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Image Denoising by using Modified SGHP Algorithm

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Article Info	ABSTRACT
	In real time applications, image denoising is a predominant task. This task makes adequate preparation for images looks prominent. But there are several denoising algorithms and every algorithm has its own distinctive attribute based upon different natural images. In this paper, we proposed a perspective that is modified parameter in S-Gradient Histogram Preservation denoising method. S-Gradient Histogram Preservation is a method to compute the structure gradient histogram from the noisy observation by taking different noise standard deviations of different images. The performance of this method is enumerated in terms of peak signal to noise ratio and structural similarity index of a particular image. In this paper, mainly focus on peak signal to noise ratio, structural similarity index, noise estimation and a measure of structure gradient histogram of a given image.

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1.   INTRODUCTION

Images affected by unwanted noise from different sources like traditional film cameras and digital cameras. These noise elements will create some serious issues for further processing of images in practical applications such as computer vision, artistic work or marketing and also in many fields. So, different classification of noises likes salt and pepper, Gaussian, shot and quantization. In salt and pepper noise, all the images are constructed with pixels in a two-dimensional array. In that pixel to pixel, the difference is observed when the image is affected by noise that is in terms of intensity of neighbouring pixels. So, it is identified pixels and neighbouring pixels only the small number of pixels is affected in an image. The salt and pepper noise is clearly identified in an image by it contains black and white speckles. When we viewed an image which is affected by salt and pepper noise, the image contains black and white dots, hence it terms as salt and pepper noise.

In Gaussian noise, noisy pixel value will be a small change of the original value of a pixel. A diagram consisting of rectangles whose area is proportional to the frequency of a variable or PSNR and whose width is equal to the different noise standard deviations is a histogram. Other Gaussian models are present mainly depends upon the central limit theorem shows that addition of different noises from different sources to associated with Gaussian distribution.

Denoising of an image involves the manipulation of the image data to produce a visually high-quality image. There are numerous models that have been published so far which are used for denoising an image [1]. Sparse representation for image restoration [2], [3], Total variation model [4], Wavelet-based model [5], BM3D [6] model and histogram preservation algorithm [7] are some of them. Each method has its own characteristics, benefit and also demerit. Two major classes of denoising methods are (a) model based

and (b) Learning-based method. In the model, based method, a statistical/mathematical model will be used for the denoising. Whereas in Learning based method, an algorithm will be trained by using sufficient parameters and then the model is allowed to work based on its weightage function [8].

2. PROPOSED METHOD

In the present work, the denoising is done in a more realistic way as in practical situations, only the noisy image will be available. A noisy image is taken as input to the algorithm is shown in Figure 1. We have adopted patch-based noise level estimation algorithm by Xinhao Liu et al [9]. Patches are generated from the single noisy image and its weak textured patches are identified. The Noise level is estimated from the Principal Component Analysis [10], [11].
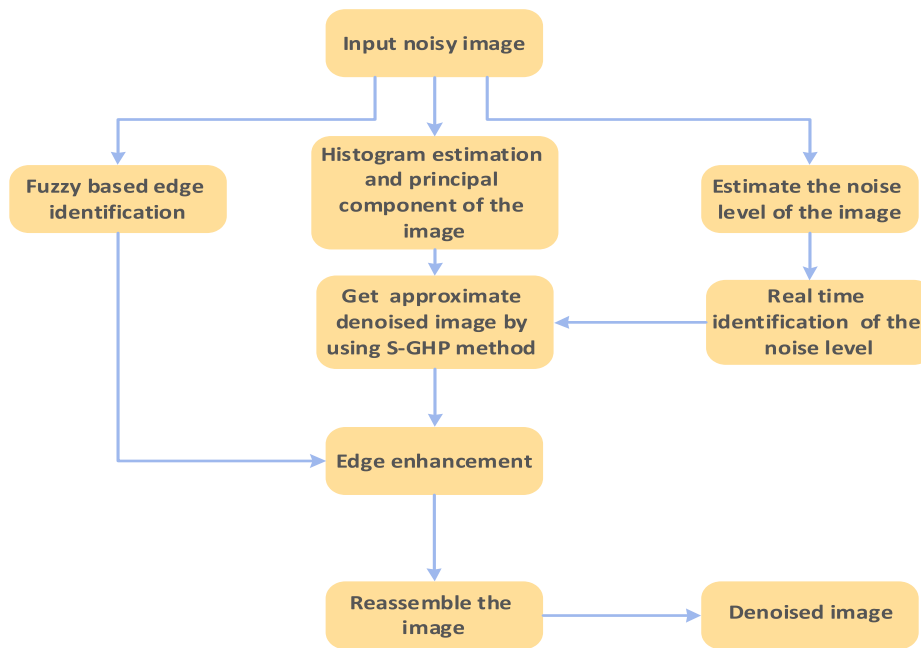

