Total Variation Denoising for Optical Coherence Tomography

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***Abstract*—This paper introduces a new method of combining total variation denoising (TVD) and median filtering to reduce noise in optical coherence tomography (OCT) image volumes. Both noise from image acquisition and digital processing severely degrade the quality of the OCT volumes. The OCT volume consists of the anatomical structures of interest and speckle noise. For denoising purposes we model speckle noise as a combination of additive white Gaussian noise (AWGN) and sparse salt and pepper noise. The proposed method recovers the anatomical structures of interest by using a Median filter to remove the sparse salt and pepper noise and by using TVD to remove the AWGN while preserving the edges in the image. The proposed method reduces noise without much loss in structural detail. When compared to other leading methods, our method produces similar results significantly faster.**

***Index Terms*—Total Variation Denoising, Median Filtering, Optical Coherence Tomography**

I. Introduction

Optical Coherence Tomography (OCT), a non-invasive in vivo imaging technique, provides images of internal tissue microstructures of the eye [1]. OCT imaging works by directing light beams at a target tissue and then capturing and processing the backscattered light [2]. To create a 3D volume image of the eye, the OCT device scans the eye laterally [2]. However, current OCT imaging techniques inherently introduce speckle noise [3]. This speckle noise reduces the image's contrast and obscures the boundaries of the structures in the image [3]. An image's structure refers to the lines, curves and edges within the image. The reduced image quality negatively impacts necessary subsequent image analysis, such as segmentation, object detection and pattern identification, which all depend on reliable and clean structural details.

The 3D OCT image volume may be viewed by extracting 2D image slices along any of the three dimensions, as illustrated in Fig. 1. Additionally an en face representation of the OCT volume, commonly referred to as projection OCT fundus imaging, may be used for detecting retinal abnormalities and comparing with color fundus photography. The projection OCT fundus image is produced by summing the retinal layers along the depth axis, which helps reduce the effects of the noise [4]. A sample projection OCT fundus image is provided in Fig. 2 part Z.

The main objective of OCT volume denoising is to be able to extract as much structural detail as possible in an efficient manner. In this case, efficiency refers to monetary cost, run time, and implementation complexity. A set of widely used methods to reduce speckle noise during data acquisition are the compounding techniques, which average multiple uncorrelated recordings [5]. However, these methods are time consuming and require hardware modifications.

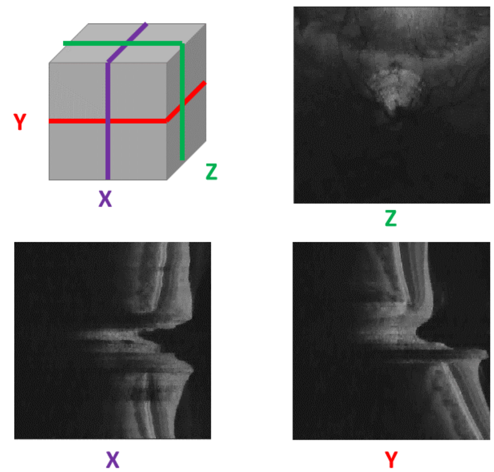

Fig. 1. 2D slices of a sample retinal OCT volume.

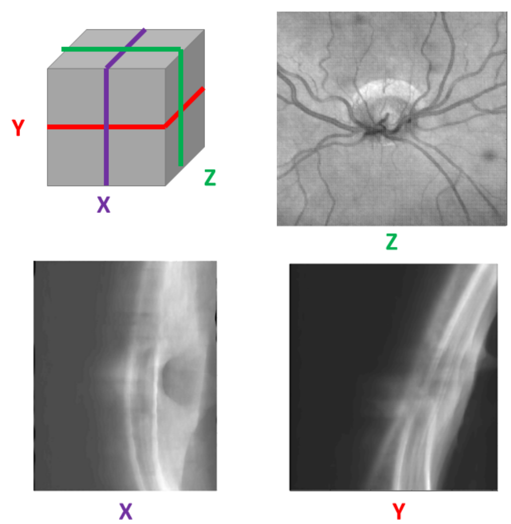

Fig. 2. Directional projections of a sample retinal OCT volume.

Generally software updates are quicker, easier and cheaper to implement compared to hardware updates. Therefore, digital image processing techniques are preferred. Some standard basic image denoising techniques are mean, median and Gaussian filtering. The current state of the art technique across the board is BM4D, a patch based denoising method [6], [7]. Some general speckle denoising algorithms are tested and compared in Ref. [8]. Some speckle noise reduction techniques have been developed specifically for OCT volumes based on locally adaptive filtering [9], soft thresholding of wavelet sub-bands [10], neural networks [11], and a hybrid wavelet-total variation denoising [12].

