Speckle Reduction in Optical Coherence Tomography by Matrix Completion using Bilateral Random Projection

Jun Cheng, Lixin Duan, Damon Wing Kee Wong, Masahiro Akiba and Jiang Liu

Abstract— **Speckle noise is problematic in optical coherence tomography (OCT) and often obscures the structure details. In this paper, we propose a new method to reduce speckle noise from multiply scanned OCT slices. The proposed method registers the OCT scans using a global alignment followed by a local alignment based on global and local motion estimation. Then low rank matrix completion using bilateral random projection is utilized to estimate the noise and recover the clean image. Experimental results show that the proposed method archives average contrast to noise ratio 14.90, better than 13.78 by the state-of-the-art method used in current OCT machines. The technology can be embedded into current OCT machines to enhance the image quality.**

Keywords: Speckle noise, low rank, matrix completion, bilateral random projection.

I. Introduction

Optical coherence tomography (OCT) is an optical signal acquisition and processing method. It captures micrometer-resolution, three-dimensional images from optical scattering media. OCT images often suffer from speckle noise due to the scattering. Recently, Topcon has developed DRI OCT-1, a swept source OCT for posterior imaging, utilizing a wavelength of 1,050 nm. It has a fast scanning speed of 100,000 A-scans/sec. Similar to other OCT equipment, speckle noise reduction is important to improve the image quality of the OCT images in the DRI OCT-1. In DRI OCT-1, a single frame or slice of the image usually has very poor quality due to large speckle noise. Fig. 1 shows an example of raw slice.

Speckle is problematic for OCT, similar to that in ultrasound, sonar, etc. In these fields, many algorithms have been proposed for speckle reduction such as filter based methods, e.g., Lee filter [1], Kuan filter [2], enhanced Lee [3], adaptive Wiener filter [4], etc. and the diffusion based methods e.g., anisotropic diffusion [5], speckle reduction anisotropic diffusion [6], etc. Although these methods are efficient in removing speckles, they often remove details.

With the fast imaging speed, DRI OCT-1 scans multiple times at the same or approximately the same position and computes an average image to reduce noise [7], expecting the cancel out of speckle noise from the multiple scans. As eye movement is inevitable during the capture, these slices are not well aligned or registered and registration of the slices is important. In DRI OCT-1, a rigid sub-pixel registration algorithm [8] is used to register the slices. It minimizes the mean square intensity difference between one slice and its reference through rotation and translation. However, it is not robust in presence of large speckle noise. In addition, the rigid registration has a limitation when the retinal layers vary among the repeated scans.

J. Cheng, L. Duan, D. W. K. Wong, and J. Liu are with Institute for Infocomm Research, A*Star, Singapore. M. Akiba is with Topcon Corporation, Japan.

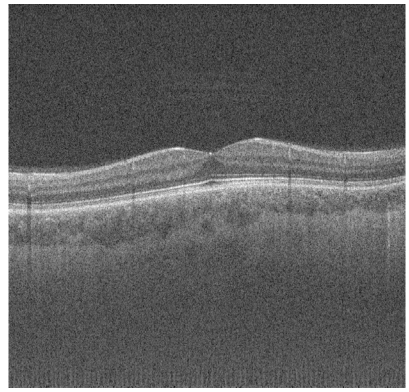

Fig. 1. A raw slice of OCT image captured by DRI OCT-1

In this paper, we propose to apply a preliminary speckle reduction on the raw slices before registration. A non-rigid two-step registration is then proposed to register the slices. After the registration, low rank matrix completion is proposed to replace averaging to compute the clean image. Instead of relying on the cancel out of the noise from different slices, low rank approach estimates the noise and relying on the estimation accuracy. The basic idea of low rank matrix completion is to formulate the k^{th} OCT slice I_k as a sum of its underlying clean image l_k and noise n_k, i.e., $I_k = l_k + n_k$. Defining $X = [\tilde{I}_1, \tilde{I}_2, \cdots, \tilde{I}_m]$, $L = [\tilde{l}_1, \tilde{l}_2, \cdots, \tilde{l}_m]$, and $N = [\tilde{n}_1, \tilde{n}_2, \cdots, \tilde{n}_m]$, we have $X = L + N$, where $\tilde{I}_k$, $\tilde{l}_k$, and $\tilde{n}_k$ are strung out of I_k, l_k and n_k into column vectors, $k = 1, 2, \cdots, m$. Although each $\tilde{I}_k$ can be significantly different because of the different noise $\tilde{n}_k$, $\tilde{l}_k$ is the clean image for the approximately same location and is expected to be similar or even identical. The rank of L is thus low. In low rank matrix completion, we want to solve L from given X.

