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Automated Montaging of Ultrasound Scans for Determination of Ocular Globe Shape

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Abstract

Introduction: The global increase in myopia highlights the urgent need for reliable and automated methods to monitor structural changes in the eye, especially in the peripheral regions beyond the central fovea, where conventional imaging is limited. This study develops and validates an automated pipeline that enables comprehensive assessment of posterior eye shape from extended-range B-scan ultrasonography, addressing the limitations of current partial coherence interferometry and manual alignment approaches.

Methods: Extended-range B-scan ultrasound images were acquired at three gaze angles to capture peripheral retinal dimensions. The method utilizes the Segment Anything Model (SAM) for interactive and accurate boundary segmentation, followed by translation-based alignment to merge the triplet of images into a unified posterior eye wall representation. Multi-set averaging across repeated acquisitions was further evaluated for enhancing reproducibility. SAM results were compared to those from manual merging of images.

Results: Averaging multiple frames before merging significantly reduced the standard deviation of measurements and improved consistency compared with merging a single image. Using this automated triplet-merging approach, reproducibility yielded mean absolute improvements of 31.46 microns (30.12%) in

the horizontal view and 29.04 microns (39.53%) in the vertical view relative to manual merging, indicating greater reproducibility and stability across acquisitions.

Conclusion: The proposed operator-independent pipeline provides a scalable, consistent assessment of peripheral eye morphology. By enabling automated quantification of retinal curvature and globe shape, this approach supports more precise monitoring of myopia progression and enhances the reliability of evaluating treatment efficacy in both clinical trials and routine practice.

Keywords: myopia, globe shape, ultrasound, artificial intelligence, retinal curvature

1 Introduction

The prevalence of myopia, or nearsightedness, is rapidly rising worldwide [1–3]. Myopia results from the axial length of the eye exceeding the focal point of its dioptric structures, causing optical blur of distance vision. While myopic blur is managed with corrective lenses or refractive surgery, the potential comorbidities that result from excessive ocular enlargement, including cataracts, glaucoma, and retinal pathology, make increasing myopic prevalence a substantial public health concern [4–6].

Treatments to slow the growth of the young myopic eye, therefore reducing both the amount of the eventual spectacle prescription and the risk of comorbidities, are increasingly common in clinical practice. Treatments range from optical interventions, such as contact lenses and spectacles that provide peripheral retinal defocus, to pharmaceutical treatments, like low-dose atropine eye drops, and light therapy of varying wavelengths [7–13]. However, these treatments come with some unfortunate limitations. First, across different treatments, the effect is consistently strongest in the first year of treatment, with diminishing returns over the following two years, suggesting that treatment beyond three years will not result in any substantial additional benefit [11, 14]. Additionally, the absolute treatment effect appears to be nearly constant across the range of underlying refractive error or axial length [15].

Treatment effects for myopia control have historically been analyzed as differences in myopic progression or axial elongation between treated and control groups, both of which use central eye measurements. More recently, analysis of eye growth beyond the fovea, or central portion of the eye, has shown diminishing treatment effects in the retinal periphery [16]. This finding raises the question: myopia control results in a shorter eye, but is the shorter eye also a smaller eye? Peripheral eye size and shape measurement is performed using partial coherence interferometry, but is limited to 30 degrees from the fovea in each direction, corresponding to a sagittal depth of approximately 2-3 mm. This technique leaves a large portion of the retinal periphery currently unstudied. Understanding myopia control’s impact on globe size and growth in the retinal periphery are important, due to the fact that excessive growth in this area leads to many of the aforementioned retinal comorbidities.

Therefore, the need exists to study the whole eye in myopia control, a research priority recognized recently by the National Academies of Sciences, Engineering, and

Medicine report in 2024 [14]. Magnetic resonance imaging (MRI) is capable of making these measurements; however, it is expensive and often difficult to access for clinical study sites. This study sought to use a novel technique, extended range B-scan ultrasonography, to measure the size of the globe and the retinal curvature, therefore allowing for longitudinal evaluation of the overall effectiveness of myopia control. Extended range B-scan ultrasonography captures three images of the vitreous-retinal interface in each meridian: one in each of primary, right, and left gazes in the horizontal meridian and one in each of primary, superior, and inferior gazes in the vertical meridian. The merging of these images provides one retinal contour in each meridian. The challenge in extended-range B-scan analysis is achieving reproducible image merging across repeated acquisitions. Manual alignment of multi-gaze ultrasound images is inherently operator-dependent and can introduce variability even when input images are visually similar. Hence, we employ an automated triplet-merging strategy that combines machine learning-based segmentation with translation-guided alignment. By reducing variability between single merged images and averaged merged acquisitions, the automated approach improves measurement stability and consistency. This enhanced reproducibility is essential for detecting subtle peripheral shape changes associated with myopia progression and ensures that downstream curvature analysis reflects true anatomical variation rather than merging artifacts.