In this paper we propose a novel method to reduce noise in OCT volumes using a 2-stage process. Using information about the specific form and content of a signal helps lead to more accurate and beneficial signal processing techniques. The speckle noise affecting the anatomical structures of interest in the OCT volumes can be modeled as the combination of additive white Gaussian noise (AWGN) and sparse salt and pepper noise. By treating the speckle noise as the combination of AWGN and sparse salt and pepper noise, a better 2-stage denoising technique was developed. The first stage consists of using median filters to reduce the salt and pepper noise. The second stage consists of using total variation denoising (TVD) to reduce AWGN while persevering edges in the important structural detail.

The rest of this paper is organized as follows. Background information on the methods used are explained in Section II. A thorough explanation of our method, including implementation details, is provided in Section III. The results obtained and comparisons made to other methods are discussed in Section IV. Future directions of this research are discussed in Section V.

II. Preliminaries

Signal reconstruction and restoration techniques attempt to recover signal information lost in either the acquisition, storage or processing of the signal. Using information about the specific form and content of a signal helps lead to more accurate and beneficial signal processing techniques. The speckle noise degrading the OCT volume can be modeled as a composition of AWGN and sparse salt and pepper Noise. Median filtering and TVD help to reduce such noise.

A. Median Filtering

Median filtering is a nonlinear digital signal processing technique often used to reduce salt and pepper noise. In median filtering, each pixel value is replaced by the median value of the set of neighboring pixels. The kernel used defines the set of neighboring points to be used. In the 1D case with a kernel of size K, where K is an odd positive integer, each pixel value at position n is replaced by the median value in the set of pixel values located between $\{n-\frac{K-1}{2}, n+\frac{K-1}{2}\}$. Various padding methods have been devised to handle calculations at edges. This method can be extended to signals of any dimension size, and the kernel length may be defined for each dimension. For more details on median filtering, refer to [13], [14].

B. Total Variation

Total variation denoising (TVD), is a widely used denoising method in image processing [15], [16], [17]. TVD works best when the signal to be recovered has a sparse gradient, meaning that the signal is piecewise constant. The OCT volume to a certain extent is piecewise constant. TVD can denoise signals without significant smoothing of edges or loss of structural detail with a relatively fast processing time.

The general TVD problem can be formulated as represented in Eq. 1. Where, $E(y,x)$ is the measure of closeness between the denoised and noisy signal, and $\text{TV}(x)$ is the total variation of the noisy signal.

$$x^* = \arg\min_x \quad E(y,x) + \lambda \text{TV}(x) \tag{1}$$

For the 1D case, TVD is defined by the objective function represented in Eq. 2, which is the sum of a quadratic data fidelity term and a total variation regularization term.

$$F(x) = \frac{1}{2}||y-x||_2^2 + \lambda||Dx||_1 \tag{2}$$

The solution to the 1D TVD problem is represented in Eq. 3.

$$x^* = \arg\min_x \quad F(x) \tag{3}$$

It is assumed that the observed image, y, is a composite of the original image, x, and noise, w.

$$y = x + w \qquad y, x, w \in \mathbf{R}^N \tag{4}$$

Note that the noise assumed may be a composite of many different types of noises.

In Eq. 2, $\lambda > 0$ is the regularization parameter, which sets the intensity of the penalty. The matrix D is the $(N-1)\times N$ matrix shown below, where the notation $||Dx||_1$ represents the L1-norm of Dx.

$$D = \begin{bmatrix} -1 & 1 & & & \\ & -1 & 1 & & \\ & & \ddots & \ddots & \\ & & & -1 & 1 \end{bmatrix} \tag{5}$$

In traditional one-dimensional TVD, the original signal is estimated by minimizing F with respect to $x \in \mathbf{R}^N$. In this case, F is strictly convex in $\mathbf{R}^N$, resulting in a unique minimizer. Many methods may be used to solve this convex optimization problem. The majorization-minimization algorithm [18], the fast iterative shrinkage thresholding algorithm (fista) [19], the primal-dual method [20], as well as other iterative methods [21], may all be used to solve the convex TVD problem.

Additionally, many variations of TVD exist for better performance under specific conditions: TVD in 2D [15], [16], 3D TVD for color images [22], higher-order TVD for smoother results [23], TVD using a non-convex penalty function to promote greater sparsity [24], [25], TVD for images with a dominant gradient direction [26], and 1D TVD for 2D images [27], [28].

While many denoising algorithms and techniques exist, TVD offers a nice trade-off between computational complexity and performance. The actual runtime varies depending on the method chosen to implement TVD. Manually tuning λ for better results may also add a significant amount of time to the denoising process.

