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An approach for de-noising and contrast enhancement of retinal fundus image using CLAHE

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ABSTRACT

Now-a-days medical fundus images are widely used in clinical diagnosis for the detection of retinal disorders. Fundus images are generally degraded by noise and suffer from low contrast issues. These issues make it difficult for ophthalmologist to detect and interpret diseases in fundus images. This paper presents a noise removal and contrast enhancement algorithm for fundus image. Integration of filters and contrast limited adaptive histogram equalization (CLAHE) technique is applied for solving the issues of de-noising and enhancement of color fundus image. The efficacy of the proposed method is evaluated through different performance parameters like Peak Signal to Noise Ratio (PSNR), Structural Similarity Index (SSIM), Correlation coefficient (CoC) and Edge preservation index (EPI). The proposed method achieved 7.85% improvement in PSNR, 1.19% improvement in SSIM, 0.12% improvement in CoC and 1.28% improvement in EPI when compared to the state of the art method.

1. Introduction

Digital images cover a vast area of application and various applications are implemented in the processing of digital images [23–25]. Medical image processing involves input of medical images, processing and output of result. Preprocessing of medical images is carried out at the very beginning before execution of processing step in order to enhance the image by denoising and contrast enhancement [1,2,9,18,19]. Now-a-days, medical image enhancement for better diagnosis of diseases is one of the uplifting areas of interest among researchers and physicians. The main aim of medical image enhancement is reduction of noise level and improvement of the contrast of medical images [3]. One of the featured and important medical images is fundus image (i.e. retinal scan). Fundus camera is used to image digital fundus images which are used for retrieving the features like the retina, optic disc area and cup area, the posterior surface of an eye and macular regions. Digital Fundus images are widely applied for the detection of the multiple disorders related to eye [5,7,8,10,12,14]. Abnormal eye conditions like age-related macular degeneration (AMD), glaucoma, diabetic retinopathy (DR) and neovascularization are diagnosed using fundus image [20]. Fundus image is captured using standard modality of imaging i.e. Fundus camera, which is popularly used in hospitals and eye specialist clinics. Fig. 1 shows the retinal fundus image. It is useful in the extraction of some essential features of the retina like Optic Disk Area (ODA), Cup Area Fovea, exudates and mainly the blood vessels. Some of the disorders that can be diagnosed by these features analysis in fundus images are Diabetic Retinopathy [7,12], glaucoma [10], hypertension, etc.

Noise in fundus image can be acquired due to multiple causes like type of image modality used to capture fundus image, image acquisition procedure through fundus camera, transmission also cause noisy pixels to occur in fundus image and uneven illumination is also a key factor for presence of noise in the fundus image. Different undesirable patterns also result noise in fundus image and are caused due to following reasons [16]:

(a) Digitization process causes low intensity white noise
(b) Noise may occur due to different linear and non-linear patterns like large or small bright and dark irregular areas.

Fundus image is mainly affected by Gaussian (white) noise and salt and pepper (impulse) noise. In order to properly diagnose the fundus image, pre-processing or image enhancement is a key step. Quality of fundus image is a key aspect in order to execute proper diagnosis of the disease by the ophthalmologist (with the help of fundus image). Presence of noise effects the two main aspects of the fundus image i.e. sensitivity (Probability measure which

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Fig. 1. Showing retinal fundus RGB image.

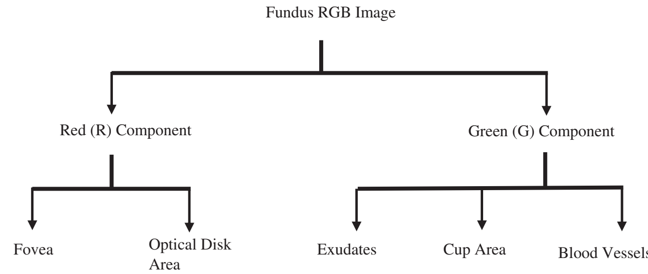

Fig. 3. Diagnostic parameters extracted from fundus R and G components.

specify whether fundus image classified (by any proposed model) abnormal is abnormal in real) and specificity (Probability measure which specify whether fundus image classified (by any proposed model) normal is normal in real) [10].

Preprocessing step in fundus image processing is a crucial step in order to detect and remove noise from it [3]. Feature extraction from fundus image like fovea, blood vessels, optical disk [8] and normalization of fundus images are employed for the convenience of the doctors to efficiently detect abnormalities in the eye. Fundus image is RGB in nature. Green component of fundus image is the most important as it provides most of the feature extraction while blue component is the least important one. Fundus RGB image can be decomposed into red (R), green (G) and blue (B) components as shown in Fig. 2 and then essential features can be extracted from them [6], separate pre-processing can be done on them, and separate de-noising can be performed on these segments. The most important channel is Green channel as most of the important features can be extracted through it [5]. Fig. 3 shows the diagnostic features that can be extracted from individual components of fundus image.

The rest of the paper is organized as follows: Section 2 discusses about the standard filters used to remove the noise from fundus image. Related noises associated with the fundus image are discussed in this section. This section also reviews the current work in the area of fundus image enhancement and feature extraction from it. Major contributions of proposed work towards the fundus image enhancement are also discussed in this section. The proposed model and algorithm are given in Section 3. The results and analysis of the work are discussed in Section 4. Conclusion of the proposed work is given in Section 5.

2. Background

This paper mainly focuses on the enhancement of digital fundus image by removing noise from all the three channels of the image (R, G and B) and improving its low contrast with CLAHE technique [4]. Different filters like median, Gaussian, wiener, average and weighted median are used separately for the purpose of de-noising of fundus image.

2.1. De-noising and enhancement of fundus image

Table 1 explains briefly about various filters used for removing noise from fundus image. These filters are quite effective in the removal of noises present in fundus image like Gaussian (white noise) and salt and pepper (Impulsive noise), which are explained in table 2. The distribution plot for Gaussian and salt and pepper noise distribution is shown in Fig. 4.

2.2. Contrast limited adaptive histogram Equalization (CLAHE) technique

Contrast Limited Adaptive Histogram Equalization (CLAHE) is the method which improves the low contrast issue for the digital images especially medical images. Particularly in medical imaging, outperforming results of CLAHE makes it superior than Adaptive Histogram Equalization (AHE) and ordinary Histogram Equalization (HE) [4]. CLAHE basically operates by limiting the contrast enhancement that is usually performed by ordinary HE which

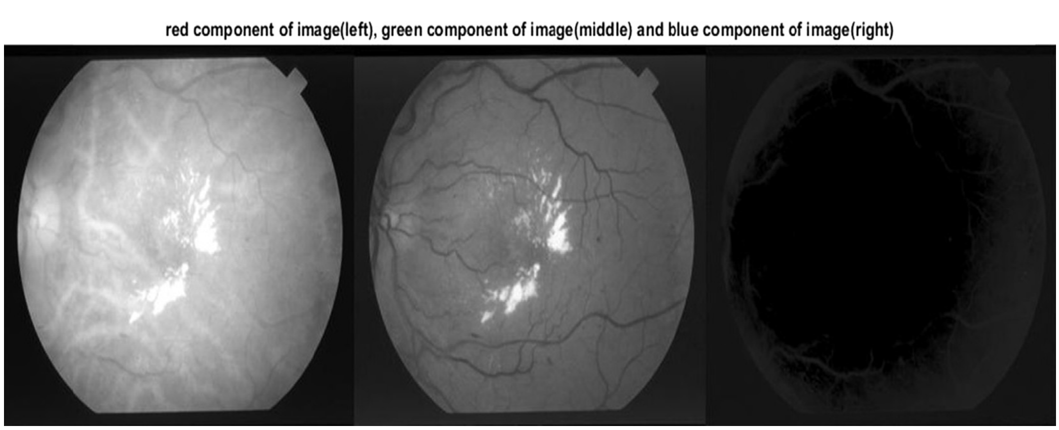

Fig. 2. R, G and B components of fundus image.

