CLASSIFICATION OF SCAN LOCATION IN RETINAL OPTICAL COHERENCE TOMOGRAPHY

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ABSTRACT
Spectral-domain optical coherence tomography is a new imaging tool to aid the diagnosis of various diseases of the eye. Two commonly used scan patterns focus on different areas of the retina and are used to measure different properties. We developed an efficient automated classification technique that distinguishes scans of the two types so that algorithms tuned to the specific scan type can be applied during computer-aided analysis. Our algorithm differentiates between scan types based on the presence or absence of vessels converging on the optic disc. We tested its performance on an extensive dataset containing a total of 1015 scans from both healthy and diseased subjects and achieved a sensitivity of 100% and a specificity of 99.7%.

Index Terms— Image classification, Blood vessels, Optical tomography imaging

1. INTRODUCTION
Spectral-domain optical coherence tomography (SD-OCT) provides ophthalmologists with a powerful tool for the diagnosis of eye diseases. SD-OCT is also called 3D-OCT because it can generate a three-dimensional measurement of the retinal tissues, recording tissue reflectivity at each point in a $6\times6\times2$ mm volume. The resolution of the scans used in this study is $200\times200\times1024$ voxels. Collapsing the volume along the depth dimension by adding reflectivity values produces an en face image. The en face image, which is analogous to the traditional fundus image of the retina, provides a familiar and intuitive way to visualize the SD-OCT volume. Meanwhile, the availability of the underlying 3D data makes it possible to extract diagnostically relevant properties not recoverable from traditional fundus images. There is growing interest in computer-aided analysis of SD-OCT data.

Two common scan patterns used in SD-OCT are the Optic Disc Cube (ODC) and the Macular Cube (MC). Example en face images from the two types of scans are shown in Figure 1. The two scan patterns focus on different portions of the retina and therefore merit different treatment. Studies utilizing computer-aided analysis will need to first classify scan types so as to select the corresponding analysis algorithm. Even algorithms that apply to both scan types may require different parameter settings. For example, we classify scan location to select scale parameters for vessel detection, differentiating thick ODC vessels from thin MC vessels. Although scan type may be extracted from the metadata provided by the SD-OCT scanner, this is unreliable, as significant eye movement during acquisition can alter the location of the scan. In theory, trained experts should screen and label scans at acquisition, but this may not always be feasible in the reality of a hectic clinical practice. In fact, even the carefully collected dataset used in this study contained a scan that was mislabeled at acquisition. A robust approach is to directly analyze the OCT data for classification, supplementing with expert labeling or other metadata when available so as to achieve both accurate and efficient classification.

This paper presents a fully automated algorithm to classify SD-OCT volumes based on their scan patterns by analyzing the convergence of major vessels detected in the en face images. Our approach is insensitive to diverse retinal pathologies and does not depend on unreliable properties such as the appearance of the optic disc.

2. RELATED WORK
ODC scans contain the optic disc while MC scans do not. Thus, our classification task is closely related to the problem

(a) Optic Disc Cube (ODC) (b) Macular Cube (MC)

Fig. 1. En face images created from the two different scan patterns. The Optic Disc Cube is centered at the optic nerve head, while the Macular Cube is centered at the fovea.
of optic disc localization. Most prior work on optic disc localization detects the position of the optic disc in retinal fundus images. In fundus images, the optic disc appears as the brightest portion of the image. Consequently some optic disc detection algorithms simply search for the area of highest intensity [1]. Another intensity-based method searches for the region with the most intensity variation because the bright optic disc region is divided by ribbons of dark blood vessels [2]. While these techniques appear to work well on fundus images of healthy retinas, they do not directly apply to OCT en face images where the intensity of the optic disc is often equivalent to or darker than that of the surrounding tissue (see Figure 1(a) for an example).

Some retinal diseases manifest as bright spots on the macula, making brightness alone an unreliable feature for detection. Sekhar et al. [3] suggest using the Hough transform on the gradient image to look for circular features with high contrast, rather than high intensity. Other optic disc detection methods use the retinal vasculature structure to locate the optic disc, drawing on brightness as a secondary feature. These methods search for the characteristic pattern of vessels converging on the optic nerve head, located in the center of the optic disc. Hoover and Goldbaum’s fuzzy convergence algorithm [4] is the most closely related to the techniques presented here. Their method searches for the location of the greatest vessel convergence by fitting fuzzy line segments to extracted blood vessels. They successfully locate the optic disc in 79% of 81 fundus images and improve performance to 89% when combining vessel convergence information with the relative brightness of candidate pixels. A summary of the reported performances of many algorithms developed for fundus images, including those mentioned above, can be found in the review by Youssif et al. [5].

