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Automatic estimation of retinal nerve fiber bundle orientation in SD-OCT images using a structure-oriented smoothing filter

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ABSTRACT

Optical coherence tomography (OCT) yields high-resolution, three-dimensional images of the retina. A better understanding of retinal nerve fiber bundle (RNFB) trajectories in combination with visual field data may be used for future diagnosis and monitoring of glaucoma. However, manual tracing of these bundles is a tedious task. In this work, we present an automatic technique to estimate the orientation of RNFBs from volumetric OCT scans. Our method consists of several steps, starting from automatic segmentation of the RNFL. Then, a stack of en face images around the posterior nerve fiber layer interface was extracted. The image showing the best visibility of RNFB trajectories was selected for further processing. After denoising the selected en face image, a semblance structure-oriented filter was applied to probe the strength of local linear structure in a discrete set of orientations creating an orientation space. Gaussian filtering along the orientation axis in this space is used to find the dominant orientation. Next, a confidence map was created to supplement the estimated orientation. This confidence map was used as pixel weight in normalized convolution to regularize the semblance filter response after which a new orientation estimate can be obtained. Finally, after several iterations an orientation field corresponding to the strongest local orientation was obtained. The RNFB orientations of six macular scans from three subjects were estimated. For all scans, visual inspection shows a good agreement between the estimated orientation fields and the RNFB trajectories in the en face images. Additionally, a good correlation between the orientation fields of two scans of the same subject was observed. Our method was also applied to a larger field of view around the macula. Manual tracing of the RNFB trajectories shows a good agreement with the automatically obtained streamlines obtained by fiber tracking.

KEYWORDS: OCT, retinal nerve fiber bundle, semblance, normalized convolution, steerable filter.

1. INTRODUCTION

The retinal nerve fiber layer (RNFL) carries visual information from the eye to the visual cortex of the brain. The retinal nerve fiber bundles (RNFBs), which consist of retinal ganglion cell axons, may degenerate in the retina of glaucoma patients. A patient-specific RNFB trajectory pattern in combination with visual field data can give us a better understanding of glaucomatous damage [1]. However, manual tracing of the RNFBs in fundus images is time consuming, error-prone and grader-dependent. Recently, a method has been developed to create a map of RNFB trajectories using the mean RNFL thickness at each grid sector of the visual field [1,2]. However, this map is limited to the resolution of the visual field grid and does not use patient-specific information of RNFB trajectories. In this paper, we present a method to automatically estimate the RNFB orientations in volumetric spectral-domain OCT (SD-OCT) images. Our method applies a 2D structure-oriented semblance filter to probe the orientation responses from an en face OCT image with visible trajectories of RNFBs.

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2. METHOD

Since RNFBs traverse across the structure of the RNFL, their trajectory is not visible in a single C-scan. Therefore, to visualize the RNFBs, en face images oriented along the RNFL were extracted. In the first step, 3D macular SD-OCT scans were automatically segmented using coupled level sets [3] since the built-in segmentation of RNFL by the scanner was not accurate for some of the B-scans. Then, the en face image showing the best visibility of the RNFB trajectories was selected for further processing. This image was extracted from a 3.9 µm (1 pixel) thin slice located 7.8 µm (2 pixels) anterior to the segmented posterior nerve fiber layer interface (Figure 1.a). The horizontal band artifacts in the en face image results from the fast horizontal scanning direction. To eliminate these artifacts in the en face image, the following steps have been performed. First, the low frequencies of the en face image were removed using a 2D Gaussian filter (Figure 1.b). Second, since the banding artifact is the dominant orientation at each column of the en face image, a principal component analysis (PCA) was applied to the columns of an image and the image was reconstructed without the first four components, which are dominated by the horizontal band artifacts (Figure 1.c).

To estimate the orientation of the image structures, a 2D structure oriented semblance filter was used [6]. Semblance, s, is a measure of similarity along vector j', smoothed along its orthonormal vector i' at each location in image I,

$$s_{i',j'} = \frac{\langle\langle I\rangle_{j'}^{2}\rangle_{i'}}{\langle\langle I^{2}\rangle_{j'}\rangle_{i'}}\ , \tag{1}$$

where $\langle . \rangle_k$ indicates smoothing along k, usually by a 1D Gaussian kernel. At each pixel, the orientation responses, which are the similarity measurements for each orientation of the filter, were obtained with N equally spaced orientations of the semblance filter between 0 and π. Stacking the filter outputs as a function of the probed orientation yields a so-called orientation space.

