Regressive Damped Linear Filterative Spatial Convoluted Edge Smoothing for Image Quality Enhancement

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Abstract

Image quality enhancement aims to improve the rich details from degraded images, which is applied in many fields, such as medical imaging, video surveillance, criminal investigations, remote sensing, etc. Natural images captured under varying light conditions have poor contrast, low brightness, hidden colors, and high noise. Therefore, image processing methods are developed for image enhancement. Image processing is the method of performing the analysis and manipulation of digitized images for increasing the image quality by minimizing noise and contrast enhancement. Numerous techniques have been developed for image enhancement. However, these techniques are only suitable for enhancing the images but it fails to remove the artifact-free quality improved results for various other types of images. Therefore, to meet this aim, in this paper, an automatic image enhancement technique called Piecewise Regressive Damped Linear Filterative Spatial Convoluted Edge Smoothing (RDL-SCES) is introduced for image preprocessing to enhance the image quality with the higher peak signal-to-noise ratio and minimum error. The proposed RDL-SCES technique performs image preprocessing that includes two processes namely filtering and edge smoothing. In the RDL-SCES technique, number of natural images are collected from the dataset and considered as input. Then, every natural image gets pre-processed by using Piecewise regressive damped Bryson–Frazier Fixed Interval Filter. The designed filter employs the series of measurements observed over the different states including the statistical noise. The proposed filtering technique performs image pixels analysis at every observation state to determine the smoothed image and covariance with help of piecewise regression and the Damped Least-Squares method. After the noise removal, the RDL-SCES technique performs the edge smoothing by using spatial convolutive Marr–Hildreth edge smoothing. This in turn helps to enhance the image quality. Experimental evaluation is carried out using natural images with different factors such as mean square error, peak signal-to-noise ratio, pre-processing time, and memory consumption with respect to a number of natural images and sizes.

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1. INTRODUCTION

Image enhancement and restoration are the fundamental processing steps of real vision systems. Therefore, the main purpose is to enhance the visual quality of images and offers reliable information for subsequent visual decision-making. Images collected in low-brightness environments often direct to poor visibility and reveal artifacts. These artifacts affect the visual observation of the human eye. The existing method-based image enhancements technique is faced many problems for accurate preprocessing.

A new Adaptive Weighted Guided Image Filtering (AWGIF) technique was proposed in [1] to decompose an initial depth and to preserve the edges accurately. However, the performance of time consumption on image enhancement was not minimized. A Low Light Enhancement and Denoising (LLEAD) method was introduced in [2] for better-enhanced image contrast and minimizing the mean squared error. But it failed to develop a statistical model for the distortion of colors. An ensemble spatial method was developed in [3] for image enhancement. But, the designed method failed to improve the model with lesser mean squared error.

An adaptive guided image filtering using a modified cuckoo search algorithm was designed in [4] for removing the noisy image. However, the performance of the peak signal-to-noise ratio was improved but it failed to minimize the time complexity. A Global-Local Image Enhancement, (GLIE) was developed in [5] for contrast enhancement and structural preservation. But, the performance of the peak signal-to-noise ratio was not improved.

A color correction and adaptive contrast enhancement method were designed in [6] for underwater image quality improvement. But, the designed approach enhances the complexity of the algorithm. A simple and effective image contrast enhancement technique was introduced in [7] to achieve high dynamic range imaging. But, the performance of mean square error was not minimized.

A two-step image enhancement was introduced in [8] for the high qualitative enhancement capability of underwater images. However, the designed method consumed more time for image enhancement. A Simultaneous Contrast Enhancement and Noise Suppression (SCENS) framework was introduced in [9] for the low light image. But the framework was not efficient to improve the PSNR with lesser mean square error. A Sparse Gradient Minimization sub-Network (SGM-Net) was introduced in [10] to remove the low-amplitude structures and preserve edge information from the low/normal-light image. However, the processing time of SGM-Net was not minimized.

Major contribution

To overcome the above-mentioned conventional issues of image enhancement, a novel RDL-SCES technique is introduced. The contributing factors of the RDL-SCES technique are listed below,

- To improve the performance of image enhancement, a novel RDL-SCES technique is introduced by including two major processes namely Piecewise regressive damped Bryson–Frazier Fixed Interval Filter and spatial convolutive Marr–Hildreth edge smoothing.
- First, the RDL-SCES technique uses the Modified Bryson–Frazier Fixed Interval Filtering technique to analyze the image pixels with help of Piecewise regression and identify the noisy and normal pixels. The Piecewise regression increases the performance of the filtering technique to find the noisy pixels with minimum time by the means of the damped least square method.
- Secondly, the edge smoothing is performed in RDL-SCES by using the spatial convolutive Marr–Hildreth technique. The convolution of Laplacian and Gaussian functions is performed in the spatial domain to smooth the edge pixels in the given natural images.
- Finally, a series of experiments were conducted to prove the performance improvement of the proposed RDL-SCES technique than other baseline approaches with help of different metrics.

Paper outline

The remaining sub-sections of this paper are as follows. Section 2 presents the related work of conventional image quality enhancement models. The proposed RDL-SCES technique is described in Section 3, while Section 4 contains the setup ad dataset description. Section 5 provides the results and discussion of different performance metrics. Finally, the conclusion is presented in Section 6.

2. RELATED WORKS

A fast and lightweight deep learning-based algorithm was introduced in [11] for low-light image enhancement. However, the designed algorithm was not efficient in further improving the information in the enhanced image. The morphological operator-based image fusion algorithm was designed in [12] for improving the efficiency of enhancement using spatial filtering. But, the computational complexity was not minimized at optimum levels.

A regularized illumination optimization approach was developed in [13] to improve the quality of low-light images by eliminating the negative effect of unwanted noise. However, the performance of processing time and space consumption was not minimized. A new Retinex-based lowlight image enhancement approach was introduced in [14] using Retinex image decomposition. But, the efficient filtering technique was not applied to achieve better image enhancement.

An automatic image enhancement approach was introduced in [15] to provide better quality results for all types of images. But it failed to properly handle the image enhancement approach for particularly dark regions. A novel traffic image enhancement algorithm was designed in [16] based on illumination adjustment and depth difference. But the algorithm failed to effectively handle the uneven illumination and haze images for improving the image enhancement. A multi-exposure fusion framework was introduced in [17] for image enhancement for low-light images. But the framework failed to produce high-quality enhanced images.