Recent advances in computer vision and machine learning for ophthalmic imaging have highlighted the importance of automated and scalable methods in ocular analysis. For example, semi-supervised learning approaches have facilitated the analysis of both OCT and fundus camera images [17–23]. These studies demonstrate the potential of computational pipelines to enhance both efficiency and reproducibility in eye-related measurements, motivating the integration of similar approaches into myopia research.

To address the limitations of current myopia control measurements, which focus mainly on the central eye, a novel pipeline combining multi-angle extended-range B-scan ultrasonography and advanced segmentation and image alignment techniques is proposed. This integrated method overcomes prior limitations by enabling consistent, reproducible, and spatially extensive measurement of eye shape changes relevant to myopia control.

2 Dataset

A total of twenty adult participants aged 21–29 years (inclusive) completed study visits at the Ohio State University (OSU) Wildermuth Optometric Research Clinic after providing informed consent. Table 1 provides demographic information, including refractive error and axial length. The study protocol was approved by the OSU Institutional Review Board, and all data collection adhered to the tenets of the Declaration of Helsinki. All participants had monocular visual acuity of 20/25 or better in each eye, measured with an Early Treatment of Diabetic Retinopathy Study (ETDRS) visual acuity chart (Precision Vision, Woodstock, Illinois, USA). Exclusion criteria included ocular pathology such as amblyopia or strabismus, prior myopia control treatment, and pregnancy or nursing. Ocular health eligibility was confirmed with slit lamp biomicroscopy and dilated binocular indirect ophthalmoscopy.

Table 1: Participant demographics. The 20 participants were mostly female young adults with a range of refractive errors and axial lengths.

Characteristic	Mean (SD)	Range
Age (years)	24.99 (2.01)	21.38 – 29.69
Sex (% female)	80	–
Refractive error (D)	-1.89 (2.42)	-9.58 – +2.45
Axial length (mm)	24.20 (1.52)	22.57 – 29.30

The right eye of each participant was imaged with the ABSolu 20 MHz B-scan device (Quantel Medical; Cournon-d’Auvergne, France) in both the horizontal and vertical meridians. For each meridian, five images are captured from three positions (i) primary gaze and (ii & iii) $\pm 30^\circ$ off-axis gaze angles (e.g., left, primary, right or up, primary, down). These images provide comprehensive coverage of the posterior eye wall and serve as the foundation for the alignment, merging, and curvature analysis described in this study. Multiple images were collected to improve reliability and to reduce the influence of motion artifacts, variability in alignment, or occasional suboptimal captures. Example images for one subject are shown in Fig. 1.

Ultrasound photographs were acquired 30 minutes after instillation of two drops of 1% tropicamide, followed by 0.5% proparacaine in each eye to enhance comfort and minimize blinking. For each participant, five sets of image triplets were collected. GenTeal ocular gel (Alcon, Fort Worth, Texas, USA) was applied to the probe. Participants fixated on a central target with the left eye, while the B-scan probe was aligned with the right eye in horizontal and vertical orientations, Fig. 2. The right eye was designated as the measured eye, while the left eye served as the fixation eye. The fixation target was positioned at the participant’s interpupillary distance and rotated about the left eye’s estimated center of rotation, 15 mm posterior to the cornea [24].

3 Methodology: Machine Learning-Merging

The methodology combines advanced computer vision techniques with a recent machine learning (ML) model (Segment Anything Model (SAM) [25]) and custom curve alignment to achieve robust segmentation, merging, and curvature analysis of retinal B-scan images. SAM is a foundation model for image segmentation trained on the SA-1B dataset [26] containing over 1.1 billion masks, introducing a promptable segmentation paradigm that generalizes across diverse visual domains. It consists of three main components: a Vision Transformer (ViT)-based image encoder, a prompt encoder that processes point or box prompts, and a lightweight mask decoder that generates high-resolution segmentation masks.