The rest of paper is organized as follows. In Section II, we introduce the method including the preprocess to remove speckle noise, the image alignment for registration, and the image recovery by low rank matrix completion. Section III shows the experimental results followed by conclusions in the last section.

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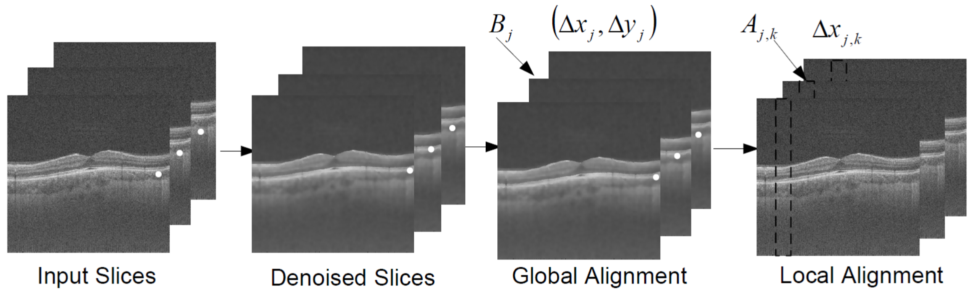


Fig. 2. A single raw slice of swept-source OCT scan

II. Method

A. Denoising

Because of the inevitable eye movement, the original image slices are often not well aligned. It is necessary to re-align them to minimize the error. However, the original OCT slices are corrupted by large speckle noise and applying image registration algorithm directly on these OCT slices often lead to unexpected results. In this paper, we propose to use the speckle reduction anisotropic diffusion (SRAD) [6] to remove noise. Our tests show that SRAD is able to remove the noise though some details are removed as well. The basic principle of SRAD is as follows. Given an intensity image $I_0(x, y)$, the output image $I(x, y, t)$ is evolved according to following partial differential equations in SRAD:

$$\begin{cases} \partial I/\partial t = div[c \cdot \nabla I] \\ I(t = 0) = I_0, \end{cases} \tag{1}$$

where c denotes the diffusion coefficient computed from I.

B. Image Alignment

The image registration or alignment between two slices is done by a global alignment followed by a local alignment. In the global alignment, a translation $(\Delta x, \Delta y)$ including both horizontal and vertical direction is applied on the entire slice. Take I_i as a reference, for each I_j, $j = 1, 2, \cdots, K$ and $j \neq i$, find the alignment $(\Delta x_j, \Delta y_j)$ between I_i and I_j such that their difference is minimized.

In the local alignment, an A-scan line or a group of neighboring A-scan lines from one B-scan slice are translated vertically for best matching to the corresponding A-scan lines in the reference B-scan slice. Divide B_i to non-overlapping A-scan patch $A_{i,k}, k = 1, 2, \cdots, P$, where P is the number of A-scan patches in B_i. Each patch has l A-scan lines. For two patches $A_{i,k}$ and $A_{j,k}$ from B_i and B_j, find the vertical translation $\Delta x_{j,k}$ between them such that their error is minimized. The local alignment is done for each A-scan because each vertical line is an outcome of an A-scan and the movement within one A-scan is ignored. Patient eye movements may be more obvious between different A-scans as time goes. Fig. 2 illustrates the image alignment process.

In the above, many block matching algorithms can be used to find the alignment, we use the diamond search strategy [9] because of its efficiency and easy implementation.

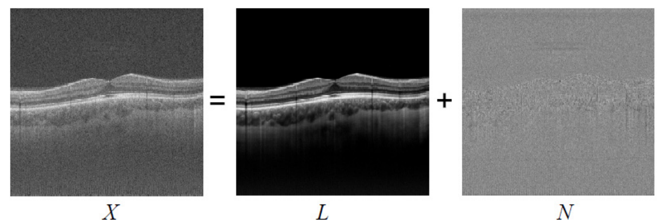


Fig. 3. Illustration of low rank model model : each image corresponds to a row in the corresponding matrix X, L, N.

