Reliable Single-image Denoising for Adaptive Optics Scanning Laser Ophthalmoscopy

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Abstract. A reliable single-image denoising method is presented for adaptive optics scanning laser ophthalmoscopy. This method firstly averaged multiple images and then used the averaged image as the reference to adjust the parameters of the filtering process that was subsequently applied to other individual images. Six filtering methods, including the mean, median, Gaussian, fast adaptive nonlocal synthetic aperture radar despeckling, K-single value decomposition, and block matching and three-dimensional filtering, were utilized. The effectiveness of our method was verified based on the comparison of sets of images without and with parameter adjustments. Furthermore, we applied the same parameter settings as those obtained from the filter adjustments of another adaptive optics scanning laser ophthalmoscope image acquired by the same instrument. The filtered images showed that the parameter-adjusted filters work well on other images, which is helpful for improving the image quality of adaptive optics scanning laser ophthalmoscope images.

1. Introduction
The adaptive optics scanning laser ophthalmoscope (AO-SLO) is an important high-resolution imaging tool used for ophthalmic diagnosis and the study of eye diseases [1-3]. Despite its high-imaging resolution, AO-SLO images suffer from low-signal-to-noise ratio (SNR) characteristics. One solution adopted to ameliorate this issue is the averaging of multiple AO-SLO images to improve the SNR. Even though this solution is reliable, it needs acquiring multiple images for generating one single denoised image and additional software or hardware to accurately register the images [4-12]. Another solution is the filtering of single AO-SLO images [5, 13-17]. Even though this approach is cheap and easy, it is difficult to adjust the parameters of the filtering process to prevent under- and overfiltering.

To prevent under- and overfiltering of single AO-SLO image, we propose the use of a reliable, single-image denoising method that considers an averaged image as the reference image, and uses it to adjust the parameters of the filtering process. The registration method presented in our previous study [4] was adopted to generate averaged images. To facilitate the adjustment of the filtering process, the single AO-SLO image was magnified and up-interpolated with bicubic interpolation before it was
filtered, and was then minified to its original size after it was filtered. In this way, the parameters of the six filtering methods, including the mean [18], median [19], Gaussian [18], fast adaptive nonlocal SAR despeckling (FANS) [20], K-single value decomposition (K-SVD) [21], and BM3D filtering [22], were adjusted for an AO-SLO image. To verify the effectiveness of this approach, we compared images acquired without and with parameter adjustments. Subsequently, we applied the same parameter settings (for the same AO-SLO) obtained from prior adjustments to filter other AO-SLO images to assess the method’s effectiveness.

2. Methods

2.1. Mean filtering
Mean filtering is a smoothing image method that can be used for denoising. In this process, we replace each image pixel value with the mean value of its neighboring pixels [18]. Our AO-SLO images include retinal photoreceptor cells whose sizes span only several pixels. Thus, the retinal photoreceptor cell structures are easy to be blurred with mean filtering. As shown in Fig. 1(c), the retinal photoreceptor cell structures are blurred with mean filtering with a 5 × 5 pixel kernel. To obtain a large range of kernel sizes, we magnified the tested image 9 times isotropically with bicubic interpolation before mean filtering, and we then minified it to their original size after mean filtering. To identify the best kernel size for mean filtering, we used different kernel sizes and selected the size that yielded the highest similarity with the averaged image (Fig. 1(b)) visually and subjectively. As shown in Fig. 1(d), we selected a 7 × 7 pixel kernel as the optimal size for mean filtering. Figs. 1(e) and 1(f) show the underfiltered (obtained with a 3 × 3 pixel kernel) and overfiltered results (with a 17 × 17 pixel kernel).

Figure 1. Original and denoised images. (a) Original image. (b) Averaged image. (c) Image filtered directly with a mean filter. (d) Optimally filtered image with a mean filter. (e) Underfiltered image with a mean filter. (f) Overfiltered image with a mean filter.
2.2. Median filtering
The median filtering is a nonlinear filtering technique introduced by Tukey in 1977 [19], and it can be used for image denoising. During the median filtering process, each pixel value of the filtered image is replaced with the median value of its neighboring pixels [18]. Given that our AO-SLO images include retinal photoreceptor cells whose sizes are only several pixels, the retinal photoreceptor cell structures are easy to be blurred by median filtering. As shown in Fig. 2(c), the retinal photoreceptor cell structures are blurred with median filtering with a 5 × 5 pixel kernel. To obtain a large range of kernel sizes, we magnified the image nine times isotropically and up-interpolated it with bicubic interpolation before median filtering. We then minified it to its original size after median filtering. To identify the best kernel size for the median filter, we tried to use different kernel sizes and selected the one which provided the highest similarity with the averaged image (Fig. 2(b)) visually and subjectively. As shown in Fig. 2(d), we selected a kernel with a size of 7 × 7 pixels as the optimal kernel size for median filtering. In Figs. 2(e) and 2(f), we also show the underfiltered (achieved with a 3 × 3 pixel kernel) and overfiltered images (achieved with a 17 × 17 pixel kernel).

