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A two-step iteration mechanism for speckle reduction in optical coherence tomography

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Abstract

Optical coherence tomography (OCT) is an imaging tool that has been widely utilized for various disease diagnoses for its noninvasive and high-resolution properties. Due to the dual role of speckles in the imaging process, however, OCT images suffer from the unavoidable speckle noise, which is usually regarded to be multiplicative in nature and reduces image contrast and resolution. In this study, we propose to categorize OCT speckle noise into additive portion and multiplicative portion, and present a simple two-step iteration (TSI) mechanism to suppress such noises separately. With the augmented Lagrange minimization (ALM) method adopted to recover a low-rank image, the first step of TSI is to remove the additive Gaussian noise, while the second step of TSI is to suppress the multiplicative noise by employing a split Bregman method (SBM) to solve the total-variation (TV) de-noising problem. Extensive experiments with OCT images of the swine eye, human and rabbit retina are conducted to verify the effectiveness of the proposed method. Results show that the proposed TSI method outperforms the existing methods in different cases. Specifically, TSI helps improve the peak signal-to-noise ratio (PSNR) and structure similarity (SSIM) of the swine eye

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images from 17.19 dB to 33 dB and 0.12 to 0.92, respectively, with the important structural details well preserved. The clearer boundaries and higher image contrast obtained with the TSI method would largely facilitate image analyses and interpretations for the clinical applications of OCT systems.

Keywords: Optical coherence tomography; Image processing; Noise in imaging systems; Image enhancement

1. Introduction

Optical coherence tomography (OCT) is a low-coherence interferometry based imaging tool capable of providing high-resolution cross-sectional images of tissue microstructures [1]. Due to its noninvasive and high-resolution properties, OCT has received extensive research interests since its invention and been utilized in various areas. In recent years, with the advents of ultrahigh resolution OCT (UHR-OCT) and swept-source OCT (SS-OCT), the application areas of OCT have been further broadened for the improved system resolutions and scanning speed [2]. Currently, OCT has not only been utilized for eye disease diagnoses in clinical practice [3], but also been utilized in some other research areas, such as for airway function evaluations [4], cardiology and gastroenterology system imaging [5, 6], and individual identifications in forensic science [7], etc..

As an interferometric imaging technique, however, OCT suffers from speckle noise like some other similar technologies, such as the synthetic aperture radar (SAR), remote sensing, ultrasound and sonar, etc. [8]. Speckle is an inherent characteristic of OCT images, which typically arises from the random interference between reflected wave signals that are mutually coherent. Among all those factors impacting on spatial coherence of the detection waves, the multiple backscattering of the incident beam inside and outside volumetric specimen as well as multiple forward scattering caused detection wave random delays are the two main ones. Both factors could change wave front shapes of the returning waves, which thus generates speckles due to the constructive and destructive interference effects. In OCT images, speckle plays a dual role as both source of speckle noise components and carrier of information about tissue microstructures[9]. Such a dual role makes speckle noise unavoidable in OCT images, which thus reduces the image contrast and resolution, making the tissue boundaries difficult to be resolved. To meet the rapid development and wide applications of OCT in different areas,

30 especially for high-scattering tissues imaging, speckle noise reduction tech-
31 niques are highly desired for resolving the tissue microstructures in clinical
32 practice.

33 Extensive efforts devoted either to the hardware-side system design or to
34 the software-side image post-processing mechanisms for OCT image speckle
35 reduction have been made in literature. By acquiring multiple images with
36 uncorrelated speckle patterns, the hardware design methods typically try to
37 average the acquired images to reduce speckle noises. Angular compounding
38 [10–12], frequency compounding [13], and spatial diversity based design [14–
39 16] are representative hardware-side methods. In practice, however, such
40 methods usually impose extensive changes upon the OCT systems, which
41 thus makes the system bulky and complex. In addition, the denoising effects
42 of such methods are also limited. On the contrary, those software-side meth-
43 ods are post-processing techniques, and mainly include the digital filtering
44 and sparse coding mechanisms. Various image processing algorithms using
45 either a single frame or multiple frames have been proposed thus far [17–24].
46 Based on wavelet-filter design and parametric optimization, the proposed dig-
47 ital filtering mechanisms have achieved encouraging results [17–20]. While
48 with the volumetric intra-frame redundancy or inter-frame redundancy or
49 both taken into consideration, the sparse coding mechanism has gained much
50 research interests in recent years [21–24]. However, although such software-
51 side methods achieve improved signal to noise ratio (SNR) without introduc-
52 ing any artifacts, they are still computational extensive and time-consuming.
53 For example, the multi-frame methods [18, 20, 21, 23–25] requires the acquisi-
54 tions of multiple frames for noise reduction processing, which thus slows down
55 the scanning speed and limit their practical applications in clinical practice,
56 while the single-frame methods, including image-domain methods [26–29],
57 and wavelet methods[19, 30, 31], either suffer from the high-computational
58 cost or the wavelet domain processing artifacts. Those drawbacks largely
59 limit the practical applications of those methods, especially for in vivo imag-
60 ing. Furthermore, it is also worth noting that all previous studies assumed
61 that the OCT speckle noise consists mainly of multiplicative noise, and the
62 additive noise, which consists mainly of the inherent shot noise, light intensity
63 noise and electronic noise, is relatively small and could be negligible as com-
64 pared to the multiplicative noise [19, 22, 24, 28, 32, 33]. However, although
65 such multiplicative noise model is relatively reasonable, and both simulation
66 and experimental results agree well with predicted Gamma distribution [32],
67 there still exists certain difference between the simulation and experimental

results, and OCT images still suffer from the inherent additive noises in OCT systems [19]. The SNR improvements with those proposed methods are also limited, especially for tissues with high speckle noise contamination. So far, no previous studies have ever evaluated the influences of additive noise to OCT images, to the best of our knowledge. Specifically, all such existing algorithms regard the speckle noise to be multiplicative in nature, and thus the SNR improvements with those methods are limited, especially for tissues with high speckle noise contamination.

