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Optimizing Noise Reduction in Images with the Lord Rama Devotee Algorithm

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ABSTRACT
In this study, the Lord Rama Devotee Algorithm (LRDA), a novel evolutionary optimization technique inspired by the devotion of Lord Rama's followers to optimizing noise reduction in image processing is presented. LRDA is a new idea that is inspired by the Indian Knowledge. LRDA simulates the collective intelligence of devotees to search for optimal solutions through position and velocity updates. The algorithm is applied to optimize filtering parameters for two types of noise: Gaussian noise and Salt and Pepper noise. For Gaussian noise, LRDA optimizes the sigma value of a Gaussian filter, improving the Peak Signal-to-Noise Ratio (PSNR) to reduce noise while preserving image details. Similarly, for Salt & Pepper noise, the algorithm adjusts the window size of a median filter, aiming to achieve the best noise removal performance without compromising image quality. By simulating the behavior of devotees and non-devotees, LRDA updates both personal and global bests to maximize the PSNR. Experimental results demonstrate that LRDA effectively optimized the Gaussian filter's sigma value to achieve a PSNR of 25.34, while the median filter for Salt & Pepper noise was optimized to yield a PSNR of 27.02. These results confirm LRDA's ability to handle different noise types, providing an adaptive and flexible solution for image noise reduction while maintaining visual detail. The algorithm's devotion-inspired mechanism efficiently balances noise reduction with image preservation, making LRDA a promising tool for image processing applications.

Keywords
Digital Image Processing, Gaussian Filter, LRDA, Median Filter, MSE, Salt and Pepper noise, PSNR.

1. INTRODUCTION
The main goals of image processing, a crucial area of study in digital signal processing, are to improve image quality, extract meaningful information from images, and restore damaged images. Eliminating noise from images has become a major task in the fields of computer vision and digital image processing (DIP) in the multimedia era [1]. Typically, noise in images comes from a variety of sources, including transmission problems, environmental factors, and errors in sensors. Two popular forms of noise are Gaussian noise, which has a normal distribution, and Salt & Pepper noise, which is typified by sporadic black and white pixel occurrences. Optimization algorithms are used in contemporary image processing to reduce error and identify the best answers based on predetermined standards [2]. The diagnosis and subsequent course of treatment of a disease are influenced by the quality of the Magnetic Resonance Imaging (MRI) image. Noise distortion, however, has a negative influence on these images and often obstructs diagnosis while data is being acquired or transmitted [3]. In this work, a fast non-local mean (FNLM) based noise reduction algorithm is proposed and apply it to CT images of a 3D printed phantom. The filaments used to create the self-produced phantom had densities comparable to those of human brain tissue [4]. Image processing clearly plays a role in the data collection of brain pictures. Physicians can identify diseases with the help of vital information provided by magnetic resonance imaging (MRI) [5]. In this work, noise reduction in preprocessing is achieved through the application of the Cuckoo Optimization Algorithm (COA). COA has demonstrated its superior ability to achieve faster convergence and more optimal performance globally [6]. This work addresses this challenge by proposing two nature-inspired algorithms and two optimal filters that preserve image information while reducing noise [7]. One of the main inverse problems is image denoising, which aims to eliminate artifacts and noise from input images. Generally, computer-based digital image denoising algorithms have latency because of multiple iterations implemented in, for example, graphics processing units (GPUs) [8]. Image denoising is a critical challenge in digital image processing, especially in medical imaging like MRI, where noise can obscure diagnostic information. Noise in images, often from environmental or sensor errors, needs to be efficiently reduced while preserving vital image details. This work proposes optimized nature-inspired algorithms and filters, aiming to enhance noise reduction while maintaining high image quality for accurate diagnosis.

Both non-devotees and devotees of Lord Rama make up the population. The human is categorized as either a Lord Rama devotee or non-devotee based on the random number generator and Lord Rama Devotee Probability. Success or failure does not affect Lord Rama Devotee; he travels through search space without stopping [9].

