A New Joint De-Speckling Framework for Real Optical Coherence Tomography Images

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Abstract: Now a day’s OCT is a most frequently used method to diagnose the eye related diseases. The acquisition procedure of OCT images added the speckle noise in the images. Speckle noise degrades the quality of the image. Presence of speckle noise makes diagnosis tasks difficult. This researcher paper, proposed a hybrid de-noising approach that reduce the effect of speckle noise. This framework used the preprocessing filter, post processing filter along with curvelet transform. Due to various advantages of SRAD filter, this filter is used as a pre-processing filter. After pre-processing Curvelet transform is exploited to improve the performance of the proposed framework. In the last of proposed framework a variant of total variation regularization is used for smoothing the output. The proposed framework is evaluated on real OCT images. The results of experiments conducted on real OCT images shows better performance in comparison to various traditional filters. The proposed framework shows the strong de-noising capability along with edge preservation.

Keywords: diagnose, OCT, Curvelet transform, SRAD filter.

I. INTRODUCTION

Enhancement of OCT images is always prime concern for the accurate diagnosis of retinal diseases. At present OCT widely used in ophthalmology for the detection of glaucoma, cataract disease [2-3]. OCT imaging technique used the detection of coherence source for the formation of image, therefore OCT images have inherent feature of speckle noise therefore the image analysis of OCT images is a very difficult task [4]. It is a locally correlated and multiplicative in nature noise. Therefore pre-processing is a necessary step in OCT image analysis. A number of de-speckling filters already has been proposed for de-speckling the OCT images. In the literature different types of spatial and non-linear filters [5], [6] are used to de-speckling the OCT images. These filters are tradeoff between speckle noise reduction capability and edge preservation ability of image. Linear filters also admits blur into the images and therefore degrades the contrast of the image [7]. Partial diffusion equation are used to proposed Speckle Reducing Anisotropic Diffusion (SRAD) filter [8]. The noise reduction capability of these filters are depends on different variables. Adaptive filters like hybrid median filter [18] used the local neighborhood concept to calculate the de-noised pixel value. The structural information of image are restored by bilateral filter [9] and trilateral filter [10]. The drawback of these type filters is that the performance of these filters is noise dependent. To deal with the correlated noise wavelet-based filters are proposed. These filters decompose the image by using multi-scale resolutions. Out of different variants of wavelet transform, shift invariant wavelet give better results [26]. Recently dual tree complex wavelet [23] and Curvelet transform [25] are also used to remove the speckle noise from the OCT images. These transforms give better result in comparison to conventional wavelets. The speckle noise from the OCT images can also be reduced by Sparse and redundant representation of image along with K-SVD algorithm [10]. Discrete wavelet transform with Bayesian threshold is also used for speckle noise removal from OCT images [11]. Recently a number of hybrid techniques are also being used to improve the performance of different filters. These techniques exploited properties of different filters to achieve the better performance. In hybrid techniques one or two filters are used serially. A number of hybrid techniques are being proposed in literature. Combination of Discrete Wavelet Transform and Anisotropic Diffusion filter has been used to improve the de-speckling capability of the filter. This technique also has the capability of edge preservation [12]. SRAD filter, wavelet soft thresholding along with guided filter is also used to design a hybrid technique [13]. In hybrid technique, there is a trade of between de-speckling capability and edge preservation ability of the filter. Therefore in this article a hybrid de-speckling framework is proposed that reduce the speckle noise along with edge preservation capability. The proposed framework used a preprocessing filter, Curvelet transform along with post processing filter. The remaining sections of this paper are section 2 describes about mathematical representation of speckle noise and Section 3 about the proposed hybrid framework with block diagram. Sections 4 tells about the materials and methods used in this paper. Sections 5 discuss about the results and Sections 6 concludes the outcome of the proposed hybrid framework.

