

Image Denoising by using Modified SGHP Algorithm

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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].

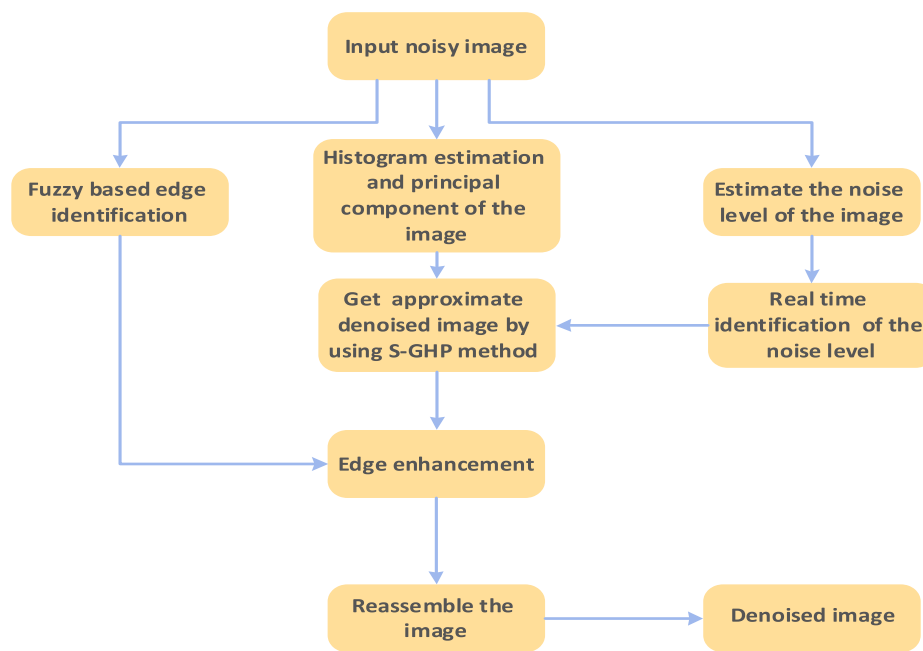


Figure 1. Flowchart of the proposed algorithm

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

$$y_i = z_i + n_i \quad (1)$$

Where z_i has represented the original image patch with the i th pixel at its centre and 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 G_y is obtained by taking $[D_h y D_v y]$.

Now the covariance matrix Cov_y is calculated by

$$Cov_y = G_y^T G_y \quad (2)$$

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

$$D = tr(D_h \times D_h + D_v \times D_v) \quad (3)$$

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]

$$\tau_0 = \Gamma_{inv}(\delta, \alpha, \beta) \quad (4)$$

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

$$\tau = \sigma(k-1) \times \tau_0 \quad (5)$$

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

$$y = x + v \quad (6)$$

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

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

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

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

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 $i = 1, 2, \dots, N$, 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

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

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

$$R(x) = \sum_i \|\alpha_i - \beta_i\|_1 \quad (10)$$

Where weighted average of α_i^q is β_i then

$$\beta_i = \sum_q w_i^q \alpha_i^q \quad (11)$$

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

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

Such that

$$x = D \circ \alpha, \quad h_F = h_r \quad (13)$$

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.

