

Reducing Speckle Noise in Optical Coherence Tomography Images

FIELD OF THE INVENTION

5 Embodiments of the present invention relate to computer implemented methods and computer systems for processing optical coherence tomography image data to obtain reduced speckle noise images.

BACKGROUND OF THE INVENTION

10

Optical coherence tomography (OCT) is an optical signal acquisition and processing method. It captures micrometre-resolution, three-dimensional images from within optical scattering media (e.g., biological tissue). The principle of ocular imaging with OCT is based upon measuring the time-delay of the light reflected from each optical interface (A-scan) when a pencil of light enters the eye. A series of A-scans across the structure permits a cross-sectional reconstruction of a plane through the anterior or posterior segment of the eye. This is known as a B-scan.

15

Speckle noise is problematic for OCT imaging as well as other imaging modalities including synthetic aperture radar (SAR), remote sensing, ultrasound, sonar, etc. In these fields, a substantial amount of signal processing research has been conducted to combat speckle noise, resulting in the development of powerful digital filters for reducing speckle while preserving edge sharpness. Speckle reduction in OCT has been addressed by modifying imaging configurations and through the use of signal processing and image filtering. However, these methods often remove some details of the images and are unsuitable for OCT images in medical applications.

20

25

In typical OCT imaging, a single frame or slice of the image usually has very poor quality due to large speckle noise. Therefore, multiple scans are obtained and image averaging is applied, i.e., an average image is computed from the multiple image slices.

30

An example of an OCT system is the Topcon DRI OCT-1, a swept source OCT for posterior imaging, utilizing a wavelength of 1,050 nm. It has a scanning speed of 100,000 A-scans/sec. Utilizing this 1,050 nm wavelength, DRI OCT-1 can penetrate

35

deeper compared to the current conventional OCTs with wavelength in the 850 nm range. Visualizing ocular tissues such as choroid or even sclera, can be done within a very short time. Deep range imaging DRI OCT-1 displays detail structures of not only retina but choroid and even sclera. With the capability of imaging deeper anatomic structures with less influence in scattering, DRI OCT-1 can visualize the entire tomogram with high sensitivity.

Depending on different applications and resolutions, different modes of scanning are provided in DRI OCT-1 including the line mode, 5 lines cross mode, 12 radial mode, circle line mode and 3D horizontal/vertical mode. In line mode, a line scan is conducted and repeated for a maximum of 96 times. In 5 line cross mode, 5 horizontal line scan and 5 vertical line scan are conducted with each line scan repeated for a maximum of 32 times. In 3D mode, a current swept source machine allows 4 repeated scans in 3D vertical mode with resolution 512x64 while each location is scanned only once in 3D horizontal model with 512x256 resolution. Since these scans are obtained from one location, they are averaged to get the final result with some help of image registration to overcome possible eye movement between different scans.

SUMMARY OF THE INVENTION

The present invention aims to provide a method of reducing speckle noise in optical coherence tomography (OCT) images. Matrix completion is used to reduce speckle noise. Matrix completion is the process of adding entries to a matrix which has some unknown or missing values. In general, given no assumptions about the nature of the entries, matrix completion is theoretically impossible, because the missing entries could be anything. However, given a few assumptions about the nature of the matrix, various algorithms allow it to be reconstructed. Matrix completion has been proven to be useful in noise reduction in other applications such as video and computed tomography imaging.

In order for matrix completion to be carried out, the input to the method is OCT image data which includes a plurality of cross sectional images of a subject. The cross sectional images each comprise a plurality of scan lines obtained by measuring the time delay of light reflected, in a depth direction, from optical interfaces within the subject.

The cross sectional images may be images of the same part of the subject, or they may be from neighbouring slices which can be used as the neighbouring slices have strong similarity.

5 The method comprises aligning the cross sectional images by determining relative translations for each cross sectional image in the depth direction and in a lateral direction, perpendicular to the depth direction, to form a set of aligned cross sectional images; aligning image patches of the aligned cross sectional images, each image patch comprising at least one scan line, by determining relative translations for each
10 patch in the depth direction to form a set of aligned patches; forming an image matrix from the aligned patches; and applying matrix completion to the image matrix to obtain a reduced speckle noise image of the subject.

15 The application of matrix completion may involve decomposing the image matrix into a matrix representing a clean image part and a matrix representing a noise part.

