

PARTICLE FILTERING BASED AUTOMATED IRIS TRACKING AND BLINK DETECTION

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ABSTRACT

Eye blinking is a physiological necessity for humans. This system is intended to provide an alternate input modality to allow people with severe disabilities to access a computer. The system is efficient for Human Computer Interface (HCI) that can detect and track the human eyes. It can also capture the eye blinks and duration of the blinks, using them to provide input to the computer in the form of a mouse click. The system consist of mainly three phases eye detection, blink detection and eye tracking .The system is capable to work under variable lightning conditions and several different face orientations in a real-time sequence of images. The system is designed for use by people that are severely paralyzed. The system works with inexpensive USB cameras and runs at a frame rate of 30 frames per second.

Keywords—*Hci, Eye Detection, Eye Tracking, Blink Detection, Template Creation , Particle Filters*

I. INTRODUCTION

The motivation for the system proposed here is to provide an inexpensive ,unobtrusive means for disabled people to interact with simple computer applications in a meaningful way that requires minimal effort.The eye detection stage uses an automatic initialization phase triggered by the analysis of involuntary blinking of the current user of the system which creates an online template of the eye to be used for tracking.This phase occurs each time the current correlation score of the tracked eye falls below a defined threshold in order to allow the system to recover and regain its accuracy in detecting the blinks.The eye tracking is a mechanism for finding and tracking human eye in a set of real time images.The process of tracking human eye can be used to estimate the direction of interest of the eye gaze.Eye tracking can be applied to a wide variety of areas including human vigilance, driver fatigue detection and assisting people with any type of disability.The eye tracking is implemented through the use of particle filters.that are under variable lightning conditions.The detection and analysis of blink duration is based on observation of correlation scores.As the users eyes closes during the process of a blink its similarity to the open eye decreases.It regains its similarity to the open eye as the blink ends and the users eye becomes fully open again.

II. RELATED WORKS

To detect the eyes and to track the eyes several methods are there:

2.1 Eye Detection Methods

During the last years an iterative thresholding [1] algorithm was there to detect the eye regions on a human face. This method is robust under variable lightning conditions and without any marks in the user's face. Another method to detect human eyes is using Mean shift [2]. This method detects facial features through image processing techniques and then separates eye from the face.

For eye detection cascaded Haar classifiers [3] can also be used, proposed by Viola and Jones. The main principle behind Haar classifier object detection is the Haar-like features. Haar-like features can be used to detect and recognize specific features in facial images such as nose and eyes. The cascading of the classifiers allows that the detection system only selects the main points of interest in an image that have highest probability to be defined for all Haar-features that constitute an object. To train the classifiers are used two different set of images defined as negative and positive images. Positive images contain the objects to be detected, here the faces and the eyes. Negative images do not contain the objects that we are interested in their detection.

2.2 Eye Tracking Methods

Detection and tracking of the human eye is a complex task and normally the existing eye tracking system has a high cost and requires high computational resources. A method for gaze tracking using neural networks [4] was proposed earlier. Results demonstrate that neural networks can be successfully applied in the estimation of the position of the eye gaze using as input a sequence of people images. Kalman filtering [5] and Mean shift tracking can be also used for eye tracking. The eye tracking system is fast on the control of the eye movements, automated and it needs small computational requirements. A discrete Kalman filter is developed for the recursive estimation of the eye regions. Its application allows encompass the system information and the measurement noise in its dynamics model, and deal with signals that change with time.