A Probabilistic Decision-based Improved Trimmed Median filter (PDITMF) algorithm was designed in [18] for obtaining noise-free pixels. However, the designed algorithm failed to focus on removing the range-based impulsive noise. A low-light image enhancement algorithm was designed in [19] with brightness equalization and detail preservation. However, it has more time consumption for image enhancement. Deep learning models were developed in [20] for continuously performing image enhancement. But the storage consumption of Image restoration was not minimal.

3. PROPOSAL METHODOLOGY

Image quality enhancement aims to increase the quality of images in terms of colors, brightness, and contrasts. Since the images captured in low-brightness situations often direct to poor visibility and illustrate the artifacts such as distortion. These artifacts not only change the visual observation of the human eye but also reduce the performance of computer vision. Various denoising methods have been proposed to enhance image contrast and noise also removed. Conversely, the conventional denoising methods did not provide satisfactory performance in the image quality enhancement. Therefore, a novel fast technique called RDL-SCES is introduced for enhancing the image enhancement and consequently, it is highly desired to improve the contrast enhancement by noise suppression as well as edge smoothing.

Figure 1 illustrates the architecture diagram of the proposed RDL-SCES technique to perform the image quality enhancement with poor quality images. The input natural images are collected from the dataset. Let us consider the natural image dataset as input for quality enhancement. The „$\square$" number of low-quality natural images $\square_1, \square_2, \square_3 \ldots \square_n$ are collected from the dataset.

The collected images are first given to the Piecewise regressive damped Bryson–Frazier Fixed Interval Filtering technique for noise removal. The Modified Bryson–Frazier Fixed Interval Filtering technique analyzes the image pixels by using piecewise regression and identifies the normal and noisy pixels. The Piecewise regression is a machine learning technique for analyzing the pixels of input images and partitioning them into two segments (i.e. normal or noisy pixels). Then the Piecewise regression analyzes the relationship between the center pixels and other neighboring pixels. Then the regression function uses the Damped least-squares method to find the pixels with minimum deviation from the center pixels value. A damped least-square method is a mathematical model used to find the local minimum by reducing the non-linear least squares problems. As a result, the pixels with minimum deviation are called as normal. Otherwise, the pixels are said to be noisy. These noise pixels are removed from the image. Finally, the denoised image is obtained.

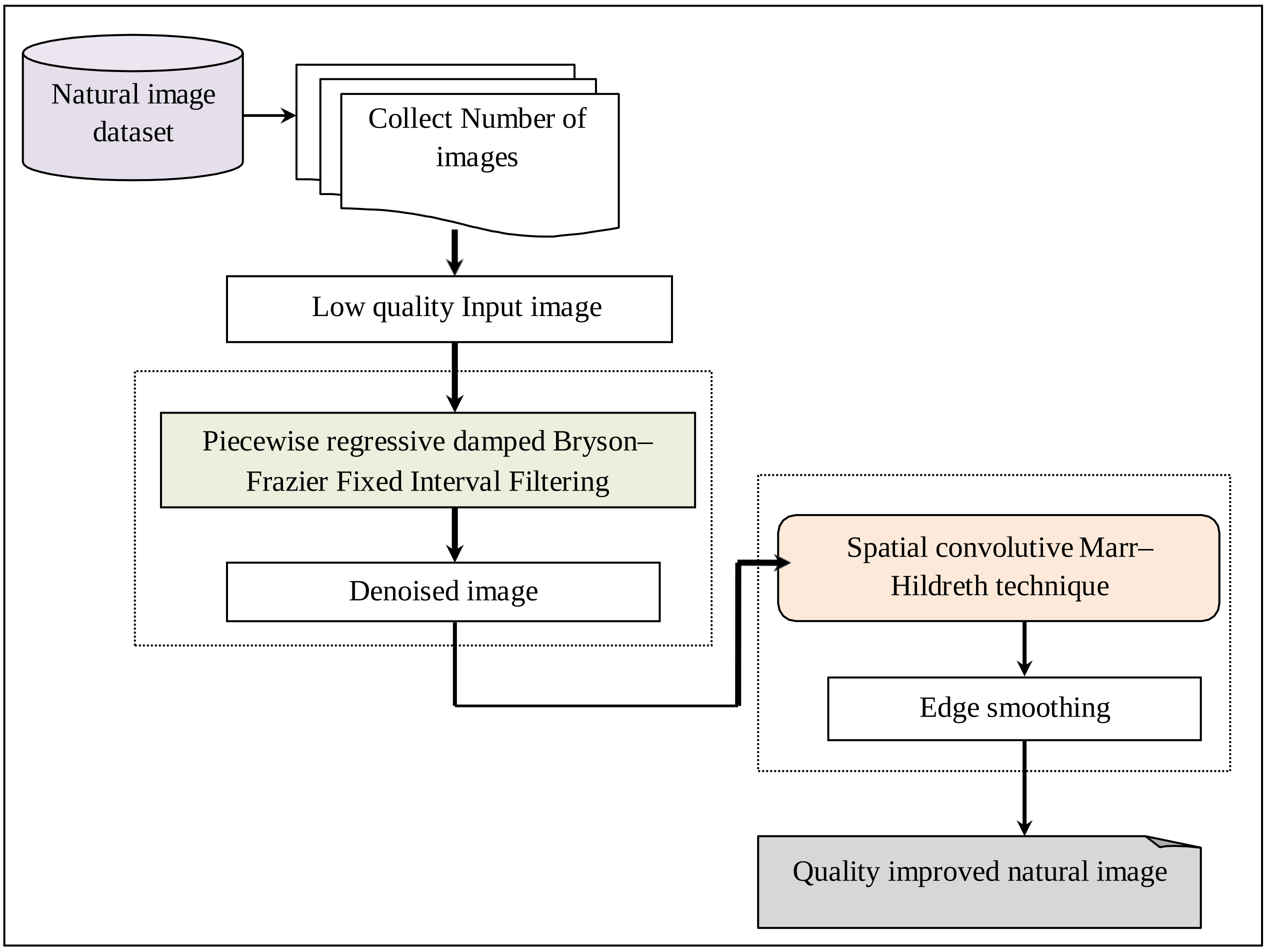

Figure 1 Architecture Diagram of Proposed RDL-SCES Technique

After the image noise removal, the edge smoothing process is performed for improving the image quality. The proposed RDL-SCES uses the spatial convolutive Marr–Hildreth technique for smoothing the edges of the image in the two-dimensional space through the convolution of Laplace and Gaussian function. Finally, the quality-enhanced image is obtained with minimum time as well as minimizing error. The preprocessing step also minimizes memory consumption. The different process of the proposed RDL-SCES technique is briefly explained in the following subsections.