In this framework, SAM is adapted for medical imaging applications following recent studies [27–29]. It is employed to extract both vitreous and retinal boundaries, where interactive point prompts are provided to refine segmentation results. The highest-confidence mask is then selected for downstream analysis. Integrated

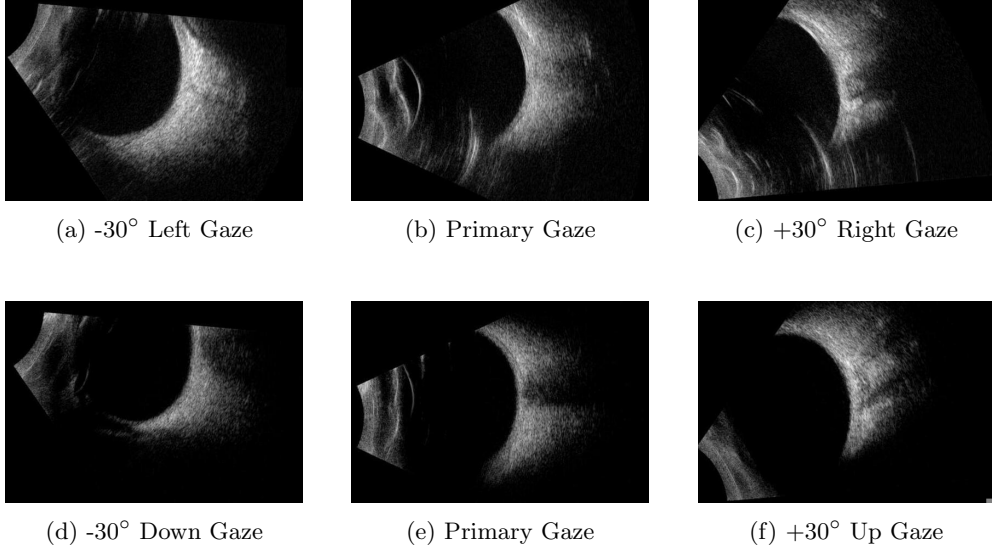


Fig. 1: Eye gaze images in the two meridians

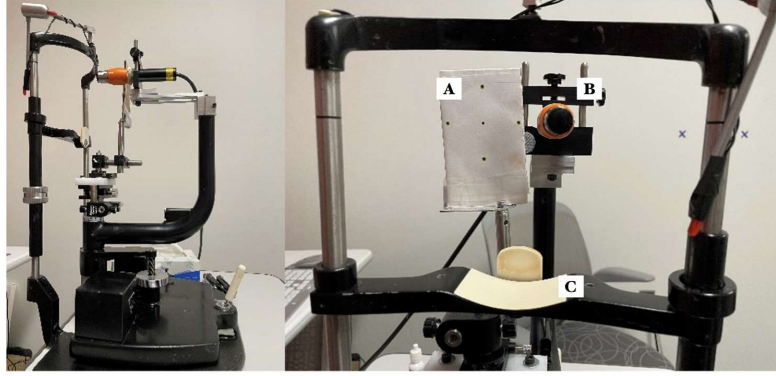


Fig. 2: The extended range B-scan ultrasonography set-up. A. Fixation target (primary, and -30° in each of up, down, right, and left gaze) for the left eye. Fixation targets are adjustable for pupillary distance as well as convergence and divergence. B. Ultrasound probe, applied to the right eye. C. Chin rest, adjustable vertically to properly align the subject with the fixation targets and ultrasound probe.

with subsequent averaging and merging steps, SAM enables the generation of clean, topologically consistent boundary maps for accurate curvature computation.

Let $\mathcal{I} = \{I_1, I_2, I_3\}$ denote the set of input images, where each image $I_i \in \mathbb{R}^{H \times W}$ corresponds to a distinct gaze direction. Each I_i is a two-dimensional grayscale ultrasound image, with H and W denoting the image height and width in pixels,

respectively, and $\mathbb{R}^{H \times W}$ indicating real-valued intensity measurements arranged on an $H \times W$ grid.

3.1 Image rotation

The initial preprocessing step applies affine rotations to align image pairs. Specifically, I_2 is designated as the primary gaze image, while I_1 is rotated by -30° and I_3 by $+30^\circ$, with translations applied to maintain the image center. This alignment facilitates consistent downstream processing.

3.2 Image Averaging

To ensure robustness against acquisition variability, an averaging strategy was implemented prior to merging. Within each subject, images were grouped by gaze direction (I_1, I_2, I_3) and spatially aligned using the same translation parameters as in preprocessing. A pixel-wise averaging operation was then applied across the image stack:

$$I_{\text{avg}}(x, y) = \frac{1}{N} \sum_{k=1}^N I_k(x, y)$$

where (x, y) denote the pixel coordinates, $I_k(x, y)$ represents the k -th aligned image and $N = 5$ is the group size.