III. SYSTEM ARCHITECTURE

This system mainly consist of three parts

- Eye Detection
- Blink Detection
- Eye Tracking

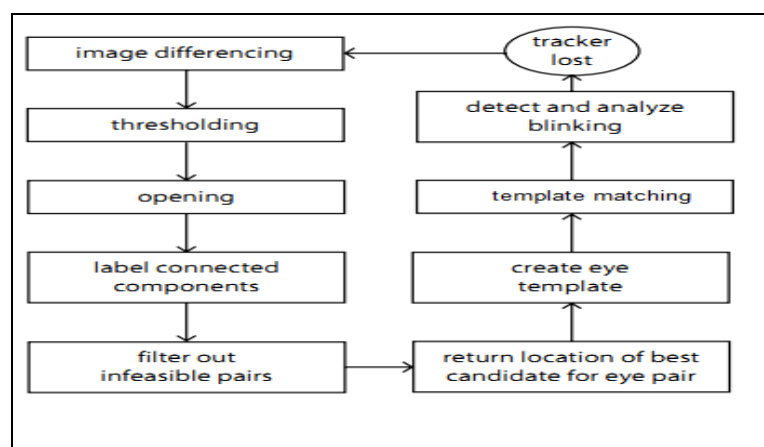


Fig 1: Overview of Main Stages of the System

3.1 Eye Detection

The eye detection technique used in this system is based on the online creation of a template of the open eye to be used for the subsequent tracking and template matching that is carried out at each frame. The first step in analyzing the blinking of the users is to locate the eyes. It mainly consist of two steps.

- Automatic Initialization
- Template Creation
- Template Matching

3.1.1 Automatic Initialization

To locate the eyes the difference image of each frame and the previous frame is created and then thresholded, resulting in a binary image showing the regions of movement that occurred between the two frames. To eliminate a great deal of noise and naturally-occurring jitter that is present around the user in the frame due to the lighting conditions and the camera resolution, as well as the possibility of background movement an Opening Morphological operation [6] is used. For that a 3x3 star-shaped convolution kernel is passed over the binary difference image. this Opening operation also produces fewer and larger connected components in the vicinity of the eyes (when a blink happens to occur).

A recursive labeling procedure is applied next to recover the number of connected components in the resultant binary image. Under the circumstances in which this system was optimally designed to function, in which the users are for the most part paralyzed, this procedure yields only a few connected components, with the ideal number being two (the left eye and the right eye). If other movements occurred it will produce a larger number of components then the system discards the current binary image and waits to process the next involuntary blink in order to maintain efficiency and accuracy in locating the eyes.

For an image with a small number of connected components output from the previous processing steps, the system is able to proceed efficiently by considering each pair of components as a possible match for the user's left and right eyes. The filtering of unlikely eye pair matches is based on the computation of six parameters for each component pair: the width and height of each of the two components and the horizontal and vertical distance between the centroids of the two components. A number of experimentally-derived heuristics are applied to these statistics to pinpoint the exact pair that most likely represents the user's eyes. If there is a large difference in either the width or height of each of the two components, then they likely are not the user's eyes. Also if there is a large vertical distance between the centroids of the two components, then they are also not likely to be the user's eyes, since such a property would not be humanly possible. These observations not only lead to accurate detection of the user's eyes, but also speed up the search greatly by eliminating unlikely components immediately.

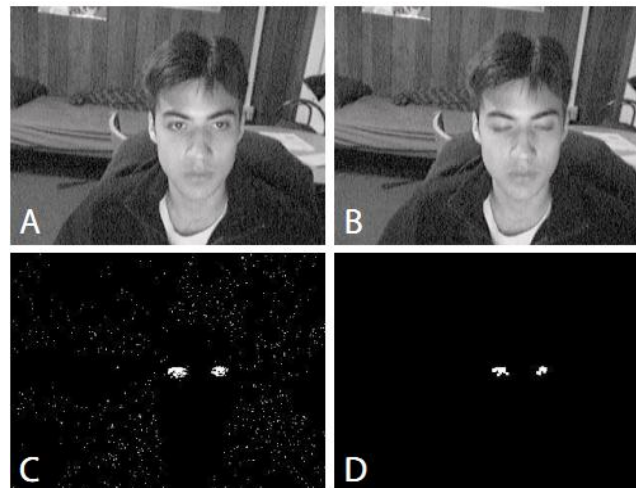


Fig 2: Formation of Connected Components through Frame Differencing and Result of Opening

Operation (A) User at frame f . (B) User at frame $f+1$, having just blinked. (C) Initial difference of the two frames f and $f+1$. Note the great deal of noise in the background due to the lighting conditions and camera properties. (D) Difference image used to locate the eyes after performing the Opening operation.

