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Validation of Macular Choroidal Thickness Measurements from Automated SD-OCT Image Segmentation

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Abstract

Purpose—Spectral domain optical coherence tomography (SD-OCT) imaging permits *in vivo* visualization of the choroid with micron-level resolution over wide areas and is of interest for studies of ocular growth and myopia control. We evaluated the speed, repeatability and accuracy of a new image segmentation method to quantify choroid thickness compared to manual segmentation.

Methods—Two macular volumetric scans ($25 \times 30^\circ$) were taken from 30 eyes of 30 young adult subjects in two sessions, one hour apart. A single rater manually delineated choroid thickness as the distance between Bruch's membrane and sclera across three B-scans (foveal, inferior and superior-most scan locations). Manual segmentation was compared to an automated method based on graph theory, dynamic programming, and wavelet-based texture analysis. Segmentation performance comparisons included processing speed, choroid thickness measurements across the foveal horizontal midline, and measurement repeatability (95% limits of agreement (LoA)).

Results—Subjects were healthy young adults ($n=30$; 24 ± 2 y; mean $\pm$ SD; 63% female) with spherical equivalent refractive error of: -3.46 ± 2.69 D (range: $+2.62$ to -8.50 D). Manual segmentation took 200 times longer than automated segmentation (780 vs 4 seconds). Mean choroid thickness at the foveal center was 263 ± 24 μ m (manual) and 259 ± 23 μ m (automated), and this difference was not significant ($P = .10$). Regional segmentation errors across the foveal horizontal midline ($\pm 15^\circ$) were 9 μ m (median) except for nasal-most regions closest to the nasal peripapillary margin— 15° (19 μ m) and 12° (16 μ m) from the foveal center. Repeatability of choroidal thickness measurements had similar repeatability between segmentation methods (manual LoA: ± 15 μ m; automated LoA: ± 14 μ m).

Conclusions—Automated segmentation of SD-OCT data by graph theory and dynamic programming is a fast, accurate, and reliable method to delineate the choroid. This approach will facilitate longitudinal studies evaluating changes in choroid thickness in response to novel optical corrections and in ocular disease.

Keywords

biomedical optics; choroid; optical coherence tomography; ocular imaging; image processing; biomedical optics; tissue characterization

The choroid is a highly vascular tissue with several distinct anatomical zones that is separated from the neuroretina by the retinal pigmented epithelium (RPE) and Bruch's membrane.^{1, 2} *In-vivo* visualization of the vascular choroid is typically limited by the reflectivity and optical absorption of the overlying RPE, and in the recent past has only been visible through other invasive imaging modalities (e.g. *en face* indocyanine green angiography).³

There is increasing interest in the choroid as an important tissue in the regulation of ocular growth and refractive error development.⁴⁻¹² It has been shown that visual signals, e.g. form deprivation or defocus, can lead to refractive error.¹³⁻¹⁶ Although the precise physiological mechanisms are not established, it is believed that the choroid plays a central role. Changes in subfoveal choroidal thickness in response to retinal defocus have been reported in both animal models and humans,^{17,18} and quantitative analysis of choroidal morphology may bring important insights on factors involved in the eye's response to defocus. Specifically, understanding the time course, spatial localization, and persistence of any choroidal changes in response to optical defocus could provide insights on how the eye processes retinal defocus information to regulate eye growth.

Spectral-domain optical coherence tomography (SD-OCT) imaging provides unprecedented access to the choroid *in vivo*, allowing clinicians and researchers new tools to assess the role that this richly innervated and highly vascular tissue may have in degenerative retinal diseases^{19, 20} ocular inflammation,²¹ glaucoma,²² emmetropization of the eye, and myopia progression.^{7-10,12,13,23-26} Further development and optimization of OCT imaging (e.g. higher imaging rates from swept-source designs) and better penetration from longer wavelength IR sources (e.g. ~1 μm) will continue to improve choroidal imaging over the next several years.²⁷⁻³⁰ Nevertheless, reliable methods of processing and analyzing the image data (e.g. feature detection and image segmentation) are essential to make full use of the information obtained from these enhanced imaging capabilities and is an area of active research.^{29,31,32}