There has been some work published on localizing the optic disc in OCT data, although OCT imaging has only recently become widely used. Koozekanani et al. [6] attempt to track the location of the optic disc during time-domain OCT imaging by updating a model of the vasculature structure at each frame using appearance-based features. Other work focuses on localizing the optic disc in individual time-domain OCT B-scans by segmenting layers of important tissue [7].

Each of these algorithms assumes the optic disc exists within the image boundary and can simply be located. In contrast, to correctly differentiate between scan patterns, we need to find the location of the optic disc in cases where it is outside the scan’s field of view. Like others, we use the vasculature structure to locate the optic disc; however, our method allows the center of vessel convergence to be located outside the boundary of the image being analyzed.

3. SCAN PATTERN CLASSIFICATION

The appearance of the optic disc in SD-OCT data varies significantly between subjects. In contrast, the appearance of the major retinal vessels remains relatively constant, and these vessels always converge to the optic nerve head. Our classification algorithm estimates the point to which most of the major vessels converge and concludes that a scan uses the ODC pattern if this point is centered in the field of view.

Given a novel SD-OCT volume, the first step in scan classification is to detect vessels in the en face image. In our experiments, we achieved better vessel detection performance in the en face image than in the raw volume data. We create the en face image by summing the voxel values (reflectivity intensities) along the depth axis from the front of the eye to the back. We enhance the resulting image contrast by stretching pixel values so that 1% of the pixels map to the lowest and highest image intensities (0 and 255). Our vessel detection technique is a simplified implementation of that proposed by Lam and Yan [8]. Vessels appear as thin dark bands surrounded by reflective tissues, so they coincide with locations with high divergence of the image gradient field. Non-vessel regions have relatively constant intensity, resulting in low divergence of the gradient field. We find peaks in the divergence of the image gradient using hysteresis thresholding. We are concerned primarily with detecting the major vessels that converge on the optic nerve head; we choose to miss the distracting thin vessels branching off these main vessels. We accomplish this by rejecting detected regions that do not contain large connected components above the upper hysteresis threshold. Another vessel detection algorithm could be substituted here, assuming it can be tuned to detect vessels at the desired scales.

Ideally, we should be able to distinguish between scan types immediately based on the number of vessels detected. The ODC scan is centered on the point where major vessels enter the retina and should contain numerous major vessels. Conversely, the MC scan is centered on the fovea, which is vessel-free in healthy subjects. However, accurate detection of major vessels only is challenging. In practice, some minor vessels will be detected. With the specific settings of our vessel detection algorithm, if less than 1% of the pixels in the image are detected as vessels, we can reliably conclude that there are no major vessels present and that the scan is an MC scan. Above this threshold, however, we need to examine the geometry of the detected vessel network to ensure robust classification.

We cannot simply trace the vessel network back to its origin because the optic nerve head is located outside the field of view in MC scans. Instead, we apply morphological thinning to vessel regions to retain only the vessel centerlines, break the vessel centerlines at branch points, fit a line to each segment longer than a given threshold (5 pixels), and compute the location of the intersection of each pair of lines. We use these computed intersection points to determine whether vessels are converging to a location inside the scan volume or not.
Fig. 2. Calculation of the amount of vessel convergence contained within the boundary of the image. The original en face images for an ODC and an MC scan are shown in (a) and (c), respectively. The vessels detected in these images are shown in (b) and (d), with the lines fit to centerline segments marked (green dashed lines). Lines fit to segments defined by fewer than five vessel pixels have been removed from these images for clarity but are included when calculating \( p \). For the ODC scan, \( p = 0.8442 \). For the MC scan, \( p = 0.4505 \).

Line-pairs fall into three categories:

1. The two lines are fit to vessels that share a branch point removed during the line fitting procedure.
2. Both lines come from separate strong vessels that converge at the optic nerve head.
3. The two lines are fit to separate vessels which do not share a branch point and do not converge to the optic nerve head.

Case (2) is the only one that is indicative of the scan pattern. In case (1), assuming the linear fit is a good approximation to the vessels, the intersection point should lie at the branch point, and therefore within the image boundary for either scan type. In case (3), our investigation showed that these intersection points happen to fall within the field of view of either scan type roughly 50% of the time. In case (2), however, the intersection point should be located at the optic nerve head, again assuming that the lines are good approximations of the vessels. In an MC scan, the optic nerve head is outside the field of view; in the ODC scan, the optic nerve head is centered in the field of view. Thus, theoretically, all intersection points of type (2) should lie within the image boundary if the scan is an ODC scan, and none should lie within the image boundary if the scan is an MC scan. Consequently, we can measure the percentage of intersection points located within the field of view (denoted \( p \)) to classify scan type; if \( p \) is high, the scan should be classified as the ODC pattern. Figure 2 shows an example of the calculation of \( p \) for an example ODC scan and MC scan.