The orientation coordinate of this orientation space is periodic with 180 degrees, such that the orientations 0 and π are the same. Taking this into account, the following normalized Gaussian-based kernel for different θ_i was used to find the best orientation response,

$$G_i(\theta) = \frac{g_i(\theta) + g_i(\theta+\pi) + g_i(\theta-\pi)}{\sum_{\emptyset\in\Phi}\ g_i(\emptyset) + g_i(\emptyset+\pi) + g_i(\emptyset-\pi)} \quad ,\theta \in \Phi, \tag{2}$$

where Φ is a set of orientations and

$$g_i(\theta) = e^{\frac{-(\theta-\theta_i)^2}{2\sigma^2}}. \tag{3}$$

The standard deviation σ is set to the (uniform) orientation sampling pitch, $\sigma = \pi/N.$ At each pixel, we calculated the variance of the residual between the Gaussian-based kernel centered at θ_i and the orientation measurements. The dominant orientation at each pixel corresponds to the orientation with the minimum residual variance.

A normalized convolution was used to regularize the orientation responses F for all orientations θ_i, using a certainty weight image C [7], such that:

$$R_s = \frac{(F.C) * G}{F * G}, \tag{4}$$

where $*$ indicates convolution, R_s is the regularized orientation response, and G is a Gaussian filter.

The certainty weight image was obtained by the scalar products of two confidence maps and two binary masks. The first confidence map is the relative strength of the strongest response. This is the inverse of the variance of the residue between the best-fitted Gaussian kernel and the measured orientation responses, normalized by the maximum value of the