Piecewise Regressive Damped Bryson–Frazier Fixed Interval Filtering

First, the numbers of natural images are collected from the dataset. The collected images are affected by some unwanted noise resulting in minimizing the visual quality of images. Therefore, the preprocessing step is necessary for image processing to improve the quality of the image by removing the noise. The proposed RDL-SCES technique uses the Piecewise Regressive Damped

Bryson–Frazier Fixed Interval Filtering technique for pre-processing the input natural image by finding the covariance between the pixels.

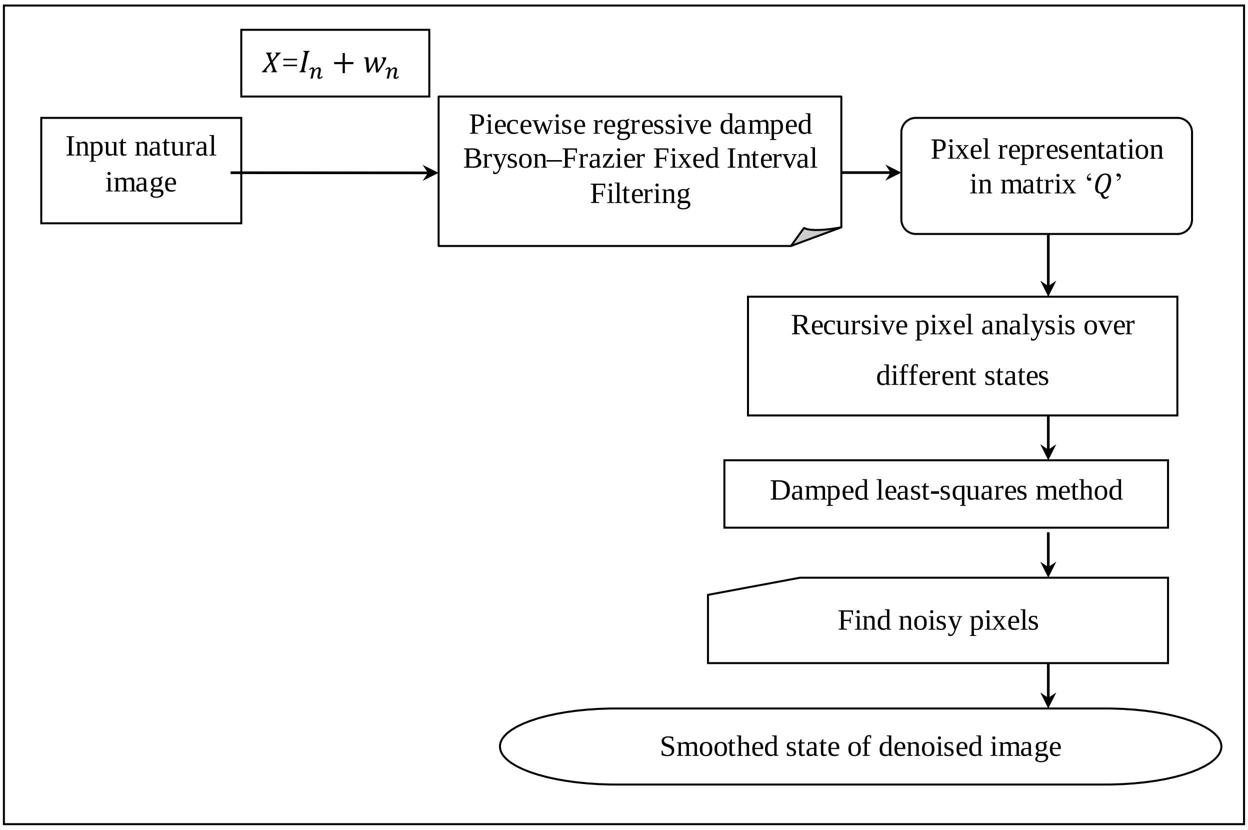

Figure 2 Flow Process of Piecewise Regressive Damped Bryson–Frazier Fixed Interval Filtering

Figure 2 flow process of damped least-squares Modified Bryson–Frazier fixed interval filter for obtaining the Smoothed state of input denoised image. The number of collected natural images from the dataset is $\mathrm{I}_1, \mathrm{I}_2, \mathrm{I}_3 \dots \mathrm{I}_\mathrm{n}$ and each image comprises the number of pixels $\mathrm{k}_1, \mathrm{k}_2, \mathrm{k}_3 \dots \mathrm{k}_\mathrm{m}$. The designed filtering technique employs the series of measurements examined over time including statistical noise.

$$\mathrm{X} = \mathrm{I}_\mathrm{n} + \mathrm{w}_\mathrm{n} \quad (1)$$

Where, X denotes an input to the filter, I_n indicates an input image and added with the some noisy 'w_n'. Each image has a number of pixels. A pixel is the minimum unit of a digital image and it is combined to form a total image. Therefore, these pixels are arranged into the matrix for simple computation and fast quality assessment. Each pixel is represented by means of a numerical value.

The matrix is formed based on the number of columns (*m)* and the number of rows (*n*) of the image matrix (*m*n).*

‘t-1’ ‘t’ ‘t+1’

$$Q = \begin{bmatrix} k_{11} & k_{12} & k_{13} & \dots & k_{m1} \\ k_{21} & k_{22} & k_{23} & \dots & k_{m2} \\ k_{31} & k_{32} & k_{33} & \dots & k_{m3} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ k_{n1} & k_{n2} & k_{n3} & \dots & k_{mn} \end{bmatrix} \quad (2)$$

Where, Q denotes an image matrix with respect to ‘m’ column and the ‘n’ number of rows. ‘t-1’ indicates a previous state of the neighboring pixels, t’ indicates a current state of pixels, ‘t+1’ denotes a next state of the neighboring pixels.