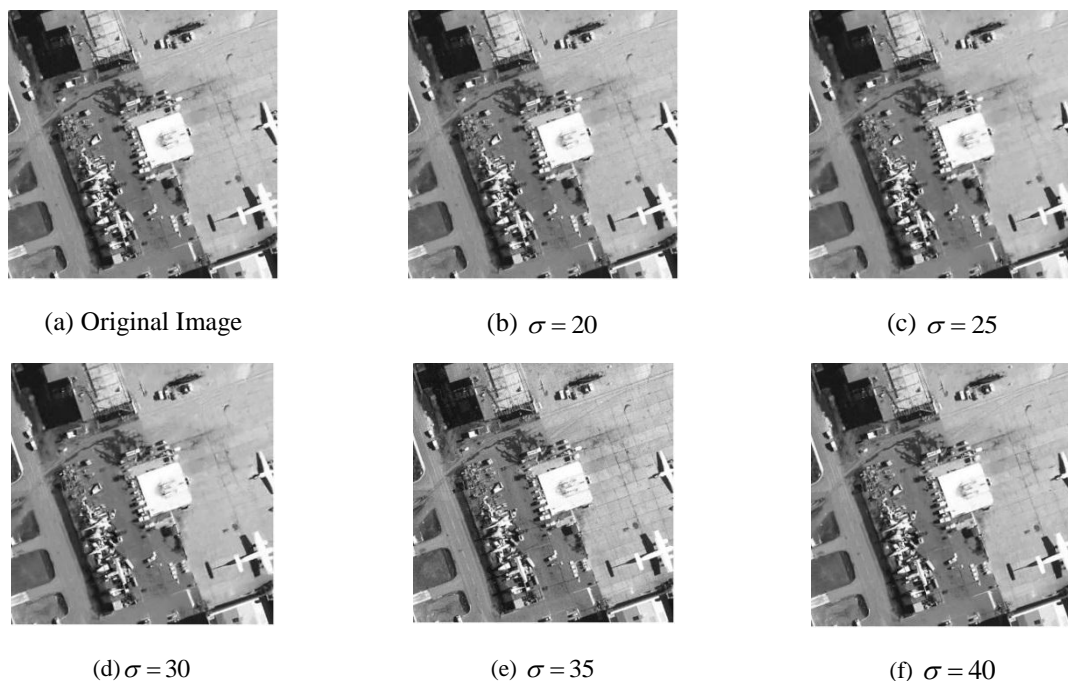


Figure 2. Denoised image-3 under different noise levels

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 0.738	26.440 0.678	25.297 0.621	24.842 0.600	24.031 0.556
2	27.957 0.748	26.771 0.698	25.779 0.651	25.400 0.640	24.766 0.608
3	28.093 0.755	27.015 0.713	26.138 0.675	25.684 0.660	25.127 0.637
4	28.161 0.757	27.147 0.719	26.334 0.687	25.736 0.660	25.190 0.638
5	28.174 0.755	27.193 0.719	26.406 0.689	25.727 0.656	25.186 0.634
6	28.157 0.752	27.192 0.716	26.417 0.687	25.708 0.654	25.169 0.632
Average PSNR and SSIM	28.051 0.750	26.959 0.707	26.061 0.668	25.516 0.645	24.911 0.617

