JOURNAL OF
EMERGING INVESTIGATORS

Article

Exotropia detection using computer vision, image processing and facial landmark detection

Pranav Narsipur[1], Keshav Narsipur[1]

[1] Redmond High School, Redmond, Washington

SUMMARY

Strabismus is a common medical condition where both eyes are misaligned at the same time. As a form of strabismus, exotropia is a medical condition where the eye deviates outward, impacting 4.6% of adults over 20 years old and 1% of individuals under 20 years old. This condition can cause various visual and cognitive issues. Current medical protocols for assessing the degree of exotropia, such as the prism cover test, are subjective and take time to perform, making early detection and treatment challenging. Our study investigated the use of computer vision techniques for assessing the degree of exotropia quantitatively. We hypothesized that the ratio of visible sclera area to total eye area would positively correlate with the root mean square (RMS) of the iris offsets from both eyes. We used OpenCV and dlib libraries to analyze images of a subject with varying degrees of simulated exotropia. Our results showed a strong positive correlation between RMS iris offset and visible sclera-to-eye area ratio ($r = 0.905$, $p = 0.0131$), with a 2.8% increase in visible sclera ratio per 0.05 increase in RMS offset. These findings suggest our approach of using computer vision to calculate the sclera to eye area ratio could provide a new, quantifiable method for assessing the degree of exotropia. This could supplement current medical protocols to measure and assess exotropia, making tracking and monitoring of exotropia easier, helping patients worldwide.

INTRODUCTION

Exotropia is the outward deviation of either one or both eyes, which can be present persistently or intermittently where the eyes turn out only occasionally (1). It is estimated that 4.6% of adults over 20 years old and about 1% of individuals under 20 years old have exotropia (2). Symptoms of this medical condition range from eye strain, headaches, double vision, and decreased depth perception to psychiatric disorders later in life (3, 4). Research studies have indicated better outcomes, including improved quality of life for patients, when exotropia is detected early (5, 6).

While exotropia is clinically classified by frequency (exophoria, intermittent, or constant), there is currently no standardized quantitative severity scale comparable to systems used for other medical conditions. To diagnose, treat, and monitor exotropia, easy and accurate quantification of exotropia severity in patients is crucial. However, severity quantification requires access to specialists, takes time, is expensive, and there is no clear standardization for measuring the degree of exotropia (7). There are existing clinical approaches to measure exotropia severity, and they include the prism cover test, Hirschberg test, and Krimsky test (8, 9). Significant skill and experience are required by the medical practitioner for administering all of the aforementioned tests, making the tests less accessible for frequent monitoring. For example, the Hirschberg test involves shining a light into a patient's eyes and observing for any deviation from the resulting reflection on the corneas (9). The cost associated with these tests may also be steep due to the possible lack of insurance coverage. Furthermore, these tests do not detect small or complex deviations of the eye accurately and thus do not assess the full range of eye movement. These tests could benefit from the addition of automated measurement tools complementing existing clinical methods.

There have been several recent advances in machine learning and computer vision and their use to analyze medical images, including those related to eye conditions (10). Many of these studies have researched digital image analysis for detecting strabismus — a general misalignment of eyes — providing insight into how these technologies can be applied in ophthalmology (11, 12). However, these studies focus on detecting strabismus (general eye misalignment), not exotropia specifically, which is a specific form of strabismus where the eye deviates outward. Therefore, they do not address standardization of how to measure or quantify the severity of exotropia.

Previous studies have used the sclera visibility for gaze tracking, and automated video analysis for strabismus detection, but none have specifically quantified exotropia severity (11-14). In exotropia, where the eye deviates outward, we expect to see an increase in the visible sclera on the nasal side (inner corner) of the eye, when the eye deviates towards the temporal side. Additionally, the center of the iris in relation to the center of the eye, i.e. the iris offset, can indicate the degree of the gaze and eye alignment (11).

In this study, we propose a new method to quantify the severity of exotropia using computer vision and artificial intelligence techniques. We suggest two new measurements: the ratio of the visible sclera (the white outer coating of the eye) to the total eye area (sclera-to-eye area ratio), and the offset of the iris from the eye center.

We hypothesized that the ratio of visible sclera area to total eye area would positively correlate with the root mean square (RMS) of the iris offsets from both eyes in individuals with exotropia. To test this hypothesis, we analyzed images of a single individual with simulated varying degrees of exotropia. Our results show that there is a strong correlation between the RMS iris offset and the average sclera to eye ratio. There

https://doi.org/10.59720/24-285

was a 2.8% increase in average visible sclera ratio per 0.05 increase in RMS iris offset.