Figure 1. Flowchart of the proposed algorithm

In most of the denoising method, it is seen that, after its implementation, the image will be blurred than that of the original image. Also, the edge of the denoised image gets smoothened and will have lesser details than that of the original image. A study has been conducted to find the edge of the original and noisy image by using sample data. In this study, it is found that there fewer details of edges in the denoised image. To address this issue, we have employed fuzzy based edge detection and then the edge is enhanced in the denoised image that we have received by using our method. Now the denoising is performed based on the modified parameter S-GHP focus on smoothing of the image by implementing the gradient histogram preservation.

2.1. Noise estimation

Input image is decomposed into overlapping patches by

$$y_i = z_i + n_i \tag{1}$$

Where z_i has represented the original image patch with the ith pixel at its centre and $\mathbf{y}_i$ is the observed vectorized patch corrupted by zero-mean Gaussian noise [12] vector n_i. The objective of the noise level estimation is to compute the standard deviation σ_n of the noisy image is given. In this method, the Horizontal and vertical derivative ($D_h y$ and $D_v y$ are calculated and then the gradient vector $\mathbf{G}_y$ is obtained by taking

$[D_h y D_v y]$.

Now the covariance matrix Cov_y is calculated by

$$Cov_y = G_y^T G_y \tag{2}$$

The Directional Derivative in both Horizontal Direction and Vertical Direction is calculated and trace of Gradient Matrix is calculated by

$$D = tr\left(D_h \times D_h + D_v \times D_v\right) \tag{3}$$

Now the initial noise level is estimated by computing the First component of Eigenvalue of the covariant matrix. This is taken as the initial value for calculating noise level by using iterative noise estimation [13]

$$\tau_0 = \Gamma_{inv}\left(\delta, \alpha, \beta\right) \tag{4}$$

Now the noise level estimation form weak textured patch is performed [14]. For this Inverse gamma function $\tau_0 = \Gamma_{inv}\left(\delta, \alpha, \beta\right)$ with the shape parameter α and scale parameter β is used

$$\tau = \sigma\left(k - 1\right) \times \tau_0 \tag{5}$$

If the selected patch size is less than τ then the patch is selected as a Weak Texture Patch. Maximum eigenvalues of the gradient covariance are computed when the strength of image patches are to be estimated.

Now the Noise Level of Weak Texture Patch is found by using the EigenValue of Covariance Matrix of the weak textured patch and its principal component [15], [16]. The iteration is continued until the difference between sigma in step n-1 and n is less than 10^{-4}.

2.2. Image denoising frame work
The noisy image is defined by the Equation (6) that is

$$y = x + v \tag{6}$$

Where the noisy image is represented with y, the Original image is represented with x, Additive white Gaussian noise (AWGN) with zero mean is represented with v and the standard deviation is denoted with σ. The main purpose of image denoising is to compute the clean image x from noisy image y. The vibrational method is the best denoising approach is obtained by

$$\hat{x} = \arg\min_x \left\{ \frac{1}{2\sigma^2}\|y - x\|^2 + \lambda R(x) \right\} \tag{7}$$

Where regularization term is denoted with $R(x)$ and positive constant is with λ. The $R(x)$ relies on existing images.

Image denoising methods have a general issue that image quality scale characteristics such as structures like texture will be over-smoothed. The original image has substantial gradients than the gradients of over smoothed image. Inherently, a structure like texture doesn't depend on over smoothing and the texture have an indistinguishable gradient distribution of x for good evaluation of x. For this reason, we propose a modified parameter in S-GHP method by taking different database images. The gradient histogram of the denoised image $\hat{x}$ very close to the reference histogram h_r based on the compute of the gradient histogram of x, denote h_r. The following proposed S-GHP denoising method is defined as

$$\hat{x} = \arg\min_{x,F} \left\{ \frac{1}{2\sigma^2}\|y - x\|^2 + \lambda R(x) + \mu\|F\left(\nabla x\right) - \nabla x\|^2 \right\} \text{ s.t. } h_F = h_r \tag{8}$$

Where the odd function is F uniformly non-descending, h_F is histogram of the transformed gradient image $|F (\nabla x)|$, ∇ is gradient operator and positive constant is μ. The proposed modified parameter in S-GHP method acquires the alternating optimization approach. For given F, then $\nabla x_0 = F(\nabla x)$ and update to x. For given x, based on equation $\nabla x_0 = F(\nabla x)$ F is updated by using modified parameter S-GHP specification operator.