In this research work, a new algorithm based on the Lord Rama Devotee algorithm (LRDA) is proposed [9]. It has been shown that the LRDA can efficiently optimize image processing filters for noise reduction. LRDA effectively adjusted parameters for both Gaussian and Salt & Pepper noise filtering, balancing noise reduction with the preservation of image details by modeling the collective intelligence of followers. The sigma value of the Gaussian filter was optimized by LRDA for Gaussian noise, leading to a Peak Signal-to-Noise Ratio (PSNR) of 25.34. This resulted in a notable improvement in noise reduction, albeit with some image blurring because of the inherent characteristics of Gaussian filtering.

However, even better outcomes were obtained when LRDA was applied to the median filter for Salt & Pepper noise. A PSNR of 27.02 was obtained by optimizing the median filter's window size to 3 using the algorithm. This outcome demonstrates how well the median filter handles impulse noise since the noise was effectively eliminated without compromising the quality of the image's edges or details. The higher PSNR attained with Salt & Pepper noise reduction demonstrates how effective LRDA is at adjusting filter parameters that are unique to various noise kinds.

The two noise types of comparison demonstrate how flexible and adaptive LRDA is for optimizing both continuous and discrete variables. The algorithm optimized a discrete parameter (the window size of the median filter) for Salt & Pepper noise and a continuous parameter (the sigma of the Gaussian filter) for Gaussian noise. This adaptability to various filter types and noise levels demonstrates LRDA's potential as a powerful optimization tool for image processing.

In the end, the Lord Rama Devotee Algorithm has shown to be a useful method for enhancing image quality across various noise types. It is an efficient and adaptive technique for optimizing filtering parameters. It is a promising solution for image denoising applications because of its ability to balance noise reduction with the preservation of visual details, especially in situations where maintaining image clarity is crucial. This work shows how LRDA can be improved upon and used for a variety of image processing applications.

2. LORD RAMA DEVOTEE ALGORITHM (LRDA)

The Lord Ram Bhakt Algorithm (LRDA) is a sophisticated evolutionary optimization method for handling challenging issues. It was created with inspiration from the favour and commitment of Lord Rama's followers. The foundation of this algorithm is the idea of a global intelligence whose adherents use their commitment and expertise to search for better answers. To get the optimal outcome, the devotees' position, velocity, and other factors are changed during the LRDA process. Think about this algorithm.

The first step in the Lord Ram Bhakt algorithm is figuring out the devotees' starting position and speed. A conceivable area of problem solving is represented by the initial state of each node or particle. Every devotee is also given a beginning velocity, which denotes their direction and pace.

Following initialization, the algorithm's primary steps involve identifying the optimum location for each devotee individually (Parcel optimum) and the best position for all devotees combined (Global Best). Parcel finest refers to the circumstance where a devotee has obtained the finest outcome from his search. The scenario where the best outcome is achieved among all devotees is known as the "global best."

Finding the objective function is the next stage in the algorithm. The mathematical formula that serves as the foundation for evaluating the quality of the solution is known as the objective function. For instance, maximizing the peak signal-to-noise ratio (PSNR) may be a typical goal in image processing. PSNR is a crucial metric for assessing the quality of images. The position and velocity of the objective function are updated by applying mathematical procedures once the objective function has been established. The direction and speed of the devotees' search are regulated by this procedure, which helps them find better answers. The velocity is updated using the following mathematical formula (equation 1):

$$v_{i,d} = w.v_{i,d} + C1 \cdot rand \cdot (p_{best,i,d} - x_{i,d}) + C2 \cdot rand \cdot (g_{best,d} - x_{i,d}) \tag{1}$$

This formula adjusts the follower's velocity according to its previous position, individual best position (Parcel Best), and global best position (Global Best).

The position is updated using the following mathematical formula (equation 2):

$$x_{i,d} = x_{i,d} + v_{i,d} \tag{2}$$

Based on the fan's velocity, this equation modifies its position.

