# Eye Movement Biometrics on Wearable Devices: What Are the Limits?

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## Abstract
This paper presents a preliminary study on the perspectives of eye movement biometrics on wearable devices, e.g. the Google Glass. In such devices, the reduction in power consumption is of utmost importance, and can be partially achieved by reducing of the size of the imaging sensor used for eye-tracking. For this reason, we initially explore the interrelationship between the resolution of the captured eye images and the resulting eye-tracking precision, and then, we simulate the effects from varying the level of eye-tracking precision on the performance of eye movement biometrics. The evaluation results provide an important insight towards the biometric performance potential in resource constrained systems.

## Author Keywords
Eye-image resolution; eye-tracking precision; eye movement biometrics;

## ACM Classification Keywords
H.5.2. [User Interfaces] - Input devices and strategies - Evaluation/methodology, K.6.5 [Security and Protection] - Authentication.

## Introduction
Modern computing systems like smartphones and cloud storages contain increasingly large amounts of sensitive

information about a person. Although several steps have been implemented for protecting the security of personal data from intrusion threats there are still some thorny issues. For example, even when a log-in session is opened with a secure scheme, it remains still vulnerable to intrusion attempts known as 'hijacking' attacks [1], where the attacker attempts to gain access to a system after a genuine user has logged-in. A continuous verification scheme based on biometric cues can provide an effective countermeasure against the 'hijacking' attacks. To this context, eye movement biometrics offer great prospects for the creation of highly secure applications due to the unobtrusive nature of the recording procedure and the inherent counterfeit resistance [2].

Previous research has demonstrated that it is possible to build a video-based eye tracker using an unmodified compact mobile device with a webcam [3, 4]. Thus, it can be hypothesized that wearable devices like the Google Glass can also be used for the creation of eye-tracking applications that would provide continuous security screening during the connection of the users to their private data. Our work examines this hypothesis by practically exploring the issues related to the implementation of an eye-tracking biometric application in mobile/wearable devices. In such devices, the requirements of low power consumption place certain limitations on the computational processing budget. For video-based eye-tracking applications, one of the most important aspects dictating the power consumption is the sensor resolution of the eye-tracking camera. Thus, we were motivated to investigate the relation between the eye imaging parameters and the resulting eye-tracking precision, and their effects on the resulting eye movement biometric performance.

Our contribution can be summarized as follows:

1) We explore the impact of low image resolution on the resulting eye-tracking precision using a low-cost eye-tracker based on open source software.

2) We evaluate the effects of degradation in eye-tracking precision (for different sampling rates) on the biometric verification performance of a state-of-the-art eye movement biometrics algorithm [5].

## Previous Work

In an attempt to increase the affordability of eye-tracking systems several efforts in the past explored the possibility of performing eye-tracking using low resolution images via a low-cost basic setup of an IR light source and a low-resolution webcam [6, 7]. The attempts for creating such low-cost solutions were further facilitated by several projects offering open-source eye-tracking software, e.g. the ITU GazeTracker [8]. Whereas the technical specifications of commercial eye-trackers are usually well-documented, an eye-tracking setup based on open-source software and third-party hardware needs to be evaluated to determine its exact technical characteristics. In the past, there were studies examining methods for the general evaluation of parameters such as the calibration accuracy and eye-tracking precision, and their relation to the data quality of eye-trackers [9].

In the field of eye movement biometrics, the eye-tracking precision is of crucial importance since it can affect the exact values of the extracted features. Previous research on eye movement biometrics [10] has shown that both the eye-tracker precision and the sampling frequency can affect the biometric recognition performance considerably.

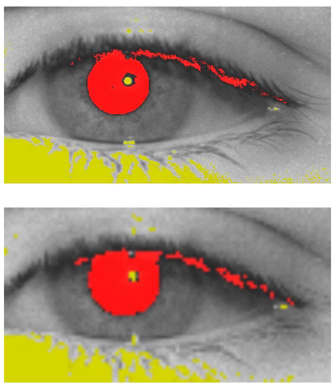


**Figure 1** *Detection of pupil and corneal reflection regions in eye images of high (left) and low (right) resolution.*

## Methodology

Our experimental methodology involved two separate parts. First, we employed a low-cost eye-tracking solution suitable to assess the results from reduced image resolution on the eye-tracking precision. Then, we used a high-grade eye-tracking device to evaluate the effects from the simulated degradation in precision on the biometric performance for a large database of 100 subjects.