Due to the depth of imaging required, the complex anatomical structure of the choroid, and the variable reflectivity of tissues, automated segmentation of choroid OCT imaging is a challenging problem. A majority of previous publications are based on manual or semi-automated delineation of features and point-wise determination of thickness.³²⁻³⁶ Automated image segmentation methods have been described,^{29,37-40} and evaluated on clinical populations.^{31,41,42} These algorithms are desirable because they permit more efficient analysis of larger datasets, typically with greater precision than manual methods. However, current methods which utilize three-dimensional algorithms limit their functionality to volumetric scans and require heavier pre-processing steps such as registration across all B-scans.^{29,39} Other reported methods either require training datasets with computationally intensive statistical methods,³⁷ or they rely on local minima analysis which often has false

positives caused by choroidal blood vessels or noise.³⁸ In this manuscript, we describe an automated segmentation method based on graph theory and dynamic programming which utilizes wavelet-based texture analysis to identify the choroid.

We are specifically interested in the morphological response of the choroid to optical corrections being studied to slow myopia progression. The broader goal of this research is to develop reliable and repeatable methods to quantify the morphology of the choroid for clinical studies. Despite several previous investigations on image segmentations methods, few have evaluated spatial variations in choroid morphology^{34,35,43-50} and fewer still have assessed the accuracy of automated segmentation methods across the macula.^{29,40,41,51} In this research, we compare the speed, repeatability and accuracy of an automated segmentation routine based on graph theory and dynamic programming compared to manual image segmentation for the measurement of choroidal thickness profiles from SD-OCT imaging across the macula in a cohort of healthy young adults.

METHODS

Subjects and Image Acquisition

The use of human subjects in this research was reviewed and approved by the University of Houston's Institutional Review Board; all research activities conformed to the ethical principles for medical research involving human subjects as stated in the Declaration of Helsinki. Young healthy subjects were recruited as participants. Participants provided written informed consent. To be eligible, participants were required to be non-presbyopic, free of ocular disease, have no history of ocular trauma or ocular surgery (including refractive surgery), and free of any systemic disease known to cause variability in refractive error.

The left eye of each subject was imaged twice during a single session (1 hour apart) using the Spectralis SD-OCT imaging system (Heidelberg Engineering, Carlsbad, CA, USA). A volume scan pattern ($25^\circ \times 30^\circ$; 32 total B-scans) was centered on the fovea and its position stabilized during scans using the instrument's image registration software routines (ART) and enhanced depth imaging feature to further enhance contrast of the choroid. Each B-scan in the volume was a composite average of 35 individual line-scan images. This scan protocol was selected because it provides dense and regular sampling across the macular region. Images taken during the second imaging session were acquired using the instruments *Follow-up* mode to insure that imaging was aligned between sessions. Exam data were exported as binary files and numeric arrays of pixel intensity were generated from these files. These numeric arrays were then subjected to two different analysis routines—manual segmentation by a trained evaluator and an automated graph-based segmentation method.

Image Segmentation Methods

Three horizontal B-scans were selected from each macular volume for analysis— 12.5° above the fovea, at the fovea, and 12.5° below the fovea. A single trained evaluator (KS) performed manual image segmentation using custom designed image annotation software. The evaluator reviewed each individual B-scan noting the boundaries between the vitreous

and internal limiting membrane, between the retinal pigmented epithelium and the anterior choroid, and between the posterior choroid and sclera. This involved choosing points along each anatomical structure that were then joined using a Bezier curve-fitting routine. The evaluator was permitted to adjust the location of placed points, delete previously placed points, and view adjacent B-scans as needed to achieve a best-fit to the anatomical boundaries. Final segmentation boundaries were then saved as the standard for comparison with repeated measurements and automated segmentation.