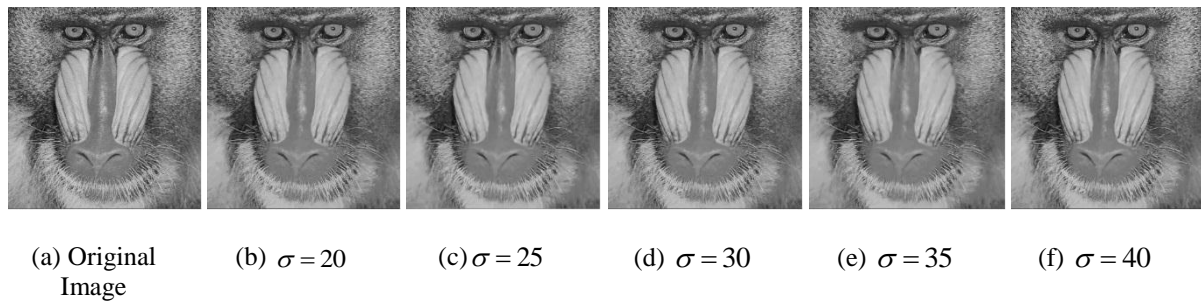


Figure 3. Denoised image-4 using under different noise levels

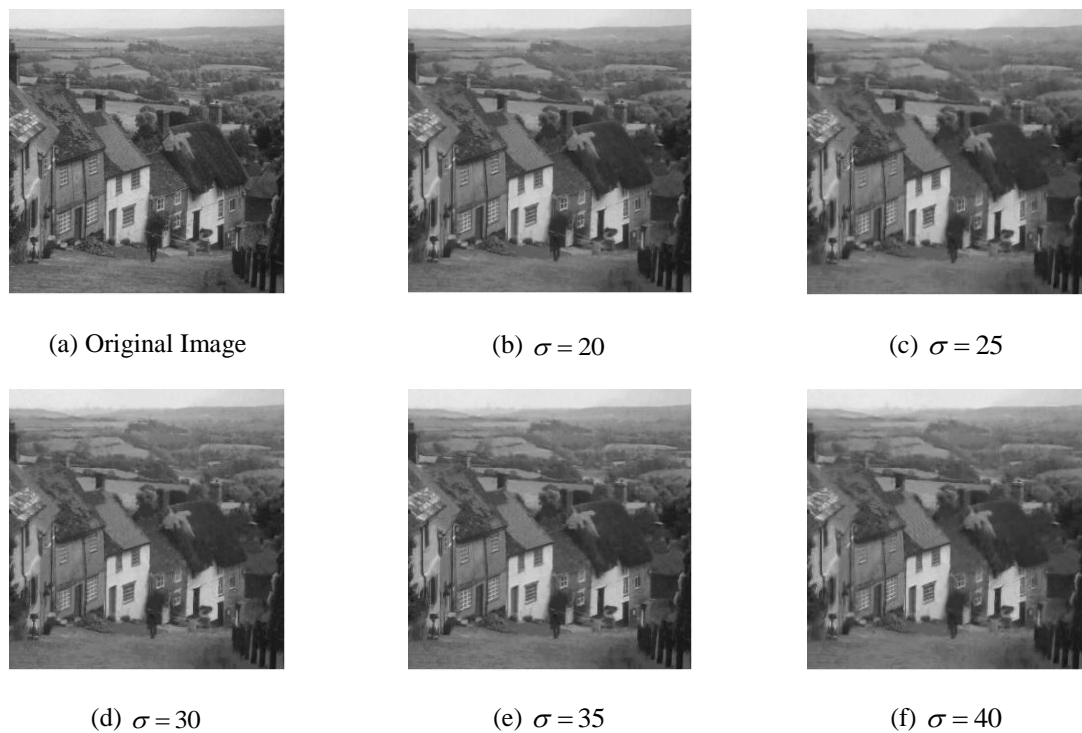


Figure 4. Denoised image-5 using under different noise levels

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 0.772	25.120 0.708	24.033 0.648	23.495 0.615	22.770 0.568
2	26.547 0.780	25.256 0.720	24.213 0.663	23.715 0.637	23.068 0.595
3	26.638 0.788	25.396 0.733	24.405 0.681	23.927 0.662	23.326 0.627
4	26.704 0.795	25.506 0.745	24.556 0.699	24.020 0.673	23.421 0.639
5	26.741 0.800	25.577 0.753	24.654 0.711	24.036 0.674	23.428 0.638
6	26.744 0.801	25.600 0.757	24.689 0.715	24.018 0.672	23.398 0.637
Average PSNR and SSIM	26.637 0.789	25.409 0.736	24.425 0.686	23.868 0.655	23.235 0.617