C. Image Recovery

After the image alignment, a set of aligned slices are obtained. Then, they are vectorized and stacked to form matrix X. Low rank matrix completion is then applied to compute the underline clean image. In this paper, we propose $X = L + N$ for OCT images as illustrated in Fig. 3. In this model, X is decomposed as a sum of low rank part L and noise part N, i.e.,

$$X = L + N, rank(L) \leq r, \tag{2}$$

where L is the low rank part, and N is the noise. The above decomposition is solved by minimizing the decomposition error:

$$\begin{aligned} \min_L \quad & \|X - L\|_F^2 \\ s.t., \quad & \texttt{rank}(L) \leq r, \end{aligned} \tag{3}$$

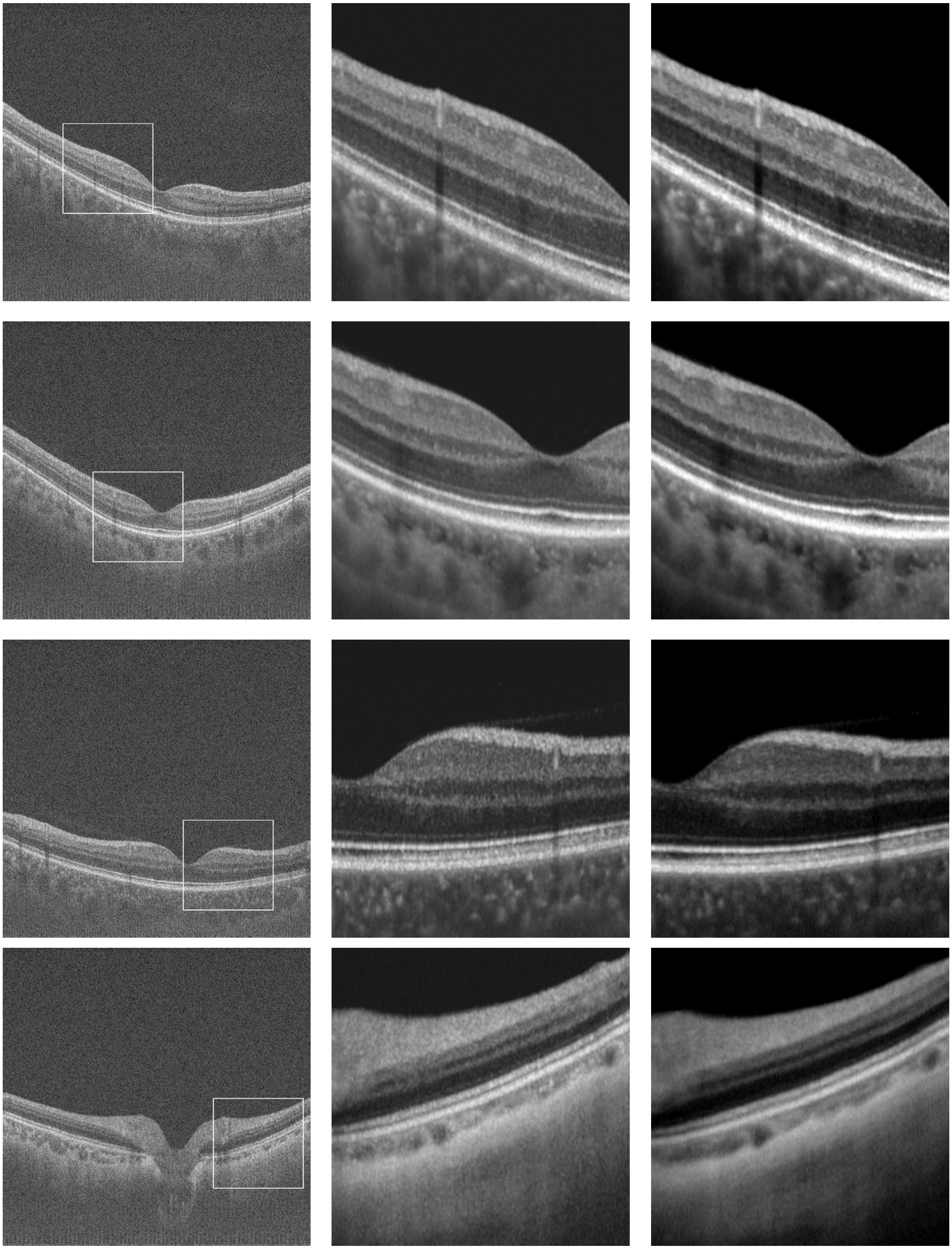
In this paper, the above problem is solved by the bilateral random projection (BRP) [10],[11]. Given the BRP of a $m \times n$ dense matrix X $(m > n)$, i.e., $Y_1 = XA_1$ and $Y_2 = X^T A_2$, wherein $A_1 \in R^{n \times r}$ and $A_2 \in R^{m \times r}$ are random matrices,

$$L = Y_1 (A_2^T Y_1)^{-1} Y_2^T \tag{4}$$

is a fast rank-r approximation of X.