II. MATHEMATICAL REPRESENTATION OF SPECKLE NOISE

The nature of the speckle noise present in the OCT image is multiplicative therefore the mathematical model of the speckle noise can be represented as

\[ I_o = I N_m + N_a \]  \hspace{1cm} (1)

\( I \) represent noise free image, \( I_o \) represent the output image corresponding to input image \( I \), \( N_m \) represent the multiplicative part of speckle noise and \( N_a \) represent the additive part of the speckle noise [16].
III. PROPOSED HYBRID FRAMEWORK

The proposed de-speckling framework is a type of hybrid approach. This approach is a three step approach. In first step pre-processing filtering is performed by using SRAD filter. SRAD filter gives better result for lower noise variance in comparison to conventional methods [13]. In second step the proposed framework used Curvelet transform. It is the extension of wavelet transform. In this transform image is decomposed at specified scales, locations and orientations. The Curvelet transform is helpful to preserve the structure of the image [14]. The last step of proposed framework used a post processing filter. In this step a modified variant of total variation regularization is used. Last step of the proposed framework is used for edge preservation [15]. The procedural steps of our proposed framework are:

Step 1: Apply SRAD filtering on noisy OCT image using eq. (2).
Step 2: Apply Curvelet transform de-noising on output of step 1.
Step 3: Apply Huber variant of TV regularization on the output of step 2 to get the de-noised image.

A. Speckle Reducing Anisotropic Diffusion Filter
OCT image despeckling can be perform by SRAD filter. SRAD filter is a Partial Differential Equation (PDE)-based speckle reducing filter. SRAD filter is used to preserves the edge details of image along with reducing the speckle noise. Let \( I_0(x, y) \) is given gray level image having finite power and no zero values over the image support \( \Omega \), corresponding to this \( I_0(x, y; t) \) is the output image as per the following equation

\[
\begin{align*}
\frac{\partial (x, y, t)}{\partial t} &= div[c(q) \nabla I(x, y; t)] \\
I_0(x, y; 0) &= I_0(x, y), \frac{\partial (x, y, t)}{\partial t} \bigg|_{t=0} = 0
\end{align*}
\]  
(2)

here div, \( \nabla \) represent divergence and gradient [8].

B. Curvelet transform
Curvelet transform that is helpful to represent the image at various scale, and orientation is proposed. This transform decompose the image using a linear and weighted combination of basis function. It has time-frequency localization properties of wavelets [14]. The main advantage of curvelet transform, it has superior performance over local Ridgelet transform. Basically 2D-curves are 2D extension of wavelets. Scale, orientation and two translation parameters decide the Curvelets. Curvelets used a spatial band-pass filter with multiscale ridgelets to isolate different scales [17]. Basically in Curvelet transform to decompose the image into its constituents the following steps are used

1. Subband Decomposition- The object \( O \) is decomposed into subbands such that

\[
O \leftrightarrow (\Delta_0 O, \Delta_1 O, \Delta_2 O \ldots \ldots \ldots \ldots)
\]

2. Smooth Partitioning- Each subband is smoothly windowed into sequence of an appropriate scale

\[
\Delta_s O \leftrightarrow (w_0 \Delta_s O)_{q \in Q_s}
\]

3. Renormalization- output of step 2 is convert into unit scale.

\[
gQ = \left(T_0^{-1}\right)(w_0 \Delta_s O), \quad Q \in Q_s
\]

4. Ridgelet Analysis- Each square is analyzed via the discrete ridgelet transform.

C. Huber variant of TV regularization
In step 3 of the proposed framework a modified variant of TV regularization is used. Last step of the proposed framework is used for preserving the structure with speckle noise reduction. During this post processing step of proposed framework it is assume that speckle is a multiplicative noise and converted into a Gaussian distribution with a square-root transformation [15]. Staircase artifacts due to Traditional TV regularization are remove by Huber penalty function.

D. Ablation Experiment
To demonstrated the effectiveness of each step of the proposed framework a ablation experiment was conducted for the image 1 and image 2 at noise variance 0.6.
These nonlinear co-noising process. SR2rHMF) [18] decomposition filter −𝜎

mM0nisotropic diffusion (SRAD)
df

q

c

edes−𝜎

isotropic diffusion filter (NCF) [19], dual tree complex wavelet(DTCWT) using soft thresholding [23], adaptive weighted bilateral filter (AWBF) [24], classical non local mean filter (NLM) [27] weighted guided filter [22] and second order total generalized variation decomposition filter (TGVD) [21].