3.2 Template Creation

The results from the previous stage that passes the set of filters then it is a good indication that the user's eyes have been successfully located. The location of the larger of the two components is chosen for creation of the template. The size of the template that is to be created is directly proportional to the size of the chosen component, the larger one is chosen for the purpose of having more brightness information, which will result in more accurate tracking and correlation scores.

The system will be tracking the user's open eye, it would be a mistake to create the template at the instant that the eye was located, since the user was blinking at this moment. Once the eye is believed to be located, a timer is triggered. After a small number of frames elapse, which is judged to be the approximate time needed for the user's eye to become open again after an involuntary blink, the template of the user's open eye is created. Therefore, during initialization, the user is assumed to be blinking at a normal rate of one involuntary blink every few moments. No offline templates are necessary and the creation of this online template is completely independent of any past templates that may have been created during the run of the system.



Fig 3: Open Eye Templates from Very Small To Large In Overall Size

3.3 Template Matching

Template matching is necessary for the desired accuracy in analyzing the user's blinking since it allows the user some freedom to move around slightly. The primary purpose of such a system is to serve people with paralysis, it is a desirable feature to allow for some slight movement by the user or the camera that would not be feasible if motion analysis were used alone. To perform the template matching the normalized correlation coefficient is computed using the formula:

$$\frac{\sum_{x,y} [f(x,y) - \bar{f}_{u,v}] [t(x-u, y-v) - \bar{t}]}{\sqrt{\sum_{x,y} [f(x,y) - \bar{f}_{u,v}]^2 \sum_{x,y} [t(x-u, y-v) - \bar{t}]^2}}$$

where $f(x,y)$ is the brightness of the video frame at the point (x,y) , $\bar{f}_{u,v}$ is the average value of the video frame in the current search region, $t(x,y)$ is the brightness of the template image at the point (x,y) , and \bar{t} is the average value of the template image. The result of this computation is a correlation score between -1 and 1 that indicates the similarity between the open eye template and all points in the search region of the video frame. Scores closer to 0 indicate a low level of similarity, while scores closer to 1 indicate a probable match for the open eye template. A major benefit of using this similarity measure to perform the tracking is that it is insensitive to changing lighting conditions.

This method requires an extensive amount of computation and is performed 30 times per second, the search region is restricted to a small area around the user's eye. This reduced search space allows the system to remain running smoothly in real time since it drastically reduces the computation needed to perform the correlation search at each frame.

3.4 Blink Detection

The detection of blinking and the analysis of blink duration are based solely on observation of the correlation scores generated by the template matching[7] at the previous step using the online template of the user's eye. As the user's eye closes during the process of a blink, its similarity to the open eye template decreases. Likewise, it regains its similarity to the template as the blink ends and the user's eye becomes fully open again. This decrease and increase in similarity corresponds directly to the correlation scores[7] returned by the template matching procedure. Close examination of the correlation scores over time for a number of different users of the system reveals rather clear boundaries that allow for the detection of the blinks. As the user's eye is in the normal open state, very high correlation scores of about 0.85 to 1.0 are reported. As the user blinks, the scores fall to values of about 0.5 to 0.55. Finally, a very important range to note is the one containing scores below about 0.45. Scores in this range normally indicate that the tracker has lost the location of the eye. In such cases, the system must be reinitialized to relocate and track the new position of the eye.



Fig 4: Sample frames of a typical session: (A) The system is in this state during themotion analysis phase.

The red rectangle represents the region that is considered during theframe differencing and labeling of connected components.(B) The system enters this state once the eye is located and remains this way as long as the eye is not believed to be lost. The green rectangle represents the region at which the open eye template was selected and the red rectangle now represents the drastically reduced search space for perform-ing the correlation. (C) User at frame f , with eyes alreadyclosed for the defined voluntary blink duration and (D) user at frame $f + 1$, opening his eyes, with a yellow dot being drawn on the eye to indicate that a voluntary blink just occurred.