Another case in the S-GHP method is what way to perceive the reference histogram h_r of unspecified image x. Computation of h_r depends on the noisy observation y. For finding h_r, new methods are proposed first one is a regularized deconvolution method and the second one is an iterative deconvolution method from the noisy image [17] depends upon different noise levels [18]. After reference histogram is attained, then modified parameter in S-GHP method is applied for image denoising.

3.   S-GRADIENT HISTOGRAM PRESERVATION DENOISING METHOD

S-GHP is a proposed method based on the patch method. Let $x_i = R_i x$ is a patch take out at position i = 1, 2... N, where patch extraction operator is R_i and N indicates pixels in the image. Given a dictionary D, infrequently encode the patch x_i over D, gives the sparse coding vector α_i. Image patches having coding vectors are attained, the image x can be renovated by

$$x = D \circ \alpha \overset{\Delta}{=} \left(\sum_{i=1}^{N} R_i^T R_i \right)^{-1} \sum_{i=1}^{N} R_i^T D \alpha_i \tag{9}$$

Where concatenation belongs to α for all the values of α_i.

Images are taken from databases are testing modified parameter S-GHP Method. So, the combination regarding identical priors refines the modified parameter S-GHP. For example, the estimation procedures in [19]-[23] merge image non-local NSS prior to image local sparsity prior and we have better denoising results. In the method modified parameter in S-GHP, the R(x), which is sparse non-local regularization term proposed in the non-locally centralized sparse representation (NCSR) model [24] is

$$R(x) = \sum_i \left\| \alpha_i - \beta_i \right\|_1 \tag{10}$$

Where weighted average of α_i^q is β_i then

$$\beta_i = \sum_q w_i^q \alpha_i^q \tag{11}$$

and coding vector of the qth nearest patch (x_i^q) to x_i is α_i^q. Weight is denoted as $w_i^q = \frac{1}{W} \exp\left(-\frac{1}{h} \left\| \hat{x}_i - \hat{x}_i^q \right\|^2 \right)$, where the predefined constant is h and normalization factor is W.

The formula for modified parameter S-GHP method is defined as by using Equation (3) is

$$\hat{x} = \arg\min_{x,F} \left\{ \frac{1}{2\sigma^2} \left\| y - x \right\|^2 + \lambda \sum_i \left\| \alpha_i - \beta_i \right\|_1 + \mu \left\| F(\nabla x) - \nabla x \right\|^2 \right\} \tag{12}$$

Such that

$$x = D \circ \alpha, \; h_F = h_r \tag{13}$$

From the S-GHP method, using Equation (7), $F (\nabla x)$ is approximate to ∇x when histogram parameter leads to larger and we can achieve required histogram parameter for S-GHP. When the histogram h_F of $|F (\nabla x)|$ is

required and approximate to the h_r, (histogram of $\nabla x = h_r$) then acquire the required gradient histogram parameter for S-GHP.

4. RESULTS AND DISCUSSION

4.1. Performance analysis

The proposed method is verified by using three different images like image-3, image-4 and image-5. Here, three images are grey-scale images having a range between 0 to 255. For image-3, image-4 and image-5 are taking five different noise levels are 20, 25, 30, 35 and 40 with respect to that different PSNR and SSIM values are obtained. In Figure 2, Figure 3 and Figure 4, there is original image and different enhanced images with different noise levels. In Figure 5, numbers of iterations are increased then PSNR value increases. When noise standard deviation is increased then the structural similarity index is decreased. From the Figure 5, image-3 having more structural similarity index. In Table 1, Table 2 and Table 3 give the structural similarity index and PSNR values of image-3, image-4 and image-5 by using a modified parameter in S-GHP method.