This averaging process not only enhances stable retinal features but also mitigates errors that may occur when an individual image is inaccurately captured (e.g., due to eye motion or transient acquisition artifacts). By suppressing such frame-specific deviations, the averaged image provides a more reliable representation of retinal boundaries, which are subsequently segmented using SAM (Fig. 3).

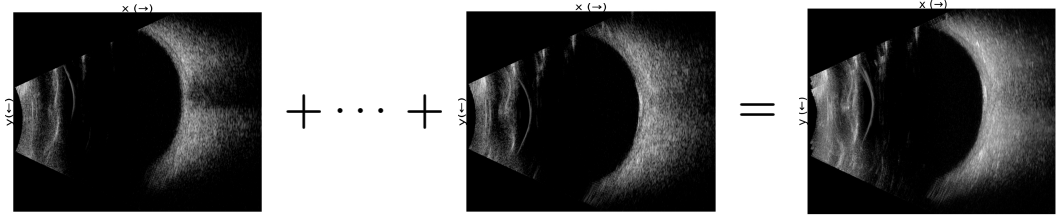


Fig. 3: Image Averaging over 5 frames

3.3 Machine Learning-enhanced Image Merging

To integrate information from multiple gaze directions, each image ($I_{-30^\circ}, I_{0^\circ}, I_{+30^\circ}$) was segmented using SAM to identify the vitreous and retinal boundaries. For each aligned image I_θ , SAM generates binary masks $M_{\text{vitreous}}^\theta$ and M_{retina}^θ , corresponding to the vitreous and retinal surfaces. Contours of vitreous (blue) and retinal area (green),

are extracted from these masks, and the overlapping area between the vitreous and retinal contours, shown as the red curve in Fig.4, is identified to produce a continuous, reliable boundary curve C_θ for each image.

The extracted curves $\{C_\theta\}_{\theta \in \{-30^\circ, 0^\circ, +30^\circ\}}$ are then aligned to the reference curve of the primary gaze image C_{0° via optimal translation. For $\{C_\theta\}_{\theta \in \{-30^\circ, 0^\circ, +30^\circ\}}$, the translation vector $T_\theta^* = (t_x^\theta, t_y^\theta)$ is computed by minimizing the sum of minimum point-wise distances to the reference curve:

$$T_\theta^* = \arg \min_T \sum_i \min_j \|(x_i^\theta + t_x, y_i^\theta + t_y) - (x_j^0, y_j^0)\|_2 \quad (1)$$

The translated curves are then:

$$C'_\theta = \{(x_i^\theta + t_x^*, y_i^\theta + t_y^*) \mid (x_i^\theta, y_i^\theta) \in C_\theta\}, \quad \theta \in \{-30^\circ, 0^\circ, +30^\circ\} \quad (2)$$

with $C'_{0^\circ} = C_{0^\circ}$ remaining unchanged. These aligned curves serve as guides for translating the corresponding images I_{-30° and I_{+30° to the reference frame of I_{0° (Fig. 4).

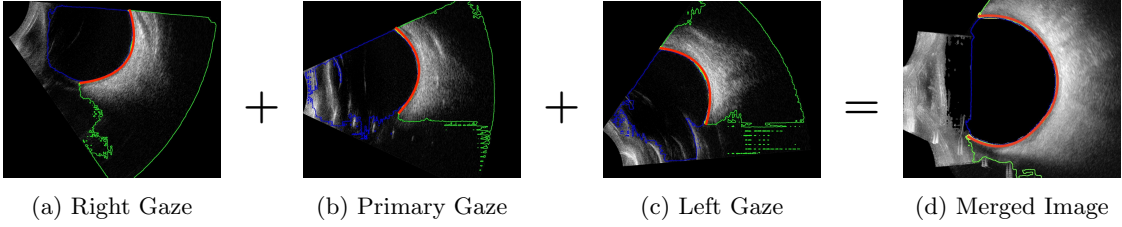


Fig. 4: Curve Extraction and Image Merging Process. The blue curve indicates the contour of the vitreous region, and the green curve indicates the contour of the retinal region. The red curve indicates the overlapping area of the vitreous and retinal regions.