Table 1
Filters used for de-noising of fundus image.

Filter	Description
Mean Filter or average filter	It is a spatial (linear) filtering technique that replaces the value of pixels in the window with the mean of the pixels value in that window. It is usually used for the purpose of de-noising and smoothening of the image. The noise that mean filter efficiently removes from fundus image is grainy noise. Poor in preservation of useful details in image after noise removal.
Median Filter	It is also a spatial but non-linear filtering technique to remove noise from the image as well as preserve the edge degradation that happens in average filtering. In median filtering, the pixel value that is corrupted is replaced by the median of that window pixel values. Median filter works well for the fundus image enhancement as compared to other linear filters.
Wiener Filter	It is a linear filter that is applied often in frequency domain. Wiener filter is best for the removal of additive noise and blur effect in fundus image. It is also known to be Mean Square Error favorable filter. It works on the noisy signal of the image and outputs the estimate of the original (uncorrupted) image.
Gaussian Filter	It is a linear filter that is used to remove noise from the image along with the blurring of image similar to average filter. It differs from average filter in the aspect that it uses different kernel from mean filter which is in the shape of bell curve (Gaussian PDF). In 2-Dimensional, Gaussian has the equation: $G'(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}$ Here mean is (0,0) and σ^2 is the variance (default 1).
Weighted Median Filter	In weighted median filter, the only difference is that mask is not empty by which we multiply the window. In weighted median filter a proper mask is selected with some weights and that is averaged and then that mask is multiplied by the window and then median is find out and center value is replaced by that median. This filter outperforms the median filter performance in the edge preservation aspect and detail preservation.

Table 2
Noise in medical fundus image.

Types of Noise	explanation
Salt and Pepper	• Impulse noise is most commonly found in fundus image and occurred during acquisition process, storage transaction and processing of images. • Impulse noise lost the information details and degrades the quality of image. • This noise is of impulse type. It is also known as intensity spikes. It is caused due to the error occurred in the transmitted data. • The following expression shows the distribution of impulse noise $f(\mathrm{N}) = \begin{cases} \mathrm{p_a} \mathrm{for} \mathrm{N} = \mathrm{a} \\ \mathrm{p_b} \mathrm{for} \mathrm{N} = \mathrm{b} \\ 0 \mathrm{otherwise} \end{cases}$ Where $a, b \in \mathcal{R}$, $\mathrm{p_a}$ =Probability of a, $\mathrm{p_b}$ = Probability of b and N = Random Variable
Gaussian	• Amplifier noise, thermal vibration of atoms and radiation of warm objects generate Gaussian noise in fundus image. • It is also termed as amplifier noise or white noise. • This noise causes change in the pixel values. • This noise is Gaussian distribution in structure. • It has bell shaped probability distribution function (PDF) and is expressed as [1]: $W(N) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(N-m)^2}{\sigma^2}}$ Where, N is the gray level, $m$is the mean value of PDF and σ standard deviation of the noise

results in the noise enhancement as well. Therefore by limiting the contrast enhancement in HE, desired results were achieved in the cases where noise become too prominent by enhancing contrast i.e. specifically medical images. Basically contrast enhancement can be stated as the slope of the function that is relating input image intensity value to desired resultant image intensities. Contrast can be limited by limiting the slope of this relating function. Also, contrast enhancement is directly related to the height of the histogram at that intensity value [4]. Therefore, limiting the slope and clipping the height of histogram are both same functions that control contrast enhancement. So user can limit the contrast by specifying the clip limit (i.e. height of histogram) according to the need of the contrast. Fig. 5 shows the histogram of Fig. 1 before and after CLAHE with clip limit 0.0005.

2.3. Current State-of-the-art de-noising and enhancement techniques for fundus image

Now-a-days medical image processing is one of the interesting area of interest among researchers. Image enhancement and feature extraction are important steps of medical image processing.

Ab Rahim et al. [7] proposed three different algorithms for the detection of diabetic retinopathy by using digital fundus image. The authors employed CLAHE, Mahalanobis Distance (MD) and Histogram Equalization (HE) enhancement techniques in the green channel for the detection of the blood vessels in the fundus image. Among these three enhancement techniques, MD worked best in the detection process.

Salem et al. [6] on the other hand showed the importance of red channel along with the green one in the preprocessing of the digital fundus image. In their proposed solution, they used the merging of red and green channel histograms and then compared the sensitivity and specificity of proposed histogram matching solution with standalone green and red channel. Results showed that proposed solution outperformed naive red and green channel computation. Hence red channel is also important in the preprocessing along with green channel.

Nayak et al. [10] used both green and red channel of the fundus image to extract the details that are required to detect glaucoma with the help of fundus image. They applied morphological operations on the different channels to dig out details like cup to disk ratio, blood area of vessels, etc. to classify whether the fundus image have glaucoma or not.

Intajag et al. [12] proposed histogram analysis method to improve the contrast and issue of dynamic range in digital fundus image. The authors utilized the green channel components of the fundus image. They applied histogram partitioning and index of fuzziness logic to the green channel. They found that the proposed algorithm showed better results than the Naive Histogram Equalization (HE) technique.

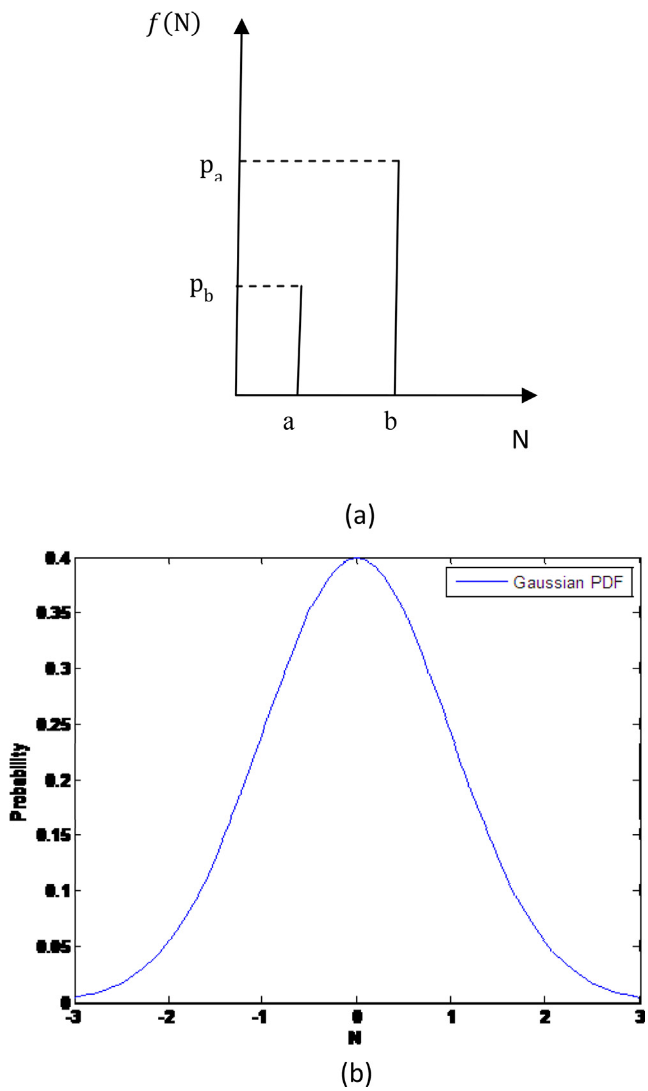

Fig. 4. Distribution plot (a) Salt and pepper noise (b) Gaussian noise.