It means that the pixel computation s performed for the previous, current as well as next state of the neighboring pixels. The Modified Bryson–Frazier smoother is applied for analyzing the pixels with different states. Therefore, the linear discrete-time system of Modified Bryson–Frazier smoother is given below,

$$\mathrm{Z_t = B_t k_{t-1} + H_t f_t + n} \quad (3)$$

From (3), $\mathrm{Z_t}$ denotes a linear discrete-time system at the current state, $\mathrm{B_t}$ symbolizes the state transition model applied to the pixels with the prior state ‘ $\mathrm{k_{t-1}}$ ’, $\mathrm{H_t}$ denotes a control input model which is applied to control vector $\mathrm{f_t}$, n indicate a process noise. The Modified Bryson–Frazier smoother estimate the covariances between the two pixels to obtain the smoothed state. The covariance measure is used to find the deviation between the two variables such as pixels and the mean value.

The mean value of the pixels (μ_{ij}) are measured as follows,

$$\mu_{ij} = \frac{1}{n} \sum_{i=1}^{n} \sum_{j=1}^{m} k_{ij} \quad (4)$$

Where, μ_{ij} denotes a mean, k_{ij} denotes pixels in the matrix ‘Q’. The mean value pixels are replaced as center value as given below.

‘t-1’ ‘t’ ‘t+1’

$$Q = \begin{bmatrix} k_{11} & k_{12} & k_{13} & \dots & k_{m1} \\ k_{21} & k_{22} & k_{23} & \dots & k_{m2} \\ k_{31} & k_{32} & \mu_{ij} & \dots & k_{m3} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ k_{n1} & k_{n2} & k_{n3} & \dots & k_{mn} \end{bmatrix} (5)$$

With the estimated mean value, the Modified Bryson–Frazier smoother measures the covariance to find the noisy pixels.

$$\mathrm{Z_{t+1}} = \mathrm{cov}\,(\mathrm{k_{ij}}, \mathrm{\mu_{ij}}) \quad (6)$$

$$\mathrm{cov}\,(\mathrm{k_{ij}}, \mathrm{\mu_{ij}}) = \left[\sum_{i=1}^{n} (\mathrm{k_{ij}} - \mathrm{\mu_{ij}})^2\right] \quad (7)$$

Where, $\mathrm{Z_{t+1}}$ denotes an updated state of filter, $\mathrm{cov}\,(\mathrm{k_{ij}}, \mathrm{\mu_{ij}})$ denotes a covariance between the mean, and the pixels. After that, the noise pixels and normal pixels are identified by applying the piecewise regression with the help of the damped least-squares method. The damped least-squares method is used to solve non-linear least squares problems i.e. find the minimum deviation between the two variables.

$$\mathrm{Y} = \arg\min \left[\sum_{i=1}^{n} (\mathrm{k_{ij}} - \mathrm{\mu_{ij}})^2\right] \quad (8)$$

Where, Y denotes an output of the damped least-squares method, $\arg\min$ indicates an argument of the minimum function.

$$\mathrm{R} = \begin{cases} \arg\min \left[\sum_{i=1}^{n} (\mathrm{k_{ij}} - \mathrm{\mu_{ij}})^2\right], & \textit{normal pixels} \\ \quad \text{otherwise} & , \text{noisy pixels} \end{cases} \quad (9)$$

Where R denotes a regression outcome. The pixels with minimum deviation from the mean value is said to be normal pixel. The pixels with a maximum deviation from the mean value is said to be noise pixel. These noisy pixels are removed and obtain the denoised output. As a result, the recursive pixel computation is performed at each time to obtain the smoothed state of the image.

3.1 Spatial Convolutive Marr–Hildreth Edge Smoothing

After removing the noise in an image, edge smoothing is performed to enhance the quality of the image. Edge smoothing an image preprocessing step is used to smooth and retain the sharp edges. The purpose of detecting sharp edges in image brightness is to capture important objects with clear vision. Therefore, the proposed technique uses the Spatial Convolutive Marr–Hildreth edge smoothing approach to obtain the quality improved image. The proposed edge smoothing method has functioned on the basis of convolution of the noise-free image with the Laplacian of the Gaussian functions. The edge smoothing is performed in the spatial domain method that refers to the partition of the image space into uniform pixels according to the spatial coordinates (i.e. x,y) with a particular resolution. Here, Marr–Hildreth represents the author who derives the edge smoothing technique to obtain the quality improved image. Hence the proposed smoothing technique is called spatial convolutive Marr–Hildreth edge smoothing.

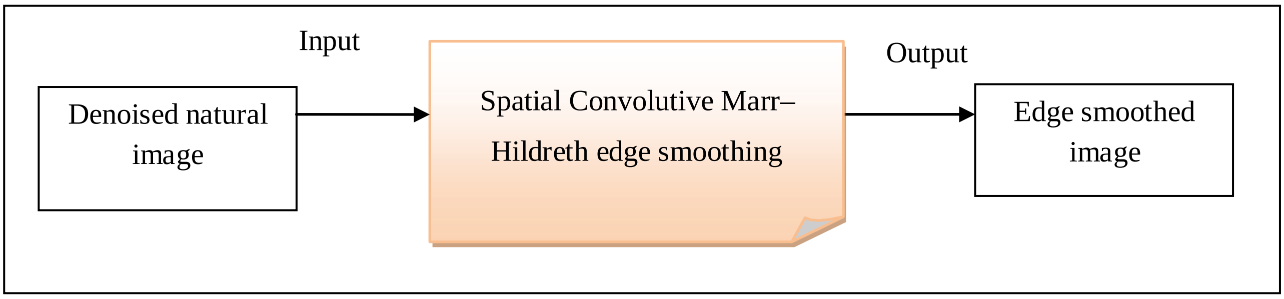

Figure 3 Spatial Convolutive Marr–Hildreth Edge Smoothing

Figure 3 illustrates the block diagram of the Spatial Convolutive Marr–Hildreth edge smoothing. In two dimension spatial domain, the edge smoothing is performed as given below,

$$\mathrm{E_s} = -\frac{1}{\pi \mathrm{d}^4}\left[1 - 0.5 * \frac{\mathrm{x}^2+\mathrm{y}^2}{\mathrm{d}^2}\right] * \exp\left[-\frac{\mathrm{x}^2+\mathrm{y}^2}{2\mathrm{d}^2}\right] \quad (10)$$