The system detects voluntary blinks by using a timer that is triggered each time the correlation scores fall below the threshold of scores that represent an open eye. If the correlation scores remain below this threshold and above the threshold that results in reinitialization of the system for a defined number of frames that can be set by the user, then a voluntary blink is judged to have occurred, causing a mouse click to be issued to the operating system.

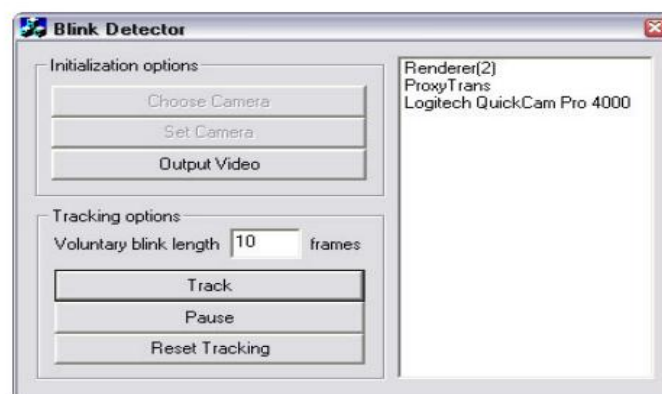


Fig 5: System Interface

3.5 Eye Tracking

For Eye tracking a particle filtering approach is used. Particle filters are sequential analogues of Markov chain Monte Carlo (MCMC) batch methods. They are also known as Sequential Monte Carlo (SMC) methods.

Particle filters are widely used in positioning, navigation, and tracking for modeling dynamic systems. The basic idea of particle filtering is to use point mass, or particles, to represent the probability densities. The tracking problem can be expressed as a Bayes filtering problem, in which the posterior distribution of the target state is updated recursively.

3.5.1 Particle Filters

Bayesian algorithms define an effective framework to deal with dynamic state estimation problems. Bayes filters are applied in the problem of estimating the state of a dynamical system using all available sensory information. The main aim of Bayesian approach consists in recursively estimate the posterior Probability Density Function (PDF) over the state space based on all obtained data. The main aim of particle filtering is to track the behavior of a variable of interest over time. During the last years, particle filters have been applied with great success to several different real world estimation tasks such as visual tracking, speech recognition and mobile robotics.

Particle filters operation relies on the estimation of the posterior probability density over the state space of a dynamic system from sensor information [8]. The goal consists in the representation of probability densities through sets of samples, or particles. One of the main advantages of particle filters is their capacity to approximate a wide range of probability distributions, not just normal distributions as Kalman filters. Particle filters are a variant of Bayes filters, that recursively estimate posterior densities of the state space of a dynamic system :

$$\text{Bel}(x_t) \propto p(z_t|x_t) \int p(x_t|x_{t-1}, u_{t-1}) \text{Bel}(x_{t-1}) dx_{t-1}$$

In the previous equation x_t is the state of the dynamic system, z_t is a sensor measurement and u_{t-1} defines control information that represents the dynamics of the system. The beliefs and the motion model is defined by p . The most basic particle filter can be viewed as a direct formalization of the Bayesian filter. This simple algorithm is normally called the Sampling Importance Resampling (SIR) filter [9]. SIR filter is a Monte Carlo method that can be applied to recursive Bayesian filtering problems. This is the classic particle filtering algorithm where importance sampling is applied. The main requisites of this particle filter consists in the possibility of the likelihood function to be evaluated and that the states can be simulated.

In this work an SIR particle filter is used to track the movements of the eyes. Particle filter is suitable for pupil tracking because variations in pupil position are fast and do not have a specific and particular pattern. On the other hand, the use of particle filters in real-time video images may require a large number of particles to improve the accuracy of the system. However, the use of high sets of particles increase the computational requirements and is necessary to find a consistent number of particles which ensures the proper operation of the eye tracking system.

3.5.2 Eye Dynamics Model

A dynamic system can be described by two mathematical models. One is the state-transition model, which describes the system evolution rules, represented by the stochastic process. The other one is the observation model, which shows the relationship between the observable measurement of the system and the underlying hidden state variables. The dynamic system is observed at discrete times t via realization of the stochastic process.