In this study, we propose a two-step iteration (TSI) mechanism for speckle reduction for OCT systems. Specifically, we propose to categorize OCT speckle noise into multiplicative portion and additive portion as compared with the existing methods, and adopt an augmented Lagrangian minimization (ALM) method together with a split-Bregman method (SBM) to suppress such noises separately. Extensive experiments with images of the swine eye, human and rabbit retina are conducted to verify the effectiveness of the proposed TSI method. Results show that the TSI method largely outperforms the existing methods in achieving higher peak SNR (PSNR) and structure similarity (SSIM) in different cases.

2. TSI Method

2.1. OCT image noise modeling

Speckle noise in OCT images is usually considered to be multiplicative in nature due to the multiple backscattering effects [34]. However, since an OCT system also includes both laser source and electronics components, e.g., charge coupled devices (CCD) in spectrometer, OCT images also suffer from the inherent laser intensity noise, photonics shot noises as well as thermal noise from electronics. Both intensity noise and photonics shot noise are distributed with random-rate Poisson distribution and could be indistinguishable from true Gaussian noise with high laser power, while thermal noise itself is white Gaussian noise [15, 32, 35], therefore, we reasonably assume that an OCT image contains both multiplicative noise and additive noise with the latter one being Gaussian white noise in this study. Furthermore, due to the different tissue scattering capabilities at different tissue positions, the signal intensities collected from the tissue are different, and therefore, both multiplicative noise and additive noise are dependent with the imaging position. Since the system inherent additive noise is independent of the interference signals, and it is also smaller as compared with the multiplicative noise, both

additive and multiplicative noise could be processed independently from each other.

Denote a random position in an imaging area of the tissue to be x . Let $L(x)$ be a noise free B-scan frame of the tissue containing x , $N(x)$ be the speckle noise, and $E(x)$ be the Gaussian white noise, we adopt the same expression in [19] to express an obtained B-scan frame $M(x)$ as follows,

$$M(x) = L(x) \times N(x) + E(x) \quad (1)$$

where the symbols $M(x)$, $L(x)$, $N(x)$ and $E(x)$ are two-dimensional (2D) matrices $\in R^{m \times n}$, and would be used interchangeably with M , L , N and E throughout this paper.

Through utilizing such a noise model, it is expected that the multiplicative noise and the additive white noise could be differentiated and processed separately, and therefore, the overall image noise could be suppressed. The TSI method described below is proposed for such purpose.

2.2. The TSI method

Figure 1 presents the main flow diagram of the TSI method. As can be seen, the TSI method includes a pre-processing step, namely image registration, together with two iteration steps, which are for the additive noise reduction and multiplicative noise suppression, respectively. Below we give a detailed description of each step.

2.2.1. Pre-processing for image registration

Although the typical scanning speed of OCT systems is high, misalignment of the same imaging point among different OCT images still exists due to the motions of both OCT scanners and the imaging object, especially for in vivo imaging, which thus could introduce motion artifacts to OCT images. To alleviate the influences of those motion artifacts while obtain the full information of a certain imaging point, image registration has to be performed to align the related images [36]. Specifically, a single frame has to be chosen as the standard reference first, and then a number of consecutive frames are selected, and then they are either rotated or translated to a certain degree to align with this reference frame accordingly, such that the image difference between these frames are minimized. Such a process is called the image registration process, and once such a process is performed, both image rotation and translation parameters could be found, and then could be utilized as

Figure 1: Flow diagram of the proposed TSI method. An image M includes the noise-free part L , multiplicative portion N and additive portion E . After the first iteration, the additive noise E is separated from the noise model with the ALM method, and then, the second iteration step adopts split-Bregman method to solve the total variation (TV) de-noising problem to obtain the noise-free image L .

137 the input parameters of the TSI mechanism. Finally, the TSI mechanism is
 138 applied to the averaged frame of those selected consecutive frames for speckle
 139 noise suppression.

140 In this study, we adopted the Matlab built-in Powells optimizer to min-
 141 imize the sum of squared distances (SSD) between different OCT images in
 142 the image registration process, and 8 frames were utilized for image registra-
 143 tion, which gives the best noise suppression effects and will be verified in Sec.
 144 3. Note that different number of images utilized for registration may lead
 145 results to be slightly different, yet it has no influences on TSI effectiveness
 146 in speckle noise suppression.

147 2.2.2. Additive noise reduction using ALM

148 As shown in Eq. (1), an OCT image M mainly consists of three portions,
 149 i.e., the noise free image L , the multiplicative speckle noise N and the additive
 150 Gaussian noise E , and it can be further expressed as $M = R + E$ with
 151 $R = L \times N$. Since both multiplicative noise and additive Gaussian noise are
 152 sparse in nature, we can model the suppression of additive Gaussian noise E
 153 as the l^1 -minimization problem, and such a problem can be described by Eq.
 154 (2) [37]

$$\{R^*, E^*\} = \arg \min \|R\|_* + \lambda \|E\|_1 \quad s.t. \quad M = R + E \quad (2)$$

155 where λ is a random constant, $\|M\|_*$ is the nuclear norm of matrix M , and
 156 $\|E\|_1$ is the l^1 -norm of matrix E . Such a model indicates that once the lowest
 157 rank of R is found for the acquired OCT images, the additive noise E could
 158 be suppressed.