The value \( p \) is a good indicator of scan type except in a few cases. Figure 3 (a)-(b) shows an example of one of these exceptions. In this case no major vessels were detected. Instead, lines were fit to detected minor vessels as well as some image noise. Their intersections happen to lie within the image, resulting in a high value of \( p \). To correctly classify such cases, we add to our classifier the location of the center of vessel convergence. For each pixel in the en face image, we count the number of intersection points that lie within a 10 pixel radius. The pixel with the most nearby intersection points is considered the center of vessel convergence. For ODC scans, the center of vessel convergence is located within the optic disc, and should therefore be close to the center of the image. For MC scans, this point usually coincides with a branch point of a vessel and is often located on the periphery of the image. Figure 3 (c)-(d) shows the estimated center of vessel convergence for the example ODC and MC scans from Figure 2. Let \( d \) be the Euclidean distance from the center of vessel convergence to the image center, measured in pixels. To combine \( d \) effectively with \( p \), we normalize it to \([0, 1]\), with the value close to 1 for ODC scans. The final feature is \( l = e^{-0.5(\frac{s}{\sigma})^2} \), where a value for \( s \) of 28.3 pixels was selected by fitting a Gaussian, \( N(\mu, \sigma^2) \), to the distribution of distances from a training set of 10 ODC scans, then setting \( s = \mu + \sigma \). (This training set is separate from the testing set described in Section 4.)

Finally, we merge \( p \) and \( l \) into a single feature \( f \) using linear combination: \( f = \lambda p + (1 - \lambda)l \). In our experiments, \( \lambda = 0.925 \), and we classify as the Optic Disc Cube scan pattern if \( f \geq 0.6738 \). These values were determined empirically to maximize performance on our testing set. However, no values for \( \lambda \) between 0.75 and 1 (with appropriate thresholds) increased misclassifications by more than four cases.

4. EXPERIMENTAL RESULTS

We tested our algorithm on an extensive collection of SD-OCT scans of both healthy and diseased subjects. Our test set contains a total of 537 scans of healthy eyes, 346 scans of glaucomatous eyes, and 132 scans of eyes with various retinal pathologies (cystoid macular edema, age-related macular degeneration, macular pucker, macular hole, and central serous...
Table 1. Overall performance on the three different collections of scans. There are 537 scans of healthy eyes (112 ODC, 425 MC), 346 scans of subjects with glaucoma (171 ODC, 175 MC), and 132 scans of subjects with retinal pathologies (2 ODC, 130 MC, see Section 4 for list of pathologies).

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Sensitivity</th>
<th>Specificity</th>
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</thead>
<tbody>
<tr>
<td>Healthy</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td>Glaucomatous</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td>Retinal pathology</td>
<td>100%</td>
<td>98.46%</td>
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![Fig. 4](image)

Fig. 4. The two examples misclassified by our algorithm. Both scans are MC scans of subjects with retinal pathologies, but are erroneously classified as ODC scans.

- Retinopathy. A Matlab prototype of our algorithm took an average of 0.36 seconds to classify scans on a standard desktop system (Intel Pentium 3.2GHz, 2GB RAM). Our classification performance is summarized in Table 1. Out of 1015 total examples, we misclassified only two. Both misclassified examples (shown in Figure 4) are MC scans of diseased retinas erroneously classified as ODC scans. Our total sensitivity is 100%; our total specificity is 99.7%.

5. LOCALIZATION OF THE OPTIC DISC

Although our primary goal was not necessarily to precisely locate the optic disc, the center of vessel convergence found when computing \( l \) is a good approximation of the optic disc location in ODC scans. Out of the 285 ODC scans in our dataset, the detected center of vessel convergence was inside the optic disc in 255 examples, yielding a success rate of 89.47%. This performance compares favorably to Hoover and Goldbaum’s 79% success rate on fundus images when they used information about vessel convergence only [4].

6. CONCLUSION

We have developed a fully automated algorithm that differentiates between retinal SD-OCT volumes taken with the Optic Disc Cube scan pattern and Macular Cube scan pattern. Our classifier is robust to retinal pathologies and performs particularly well on scans of subjects suffering from glaucoma. Because of the simplicity of the technique, a typical 3D scan can be classified in a third of a second (in Matlab, before performing any optimization), making it feasible to use our algorithm as a pre-processing step to computer-aided analysis/diagnosis without impeding the workflow of a busy clinic.

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8. REFERENCES