Automated image segmentation was performed on the same set of images that were manually segmented. Images (1024 pixels total) were cropped by 100 pixels from each side to remove the optic nerve head and most peripheral pixels as a pre-processing step to reduce the possible influence of artifacts due to initialization conditions at the boundary. The graph theory and dynamic programming segmentation framework has been described in detail in our previous publications.⁵²⁻⁵⁵ In summary, graph theory and dynamic programming is a technique that models an image and its associated characteristics (e.g. intensity, gradient, distance) as a weighted graph and determines preferred paths across the graph by minimizing cumulative weights. In graph theory, the image is represented by a graph of nodes and edges (Figure 1), where each pixel is a node on the graph, and edges are the possible paths that connect adjacent nodes (pixels) to each other.⁴⁰ By giving edges different mathematical weights or probabilities, a preferred path from one pixel to an adjacent pixel is chosen from other less likely options. Taken together, the preferred edges define pathways or segmentation boundaries that delineate anatomical boundaries within an image. The graph theory and dynamic programming segmentation approach is a computationally efficient method for finding the shortest and most probable path that works well with images that have a low signal-to-noise ratio.^{52-54, 56}

Using the graph theory and dynamic programming framework, we developed an automatic algorithm to segment three retinal layer boundaries: the inner limiting membrane, Bruch's membrane, and outer choroidal boundary. Following our previous implementations,^{52, 53} the images were first standardized to an axial resolution of 6.7 $\mu\text{m}/\text{pixel}$ and 0.75 times the original image width. We then Gaussian filtered the image (10 $\times$ 10 pixel filter, $\sigma=2$) and computed the light-to-dark and dark-to-light gradient images.⁵³ To isolate locations of maximum gradient, the dark-to-light image was further refined by keeping only the local maxima in each column and setting all other regions to zero. Using a combination of light-to-dark weights (ranging from 0–1) and distance weights (ranging from 0–0.1),⁵² we used graph theory and dynamic programming to generate a pilot estimate of Bruch's membrane. We then limited the search region to range from the top of the image to 20 pixels above the pilot Bruch's membrane boundary and used dark-to-light image weights to segment the inner limiting membrane. To refine Bruch's membrane, we took the mean of the inner limiting membrane and Bruch's membrane for each A-scan and smoothed the result using a moving average filter, resulting in the boundary b . We then subtracted b from Bruch's membrane and computed the median. Next, we set the lower bounds of the search region to ten pixels below b plus the median value. The upper boundary of the search region was then set to ten pixels above the lower bounds or ten pixels above the pilot Bruch's membrane, whichever was higher. Finally, we used the same light-to-dark / distance weight combination to re-segment Bruch's membrane.

Next, to shorten the path of the choroid, we flattened the retina based on Bruch's membrane by circularly shifting the A-scans until the Bruch's membrane estimate became a horizontal line (Figure 2A-B).⁵³ To generate a final estimate of Bruch's membrane, we applied graph theory and dynamic programming on the flattened image using the same weight combination and a search region limited to two pixels above and below the second Bruch's membrane estimate. To segment the outer choroidal boundary, we first identified the choroid, or regions below Bruch's membrane with strong amounts of texture. To do this, we Gaussian filtered the image (20×20 pixel filter, $\sigma=5$; Figure 2C) and decomposed the smoothed image into a three-level Coiflet wavelet decomposition. For each level, the horizontal, vertical and detail coefficients were summed together. The three resulting detail images along with the level-three approximation image were resized to the original image size. Finally, all four images were summed together to create a wavelet energy map,⁵⁷ which accentuated the texture within the choroid (Figure 2D). Graph weights for the choroid were then generated by combining the energy map weights (ranging from 0–1) with distance weights (ranging from 1.8–2.0). With this weighting scheme, regions with high amounts of texture (e.g. the choroid) were penalized with high weights, and regions with low texture (e.g. the outer choroidal boundary) were assigned low weights. To establish the upper boundary of the search region, linear interpolation was performed between three points: Bruch's membrane on the first A-scan, 40 pixels below Bruch's membrane on the middle A-scan, and Bruch's membrane on the last A-scan. The lower search region boundary was then set to a linearly-interpolated line formed by four points: Bruch's membrane on the first and last A-scans, and 80 pixels below Bruch's membrane for the two A-scans one-quarter of the width into either end of the image (Figure 2E). Finally, we used graph theory and dynamic programming to segment an estimate of the outer choroidal boundary. To refine the segmentation, a new set of graph weights were computed by combining dark-to-light weights (ranging from 0–1), intensity weights⁵² (ranging from 1.0–1.5), and distance weights (ranging from 1.8–2.0). After limiting the search region to range from the choroid segmentation to ten pixels below the estimate, we used graph theory and dynamic programming to obtain the final outer choroidal boundary path (Figure 2F). Lastly, all boundaries were unflattened, resampled to the original image size, and smoothed with a moving average filter.

