Hybrid filtering and enhancement of high-resolution adaptive-optics retinal images

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Adaptive optics flood-illuminated imaging technology has been successfully used to correct the wavefront aberration of human eyes to obtain high-resolution retinal images. However, because of the pollution of various types of noise and the degradation caused by residual aberration, the noisy images are not very clear and weak edges are difficult to discern. To reveal the abundant detail hidden by large-scale noise and to enhance low-contrast edges, a hybrid filtering and enhancement method is proposed combining bilateral filtering, coherence diffusion, and edge enhancement. Results show that it is effective to improve the visual quality of retinal cell images. © 2009 Optical Society of America

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The human retina is a complex, multilayer structure with several layers of cell. Cone photoreceptors have been proved particularly accessible to in vivo cellular imaging because their waveguide properties cause them to return light preferentially back through the eye’s pupil. In previous works [1–5] on obtaining high-resolution retinal images by adaptive optics (AO), Liang et al. [1] made the first successful attempt by correcting the aberration of the eye, then Hofer et al. [2] improved in vivo retinal imaging technology by means of dynamic compensation, and Ling et al. [5] built a table-top flood-illuminated retinal imaging system. However, because of the limited closed-loop bandwidth of an AO imaging system, and its limited aberration measurement and correction accuracy, residual aberration still degrades image quality. Further, intraocular scatter and the uncontrolled physiological vibration of the eye accompanied by cardiopulmonary movement also blur retinal images. Moreover, the pollution by various sources of noise, such as stray light and CCD readout noise, further degrades the visual quality of retinal images.

In the medical imaging field, many algorithms have been constructed to improve image visual quality, among which coherence diffusion (CD) has been successfully used to reduce speckle noise in clinical ultrasound images [6]. We have known [6,7] that CD does not depend on a noise model but utilizes a region’s geometric features to smooth edges along the tangent direction, so it can be used to regularize and enhance cell edges. But in high-noise conditions, CD tends to produce false edges, so it is necessary to suppress large-scale noise before CD. In this Letter, according to the noise model of retinal images, bilateral filtering (BF) [8] is adopted to finish this work. In contrast to traditional filters, BF takes noise distribution into account and thereby increases the capability of noise-reducing and edge-preserving, but its results rely on parameters set by the user.

On the basis of the above discussion, a hybrid filtering and enhancing method for AO retinal images is proposed that can be described as the following three steps: first, BF is used to reduce large-scale noise according to the noise model and distribution in retinal images; second, an improved CD is constructed to smooth cell edges and filter the residual noise; third, a novel edge enhancement algorithm is provided to improve contrast, while keeping the brightness the same as the original image. The algorithm flow chart is displayed in Fig. 1.

In our retinal imaging system [5], the theoretical average speckle size is smaller than 2.3 μm and the variance of CCD readout noise is less than 0.2 for an eight-bit image, so we can assume that the large-scale noise in obtained retinal cell images is caused mostly by stray light; moreover, the spatial distribution of stray light is uniform in retinal images. To analyze the noise distribution and its intensity, estimation zones containing fully developed stray light are extracted from the image background, and for the convenience of detection, the four corners of the image are chosen for estimation (see Fig. 2A). Their corresponding gray histogram is shown in Fig. 2B.

It can be seen in Fig. 2B that the noise distribution takes on a Gaussian shape, so the noise model of AO retinal cell images could be regarded as Gaussian

![Fig. 1. Flow chart of hybrid filtering and enhancing method for AO retinal cell images, in which CD is stopped by MSE between two adjacent diffused images.](https://example.com/image.png)
noise. Reference [8] pointed out that BF has better performance for Gaussian noise than traditional filters. The definition of BF is given by

$$B_{x,y} = k_{x,y} \sum_{i,j \in G} I_{i,j} \exp \left[ \frac{(x-i)^2 + (y-j)^2}{{2} \sigma^2} + \frac{(I_{x,y} - I_{i,j})^2}{{2} \delta^2} \right],$$  

where $G$ is the filter window located at $I_{x,y}$, $I_{i,j}$ represents pixels in window $G$, $\sigma$ is the pixel geometric spacing, $\delta$ is rms of the image noise, and $k_{x,y}$ is used for normalization. In a real application, the results of BF depend on the noise estimation: if $\delta$ is too large, a BF degrades into a Gaussian filter and edges will be blurred; if $\delta$ is too small, the BF cannot suppress noise sufficiently. According to our assumption, stray light is uniformly distributed in the image, so we can use the estimation zones of every retinal image to compute the noise intensity, namely, parameter $\delta$, which takes the form

$$\delta = \sqrt{\frac{\sum_{i=1}^{m-1} \sum_{j=0}^{n-1} (g_{i,j} - \bar{g})^2}{m \times n}},$$

where $m$ and $n$ are the sizes of the estimation zone, $g_{i,j}$ represents pixels in the zone, and $\bar{g}$ is the corresponding mean value of stray light.