159 To find the lowest rank of R , the augmented Lagrangian function mini-
 160 mization (ALFM), which has the same minimizer as the original constrained
 161 optimization problem [38], can be adopted. Such an ALFM problem can be
 162 described as below,

$$L(R, E, Y, \mu) = \|R\|_* + \lambda \|E\|_1 + \langle Y, M - R - E \rangle + \frac{\mu}{2} \|M - R - E\|_F^2 \quad (3)$$

163 where Y is the Lagrange multiplier matrix, μ is a random positive scalar
 164 that is updated in the iteration process, $\langle X, Y \rangle := \text{trace}(X * Y)$ is the
 165 Euclidean inner product between the two matrices X and Y , and $\|\cdot\|_F$
 166 denotes the Frobenius norm. Once the appropriate Y and μ are found, the
 167 de-noised low-rank matrices R could be obtained.

Algorithm 1 presents the ALM de-noising method adopted in this study: step 1 initializes all the parameters utilized, and steps 2-8 conduct an iterative unconstraint minimization of Y starting from Y_0 . Specifically, steps 3 and 4 try to find the lowest rank matrices R_{k+1} and E_{k+1} iteratively from Lagrange multiplier matrix Y_k , and step 5 utilizes the obtained lowest rank matrices R_{k+1} and E_{k+1} to optimize the Lagrange multiplier matrix Y_{k+1} iteratively, steps 6-7 update the random iteration scalar μ . Such a process repeats until the difference between the two Lagrange multiplier matrices Y_k and Y_{k+1} is smaller than a predefined threshold, and once the iteration process terminates, it is assumed that the additive noise is eliminated. In the expression, $J(M)$ denotes the Jacobian matrix of M [39].

Algorithm 1: ALM de-noising method

input : raw image M , constant λ
output: R_k, E_k
1 Initialization: $Y_0 = M/J(M)$, $E_0 = 0$, $\mu_0 > 0$, $k = 0$;
2 **while** $\|Y_k - Y_{k-1}\|_2 > tol_1$ **do**
3 solve $R_{k+1} = \arg \min L(R, E_k, Y_k, \mu_k)$;
4 solve $E_{k+1} = \arg \min L(R_{k+1}, E, Y_k, \mu_k)$;
5 $Y_{k+1} = Y_k + \mu_k(M - R_{k+1} - E_{k+1})$;
6 $\mu_{k+1} = \mu_k$;
7 $k = k + 1$.
8 **end**

2.2.3. *Multiplicative noise suppression with Total-Variation (TV) de-noising*

With the ALM de-noising method performed, the additive noise of the OCT images could be largely suppressed, and thus, images with only multiplicative noise, i.e., $R = L \times N$, could be obtained. To further obtain the noise free image L from the obtained image R , such a problem can be further considered as a 2D anisotropic TV minimization problem, and thus, the simple and efficient Split Bregman technique [40] can be adopted for such minimization problem,

$$\min_{d_x, d_y, L} |d_x| + |d_y| + \frac{\alpha}{2} \|L - R\|_2^2 + \frac{\beta}{2} \|d_x - \nabla_x L - b_x^k\|_2^2 + \frac{\beta}{2} \|d_y - \nabla_y L - b_y^k\|_2^2 \quad (4)$$

where α and β are positive constants, $d_x = \nabla_x$ and $d_y = \nabla_y$ are difference operations, while b_x^k and b_y^k are proper values chosen for Bregman iterations.

189 The main idea of such an de-noising mechanism is to solve the unconstrained
 190 anisotropic problem iteratively such that the multiplicative noise could be
 191 suppressed to a certain tolerance, and therefore, the multiplicative noise is
 192 regarded to be removed.

To achieve the optimal efficiency, the fast Gauss-Seidel iteration method [41] is adopted to solve this 2D minimization problem. Hence, the k -th Gauss-Seidel solution $L_{i,j}^{k+1} = G_{i,j}^k$ could be expressed as follows,

$$G_{i,j}^k = \frac{\beta}{\alpha + \beta} \left(L_{i+1,j}^k + L_{i-1,j}^k + L_{i,j+1}^k + L_{i,j-1}^k + d_{x,i-1,j}^k - d_{x,i,j}^k + d_{y,i,j-1}^k - d_{y,i,j}^k - b_{x,i-1,j}^k + b_{x,i,j}^k - b_{y,i,j-1}^k + b_{y,i,j}^k \right) + \frac{\alpha}{\alpha + \beta} R_{i,j} \quad (5)$$

193 Define shrinkage operator to be,

$$shrink(\psi, \gamma) = \frac{\psi}{|\psi|} * \max(|\psi| - \gamma, 0) \quad (6)$$

194 where ψ and γ are two variables, and then, the Split-Bregman Anisotropic
 195 TV denoising mechanism can be described by algorithm 2,