20 Alternatively, applying matrix completion may involve decomposing the image matrix into a matrix representing a clean image part, a matrix representing a sparse part and a matrix representing a noise part.

In either of the methods discussed above the matrix representing the clean image part is a low rank matrix.

25 Before the cross sectional images are aligned, a preliminary de-noising process may be applied to reduce the speckle noise in the cross sectional images. The preliminary de-noising process may be, for example a speckle reduction anisotropic diffusion algorithm.

30 Following the method a filter such as an adaptive Wiener filter may be applied to the reduced speckle noise image of the subject.

A block matching algorithm may be applied to align the cross sectional images or to align image patches of the aligned cross sectional images. The block matching algorithm may be, for example the diamond search algorithm.

A smoothing process may be applied to the relative translations in the depth direction for each slice in the same cross sectional image to form the set of aligned patches.

5 As an embodiment of the invention, we propose a fast non-rigid two-step image registration algorithm for OCT images, where the first step is a global alignment and the second step is a local alignment. In addition, in the global and local alignments, we align the original raw OCT images based on their denoised version using a preliminary denosing process (speckle reduction anisotropic diffusion in our implementation).

10 Another technical feature is that we use bilateral random projections in low rank matrix completion to approximate the underlying clean images. Two models are used with the first model considering the OCT image as a sum of an underlying clean image part and a noise part, the second model considering the OCT image as a sum of an underlying clean image part, a sparse part due to movement and a noise part.

15

BRIEF DESCRIPTION OF THE DRAWINGS

In the following an embodiment of the present invention is described by way of example only with reference to the drawings, in which:

20

Figure 1 is a flow chart illustrating a method of processing optical coherence tomography (OCT) data according to an embodiment of the present invention.

Figure 2 shows an example of the preliminary de-noising process in an embodiment;

25

Figure 3, which is composed of Figures 3a and 3b, illustrates the image registration steps; Figure 3a illustrates a global registration and Figure 3b illustrates a local registration;

30 Figure 4 shows an example of image recovery according a method in which an original image X is decomposed into the recovered image L and the noise N ;

Figure 5 shows an example of image recovery according a method in which an original image X is decomposed into the recovered image L a sparse part S and the noise N ;

35

Figure 6, which is composed of Figures 6a and 6b, shows a plot of the contrast to noise ratio (CNR) for the methods illustrated in Figures 4 and 5 with different numbers of slices; Figure 6a shows results obtained using the Image J noise model; and Figure 6b shows results obtained using the Motion noise model.

5

DETAILED DESCRIPTION OF THE EMBODIMENT

Figure 1 is a flow chart illustrating a method of processing optical coherence tomography (OCT) data according to an embodiment of the present invention. The method may be performed by a computer system such as a standard generally programmed computer, having a data storage device storing program instructions to implement the method steps.

The input to the method is OCT data comprising a plurality of OCT slices. A requirement to use matrix completion is to obtain multiple slices for each scan. This is easy for line scan mode as each slice is scanned 96 times. For other modes such as 5 line-cross mode, 3D vertical and 3D horizontal mode, the scan from the neighbouring slice can be used as the neighbouring slices have strong similarity.

For example, in 5 lines cross mode, we use all the horizontal/vertical scans ($5 \times 32 = 160$) for a horizontal/vertical slice. For 3D scans, we can use all 256 scans. Although many of these scans are obtained from different locations, many of the A-scans from the slices are similar. Therefore, we might make use of this similarity for noise reduction.

For simplicity, we assume that the input has K slices of OCT scans, including both the repeated scans from the same location and other scans from nearby locations. Each slice has $p \times q$ pixels.

In step 1 of the method, preliminary noise reduction is performed. Because of the inevitable movement when capturing the image slices, the original image slices may not match well. Therefore, it is necessary to align them to minimize the error. The original OCT slices are likely to be corrupted by large speckle noise.

Applying an image matching algorithm directly on these OCT slices may result in an unpredictable outcome due to the speckle noise. A pre-processing step is used to

reduce the noise. Many algorithms can be used. In this embodiment we use the speckle reduction anisotropic diffusion algorithm.