A. Image database

To find out the result of proposed framework, real images of OCT provided by Jinming Duan, School of Computer Science, University of Nottingham, UK [21] was used.

B. Quality matrices

The different quality matrices used in this proposed framework are: Peak Signal to Noise Ratio(PSNR), Contrast-to-noise ratio (CNR), Structural residual(SR) and Structure similarity index (SSIM).

C. Peak Signal to Noise Ratio(PSNR):- It is the ratio of maximum power to noise power of signal.

\[
PSNR(\text{dB}) = 10 \log_{10} \left( \frac{I_{\text{MAX}}^2}{\text{MSE}} \right)
\]  

(17)

Where \( I_{\text{MAX}} \) is the maximum power of signal \( \text{MSE} \) is Mean Square Error of signal.

D. Contrast-to-noise ratio (CNR):- It measure the contrast between interested ROI and noisy background of the image and defined as

\[
\text{CNR} = \frac{1}{N} \sum_{n=1}^{N} \frac{\mu_n - \mu_b}{\sqrt{(\sigma_n^2 + \sigma_b^2)}}
\]

where \( \mu_b, \sigma_b^2 \) are mean and variance of the background noise of the image and \( \mu_n, \sigma_n^2 \) are the \( n \)th ROI of the image.

E. Structural Residual (SR):- It measure how much original structure is preserved during denoising process. SR at pixel \( p \) is calculated by taking the weighted average of a number of nearby and similar noise samples in noise layer \( L_n \) given as [28]:

\[
L'_n(p) = \frac{1}{\Omega} \sum_{q \in \Omega} w(p,q,\sigma_d,\sigma_s) L_n(q)
\]

where \( \Omega \) is the neighbourhood pixel of \( p \), \( w \) is a weight function. after the calculation of structure residual map , we can calculate the structure residual feature SR given by the equation

\[
\text{SR} = \sqrt{\frac{\sum_{p} L'_n(p)^2}{N}}
\]

(14)

where \( N \) is the total number of pixel in the image.

F. Structural Similarity Index Metric (SSIM): It measure the similarity between the original and denoised image defined as:

\[
\text{SSIM}(I,O) = \frac{(2\mu_I\mu_O + c_1)(2\sigma_{I,O} + c_2)}{\mu_I^2 + \mu_O^2 + c_1(\sigma_I^2 + \sigma_O^2 + c_2)}
\]

(11)

from the quantitative and qualitative results it is clear that the result are improving from step to step

IV. MATERIAL AND METHODS

To demonstrate the worthiness of proposed framework, the results of proposed framework are compared with many state of art filters proposed by different researchers. These filter are Speckle reducing anisotropic diffusion (SRAD) [8], hybrid median filter (HMF) [18], nonlinear complex diffusion filter (NCF) [19], dual tree complex wavelet(DTCWT) using soft thresholding [23], adaptive weighted bilateral filter (AWBF) [24], classical non local mean filter (NLM) [27] weighted guided filter [22] and second order total generalized variation decomposition filter (TGVD) [21].

Table 1: PSNR, CNR, SR, & SSIM values for ablation Experiment

| For Noisy image 1 at noise variance=0.6 | For Noisy image2 at noise variance=0.6 |
|-----------------------------------------|-----------------------------------------|
| PSNR | CNR | SR | SSIM | PSNR | CNR | SR | SSIM |
| After Step 1 | 30.7997 | 4.90814 | 7.3545 | 0.60193 | 29.5376 | 3.9401 | 8.5047 | 0.61049 |
| After Step 2 | 34.7687 | 6.21345 | 3.4565 | 0.80164 | 33.5478 | 5.9452 | 4.4036 | 0.79849 |
| After Step 3 | 37.9474 | 7.21760 | 2.0258 | 0.99998 | 37.6950 | 7.21760 | 2.0271 | 0.99996 |

Fig 2:- Ablation Experiment Results for Image 1 and Image2

Table 1: PSNR, CNR, SR, & SSIM values for ablation Experiment
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Where \((\mu_I,\sigma_I^2)\) and \((\mu_O,\sigma_O^2)\) are the mean and variance of the input and output images respectively. \(\sigma_{I,O}\) is the covariance between the input and output images and \((c_I,c_O)\) are constant.