Our computer vision approach provides a novel and objective method of quantifying the severity of exotropia using sclera-to-eye area ratio. This has the potential to automate exotropia monitoring and make it more accessible, enabling a monitoring process within a home setting to complement clinical evaluations.

RESULTS

To validate the hypothesis, we developed a program in Python using computer vision. We specifically used the Open CV and dlib libraries and analyzed the images of a single subject with varying severities of digitally induced exotropia and different degrees of iris offset. We used a computer program to find a correlation between the RMS iris offset and average sclera-to-eye area. The analysis of the six images of a single subject without exotropia, with varying degrees of digitally simulated exotropia showed a strong positive correlation between RMS iris offset and average sclera-to-eye area ratio (Pearson's correlation, $r = 0.905$, $p = 0.0131$) (**Figure 1**). While the RMS iris offset increased, there was a consistent increase in the average visible sclera ratio. Between 0.046–0.249 for RMS iris offset, the visible sclera ratio ranged from 0.176–0.637. This is 3.6-fold increase across the range of offsets studied. This demonstrates a strong relationship between these variables.

We then calculated the percentage increase in average visible sclera ratio for every 0.05 increase in RMS iris offset to quantify the relationship between RMS iris offset and average visible sclera ratio (**Figure 1**). For every 0.05 increase in RMS iris offset, our analysis showed a 2.8% increase in average visible sclera ratio (linear regression analysis, 95% CI: 1.58–4.02%, $p = 0.0131$). Furthermore, this suggests that the sclera-to-eye area ratio could serve as a quantitative measure of exotropia severity.

DISCUSSION

We hypothesized that the ratio of visible sclera area to total eye area would positively correlate with the RMS iris offset from both eyes. Our results support this hypothesis, demonstrating a strong positive correlation ($r = 0.905$, $p = 0.0131$). Our study shows the applicability of computer vision techniques, specifically the relationship between sclera-to-eye area ratio and RMS iris offset, in quantifying exotropia severity. Several previous approaches have developed computational analysis of strabismus, including convolutional neural networks for detecting its presence and automated video analysis through cover tests (11, 12). Additional studies have used correlations between sclera visibility and eye gaze direction, while others have used sclera measurements for eye tracking (13, 14).

The computer vision approach we used explores the direct measurement of various facial features. Unlike neural networks which require large amounts of training data, our method relies on direct measurable features that could help enable more frequent monitoring. Our method is also able to simultaneously record data from both eyes, unlike prior automated video analysis, while using common hardware (12). By reducing the need for specialized equipment or practitioners, this approach could help make exotropia measurements more accessible, while maintaining consistency.

This approach addresses many of the limitations of the current tests for exotropia. These new measurements are objective, quantitatively precise, and more accessible to patients. Furthermore, by automating the measurement, we reduce the subjectivity inherent in the current testing approach, improving consistency across different medical practitioners.

However, our study has limitations. We worked with a data set of six images obtained from a single subject. This limited sample size due to a single subject prevents us from drawing broad clinic conclusions. Without multiple subjects, we cannot perform robust statistical analyses. Even though this study demonstrates that computer vision techniques can quantify