Algorithm 2: Split Bregman anisotropic TV de-noising

input : Constants α, β , and additive noise suppressed image R .
output: Noise suppressed image L_k .
 1 Initialization: $L_0 = R$, and $d_x^0 = d_y^0 = b_x^0 = b_y^0 = 0$;
 2 **while** $\|L_k - L_{k-1}\|_2 > tol_2$ **do**
 3 $L_{k+1} = G_k$;
 4 $d_x^{k+1} = shrink(\nabla_x L_{k+1} + b_x^k, \frac{1}{\beta})$;
 5 $d_y^{k+1} = shrink(\nabla_y L_{k+1} + b_y^k, \frac{1}{\beta})$;
 6 $b_x^{k+1} = b_x^k + (\nabla_x L_{k+1} - d_x^{k+1})$;
 7 $b_y^{k+1} = b_y^k + (\nabla_y L_{k+1} - d_y^{k+1})$;
 8 $k = k + 1$.
 9 **end**

196 Compared with the other existing methods, this adopted anisotropic TV
 197 de-noising method converges faster and can be implemented easier with par-
 198 allel computation. In addition, it also requires relatively smaller memory,
 199 and thus could be applied for large-scale problems.

200 It is worth noting that four regulation parameters, i.e., $\mu, \lambda, \alpha, \beta$, were
 201 utilized in TSI mechanism, and all those parameters play an important role

in determining the denoising performance. In our study, the average of pre-registered frames utilized as the initialization of the denoising frame, and the values of those parameters were set to be 0.4, 2, 0.002 and 0.98, respectively. Such values were obtained empirically with TSI using the imaging data, such that the best TSI performance was obtained with minimum running time. When adopted for practical applications, it is possible for the TSI method to include a pre-calculation step in its image registration process to find the appropriate values for such regulation parameters.

3. Experimental results

Extensive experiments are conducted to verify the effectiveness of the proposed TSI method. Specifically, experiments with the public accessible swine eye images are conducted first to find an optimal number of images averaged for de-noising, and then denoised images obtained with TSI are compared with those processed using four other state-of-art de-noising methods, i.e., anisotropic diffusion method [42], Bayesian method [28], multi-frame wavelet method [20] and inter-intra method [24], for performance evaluations. Finally, experiments with human and rabbit retina images are also conducted for evaluations.

3.1. Performance metrics

To verify the performances of the TSI method, two typical de-noising performance metrics, i.e., the PSNR and the SSIM, are utilized for evaluations. Specifically, PSNR measures the intensity difference between the obtained noise free image and the ground truth image, and for a de-noised image L , the higher PSNR is, the higher image quality as compared with its ground truth image. On the contrary, SSIM measures the structural similarity between two images, and the higher SSIM is, the more similar structural information between the denoised image and the ground truth image. The value of SSIM is within the range from 0 to 1, and those constants defining PSNR and SSIM are their default settings.

3.2. Experiments with swine eye images

The public accessible swine eye image dataset [20] was processed to verify the performances of TSI method first. Such images were acquired using Spectralis HRA & OCT (Heidelberg Engineering) with high speed mode *ex vivo* at a system resolution of $7\ \mu m$ and $14\ \mu m$ in axial and lateral directions,

236 respectively. The dataset consists of 35 subsets, with each containing 13
 237 frames acquired at the same position. To obtain the ground truth image,
 238 the average of all 455 images was utilized as the noise free reference image
 239 as those in [20, 24].

240 Since the number of frames averaged in TSI method impacts on the de-
 241 noising effect, we first investigate the PSNR and SSIM improvements under
 242 different number of frames averaged. The TSI method was implemented with
 243 Matlab programing, and was ran on an Intel E5-2697, 2.6 Ghz workstation
 244 (64GB RAM and 64 bit Windows 7 system). The number of frames averaged
 245 was set to be within 5 to 13, while both the tolerance values tol_1 and tol_2
 246 were set to be 10^{-7} in this study.

247 Figure 2 presents the PSNR and SSIM improvement versus the different
 248 number of swine eye images averaged. As can be seen Fig. 2(a) and Fig.
 249 2(b), both PSNR and SSIM improve gradually with an increasing number of
 250 averaged frames. Specifically, as shown in Figs. 2(a) and 2(b), when the av-
 251 eraged frame number is less than 10, the improving rates of both PSNR and
 252 SSIM raise faster, e.g., with the frame number increased from 5 to 10, PSNR
 253 and SSIM improves from 31.3 dB to 32.9 dB and 0.897 to 0.917, respectively.
 254 Once the number is larger than 10, however, such improving rates slow down,
 255 e.g., when the frame number increases from 10 to 13, PSNR and SSIM im-
 256 prove from 32.9 dB to 33.1 dB and 0.917 to 0.922, respectively. The slops of
 257 PSNR and SSIM curves at the points 6 and 11 in Figs. 2(a) and 2(b), which
 258 indicate the changing rates of PSNR and SSIM at the corresponding points,
 259 clearly demonstrate that the improving rates of both PSNR and SSIM slow
 260 down once the averaged frame number is larger than 10. Such is because av-
 261 eraging multiple frames could suppress speckle noise effectively, and once the
 262 speckle noise is suppressed down to a certain level, however, the de-noising
 263 effects of frame averaging become limited. To make a compromise between
 264 the image improvement and the computational complexity, 8 frames were
 265 utilized when processing those images in this study.