Where, $\mathrm{E_s}$ denotes an edge smoothing output, d indicates a deviation, x denotes the distance from the origin in the horizontal axis, y indicates the distance from the origin in the perpendicular axis. From (10), '$*$' indicates a convolution mathematical operation that produces a final smoothed result. Based on image denoising and edge smoothing, the quality improved images are obtained. The algorithmic process of image denoising and edge smoothing is given below,

// Algorithm 1: Piecewise Regressive Damped Linear Filterative Spatial Convoluted Edge Smoothing based image preprocessing
Input: image dataset (D), Number of natural images $I_1, I_2, I_3 \dots, I_n$ **Output:** Obtain preprocessed image
Begin **1.** Collect a number of neural images $I_1, I_2, I_3 \dots, I_n$ from the image dataset D **2.** **For each image** I_i **3.** Extract the image pixels

4. Arrange the pixels in the matrix 'Q'
5. **Apply** linear discrete-time system
6. **Measure the mean value 'μ_{ij}'**
7. Replace the center value of the matrix with the **mean value '**μ_{ij}
8. **For each** pixel in the matrix and **mean value '**μ_{ij}
9. Measure the covariance $cov\left(k_{ij}, \mu_{ij}\right)$
10. **end for**
11. Apply the damped least-squares method
12. **if** (**R**=$\arg\min\ [\sum_{i=1}^{n}\left(k_{ij} - \mu_{ij}\right)^2]$) **then**
13. pixel is said to be a normal
14. **else**
15. pixel is said to be a noisy
16. Remove noisy pixels
17. **end if**
18. Obtain denoised image
19. **End for**
20. **For each** denoised image
21. Perform Spatial Convolutive Marr–Hildreth edge smoothing ' E_s'
22. **end for**
23. Return (quality improved image)

End

Algorithm 1 explains the step-by-step process of image preprocessing. Initially, the numbers of natural images are collected from the dataset. The image pixels are arranged in the form of a matrix. Apply the linear discrete-time system for analyzing the pixels to identify the noise pixels. Then the mean is taken for all the pixels in the matrix and the center value is replaced with the mean. After that, the covariance between the center and the neighboring state pixels is estimated. The damped least-squares method finds the minimum deviation pixels. These pixels are called normal and other peels are noisy. The noisy pixels are removed from the matrix. Finally, the denoised results are obtained. After the denoising, the Spatial Convolutive Marr–Hildreth method is applied for smoothing the edge of the images. Finally, the quality-enhanced image is obtained. In this way, efficient natural image preprocessing is performed by using the RDL-SCES technique to minimize the preprocessing time and space consumption.

4. EXPERIMENTAL SETTINGS

In this section, experimental evaluation of the proposed RDL-SCES technique and existing methods namely AWGIF [1] and LLEAD [2] are implemented using MATLAB with Natural Images dataset. This dataset is taken from https://www.kaggle.com/prasunroy/natural-images. This dataset contains 6,899 images from 8 different classes collected from various sources including airplane, cars, cat, dog, flower, fruit, motorbike and person. These images are used for quality improvement analysis based on noise removal and edge smoothing. The number of images for each class is listed in table 1.

Table 1 Image Details

S.No	**Different classes**	**Number of images**
1.	airplane	727
2.	car	968
3.	cat	885
4.	Dog	702
5.	flower	843
6.	fruit	1000
7.	motorbike	788
8.	person	986

5. RESULTS AND DISCUSSION

The experimental result of the proposed RDL-SCES technique and existing methods namely AWGIF [1] and LLEAD [2] are discussed in this section with the various performance metrics such as mean square error, and peak signal-to-noise ratio, preprocessing time, and memory consumption. Performance analyses are explained with the help of tables and graphical representation.

Impact of Mean Square Error

Mean Square Error is measured based on the squared difference between the number of images and the number of natural images that are accurately preprocessed. The formula for calculating the Mean Square Error is given below,

$$MSE = \frac{1}{n} \sum \left(n_I - n_{Icp}\right)^2 (11)$$

Where MSE denotes a mean square error which is defined as the squared error between the number of images n_{Icp} and accurately preprocessed images.

Table 1 Mean Square Error

Number of natural images	Mean Square Error		
	RDL-SCES	AWGIF	LLEAD
600	0.166	0.24	0.326
1200	0.1875	0.24	0.333
1800	0.2	0.268	0.347
2400	0.24	0.281	0.375
3000	0.243	0.3	0.385
3600	0.25	0.302	0.401
4200	0.275	0.325	0.42
4900	0.316	0.35	0.421
5600	0.326	0.375	0.444
6000	0.368	0.4	0.486

Table 2 reports the performance results of the mean square error against the number of natural images for different enhancement methods namely RDL-SCES technique and existing methods namely AWGIF [1] and LLEAD [2]. The number of natural images collected from the dataset is taken in ranges from 600 to 6000. The observed results validate that the mean square error of the image preprocessing of the RDL-SCES technique is found to be minimized than the other existing image enhancement methods [1], [2]. This is proved through statistical estimation. Let us consider 600 natural images in the first iteration and the performance result of the mean square error is 0.166 using the RDL-SCES technique. By applying, AWGIF [1] and LLEAD [2] to calculate the mean square error with 600 natural images, the observed means the square error is 0.24, and 0.326. Similarly, remaining iterations are performed for each method with respect to a different number of images. After that, the observed error values of the RDL-SCES technique are compared to the existing methods. Finally, the average is taken for ten comparison results. The overall comparison result indicates that the mean square error of the RDL-SCES technique is considerably improved by 18% when compared to [1] and 34% when compared to [2].

