.

However, this method tracks only the contour of the eye, without the iris center. Our method also tracks the irises. The root mean square error of the method proposed in (Li, 2010) was computed on an image sequence with 950 frames where the width of a single eye region is approximately 32 pixels. The reported error is on average 4 pixels; the error is approximately 12.5% of the eye width.

We tested our method on the Extended Cohn-Kanade database, where the mean eye width is about 50 pixels and obtained an average error of 4.29 pixels (9.73% of the eye width), which is at least comparable if not better with the one obtained by (Li, 2010). In addition, in (Li, 2010) "for initial frames, the locations of the eye corners and the apexes of eyelids are manually marked". Our method does not involve any manual initialization.

5 CONCLUSIONS

In this paper, we present a fast multi-stage particle filter framework to detect and track multiple eye features: iris centers, blinks, eye contours. The method uses a coarse-to-fine approach to find all these features: first, a simple particle filter is used to approximate the iris center positions and the eye orientation. Next, a simple threshold of the score of this estimate is used to decide whether the eye is closed or not. If the eyes are open, two particle filters are updated and used to estimate the full contour of the eye. The algorithm runs in less than 11 millisecond on a regular PC.

The method is robust to short time eye occlusions and it can detect and track the human eyes without any type of manual initialization, camera calibration or user preregistration.

As a future work, we plan to improve our eye blink detection method. The current method, the simple thresholding of the iris particle estimation, is not very robust and can be strongly influenced by illumination changes. We intend to train a classifier, for example, a support vector machine (SVM), to decide whether the eye is closed or not.

Another improvement will involve using optical flow in order to guide the particle filters, by updating the state changes of the eyes.

The performed experiments demonstrate the effectiveness of the proposed solution under different facial expressions and illumination conditions.

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