Privacy-Preserving Eye Videos using Rubber Sheet Model

Aayush K. Chaudhary
ack5959@rit.edu
Rochester Institute of Technology
Rochester, NY, USA

Jeff B. Pelz
pelz@cis.rit.edu
Rochester Institute of Technology
Rochester, NY, USA

ABSTRACT
Video-based eye trackers estimate gaze based on eye images/videos. As security and privacy concerns loom over technological advancements, tackling such challenges is crucial. We present a new approach to handle privacy issues in eye videos by replacing the current identifiable iris texture with a different iris template in the video capture pipeline based on the Rubber Sheet Model. We extend to image blending and median-value representations to demonstrate that videos can be manipulated without significantly degrading segmentation and pupil detection accuracy.

CCS CONCEPTS
• Human-centered computing → Ubiquitous and mobile computing; • Security and privacy → Privacy protections.

KEYWORDS
Privacy, Security, Eye tracking, Iris Recognition, Rubber Sheet Model, Eye Segmentation

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1 INTRODUCTION
Due to advances in the fields of augmented and virtual reality, the use of eye-tracking is being rapidly extended beyond traditional research, medical diagnosis, and behavioral studies. As the technology extends to the general public, the essential concern of data privacy needs to be addressed. Eye data is valuable privacy-sensitive information that provides insight about human behavior, private life, health data, biometric signatures, etc. [Bozkir et al. 2019; John et al. 2019; Liu et al. 2019; Steil et al. 2019a,b]. According to a survey conducted by Steil et al. [2019a], people are interested in sharing eye-tracking data if it helps them in medical diagnosis or in improving their user experience but not for use in personal or behavioral study. This demands proper privacy regulations and changes in data capture mechanisms to protect user’s privacy [Liu et al. 2019].

Figure 1: Basic flow of proposed method (Section 2). The source image [Garbin et al. 2019] is passed to a CNN to annotate the eye regions. The target iris undergoes a rubber sheet model transformation [Daugman 2009] followed by other transformations based on the information from the source image. This results in a generated iris similar to the source iris shape, which is then mixed with the source image to get the final image after the glints are replaced.

Recently [Bozkir et al. 2019; John et al. 2019; Liu et al. 2019; Steil et al. 2019a,b] have proposed solutions for eye-tracking data privacy. Some of these efforts [Liu et al. 2019; Steil et al. 2019a] are related to preserving privacy in gaze data in addition to the eye images, as it also provides important information regarding
the individual’s attention, cognitive ability, health, and emotions. The proposed solutions have been to limit the ability to identify individuals’ data by aggregating data of multiple participants into a statistical database/representations (differential privacy) [Liu et al. 2019; Steil et al. 2019a]. Similarly, Steil et al. [2019b] proposed a solution to capture the eye tracker’s first-person video, based on scene image and eye movements.

To our knowledge, only [Bozkir et al. 2019; John et al. 2019] have considered the possibility of identifying individuals based on eye videos. Eye videos contain information about the pupil, iris, sclera, eye corners, eyelids, and face in addition to the eye movements. Among these, the iris contains the most important biometric data, as iris patterns are unique among individuals [Daugman 2003]. John et al. [2019] proposed a technique to improve privacy by defocusing the eye image (optically or through digital blurring) while retaining satisfactory accuracy in gaze estimation. Both Phillips and Komogortsev [2011], and John et al. [2019] showed that iris recognition accuracy degrades when the eye image is blurred.

John et al. [2019] showed that pupil detection rates started to deteriorate with increased Gaussian blur, though their results indicated that iris recognition was maintained over certain ranges of Gaussian blur. Thus, there exists a trade-off between pupil detection and iris identification. Further, providing a detailed (unsmoothed) texture to eye images is vital for most of the deep learning-based architectures such as [Park et al. 2018a,b; Yiu et al. 2019], which learns eye characteristics, such as pupil and iris, based on features from the whole image. Another area of interest for some researchers is tracking the iris textures for gaze estimation, as in [Chaudhary and Pelz 2019; Pelz and Witzner Hansen 2017].

The main contribution of this paper is a method to prevent iris identification by a transformation technique based on the rubber sheet model [Daugman 1993] which maps every point in the Cartesian coordinate system to a rectangular approximation of its polar coordinates to generate a new uncorrelated iris texture eye image without degrading the estimation of gaze. Figure 2 shows our proposed video capture pipeline.