The state of the eye region is defined as a circle with position (x,y) in pixels. The state vector to be estimated is:

$$X=(x,y)$$

where x and y are the coordinates, in pixels, of the position of the eye in the real-time video image. The movements of the eyes can be very fast, therefore we only model the eye position and not its acceleration or velocity. The used dynamical model is defined as:

$$X_{t+1}=X_t+v_t, v_t\sim N(0,\sum_t)$$

Where \sum_t defines the covariance matrix of the gaussian noise v_t at each instant of time t. The state X_t of the system can store the coordinates x or y that define the position of the eye in the image. We include time dependence because size changes may vary the movements of the eye region. Through this dynamics model we estimate the position x and y of the eye in the image.

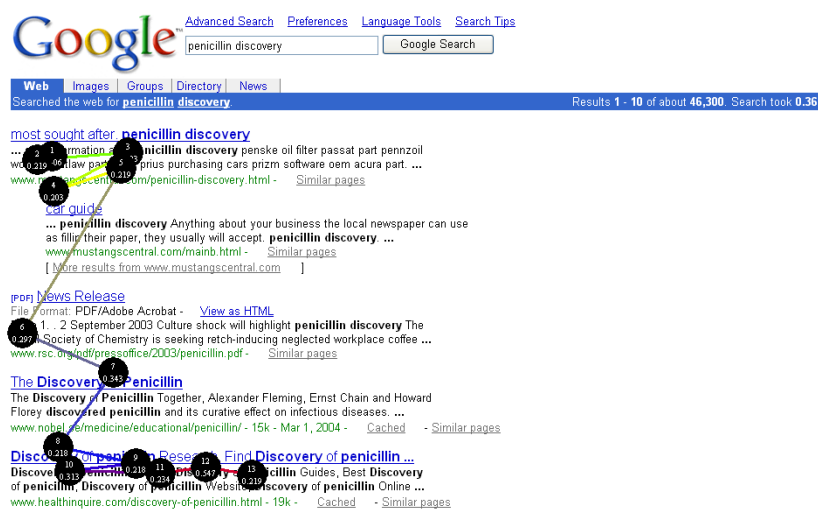


Fig 6: Eye Tracking Results

IV . ADVANTAGES

Eye Tracking adds detailed, quantitative data to the usability testing process. We are no longer limited to just general measures (e.g. success rate, errors) or subjective feedback (e.g. comments and ratings). Rather, we can pair traditional usability findings with Eye Tracking data to gain a fuller understanding of the effectiveness of an interface's design and content. This type of technology will have a big impact in computing. The research above will allow users to effectively research on what areas people focus. This can help when developing websites or displaying information. Eye tracking is a valuable yet cost-effective addition to any usability testing and compliments task-based observation methods well. Eye Tracking can tell whether users are looking at the screen, reading information or scanning information. It can also show the intensity of the user's attention and can determine whether a user is searching for specific information.

- Eye movement is faster than other current input media.
- No training or particular coordination is required of normal users.
- Can determine where the users interest is focused automatically.
- Robust against different lightning conditions.

- It is helpful for people having disabilities to interact with the computer.
- It can be used in android phones for a user friendly interaction.
- No calibration is required for many applications.

V. CONCLUSION

With the rapid advancement of technology and hardware in use by modern computers, the proposed system could potentially be utilized not just by handicapped people, but by the general population as an additional binary input. Higher frame rates and finer camera resolutions could lead to more robust eye detection and tracking that is less restrictive on the user, while increased processing power could be used to enhance the tracking to more accurately follow the user's eye and recover more gracefully when it is lost. The ease of use and potential for rapid input that this system provides could be used to enhance productivity by incorporating it to generate input for a task in any general software program. As the system is robust under variable lighting conditions this can be used in any circumstances.

VI. ACKNOWLEDGEMENT

I am highly indebted to Mr. Gopu Darsan for the guidance and constant supervision as well as for providing necessary information regarding this work and also for the support in completing the work. I would like to express my gratitude towards my parents and friends for their kind co-operation and encouragement which help us in completion of this work.

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