The algorithm separates followers into two groups: followers of Lord Rama (also known as Lord Ram Bhakt) and other followers (also known as non-devotees). Lord Ram devotees update their status according to what is best for them personally and globally. The procedure showcases the commitment and passion of the followers as they advance according to their optimal state and the overall best.

Conversely, non-devotees merely update their status in response to a certain likelihood of success. Their odds of success are minimal, but this method strives to better their status based on their efforts and circumstances. The individual and global best are updated at each iteration. A devotee's personal best position and worldwide best position are updated if they accomplish a better result.

Until the maximum number of iterations is reached or a termination condition is met, the algorithm is executed. This procedure guarantees that the algorithm can find the best results and searches for solutions sufficiently. Ultimately, the ultimate solution—the Global Best—is displayed as the best outcome. This outcome demonstrates the algorithm's efficacy as well as how the followers' diligence and devotion allowed them to identify the ideal answer. The strong and inspirational Lord Ram Devotees Algorithm (LRDA) is a search algorithm which is given below in Algorithm 1:

3. EXPERIMENTAL RESULTS AND DISCUSSION

In this research, the experimental work has been done with help of MATLAB software.

3.1 Gaussian Noise

Statistical noise called Gaussian noise or additive white Gaussian noise (AWGN) has a probability density function (PDF) that matches the normal distribution (Gaussian distribution). It is defined by two parameters.

$$P(x) = \frac{1}{\sqrt{2\pi}\sigma} \cdot e^{-(x-\mu)^2/2\mu^2}$$

Mean (μ): In many cases, the noise's expected value is often set to zero (zero-mean Gaussian noise).

Variance (σ²): The variance regulates how widely the noise distribution spreads. More variation corresponds to higher noise levels.

Algorithm 1: Lord Ram Devotees Algorithm (LRDA)

Intialiaze all devoters with random positions and velocities.

iterations = 0

do

for each devotee i do

If ($f(x_i) < f(pbest_i)$) then

$pbesti = xi_i$

end if

if ($f(pbest_i) < f(gbest)$) then

$gbest = pbest_i$

end if

end for

for each devotee i do

if ($random(0,1) < LordRamaDevoteeProbability$) then

for each dimension d do

$v_{i,d} = w * v_{i,d} + C1 * Random(0,1) * (pbest_{i,d} - x_{i,d}) + C2 * Random(0,1) * (gbest_d - x_{i,d})$

$x_{i,d} = x_{i,d} + v_{i,d}$

end for

else

if ($random(0,1) < NonDevoteeSuccessProbability$) then

for each dimension d do

$v_{i,d} = w * v_{i,d} + C1 * Random(0,1) * (pbest_{i,d} - x_{i,d}) + C2 * Random(0,1) * (gbest_d - x_{i,d})$

$x_{i,d} = x_{i,d} + v_{i,d}$

end for

else

end if

end if

end for

$iterations = iterations + 1$

while (termination condition is false)

Steps for Applying LRDA (Lord Rama Devotees Algorithm) for Gaussian Noise Optimization:

Read the Original Image (Grayscale): The grayscale image is read and converted to a double format for processing.

Add Gaussian Noise to the Image: Gaussian noise with a mean of 0 and variance of 0.01 is added to simulate noisy data.

Define Parameters for LRDA: The algorithm parameters include:

- The number of devotees (particles) and dimensions (filter sigma).
- Weights for velocity updates (inertia weight, cognitive constant, social constant).
- Maximum number of iterations to run.
- Probabilities for a devotee to act as a Lord Rama devotee or a successful non-devotee.
- Range for the Gaussian filter’s sigma values (minimum and maximum bounds).

Initialize Devotees

- Randomly generate initial sigma values for the Gaussian filter for each devotee.
- Set initial velocities for each devotee to zero.
- Set each devotee’s personal best position as their current sigma value.
- Initialize the global best to the sigma value of the first devotee.