5 The anisotropic diffusion algorithm is implemented as follows. Given an intensity image, the output image is evolved according to the partial differential equation (PDE):

$$\begin{cases} \frac{\partial I}{\partial t} = \text{div}[c(q) \cdot \nabla I] \\ I(t=0) = I_0 \end{cases},$$

where $c(q)$ denotes the diffusion coefficient computed with:

10
$$c(q) = 1 / (1 + [q^2(x, y; t) - q_0^2(t)] / [q_0^2(t)(1 + q_0^2(t))]) \text{ or}$$

$$c(q) = \exp \{ - [q^2(x, y; t) - q_0^2(t)] / [q_0^2(t)(1 + q_0^2(t))] \} \text{ and}$$

15 Figure 2 shows an example of the preliminary de-noising process in an embodiment. Three input slices shown on the left hand side of Figure 3 are processed using the speckle reduction anisotropic diffusion algorithm to provide the de-noised slices shown on the right hand side of Figure 2.

20 Following the preliminary noise reduction, image registration between slices is carried out. The image registration between two slices (*B*-scans) is done by a global registration in step 2 followed by a local registration in step 3. Many methods can be used in the global registration.

25 Figure 3 illustrates the image registration steps. Figure 3a illustrates the global registration which is carried out in step 2 and Figure 3b illustrates the local registration which is carried out in step 3.

30 In our implementation, the global registration is done by a global alignment, i.e., the entire slice (*B*-scan) is used in the matching by a translation in both horizontal (the *y*-direction) and vertical direction (the *x*-direction). The *x*-axis represents the direction in this the *A*-scans are carried out, that is a depth direction into the eye or subject being imaged. The *y*-axis represents a lateral direction, in which the *A*-scans are combined to form *B*-scans, perpendicular to the depth direction.

As shown in Figure 3a, each slice B_j is first translated by $(\Delta x_j, \Delta y_j)$ in the global registration. This is carried out according to the following process. Take an image I_i as a reference, for each j , $j = 1, 2, \dots, K$ and $j \neq i$ find the translation $(\Delta x_j, \Delta y_j)$ between I_i and I_j such that their error is minimized. Therefore, we obtain a set of globally registered B -scan slices $B_i, i = 1, 2, \dots, K$.

In the local registration, which is shown in Figure 3b, an A -scan line or a group of neighbouring A -scan lines from one B -scan slice are translated vertically for best matching in the corresponding A -scans in the another B -scan slice.

10

This is carried out according to the following process. Divide B_i to non-overlapping patches $A_{i,k}, k = 1, 2, \dots, P$, where P is the number of patches obtained. Each patch has l columns or A -scan lines. For two corresponding patches $A_{i,k}$ and $A_{j,k}$ from two B -scans B_i and B_j , find the vertical translation $\Delta x_{j,k}$ between them such that their error is minimized.

15

In order to avoid large error, patches/lines with poor matching can be discarded. Lines with poor matching may be identified and discarded by comparing the error with a threshold and discarding patches/lines with an error larger than the threshold. We apply vertical matching because each vertical line is an outcome of an A -scan and the movement within one A -scan is ignored.

20

Patient eye movements may be more obvious between different A -scans as time goes. Since the eye movement is expected to be smooth, a smoothing process is applied to the vertical translations $\Delta x_{j,k}, k = 1, 2, \dots$ for lines in the same slice. It should be noted that the above patch is a line or an A -scan if we set $l=1$. Including multiple scan lines in the same patch helps to obtain a robust vertical translation. In another words, if we align one scan line with another line, the result may be more sensitive to the noise.

25

Many block matching algorithms can be used to find the alignment. In our implementation, we use the diamond search strategy for both global and local alignments because of its efficiency and easy implementation.

30

Once a set of aligned patches has been obtained in step 3, image recovery is carried out in step 4. After the image alignment, a set of aligned patches are obtained based on the global translation and the smoothed local translation. In order to recover an image, each aligned patch is vectorised to a row and stacked to form a matrix X with m rows. Each row in X has $p \cdot l$ elements from each vectorized patch. Each row of the matrix X has $p \cdot l$ elements and the matrix X has the number of B-slices of rows.

Once the image matrix, has been constructed, two possible methods of determining a reduced speckle noise image are possible.

Method 1: Decompose the X as a sum of low rank part and noise part, i.e.,

$$X = L + N, \quad (1)$$

Where L is the low rank part with $\text{rank}(L) \leq r$, and N is the noise. In an implementation r is set to 2.

The above decomposition is solved by minimizing the decomposition error:

$$\min_L \|X - L\|_F^2, \quad \text{s.t.} \quad \text{rank}(L) \leq r \quad (2)$$

The optimization problem above is solved by the bilateral random projections (BRP) algorithm.