![Figure 2: Proposed Video Capture pipeline.](image-url)

2 METHODS

In this section, we discuss the mapping of the identifiable source original image to the non-identifiable target iris by the following steps: eye segmentation, iris transformation, and glint replacement.

2.1 Eye Segmentation

Initially, to proceed with a rubber sheet model, we need to segment the region of interest, namely pupil and iris, as we require the pupillary and limbus border points for the rubber sheet model [Daugman 1993]. Segmentation algorithms proposed by [Chaudhary et al. 2019; Garbin et al. 2019; Kim et al. 2019; Vera-Olmos et al. 2019; Yiu et al. 2019; Zhang et al. 2015] have been used to annotate these regions. As our main concern lies in the proof of concept of the iris transformation approach and not on designing an eye segmentation model, we use the pre-trained RITnet model [Chaudhary et al. 2019] as it is capable of isolating the pupil, iris, and sclera regions with high accuracy in real-time.

2.2 Iris transformation

After the region of the iris and pupil are segmented, we transform the source images to target iris images. A complex solution is required to replace the iris texture in the given images with a new texture because we must take into account factors such as perspective deformation, pupil dilation, and occlusion with the eyelids. We apply a rubber sheet transformation on the target iris with the distance between the iris and pupil boundary being represented by $r$. Note that the rubber sheet model takes into account factors such as pupil dilation and iris deformation [Masek et al. 2003].

The goal is to match the target iris to the source iris, so the iris orientation, position, and size of target and source should be the same. Thus, after the transformation of the target iris to an unwrapped rectangular form, we use cubic interpolation along the $r$ direction to match the maximum source iris radius ($R$). To account for iris rotation, we shift the interpolated iris template along the $\pm e x$-direction ($\theta$) based on the elliptical rotation of the source iris. It would be preferable, however, to find the actual iris rotation by incorporating a measure of ocular torsion with the Rubber Sheet model [Lee et al. 2007; Ong and Haslwanter 2010] or by tracking iris texture features [Chaudhary and Pelz 2019; Pelz and Witzner Hansen 2017] in the source images, which would support the measurement of torsional eye movements.

Every point on the template generated after rotation must be matched with the source iris, taking into account factors such as iris deformation, ellipse shape, non-concentric pupil-iris displacement, and extreme eye positions. To do this, we use a ratio of the number of pixels of the sclera/eyelid, pupil, and iris in the source image along $R$ and fit along the $\theta$ direction through interpolation and matching, as shown in Figure 3.

After the properties of iris deformation and eye-region are correctly identified, the rectangular unwrapped region is converted back into the Cartesian coordinate system with the inverse process of the rubber sheet model. The result is that the derived position of the iris is in the same position as the iris in the source image. It is also necessary to match the source iris and generated iris intensity distribution, which is done by histogram equalization. Finally, each pixel of the iris in the source image is replaced by the same pixel in the generated iris image to get the final generated image. Refer to Figure 1 for the basic flow of our methodology.

2.3 Glints

The glints were removed from the target iris image before the transformations described in section 2.2. Because some eye-tracking methodologies rely on glints for gaze estimation, we replace the glints in the same position on the generated image. The glints are the brightest region in an image; we threshold these glints based
This region in the following sections.

Phillips and Komogortsev [2011] and John et al. [2019] convolved the entire eye image with Gaussian kernels to degrade the iris recognition process. Our transformation step does not degrade the eye image; instead, it replaces the iris region with a different high-quality iris texture image even when there is motion blur. We also propose a way to improve on our transformation pipeline by blending the source iris with the generated iris. The pipeline replaces the region indicated in the blue shaded color box in Figure 1. As we are confident in pupil segmentation, we isolate an elliptical region of 5 pixels around the pupil boundary and find the median digital count. This region in the generated iris is replaced by this median digital count allowing pupil detection algorithms to detect the original pupil robustly. Then we blend the source iris and the generated iris with a weighted elliptical gradient function (Equation 1) [Hendricks 2012] giving high importance to the generated iris towards the boundary. These images are referred to as blended images in the following sections.

\[
w = \frac{(x-h)\cos\theta + (y-k)\sin\theta)^2}{a^2} + \frac{(y-k)\cos\theta - (x-h)\sin\theta)^2}{b^2}
\]

where \((h,k,a,b,\theta)\) are standard ellipse parameters.