Define Objective Function: The objective function is the Peak Signal-to-Noise Ratio (PSNR), which is to be maximized. The PSNR evaluates the quality of the filtered image against the original image.

Evaluate Initial Personal and Global Bests: For each devotee:

- Apply the Gaussian filter with the devotee's sigma value to the noisy image.
- Compute the PSNR of the filtered image.

The mean square error mostly describes PSNR. Let a noise-free grayscale image (I) and its noisy approximation (K) then MSE is defined as:

$$MSE = \frac{1}{m \cdot n} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} [I(i,j) - K(i,j,)]^2 \qquad (3)$$

And the PSNR is defined by equation (4)

$$PSNR = 10 \cdot \log_{10}\left(\frac{max_I^2}{MSE}\right) \quad (4)$$

Where max_I is the maximum pixel value of the original image.

- If the PSNR is better than the devotee's personal best, update the personal best.
- If the PSNR is better than the global best, update the global best.

Start Iterations: For a defined number of iterations:

Update the sigma values based on the behavior of Lord Rama devotees or non-devotees:

Lord Rama devotees: Update velocities and positions based on personal and global bests.

Non-devotees: With a certain success probability, update velocities and positions similarly. Ensure the sigma values remain within the predefined valid range.

Update Personal and Global Bests After each update, reapply the Gaussian filter with the new sigma values. Update personal bests and the global best based on the new PSNR values.

Display Results: After completing the iterations, display the optimized sigma value. Apply the optimized Gaussian filter with the best-found sigma value to the noisy image.

Show Images: Display the original image, the noisy image, and the filtered image after applying the optimized filter.

Compute PSNR of the Optimized Image: Compute and display the PSNR of the filtered image to assess the improvement in image quality after denoising.

This process optimizes the Gaussian filter's sigma value using LRDA to achieve the best possible image denoising by maximizing PSNR. Through the application of LRDA, the Gaussian filter's sigma value was optimized to enhance the image quality by maximizing the PSNR. The final optimized sigma value of 0.7198 resulted in a PSNR of 25.3405, demonstrating that the algorithm effectively reduced the Gaussian noise in the image while maintaining important visual details. Figure 1 shows the experimental results of Lord Rama Devotees Algorithm for the Gaussian filter.

3.2 Median Filter

A non-linear digital filter called a median filter is used to eliminate noise from signals and images. It is frequently applied as a preliminary step to enhance the outcomes of subsequent processing. Steps for Applying LRDA for Salt & Pepper Noise Optimization. Because it has uses in signal processing and can preserve edges while eliminating noise under certain circumstances, median filtering is a particularly popular technique in digital image processing. However, more on that later.

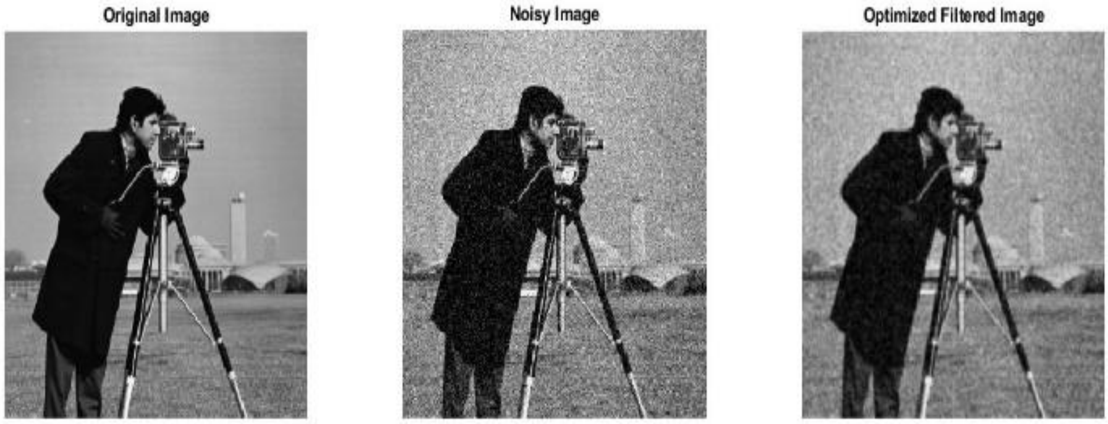

Fig 1: Experimental Results of Lord Rama Devotees Algorithm for Gaussian Noise Optimization

Read the Original Image (Grayscale)

- Load a grayscale image (e.g., 'cameraman.tif') for processing.
- Convert the image to a double precision format for computation.