Hani et al. [13] proposed the three variations of adaptive wiener filter to remove additive, multiplicative and combination of both noises in the fundus image. The proposed method showed better PSNR value when filter was applied after retinex algorithm. In 2014, Hani et al. [14] proposed an algorithm to enhance fundus image by removing noise from it using time domain constraint estimator (TDCE) and compared it with other algorithms and concluded that the proposed algorithm works more efficiently in terms of PSNR improvement.

Noronha et al. [8] proposed different algorithms to extract different features from fundus image and then combining them again to give more enhanced fundus image that can be used to detect more accurately the abnormalities in the eye. These algorithms extracted the most important features like optic disk, fovea, blood vessels and exudates from fundus image and then combining these extracted features to give better image for diagnosis.

Setiawan et al. [5] in 2013 used the concept of CLAHE in the green channel of the digital retinal image to improve the contrast and then compared it to naive histogram equalization method of contrast improvement. They also showed that CLAHE works best in standalone green channel as compared to others channels of fundus image and the image after applying CLAHE in green channel was better than applying CLAHE in all channels of fundus image.

Malathi et al. [11] compared various filters like median, wiener, average, gaussian and haar filter on various types of noises like Gaussian, poisson, salt and pepper and speckle noise for fundus image enhancement. They concluded that wiener and haar filter works best for all the noises except salt and pepper noise. Median filter works best for salt and pepper type of noise. Multiple performance parameters like Mean Square Error (MSE), PSNR, Normalized Absolute Error (NAE) and Normalized Cross Correlation (NCC) were used for evaluation of result.

Elloumi et al. [20] proposed an image processing pipeline for enhancement and de-noising of smart-phone captured fundus image. The authors applied CLAHE technique for enhancement and Butterworth filter for reducing high frequency noise.

Khan et al. [21] proposed a method for extraction of blood vessels from retinal fundus image. Preprocessing was applied for removing noise from fundus image. The local noise was removed using high boost filtered image and top-hat filtered image. Enhancement of blood vessels was carried out using Frangi filter at multiscale level.

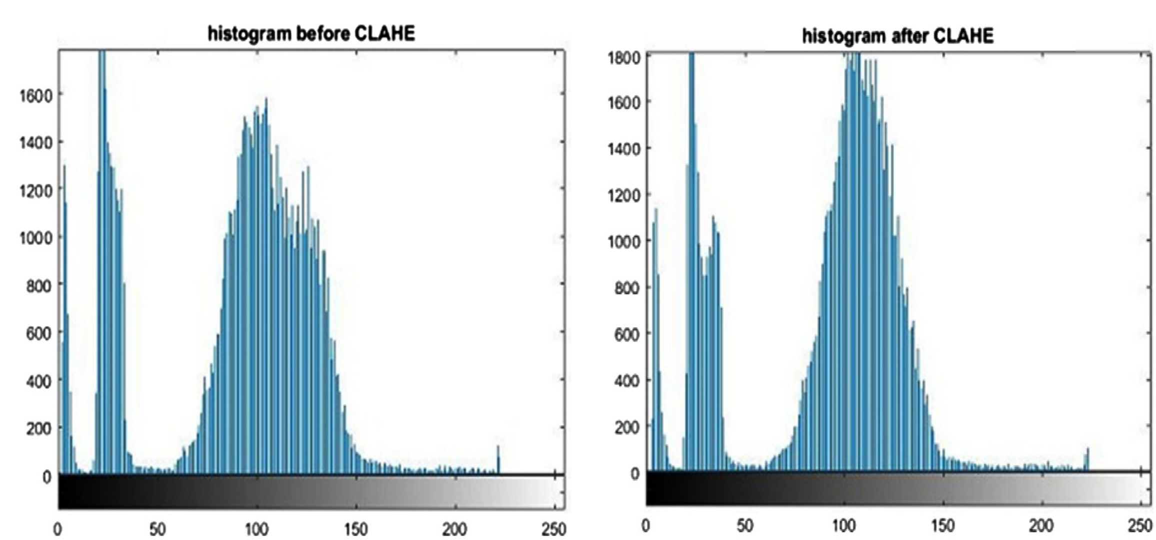

Fig. 5. Histogram of Fig. 1 before and after CLAHE.

This paper presents a medical fundus image enhancement technique by integrating features of filtering and CLAHE. The proposed model provides contrast enhancement and de-noising at R, G and B components of fundus image. The trade off in the performance parameters is tried to overcome which encountered when using both de-noising and contrast enhancement in all the three channels of fundus image. The contributions of the proposed work are as follows.

- Individual channels of the RGB fundus image are processed separately and features of these channels are preserved.
- **Improved image contrast:** CLAHE improves the contrast of the image and make detection of abnormalities more precise.
- **Noise Removal:** Proposed method is efficient in removal of almost every type of noise from fundus image and performance parameters shows the positive improvements in the image after the application of proposed method.
- Effective and not so complex method to enhance overall visibility of RGB fundus image.

3. Proposed model and algorithm

The proposed model uses different filters along with CLAHE technique to remove Gaussian and salt and pepper noise and enhance the red, green and blue channels of fundus image. The combined features of CLAHE and filtering approach enhances and removes the affected noise from the R, G and B channels thus results contrast enhanced and de-noised fundus image. Fig. 6 shows the detailed diagram of proposed method. The details of algorithmic steps of the proposed method are given below:

STEP 1: Reading noisy fundus image

$$N(x,y) = I(x,y) + \eta(x,y) \tag{1}$$

where $N(x,y)$ is the noisy fundus image, $I(x,y)$ is the original image and $\eta(x,y)$ is the additional noisy pixels.

STEP 2: Decomposition of fundus image into its red, green and blue channel.
STEP 3: Applying filtering technique to remove noise from the individual channel, results de-noised red channel, de-noised green channel and de-noised blue channel.
STEP 4: Contrast enhancement and smoothening of de-noised image by CLAHE, results de-noised and enhanced red channel, de-noised and enhanced green channel and de-noised and enhanced blue channel.
STEP 5: Merge all the three denoised and enhanced components together to form denoised and enhanced RGB fundus image.
STEP 6: Repeat step 1 to 5 for different types of filters, noise and noise variances.