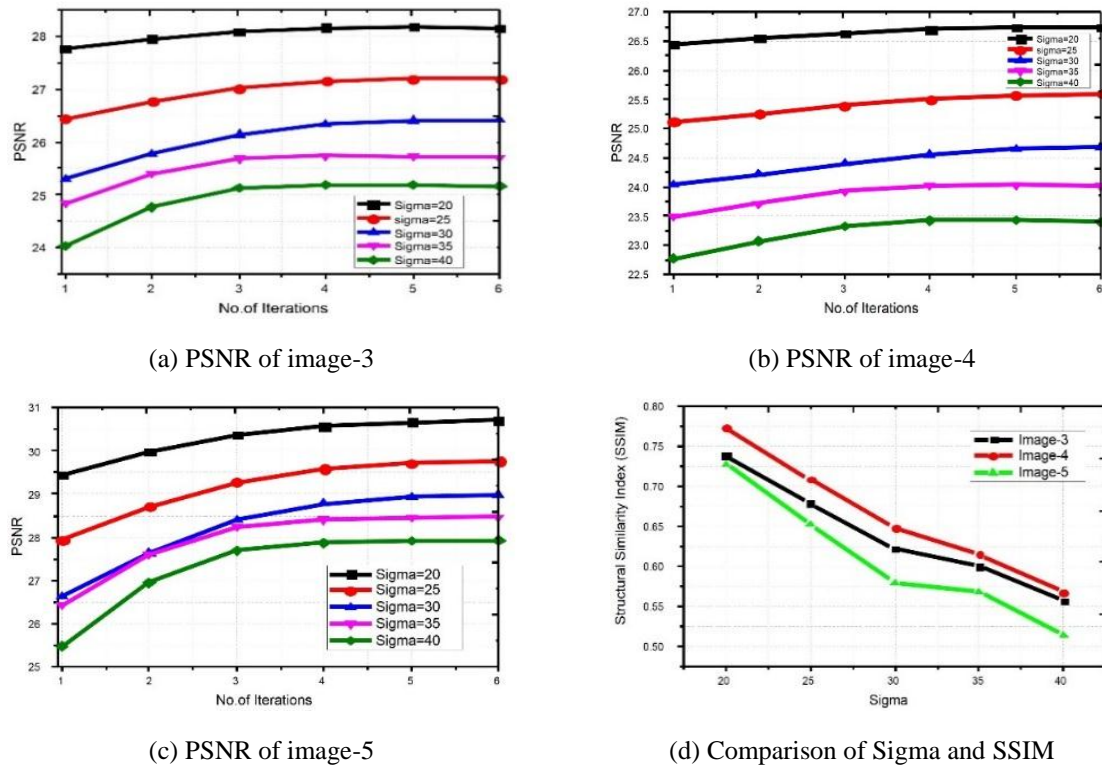


Figure 5. Variation of PSNR of image-3, image-4, image-5 using different sigma values and its SSIM

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 0.728	27.936 0.652	26.617 0.580	26.421 0.568	25.469 0.513
2	29.972 0.760	28.703 0.701	27.637 0.647	27.606 0.655	26.939 0.620
3	30.361 0.785	29.280 0.742	28.398 0.703	28.243 0.709	27.690 0.687
4	30.570 0.799	29.585 0.764	28.779 0.733	28.403 0.722	27.863 0.701
5	30.667 0.804	29.711 0.772	28.930 0.744	28.454 0.724	27.914 0.704
6	30.707 0.806	29.761 0.774	28.986 0.747	28.473 0.726	27.930 0.706
Average PSNR and SSIM	30.288 0.780	29.163 0.734	28.224 0.692	27.933 0.684	27.300 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 Modified S-GHP
	B-GHP PSNR	APBS PSNR	
3	27.01	26.05	28.051
4	25.49	25.11	26.637
5	29.90	28.66	30.288

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.