Add Salt & Pepper Noise to the Image: Introduce Salt and Pepper noise to the image with a noise density of 0.02 to simulate image degradation.

Define Parameters for LRDA: Set key parameters for the optimization process:

- Number of devotees: Number of devotees (particles) in the algorithm.
- Dimension: Number of dimensions (in this case, window size for median filter).
- w: Inertia weight for velocity updates.
- C1, C2: Cognitive and social constants to control the influence of personal and global bests.
- Maximum Number of iterations: Number of iterations for running the optimization.
- Lord Rama Devotee Probability: Probability of behaving as a Lord Rama devotee.
- Non-Devotee Success Probability: Probability of a non-devotee being successful.
- Minimum and maximum window: Minimum and maximum window sizes for the median filter (ensuring they remain odd).

Initialize Devotees

- Randomly initialize the window sizes for each devotee (between the minimum and maximum allowed values).
- Round the values to ensure they are odd (required for median filtering).
- Set the initial velocity of each devotee to zero.
- Set the initial personal best positions to each devotee's starting window size.
- Set the global best to the window size of the first devotee.

Define Objective Function: Use the Peak Signal-to-Noise Ratio (PSNR) as the objective function, which needs to be maximized. The PSNR compares the quality of the filtered image to the original image.

Evaluate Initial Personal Bests and Global Best: For each devotee:

- Apply the median filter to the noisy image using the devotee's window size.
- Compute the PSNR between the filtered and original image.
- If the PSNR is higher than the devotee's current personal best, update the personal best.
- If the PSNR is higher than the global best, update the global best.

Start Iterations: For each iteration, update personal and global bests:

- For Lord Rama devotees (based on probability), update the velocities and window sizes based on personal and global bests.
- For non-devotees (with success probability), similarly update velocities and window sizes.
- Ensure that window sizes remain within the defined valid range and are always odd.

Update Personal and Global Bests

- After each update, reapply the median filter with the updated window sizes.
- Recalculate the PSNR for the filtered image and update personal and global bests as needed.

Display Optimized Results

- After the iterations are complete, display the optimized window size (filter size) found by LRDA.
- Apply the median filter with the optimized window size to the noisy image.

Show Images: Display the original image, the noisy image with Salt & Pepper noise, and the filtered image after applying the optimized median filter.

Compute PSNR of the Optimized Image: Compute and display the PSNR of the filtered image to evaluate the improvement in quality after noise reduction using the optimized filter size.

This process uses LRDA to optimize the window size for the median filter, aiming to maximize PSNR and achieve the best possible image denoising performance for Salt & Pepper noise. Figure 2 shows the experimental results of Lord Rama Devotees Algorithm for the median filter.

The application of the Lord Rama Devotees Algorithm (LRDA) for optimizing the median filter to reduce Salt & Pepper noise begins with reading a grayscale image (e.g., '*cameraman.tif*'). This image is converted to a double precision format for accurate computational processing. To simulate noise, Salt & Pepper noise is added with a noise density of 0.02, introducing random black and white pixels that degrade the image quality. The next step involves setting up the key parameters for the LRDA, such as the number of devotees (particles), dimensionality (which, in this case, refers to the window size of the median filter), and weights for updating velocities, including inertia weight and cognitive and social constants (C1 and C2) that guide the algorithm's exploration. Additional parameters include the maximum number of iterations for optimization, and probabilities for the devotee's behavior, such as the likelihood of acting as a Lord Rama devotee or succeeding as a non-devotee. The window size for the median filter is constrained between a defined minimum and maximum, ensuring that all values are odd, as required for median filtering.