2.3. Gaussian filtering
Gaussian filtering is a smoothing image method used for denoising. During the Gaussian filtering process, we replace each pixel value in the filtered image with the weighted mean value of its neighboring pixels [18]. The weights are given by the Gaussian function [18],

\[ \text{Gaussian}(x, y) = Ke^{-\frac{x^2+y^2}{2\sigma^2}}, \]

where \( x \) and \( y \) are the horizontal and vertical pixel lengths relative to target pixel, respectively, \( \sigma \) is the standard deviation of the Gaussian function, and \( K \) is the normalized factor. The only parameter needed to be selected is \( \sigma \). Because our AO-SLO images include retinal photoreceptor cells whose
sizes span a few pixels, the retinal photoreceptor cells structures are easy to be blurred by Gaussian filtering. As shown in Fig. 3(c), the retinal photoreceptor cell structures are blurred with Gaussian filtering with \( \sigma = 3 \). To achieve a large adjustment range for \( \sigma \), we magnified the image five times isotropically and up-interpolated it with bicubic interpolation before Gaussian filtering. We then minified it to its original size after Gaussian filtering. To identify the best \( \sigma \) value for median filtering, we tried to use different kernel sizes and selected the one which provided the lowest noise level and highest similarity with the averaged image (Fig. 3(b)) according to the highest evaluation score as follows,

\[
\text{Evaluation Score} = \frac{\text{SSIM}(\text{filtered image, averaged image})}{\text{ENL}(\text{filtered image})},
\]

where SSIM is the structural similarity index [23], and ENL is the estimated noise level [24]. We optimized the \( \sigma \) value with a traversal algorithm. As shown in Fig. 3(d), we selected the value of 3.39 pixels as the best \( \sigma \) value. Figs. 3(e) and 3(f) show the underfiltered (\( \sigma = 1 \)) and overfiltered (\( \sigma = 8 \)) images.

\[\text{Figure 3. Original and denoised images. (a) Original image. (b) Averaged image. (c) Image filtered directly with a Gaussian filter. (d) Optimally filtered image with a Gaussian filter. (e) Underfiltered image with a Gaussian filter. (f) Overfiltered image with a Gaussian filter.}\]

2.4 FANS denoising

FANS is a despeckling method that can be used for image denoising [20]. Given that our AO-SLO images include retinal photoreceptor cells whose sizes span a few pixels, the retinal photoreceptor cell structures can be easily blurred by FANS denoising. As shown in Fig. 4(c), the retinal photoreceptor cell structures are blurred with FANS. To overcome the blurring issue, we magnified the image and up-interpolated it with bicubic interpolation before FANS and minified it to its original size after FANS. The line magnification was denoted as \( m \). To identify the best line magnification for FANS, we used different line magnification values and selected the one that yielded the highest similarity with the averaged image (Fig. 4(b)) visually and subjectively. As shown in Fig. 4(d), we selected \( m = 4 \) as the best line magnification for FANS. Figs. 4(e) and 4(f) show the underfiltered (\( m = 8 \)) and overfiltered images (\( m = 2 \)).
2.5. K-SVD denoising
K-SVD is a method used for designing overcomplete dictionaries for sparse representation, but can also be used for image denoising [21]. Because our AO-SLO images include retinal photoreceptor cells whose sizes span only a few pixels, the retinal photoreceptor cell structures are easily blurred by K-SVD denoising. As shown in Fig. 5(c), the retinal photoreceptor cell structures are blurred with the use of K-SVD whose block size is equal to eight, a redundancy factor of four, and a standard deviation equal to ten. To solve this blurring, we magnified the image with bicubic interpolation before K-SVD and reduced it to its original size after K-SVD. The line magnification is denoted as s. To identify the best magnification for K-SVD, we tried different line magnification values and selected the one which provided the highest similarity with the averaged image (Fig. 5(b)) visually and subjectively. As shown in Fig. 5(d), we selected the value of s = 5 as the best line magnification for K-SVD. Figs. 5(e) and 5(f) show the underfiltered (s = 8) and overfiltered images (s = 2).
2.6. BM3D denoising