REFERENCES

- [1] Buades, B. Coll, and J. Morel, "A review of image denoising methods, with a new one", *Multiscale Model. Simul.*, vol. 4, no. 2, pp. 490530, 2005.
- [2] K. Dabov, A. Foi, V. Katkovnik, and K. Egiazarian, "Image denoising by sparse 3-D transform-domain collaborative filtering", *IEEE Trans. Image Process.*, vol. 16, no. 8, pp. 2080-2095, Aug. 2007.
- [3] W. Dong, L. Zhang, G. Shi, and X. Li, "Nonlocally centralized sparse representation for image restoration", *IEEE Trans. Image Process.*, vol. 22, no. 4, pp. 1620-1630, Apr. 2013.
- [4] L. Rudin, S. Osher, and E. Fatemi, "Nonlinear total variation based noise removal algorithms", *Phys. D*, vol. 60, nos. 14, pp. 259-268, Nov. 1992.
- [5] Pankaj Hedao and Swati S Godbole, "Wavelet Thresholding Approach for Image Denoising", *International Journal of Network Security Its Applications (IJNSA)*, vol. 3, no. 4, July 2011.
- [6] H. C. Burger, C. J. Schuler, and S. Harmeling, "Image denoising: Canplain neural networks compete with BM3D", in *Proc. Int. Conf. CVPR*, Jun. 2012, pp. 2392-2399.
- [7] S. Subha, I. Jesudass and K. Thanushkodi, "Image denoising by using iterative histogram and preservative algorithm", *ARPJ Journal of Engineering and Applied Sciences*, vol. 10, no. 11, June 2015.
- [8] P. Koltsov, "Comparative study of texture detection and classification algorithms," *Comput. Math. Math. Phys.*, vol. 51, no. 8, pp. 1460-1466, 2011.
- [9] Liu, Xinhao, Mitsuru Tanaka, and Masatoshi Okutomi, "Noise level estimation using weak textured patches of a single noisy image", *Image Processing (ICIP), 2012 19th IEEE International Conference on. IEEE*, 2012.
- [10] S. Pyatykh, J. Hesser and L. Zheng, "Image Noise Level Estimation by Principal Component Analysis," in *IEEE Transactions on Image Processing*, vol. 22, no. 2, pp. 687-699, Feb. 2013.doi: 10.1109/TIP.2012.2221728.
- [11] Jolliffe, "Principal component analysis," in *Encyclopedia of Statistics in Behavioral Science*. New York: Springer-Verlag, 2002.
- [12] D. Pastor, "A theoretical result for processing signals that have unknown distributions and priors in white Gaussian noise," *Comput. Stat. Data Anal.*, vol. 52, no. 6, pp. 3167-3186, 2008.
- [13] Liu, "A fast method of estimating Gaussian noise," in *Proc. 1st Int. Conf. Inf. Sci. Eng.*, 2009, pp. 441-444.
- [14] C. Kervrann and J. Boulanger, "Optimal spatial adaptation for patch-based image denoising," *IEEE Trans. Image Process.*, vol. 15, no. 10, pp. 2866-2878, Oct. 2006.
- [15] R. Bilcu and M. Vehvilainen, "New method for noise estimation in images," in *Proc. IEEE-Eurasip Nonlinear Signal Image Process.*, May 2005.
- [16] G. Smith and I. Burns, "Measuring texture classification algorithms," *Pattern Recognit. Lett.*, vol. 18, no. 14, pp. 1495-1501, 1997.
- [17] D. Makovoz, "Noise variance estimation in signal processing," in *Proc. IEEE Int. Symp. Signal Process. Inf. Technol.*, Jul. 2006, pp. 364-369.
- [18] M. Uss, B. Vozel, V. Lukin, S. Abramov, I. Baryshev, and K. Chehdi, "Image informative maps for estimating noise standard deviation and texture parameters," *EURASIP J. Adv. Signal Process.*, vol. 2011, pp. 806516-1-806516-12, Mar. 2011.
- [19] M. Elad and M. Aharon, "Image denoising via sparse and redundant representations over learned dictionaries", *IEEE Trans. Image Process.*, vol. 15, no. 12, pp. 3736-3745, Dec. 2006.
- [20] J. Jancsary, S. Nowozin, and C. Rother, "Loss-specific training of nonparametric image restoration models: a new state of the art," in *Proc. Eur. Conf. Comput. Vis.*, 2012.
- [21] M. Hashemi and S. Beheshti, "Adaptive noise variance estimation in Bayes shrink", *IEEE Signal Process. Lett.*, vol. 17, no. 1, pp. 12-15, Jan. 2010.
- [22] T. Tasdizen, "Principal components for non-local means image denoising," in *Proc. IEEE Int. Conf. Image Process.*, Feb. 2008, pp. 1728-1731.
- [23] V. Rajanesh and Kollem Sreedhar, "A New Approach to Image Denoising by Patch-Based Algorithm", in *International Journal of Advanced Research in Computer and Communication Engineering*, vol. 5, no. 12, pp. 212-218, 2016.
- [24] Yasmin, Sabina, and Md Masud Rana, "Performance Study of Soft Local Binary Pattern over Local Binary Pattern under Noisy Images", *International Journal of Electrical and Computer Engineering*, vol. 6, no. 3 (2016), p. 1161.
- [25] Omidiora, E. O., S. O. Olabiyisi, J. A. Ojo, Abayomi-Alli Adebayo, O. Abayomi-Alli, and K. B. Erameh, "Facial Image Verification and Quality Assessment System-FaceIVQA", *International Journal of Electrical and Computer Engineering*, vol. 3, no. 6 (2013), p. 863.
- [26] Subramanyam, M. V., and Giri Prasad, "A New Approach for SAR Image Denoising", *International Journal of Electrical and Computer Engineering*, vol. 5, no. 5 (2015).