The merged images are therefore defined as the translated images:

$$I'_\theta(x, y) = I_\theta(x + t_x^\theta, y + t_y^\theta), \quad \theta \in \{-30^\circ, 0^\circ, +30^\circ\}, \quad I'_{0^\circ} = I_{0^\circ} \quad (3)$$

Finally, the aligned images are merged into a single composite using a pixel-wise maximum operation:

$$I_{\text{merged}} = \max(I'_{-30^\circ}, I'_{0^\circ}, I'_{+30^\circ}) \quad (4)$$

This approach ensures that the merged image preserves the most prominent retinal features across gaze directions. By using SAM segmentation to identify vitreous and retinal boundaries and focusing on their overlapping regions, the resulting composite ensures that the aligned images are spatially consistent and suitable for subsequent retinal curvature analysis.

3.4 Post-hoc Image Processing for Curve Analysis

After merging, the aligned images may still contain residual noise and irregular boundary points that lead to a jagged or non-smooth extracted contour. To improve contour quality, SAM was first employed to refine the segmentation by isolating the vitreo-retinal interface and removing spurious points, as shown in Fig. 5. Small disconnected components were subsequently filtered out. Because the extracted boundary can exhibit multiple or fluctuating y -values for a given x -location, a y -wise averaging procedure was applied to enforce smoothness. Specifically, for each horizontal coordinate x , the corresponding y -coordinates of boundary pixels were averaged to produce a single representative point. This operation reduces local oscillations, suppresses high-frequency noise, and enforces a monotonic and single-valued curve. As a result, a consistent one-to-one correspondence between x and y coordinates was achieved. The final contour was smooth and continuous, providing a reliable foundation for subsequent curvature fitting and quantitative geometric analysis.

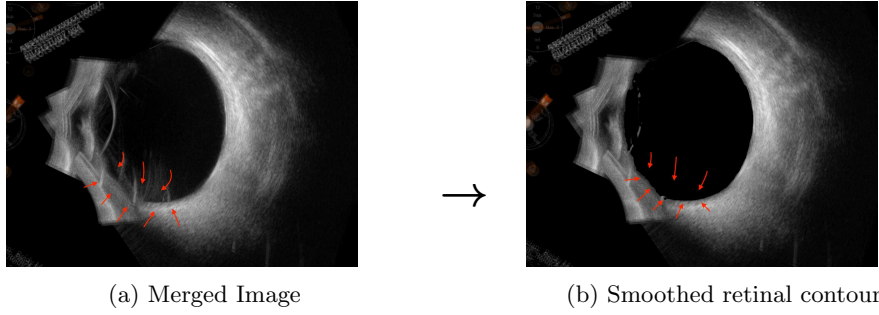


Fig. 5: Initial Merged Image after processed image after y -direction averaging. Red arrows indicate the spurious features.

3.5 Retinal Curvature Extraction from Merged B-Scans

Following merging and y -direction averaging, the composite images were processed for quantitative retinal curvature analysis (Fig. 6). For each merged image, a fixed-size region of interest (ROI) was extracted and centered at a predefined offset from the vitreous interface to localize the retinal structure. Within this ROI, edge detection was applied to identify continuous retinal boundary points based on intensity gradients and empirical heuristics.

The detected boundary points were then mapped from the ROI coordinates to the full-image coordinate system and separated into upper and lower curves. Each curve underwent polynomial fitting using a second-order model:

$$y^2 = 2rx - (1 + Q)x^2 \quad (5)$$

From these parameters, the Q-factor is calculated as $Q = -[a + 1]$ to quantify asphericity, the sagittal radius is given by $r = b/2$, and c represents the vertical offset

of the curve. These metrics provide a quantitative characterization of retinal curvature profiles. All spatial measurements were converted from pixel units to physical dimensions using a calibration factor of $40.33 \mu\text{m}/\text{pixel}$, ensuring that reported curvature parameters are expressed in microns.

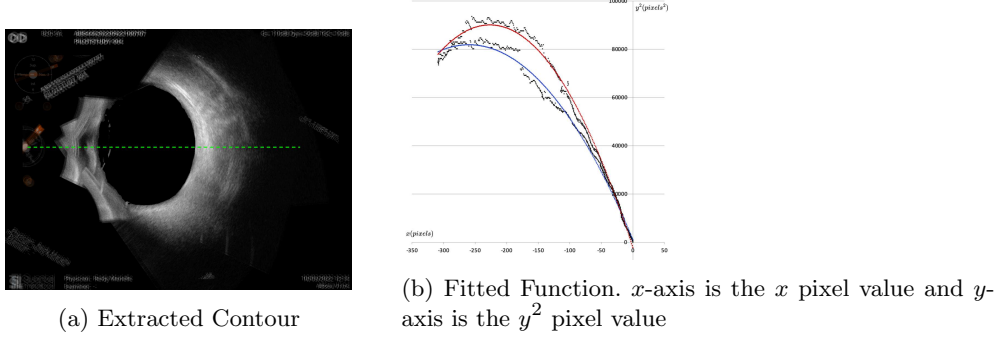


Fig. 6: (a) Extracted retinal contour and fitted polynomial function. The green dotted line indicates the midline, which separates the vitreous chamber into two curves. (b) The upper retinal contour is indicated in blue. The lower retinal contour is indicated in red (Equation 5).