### 3 DATASET AND EVALUATION

We evaluated our technique on the publicly available OpenEDS Semantic Segmentation dataset [Garbin et al. 2019] using the state-of-the-art RITnet model trained on the OpenEDS dataset. Since the ground truth of the OpenEDS test dataset is not publicly available, we compared the performance to the validation set.

To evaluate the performance of the images after alteration to protect privacy, we compared results for the source, generated and blended images based on 1) mean per-class Intersection over Union (mIoU) segmentation results when tested with the trained models; 2) center estimate based on an ellipse fit of the segmentation mask of the pupil; and 3) the reported pupil center based on the open-source software from Pupil Labs [Kassner et al. 2014]. For comparison, we also generated another privacy-preserving eye image where every pixel in the iris region was replaced by the median digital count of the iris in that image (referred to as a median image). The replacement of the iris region with the median digital count can be useful in any system not relying on the iris features in the image.

### 4 RESULTS

Figure 4 shows an iris-cropped sample of the image from the OpenEDS dataset and its transformation along with blended and median images. The results are shown in Tables 1-3. Table 1 shows the mIoU for images from the OpenEDS validation set for the source, generated, blended, and median image, respectively. There is a small decrement in mIoU performance, never exceeding 2.1% in the generated and blended image sets, though the median image set (without a replacement iris texture) reaches 2.9%. The table also shows the per-class accuracies for the pupil, iris, sclera, and background. Table 2 shows the mean square error (MSE) in the estimate of the pupil center based on an ellipse fit on the predicted labels for various images in both horizontal (x) and vertical (y) directions. Note that all the results presented are with respect to the ellipse fit on the ground truth. The \(R^2\) value for all the cases was over 0.999.
Table 1: Comparison of the mean Per class IoU for the original source, generated, blended and median images.

| Class     | Source | Generated | Blended | Median |
|-----------|--------|-----------|---------|--------|
| mIoU      | 95.75  | 93.66     | 94.44   | 92.85  |
| Pupil     | 94.82  | 93.78     | 94.14   | 93.85  |
| Iris      | 95.61  | 91.29     | 92.97   | 90.46  |
| Sclera    | 93.11  | 90.53     | 91.40   | 87.77  |
| Background| 99.46  | 99.05     | 99.25   | 99.31  |

Table 2: MSE in pupil center estimate based on ellipse fit on the segmentation mask with respect to ground truth.

| Images  | Source | Generated | Blended | Median |
|---------|--------|-----------|---------|--------|
| $MSE_x$ | 0.77   | 0.72      | 0.72    | 1.01   |
| $MSE_y$ | 0.51   | 1.40      | 0.88    | 0.98   |

Table 3: Estimates based on Pupil Labs Software [Kassner et al. 2014]

| Images | Source | Generated | Blended | Median |
|--------|--------|-----------|---------|--------|
| Detection Rate | 76.70% | 76.99% | 76.36% | 78.73% |
| > 80% confidence | 68.29% | 69.12% | 68.58% | 71.83% |
| $MSE_x$ | N/A | 0.08 | 0.06 | 0.08 |
| $MSE_y$ | N/A | 0.25 | 0.09 | 0.23 |

Table 3 represents the 2D pupil fit results of the video sequence from the images by the open-source Pupil Labs software (V1.8-26). The reported metrics are pupil detection rate, proportion of images with pupil detection confidence over 80%, and MSE in x and y directions. The MSE in this case was calculated after rejecting 5% of outliers. Note that the video was not recorded with a Pupil Lab tracker, but the videos were processed keeping all parameters (such as the region of interest, pupil intensity, minimum pupil radius, and maximum pupil radius) constant for all videos. Out of 2403 images, we saw a pupil detection increment in seven generated images and 48 median images relative to the source image, and a decrement in nine blended images. Results for samples with pupil detection confidence above 80% showed an increment of 19, 85 and six samples in generated, median and blended images, respectively. The MSE results were consistent for all the videos.