V. RESULT AND DISCUSSION

The quantitative and qualitative results of proposed framework are find out by conducting a experiment on real OCT images. all the Results are find out by MATLAB R2018. The noisy image are obtained by adding different noise 0.2,0.4,0.6,0.8, and 1.0 to the noise free image. The quantitative and qualitative result of proposed framework is compared with eight state of art filter at different noise variance.

Table 1: PSNR, CNR, SR, & SSIM Comparison for Real OCT Image 1 for different noise variance

| Filter    | PSNR 0.2 | PSNR 0.4 | PSNR 0.6 | PSNR 0.8 | PSNR 1.0 | CNR 0.2 | CNR 0.4 | CNR 0.6 | CNR 0.8 | CNR 1.0 |
|-----------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|
| SRAD[8]   | 30.8060 | 30.8026 | 30.7997 | 30.7832 | 30.7539 | 5.12806 | 5.01976 | 4.90814 | 5.32212 | 4.96632 |
| HMF[18]   | 30.8317 | 30.3385 | 29.6439 | 28.8202 | 27.9743 | 4.78824 | 4.65252 | 4.26583 | 3.97549 | 3.59154 |
| DCTWT[23] | 35.6614 | 35.2769 | 34.8363 | 34.4025 | 33.9486 | 4.86892 | 4.45936 | 4.38646 | 4.13698 | 4.04275 |
| NCDF[19]  | 22.1638 | 21.8370 | 22.2322 | 21.8602 | 20.4732 | 5.61149 | 5.85305 | 5.74181 | 5.97599 | 6.35150 |
| NLM[27]   | 37.6785 | 37.3214 | 36.2881 | 34.2995 | 32.2799 | 5.83842 | 6.19000 | 6.86127 | 7.45103 | 8.30340 |
| AWBF[24]  | 32.5473 | 31.3214 | 30.2881 | 29.2995 | 28.2690 | 4.87091 | 4.84390 | 4.01725 | 3.93299 | 3.28691 |
| WGF[22]   | 27.5493 | 26.3714 | 26.2841 | 24.2895 | 22.2599 | 2.82689 | 2.92733 | 2.65594 | 2.67693 | 3.10091 |
| TGVD[21]  | 37.5453 | 37.3214 | 36.2881 | 34.2995 | 32.2799 | 5.03256 | 5.30090 | 5.34986 | 5.31751 | 5.28452 |
| Proposed  | 39.4852 | 38.8396 | 37.9474 | 36.9345 | 35.9128 | 6.99991 | 7.05842 | 7.21760 | 7.43037 | 7.50471 |

Table 2: Visual Comparison for Real OCT Image 1 for noise variance=0.2

Noisy Image

SRAD

HMF

DCTWT

NCDF

NLM

AWBF

WGF

TGVD

Proposed

Table 2: Visual Comparison for Real OCT Image 1 for noise variance=0.4

Noisy Image

SRAD

HMF

DCTWT

NCDF

NLM

AWBF

WGF

TGVD

Proposed

Fig2 (a): The visual comparison of Real OCT image 1 for noise variance=0.2

Fig2(b): The visual comparison of Real OCT image 1 for noise variance=0.4
Table 1 shows PSNR, CNR, SR & SSIM values comparison for real OCT image 1 at different noise variance values (0.2, 0.4, 0.6, 0.8, 1.0) from the quantitative values it is clear that the proposed framework is outperform in terms of PSNR, CNR, SR & SSIM in comparison to eight most used despeckling filters in literature. fig.2(a), (b), (c), (d) & (e) shows the visual comparisons of the proposed framework with eight state of the art filters. The visual results also shows that the proposed framework preserves the fine structure of the image.