266 Figure 3 compares the swine eye images processed by TSI method with
 267 those processed by four other existing de-nosing methods. Fig. 3(a) presents
 268 one of the original images without de-noising processing, wherein the detailed
 269 microstructures, i.e., the areas of interests (AOIs) illustrated by the two
 270 insets, were largely affected by speckles and could not be resolved. Fig. 3(b)
 271 shows the true ground image averaged over 455 frames, while Fig. 3(c) is
 272 averaged over 8 frames. Figs. 3(d)-3(h) show the images processed by the
 273 anisotropic diffusion, Bayesian, multi-frame wavelet, inter-intra and the TSI

Figure 2: Reconstructed image quality VS. different number of frames averaged. (a) PSNR (blue solid line) and (b) SSIM (green solid line) improve with increasing number of frames averaged. Slops of both figures indicate that the changing rates of PSNR and SSIM slow down once the number of averaged frame number is larger than 10.

274 methods, respectively.

275 As can be seen, with 455 frames averaged, the true ground image as shown
 276 in Fig. 3(b) achieves the best de-noising effects and is hardly affected by
 277 speckle noises. With 8 frames averaged, however, although Fig. 3(c) is better
 278 than Fig. 3(a), it still suffers from the speckle noise as compared with Fig.
 279 3(b). Figs. 3(d) and 3(f) are processed with anisotropic diffusion and multi-
 280 frame wavelet de-noising methods respectively, and show clearer structural
 281 boundaries as compared with Fig. 3(c), yet the morphological details in
 282 those images are still largely affected by the speckle noise. On the contrary,
 283 although Figs. 3(e) and 3(g) present better speckle noise suppression with
 284 Bayesian and inter-intra frame de-noising method, the image contrast and
 285 morphological boundaries are degraded.

286 Figure 3(h) presents the image processed with TSI method. As can be
 287 seen, the proposed TSI method helps achieve better speckle suppression and
 288 higher contrast as compared with those existing de-noising methods, while
 289 the morphological boundaries are also preserved. As shown by the two insets
 290 of Fig. 3(h), both the blood vessels and structural details are clearly resolved,
 291 and are also comparable to those in the true ground images in Fig. 3(b).

292 A quantitative comparison between TSI and the other methods in PSNR
 293 and SSIM improvements is also shown in Table I. As can be seen, TSI method
 294 achieves the best PSNR and SSIM among all methods when processing either
 295 the entire images or the AOIs. Specifically, for the entire image, it improves

Figure 3: Swine eye images processed with the existing de-noising methods and the TSI method. (a) One typical OCT image acquired. (b) True ground image averaged over 455 frames. (c) Image averaged over 8 sequential frames. (d) Image processed with anisotropic diffusion method. (e) Image processed with Bayesian method. (f) Image processed with multi-frame wavelet method. (g) Image processed with inter-intra frame method. (h) Image obtained with TSI method. Insets on the right are enlarged AOIs.

the image PSNR and SSIM from 17.19 to 32.83 and 0.12 to 0.915, respectively. Such a comparison demonstrates that the TSI method is capable of improving the image qualities while keeping the key tissue structural details in different cases. It is also worth noting that when processing the entire image, TSI method spends 83 seconds on our workstation.

Table 1: Quantitative comparisons between TSI and the existing methods

	<i>Metric</i>	<i>Single Input</i>	<i>Average 455 frames</i>	<i>Average 8 frames</i>	<i>Diffusion</i>	<i>Bayesian</i>	<i>Wavelet</i>	<i>inter- intra</i>	<i>TSI</i>
Entire image	PSNR(dB)	Infinity	17.19	24.56	29.14	28.38	30.75	31.74	32.83
	SSIM	0.12	1	0.45	0.73	0.7	0.86	0.91	0.915
	Running time(s)	–	–	–	79 ¹	33 ¹	60 ¹	36 ¹	83 ²
Red inset	PSNR(dB)	15.03	Infinity	22.02	26.60	26.07	27.87	28.92	30.48
	SSIM	0.06	1	0.29	0.65	0.63	0.73	0.81	0.8246
Green inset	PSNR(dB)	15.13	Infinity	21.91	26.14	25.35	27.83	28.75	32.45
	SSIM	0.06	1	0.25	0.60	0.57	0.72	0.80	0.8604

¹ The running time of these algorithms are measured on an Intel E7500 2.93 GHz CPU computer with 4GB RAM and 64 bit windows 7 system with Matlab programming.

² TSI is implemented with Matlab programming on an Intel E5-2697, 2.6GHz workstation with 64GB RAM and 64 bit windows 7 system.

3.3. Experiments with human retinal images

The public dataset of human retinal OCT images presented in [23] were also utilized to test the de-noising effect of TSI method. Such images were acquired with an SD-OCT system from Bioptigen Inc., which has an axial resolution of $4.5 \mu m$ in air. The tested datasets are from 17 eye subjects with each dataset providing one raw image and one de-noised image that is averaged over 5 frames. Therefore, for human retina images, we have to the provided de-noised image for TSI processing. Furthermore, since there is no ground truth image provided, both PSNR and SSIM were not calculated for this tested dataset.

Figures 4(a) presents one of the raw image without any de-noising processing, while Figs. 4(c) and 4(e) show the de-noised images obtained with frame averaging and the TSI method, respectively. Results in Figs. 4(c), 4(e) and 4(a) shows that both frame averaging and the TSI method could largely suppress the speckle noise, and the comparison between Figs. 4(c) and 4(e)

316 proves that TSI method achieves better de-noising effects than frame aver-
 317 aging, and meanwhile, the important structural details that are critical for
 318 clinical analysis are still well preserved.