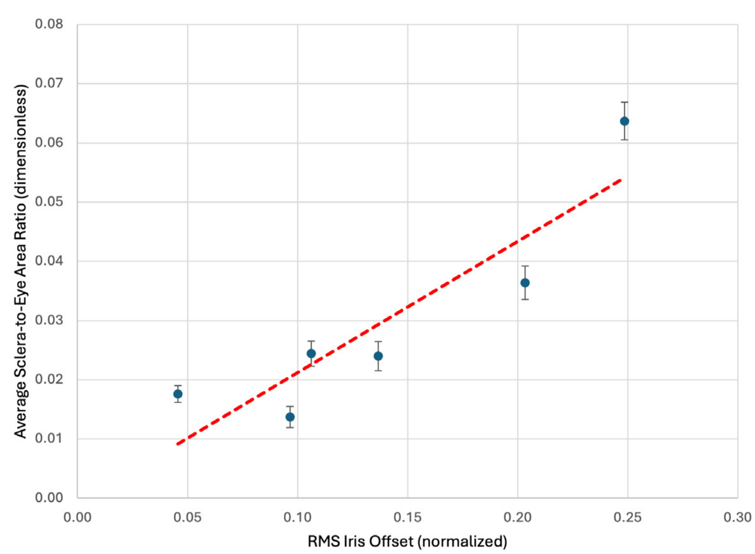

Figure 1: Root mean square iris offset with average sclera-to-eye area ratio. Scatter plot showing the relationship between root mean square (RMS) iris offset (normalized to eye-width) and mean sclera-to-eye area ratio averaged from both eyes. Each point represents one out of the six analyzed images. The red-dashed line represents the linear regression best-fit line. Computer vision was used to calculate sclera to eye ratio and iris offset. Error bars indicate standard error (n =2) for the sclera-to-eye area ratio measurements. This data shows a strong positive correlation by using the best fit linear regression ($r = 0.905$, $p = 0.0131$).

JOURNAL OF
EMERGING INVESTIGATORS

https://doi.org/10.59720/24-285

the relationship between sclera visibility and iris offset, it is important to note that it merely serves as a proof-of-concept. While our study shows promise using images from a single subject, this work establishes technical feasibility rather than clinical validity.

A real-world medical provider office or a patient home will have more variability on lighting and distance, and our approach will require more validation in these contexts. We need to validate the approach using a larger and more diverse data set, something that is challenging as there are no readily available public data sets of patients with exotropia. This will require partnering with a medical organization to collect a larger data set. We suggest more research using our proposed approach and metrics in a clinical setting where patients have different types and severities of exotropia. Testing in a clinical environment will also provide more data points, like the shape of the eye, skin color, and iris color, to further improve our approach. Future work building on this study should also validate this approach across diverse individuals with clinically diagnosed exotropia of varying severities, different age groups, sex, and ethnic backgrounds.

Our preliminary exploration of real-time image processing and telemetry suggests potential for continuous monitoring, which could benefit patients with intermittent exotropia. The development of such a system would require separate validation and testing across varying lighting conditions to ensure robustness but could enable a more frequent assessment of exotropia.

In conclusion, our investigation of sclera-to-eye area ratio measurements represents an initial exploration of quantitative assessments for exotropia severity. While additional validation amongst more diverse populations and clinical settings is required, the sclera-to-eye area ratio measurements could provide a next step into studying eye deviation. There is potential that it could complement existing methods in monitoring exotropia progression.

The potential consequences of our work extend further than individual patient care and monitoring. By creating an accessible, quantitative method for exotropia screening, this technology could improve scalability in screening larger populations. More specifically, it could help in underserved areas, which have limited access to ophthalmologist specialists. The automated nature of our approach can improve telemedicine—bridging the gap between doctor-patient connectivity. Furthermore, the objective measurements could standardize existing clinical trials for exotropia treatments, ensuring consistent outcomes, even across different research settings.

MATERIALS AND METHODS

Image dataset

Six high-resolution images of 3024 x 4032 pixels from an iPhone 12 Pro captured a single subject without exotropia, with varying degrees of exotropia digitally simulated. To simulate exotropia, we digitally altered the gaze vectors of both eyes, creating an outward drift commonly observed in exotropia. Images were captured under consistent indoor lighting conditions. Images were captured from a fixed distance of one meter from the camera.

Computer vision implementation

We developed a custom Python-based computer vision pipeline using OpenCV (v4.5.3) and dlib (v19.22.0) libraries. We used dlib's pre-trained frontal face detector to locate and isolate the face within each image. We chose dlib's pre-trained facial landmark detector, as it provides accurate frontal facial detection using groups of regression trees. This model was trained on the iBUG 300-W dataset, which contains 68 manually annotated facial landmark features from over 6,000 face images under various conditions. This model was primarily chosen as it provides more detailed points around the eyes (six points per eye), allowing for more accurate eye region isolation.

We then detected and extracted facial landmarks using dlib's pre-trained facial landmark detector to identify 68 various points across the face. Among these 68 points, 12 points surrounding the eyes were primarily used (points 37–46) (**Figure 2**).

For every eye from the detected facial landmarks, we isolated a rectangular region of interest (ROI). To ensure full coverage of each eye, we expanded these regions by 10% in every direction. These eye frames were converted to grayscale (cv2.COLOR_BGR2GRAY) and preprocessed using bilateral filtering (d= 10, sigmaColor= 15, sigmaSpace= 15) to reduce noise while preserving edge details. This was followed by a morphological erosion using a 3x3 kernel for three iterations, followed by binary thresholding (CV2.THRESH_BINARY) to isolate the sclera region. This thresholding separated the darker iris/pupil region from the lighter sclera, allowing us to quantify sclera visibility from total eye area.