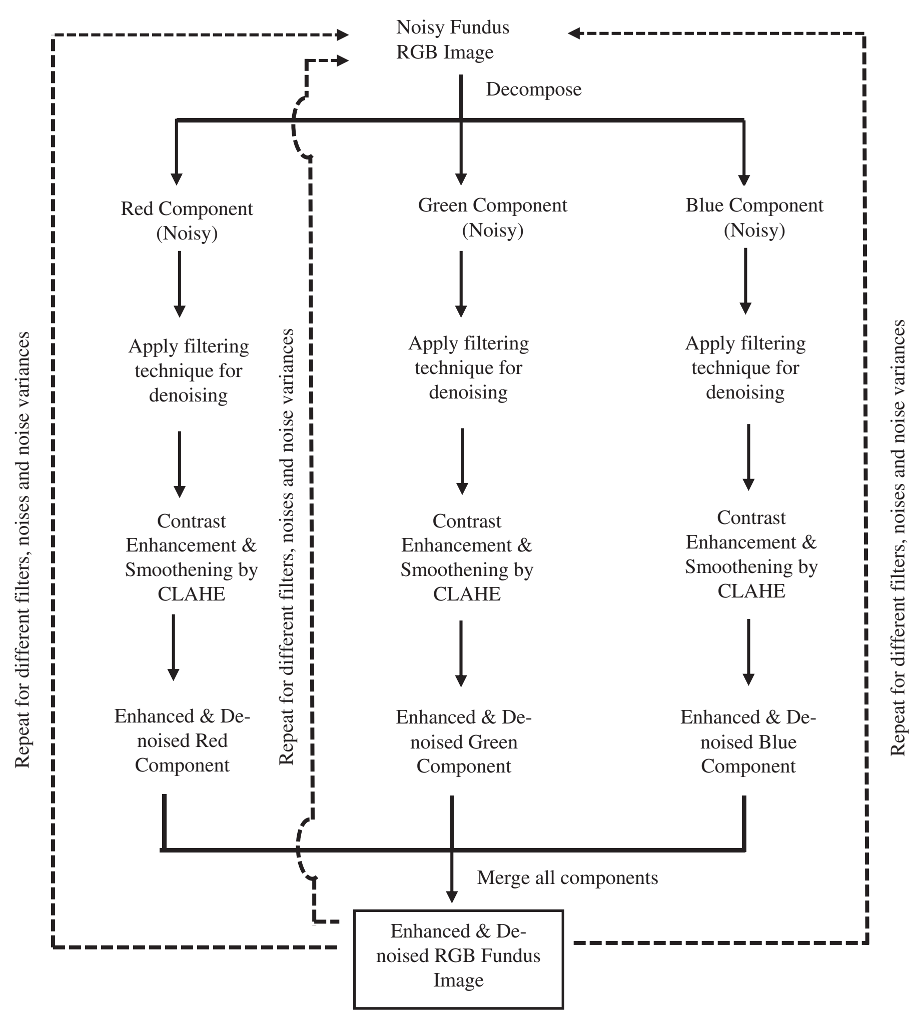

Fig. 6. Block diagram of proposed algorithm.

4. Experimental results and discussion

RGB fundus image of size (605 × 700) which is collected from the STARE database [15] is used for simulation of the proposed technique. MATLAB R2016a is the tool used to simulate the proposed algorithm. Fig. 7 shows the fundus image enhancement, going through each step of the proposed algorithm with salt and pepper noise, at 0.01 noise variance level and de-noised using median filter with CLAHE technique. Similarly simulation is done for Gaussian noise found in fundus image against all types of filters of different noise variances, to see the performance of the filters against different noises for fundus image. Fig. 8 shows the histograms of individual components before and after enhancement of the image given in Fig. 7. The performance parameters used to evaluate the efficiency are Peak Signal to Noise Ratio (PSNR), Correlation coefficient (CoC), Structural Similarity Index (SSIM) and Edge preservation index (EPI). PSNR is one of the most popular and trustworthy performance parameter used in the evaluation

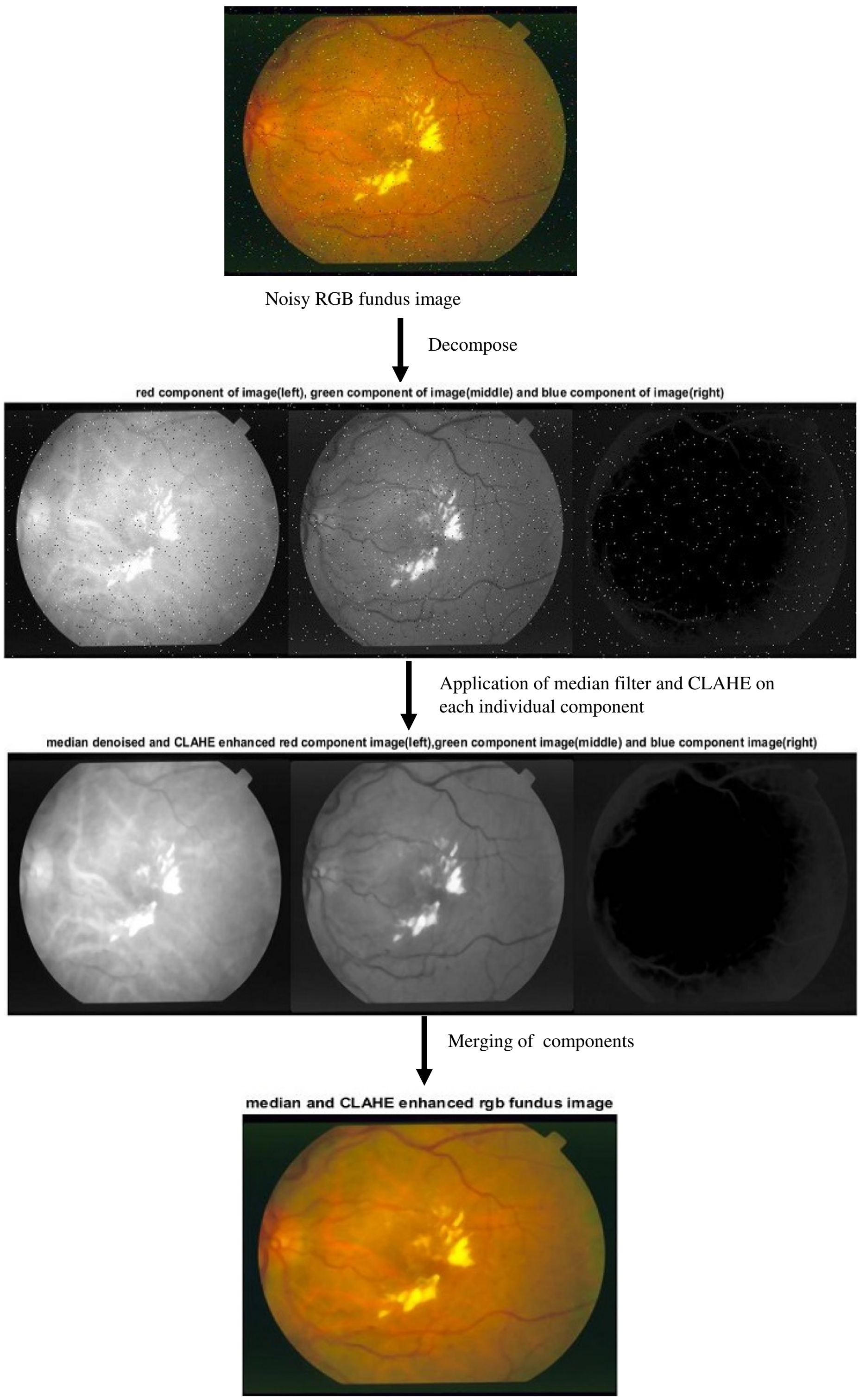

Fig. 7. Enhancement of fundus image by proposed algorithm.