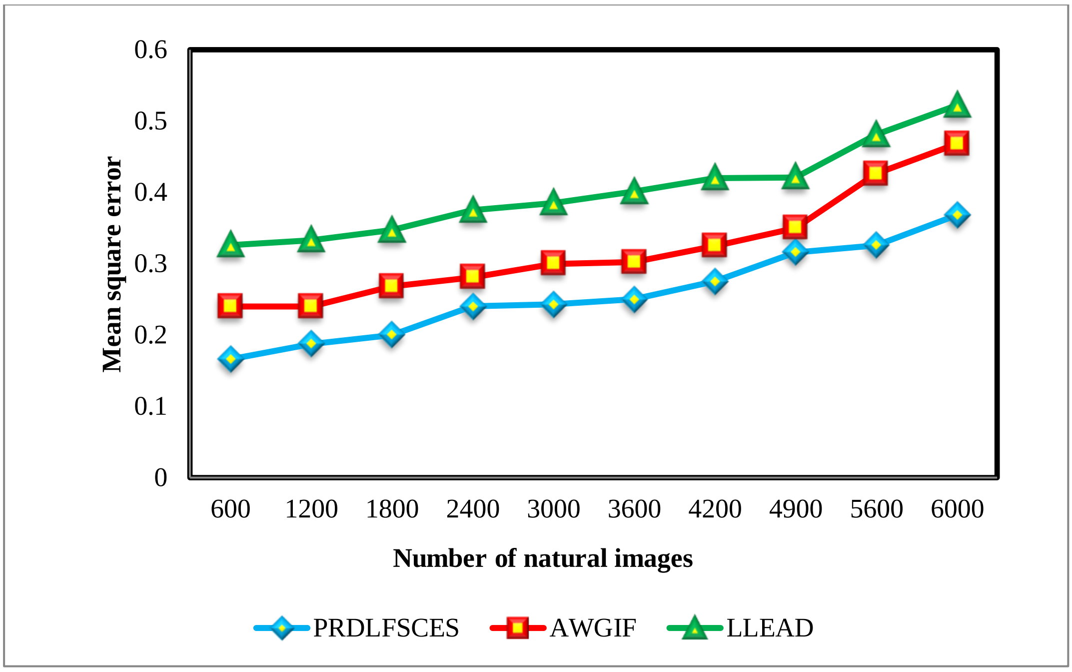

Figure 4 Performance Results of Mean Square Error

Figure 4 illustrates the performance results of the mean square error against a different number of natural images. The input natural images are taken as input on the horizontal axis whereas the performance results of the mean square error are obtained at the vertical axis. The graphical illustration indicates that the performance of the mean square error of the RDL-SCES technique is found to be minimized when compared to the other two existing methods. The reason behind this improvement is to apply the Damped Least-Squares Modified Bryson–Frazier Fixed Interval Filtering technique and Spatial Convolutive Marr–Hildreth Edge Smoothing. First, the noisy pixels in the input images are removed, and then edge smoothing is performed. The proposed technique accurately performs the preprocessing for all the images hence it minimizes the error rate.

Impact of Peak Signal-to-Noise Ratio

Peak Signal to Noise Ratio is measured based on the mean squared difference between noisy image and quality enhanced natural image after pre-processing. Higher PSNR value provides high image quality for disease detection. The peak signal-to-noise ratio is mathematically calculated using the following formula

$$\mathrm{PSNR} = 10 * \log_{10}\left[\frac{M^2}{MSE}\right] \quad (12)$$

Where 'PSNR' denotes a peak signal-to-noise ratio and 'M′ denotes a maximum possible pixel value of the images (i.e. 255) with respect to mean square error rate 'MSE'. The PSNR is measured in decibel (dB).

Table 3 Peak Signal-to-Noise Ratio

Number of natural images	Peak Signal-to-Noise Ratio (dB)		
	RDL-SCES	AWGIF	LLEAD
600	55.92	54.32	52.99
1200	55.40	54.32	52.90
1800	55.12	53.84	52.72
2400	54.32	53.64	52.39
3000	54.27	53.35	52.27
3600	54.15	53.33	52.09
4200	53.73	53.01	51.89
4900	53.13	52.69	51.88
5600	52.79	52.39	51.65
6000	51.93	51.59	51.26

As exposed in the above table 3, the performance of Peak Signal-to-Noise Ratio versus a number of natural images collected from the dataset. The observed result indicates that the performance of the proposed RDL-SCES technique achieves a higher peak signal to noise ratio when compared to conventional quality enhancement schemes. Let us consider the 600 images to conduct the experiments in the first iteration. The observed peak signal-to-noise ratio using the RDL-SCES technique is 55.92 dB. By applying, AWGIF [1] and LLEAD [2], the observed peak signal-to-noise ratio is56.08 dB, and 52.99dB. The performance result indicates that the RDL-SCES technique performs well to achieve improved PSNR. Likewise, different performance results are obtained for each method. The observed results of the RDL-SCES technique are compared to the existing methods. The average results of ten comparison outcomes indicate that the PSNR of the technique is increased by 2% and 4% when compared to the [1] and [2] respectively.

Figure 5 demonstrates the performance results of the mean square error against a different number of natural images. The input natural images are taken as input on the horizontal axis whereas the performance results of the mean square error are obtained at the vertical axis. The graphical illustration indicates that the performance of the mean square error of the RDL-SCES technique is found to be minimized than the other two existing methods. The reason behind this improvement is to apply the damped least-squares Modified Bryson–Frazier Fixed Interval Filtering technique and spatial convolutive Marr–Hildreth edge smoothing. First, the noisy pixels in the input images are removed, and then edge smoothing is performed. The proposed technique accurately performs the preprocessing for all the images hence it minimizes the error rate.