*Image Resolution versus Eye-tracking Precision*

THEORY

The typical video-based eye-tracking setup includes an infrared (IR) camera and an IR light, a computing module, and a visual stimulus display. The eye is illuminated by the IR source, and eye images are captured by the camera. The images are processed using computer vision algorithms to locate the regions representing the pupil and the corneal reflection (CR). In our approach, the computing module calculates the centers of mass for these two regions and uses an interpolation scheme (based on an initial calibration process) to translate the differences of the pupil and the CR centers into the respective gaze positions. We used a typical 9-point calibration setup (see [11]). The calibration accuracy is defined as the error between the actual positions of the calibration points and the measured gaze positions. In our experiments, we evaluated the calibration quality by measuring the average calibration accuracy over the 9 points.

Since the resolution of the camera can affect the representation of the pupil and the CR in the images, it can also affect the detection accuracy of their centers of mass and the estimated gaze positions. In Figure 1, we show examples of the detected pupil and CR regions in high and low resolution images.

*Iris-diameter resolution*: The intra-subject eye variations and the exact eye positioning can affect the apparent size of the eye in an image. Thus, we opted to use the resolution of the iris-diameter in the images as a more stable measure for exploring the effects of image resolution on the eye-tracking precision.

*Precision*: The precision is a measure of the spatial variability of the eye-tracking samples when the eye fixates on a stationary point. In this work, the precision is calculated as the root mean square (RMS) of the inter-sample angular distances [9]:

$$\theta_{RMS} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\theta_i^2}$$

where $n$ is the number of samples, and $\theta$ the Euclidean distance of two consecutive samples (in degrees).

PARTICIPANTS

The experiments for the first part were performed with 12 subjects (9 males/3 females), ages 22-30 (M = 24 years, SD = 2.2). Texas State University's institutional review board approved the study, and subjects provided informed consent.

APPARATUS AND SOFTWARE

The camera used for eye-tracking purposes was a Thorlabs DCC1545M monochrome camera with Navitar MVL7000 tele-photo lens. The camera was set up to record the left eye at the resolution of 640 x 348 pixels to achieve sampling rate of 125Hz. This was selected as the minimal sampling rate for the sufficient recording of several saccadic characteristics. The eye-tracking algorithm was based on the ITU GazeTracker open-source software suitably modified for supporting a stream of images captured at 125 Hz. The software ran on a Dell workstation (Intel Core 2 Quad D9400 2.66Hz CPU, 8 GB RAM, Windows 7). The visual stimulus was presented on a computer display with dimensions of 358 x 286 mm and resolution of 1280 x 1024 pixels, placed at a distance of 540 mm from the subjects' eyes. Subjects' eyes were aligned to the screen center.

#### EXPERIMENTAL PROCEDURE

The experiments were implemented using both real eye and artificial eye (provided by SR Research) recordings. This procedure is supported by previous research [12], considering that an artificial eye can mitigate the influence of the noise existing in real eye recordings, and thus allowing for a more comprehensive validation of the eye-tracking quality. The calibration for all recordings was done via a real eye. The calibration via a real eye when using an artificial eye is a procedure established by previous studies [9]. During the experiments we restricted the allowed calibration error to maximum values of 1.5° for the real eye, and 1° for the artificial eye. The resulting average calibration accuracy for the two cases was measured to be 0.58° (SD = 0.19°) and 0.64° (SD = 0.38°) respectively.

The recordings for the real and the artificial eyes were performed using a stimulus of a simple steady dot placed at the center of the screen. This kind of stimulus was dictated by the need to investigate of the eye-tracking precision. During the initial recordings the camera lens was adjusted so that each time the eye covered the larger possible area in the captured image.