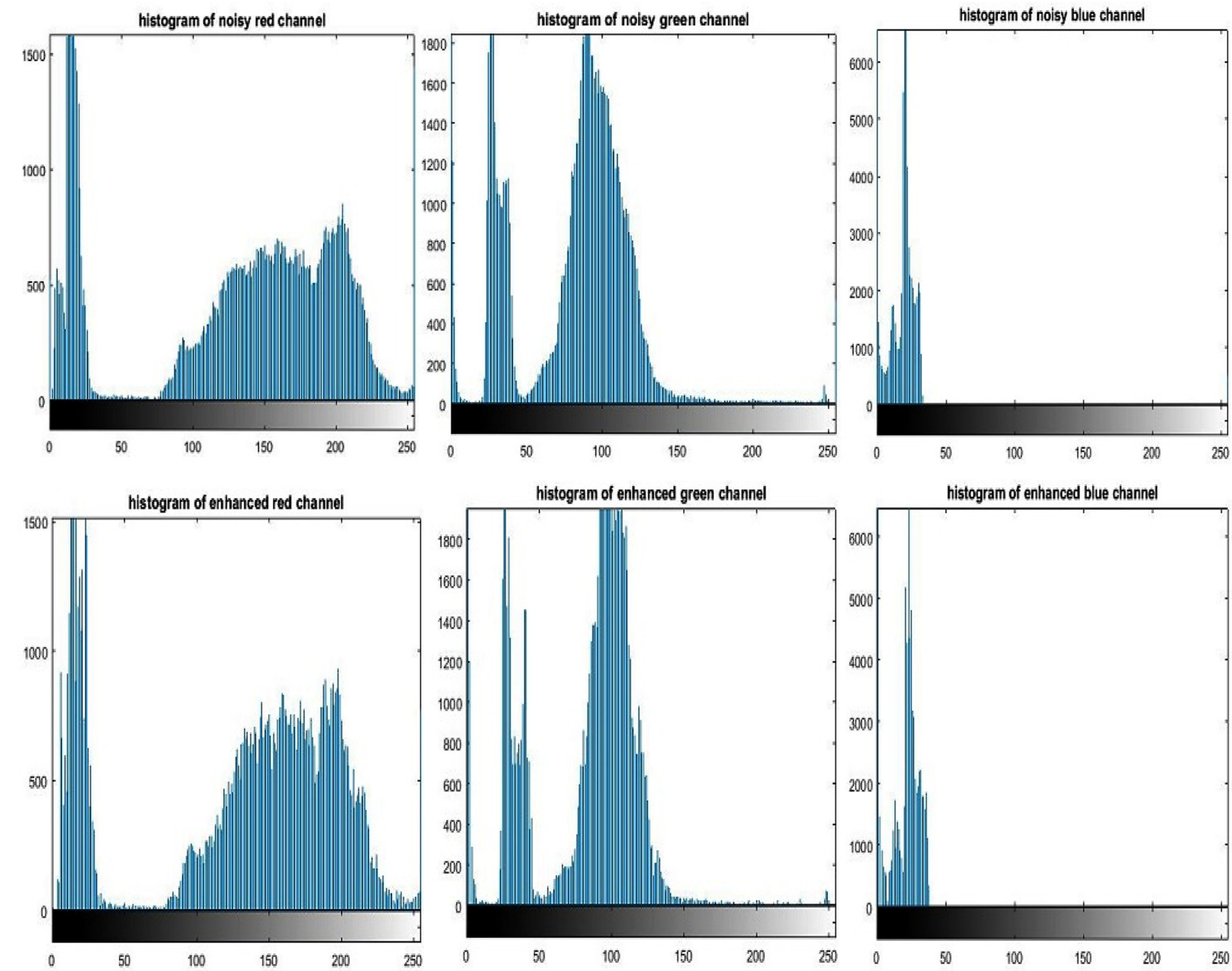

Fig. 8. Histograms of fundus image components before and after enhancement.

of image enhancement and other areas also. Higher the values of PSNR, SSIM, CoC and EPI, better the quality of image and ultimately better the performance of the algorithm. These parameters are defined as follows.

i. Peak Signal to Noise Ratio (PSNR): As the name explains, it is the ratio of the maximum/peak value of the signal to the noisy signal value [22,27]. PSNR formally describes the quality of the reconstructed image after the application of any technique on it. Higher the PSNR, better the quality of reconstructed image. The acceptable range of PSNR is 28 db (decibels) to 50 db. PSNR is expressed as:

$$PSNR = 10\ \log_{10}\frac{(Peak\,value)^2}{MSE} \tag{2}$$

where *Peak value* is the maximum difference in the input image value and MSE is Mean Square Error and is computed as

$$\mathrm{MSE} = \frac{1}{m \times n}\sum_{i=1}^{m \times n}(\hat{y}(i,j) - y(i,j))^2 \tag{3}$$

where $m \times n$ specifies the size of the image, $\hat{y}(i,j)$ is the recovered image and $y(i,j)$ is the Original image. Table 3 shows the PSNR values for different filtering techniques with CLAHE against different attacks or noises at different noise variances level (σ_n^2). The table indicated that the median filter and weighted median filter shows comparable results with CLAHE against Salt and pepper noise than

Table 3
PSNR (in dB) values for different filters with CLAHE against different attacks or noises at different noise variances.

Filters + CLAHE	Noise Type		
	Noise Variance	Salt & Pepper Noise	Gaussian Noise
Median Filter + CLAHE	0.001	35.376870	29.205802
	0.01	35.342524	27.890991
	0.1	35.011961	18.544124
	0.2	34.644201	13.685337
Wiener Filter + CLAHE	0.001	32.783764	28.612019
	0.01	28.545231	27.424313
	0.1	23.233115	18.685778
	0.2	20.894587	13.755823
Average Filter + CLAHE	0.001	32.075036	28.866618
	0.01	31.059567	27.656338
	0.1	25.302295	18.690148
	0.2	21.903061	13.740520
Gaussian Filter + CLAHE	0.001	33.921009	24.371021
	0.01	29.783372	23.836875
	0.1	21.037163	17.814673
	0.2	21.005991	13.585131
Weighted Median Filter + CLAHE	0.001	36.719707	29.718484
	0.01	35.819953	29.329734
	0.1	35.425546	19.783958
	0.2	35.171530	14.407455

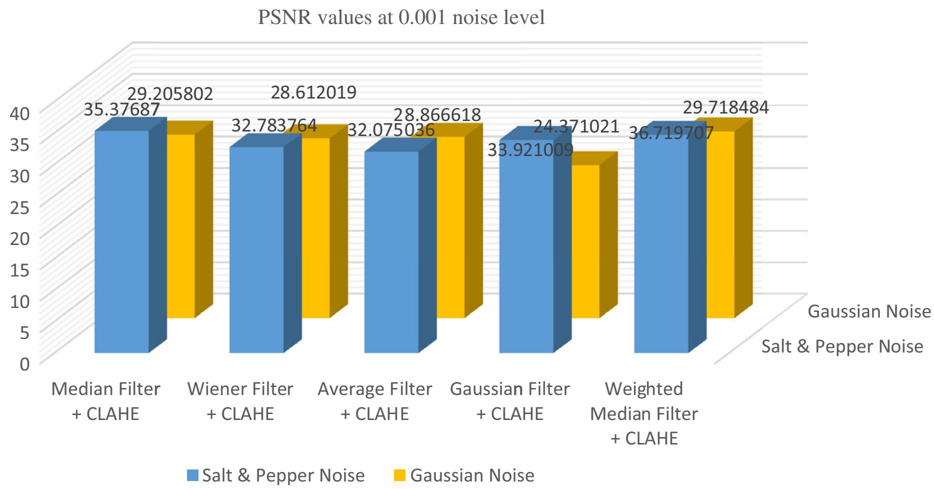

Fig. 9. Comparison of different filters in terms of PSNR (db) values for different noises against noise variance of 0.001.