Fig 2(c): The visual comparison of Real OCT image 1 for noise variance=0.6

Fig 2(d): The visual comparison of Real OCT image 1 for noise variance=0.8

Fig 2(e): The visual comparison of Real OCT image 1 for noise variance=0.8
Table 2: PSNR, CNR, SR, & SSIM Comparison for Real OCT Image 2 for different noise variance

| Filter | PSNR       | CNR       | SR | SSIM       |
|--------|------------|-----------|----|------------|
|        | 0.2 | 0.4 | 0.6 | 0.8 | 1.0 | 0.2 | 0.4 | 0.6 | 0.8 | 1.0 | 0.2 | 0.4 | 0.6 | 0.8 | 1.0 | 0.2 | 0.4 | 0.6 | 0.8 | 1.0 |
| SRA[8] | 29.5027 | 29.5229 | 29.5376 | 29.5308 | 29.5751 | 4.0022 | 3.9370 | 3.9401 | 4.0287 | 4.1081 |
| HMF[18] | 28.8313 | 28.4855 | 27.9630 | 27.3156 | 26.5936 | 5.5241 | 5.9484 | 6.2562 | 6.1474 | 6.7111 |
| DCTWT[23] | 34.6839 | 34.3270 | 33.5721 | 32.8900 | 32.0775 | 5.4566 | 5.4671 | 5.2610 | 5.3322 | 5.1708 |
| NCDF[19] | 26.2547 | 25.6695 | 24.4172 | 22.7946 | 21.1317 | 5.1851 | 5.1530 | 5.2409 | 4.7169 | 4.5599 |
| NLM[27] | 36.2447 | 35.6295 | 34.4121 | 32.7996 | 31.1117 | 6.0354 | 6.6996 | 6.8172 | 7.0270 | 8.1977 |
| AWBF[24] | 29.3261 | 28.6387 | 27.6950 | 26.6279 | 25.5866 | 4.0577 | 4.0312 | 3.7812 | 3.7569 | 3.1911 |
| WGF[22] | 29.3461 | 28.6587 | 27.6950 | 26.6279 | 25.5866 | 4.0577 | 4.0312 | 3.7812 | 3.7569 | 3.1911 |
| TGVD[21] | 24.2222 | 24.3561 | 24.0878 | 24.5905 | 24.9841 | 2.9200 | 2.4754 | 2.3907 | 2.4218 | 2.8149 |
| Proposed | 39.3261 | 38.6387 | 37.6950 | 36.6279 | 35.5866 | 6.2650 | 6.2760 | 6.2284 | 6.5654 | 6.5724 |

Fig3(a): The visual comparison of Real OCT image 2 for noise variance=0.2

Fig3(b): The visual comparison of Real OCT image 2 for noise variance=0.4
Table 2 shows PSNR, CNR, SR & SSIM values comparison for real OCT image 1 at different noise variance values (0.2, 0.4, 0.6, 0.8, 1.0) from the quantitative values it is clear that the proposed framework outperforms in terms of PSNR, CNR, SR & SSIM in comparison to eight most used despeckling filters in literature. Fig. 3(a), (b), (c), (d) & (e) shows the visual comparisons of the proposed framework with eight state of the art filters. The visual results also shows that the proposed framework preserves the fine structure of the image.

Table 3: PSNR, CNR, SR, & SSIM Comparison for Real OCT Image 3 for different noise variance