4 Results and Discussion

Measurement reproducibility was assessed by calculating the standard deviation (SD) of the differences in vertical distance between the upper and lower retinal boundaries measured from a single merged image versus progressively averaged merged multiple images. This approach evaluates how much the boundary measurements change as more images are incorporated into the average. In an ideal scenario, adding additional images would not alter the anatomical structure, and the SD of these differences would approach zero. Therefore, lower SD values indicate higher measurement consistency and reduced noise in the retinal curvature estimation.

Figure 7 illustrates the distribution of SD values for both the machine learning (ML)-merged and manually merged datasets across all 20 subjects, highlighting the overall consistency between methods. Figures 8 and 9 further present selected examples with representative horizontal (subjects 11 and 13) and vertical (subjects 1 and 20) cases, illustrating both large and minimal differences between ML and manual merging. Subjects 11 and 1 demonstrate substantial improvements with ML merging, whereas subjects 13 and 20 show cases in which the two approaches yield nearly identical results. To quantify the improvement of ML merging over manual merging, both the absolute and percentage improvements in standard deviation for horizontal and vertical views were calculated. Improvements were computed at the subject level and then averaged. For the horizontal view, the mean absolute improvement across

subjects was 31.45 microns, corresponding to a mean per-subject percentage improvement of 30.12%. The averaged standard deviation was 86.31 microns for the manual merging and 54.85 microns for the ML-based method. In the vertical view, the ML-based approach achieved a mean absolute improvement of 29.04 microns, with a mean per-subject percentage improvement of 39.53%.

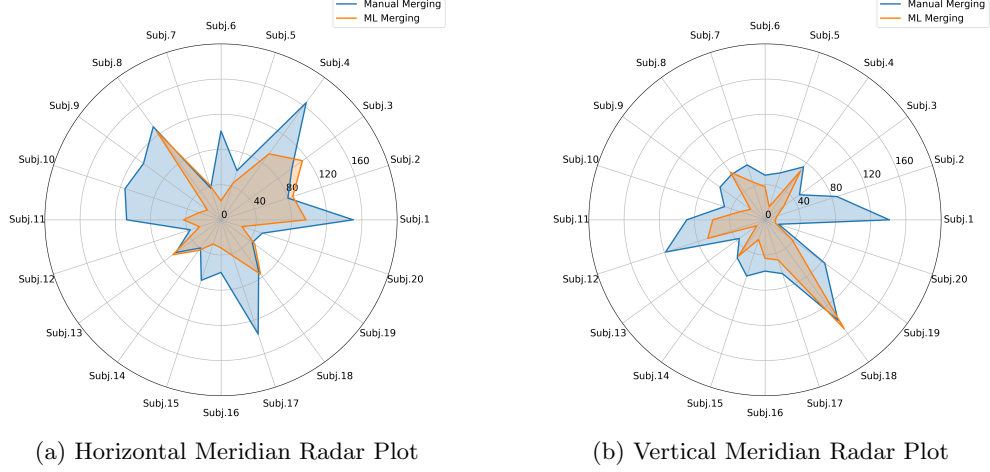


Fig. 7: Radar Plots of Standard Deviation in microns between single merged image and averaged merged image for each subject in both horizontal and vertical view. Blue region indicates the manual merging, and the orange area indicates the ML merging.

While to the naked eye, comparison between ML and manually merged images for subject 11 (Figures 8 and 9, panels (a) and (b)) does not seem much more different than comparison of the same for subject 13 (panels (c) and (d)), ML merging improved the standard deviation of the measurement by 64.48 microns for subject 11 and only 4.35 microns difference for subject 13. In 13 cases of horizontal views and 18 cases of vertical views, the ML-based approach achieved lower SDs than manual merging, indicating superior consistency. The ML pipeline, which incorporates a merged image processing step, effectively reduced merging artifacts seen in the manual merging process, resulting in substantially lower SDs and demonstrating the robustness of the automated approach in challenging imaging conditions.