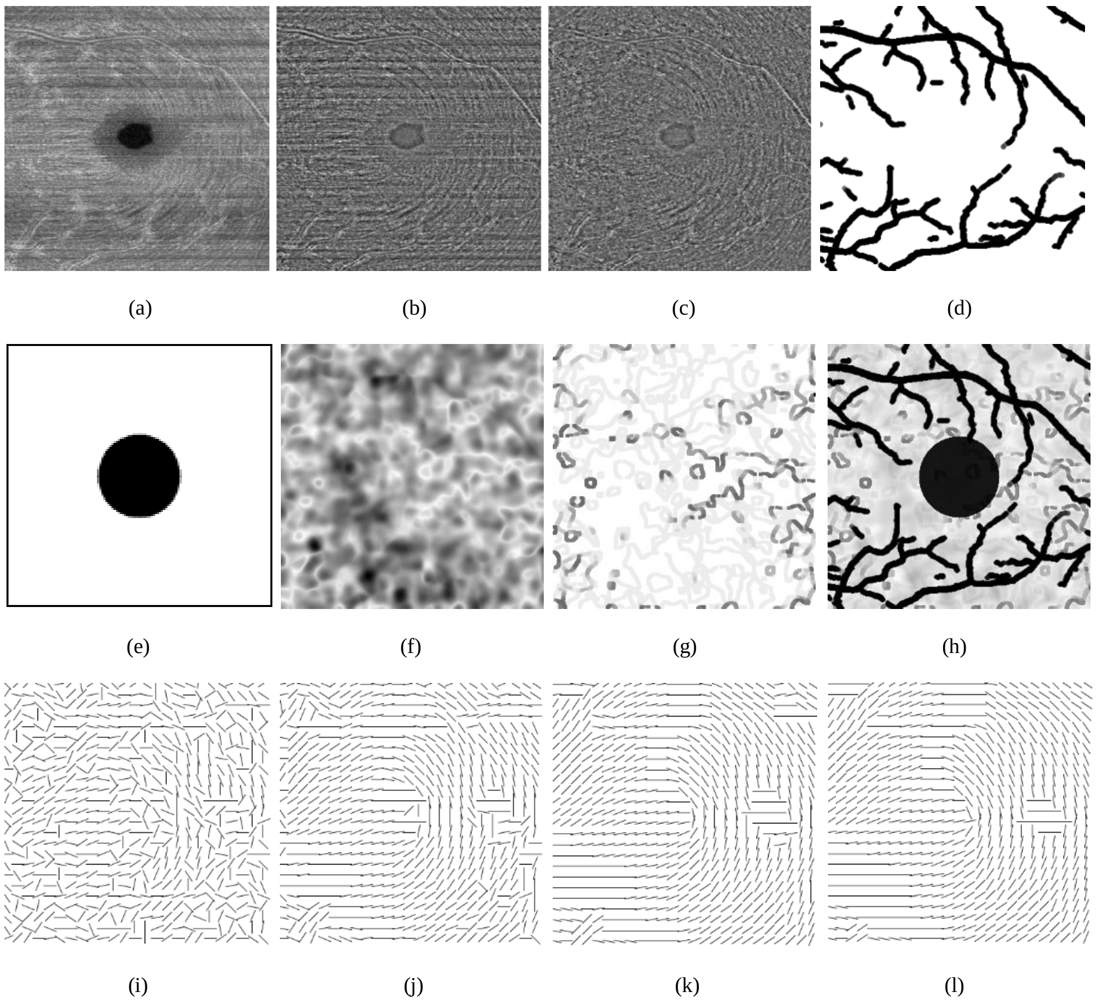

Figure 1. a) The en face image of a macular SD-OCT scan; b) after removing the low frequencies; c) after removing the horizontal band artifacts. d) The blood vessels mask. e) The macula mask. The confidence maps of: f) the variance of the residual between the best-fitted Gaussian kernel and the orientation measurements; g) the dilated inverted orientation gradient (white color shows the highest weight). h) The combined certainty weight image. i-l) The orientation fields for 0, 2, 30 and final result (after 32 iterations).

residue variances over all orientations and pixels. The second confidence map is composed of a local consistency weight, which indicates the similarity of the orientations between neighboring pixels. This can be obtained by dilating the inverted gradient of the extracted dominant orientation image. Two binary masks were used to give zero weights to areas occupied by blood vessels and by the macula.

To detect the blood vessels, an en face image was created from an axial summation of the 3D-OCT data between the vitreous-RNFL interface and RPE in the segmented retina. Then, a vesselness enhancement filter [8] based on a Gaussian kernel was applied to the extracted en face image. The scale of the Gaussian corresponded to the width of the smallest vessel. The blood vessels were segmented by thresholding the filter response and removing connected components smaller than 20 pixels. Finally, the segmented blood vessels were dilated using a round structuring element. The macula mask was considered as a circle in the center of the en face image and has an average diameter of 1.5 mm.

The result of normalized convolution is a set of regularized orientation responses. Based this set of orientation responses we can repeat the same procedure and extract the dominant orientation for each pixel. From here the entire procedure can be repeated in an iterative manner. Each iteration of the normalized convolution yields further regularized orientation responses and new weights for the next iteration. The differences between consecutive orientation fields were calculated by,

$$d(f_n, f_{n-1}) = \sum_x \sum_y \left(min\left(|f_n(x,y) - f_{n-1}(x,y)|, \left| mod\left(f_n(x,y) + \frac{\pi}{2}, \pi \right) - mod\left(f_{n-1}(x,y) + \frac{\pi}{2}, \pi \right) \right| \right) \right)^2, \quad (5)$$

where $f_n(x,y)$ is the dominant orientation at pixel (x,y) for n^{th} iteration. The following stopping criterion, $d(f_n, f_{n-1}) \geq 0.9 \times \frac{\sum_{m=n-4}^{n-1} d(f_m, f_{m-1})}{4}$, is used to terminate the iterative process.

3. EXPERIMENTS AND RESULTS

We obtained two consecutive three-dimensional macular OCT scans of three subjects using a Spectralis SD-OCT system (Heidelberg Engineering, Germany). The voxel size of all six scans was 3.9 μm in axial and 11.3 μm in both lateral directions. An en face image was subsequently extracted from the volume following anterior of the segmented posterior nerve fiber layer interface. The horizontal band artifacts were removed, as described previously. The standard deviation of the isotropic Gaussian filter to remove the low frequencies was set to 56 μm, by considering the width of the horizontal bands (Figure 1.b-c).

The distance over which the orientation and intensity of a nerve fiber is consistent was estimated to be 135 μm. This similarity distance, d_{sim}, was used for setting the parameters of the semblance filter and the normalized convolution. The standard deviation of the semblance Gaussian filter was set to $d_{sim}/4$. The number of orientations N was set to 16 between 0 and π. The standard deviation of the 1D Gaussian kernel to implement the semblance responses as a function of orientation was set to $\pi/16$. The standard deviation of the isotropic 2D Gaussian kernel as used in the normalized convolution was set to $2\times d_{sim}$. The scale of the 2D isotropic Gaussian kernel for vessel enhancement was set to 20 μm. The segmented blood vessels were dilated by using an approximately round 2D structuring elements with a radius of $d_{sim}/4$. The blood vessels and macula masks are shown in Figure 1.d-e. The confidence maps based on the variance of orientation residue and the dominant orientation gradient are shown in Figure 1.f-g. The combined certainty weight image is shown in Figure 1.h. The dominant orientation responses for 0, 2 and 30 iterations and final result (after 32 iterations). are shown in Figure 1.i-l. The estimated orientation fields of six scans from three normal subjects are shown in Figure 2.