| Filter   | PSNR   | CNR   |
|----------|--------|-------|
|          | 0.2    | 0.4   | 0.6   | 0.8   | 1.0   |
|          | 0.2    | 0.4   | 0.6   | 0.8   | 1.0   |
| SRAD[8]  | 29.6994| 29.7012| 29.7066| 29.6857| 29.6477| 4.3465| 4.3343| 4.3769| 4.4763| 4.1106|
| HMF[18]  | 29.3935| 28.8137| 28.0139| 27.1350| 26.2189| 4.5104| 4.0829| 5.1413| 5.3318| 6.5147|
| DCTWT[23]| 34.9839| 34.4506| 33.7661| 32.9315| 32.0877| 5.0636| 4.9253| 5.3298| 5.0448| 5.2210|
| NCDF[19] | 27.0172| 26.0861| 25.1030| 23.7213| 22.4235| 5.2488| 5.1021| 5.2699| 5.3739| 5.9866|
| NLM[27]  | 37.0182| 36.0851| 34.1000| 32.9703| 27.4025| 5.0444| 4.7134| 4.5502| 4.8152| 4.5827|
| AWBF[24] | 37.3261| 26.6387| 25.6950| 24.6279| 23.5866| 4.3003| 4.0962| 4.0715| 3.0514| 3.0472|
| WGF[22]  | 29.4856| 28.8390| 27.9475| 26.9346| 25.9129| 2.8268| 2.9273| 2.6559| 2.6769| 3.1009|
| TGVD[21] | 25.3803| 25.3564| 25.4160| 25.0503| 25.0964| 3.4181| 3.4994| 3.5579| 3.7968| 4.0207|
| Proposed | 39.4852| 38.8396| 37.9474| 36.9345| 35.9128| 5.8940| 6.0928| 6.6812| 8.1901| 7.2103|
| NR       |        |       |       |       |       | 0.5802| 0.5825| 0.5861| 0.5886| 0.5939|
| SSIM     |        |       |       |       |       | 0.5802| 0.5825| 0.5861| 0.5886| 0.5939|
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| Method   | HMF     | DCFTWT | NCDF | NLM     | AWBF | WGF     | TGVD | Proposed |
|----------|---------|--------|------|---------|------|---------|------|----------|
|          | 8.6469  | 4.5430 | 3.0334 | 3.5944  | 2.5990 | 3.0270  | 3.7254 | 2.0198   |
|          | 9.2438  | 4.8306 | 3.0357 | 4.0020  | 2.6561 | 3.0291  | 3.7632 | 2.0242   |
|          | 10.135  | 5.2267 | 3.0394 | 5.0296  | 2.0160 | 3.0323  | 3.6691 | 2.0299   |
|          | 11.188  | 5.7538 | 3.0439 | 6.3449  | 2.0890 | 3.0362  | 4.2569 | 2.0365   |
|          | 12.4622 | 6.3409 | 3.0492 | 6.2137  | 2.1950 | 3.0408  | 4.1814 | 2.0432   |
|          | 0.6171  | 0.8186 | 0.9999 | 0.9022  | 0.7821 | 0.9999  | 0.7270 | 0.9999   |
|          | 0.5930  | 0.8051 | 0.9999 | 0.8957  | 0.7590 | 0.9999  | 0.7152 | 0.9999   |
|          | 0.5621  | 0.7905 | 0.9999 | 0.8621  | 0.7226 | 0.9999  | 0.6967 | 0.9999   |
|          | 0.5317  | 0.7950 | 0.9999 | 0.7086  | 0.7145 | 0.9999  | 0.6718 | 0.9999   |
|          | 0.5005  | 0.7560 | 0.9999 | 0.6012  | 0.6972 | 0.9999  | 0.6455 | 0.9999   |

| Noisy Image3 | SRAD | HMF | DCTWT | NCDF | NLM | AWBF | WGF | TGVD | Proposed |
|--------------|------|-----|-------|------|-----|------|-----|------|----------|
| Fig4(a): The visual comparison of Real OCT image 3 for noise variance=0.2 |
| Noisy Image3 | SRAD | HMF | DCTWT | NCDF | NLM | AWBF | WGF | TGVD | Proposed |
| Fig4(b): The visual comparison of Real OCT image 3 for noise variance=0.4 |
| Noisy Image3 | SRAD | HMF | DCTWT | NCDF | NLM | AWBF | WGF | TGVD | Proposed |
| Fig4(c): The visual comparison of Real OCT image 3 for noise variance=0.6 |
Table 3 shows PSNR, CNR, SR & SSIM values comparison for real OCT image1 at different noise variance values (0.2, 0.4, 0.6, 0.8, 1.0) from the quantitative values it is clear that the proposed framework is outperform in terms of PSNR, CNR, SR & SSIM in comparison to eight most used despeckling filters in literature. Fig.4(a),(b),(c),(d) & (e) shows the visual comparisons of the proposed framework with eight state of the art filters. The visual results also shows that the proposed framework preserves the fine structure of the image.

VI. CONCLUSION

This researcher paper proposed a hybrid de-speckling framework for real OCT image. The proposed framework shows the ability of speckle noise reduction with the preservation of fine detail. An experiment has been conducted on real OCT images to find out the PSNR, CNR, SR and SSIM values. The results obtained for proposed framework are compared with the existing de-speckle filters. The results shows that the proposed framework outperforms in comparison to various filters. Visual results of proposed framework also show that, the proposed framework is able to preserve the edges and fine structures of the image.

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