From a clinical standpoint, the combination of ML-based merging and multi-set averaging has clear advantages for longitudinal ocular imaging studies, particularly for the changes that appear in the periphery. The progression of myopia and its associated structural changes in the posterior segment often occur gradually, with magnitudes that can be obscured by measurement variability. As shown in Figures 8 and 9, lower SDs directly enhance the sensitivity to subtle, biologically meaningful changes, thereby increasing statistical power in treatment trials and observational studies. Furthermore, the elimination of extensive manual intervention reduces operator burden, minimizes

human bias, and makes the workflow feasible for high-throughput or multi-center applications.

Taken together, these results show that ML-based merging consistently improves reproducibility over manual merging. The observed improvements are not only statistically relevant but also have practical implications for ensuring reliable and scalable retinal curvature tracking in both research and clinical environments.

5 Conclusion

This study presents an automated pipeline for merging extended-range B-scan ultrasonography images that addresses critical limitations in current myopia assessment techniques. By integrating the Segment Anything Model (SAM) with geometric alignment algorithms, the approach successfully captures comprehensive peripheral retinal morphology that extends beyond the restricted field of view of conventional optical biometry. The automated triplet merging method demonstrated improved performance to expert manual processing while providing significant advantages in consistency, reproducibility, and processing efficiency. The preservation of anatomical features essential for myopia evaluation, combined with reliable extraction of geometric parameters, establishes this approach as a viable tool for comprehensive globe morphology assessment. The ability to quantify peripheral eye shape changes provides new opportunities for understanding how myopia control treatments affect overall globe development, potentially revealing differential effects not captured by conventional central measurements alone. The scalable nature of the automated processing pipeline makes comprehensive eye morphology assessment practical for large-scale clinical trials and routine clinical practice. The ability to quantify peripheral validation of automated curvature parameter extraction demonstrates that this approach maintains the precision necessary for longitudinal monitoring of myopic progression and treatment response. By enabling consistent, operator-independent assessment of three-dimensional eye shape, this method addresses fundamental gaps in current understanding of myopia-related structural changes.

6 Declarations

Consent to Publish declaration: not applicable.

Ethics and Consent to Participate declarations: not applicable.

7 Acknowledgment

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8 Conflict of Interest Statement

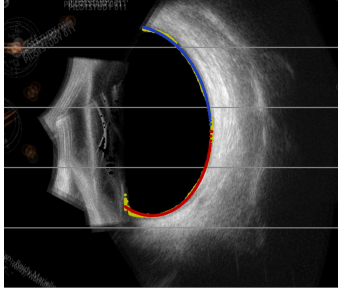
There are no conflicts of interest for this article.

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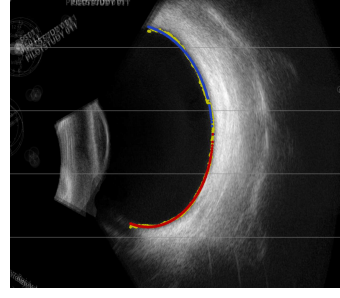
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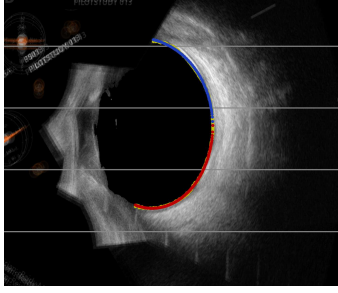
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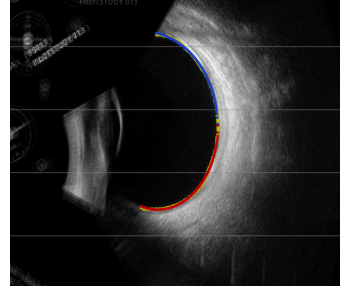
(a) Subject 011 Horizontal ML Merging



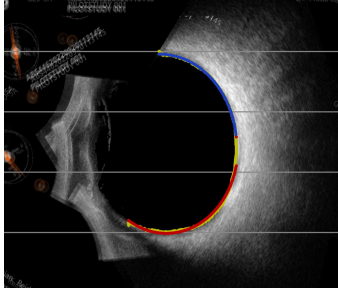
(b) Subject 011 Horizontal Manual Merging