III. Experimental Results

In this paper, we conducted the tests using 20 different subject eyes. For each subject eye, a line mode scan with 96 repeated slices are obtained. Each slice is an image with $992 \times 1024 = 1015808$ pixels. The matrix X is a 1015808×96 dimensional matrix. The state of the art result is obtained from the OCT machine directly.



(a) Raw slice (b) Baseline (c) Proposed

Fig. 4. Sample results: (a) a single raw slice with the white box indicating a 300×300 region for highlight, (b) and (c) are the corresponding portion of images obtained by the baseline and proposed method using $X = L + N$ model.

TABLE I

PERFORMANCE (CNR) BY VARIOUS METHODS.

Method	Baseline	Motion+Avg.	Proposed (Motion+$X = L + N$)
CNR	13.78	14.07	14.90

It is important to have objective measurements to evaluate the performance of speckle noise reduction. In this paper, we compute the widely used contrast to noise ratio (CNR) [7],[12], which measures the contrast between image features and noise, and defined to be

$$CNR = \frac{1}{R}\sum_{r=1}^{R}\frac{\mu_r - u_b}{\sqrt{(\sigma_r^2 + \sigma_b^2)}} \quad (5)$$

where μ_b and σ_b are the mean and variance of the same background noise region, and μ_r and σ_r are the mean and variance of all the regions of interests (R). In this paper, we randomly obtain 20 region of interests from the retina layers in each image and one background region.

Three methods are compared. The 'baseline' denotes the current method uses the sub-pixel registration and averaging as that in current DRI OCT-1. In 'Motion & Avg', we replace the sub-pixel registration with the proposed motion based registration method from the 'baseline' while the averaging is maintained. In the proposed method 'Motion & $X = L + N$', we further replace the averaging with the low rank matrix completion model $X = L + N$. Table I shows the average CNR computed from 20 images with the number of re-scanned slices $m = 96$. With a preliminary speckle reduction, the proposed motion based registration helps improve the CNR. The low rank approaches are also useful. This is because the low rank reconstruction model is not sensitive to noise from one or several slices compared with averaging. Therefore, low rank recovery is more robust. To evaluate the robustness of the proposed methods for different number of slices, we further conducted tests for the number of slices m from 16 to 96 with a step of 16. In Fig. 4, we show three sample results to visualize the difference between the baseline and proposed method. Fig. 5 plots the average CNRs for the four methods. The results are consistent. It shows that the proposed method achieve smoother region within layers. The contrast between layers is also enhanced. The last example shows a case where the edges are blurred due to averaging. The proposed method using low rank matrix recover the underlying structure better.

In this paper, we solve the low rank recovery using bilateral random projection. It is faster than traditional algorithms such as robust PCA. It takes about 5s for our method using the BRP based low rank approximation model $X = L + N$ to recover a image of 992×1024 pixels from 96 slices in a dual core 3.0 GHz PC with 3.25 GB RAM in MATLAB. For the same task, a robust PCA [13] requires 100s.

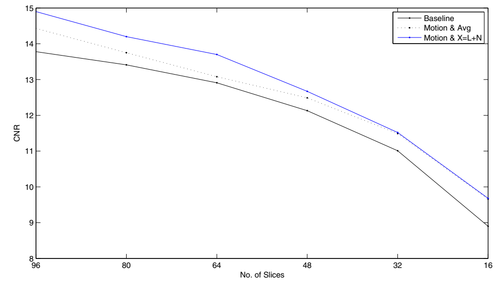


Fig. 5. Performance comparison for different number of reference images .

IV. CONCLUSIONS

In this paper, we propose a specking noise reduction method for OCT imaging. Instead of using a sub-pixel registration algorithm that minimizing the mean square intensity difference, we propose to register the OCT slices using fast motion estimation on speckle reduced slices. In addition, averaging is replaced by low rank matrix completion for image recovery. The main difference is that the former relies on the cancel out of speckle noise while the later relies on the accuracy in noise estimation. The proposed method is less sensitive to noisy slices. Our experimental results show that the proposed method outperforms the baseline method.

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