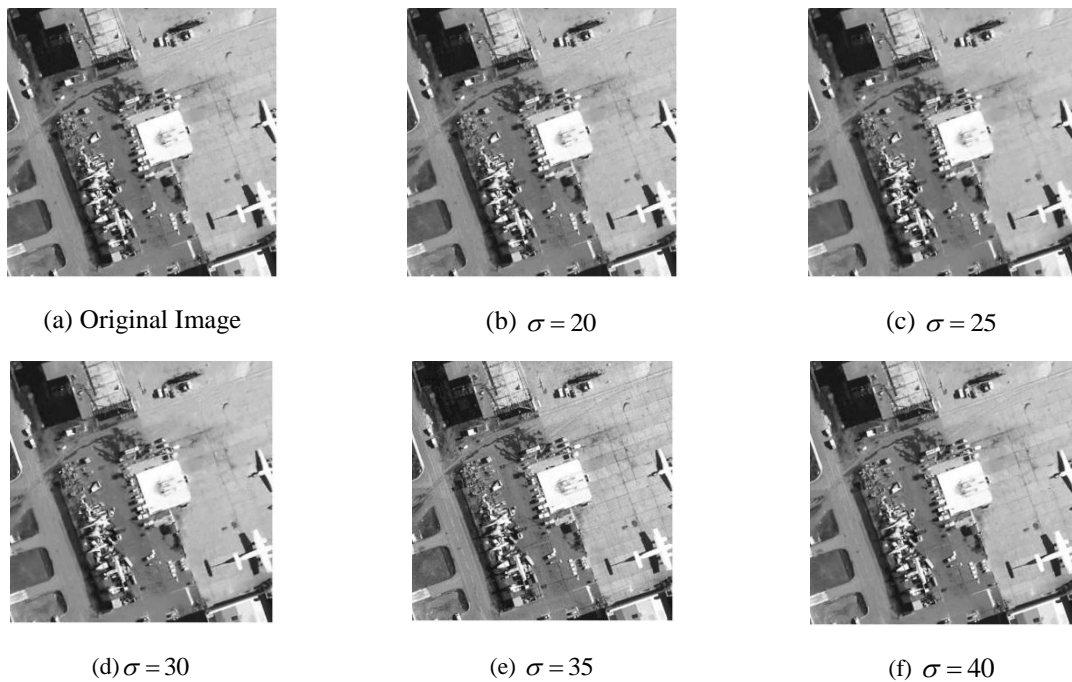| (a) Original Image	(b) $\sigma = 20$	(c) $\sigma = 25$
(d) $\sigma = 30$	(e) $\sigma = 35$	(f) $\sigma = 40$

Figure 2. Denoised image-3 under different noise levels

Table 1. Structural similarity index (SSIM) and PSNR (dB) results of s-gradient histogram preservation of image-3

No. of Iterations	Sigma=20 S-GHP	Sigma=25 S-GHP	Sigma=30 S-GHP	Sigma=35 S-GHP	Sigma=40 S-GHP
1	27.766	26.440	25.297	24.842	24.031
	0.738	0.678	0.621	0.600	0.556
2	27.957	26.771	25.779	25.400	24.766
	0.748	0.698	0.651	0.640	0.608
3	28.093	27.015	26.138	25.684	25.127
	0.755	0.713	0.675	0.660	0.637
4	28.161	27.147	26.334	25.736	25.190
	0.757	0.719	0.687	0.660	0.638
5	28.174	27.193	26.406	25.727	25.186
	0.755	0.719	0.689	0.656	0.634
6	28.157	27.192	26.417	25.708	25.169
	0.752	0.716	0.687	0.654	0.632
Average PSNR	28.051	26.959	26.061	25.516	24.911
and SSIM	0.750	0.707	0.668	0.645	0.617

| (a) Original Image | (b) $\sigma = 20$ | (c) $\sigma = 25$ | (d) $\sigma = 30$ | (e) $\sigma = 35$ | (f) $\sigma = 40$ |