In the case of the real eye recordings the stimulus presentation lasted a total of 60 s. During data analysis the most stable 10 s (without blinks or corrective eye movements) were selected by visual inspection for further processing. The videos of the initial recordings were scaled to four lower resolutions (520 x 283, 380 x 207, 260 x 141 and 140 x 76 pixels) corresponding to iris-diameter resolutions ranging from 258 down to 39 pixels. The nearest neighbor interpolation algorithm was used as the simplest approach to do the scaling. The videos were then re-processed by the eye-tracker for calculating the respective values of precision.

For the artificial eye the stimulus presentation lasted again 60 s, and during data analysis the most stable 30 s were selected for further processing. In order to cover the full range of iris-diameter resolutions of the real eyes, the videos of the original recordings were scaled to 25 resolutions in the range of 620 x 337 pixels down to 140 x 76 pixels, with a step of 20 pixels of horizontal resolution. It should be noted that the inspection of resolutions under 140 x 76 pixels was not possible due to the inability of calibration at such resolutions.

### *The Effects of Precision Degradation on Biometric Performance*

#### THEORY

The Complex Eye Movement Biometrics (CEM-B) [5] methodology was employed as the framework for the evaluation of the influence of the precision degradation on the performance of eye movement biometrics. The CEM-B utilizes eye movement features such as the fixation duration and position, and the saccadic duration, amplitude and velocity, as the basis for forming the biometric templates. Such biometric templates can be extracted in real-time from an eye

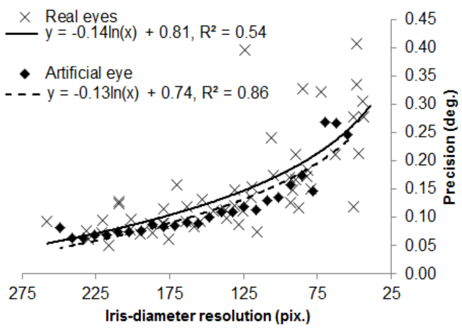
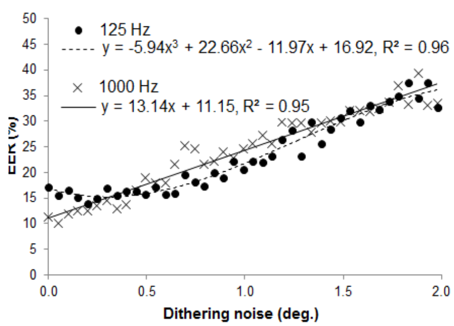



**Figure 2** *Dependency of eye-tracking precision on iris-diameter resolution.*




movement recording in response to the stimulus described below. The measure used for quantifying the biometric verification performance was the Equal Error Rate (EER), i.e. the point of a Receiver Operating Characteristic (ROC) curve where the False Acceptance Rate-FAR equals the False Rejection Rate-FRR [13].

### Participants

The experiments for assessing the effects of precision degradation on the biometric performance were performed with 100 subjects (51 males/49 females), ages 18-43 (M = 22 years, SD = 3.9). Texas State University's institutional review board approved the study, and subjects provided informed consent.

### Apparatus and Software

The recordings of the biometric samples were done with a high-grade commercial eye-tracking device, the EyeLink 1000 eye-tracker, operating at a sampling rate of 1000 Hz. The eye-tracker was set on monocular mode capturing the left eye. The experimental stimulus was presented on a computer display with dimensions of 474 x 297 mm and resolution of 1680 x 1050 pixels, placed at a distance of 550 mm from the subjects' eyes. Subjects' eyes were positioned with a positive vertical offset of 36 mm from the center of the screen.

### Experimental Procedure

The recordings for this experiment were performed using a visual stimulus consisting of text excerpts. The used text excerpts were from the poem of Lewis Caroll 'The Hunt for the Snark', and the total time given to the subjects to read the text was 1 min. This stimulus was selected to induce complex eye movements needed by the CEM-B methodology. As in previous experiment, the allowed calibration error was restricted to a maximum value of to 1.5°. The average calibration accuracy was measured to be 0.47° (SD = 0.17°), and the corresponding average calculated data validity was 94.9% (SD = 5.9%).