The algorithm is summarized as follows:

Algorithm 1 for solving L

Generate a random matrix A_1

$$A_1 \in R^{m \times r};$$

Compute $\tilde{L} = (XX^T)^q X$;

$$Y_1 = \tilde{L}A_1, A_2 = Y_1;$$

$$Y_2 = \tilde{L}^T Y_1, Y_1 = \tilde{L} Y_2$$

Calculate QR decomposition $Y_1 = Q_1 R_1, Y_2 = Q_2 R_2$;

$$L = Q_1 \left[R_1 (A_2^T Y_1)^{-1} R_2^T \right]^{1/(2q+1)} Q_2^T;$$

Method 2: In the second method, we decompose the X as a sum of low rank part, sparse part and noise part, i.e.,

$$X = L + S + N, \quad (1)$$

Where L is the low rank part with $\text{rank}(L) \leq r$, S is the sparse part with $\text{card}(S) \leq k$, k is a threshold which in one implementation is set as 30% of total elements in the matrix S , and N is the noise.

The above decomposition is solved by minimizing the decomposition error:

$$\begin{aligned} \min_{L, S} & \|X - L - S\|_F^2, \\ \text{s.t. } & \text{rank}(L) \leq r, \\ & \text{card}(S) \leq k. \end{aligned} \quad (2)$$

The optimization problem above is solved by alternatively solving the following two sub-problems until convergence.

$$\begin{cases} L_t = \arg \min_{\text{rank}(L) \leq r} \|X - L_{t-1} - S_{t-1}\|_F^2 \\ S_t = \arg \min_{\text{card}(S) \leq k} \|X - L_{t-1} - S_{t-1}\|_F^2 \end{cases}$$

The algorithm is summarized as follows:

Algorithm 2 for solving L

Initialize $t := 0; L_0 = X; S_0 = 0;$

While $\|X - L_t - S_t\|_F^2 / \|X\|_F^2 > \varepsilon$, **do**

$t := t + 1;$

$$\tilde{L} = [(X - S_{t-1})(X - S_{t-1})^T]^q (X - S_{t-1});$$

Generate a random matrix $A_1 \in R^{m \times r};$

Compute $Y_1 = \tilde{L}A_1, A_2 = Y_1;$

$$Y_2 = \tilde{L}^T Y_1, Y_1 = \tilde{L} Y_2$$

Calculate QR decomposition $Y_1 = Q_1 R_1, Y_2 = Q_2 R_2;$

If $\text{rank}(A_2^T Y_1) < r$ **then** $r = \text{rank}(A_2^T Y_1)$, go to the first step; **end if**;

$$L_t = Q_1 [R_1 (A_2^T Y_1)^{-1} R_2^T]^{1/(2q+1)} Q_2^T;$$

$S_t = \wp_{\Omega}(X - L_t)$, Ω is the nonzero subset of the first k largest entries of $|X - L_t|$; $\wp_{\Omega}$ is the projection of a matrix to Ω .

End while

5 It can be see that the first method is a special case of the second method when $S=0$.

Once the speckle noise reduced image has been determined as described above, a post-process via filtering can be applied for de-noising in step 5. Step 5 may involve, for example, enhanced Lee, adaptive Wiener filters, etc. In this embodiment, an adaptive Wiener filter is used as an example. In addition, we also apply a threshold to assist the de-noising. Mathematically, we apply the following process:

$$L(x, y) = \begin{cases} T_{low} & L(x, y) < T_{low} \\ L(x, y) & T_{low} \leq L(x, y) \leq T_{high} \\ T_{high} & L(x, y) > T_{high} \end{cases},$$

15 Where T_{low} and T_{high} are two adaptively determined thresholds.

Figure 4 shows an example of image recovery according to method 1 described above. The original image X is decomposed into the recovered image L and the noise N .

20 Figure 5 shows an example of image recovery according to method 2 described above. The original image X is decomposed into the recovered image L a sparse part S and the noise N .