5 DISCUSSION

Current video-based systems allow individuals to be identified through their eye videos, which is a privacy concern. We present an approach to preserve privacy by replacing the iris with uncorrelated iris texture maps (Hamming Distance (HD) = 0.47 ± 0.01 with its source iris based on encoding procedure of Masek et al. [2003] and matching technique of Daugman [2009]). The iris texture is replaced by taking advantage of the Daugman’s rubber sheet model and RITnet. The proposed method handles iris deformation due to perspective projection, specular glints, and elliptical-shaped iris/pupil transformation. We show that this transformation degrades the performance by 2.09% in mIoU, 1.04% in pupil segmentation, and 0.47 pixels root MSE. Instead of an uncorrelated image, the introduction of the weighted elliptical gradient blending (HD = 0.27 ± 0.04) with the source image only degraded the performance by 1.31%, 0.68%, 0.23 pixels, respectively.

We also show similar results when the videos are fed to the open-source Pupil Labs software. There is a boost of over 2% in the pupil detection and proportion of the confidence over 80% metric in the median image since it is easy for the algorithm to detect the clean pupil/iris boundary. This suggests that any eye-tracking methodology focused on detecting pupil based on edges can simply use the median image. However, the disadvantage of the use of the median iris image is a significant decrement in neural network-based performance in the segmentation task. We can argue that the results for the segmentation can be improved if such a network is trained on generated, blended, and median images, but the primary concern of this paper lies in the performance comparison without re-training the architectures. Overall, our results for all the cases are comparable to real video results (source) and shows the benefit of using this approach instead of degrading eye videos by blurring.

The proposed approach handles the image generation with artificial/real eye images. With the evolution of deep learning architectures, especially generative adversarial networks (GANs) [Goodfellow et al. 2014], there is the possibility of creating unidentifiable videos based on learned features. However, the more significant challenges for such architectures are the requirement of huge databases with proper ground truth, no proper validation metric, and no study of gaze estimation on GAN generated images.

Our method improves on previous attempts to limit identification through iris recognition in eye-tracking videos. However, the study has a number of limitations. First, a person can be identified by eye features other than the iris, such as the sclera, eye corners, eyelids, facial structure, and even eye movements. Our current study does not account for such factors. Since we also segment the sclera, a similar sclera-generation technique could be implemented in our pipeline. Secondly, we have tried to adapt the lighting condition of the iris-based histogram equalization, but it does not account for positioning and occlusion of the IRLEDs. Note that histogram equalization (as in Figure 1) boosted the performance by 2%. A more general technique to match lighting and other performance would be valuable for our model. Furthermore, the replacement of a part of one image with another can have unintended consequences. One example of this is when was features like eyelashes covering the iris are replaced by the generated iris without the eyelashes, leading to discontinuities in the iris/pupil border. In the future, we plan to incorporate GANs in order to generate more realistic iris textures that can simulate other textures. In the future we plan to study the processing load of pre-processing steps, light-weight architecture [Chaudhary et al. 2019], rubber sheet mapping, and its inverse with possible vectorization techniques to support real-time use.