Analysis Methods

Choroid thickness was defined as the distance between Bruch's membrane and the outer choroidal boundary. These distances were calculated column-wise across the entire B-scan image and are reported as a global average (mean $\pm$ SD). Regional variations in choroid thickness measurements (nasal to temporal) were calculated for each 30° B-scan. Each scan was divided into 11 segments (2.7° each) and the distribution of thickness measurements across subjects was summarized by scan segment to provide a description of gross regional variations in choroid morphology as well as the regional differences between manual and automated segmentation by retinal position. We also report a comparison of the time taken to determine these measurements from manual and automatic segmentation routines for a single B-scan image.

The repeatability of each segmentation method is reported as the coefficient of variation (CV) and 95% limits of agreement (LoA).⁵⁸ Repeatability is shown graphically as the residual difference between the measurements repeated between sessions (1 hour apart) as a function of the mean of the two measurements. Similarly, the 95% LoA is reported for the comparison of the manual and automated segmentation methods.

RESULTS

The study participants were 30 young adults (24 ± 2 years), predominantly female (19/30), with myopic spherical equivalent refractive error of -3.46 ± 2.69 D (mean $\pm$ SD; range: $+2.62$ to -8.50 D). A total of 180 B-scan images (30 subjects $\times$ 3 scan positions [superior macula, fovea, and inferior macula] $\times$ 2 imaging sessions) were analyzed from the left eye of each subject. The mean scan quality—a measure of signal to noise reported by the instrument software—was highest in the foveal scan location (31.6; 95% CI: 30.2 to 32.9) and this was significantly different from the inferior (28.1; 26.6 to 29.6; $p = .002$) and superior retinal scan locations (27.8; 95% CI=26.7 to 28.9; $p = .001$). The inferior and superior scan positions were not different from each other (one-way ANOVA with Scheffe's adjustment for multiple comparisons; $p = .943$). Each B-scan was analyzed using manual and automated image segmentation methods as described above. On average, manual image segmentation took 780 seconds to process a single B-scan image; by comparison, automated image segmentation took 4 seconds on average. The number of anchor points selected during manual segmentation was 13 ± 4 (range: 6 to 24). The number of points selected was not related to scan quality values (linear regression; $p > .10$) for all retinal scan locations. Figure 3 shows a comparison of manual (green) and automated (yellow) choroid segmentation boundaries for four images—two with good agreement (one foveal and one peripheral location), one with disagreement in an isolated region, and one with global disagreement in the posterior choroid segmentation boundary location.

Regional variations in macular choroid thickness by lateral position from manual image segmentation measurements are summarized in Figure 4. As can be seen Figures 4A-4C, regardless of scan position (inferior macula, fovea, and superior macula), the choroid was thinnest in the nasal retina, increased towards the center of the scan (fovea), and then remained fairly constant in thickness temporal to the fovea. The foveal B-scan ranged from a median thickness of 137 μ m (nasal) to 297 μ m (temporal). Median choroid thickness across the superior macular B-scan position ranged from 251 μ m (nasal) to 300 μ m (temporal). Median thickness at the inferior scan position ranged from 188 μ m (nasal) to 266 μ m (temporal).

Segmentation Performance

The distribution of residual error between manual and automatic image segmentation across the B-scan is summarized for each retinal scan location (inferior, foveal and superior) in Figure 5. In summary, the errors were of low magnitude and tightly distributed for the inferior and foveal scan positions. There were notable outliers with large amplitude errors in the temporal scan regions (especially superiorly) due to automated segmentation underestimating choroid thickness compared to manual segmentation (Figure 5). After

correction for multiple comparisons (Benjamini-Hochberg method), several of the foveal and superior scan locations were statistically different from 0 due to either the magnitude of the mean difference or distribution of the residual errors.

