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Shape Decomposition of Foveal Pit Morphology using Scan Geometry Corrected OCT

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Abstract

The fovea is an important structure that allows for the high acuity at the center of our visual system. While the fovea has been well studied, the role of the foveal pit in the human retina is still largely unknown. In this study we analyze the shape morphology of the foveal pit using a statistical shape model to find the principal shape variations in a cohort of 50 healthy subjects. Our analysis includes the use of scan geometry correction to reduce the error from inherent distortions in OCT images, and a method for aligning foveal pit surfaces to remove translational and rotational variability between the subjects. Our results show that foveal pit morphology can be represented using less than five principal modes of variation. And we find that the shape variations discovered through our analysis are closely related to the main metrics (depth and diameter) used to study the foveal pit in current literature. Lastly, we evaluated the relationship between the first principal mode of variation in the cohort and the axial length from each subject. Our findings showed a modest inverse relationship between axial length and foveal pit depth that can be confirmed independently by existing studies.

Keywords

Shape Analysis; Distortion Correction; Retina; Fovea; OCT

1 Introduction

The fovea is a critical structure in the retina that consists of tightly packed cone photoreceptor cells, which allows for the high acuity at the center of our visual system. In humans, the fovea is characterized by a depression (*foveal pit*) where the retinal ganglion and bipolar cells are displaced. While studies have characterized the variability of the fovea [1], the role of the foveal pit in our visual system is still unclear. Recent studies have shown that subjects who lack a foveal pit can still maintain cone specialization and normal acuity [2,3]. Given the importance of the fovea, studying the morphology and structure of the foveal pit can lead to a better understanding of diseases that affect our central vision.

Foveal pit morphology has been studied in relationship with other retinal measures such as thickness [4], foveal avascular zone [5], and visual acuity [6]. Notably, Wilk et al. [3] presented a study using multi-modal imaging to evaluate the relationship between foveal pit morphology from optical coherence tomography (OCT) imaging and cone density measures from adaptive optics scanning laser ophthalmoscopy (AOSLO) from subjects with albinism, showing considerable variation between the two measures. One limitation of these existing studies is their reliance on the evaluation of summary measurements (pit depth, diameter and slope) [7] or parametric models [8] of the foveal pit. Such analysis are restricted by the location of the measurement or the fit of the model, and do not observe the 3D local or spatial relationship of the foveal pit morphology across a population.

OCT offers in-vivo 3D imaging of the retina, and is currently the most effective imaging modality for observing the shape morphology of the foveal pit. However, one challenge with studying shape morphology in OCT is the presence of scan geometry distortion due to the instrument acquiring the images in a fan-beam pattern, but representing it as a rectangular grid. [9,10] Currently, such distortions are not corrected before analyzing the shape morphology of the foveal pit, which can have significant impact on the shape analysis.

The goal of this work is to improve on existing analysis of the foveal pit shape morphology through the use of a statistical shape model to decompose the principal modes of shape variation across a cohort of 50 subjects. In addition, we aim to improve the general reliability of foveal pit shape analysis by correcting the OCT geometry of our scans [10] and addressing the translational and rotational variability of the foveal pit surfaces between subjects.

2 Method

2.1 OCT Geometry Correction and Surface Construction

It is well established that OCT images do not represent a Euclidean space despite their presentation of the data in a rectangular pattern. [9,10] The individual columns (A-scans) of an OCT are path measurements that traverse a fan-beam pattern that spreads out from a central nodal point located in the eye. The distance between the A-scans are in units of degrees, and in actual Euclidean space the OCT image would look similar to an ultrasound image, where the top of the image is more narrow than the bottom. This misrepresentation of the OCT scan geometry results in a distortion of the retina morphology that can impact our shape analysis. To address this distortion, we use a digital model [11] of each of our OCT images to approximate the location of the A-scan nodal point. We then correct the scan geometry (Fig. 1c) of the OCT using an established model for distortion correction [10] and interpolating the OCT within this corrected space. From the OCT we segment the inner limiting membrane and extract a 1mm by 1mm region surrounding the fovea to get a surface representation of the foveal pit (Fig. 1d).