After bilateral filtering, large-scale noise has been suppressed, but cell edges are irregular and the image exhibits residual noise. CD can be used to filter residual noise and enhance coherence structures by applying particular diffusion behaviors to different image regions: in a flat region, isotropic diffusion is carried out to reduce noise; near region edges, anisotropic coherent diffusion and mean curvature motion are utilized to regularize and enhance cell edges. The general expression of CD can be written as

$$\frac{\partial I(i,j,t)}{\partial t} = \text{div}(D \cdot \nabla I(i,j)),$$  

where $D$ is a diffusion tensor that is constructed from the structure tensor. Using eigenvalue decomposition, the structure tensor $C(x,y)$ can be described as

$$C(x,y) = \begin{bmatrix} U & V \end{bmatrix} \begin{bmatrix} \lambda_{\text{min}} & 0 \\ 0 & \lambda_{\text{max}} \end{bmatrix} \begin{bmatrix} U^T \\ V^T \end{bmatrix},$$

where the eigenvalues $\lambda_{\text{min}}, \lambda_{\text{max}}$ and the eigenvectors $U, V$ are the strengths and directions of minimum and maximum variations, respectively. The geometric properties of $C(x,y)$ have been completely discussed in [9], and we use its conclusions to design a new diffusion tensor with the following description:

$$D(x,y) = \begin{bmatrix} U & V \end{bmatrix} \begin{bmatrix} \beta_{\text{min}} & 0 \\ 0 & \beta_{\text{max}} \end{bmatrix} \begin{bmatrix} U^T \\ V^T \end{bmatrix},$$

where $\beta_{\text{min}}$ and $\beta_{\text{max}}$ are diffusion intensities of tangent and normal directions that take the form

$$\beta_{\text{min}} = \begin{cases} 0, & \text{if } \lambda_{\text{max}} - \lambda_{\text{min}} < \delta_{\text{min}}, \lambda_{\text{min}} > \delta_{\text{max}} \\ \alpha, & \text{else} \end{cases}$$

$$\beta_{\text{max}} = \begin{cases} \alpha \times \left(1 - \frac{(\lambda_{\text{max}} - \lambda_{\text{min}})^2}{\lambda_{\text{max}} - \lambda_{\text{min}}}\right), & \text{if } \beta_{\text{min}} \neq 0 \\ 0, & \text{else} \end{cases}$$

In contrast to the traditional CD method [6], the new diffusion tensor has the capability of protecting image corners, such as branch points of blood vessels. In our method, CD will assume four different diffusion behaviors according to structure estimations [9]: if the detection window is at a corner, then $\lambda_{\text{max}} = \lambda_{\text{min}} > \delta_{\text{max}}$, $\beta_{\text{max}} = \beta_{\text{min}} = 0$, and diffusion will be stopped there (see Fig. 3A); if the detection window is near edges, then $\lambda_{\text{max}} \approx \lambda_{\text{min}} \approx 0$, $\beta_{\text{min}} \approx \alpha$, $\beta_{\text{max}} = 0$, and CD will diffuse along the tangent direction (see Figs. 3B and 3C); finally, if the detection window is in a flat region, then $\lambda_{\text{max}} = \lambda_{\text{min}} = 0$, $\beta_{\text{max}} \approx \beta_{\text{min}} = \alpha$, and isotropic diffusion will be carried out (see Fig. 3D).

After this processing, CD has filtered residual noise sufficiently and enhanced coherence structures. The following work is to improve the contrast of weak edges. In this step, image edges and brightness are extracted and both of them are merged into the diffused result. The proposed algorithm takes the form

$$R = a \times E(I) + b \times B(I) + c \times I,$$  

where $a, b,$ and $c$ are averaging weights; $I$ is the diffused image; $E(\cdot)$ is the edge image detected by a Sobel operator; and $B(\cdot)$ is the image brightness, extracted by two overlapping windows (see Fig. 5), which can be described as

$$B(x,y) = \frac{\sum_{i,j \in M_1} I_{i,j} \times g(i,j)}{M_1} - \frac{\sum_{i,j \in M_2} I_{i,j} \times g(i,j)}{M_2 - M_1},$$

where $g(i,j)$ is a normalized Gaussian function, $M_1$ and $M_2$ are the detecting windows, and $M_2$ is larger than $M_1$.