Manual and automatic image segmentation were both highly repeatable. The mean difference in overall choroid thickness between imaging sessions for the manually segmented foveal B-scans was $3.0 \mu\text{m}$ ($\text{LoA} \pm 14.7 \mu\text{m}$), Figure 6A. The mean difference in between-session measurements for choroid thickness determined by automated image segmentation was comparable ($P > .05$) at $2.1 \mu\text{m}$ ($\text{LoA} \pm 13.5 \mu\text{m}$), Figure 6B. The residual difference between manual and automated segmentation methods is shown in Figure 7. The mean automated segmentation error was $1.2 \mu\text{m}$ ($\text{LoA} \pm 31.0 \mu\text{m}$).

The average choroid thickness across each B-scan location (foveal, superior macula, and inferior macula) is summarized in Table 1. B-scan thickness measurements were not significantly different by segmentation method (manual or automated) for the foveal (paired t-test; $P = .1$) and inferior macular (paired t-test; $P = .6$) B-scan locations, but were on average $8 \mu\text{m}$ (~2 pixels) thicker by manual segmentation in the superior macular B-scan (paired t-test; $P = .005$). The coefficient of variation was the same for both segmentation methods for the foveal B-scan ($\text{CV} = .22$). The inferior macular (manual: $\text{CV} = .17$; automated: $\text{CV} = .20$) and superior macular (manual: $\text{CV} = .19$; automated: $\text{CV} = .21$) coefficients of variation were similar.

DISCUSSION

The major advantages of automated segmentation are repeatability and speed. The graph theory and dynamic programming segmentation methods evaluated in this study were approximately 200 times faster than manual segmentation methods and highly repeatable between sessions ($\text{LoA} \pm 14 \mu\text{m}$). Any automated image segmentation method also includes error and evaluation of our graph theory and dynamic programming results were excellent agreement with expert manual segmentation methods (mean error: $1.2 \mu\text{m}$; $\text{LoA} \pm 31.0 \mu\text{m}$).

These results show that the choroid thickness measurements from this graph theory and dynamic programming automated segmentation method provides excellent test-retest reliability. This precision will be an important determinant of the ability to detect changes in choroid thickness due to clinical interventions in longitudinal studies. By comparison, the 95% limits of agreement for the automated method used in this study was somewhat better than previously reported results by Gupta and colleagues using other graph-based automated segmentation techniques (95% $\text{LoA} = \pm 21 \mu\text{m}$)³¹ and very similar to the observer repeatability results reported by Alonso-Caneiro and colleagues ($-1.3 \mu\text{m}$; $\text{LoA} \pm 11.9$).⁴⁰

Another important consideration is accuracy, or agreement between manual and automated segmentation methods. Our results showed excellent agreement between our benchmark standard (manual choroid segmentation) and automated image segmentation (mean difference: $1.2 \mu\text{m}$; $\text{LoA} \pm 31.0 \mu\text{m}$). In summary, our results indicate that these two methods have comparable precision and excellent overall agreement. Despite the fact that there were automated segmentation errors in the periphery of a small number of B-scans, the

repeatability was similar to our benchmark standard, manual segmentation (manual 95% LoA: $\pm 15 \mu\text{m}$; automated LoA: $\pm 14 \mu\text{m}$).