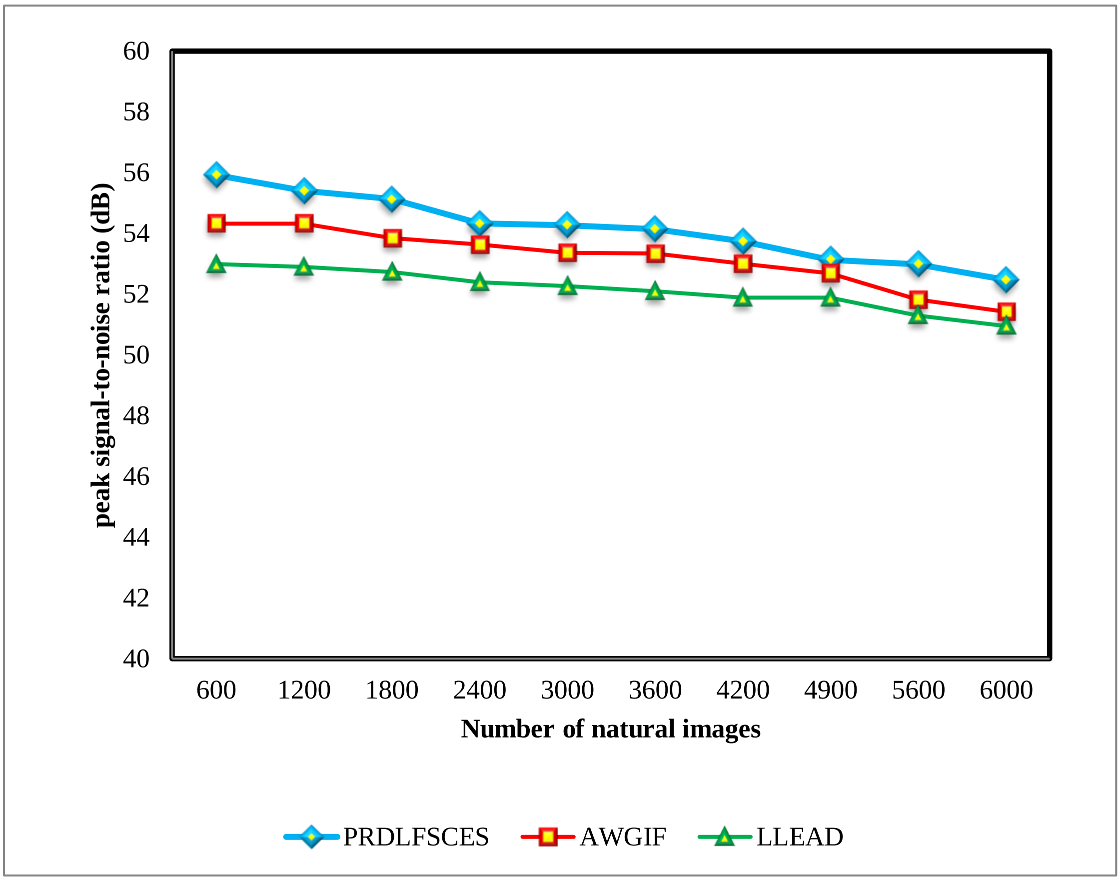

Figure 5 Performance Results of Peak Signal to Noise Ratio

Impact of Preprocessing Time

Image Preprocessing Time is defined as the amount of time taken by an algorithm for image denoising as well as edge smoothing process. The formula for calculating the time is given below,

$$IPT = n * \text{time}\ [DN + ES]\ (13)$$

Where ‘PT′ denotes an Image preprocessing time, n denotes the number of images,DN indicates denoising and ES denotes edge smoothing. The overall time is measured in terms of milliseconds (ms).

Table 4 provides the performance results of Preprocessing Time versus the number of natural images collected from the dataset. The time taken for image preprocessing is significantly reduced by applying the RDL-SCES technique when compared to the other two conventional preprocessing methods.

Table 4 Preprocessing Time

Number of natural images	Preprocessing Time (ms)		
	RDL-SCES	AWGIF	LLEAD
600	27	30.6	33.6
1200	32.4	35.4	38.4
1800	36	39.6	43.2
2400	40.8	45.6	48.48
3000	45	51	55.5
3600	48.6	54	59.4
4200	53.76	58.38	63
4900	57.33	60.76	66.15
5600	61.6	65.52	70
6000	64.2	70.8	75.6

Let us consider '600 images for conducting experiments, the time consumption of improving the image quality using the RDL-SCES technique is 27ms', whereas '30.6ms and' 33.6ms of time consumed by applying existing techniques AWGIF [1] and LLEAD [2]. The overall outcomes of the proposed RDL-SCES technique are compared to other techniques. The average of ten comparison results demonstrates that the preprocessing time is notably minimized by 9% and 16% than the state-of-the-art methods.

The performance analysis of preprocessing time versus the number of natural images is shown in figure 6. The graphical chart designates that the preprocessing time is progressively increased while increasing the number of natural images. From the observed results, it is obvious that the preprocessing time is noticeably decreased using the RDL-SCES technique. This

improvement is accomplished by applying filtering-based image denoising and edge smoothing. The proposed filtering technique accurately finds the noisy pixels from the input natural image with the help of piecewise regression along with the damped least-squares method. This helps to minimize image denoising time. Similarly, edge smoothing is performed by applying the spatial convolution of Laplace and the Gaussian function. In this way, efficient preprocessing is performed with minimum time consumption.