For iris detection, we used a contour analysis (cv2.findCountours with RETR_TREE) on the processed eye regions. Using image moments (cv2.moments), the iris center was automatically calculated from the detected contours. The horizontal position ratio was calculated as the normalized distance of the iris center relative to the eye center, which directly corresponds to the proportion of visible sclera—as the eye deviates outward in exotropia, this ratio reflects the increased sclera visibility on the nasal side of the eye. We then

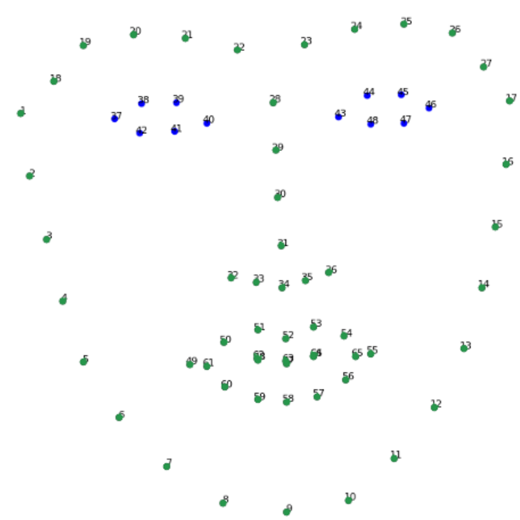

Figure 2: Eye landmarks. Visualization of dlib facial landmarks that shows the 68 points across the face and highlights the 12 points (37 – 46) surrounding the eyes that are of interest in blue. Green points represent the remaining 56 facial landmarks not used for eye analysis. The figure was generated using matplotlib.

derived the sclera-to-eye area ratio. This was done by dividing the total pixels classified as sclera by the number of pixels in the eye ROI.

This complete image processing pipeline, from face detection to measurement calculation was implemented using dlib and OpenCV libraries (**Figure 3**).

For each image, we calculated the normalized iris offset for both eyes:

$$\delta_n = \frac{d}{w} \qquad \textbf{(Equation 1)}$$

Where δ_n was the normalized iris offset, *d* was the distance from the iris center to eye center, and *w* was the eye width.

The combined root mean square (RMS) offset was then calculated with:

$$\delta_{RMS} = \sqrt{\frac{(\delta_L{}^2 + \delta_r{}^2)}{2}} \qquad \textbf{(Equation 2)}$$

Where δ_{RMS} was the RMS iris offset, δ_L was the normalized offset for the left eye, and δ_r was the normalized offset for the right eye.

The normalization ensures that measurements are comparable across various image scales, subject distances, and eye widths. We used the RMS iris offset to combine the normalized iris offsets as it provides a single metric that captures amount of deviation across both eyes while being sensitive to larger individual eye deviation.

The code may be found at: https://github.com/pndude/exotropia-cv.git

Statistical analysis

Statistical analyses were performed using statsmodels (v0.12.2) and SciPy (v1.7.1). For each image, we calculated the average sclera-to-eye area ratio for both eyes and RMS iris offset. For both measurements, we reported the variation between the left and right eyes. We then calculated and used Pearson's correlation coefficients to assess the relationship between the visible sclera-to-eye ratio and RMS iris offset. We then applied a linear regression model to quantify the above relationship and calculate the confidence intervals. Shapiro-Wilk, a normality test, showed our data was normally distributed, which allowed us to use linear regression. We also tested for homogeneity of variances using Levene's test, which confirmed equal variances ($p > 0.05$). All p-values below 0.05 were considered statistically significant.

Hardware and dependencies

All image analysis processes were run on a MacBook Air M2 running macOS X 14.6.1. For programming and analysis tasks, Python (v3.8) was used.

Ethical considerations

All images used in this study were of a single subject approved for research use by the Scientific Review Committee (SRC).

Received: March 30, 2024
Accepted: February 21, 2025
Published: February 22, 2026