In a second experiment, the scans of a normal subject was obtained for a larger field of view covering the temporal region of macula (Figure 3). The estimated orientations are shown both as vector field (second column) and as streamlines (third column) [MATLAB 2013b and image processing Toolbox, The MathWorks, Inc]. To obtain the streamlines, the direction of the estimated vectors were forced to run from the right to the left side of the image, which is aligned with the direction of the photoreceptors in the RNFB to the brain. The streamlines propagate along the orientation of the vectors in both directions, starting from a regular grid of points with a uniform spacing in both *x* and *y* direction over the entire image. The last column shows the comparison of some of the automatically estimated (red curves) and manually traced (dashed yellow curves) RNF bundles. The manual tracing was performed from the starting point of the streamline until the trajectory of RNF bundle is no longer visible by the human eye.

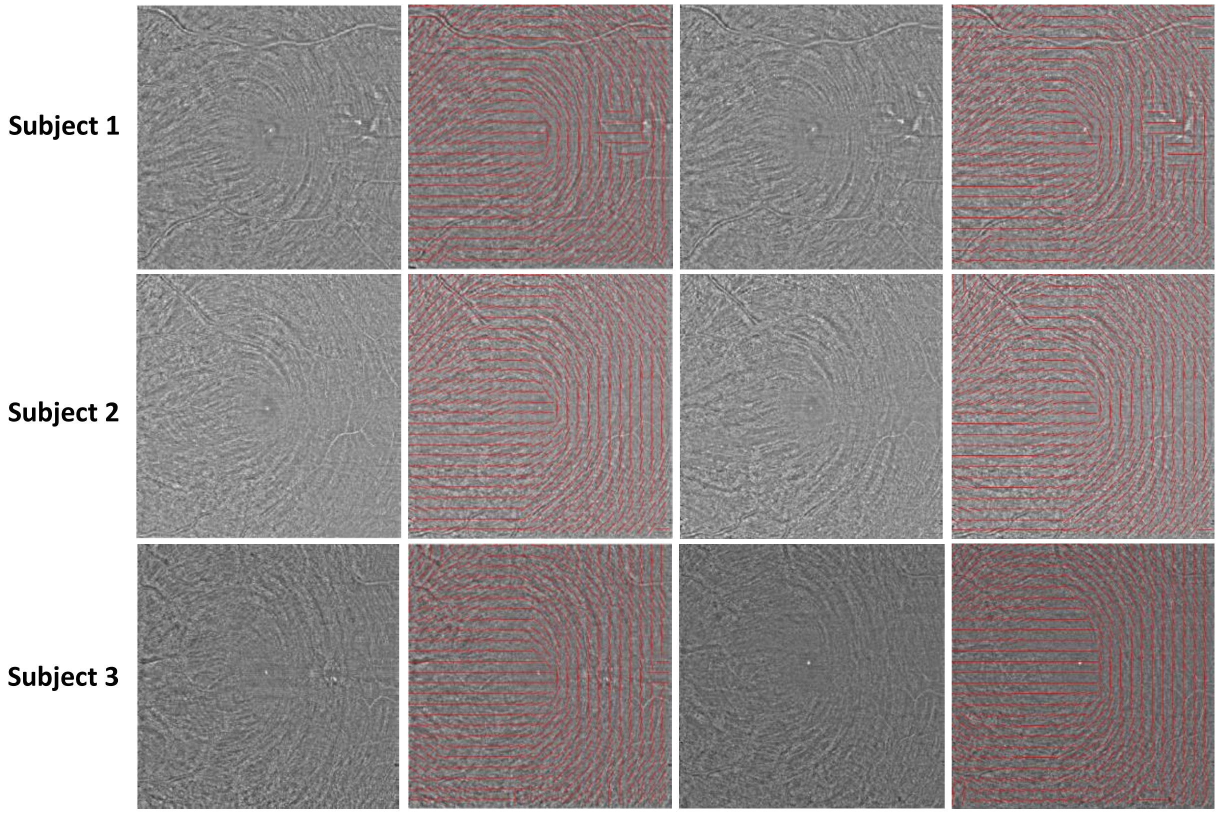

Figure 2. The en face images after removing the horizontal band artifacts and the estimated orientation field (superimposed in red) for three normal subjects and two subsequently made scans per each subject.

4. CONCLUSION

In this paper, we presented an automatic method for estimating the orientation of RNFBs from volumetric SD-OCT images. The method is based on an orientation map estimated based on the responses of the structure-oriented semblance filter in 16 uniformly sampled probe orientations between 0 and 180 degrees. The estimated orientations show a good agreement with visual inspection of the RNFBs in en face images following the anterior of the segmented posterior nerve fiber layer interface. In Figure 2 and subject 1, the orientation field at the bottom-left corner is influenced by the presence of a blood vessel. A more accurate vessel segmentation tool can improve the results for these regions. The automatic tracing of RNF bundles over a larger field of view shows an acceptable correlation with the manual tracing in the area where the bundles are visible.