III. Proposed Method

Given that the speckle noise of the OCT volume can be modeled as the additive combination of AWGN and sparse salt and pepper noise, we propose a 2-stage algorithm for denoising, as illustrated in Alg. 1. The first stage consists of median filtering the volume along each dimension independently. This procedure produces 3 different denoised volumes which are then averaged together to make one denoised volume. This volume is then passed to the second stage. The second stage performs TVD at each vector along the longest dimension independently, and separately calculates λ for each such vector.

In order to reduce complexity and run time, and to prevent over denoising, we chose to perform TVD in only one direction. Our previous experiments showed that performing TVD along the longest side, which presumably contains the most information, provides the best results.

Algorithm 1 OCT Volume Denoising

Input: Noisy OCT Volume
Output: Denoised OCT Volume

$\mathbf{V}, \mathbf{V_x}, \mathbf{V_y}, \mathbf{V_z} \leftarrow$ Noisy OCT Volume
P$\{\mathbf{A}; (a, b)\}$: array at (a,b) along 3^{rd} dimension of $\mathbf{A}$
$m =$ length of width (X-dimension)
$n =$ length of height (Y-dimension)
$p =$ length of depth (Z-dimension)
procedure Stage 1: Median Filtering
  for i = 1,...,n **do**
    for j = 1,...,p **do**
      P$\{\mathbf{V_x}; (n, p)\}$ = $MedFilt$(P$\{\mathbf{V}; (n, p)\}$)
  for i = 1,...,m **do**
    for j = 1,...,p **do**
      P$\{\mathbf{V_y}; (m, p)\}$ = $MedFilt$(P$\{\mathbf{V}; (m, p)\}$)
  for i = 1,...,m **do**
    for j = 1,...,n **do**
      P$\{\mathbf{V_z}; (m, n)\}$ = $MedFilt$(P$\{\mathbf{V}; (m, n)\}$)
  $\mathbf{V} = (\mathbf{V_x} + \mathbf{V_y} + \mathbf{V_z})/3$
procedure Stage 2: TVD
  for i = 1,...,m **do**
    for j = 1,...,n **do**
      $\lambda = (\sqrt[5]{p} + 1)\sqrt{STD(\mathbf{P}\{\mathbf{V}; (m, n)\})}$
      P$\{\mathbf{V}; (m, n)\}$ = TVD(P$\{\mathbf{V}; (m, n)\}$,λ)

A. Implementation Details

The authors' of Ref. [24] and Ref. [29] propose a formula for calculating λ, as represented in Eq. 6, where N is the length of the signal, and σ is the standard deviation of the noise of the signal. However, for this particular application, Eq. 6 tends to overestimate λ.

$$\lambda = \frac{\sqrt{N}\sigma}{4} \tag{6}$$

Using a decent sized data set of OCT volumes a formula for λ was empirically derived, as provided in Eq. 7, where N is the length of the signal, and $\tilde{\sigma}$ is the standard deviation of the noisy signal.

$$\lambda = (\sqrt[5]{N} + 1)\sqrt{\tilde{\sigma}} \tag{7}$$

We provide a formula for calculating λ to help create an all-in-one fast algorithm that does not require extra effort from the user to tune parameters. However, an operator may and can fine tune λ manually.

While many algorithms exist to solve the TVD convex optimization problem, we use the method proposed by Condat [30]. Condat's method provides a fast exact solution to the TVD problem.

IV. Results and Evaluation

We ran experiments using Matlab programming on a commodity PC. We compared our method with BM4D [6], and Wavelet-TV [12]. The 3D OCT volumes dimensions were 200x1024x200. The results of the processing time, 2D slices and projection images are shown in Fig. 3.

Wavelet-TV provides a slightly smoother image, but our method finishes in 1/45 the amount of time. However, our method significantly outperforms BM4D and in 1/159 the amount of time. In a medical setting, timing can be very important.

Wavelet-TV tends to over smooth certain regions, causing slight blurring at edges. BM4D preserves the edges better, but does not remove enough of the speckle noise. The limitation of our method is that since we only perform TVD in one direction, it leaves slight artifacts in the other directions. Also, since the set of median filters are averaged, some sparse salt and pepper noise remains. Unfortunately ground truth data is missing to calculate accurately the error or signal-to-noise ratio of the different methods for better comparison.

Interestingly, the λ values calculated for a sample OCT volume, as shown in Fig. 4, resemble the OCT projection images.

V. Conclusion

Our proposed 2-stage denoising algorithm successfully reduces speckle noise in OCT volumes. Our method provides comparable results to Wavelet-TV and better results than BM4D, but with a significantly decreased processing time. With a larger data set a better formula for tuning λ could be found. Our proposed method also allows for the OCT operator to either use the predefined formula to compute λ or manually adjust a single parameter to achieve the desired results.