319 To further validate the effectiveness of TSI method, we also analyzed
 320 those images by detecting their respective critical layers using Matlab built-in
 321 canny detector function under the default settings. The obtained results are
 322 shown in Figs. 4(b), 4(d) and 4(f). As can be seen, the TSI method largely
 323 suppresses the speckle noise as compared with frame averaging; furthermore,
 324 the critical layer boundaries are preserved and are even better seen than those
 325 in Figs. 4(b) and 4(d). Such clear layer boundaries could help facilitate the
 326 image interpretations and analyses in clinical practice.

Figure 4: De-noising effect verification using the human retinal images. 5 images were utilized for averaging. (a-b) Original raw image and its structural boundaries obtained with edge detection function. (c-d) De-noised image obtained with frame averaging and the resulted layered boundaries. (e-f) De-noised image with TSI method and the layered boundaries obtained.

3.4. Experiments with rabbit retina images

Experiments were also conducted to validate the effectiveness of TSI method using rabbit retinal images. Such images were acquired with our lab-built spectral encoded extended source (SEES) OCT system [43], which achieves an axial resolution of $4.6 \mu\text{m}$ in air, and also allows a higher MPE than the commercial ones providing a sensitivity advantage of 5 dB. 8 frames were utilized for averaging in this case.

Figure 5(a) presents a cross-sectional rabbit retina image obtained with freshly sacrificed rabbit sample, while Fig. 5(b) shows the image processed with TSI method. As shown in Fig. 5(a), the SEES-OCT image suffers from the speckle noise, which makes the critical tissue structural boundaries difficult to be resolved. When processed with the TSI method, however, those boundaries become much clearer, and thus easier to be resolved. Such results again demonstrate that the TSI method helps largely reduce the speckle noise, and preserves the key structural details at the same time, which are of critical importance to clinical interpretations and analyses of the OCT images.

Figure 5: Experimental results with rabbit retina images. (a) A single cross-sectional raw image. (b) Image processed with TSI method for speckle noise reduction.

We also tested the performance of TSI method with the reconstructed en face images of rabbit lamina cribrosa (LC) as shown in Fig. 6. Fig. 6(a) shows a de-noised image averaged over 8 sequential frames, while Fig. 6(b) shows the image de-noised with TSI method. The comparison between

348 Figs. 6(a) and 6(b) demonstrates that the TSI method again achieves better
 349 de-noising effect than the frame averaging method, and the structural de-
 350 tails, e.g., the mesh-like hollow structures, are also well preserved and can be
 351 clearly resolved. When further process those images using the canny detector
 352 function, Figs. 6(c) and 6(d) are obtained from Figs. 6(a) and 6(b), respec-
 353 tively. Results show that the structural boundaries of Fig. 6(b), which is
 354 processed with TSI method, are well preserved and much clearer than those
 355 in Fig. 6(c). Furthermore, the image contrast of Fig. 6(d) is also much
 356 higher, which helps facilitate the image interpretations in clinical practice.

Figure 6: Speckle noise reduction with reconstructed en face rabbit lamina cribrosa images. (a) De-noised image obtained with frame averaging. (b) De-noised image obtained with the TSI method. (c-d) Edge detection of Figs. 6(a) and 6(b), respectively.

357 4. Discussions and conclusion

358 In this study, we present a TSI method for OCT image speckle noise
359 reduction. By dividing the speckle noise into multiplicative portion and ad-
360 ditive portion according to their generating natures, the proposed TSI mech-
361 anism tries to suppress them separately. Specifically, it adopts the ALM
362 method to remove the additive Gaussian noise first, and then employs the
363 SBM method to solve the TV de-noising model for multiplicative noise sup-
364 pression. Experiments with different biological tissue images, such as the
365 swine eyes, human and rabbit retina, were conducted, and the results are
366 compared to those of the other existing methods to verify the effectiveness of
367 TSI method. Result comparisons show that the TSI method outperforms the
368 existing methods, and helps improve the PSNR and SSIM of the swine eye
369 images from 17.19 dB to 33 dB and 0.12 to 0.92, respectively. When com-
370 pared with the best existing multi-frame mechanism, i.e., inter-intra method,
371 TSI still improves PSNR of the entire image by 1.09 dB and SSIM by 5.49%,
372 which demonstrates that the critical tissue structures are well preserved in
373 speckle noise suppression process. While compared to the other single frame
374 methods, e.g., Diffusion and Bayesian methods, the improvements of PSNR
375 and SSIM are even higher. The clearer boundaries together with the higher
376 image contrast also demonstrate the great potential of TSI method for image
377 interpretations and analyses in clinical practice.

378 Although TSI method helps achieve large improvement in speckle noise
379 suppression, there still exist large spaces for the TSI method to be improved.
380 First, the computational time the computation time of TSI method is too
381 long, which may hinder its practical applications in *in vivo* imaging. How-
382 ever, as the SBM based anisotropic TV denoising method could be imple-
383 mented with parallel computations, the computation time of TSI could be
384 largely reduced with more sophisticated programming skills. Second, the
385 multiplicative noise and additive noise were processed separately with two
386 different methods in this study. While in practice, both ALM and SBM
387 methods are not specified for certain types of noises, and thus, the iterative
388 steps can be easily modified to include either ALM or SBM or some other
389 more efficient noise minimization mechanisms to both suppress the speckle
390 noise and reduce the computation time. In addition, although ophthalmic
391 images were utilized for experiments in this study, the TSI method could
392 also be applied to other types of images for noise suppressions. We believe
393 that such a mechanism could provide certain significance to biophotonics and

394 biomedical image analysis in clinical practice.