In previous work, Tian and colleagues reported agreement between their graph-based automated segmentation and manual segmentation using Dice's coefficient (90.5%), which translates to 6.7 pixels or approximately $26 \mu\text{m}$.³⁸ Alonso-Caneiro and colleagues improved upon this result using another modified graph-based segmentation approach.⁴⁰ Agreement between their method and a manual observer was reported as mean error of $2.3 \mu\text{m}$ (LoA: $\pm 33.1 \mu\text{m}$). Which compares favorably with our results reported here. The largest segmentation errors in the present study occurred in superior temporal scan regions, which we hypothesize are due to low image contrast in those regions. The scan quality index provided by the Spectralis is a global measure of image quality and was not predictive of the regional segmentation failures that we observed, e.g. Figure 3C-D. Previous work comparing manual and automated image segmentation methods such as the studies cited above reported information on global measures of agreement between segmentation methods. Alonso-Caneiro and colleagues provided additional regional agreement results at 4 points (sub-foveal, central fovea, and the inner and outer macular regions), which suggested that on average, their method performed similarly across the full 30° scan path.⁴⁰

Any segmentation method, manual or automated, will be limited by the quality of the image input. Low image contrast was noted in several of the the superior peripheral B-scans and this corresponded with automated segmentation errors that were less than manual measurements of choroid thickness. The direction of this error (towards less choroid thickness) makes sense as the image contrast of the anterior choroid provides better features by which to segment the image compared to the deep choroid. So, when the image contrast is poor, the segmentation algorithm finds features in the more anterior tissue to determine where to define the segmentation boundary. While fully automated image segmentation is the ideal, the reality is that any automated system will err. The question then becomes whether or not those errors are of sufficient magnitude to make the automated system unacceptable. Our results suggest that our current methods, provide an acceptable solution to this problem providing outstanding speed, excellent repeatability and comparable accuracy to an expert manual examiner. Another strategy is to predict when these automated segmentation failures might occur and provide manual intervention in those instances. Successful prediction of these segmentation failures is a challenging problem and an area of ongoing research. In the meantime, inspection of the results by a trained examiner is necessary.

Average foveal choroid thickness in this study was $259 \pm 23 \mu\text{m}$ and is most similar to the results of Beaton and colleagues ($264 \pm 78 \mu\text{m}$) who also used a graph-based segmentation strategy.⁴³ Other similar results for foveal choroid thickness have been reported by Gupta and colleagues ($242 \pm 98 \mu\text{m}$),³¹ Shin and colleagues (286 ± 53),³² and by Read and colleagues ($308 \pm 78 \mu\text{m}$).⁵⁹ The measurements of foveal choroidal thickness reported here was collected with the same instrument and similar scan protocols to Beaton and Gupta. The study by Shin and colleagues used another SD-OCT instrument. Both Beaton and Gupta and Read and colleagues uses radial scan protocols centered at the fovea.

Likewise, our findings generally agree with the choroidal morphology reported by Gupta who summarized point estimates of choroid thickness at 13 evenly-spaced points across a foveal scan, much like our sampling of 11 bins. The nasal most location in our study was 137 μm (Gupta: 142 μm). However, we found that choroid thickness temporal to the fovea (297 μm) was greater than at the fovea (259 μm) within the macular region scanned. Read and colleagues, using a similar radial scan strategy, reported a summary of choroid morphology in a cohort of children (13 years) with and without myopia.⁵⁹ Their findings across multiple studies, showed that choroid thickness in the macula was greater among myopic children, thickest near the fovea, and thinner in the periphery (with inferior-nasal thickness less than superior-temporal).⁵⁹⁻⁶¹ Their findings agree with what Gupta has reported (i.e. that the choroid peripheral (temporal) to the fovea (208 μm) is thinner than at the fovea (242 μm). Two notable differences among these studies are the ages studied. Read and colleagues studied children (10-15 years) while Gupta et al. included both healthy and diseased subjects with a mean age of 63 years versus 24 years (present study). It is not possible to say if these reported differences in peripheral choroid thickness are due to age, refractive error, scan protocols, or ocular health status, but all bear consideration.

There is interest in the choroid as a tissue that can provide important insight on emmetropization and the development of refractive error.^{17, 62} Smith and colleagues have provided substantial evidence that visual experience can profoundly affect ocular growth.^{16, 63, 64} Clinical evidence is mounting that myopic peripheral defocus may be able to slow myopia progression and this is the most common mechanism proposed by which orthokeratology and soft bifocal contact lenses are thought to slow myopia progression.⁶⁵⁻⁶⁹ The ability to quantitatively document temporal changes in choroid morphology will enable investigation of the choroid's response to retinal defocus and its possible role in the regulation of eye growth for longitudinal studies of myopia control.