6 CONCLUSION

We have proposed a new method for altering eye videos in a manner that preserves observer privacy without significantly affecting the accuracy of feature-based and appearance-based gaze-tracking methods. The new images have no correlation with the original video in terms of iris patterns, which prevents iris recognition while permitting pupil, corneal-reflection, and iris-texture tracking.
REFERENCES
Efe Bozkir, Ali Burak Unal, Mete Akgun, Enkelejda Kasneci, and Nico Pfeifer. 2019. Privacy Preserving Gaze Estimation using Synthetic Images via a Randomized Encoding Based Framework. arXiv preprint arXiv:1911.07306 (2019).
Aayush Chaudhary and Jeff Pelz. 2019. Motion tracking of iris features to detect small eye movements. Journal of Eye Movement Research 12, 6 (Apr. 2019). https://doi.org/10.16910/jemr.12.6.4
A. K. Chaudhary, R. Kothari, M. Acharya, S. Dangi, N. Nair, R. Bailey, C. Kanan, G. Diaz, and J. B. Pelz. 2019. RTNet: Real-time Semantic Segmentation of the Eye for Gaze Tracking. In 2019 IEEE/CVF International Conference on Computer Vision Workshop (ICCVW). 3698–3702. https://doi.org/10.1109/ICCVW.2019.00568
John Daugman. 2003. The importance of being random: statistical principles of iris recognition. Pattern recognition 36, 2 (2003), 279–291.
John Daugman. 2009. How iris recognition works. In The essential guide to image processing. Elsevier, 715–739.
John G Daugman. 1993. High confidence visual recognition of persons by a test of statistical independence. IEEE transactions on pattern analysis and machine intelligence 15, 11 (1993), 1148–1161.
Stephan J Garbin, Yuu Shen, Immo Schuetz, Robert Cavin, Gregory Hughes, and Sachin S Talathi. 2019. Opensim: Open eye dataset. arXiv preprint arXiv:1905.05702 (2019).
Ian Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, and Yoshua Bengio. 2014. Generative adversarial nets. In Advances in neural information processing systems. 2672–2680.
Mark C Hendricks. 2012. Rotated ellipses and their intersections with lines.
Brendan John, Sanjeev Koppal, and Eakta Jain. 2019. EyeVEIL: degrading iris authentication in eye tracking headsets. In Proceedings of the 11th ACM Symposium on Eye Tracking Research & Applications. ACM, 1–5.
Moritz Kassner, William Patera, and Andreas Bulling. 2014. Pupil: An Open Source Platform for Pervasive Eye Tracking and Mobile Gaze-based Interaction. In Adjunct Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing (Seattle, Washington) (UbiComp ’14 Adjunct). ACM, New York, NY, USA, 1151–1160. https://doi.org/10.1145/2638728.2641695
JooEun Kim, Michael Stengel, Alexander Majercik, Shalini De Mello, David Dunn, Samuli Laine, Morgan McGuire, and David Luebke. 2019. NVGaze: An anatomically-informed dataset for low-latency, near-eye gaze estimation. In Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems. ACM, 550.
InBum Lee, ByungHun Choi, and Kwang Suk Park. 2007. Robust measurement of ocular torsion using iterative Lucas–Kanade. Computer methods and programs in biomedicine 85, 3 (2007), 238–246.
Ao Liu, Lirong Xia, Andrew Duchowski, Reynold Bailey, Kenneth Holmqvist, and Eakta Jain. 2019. Differential privacy for eye-tracking data. In Proceedings of the 11th ACM Symposium on Eye Tracking Research & Applications. 1–10.
Lihot Masek et al. 2003. Recognition of human iris patterns for biometric identification. Ph.D. Dissertation. Master’s thesis, University of Western Australia.
James KY Ong and Thomas Hashdwaner. 2010. Measuring torsional eye movements by tracking stable iris features. Journal of neuroscience methods 192, 2 (2010), 261–267.
Seonwook Park, Adrian Spurr, and Ottmar Hilliges. 2018a. Deep pictorial gaze estimation. In Proceedings of the European Conference on Computer Vision (ECCV). 721–738.
Seonwook Park, Xucong Zhang, Andreas Bulling, and Ottmar Hilliges. 2018b. Learning to find eye region landmarks for remote gaze estimation in unconstrained settings. In Proceedings of the 2018 ACM Symposium on Eye Tracking Research & Applications. ACM, 21.
Jeff B Pelz and Dan Witzner Hansen. 2017. System and method for eye tracking. International Patent Application No. PCT/US2017/034756 (2017).
Clark Phillips and Oleg V Komygortsev. 2011. Impact of Resolution and Blur on Iris Identification. Technical Report. Technical Report.
Julian Steil, Inken Hagestedt, Michael Xuelin Huang, and Andreas Bulling. 2019a. Privacy-aware tracking using differential privacy. In Proceedings of the 11th ACM Symposium on Eye Tracking Research & Applications. 1–9.
Julian Steil, Marion Koelle, Wilko Heuten, Susanne Boll, and Andreas Bulling. 2019b. Privacyeye: privacy-preserving head-mounted eye tracking using egocentric scene image and eye movement features. In Proceedings of the 11th ACM Symposium on Eye Tracking Research & Applications. 1–10.
FJ Vera-Olmos, Esteban Pardo, H Melero, and Norberto Malpica. 2019. DeepEye: Deep convolutional network for pupil detection in real environments. Integrated Computer-aided Engineering 26, 1 (2019), 85–95.
Yuk-Hoi Yiu, Moustafa Aboulatta, Theresa Raiser, Leoni Ophey, Virginia L Flanagan, Peter zu Eulenburg, and Seyed-Ahmad Ahmadi. 2019. DeepVOG: Open-source pupil segmentation and gaze estimation in neuroscience using deep learning. Journal of neuroscience methods 324 (2019), 108307.
Xucong Zhang, Yusuke Sugano, Mario Fritz, and Andreas Bulling. 2015. Appearance-based gaze estimation in the wild. In Proceedings of the IEEE conference on computer vision and pattern recognition. 4511–4520.