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402 References

- 403 [1] D. Huang, E. A. Swanson, C. P. Lin, J. S. Schuman, W. G. Stin-
404 son, W. Chang, M. R. Hee, T. Flotte, K. Gregory, C. A. Puliafito,
405 J. G. Fujimoto, Optical coherence tomography, Science (New York, NY)
406 254 (5035) (1991) 1178.
- 407 [2] W. Drexler, J. G. Fujimoto, Optical coherence tomography: technology
408 and applications, Springer Science & Business Media, 2008.
- 409 [3] W. Drexler, J. G. Fujimoto, State-of-the-art retinal optical coherence
410 tomography, Progress in retinal and eye research 27 (1) (2008) 45–88.
- 411 [4] L. Liu, K. K. Chu, G. H. Houser, B. J. Diephuis, Y. Li, E. J. Wilsterman,
412 S. Shastry, G. Dierksen, S. E. Birket, M. Mazur, S. Byan-Parker, W. E.
413 Grizzle, S. E. J., S. M. Rowe, G. J. Tearney, Method for quantitative
414 study of airway functional microanatomy using micro-optical coherence
415 tomography, PloS one 8 (1) (2013) e54473.
- 416 [5] D. C. Adler, Y. Chen, R. Huber, J. Schmitt, J. Connolly, J. G. Fujimoto,
417 Three-dimensional endomicroscopy using optical coherence tomography,
418 Nature Photonics 1 (12) (2007) 709–716.
- 419 [6] X. Yu, Y. Luo, X. Liu, S. Chen, X. Wang, S. Chen, L. Liu, Toward
420 high-speed imaging of cellular structures in rat colon using micro-optical
421 coherence tomography, IEEE Photonics Journal 8 (4) (2016) 1–8.

- 422 [7] X. Yu, Q. Xiong, Y. Luo, N. Wang, L. Wang, H. L. Tey, L. Liu, Contrast
423 enhanced subsurface fingerprint detection using high-speed optical co-
424 herence tomography, *IEEE Photonics Technology Letters* 29 (1) (2017)
425 70–73.
- 426 [8] J. M. Schmitt, S. Xiang, K. M. Yung, Speckle in optical coherence to-
427 mography: an overview, in: *Saratov Fall Meeting’98: Light Scattering*
428 *Technologies for Mechanics, Biomedicine, and Material Science*, Inter-
429 *national Society for Optics and Photonics*, 1999, pp. 450–461.
- 430 [9] J. M. Schmitt, S. Xiang, K. M. Yung, Speckle in optical coherence to-
431 mography, *Journal of biomedical optics* 4 (1) (1999) 95–105.
- 432 [10] N. Iftimia, B. E. Bouma, G. J. Tearney, Speckle reduction in optical
433 coherence tomography by path length encoded angular compounding,
434 *Journal of biomedical optics* 8 (2) (2003) 260–263.
- 435 [11] A. Desjardins, B. Vakoc, W. Oh, S. Motaghianezam, G. Tearney,
436 B. Bouma, Angle-resolved optical coherence tomography with sequential
437 angular selectivity for speckle reduction, *Optics express* 15 (10) (2007)
438 6200–6209.
- 439 [12] L. Ramrath, G. Moreno, H. Mueller, T. Bonin, G. Huettmann,
440 A. Schweikard, Towards multi-directional oct for speckle noise reduc-
441 tion, *Medical Image Computing and Computer-Assisted Intervention–*
442 *MICCAI 2008* (2008) 815–823.
- 443 [13] M. Pircher, E. Go, R. Leitgeb, A. F. Fercher, C. K. Hitzenberger, et al.,
444 Speckle reduction in optical coherence tomography by frequency com-
445 pounding, *Journal of Biomedical Optics* 8 (3) (2003) 565–569.
- 446 [14] J. Schmitt, Array detection for speckle reduction in optical coherence
447 microscopy, *Physics in Medicine and Biology* 42 (7) (1997) 1427.
- 448 [15] M. Bashkansky, J. Reintjes, Statistics and reduction of speckle in optical
449 coherence tomography, *Optics Letters* 25 (8) (2000) 545–547.
- 450 [16] D. P. Popescu, M. D. Hewko, M. G. Sowa, Speckle noise attenuation
451 in optical coherence tomography by compounding images acquired at
452 different positions of the sample, *Optics Communications* 269 (1) (2007)
453 247–251.