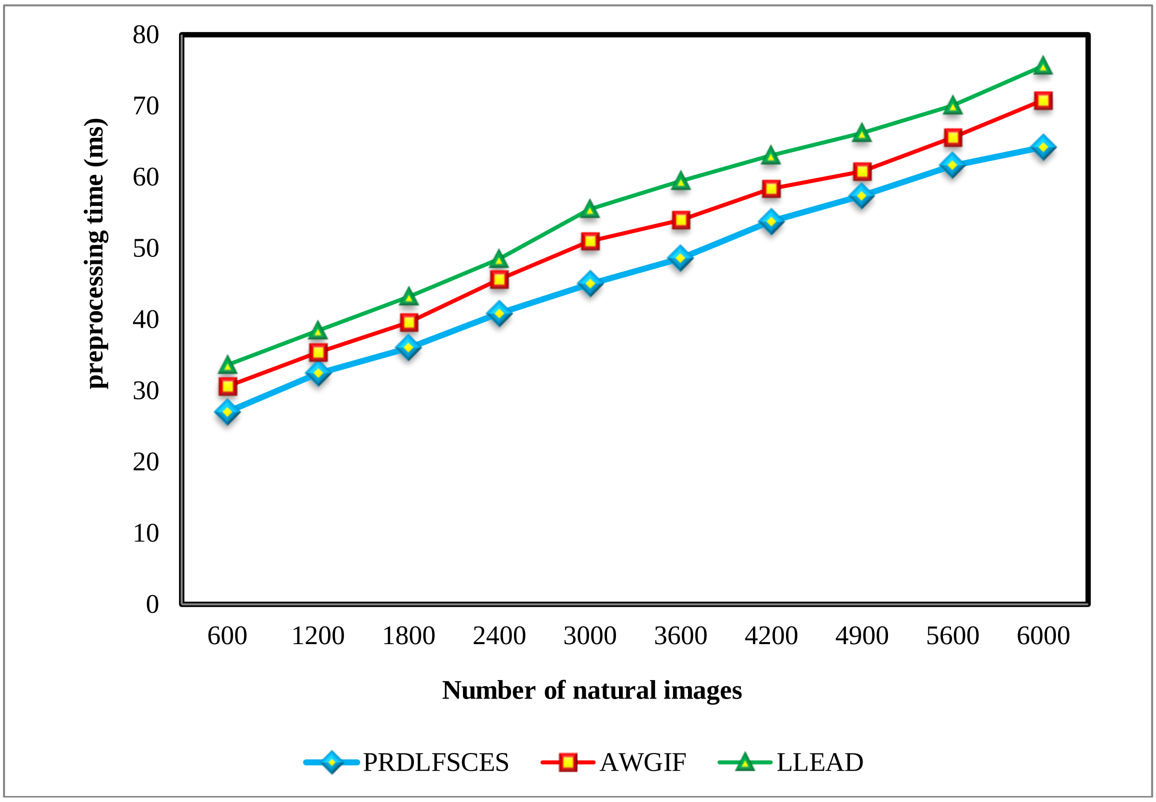

Figure 6 Performance Results of Preprocessing Time

Impact of Memory Consumption

Memory consumption is defined as the amount of memory space consumed by the algorithm to perform image denoising as well as edge smoothing. The memory consumption is calculated as follows,

$$\mathrm{Com}_{\mathrm{Mem}} = \mathrm{n} * \mathrm{Mem}\ [\mathrm{DN} + \mathrm{ES}] \quad (14)$$

Where '$\mathrm{Com}_{\mathrm{Mem}}$' denotes memory consumption, n denotes the number of images, Mem denotes memory, DN indicates denoising and ES denotes edge smoothing. The memory consumption is measured in terms of Megabytes (MB).

Table 5 Memory Consumption

Number of natural images	Memory Consumption (MB)		
	RDL-SCES	AWGIF	LLEAD
600	18	21.6	25.8
1200	22.8	26.16	30
1800	25.2	28.8	32.4
2400	28.8	33.6	37.2
3000	31.5	34.5	38.4
3600	32.4	36.72	40.32
4200	35.7	38.22	42.42
4900	36.75	40.67	44.1
5600	38.08	41.44	45.92
6000	39	44.4	48

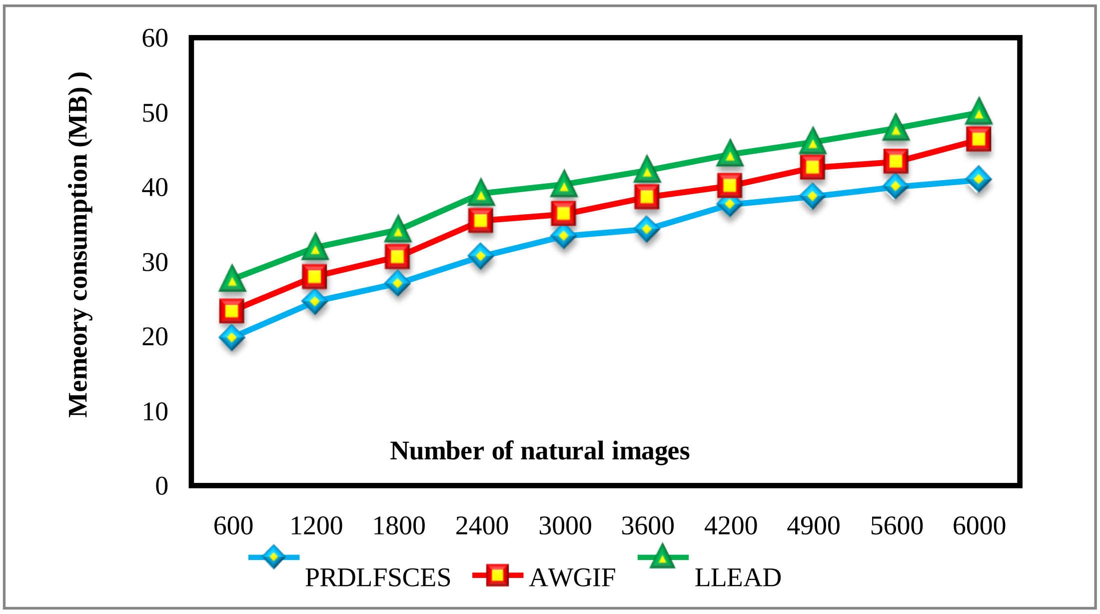

Figure 7 Performance Results of Memory Consumption

Table 5 and figure 7 illustrate the performance result of memory consumption with respect to a number of natural images taken in the ranges from 600 to 6000. By increasing the number of natural images, the memory consumption of image preprocessing also increased due to the increasing the count of input. The output result indicates that the RDL-SCES technique reduces the performance of memory consumption than the existing preprocessing techniques. The reason behind the improvement of the RDL-SCES technique is to reduce the size of the noisy pixels.

The preprocessing helps to enhance the quality of images by removing the noisy pixels. While considering 600 images collected from the dataset to conduct experimental work, the memory consumption than the existing preprocessing techniques. The reason behind the improvement of the RDL-SCES technique is to reduce the size of the noisy pixels. The preprocessing helps to enhance the quality of images by removing the noisy pixels. While considering 600 images collected from the dataset to conduct experimental work, the memory consumption was found to be $18MB$ using the proposed RDL-SCES technique. Then the memory consumption of existing AWGIF [1] and LLEAD [2] are $21.6MB$ and $25.8\,MB$ respectively. Likewise, various runs are carried out with respect to a number of input images. The observed performance of the proposed technique is compared to the existing methods. Thus, the average of ten various results indicates that the overall performance of memory consumption using the proposed RDL-SCES technique is minimized by 11% and 20% as compared to other works [1] and [2].

6. CONCLUSION

With the rapid development of image processing technology, image quality enhancement is the fundamental processing step of many real vision systems. In order to improve the quality of a given image, the RDL-SCES technique is introduced in this paper for enhancing the image contrast by removing the noise as well as preserving the depth edges. First, Piecewise regressive damped Bryson–Frazier Fixed Interval Filtering is applied to a RDL-SCES technique to denoise the input natural image by identifying the noisy pixels. Then, the edge smoothing is carried out for improving the image quality. Based on the denoising and edge smoothing, accurate image preprocessing is obtained with minimum time. The comprehensive experimental assessment is carried out with the natural image dataset. The obtained quantitative result indicates that the proposed RDL-SCES technique offers improved performance in terms of achieving higher PSNR, and lesser mean square error, as well as time consumption, and memory consumption when compared to existing methods.

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