Gaussian noise. Weighted median filter gives the acceptable value of PSNR. The percentage of improvement of PSNR for weighted median filter are 3.65%, 1.33%, 1.16% and 1.49% for noise variances of 0.001, 0.01, 0.1 and 0.2 respectively over median filter. The graph comparing PSNR values for different noises against different filters for noise variance of 0.001 is shown in Fig. 9. From Fig. 9, it can be seen that the highest PSNR is 36.719707 obtained with weighted median filter against salt and pepper noise with variance of 0.001.

ii. Structural Similarity Index (SSIM): SSIM is a quantitative measure to evaluate image quality. It basically measures the amount of similarity between the enhanced image and original image [22]. Higher the value of SSIM, more the images are structurally identical. SSIM is formulated as:

$$\mathrm{SSIM}(\mathrm{X},\mathrm{Y}) = \left[l(\mathrm{X},\mathrm{Y})^{\alpha}.\mathrm{c}(\mathrm{X},\mathrm{Y})^{\beta}.\mathrm{s}(\mathrm{X},\mathrm{Y})^{\gamma}\right] \tag{4}$$

where 'X, Y' = two windows of same dimension of original and reconstructed image respectively.

α, β, γ are the weights of these parameters
l, s and c are the luminance, structure and contrast respectively and are computed as:

$$l(X,Y) = \frac{2\mu_X\mu_Y + c_1}{\mu_X^2 + \mu_Y^2 + c_1} \tag{5}$$

$$s(X,Y) = \frac{\sigma_{XY} + c_3}{\sigma_X\sigma_Y + c_3} \tag{6}$$

$$c(X,Y) = \frac{2\sigma_X\sigma_Y + c_2}{\sigma_X^2 + \sigma_Y^2 + c_2} \tag{7}$$

Here, μ_Y = average of Y

μ_X = average of X,
σ_Y^2 = variance of Y,
σ_X^2 = variance of X,
σ_{XY} = co-variance of X and Y,

c_1 and c_2 are the two parameters to stable the division with poor denominator and $c_3 = \frac{c_2}{2}$. As SSIM approaches to 1 it indicates perfect similarity between enhanced image and original image. Comparison of SSIM of the proposed method against various noises, filters and noise variances is shown in Table 4. The percentage of improvement of SSIM for weighted median filter are 1.33%, 0.38%, 0.24% and 0.82% for noise variances of 0.001, 0.01, 0.1 and 0.2 respectively over median filter. SSIM values for different filters against different noises of noise variance of 0.001 are shown in Fig. 10. This figure shows that at noise level 0.001 weighted median filter have highest SSIM and is 0.975304 for salt and pepper noise.

Table 4
SSIM values for different filters with CLAHE against different noises at different noise variances.

Filters + CLAHE	Noise Type		
	Noise Variance	Salt & Pepper Noise	Gaussian Noise
Median Filter + CLAHE	0.001	0.962327	0.772254
	0.01	0.962192	0.767369
	0.1	0.958761	0.691514
	0.2	0.951407	0.632898
Wiener Filter + CLAHE	0.001	0.916593	0.755744
	0.01	0.736117	0.750255
	0.1	0.459403	0.692935
	0.2	0.365518	0.627231
Average Filter + CLAHE	0.001	0.926023	0.816556
	0.01	0.895237	0.810642
	0.1	0.666808	0.739105
	0.2	0.516100	0.671041
Gaussian Filter + CLAHE	0.001	0.962614	0.378019
	0.01	0.791894	0.374464
	0.1	0.237781	0.335231
	0.2	0.237073	0.311754
Weighted Median Filter + CLAHE	0.001	0.975304	0.727873
	0.01	0.965923	0.721606
	0.1	0.961078	0.663598
	0.2	0.959336	0.607094

iii. Correlation Coefficient (CoC): CoC is responsible to deduce the interdependence between the the enhanced image after the application of algorithm and the original degraded image. CoC have unit value for the perfect correlation between the two images under consideration. CoC is mathematically expressed as:

$$CoC_{X,X'} = \frac{\left(E\left[(X - \rho_X).(X' - \rho_{X'})\right]\right)}{\sigma_x\sigma_{X'}} \tag{8}$$

where σ_x and $\sigma_{X'}$ are standard deviation of original and recovered image. ρ_X and $\rho_{X'}$ are the average of the original and recovered images. Table 5 shows the CoC values for the proposed model against various filters, noises and noise variances. It concluded that

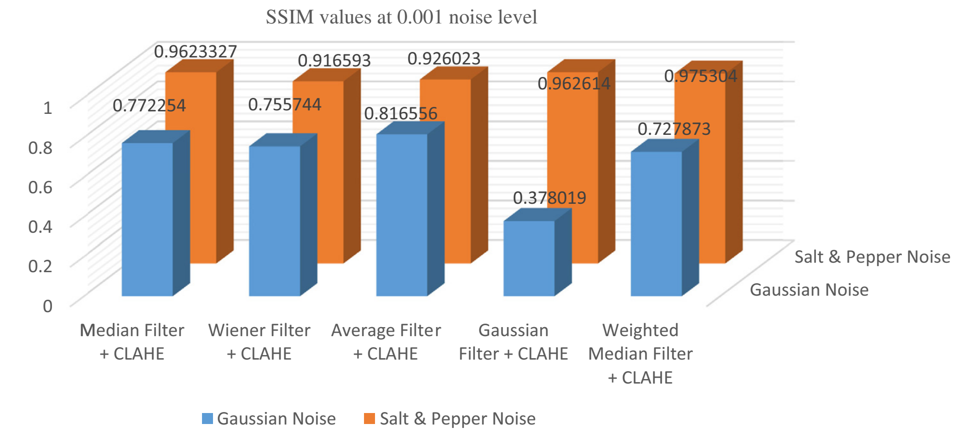

Fig. 10. Comparison of different filters in terms of SSIM values against different noises at 0.001 noise level.

Table 5
CoC values for different filters with CLAHE against different noises at different noise variances.