Block matching and three-dimensional filtering (BM3D) is a 3D block-matching method often used in image denoising [22]. Given that our AO-SLO images included retinal photoreceptor cells whose sizes spanned a few pixels, the retinal photoreceptor cell structures were easily blurred by BM3D denoising. As shown in Fig. 5(c), the retinal photoreceptor cell structures are blurred by BM3D. To solve this blurring issue, we magnified the image and up-interpolated it with bicubic interpolation before BM3D, and we then minified it to its original size after BM3D. The line magnification is denoted as $t$. To identify the best line magnification for BM3D, we tried different line magnification values and selected the one which provided the highest similarity with the averaged image (Fig. 6(b)) visually and subjectively. As shown in Fig. 6(d), we selected the value of $t = 5$ as the best line magnification for BM3D. As shown in Fig. 6(d), we selected the value of $t = 5$ as the best line magnification for BM3D. Figs. 6(e) and 6(f) show the underfiltered ($t = 8$) and overfiltered ($t = 2$) images.

Figure 5. Original and denoised images. (a) Original image. (b) Averaged image. (c) Image filtered directly with K-single value decomposition (K-SVD). (d) Optimally filtered image with K-SVD. (e) Underfiltered image with K-SVD. (f) Overfiltered image with K-SVD.
Figure 6. Original and denoised images. (a) Original image. (b) Averaged image. (c) Image filtered directly with block matching and three-dimensional filtering (BM3D) filtering. (d) Optimally filtered image with BM3D. (e) Underfiltered image with BM3D. (f) Overfiltered image

3. Results

We used AO-SLO with a 30 Hz imaging rate to demonstrate the image denoising process based on the imaging of the posterior parts of the eyes. The field-of-view (FOV) was 1.5° on the human retina with a frame size of approximately 512 × 449 pixels. Thus, a transverse area of approximately 445 µm × 445 µm was scanned based on the assumption of a focal length of 17 mm for the human eye. The details of the system are described in [25]. Drops of tropicamide (1%) and phenylephrine hydrochloride (2.5%) were administered to dilate the pupil to diameters in the range of 6–8 mm. All light exposures adhered to the maximum permissible exposure limits set by the American National Standards Institute [26].

To verify the effectiveness of our six denoising methods, we applied the same parameter settings obtained from previous adjustments to filter other AO-SLO images acquired by the same AO-SLO. We show the original, averaged, and filtered images in Fig. 7. As shown in Fig. 7, the filtered image yielded lower noise levels compared with the original image and a higher similarity with the averaged image compared with the original image. We evaluated the noise level based on ENL [24], and the similarity with the use of the averaged image and SSIM [23].

| Method       | Original | Averaged | Mean    | Median   | Gaussian | FANS | K-SVD | BM3D |
|--------------|----------|----------|---------|----------|----------|------|-------|-------|
| ENL          | 0.0477   | 0.0128   | 0.0014  | 0.0028   | 0.0014   | 0.0029| 0.0071| 0.0043|
| SSIM         | 0.8202   | -        | 0.9253  | 0.9256   | 0.9276   | 0.8974| 0.9183| 0.9136|
4. Discussion
Different noise properties are attributed to the high complexity and randomness of the source of the noise, physiological variability, and laser powers. Thus, we should reset the parameters of denoising when we measure different sets of eyes, when we change the power of the laser, or when we change the scanning pattern or the optical components.

5. Conclusions
We proposed six reliable single image denoising methods for AO-SLO images. The methods first regarded the averaged image as the reference image to adjust parameters for the denoising process. Accordingly, the same parameters were applied for denoising other images. Following the confirmation of the effectiveness of our six denoising methods, we conclude that these methods result in low-noise levels and preserve the original structures in AO-SLO images. This method may be helpful for standard ophthalmic examinations.

Acknowledgments
This work was supported in part by the Natural Science Foundation of Jiangsu Province (BK20200214); National Key R&D Program of China (2017YFB0403701); Jiangsu Province Key R&D Program (BE2019682, BE2018667); National Natural Science Foundation of China (61605210, 61675226, 61378090); Youth Innovation Promotion Association of Chinese Academy of Sciences (2019320); Frontier Science Research Project of the Chinese Academy of Sciences (QYZDB-SSW-JSC03); Strategic Priority Research Program of the Chinese Academy of Sciences (XDB02060000).

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