2.2 Foveal Pit Alignment

A statistical shape model [12] requires that the images from every subject are aligned into a common space. This allows us to establish correspondences and remove incidental variation

in the data (such as global movement) that should not be included into the analysis. For our study, we perform a two-step rigid alignment of the foveal pit surfaces. First, we automatically find the deepest point in each foveal pit as a landmark, which we refer to as the *fovea center*. Each surface is translated such that the fovea center is moved to the origin of the coordinate system. This ensures that every foveal pit surface is centered and has a coherent point of reference. However, after translation, the fovea pit may be tilted in different orientations due to the positioning of the retina and OCT scanning angle. We address this by first fitting a plane to each retinal surface (Fig. 1e). The foveal pit is then rotated around the fovea center until the retinal plane is parallel to the X-Y plane of the coordinate system (Fig. 1f).

2.3 Principal Shape Decomposition

Given a surface of the foveal pit from each subject, we represent the surface data as a vector:

$$\mathbf{X} = [x_1 \ y_1 \ z_1 \ x_2 \ y_2 \ z_2 \ \dots \ x_V \ y_V \ z_V], \quad (1)$$

where (x_v, y_v, z_v) for $v \in [1, 2, \dots, V]$ are the 3D positions of each of the V vertices in the surface. Each surface is resampled such that they have the same number of vertices and the x and y coordinates fall on a common grid. Given N subjects, we can then stack the surfaces from each subject into a single data matrix:

$$\mathbf{D} = [\mathbf{X}_1 \ \mathbf{X}_2 \ \mathbf{X}_3 \ \dots \ \mathbf{X}_N]^T, \quad (2)$$

where each row of the matrix represents the surface data from each subject. Using $\mathbf{D}$ we can perform a shape decomposition of the foveal pit using principal component analysis [13] to find the principal modes of variation in the data. To do this, we first subtract the mean from the data to prevent the principal components from being directed by the global bias in the data. This is calculated by evaluating the mean across the surfaces

$$\bar{\mathbf{X}} = \sum_{n=1}^N \mathbf{X}_n, \quad (3)$$

and then subtracting it from each surface to create a new data matrix

$$\hat{\mathbf{D}} = [(\mathbf{X}_1 - \bar{\mathbf{X}})(\mathbf{X}_2 - \bar{\mathbf{X}})(\mathbf{X}_3 - \bar{\mathbf{X}}) \dots (\mathbf{X}_N - \bar{\mathbf{X}})]^T, \quad (4)$$

which has zero mean. Singular value decomposition is then applied to $\hat{\mathbf{D}}$ to find the linear relationship:

$$\mathbf{T} = \hat{\mathbf{D}}\mathbf{W}, \quad (5)$$

where the columns of $\mathbf{W}$ are orthogonal unit vectors $\{\mathbf{w}_1 \dots \mathbf{w}_V\}$ of size V that describe the principal modes of variation (also known as the principal components [PC]) in the data, and $\mathbf{T}$ is a matrix where each row is the projection of the data from each subject into the PC space. Thus, each element of $t_{n,v} \in \mathbf{T}$ is the *PC score* of subject n with regard to v th PC. In the next section we show how each PC can be added to the mean shape of the population to

view the different types of shape variation in the data. In addition, we will demonstrate how the PC scores of the subjects can be used as a quantitative measure that can be compared to external metrics of the retina, such as axial length. This serves as a pilot study for future analysis where we aim to use this technique to establish relationships between retinal shape and clinical measures of disease.

3 Evaluation and Results

3.1 Data

We analyzed 50 macular OCT images collected from healthy subjects using a Spectralis (Heidelberg Engineering, Dossenheim, Germany) scanner. Each image covered a 30° by 20° field of view centered on the fovea and had an associated segmentation of the ILM layer delineated automatically using OCTExplorer [14]. The foveal pit was extracted from each OCT image and aligned to the atlas space as described in Sec. 2 (and shown in Fig. 1).

3.2 Shape Decomposition of the Foveal Pit

Using the shape decomposition described before, we calculated the primary modes of shape variation of the foveal pit in our cohort. Fig. 2a shows the percent of shape variation that each PC accounts for across the total shape variation in the data. We see that the first PC covers over 80% of the total shape variation, and the first 5 PCs together cover over 97% of the shape variation. Fig. 3 shows a visualization of each of the first 5 PCs as they range from -2 to +2 standard deviation of the population relative to the mean shape. We observed that the first PC represented the variability in the depth of the fovea pit. The second and third PCs represented global tilt (in orthogonal directions) of the foveal pit. The fourth PC represented the diameter of the pit. And lastly, the fifth PC represented slight changes in the regions surrounding the foveal pit.