Given that the original recordings were done with a high-precision eye-tracker, the degradation of the eye-tracking precision was simulated via the addition of dithering noise to the original recordings. This allowed for a controlled selection of the noise amplitudes in range of 0° to 2° with a step of 0.05°. The recordings were additionally downsampled to 125 Hz to match the sampling frequency of the Thorlabs camera. This allowed to inspect the biometric performance behavior for high (1000 Hz) and low (125 Hz) sampling rates.

## Results

The diagrams of Figure 2 present the calculated eye-tracking precision values when varying the iris-diameter resolution for the artificial and the real eye recordings. The curves have been fitted using logarithmic regression, and the respective regression coefficients and $R^2$ values are shown for both cases. Other fitting functions were also tried (linear, quadratic, cubic, and exponential), however, the logarithmic fit provided the optimum balance between high $R^2$, F values and reduced complexity of the fitting model. As expected, the artificial eye shows more stable behavior ($R^2 = 0.86$, $F_{1,24} = 145.4$, $p < 0.001$) than the real eye ($R^2 = 0.54$, $F_{1,53} = 62.3$, $p < 0.001$), which shows more scattering due to the inter-subject variability in the eye characteristics. It is notable that the fitted curves for the two cases are in very close resemblance, portraying the similarity of the created models for the artificial and the real eye data. The baseline precision for the large iris-diameter resolutions starts from a value of ~0.05°, and successively escalates to a worst case precision of ~0.35° for the smaller tested iris-diameter resolutions.

The diagrams of Figure 3 demonstrate the results for the impact from the reduced precision on the biometric verification performance (for sampling rates of 1000 Hz and 125 Hz). The data for the two sampling rates show differences in their behavior. The data at 1000 Hz can be accurately modeled using a linear curve ($R^2$ = 0.95, $F_{1,39}$ = 686.1, $p < 0.001$), whereas for the data at 125 Hz the escalation in the biometric performance deviates from linearity. In this case the experimental data were optimally fitted using a cubic regression model ($R^2$ = 0.96, $F_{3,37}$ = 302.4, $p < 0.001$). The performance is relatively stable for values of dithering noise up to 0.5°, and then follows a behavior similar to 1000 Hz data.

## Discussion

For low image resolutions the mass of pixels used to represent the pupil and the corneal reflection is limited, and thus, the precision of the calculated centers of mass and the estimated gaze positions deteriorates. The results from our experiments show that the eye-tracking precision remains relatively stable for iris-diameter resolutions of about 100 pixels, and degrades quickly with further reduction in resolution. Also, the similar behaviors of the artificial and the real eye data can suggest that an artificial eye can provide a reliable solution for the evaluation of precision in applied scenarios involving low-cost devices of restricted resolution specifications. The optimum analysis, though, can be achieved via the complementary analysis of both artificial and real eye data.

The addition of dithering noise seems to affect the biometric verification performance substantially for amplitudes larger than 1°. It is worth commenting that although the high frequency data (1000 Hz) present the best baseline-EER (no dithering noise), the case is reversed for noise amplitudes larger than 0.3°, where the performance of the downsampled data (125 Hz) becomes superior. This behavior can be attributed on the combined effects from dithering and downsampling on the velocity-based eye movement classification algorithm (I-VT) used by the CEM-B methodology.

In overall, based on our experimental results showing that for iris-diameter resolutions down to 50 pixels the precision values remain in all cases under 0.4°, our recommendation is that an eye-tracking camera setup for a low-power wearable device should be able to maintain the iris-diameter over a limit of 50-70 pixels, in order to keep the performance in reasonable levels and accommodate for the inter-subject eyes' variability.

## Conclusion

In this paper, we presented a preliminary analysis on the impact of eye image resolution on the eye-tracking precision and the effects on an eye movement-driven biometrics application. These results are a first-breath step towards the pursuit of the system limitations that can lead to the efficient design of human computer interaction applications in power limited wearable devices.

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