Filters + CLAHE	Noise Type		
	Noise Variance	Salt & Pepper Noise	Gaussian Noise
Median Filter + CLAHE	0.001	0.995936	0.984200
	0.01	0.995904	0.983187
	0.1	0.995609	0.980631
	0.2	0.995154	0.980155
Wiener Filter + CLAHE	0.001	0.992425	0.985162
	0.01	0.978108	0.984797
	0.1	0.933659	0.982089
	0.2	0.894428	0.979562
Average Filter + CLAHE	0.001	0.991667	0.987125
	0.01	0.989854	0.986607
	0.1	0.971225	0.983454
	0.2	0.943358	0.977634
Gaussian Filter + CLAHE	0.001	0.994516	0.947788
	0.01	0.984102	0.947453
	0.1	0.878259	0.942873
	0.2	0.876521	0.942859
Weighted Median Filter + CLAHE	0.001	0.998919	0.981838
	0.01	0.998559	0.981312
	0.1	0.998174	0.980056
	0.2	0.997298	0.979335

median filter and weighted median filter gives best results at every noise variance level for each type of noise. The percentage of improvement of CoC for weighted median filter are 0.29%, 0.26%, 0.25% and 0.21% for noise variances of 0.001, 0.01, 0.1 and 0.2 respectively over median filter. Fig. 11 shows the graph of CoC values at 0.001 noise level. This figure shows that at noise level 0.001 weighted median filter have highest CoC and is 0.998919 for salt and pepper noise.

iv. Edge Preservation Index (EPI): EPI is the quality assessment parameter that is widely used to deduce the measure of the edge preservation after de-noising the image [26,28]. Particularly in medical image enhancement, it is necessary to de-noise the image as well as preserve the edges to prevent the loss of data. Best preservation of edges in the enhanced image is achieved as EPI approaches to 1.EPI can be expressed as:

$$EPI = \frac{\left(\sum_{m=1}^{M}\sum_{n=1}^{N-1}|X'(m,n+1) - X'(m,n)|\right)}{\left(\sum_{p=1}^{M}\sum_{q=1}^{N-1}|X(m,n+1) - X(m,n)|\right)} \quad (9)$$

where 'X' is the original image, 'X′' is the reconstructed image and 'N' and 'M' are the column and row count in image respectively. Table 6 shows the EPI values for the proposed model against various filters, noises and noise variances. It concluded that median filter and weighted median filter gives best results at every noise

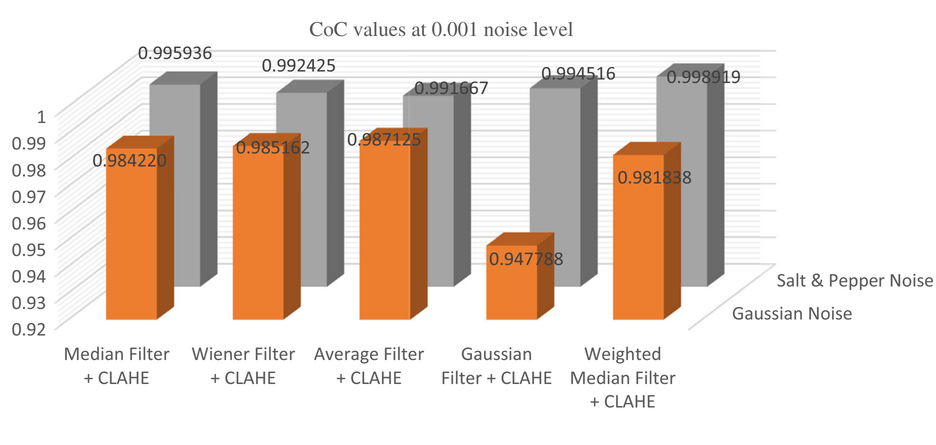

Fig. 11. Comparison of different filters in terms of CoC values at 0.001 noise level.

Table 6
EPI values for different filters with CLAHE against different noises at different noise variances.

Filters + CLAHE	Noise Type		
	Noise Variance	Salt & Pepper Noise	Gaussian Noise
Median Filter + CLAHE	0.001	0.975770	0.919333
	0.01	0.967323	0.908845
	0.1	0.932775	0.874766
	0.2	0.901980	0.802964
Wiener Filter + CLAHE	0.001	0.934824	0.814890
	0.01	0.839759	0.806004
	0.1	0.663500	0.792641
	0.2	0.582712	0.788118
Average Filter + CLAHE	0.001	0.967379	0.859345
	0.01	0.905243	0.851678
	0.1	0.833512	0.816744
	0.2	0.761389	0.799861
Gaussian Filter + CLAHE	0.001	0.971780	0.493119
	0.01	0.824640	0.482138
	0.1	0.567712	0.455450
	0.2	0.559466	0.413555
Weighted Median Filter + CLAHE	0.001	0.984367	0.889385
	0.01	0.980937	0.832670
	0.1	0.966822	0.776450
	0.2	0.961093	0.705152

variance level for each type of noise. The percentage of improvement of EPI for weighted median filter are 0.87%, 1.38%, 3.52% and 6.15% for noise variances of 0.001, 0.01, 0.1 and 0.2 respectively over median filter. Fig. 12 shows the graph of EPI values at 0.001 noise level. This figure shows that at noise level 0.001 weighted median filter have highest EPI and is 0.984367 for salt and pepper noise.

The efficiency of the proposed algorithm is evaluated by simulating RGB fundus image at four different noise levels 0.001, 0.01, 0.1 and 0.2. Then authors obtain quality parameters SSIM and CoC from fundus image and tabulated in Tables 4 and 5 respectively. It can be seen that out of all the filters used in the proposed model, Median and weighted median filters show outperforming results than other filters for all the noise type at all noise levels. Table 7 and Table 8 show the comparison between HM-LCE technique [17] and proposed model against salt and pepper noise at noise level 0.005 and 0.5, respectively. On comparison with HM-LCE technique, it is clear from both the proposed method gives outperforming results than HM-LCE technique at low as well as high noise variance level. Weighted Median filter + CLAHE technique gives the best results in all the perspective. Figs. 13–16 show the comparison between proposed technique and HM-LCE technique on the basis of PSNR, SSIM, CoC and EPI respectively at noise variance 0.005. It is clear from the Figs. 13–16 that the proposed algorithm gives better results than HM-LCE technique.

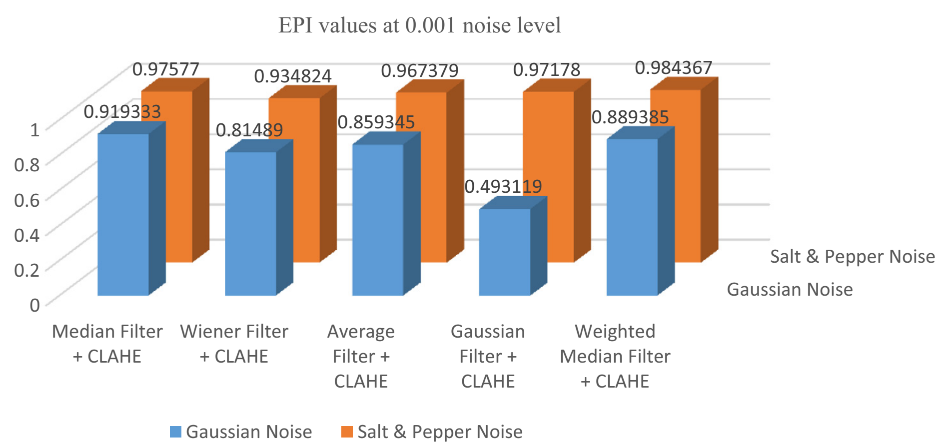

Fig. 12. Showing EPI values at 0.001 noise level.

Table 7
Showing comparison between HM-LCE technique and proposed model against salt and pepper noise at noise level 0.005.