5. ACKNOWLEDGMENT

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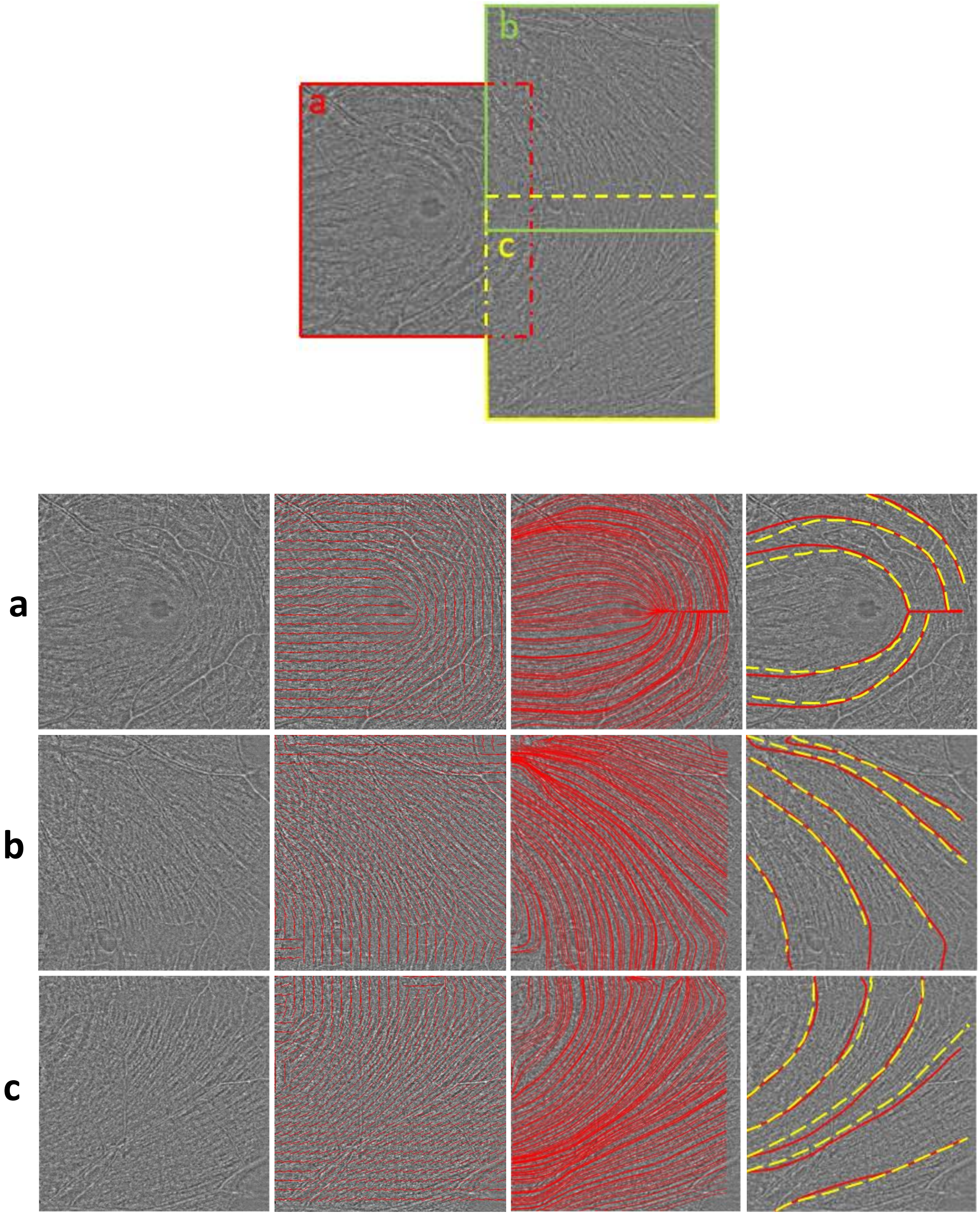

Figure 3. Top) A larger field of view of RNF bundle trajectories by stitching three en face images (a,b and c) obtained from the B-scans of macula and the temporal region. Bottom) First column: The enhanced en face images; second column: the vector field; third column: the estimated streamlines; fourth column: manually traced RNF bundles (dashed yellow curves) and the corresponding streamlines (red curve).

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