3.3 Correlation with Axial Length

One strength of performing shape decomposition is the ability to compare the PC shape scores with relevant biometric and clinical measures. Such analyses allow us to establish relationships between the shape morphology observed in the images and measures of anatomy or disease. Understanding these relationships can help us better understand the eye and also provide potential biomarkers or predictors of disease progression. To demonstrate this type of analysis, we correlate each PC1 score from our shape decomposition with the axial length of each individual's eye. Fig. 2b shows a scatter plot of this relationship. We observe from this analysis that there is a modest ($r=0.51$) Pearson's correlation between the two measures.

3.4 Impact of the Geometry Correction

To evaluate the role that the scan geometry correction had on the shape analysis, we repeated the principal shape decomposition on the foveal pit surfaces without first correcting for the distortion. Fig. 4 shows a comparison of the first PC when using and not using the geometry correction. From the figure we can see that there is a significant change to the principal mode of variation. The total range of the foveal pit depth across two standard deviations appears to be larger when the geometry is uncorrected. In addition, we note that the order of

the 3rd and 4th principal components switched places in the uncorrected case. This suggests that the variability of the foveal pit diameter (described originally by the 4th PC) also increased. Lastly, correlating PC1 from the uncorrected analysis with axial length showed a significant drop in correlation ($r = 0.42$).

4 Discussion

4.1 Principal Modes of Variation

One notable finding of this study is the relatively small number of principal components that is required to represent the shape variation in the foveal pit. PC1, which describes the depth of the foveal pit, covers over 80% of the shape variation. This is in line with existing analysis of the foveal pit [7,8], which relies on explicit measurements or modeling of pit depth and diameter. It is reassuring to see that our unsupervised analysis was able to automatically find the same characteristics (PC1 and PC4) of the foveal pit that is deemed important by the community. However, the advantage of using our PCs over the existing summary measurements is that each PC covers the shape variation across the entire foveal pit. From Fig. 3 we see that the primary modes of shape variation are more complex than simply making a single measurement of depth or diameter. Our analysis shows other distinct variations that subtly changes the structure of the pit. This allows us to establish local spatial relationships in the foveal pit that are not covered by the common summary measurements used in the current literature.

4.2 Comparison to Existing Literature

In Fig. 2b, we found a modest positive relationship between each subject's score for the first principal mode of variation (PC1) and their axial length measurement. From Fig. 3 we see that PC1 has an inverse relationship with foveal pit depth (the pit becomes more shallow as PC1 increase). Thus, our shape analysis showed a morphological relationship where foveal pit depth decreases with increasing axial length. From existing literature, it is well established that axial length measurements increase with myopia. [15] Likewise, myopic eyes have been shown to have more shallow foveal pits. [16] Thus, this relationship confirms our finding that increased axial length is related to smaller foveal pit depths.

5 Conclusion

We performed a study of foveal pit morphology over a cohort of 50 health subjects using shape decomposition. Our analysis showed that the morphology of the foveal pit can be represented by as few as 5 principal modes of variation. The modes of variation we found were strongly related with metrics (pit depth and diameter) commonly used in existing analysis of the foveal pit. A correlative study between the first PC and axial length revealed a modest inverse relationship between axial length and foveal pit depth that we were able to independently confirm from existing studies. Both of these results help confirm the validity and value of our analysis. Our future goals are to apply these techniques to observe and characterize shape differences between healthy and disease cohorts.

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Fig. 1.

Diagram showing our processing pipeline to extract the foveal pit surface from each OCT image. **(a)** shows the raw OCT image and delineations found for the retinal layers. **(b)** shows the inner limiting membrane surface prior to scan geometry correction and **(c)** shows the surface after the distortion correction. **(d)** is an extracted 1mm by 1mm region surrounding the fovea. **(e)** shows a planar fit to the retinal surface, and **(f)** shows the foveal pit surface after using the fitted plane to correct for rotations in the image.

Fig. 2.

(a) shows the percentage of the total shape variability accounted for by each principal mode of variation (PC) in our shape analysis. (b) shows a scatter plot relating each subject's PC1 score with their axial length.

Fig. 3.

Visualization of the shape variability represented by the five largest principal modes of variation (PC) found in our shape analysis. For each PC, we show the mean foveal pit shape of the population ± 2 standard deviations (σ) of the shape variability observed in the population for that PC.

Fig. 4.

Comparison of the first PC when the shape analysis was performed **(a)** with and **(b)** without OCT scan geometry correction. Shown is the mean foveal pit shape of the population ± 2 two standard deviations(σ) of the PC variability observed in the population.