Performance Parameters	Techniques					
	HM-LCE [17]	Median Filter + CLAHE	Gaussian Filter + CLAHE	Weighted Median Filter + CLAHE	Wiener Filter + CLAHE	Average Filter + CLAHE
PSNR (in dB)	33.347485	35.350071	32.156432	36.189543	31.684723	31.977563
SSIM	0.960207	0.962201	0.958962	0.971790	0.901265	0.913341
CoC	0.994712	0.994919	0.994516	0.995936	0.992425	0.991667
EPI	0.959674	0.969445	0.954491	0.972134	0.911346	0.955223

Table 8
Showing comparison between HM-LCE technique and proposed model against salt and pepper noise at noise level 0.5.

Performance Parameters	Techniques					
	HM-LCE [17]	Median Filter + CLAHE	Gaussian Filter + CLAHE	Weighted Median Filter + CLAHE	Wiener Filter + CLAHE	Average Filter + CLAHE
PSNR (in dB)	32.649113	33.775695	20.614237	34.824575	20.500871	20.964781
SSIM	0.912563	0.944113	0.209523	0.949867	0.316455	0.489056
CoC	0.977153	0.984528	0.857529	0.991619	0.856218	0.915224
EPI	0.837165	0.854892	0.511638	0.927736	0.494759	0.618762

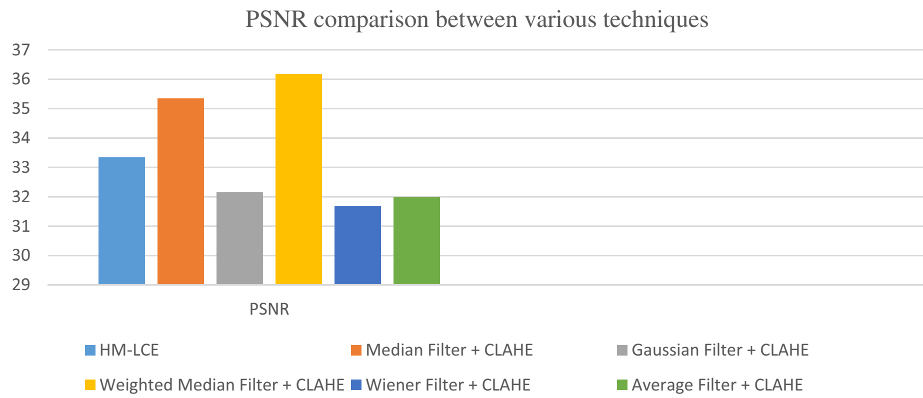

Fig. 13. Showing comparison between HM-LCE [17] and proposed algorithm in terms of PSNR.

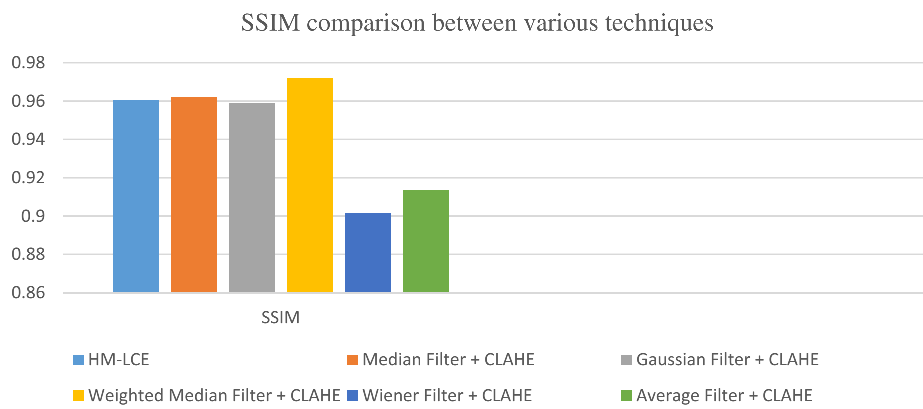

Fig. 14. Showing comparison between HM-LCE [17] and proposed algorithm in terms of SSIM.

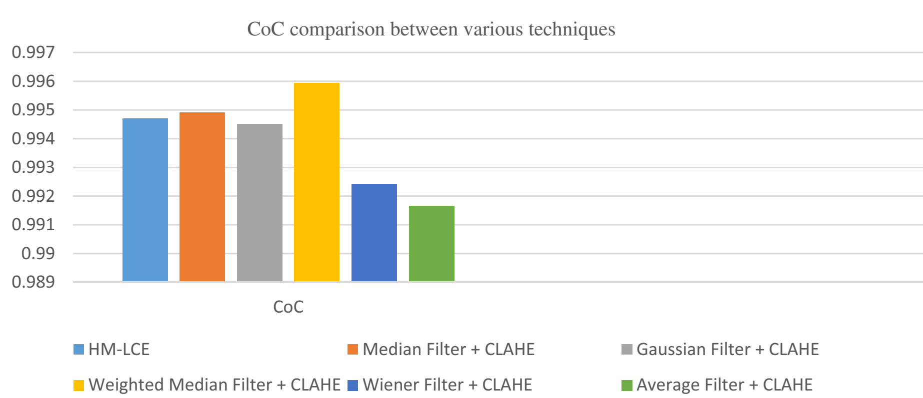

Fig. 15. Showing comparison between HM-LCE[17] and proposed algorithm in terms of CoC.

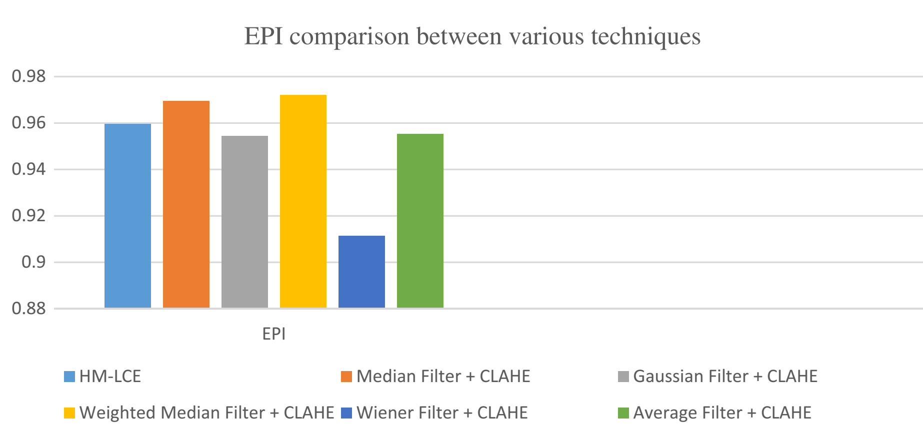

Fig. 16. Showing comparison between HM-LCE [17] and proposed algorithm in terms of EPI.

On analyzing Table 7, it is found out that the proposed method, considering Weighted Median filter with CLAHE technique gives 7.85% improvement in PSNR, 1.19% improvement in terms of SSIM, 0.12% improvement in CoC and 1.28% improvement in EPI when compared to HM-LCE [17] method.

5. Conclusion and future directions

A new medical fundus image enhancement algorithm was proposed in this paper. Fundus RGB image was first decomposed into its individual red, green and blue channels and then different filtering techniques were applied along with CLAHE to de-noise and improve contrast of the image. At last, components were merged together to form enhanced RGB fundus image. It is proved that the proposed technique removes noise and enhances contrast in fundus images effectively. Various performance and quality parameters like PSNR, SSIM, CoC and EPI are used to prove the effectiveness of the proposed method. Results showed that the performance of the proposed model is quite impressive in terms of the performance parameters value and also outperforms the state of the art method in terms of performance parameters. In future, the proposed algorithm may be applied to other colored medical images.

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Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.optlastec.2018.06.061.

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