- 454 [17] D. C. Adler, T. H. Ko, J. G. Fujimoto, Speckle reduction in optical
455 coherence tomography images by use of a spatially adaptive wavelet
456 filter, *Optics letters* 29 (24) (2004) 2878–2880.
- 457 [18] A. Ozcan, A. Bilenca, A. E. Desjardins, B. E. Bouma, G. J. Tearney,
458 Speckle reduction in optical coherence tomography images using digital
459 filtering, *JOSA A* 24 (7) (2007) 1901–1910.
- 460 [19] P. Puvanathan, K. Bizheva, Speckle noise reduction algorithm for op-
461 tical coherence tomography based on interval type ii fuzzy set, *Optics*
462 *express* 15 (24) (2007) 15747–15758.
- 463 [20] M. A. Mayer, A. Borsdorf, M. Wagner, J. Hornecker, C. Y. Mardin, R. P.
464 Tornow, Wavelet denoising of multiframe optical coherence tomography
465 data, *Biomedical optics express* 3 (3) (2012) 572–589.
- 466 [21] Z. Jian, L. Yu, B. Rao, B. J. Tromberg, Z. Chen, Three-dimensional
467 speckle suppression in optical coherence tomography based on the
468 curvelet transform, *Optics express* 18 (2) (2010) 1024–1032.
- 469 [22] P. Puvanathan, K. Bizheva, Interval type-ii fuzzy anisotropic diffusion
470 algorithm for speckle noise reduction in optical coherence tomography
471 images, *Optics express* 17 (2) (2009) 733–746.
- 472 [23] L. Fang, S. Li, Q. Nie, J. A. Izatt, C. A. Toth, S. Farsiu, Sparsity
473 based denoising of spectral domain optical coherence tomography im-
474 ages, *Biomedical optics express* 3 (5) (2012) 927–942.
- 475 [24] L. Bian, J. Suo, F. Chen, Q. Dai, Multiframe denoising of high-speed op-
476 tical coherence tomography data using interframe and intraframe priors,
477 *Journal of biomedical optics* 20 (3) (2015) 036006–036006.
- 478 [25] L. Fang, S. Li, D. Cuneffare, S. Farsiu, Segmentation based sparse recon-
479 struction of optical coherence tomography images, *IEEE Transactions*
480 *on Medical Imaging* 36 (2) (2017) 407–421.
- 481 [26] G. Gong, H. Zhang, M. Yao, Speckle noise reduction algorithm with
482 total variation regularization in optical coherence tomography, *Optics*
483 *Express* 23 (19) (2015) 24699–712.

- 484 [27] J. Duan, W. Lu, C. Tench, I. Gottlob, F. Proudlock, N. N. Samani,
485 L. Bai, Denoising optical coherence tomography using second order total
486 generalized variation decomposition, *Biomedical Signal Processing &*
487 *Control* 24 (2016) 120–127.
- 488 [28] A. Wong, A. Mishra, K. Bizheva, D. A. Clausi, General bayesian estima-
489 tion for speckle noise reduction in optical coherence tomography retinal
490 imagery, *Optics express* 18 (8) (2010) 8338–8352.
- 491 [29] A. Cameron, D. Lui, A. Boroomand, J. Glaister, A. Wong, K. Bizheva,
492 Stochastic speckle noise compensation in optical coherence tomography
493 using non-stationary spline-based speckle noise modelling., *Biomedical*
494 *Optics Express* 4 (9) (2013) 1769–85.
- 495 [30] B. Chong, Y. K. Zhu, Speckle reduction in optical coherence tomography
496 images of human finger skin by wavelet modified bm3d filter, *Optics*
497 *Communications* 291 (6) (2013) 461–469.
- 498 [31] R. Kafieh, H. Rabbani, I. Selesnick, Three dimensional data-driven
499 multi scale atomic representation of optical coherence tomography, *IEEE*
500 *Trans Med Imaging* 34 (5) (2015) 1042–1062.
- 501 [32] M. Y. Kirillin, G. Farhat, E. A. Sergeeva, M. C. Kolios, A. Vitkin,
502 Speckle statistics in oct images: Monte carlo simulations and experi-
503 mental studies., *Optics Letters* 39 (12) (2014) 3472–5.
- 504 [33] B. Choudhury, M. Li, R. Idoughi, W. Heidrich, Statistical model for oct
505 image denoising, *Biomedical Optics Express* 8 (9) (2017) 3903–3917.
- 506 [34] J. M. Schmitt, A. Knüttel, Model of optical coherence tomography of
507 heterogeneous tissue, *JOSA A* 14 (6) (1997) 1231–1242.
- 508 [35] F. Russo, A method for estimation and filtering of gaussian noise in
509 images, *IEEE Transactions on Instrumentation and Measurement* 52 (4)
510 (2003) 1148–1154.
- 511 [36] H. Zhang, Z. Li, X. Wang, X. Zhang, Speckle reduction in optical coher-
512 ence tomography by two-step image registration, *Journal of biomedical*
513 *optics* 20 (3) (2015) 036013–036013.

- 514 [37] J. Wright, Y. Ma, Dense error correction via l^1 -minimization, IEEE
515 Transactions on Information Theory 56 (7) (2010) 3540–3560.
- 516 [38] G. Di Pillo, S. Lucidi, An augmented lagrangian function with improved
517 exactness properties, SIAM Journal on Optimization 12 (2) (2002) 376–
518 406.
- 519 [39] Y. Peng, A. Ganesh, J. Wright, W. Xu, Y. Ma, Rasl: Robust alignment
520 by sparse and low-rank decomposition for linearly correlated images,
521 IEEE Transactions on Pattern Analysis & Machine Intelligence 34 (11)
522 (2012) 2233–2246.
- 523 [40] T. Goldstein, S. Osher, The split bregman method for l_1 -regularized
524 problems, SIAM journal on imaging sciences 2 (2) (2009) 323–343.
- 525 [41] A. Hefny, D. Needell, A. Ramdas, Rows vs. columns: Randomized kaczmarsz
526 or gauss-seidel for ridge regression, Mathematics 39 (5).
- 527 [42] R. Bernardes, C. Maduro, P. Serranho, A. Araújo, S. Barbeiro,
528 J. Cunha-Vaz, Improved adaptive complex diffusion despeckling filter,
529 Optics express 18 (23) (2010) 24048–24059.
- 530 [43] X. Liu, X. Yu, H. Tang, D. Cui, M. R. Beotra, M. J. Girard, D. Sun,
531 J. Gu, L. Liu, Spectrally encoded extended source optical coherence
532 tomography, Optics letters 39 (24) (2014) 6803–6806.