There are three relationships between retinal cells and detecting windows to be considered: if $M_1$ is in a new diffusion tensor, the following expression is used:

$$D(x,y) = \begin{bmatrix} U & V \end{bmatrix} \begin{bmatrix} \beta_{\text{min}} & 0 \\ 0 & \beta_{\text{max}} \end{bmatrix} \begin{bmatrix} U^T \\ V^T \end{bmatrix},$$

where $\beta_{\text{min}}$ and $\beta_{\text{max}}$ are diffusion intensities of tangent and normal directions that take the form

$$\beta_{\text{min}} = \begin{cases} 0, & \text{if } \lambda_{\text{max}} - \lambda_{\text{min}} < \delta_{\text{min}}, \lambda_{\text{min}} > \delta_{\text{max}} \\ \alpha, & \text{else} \end{cases}$$

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where $a, b,$ and $c$ are averaging weights; $I$ is the diffused image; $E(\cdot)$ is the edge image detected by a Sobel operator; and $B(\cdot)$ is the image brightness, extracted by two overlapping windows (see Fig. 5), which can be described as

$$B(x,y) = \frac{\sum_{i,j \in M_1} I_{i,j} \times g(i,j)}{M_1} - \frac{\sum_{i,j \in M_2} I_{i,j} \times g(i,j)}{M_2 - M_1},$$

where $g(i,j)$ is a normalized Gaussian function, $M_1$ and $M_2$ are the detecting windows, and $M_2$ is larger than $M_1$.

There are three relationships between retinal cells and detecting windows to be considered: if $M_1$ is in a
bright region and $M_2$ covers a dark region, the output of $B(x, y)$ is positive; conversely, if $M_1$ is in a dark region and $M_2$ covers a bright region (s), the output of $B(x, y)$ is negative; finally, if both $M_1$ and $M_2$ are in a homogeneous region, then the output of $B(x, y)$ is close to zero, and the algorithm will expand window size automatically.

In a real application for edge enhancing, because retinal cells are bright regions and their sizes are in the range between 4 × 4 and 10 × 10 pixels, $M_1$ and $M_2$ were set as 3 × 3 and 11 × 11, respectively; for BF, $\delta$ was computed according to the estimation zones by Eq. (2); for coherence diffusing, $\delta_{\text{min}}$ and $\delta_{\text{max}}$ were set as 10 and 200, and iteration was stopped when the mean square error (MSE) was smaller than 0.001, with the form

$$\text{MSE} = \frac{1}{m \times n} \sum_{i,j=m,n} (I_t(i, j) - I_{t-1}(i, j))^2,$$

where $m$ and $n$ are the image sizes, and $I_t(x, y)$ and $I_{t-1}(x, y)$ are the filtered images at time $t$ and $t-1$.

Figures 4A and 5A present two snapshot human retinal cell images obtained with dilated pupil (with Tropicamide 1%) and dark-adapted pupil, respectively. Final results are shown in Figs. 4D and 5B and interim results of Fig. 4A processed by BF and CD are provided in Figs. 4B and 4C. In the test, our retinal imaging system [5] works under the conditions of 25 Hz closed-loop measurement and correction of ocular aberration, the eye’s residual rms wavefront error less than 0.15 $\mu$m over a 6 mm pupil, a deformable mirror with 37 elements, Hartmann–Shack sensor with 97 subapertures in 11 × 11 arrays, 1.5 deg central eccentricity, and 550 nm imaging wavelength for Fig. 4A and 650 nm imaging wavelength for Fig. 5A.

To quantify the improvements of our results, image power spectra before and after processing are compared in Figs. 6A and 6B. It can be seen that at the two subjects’ cone photoreceptors frequencies, ranging from 50 to 80 cycles/deg, the image power spectra increased, while for higher frequencies, which probably correspond to noise content, the image power spectra decreased. So, our method effectively suppressed retinal image noise and enhanced cell structures.

In summary, a hybrid filtering and enhancing method for AO retinal cell images is proposed in this Letter. Experimental results proved that it is effective to filter image noise, enhance edge contrast, and improve image visual quality, which would benefit clinical diagnosis and medical image applications, such as cone photoreceptor counting and density estimation. Future studies will focus on further testing our method to improve retinal image quality of older patients, where contrast improvement is most needed.

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**References**