Figure 3. Denoised image-4 using under different noise levels

| (a) Original Image | (b) $\sigma = 20$ | (c) $\sigma = 25$ |

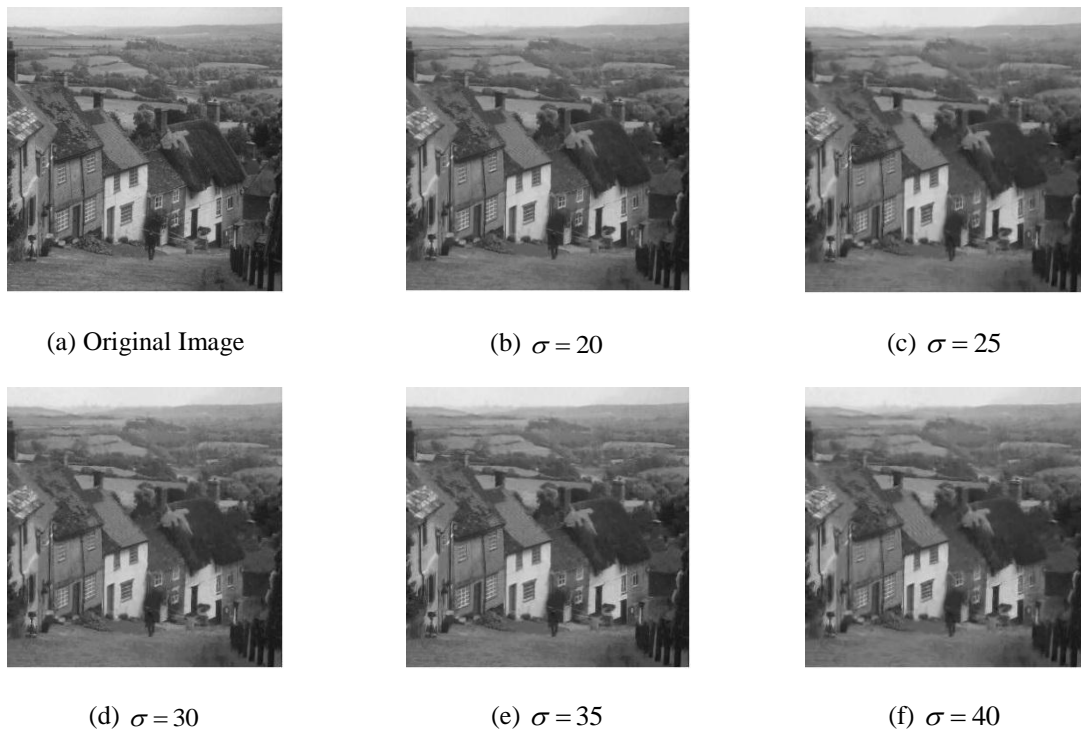| (d) $\sigma = 30$ | (e) $\sigma = 35$ | (f) $\sigma = 40$ |

Figure 4. Denoised image-5 using under different noise levels

Table 2. Structural similarity index (SSIM) and PSNR (dB) results of s-gradient histogram preservation of image-4

No. of Iterations	Sigma=20 S-GHP	Sigma=25 S-GHP	Sigma=30 S-GHP	Sigma=35 S-GHP	Sigma=40 S-GHP
1	26.449	25.120	24.033	23.495	22.770
	0.772	0.708	0.648	0.615	0.568
2	26.547	25.256	24.213	23.715	23.068
	0.780	0.720	0.663	0.637	0.595
3	26.638	25.396	24.405	23.927	23.326
	0.788	0.733	0.681	0.662	0.627
4	26.704	25.506	24.556	24.020	23.421
	0.795	0.745	0.699	0.673	0.639
5	26.741	25.577	24.654	24.036	23.428
	0.800	0.753	0.711	0.674	0.638
6	26.744	25.600	24.689	24.018	23.398
	0.801	0.757	0.715	0.672	0.637
Average PSNR and SSIM	26.637	25.409	24.425	23.868	23.235
	0.789	0.736	0.686	0.655	0.617