REFERENCES

1. Mohney, Brian G. "Common Forms of Childhood Strabismus in an Incidence Cohort." *American Journal of Ophthalmology*, vol. 144, no. 3, 2007, pp. 465-467. https://doi.org/10.1016/j.ajo.2007.06.011
2. Hashemi, Hassan, et al. "Global and Regional Prevalence of Strabismus: A Comprehensive Systematic Review and Meta-Analysis." *Strabismus*, vol. 27, no. 2, 2019, pp. 54-65. https://doi.org/10.1080/09273972.2019.1604773
3. "Exotropia." *Cleveland Clinic*, 16 Dec. 2021, https://my.clevelandclinic.org/health/diseases/23440-exotropia. Accessed 16 Aug. 2024.
4. McKenzie, Jeff A., et al. "Prevalence and Sex Differences of Psychiatric Disorders in Young Adults Who Had Intermittent Exotropia as Children." *Archives of Ophthalmology*, vol. 127, no. 6, 2009, pp. 743-747. https://doi.org/10.1001/archophthalmol.2009.68
5. Dong, Yi, et al. "Surgery at Early Versus Late for Intermittent Exotropia: A Meta-Analysis and Systematic Review." *International Journal of Ophthalmology*, vol. 14, no. 4, 18 Apr. 2021, pp. 582-588. https://doi.org/10.18240/ijo.2021.04.16
6. Holmes, Jonathan M., et al. "Improvement in Health-Related Quality of Life Following Strabismus Surgery for Children with Intermittent Exotropia." *Journal of American Association for Pediatric Ophthalmology and Strabismus*, vol. 25, no. 2, Apr. 2021, pp. 82.e1-82.e7. https://doi.org/10.1016/j.jaapos.2020.11.021
7. Lavrich, Judith B. "Intermittent Exotropia: Continued Controversies and Current Management." *Current Opinion in Ophthalmology*, vol. 26, no. 5, 2015, pp. 375-381. https://doi.org/10.1097/ICU.0000000000000188

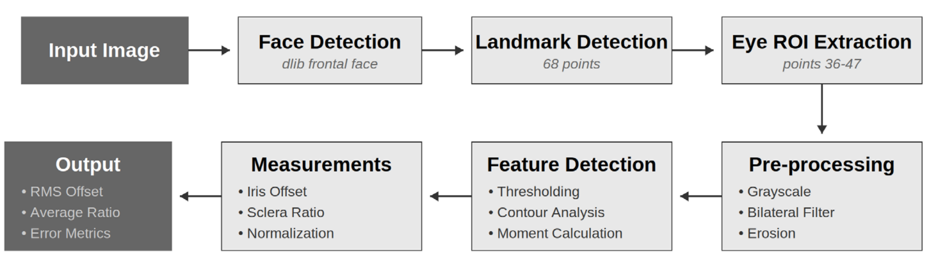

Figure 3: Image processing pipeline. Flow diagram showing the step-by-step process of our computer vision implementation. The pipeline includes face detection, landmark detection, eye region isolation and extraction, image pre-processing, feature detection, and the measurement calculation. Each step shows the specific parameters and methods used.

https://doi.org/10.59720/24-285

8. American Academy of Ophthalmology. *Pediatric Ophthalmology and Strabismus*. Basic and Clinical Science Course, Section 6, American Academy of Ophthalmology, 2020-2021.
9. Choi, Rosan Y., and Burton J. Kushner. "The Accuracy of Experienced Strabismologists Using the Hirschberg and Krimsky Tests." *Ophthalmology*, vol. 105, no. 7, 1998, pp. 1301-1306. https://doi.org/10.1016/S0161-6420(98)97037-3
10. Ting, Daniel S. W., et al. "Artificial Intelligence and Deep Learning in Ophthalmology." *British Journal of Ophthalmology*, vol. 103, no. 2, 2019, pp. 167-175. https://doi.org/10.1136/bjophthalmol-2018-313173
11. Chen, Zenghai, et al. "Strabismus Recognition Using Eye-Tracking Data and Convolutional Neural Networks." *Journal of Healthcare Engineering*, vol. 2018, 26 Apr. 2018. https://doi.org/10.1155/2018/7692198
12. Valente, Thales Levi Azevedo, et al. "Automatic Diagnosis of Strabismus in Digital Videos through Cover Test." *Computer Methods and Programs in Biomedicine*, vol. 140, 2017, pp. 295-305. https://doi.org/10.1016/j.cmpb.2017.01.002
13. Kano, Fumihiro, et al. "Experimental Evidence That Uniformly White Sclera Enhances the Visibility of Eye-Gaze Direction in Humans and Chimpanzees." *eLife*, vol. 11, 8 Mar. 2022, e74086. https://doi.org/10.7554/eLife.74086
14. Houben, Mark M. J., et al. "Recording Three-Dimensional Eye Movements: Scleral Search Coils versus Video Oculography." *Investigative Ophthalmology & Visual Science*, vol. 47, no. 1, Jan. 2006, pp. 179-187. https://doi.org/10.1167/iovs.05-0234