CONCLUSIONS

Automated image segmentation using the graph theory and dynamic programming technique can provide repeatable, accurate, and rapid quantitative measurements of choroidal thickness. The technique described here will be employed in future longitudinal studies. The ability to quantify choroid morphology can enable further progress towards understanding the physiological role that the choroid may play in ocular growth and refractive error development.

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Figure 1.

Conceptual schematic diagram of graph theory and dynamic programming approach to image segmentation. This graph shows a very simple example where the goal is to segment the darkest path across the image. Following the goal, the edge weights are computed by adding the pixel intensities of connected node pairs. Lower weights (thicker edges) are preferred over higher weights (thinner edges). The end result is the shortest preferred path from the start node to the end node (dashed path).

Figure 2.

Graph theory and dynamic programming (GTDP) image segmentation algorithm. **(A)** The B-scan from Figure 2B resized (and horizontally compressed for display purposes), **(B)** the retina flattened based on an estimate of BM (red), **(C)** the image from (B) smoothed using a Gaussian filter, **(D)** a wavelet energy map, where bluer tones result in lower edge weights, **(E)** the search region used to segment the choroid, where red regions are excluded from the search space, and **(F)** the segmented outer choroidal boundary (red) prior to unflattening and smoothing.

Figure 3.

Comparison of choroid thickness determination from OCT images using manual (green) and graph-based automated segmentation methods (yellow); (A) foveal image segmentation showing good agreement and effect of optic nerve head on automated segmentation, (B) peripheral image showing good segmentation agreement, (C) peripheral image showing local disagreement in choroid segmentation, (D) image sample showing global disagreement in choroid segmentation. Choroid thickness measurements were comparable with automated and manual image segmentation methods. The extreme left-side of image A and C show the boundary effects of segmentation near the image border and optic nerve that were cropped and not included in the analysis.

Figure 4. Box plot distribution of regional variations in macular choroid thickness determined from manual image segmentation ($n=30$); **(A)** B-scan position 12.5° superior to the fovea; **(B)** foveal horizontal midline; **(C)** 12.5° inferior to the fovea.

Figure 5.

Box plot distribution of regional variations in segmentation error between manual and automated segmentation methods where positive values represent greater choroid thickness by manual segmentation (i.e. manual – automated); differences that are statistically different from zero are indicated by the asterisk; **(A)** B-scan position 12.5° superior to the fovea; **(B)** foveal horizontal midline; **(C)** 12.5° inferior to the fovea.

Figure 6.

Plot of residual difference between repeated measurements of choroid thickness derived from (A) manual (LoA: $3.0 \pm 14.7 \mu\text{m}$) and b) automated (LoA: $2.1 \pm 13.5 \mu\text{m}$) OCT image segmentation methods. Dashed line indicates the mean difference between measurements; shaded region delineates the 95% limits of agreement (LoA).

Figure 7.

Plot of residual difference between choroid thickness measurements derived from manual and automated segmentation of OCT images (LoA: 1.2 ± 31.0). Dashed line indicates the mean difference between measurement methods; shaded region delineates the 95% limits of agreement.

Mean choroid thickness across the full B-scan from OCT image segmentation by method (manual vs. automated) and scan location.

Horizontal B-Scan location	Manual Segmentation Mean $\pm$ 95% CI	Automated Segmentation Mean $\pm$ 95% CI	Thickness Difference (Manual–Auto) Mean $\pm$ 95% CI
Central (fovea)	263 $\pm$ 24 μ m	259 $\pm$ 23 μ m	4 $\pm$ 5 μ m (P = .10)
Inferior (12.5° below fovea)	263 $\pm$ 17 μ m	264 $\pm$ 20 μ m	–1 $\pm$ 6 μ m (P = .60)
Superior (12.5° above fovea)	292 $\pm$ 23 μ m	284 $\pm$ 24 μ m	8 $\pm$ 5 μ m (P = .005)