(a) PSNR of image-3

(b) PSNR of image-4

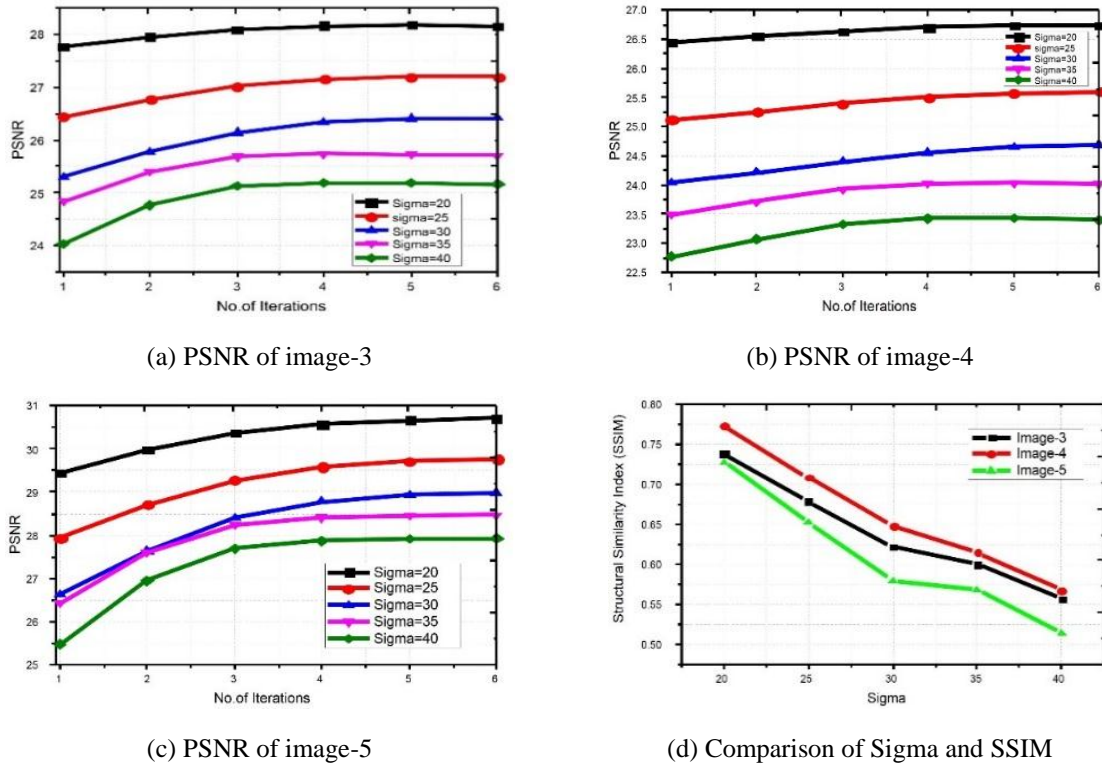(c) PSNR of image-5

(d) Comparison of Sigma and SSIM

Figure 5. Variation of PSNR of image-3, image-4, image-5 using different sigma values and its SSIM

Table 3. Structural similarity index (SSIM) and PSNR (dB) results of s-gradient histogram preservation of image-5

No. of Iterations	Sigma=20 S-GHP	Sigma=25 S-GHP	Sigma=30 S-GHP	Sigma=35 S-GHP	Sigma=40 S-GHP
1	29.451	27.936	26.617	26.421	25.469
	0.728	0.652	0.580	0.568	0.513
2	29.972	28.703	27.637	27.606	26.939
	0.760	0.701	0.647	0.655	0.620
3	30.361	29.280	28.398	28.243	27.690
	0.785	0.742	0.703	0.709	0.687
4	30.570	29.585	28.779	28.403	27.863
	0.799	0.764	0.733	0.722	0.701
5	30.667	29.711	28.930	28.454	27.914
	0.804	0.772	0.744	0.724	0.704
6	30.707	29.761	28.986	28.473	27.930
	0.806	0.774	0.747	0.726	0.706
Average PSNR	30.288	29.163	28.224	27.933	27.300
and SSIM	0.780	0.734	0.692	0.684	0.655

4.2. Comparative analysis

The existing methods and proposed method verified by using three different images like image-3, image-4 and image-5 with five different noise levels are 20, 25, 30, 35 and 40. Performance of these methods is mentioned in terms of Peak signal to noise ratio and structural similarity index [25], [26] as shown in Table 4.

Table 4. Comparison of Existing methods and proposed method in terms of PSNR (dB) results

Image No	Existing Methods		Proposed Method
	B-GHP PSNR	APBS PSNR	Modified S-GHP
PSNR			
3	27.01	26.05	28.051
4	25.49	25.11	26.637
5	29.90	28.66	30.288

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5. CONCLUSION

In this paper, the proposed method modified Structure gradient histogram preservation used for enhancing the different images by taking different noise levels like 20, 25, 30 and 40. Based on the noise levels, the PSNR and SSIM values are improved compared to other methods like APBS and B-GHP. All the above-mentioned results proved that the modified parameter S-GHP is better compared to B-GHP and APBS.

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