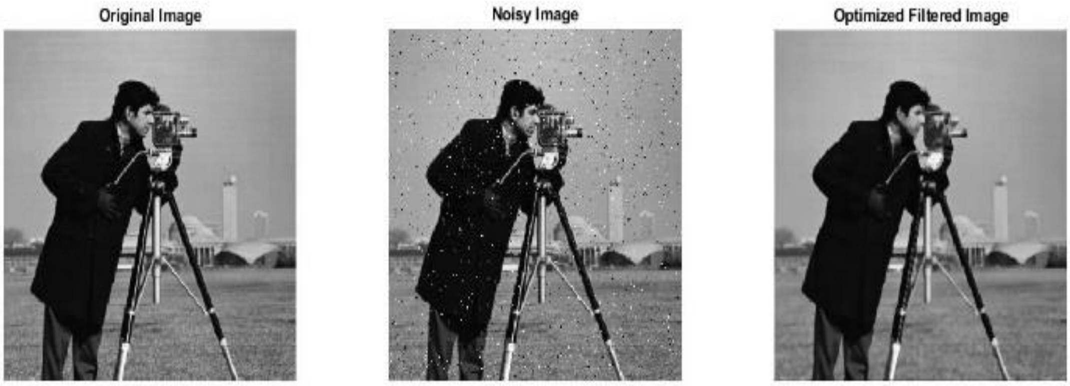

Fig 2: Experimental Results of Lord Rama Devotees Algorithm for median filter

The devotees are initialized by randomly generating window sizes within the allowed range, rounding them to the nearest odd number, and setting their initial velocities to zero. Each devotee's personal best position is set to their initial window size, while the global best is taken from the window size of the first devotee. The objective function used is the Peak Signal-to-Noise Ratio (PSNR). This metric evaluates the quality of the filtered image compared to the original image, with the goal of maximizing PSNR for optimal noise reduction.

Once initialized, the algorithm evaluates the initial personal and global bests by applying the median filter with the devotees' current window sizes to the noisy image. The PSNR for each filtered image is calculated, and if a devotee's PSNR surpasses its personal best, the personal best is updated. Similarly, if a devotee's PSNR is higher than the global best, the global best is updated. The iterative process then begins, where for each iteration, devotees update their window sizes and velocities based on personal and global bests. Lord Rama devotees and non-devotees update their positions based on different behavioral probabilities. Throughout the iterations, the algorithm ensures that the window sizes remain within the defined valid range and are always odd, which is crucial for the proper functioning of the median filter.

After each iteration, the algorithm re-applies the median filter using the updated window sizes, recalculates the PSNR, and updates personal and global bests if necessary. Once the iterations are complete, the optimized window size is displayed. This window size represents the best configuration found by LRDA to filter out Salt & Pepper noise effectively. The median filter is then applied to the noisy image using this optimized window size. The results are presented visually by displaying the original image, the noisy image with Salt & Pepper noise, and the filtered image after applying the optimized filter. Finally, the PSNR of the filtered image is calculated and displayed, showing the improvement in image quality achieved through the optimization process. In this case, the LRDA successfully optimized the window size to 3, resulting in an improved PSNR of 27.0186, reflecting the algorithm's effectiveness in reducing Salt & Pepper noise while preserving image details. This process demonstrates the capability of LRDA to fine-tune the median filter parameters for optimal image denoising performance.

Comparing the results of the Lord Rama Devotees Algorithm (LRDA) applied to optimize filters for both Gaussian noise and Salt & Pepper noise shows how effectively the algorithm tailors its approach to each type of noise while maximizing image quality. Here is a detailed comparison of the results:

Gaussian Noise Optimization:

Noise Type: Gaussian noise with a mean of 0 and variance of 0.01.

Optimization Objective: The sigma value of the Gaussian filter was optimized to improve noise reduction while preserving image quality.