25 To evaluate the image quality, the contrast to noise ratio (CNR) is computed, which measures the contrast between image features and noise.

$$CNR = (1/R) \sum_1^R (\mu_r - \mu_b) / \sqrt{\sigma_r^2 + \sigma_b^2}$$

A total of 20 subjects are tested. Table 1 shows the results by a baseline approach and the two proposed methods using different noise models. In the first noise model we assume $X=L+N$ and the second model refers to line 24 page 10 where we assume $X=L+N+S$. Although the second model gives higher CNR as shown in Table 1, we notice that the visual effect of the two models are similar.

Table 1: Objective measurement

96 slices	Image Registration	
	Image J	Motion
Baseline (Topcon)	13.78	14.07
$X=L+N$	14.42	14.90
$X=L+S+N$	14.43	15.65

5

The baseline approach relies on the estimation of noise while the averaging relies on the cancel out among noise.

10 Figure 6 shows the plot of the CNR with different numbers of slices. Figure 6a shows results obtained using the Image J noise model. Figure 6b shows results obtained using the Motion noise model. As we can observe, the proposed methods using matrix completion outperform the baseline method.

15 In the embodiment described above, we solve the low rank recovery using bilateral random projection. It is faster than traditional algorithms such as robust principal component analysis (PCA). It takes about 5s (algorithm 1) to 45s (algorithm 2) to recover an image of 992 x 1024 pixels from 96 slice of 992x1024 pixels in a dual core 3.0 GHz PC with 3.25 GB RAM. Robust PCA requires 100s for the same task for
20 algorithm 1 and 15 mins for algorithm 2.

CLAIMS

1. A computer implemented method of processing optical coherence tomography (OCT) image data, the OCT image data comprising a plurality of cross sectional
5 images of a subject, the cross sectional images each comprising a plurality of scan lines obtained by measuring the time delay of light reflected, in a depth direction, from optical interfaces within the subject, the method comprising

aligning the cross sectional images by determining relative translations for each cross sectional image in the depth direction and in a lateral direction, perpendicular to
10 the depth direction, to form a set of aligned cross sectional images;

aligning image patches of the aligned cross sectional images, each image patch comprising at least one scan line, by determining relative translations for each patch in the depth direction to form a set of aligned patches;

forming an image matrix from the aligned patches; and

15 applying matrix completion to the image matrix to obtain a reduced speckle noise image of the subject.

2. A method according to claim 1, wherein applying matrix completion to the image matrix comprises decomposing the image matrix into a matrix representing a
20 clean image part and a matrix representing a noise part.

3. A method according to claim 1, wherein applying matrix completion to the image matrix comprises decomposing the image matrix into a matrix representing a clean image part, a matrix representing a sparse part and a matrix representing a noise
25 part.

4. A method according to claim 2 or claim 3, wherein the matrix representing the clean image part is a low rank matrix.

30 5. A method according to any preceding claim, further comprising applying a preliminary de-noising process to the cross sectional images prior to aligning the cross sectional images.

35 6. A method according to claim 5, wherein the preliminary de-noising process is a speckle reduction anisotropic diffusion algorithm.

7. A method according to any preceding claim further comprising applying a filter to the reduced speckle noise image of the subject.

5 8. A method according to claim 7, wherein the filter is an adaptive Wiener filter.

9. A method according to any preceding claim wherein aligning the cross sectional images comprises applying a block matching algorithm.

10 10. A method according to any preceding claim wherein aligning image patches of the aligned cross sectional images comprises applying a block matching algorithm between image patches of different cross sectional images.

15 11. A method according to claim 9 or claim 10 wherein the block matching algorithm is the diamond search algorithm.

12. A method according to any preceding claim further comprising applying a smoothing process to the relative translations in the depth direction for each slice in the same cross sectional image to form the set of aligned patches.

20

13. A computer system for processing optical coherence tomography (OCT) image data, the OCT image data comprising a plurality of cross sectional images of a subject, the cross sectional images each comprising a plurality of scan lines obtained by measuring the time delay of light reflected, in a depth direction, from optical interfaces within the subject, the computer system having at least one processor and a data storage device storing program instructions, the program instructions being operative upon being run by the processor to cause the processor to:

25 align the cross sectional images by determining relative translations for each cross sectional image in the depth direction and in a lateral direction, perpendicular to the depth direction, to form a set of aligned cross sectional images;

30 align image patches of the aligned cross sectional images, each image patch comprising at least one scan line, by determining relative translations for each patch in the depth direction to form a set of aligned patches;

form an image matrix from the aligned patches; and

35 apply matrix completion to the image matrix to obtain a reduced speckle noise image of the subject.