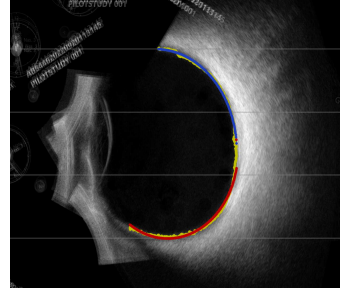
(c) Subject 013 Horizontal ML Merging



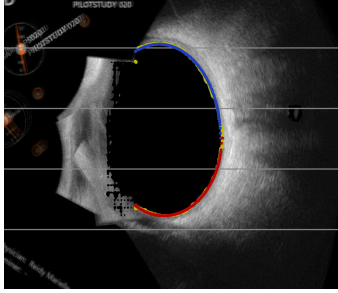
(d) Subject 013 Horizontal Manual Merging



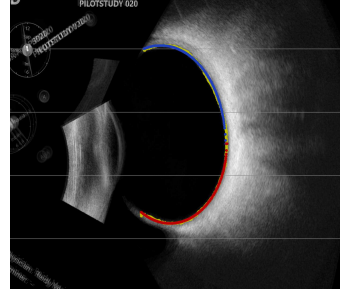
(e) Subject 001 Vertical ML Merging



(f) Subject 001 Vertical Manual Merging

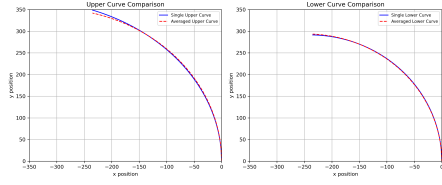


(g) Subject 020 Vertical ML Merging

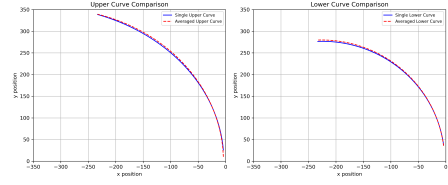


(h) Subject 020 Vertical Manual Merging

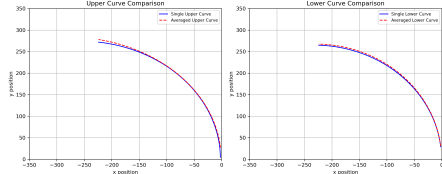
Fig. 8: Comparison of ML and Manual Merging: Detected Edge (Yellow), Fitted Upper Curve (Blue), and Fitted Lower Curve (Red) for four subjects. In the horizontal views, the Upper Curve corresponds to the temporal retina. Subfigures (a) & (b) and (e) & (f) show improvements with machine learning, while (c) & (d) and (g) & (h) show very similar results between machine learning and manual merging.



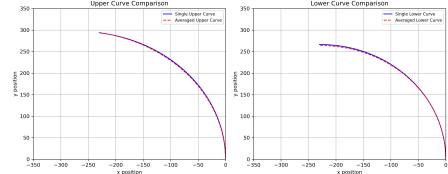
(a) Subject 011 Horizontal ML Merged SD=1.057



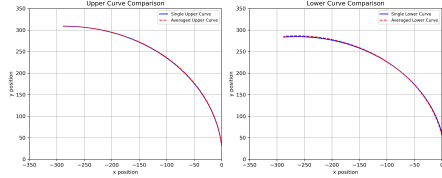
(b) Subject 011 Horizontal Manual Merged SD=2.656



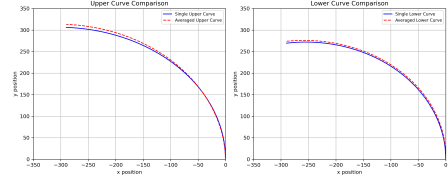
(c) Subject 013 Horizontal ML Merged SD=1.657



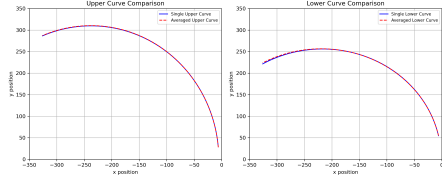
(d) Subject 013 Horizontal Manual Merged SD=1.567



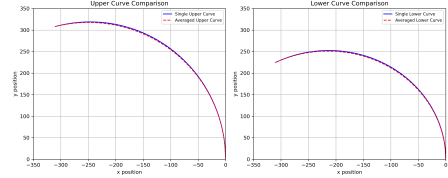
(e) Subject 001 Vertical ML Merged SD=0.292



(f) Subject 001 Vertical Manual Merged SD=3.498



(g) Subject 020 Vertical ML Merged SD=0.315



(h) Subject 020 Vertical Manual Merged SD=0.405

Fig. 9: ML Merging vs Manual Merging difference (Blue indicates the upper/lower curve of the single merged image and Red indicates the upper/lower curve of the progressively averaged merged images.)