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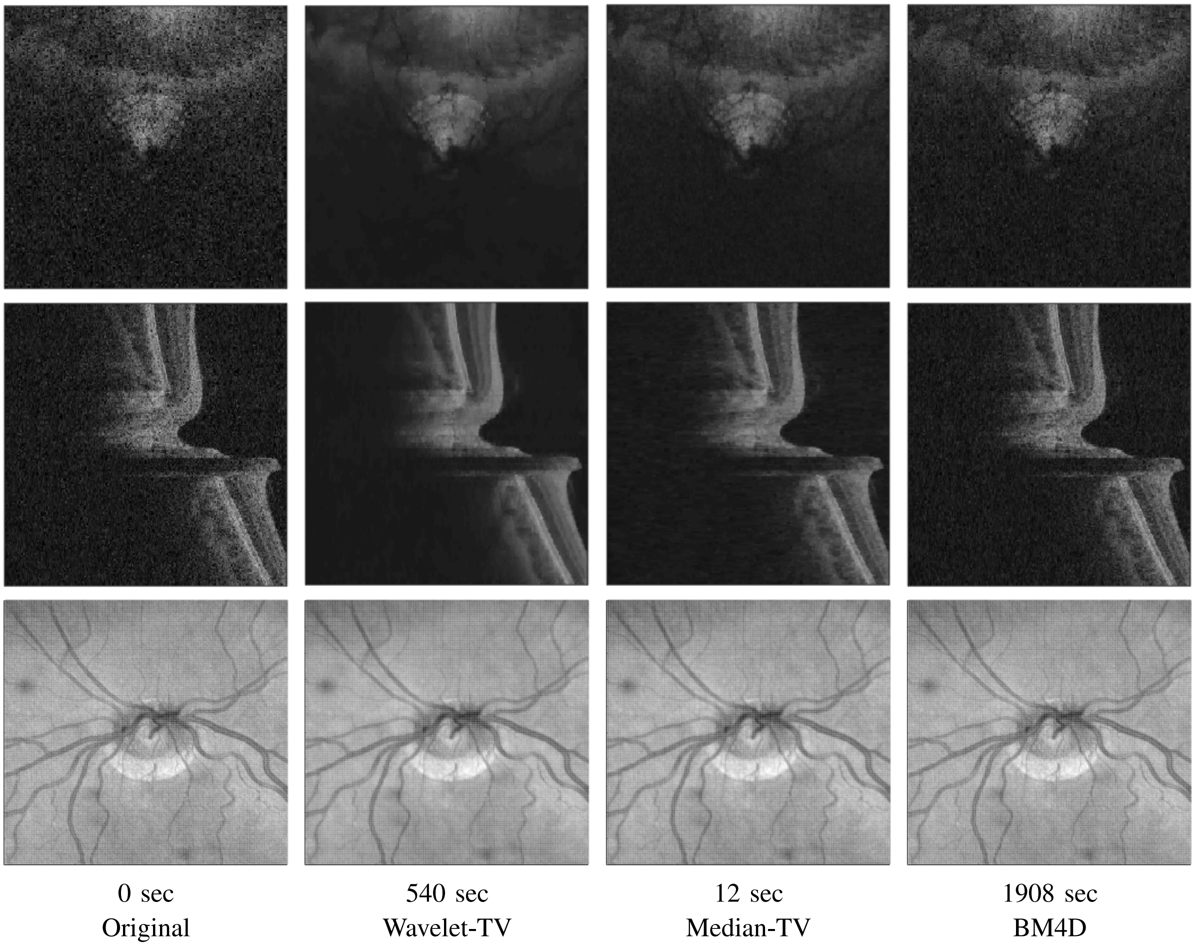

Fig. 3. Projection images, 2D slices, and processing times of the Original image compared with the three methods described, where Median-TV is the proposed method.

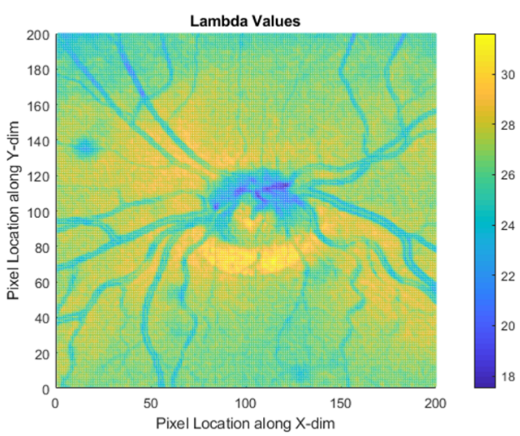

Fig. 4. λ values calculated for sample OCT volume.

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