Optimized Sigma Value: 0.7198.

Peak Signal-to-Noise Ratio (PSNR): 25.3405.

Filtered Image Quality: The application of the Gaussian filter with the optimized sigma value effectively reduced the Gaussian noise, producing a smooth and visually clean image. However, Gaussian filtering tends to blur the image slightly, which may lead to a small loss in finer details.

Salt & Pepper Noise Optimization (median filter):

Noise Type: Salt and Pepper noise with a noise density of 0.02.

Optimization Objective: The window size of the median filter was optimized to remove the noise while maintaining the structure and clarity of the image.

Optimized Window Size: 3.

Peak Signal-to-Noise Ratio (PSNR): 27.0186.

Filtered Image Quality: The median filter optimized by LRDA was highly effective at removing Salt & Pepper noise, especially since this type of filter excels at preserving edges and fine details while eliminating extreme outliers (salt and pepper pixels). The image quality after filtering showed a significant improvement without substantial blurring, resulting in a higher PSNR.

3.3 Comparison Summary

PSNR: The PSNR for the Salt & Pepper noise optimization (27.0186) was higher than that for the Gaussian noise optimization (25.3405), indicating better noise reduction performance and image quality in the case of Salt & Pepper noise. This makes sense, as median filters are particularly effective for this type of noise.

Filter Type: The Gaussian filter is generally better suited for Gaussian noise, but it may introduce some blur as it smooths out noise, leading to a slightly lower PSNR. In contrast, the median filter is designed for impulse noise like Salt & Pepper noise, offering superior noise reduction without significantly degrading image details, resulting in a higher PSNR.

Image Quality: For Gaussian noise, the filtered image using the optimized Gaussian filter had smoother gradients but lost some sharpness in fine details due to the nature of Gaussian filtering. In comparison, the median filter performed better for Salt & Pepper noise, retaining more of the image’s structural integrity and edges while effectively removing noise.

Optimization Variables: In the Gaussian noise case, LRDA optimized the continuous sigma value of the Gaussian filter, while for Salt & Pepper noise, the window size of the median filter, a discrete value, was optimized. The LRDA proved capable of optimizing both types of variables (continuous and discrete) effectively, adjusting to the nature of the filtering process required.

Both the Gaussian filter and the median filter, optimized by LRDA, performed well for their respective noise types. The Salt & Pepper noise reduction using the median filter showed superior performance in terms of PSNR and image preservation, while Gaussian noise optimization was also successful, though with a slightly lower PSNR due to the inherent blurring caused by Gaussian filters. The LRDA demonstrated flexibility and effectiveness in optimizing different filters for specific noise types, ensuring the best possible denoising results based on the nature of the noise.

4. CONCLUSION

In conclusion, the application of the Lord Rama Devotees Algorithm (LRDA) for optimizing the median filter to reduce Salt & Pepper noise demonstrates the algorithm's capacity to fine-tune filter parameters, thereby improving image quality effectively. By optimizing the median filter's window size, LRDA maximized the Peak Signal-to-Noise Ratio (PSNR), achieving a value of 27.0186 with a window size of 3. This result highlights LRDA's strength in addressing impulse noise while preserving image details, showcasing a significant improvement over the noisy image.

Furthermore, the comparison between LRDA-optimized filters for Gaussian and Salt & Pepper noise illustrates the algorithm's flexibility. While the Gaussian filter optimized for noise reduction yielded a PSNR of 25.3405, it introduced some blurring due to the nature of Gaussian filtering. On the other hand, the optimized median filter demonstrated superior performance for Salt & Pepper noise, retaining sharper edges and clearer image structure, as evidenced by the higher PSNR. Overall, the LRDA successfully adapted its optimization approach to different noise types, balancing noise reduction and image preservation. Its ability to optimize both continuous (sigma for Gaussian filter) and discrete variables (window size for median filter) showcases its versatility as an optimization tool for image processing tasks.

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