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An Optimal Patch Size based Sporadic Decomposition of Hankel Structured Matrix in Gradient Transform Domain for Impulse Noise Denoising

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***Abstract*—** Noise removal refers to the most vital process in image processing to remove the noise from a given image and reconstruct the original image. Among many denoising techniques, four types of extended versions of robust Annihilating filter-based Low-rank Hankel Matrix (r-ALOHA) approaches have been proposed in the previous researches. In those approaches, different kinds of transform domains like log-exponential, wavelet, generalized Hough, and gradient were considered separately in which that the image patch was considered as it was sparse in the considered transform domains independently to denoise the corrupted image. Even if gradient transform based denoising called e4-ALOHA achieves better performance than the other transform domains, it requires an automatic selection of Optimal Patch Size (OPS) to further improve the denoising performance. Hence in this article, an automatic selection of OPS is proposed with e4-ALOHA that searches similar image patches and selects an optimal patch size. In this technique, a Flower Pollination optimization Algorithm (FPA) is proposed to search similar patches and choose an optimal patch size adaptively according to the variance of similar patch groups. Once an optimal patch size is selected, e4-ALOHA is applied to perform the denoising process. Finally, the effectiveness of the proposed technique is evaluated through the experimental results.

***Keywords*—**Noise removal, r-ALOHA, e4-ALOHA, Optimal patch size, Flower pollination algorithm Formatting

I. INTRODUCTION

Mostly, the digital images are corrupted by noise i.e., unwanted information during image acquisition, coding, transmission and processing phases. The presence of noises may disturb the original information in the image, video and audio signals. It produces the unfavorable effects like artifacts, unrealistic edges, corners, blurred objects, etc. The removal of those noises from the digital images is very difficult without any prior knowledge of noise models. Among different types of noise models, the most well-known is impulse noise which may appear due to a failure outcome of detector pixels in the digital camera [1]. In recent years, high-density impulse noise removal using image processing techniques has been developed to be an active research with the purpose of suppressing the noises from the captured images and recovering them with a high quality [2].

Image denoising or noise removal is one of the most essential in image processing since many images captured by digital equipment or sensors commonly corrupted by noise. The aim of denoising techniques is removing the unwanted noise when the significant image features are preserved [3]. An inappropriate removal of noise may cause artifacts and blur in the images. Thus, the image denoising is still a challenging process for most of the researchers. In previous researches, robust Annihilating filter-based Low-rank Hankel Matrix (r-ALOHA) [4] was proposed in different transform domains like log-exponential transform (e1-ALOHA), wavelet transform (e2-ALOHA), radon transform (e3-ALOHA) and gradient transform (e4-ALOHA) domains to improve the denoising performance by considering the image patch was sparse in different considered transform domains efficiently [5-6]. Among these transform domains, gradient transform i.e., e4-ALOHA outperforms than the other transform domains. However, an optimal patch size was not automatically selected during the denoising process.

Hence in this article, an automatic selection of optimal patch size is proposed to further improve the denoising performance. In this technique, similar image patches are initially searched based on the adaptive patch size. After that, ALOHA is applied by making use of similar image patches obtained during the initial phase. It adopts an appropriate random sampling strategy i.e., Markov-Chain Monte Carlo

(MCMC) method to search the similar image patches. However, its computational complexity is high so that, an FPA optimization algorithm is proposed in this article to search similar patches and adaptively select the OPS for corresponding similar patch groups. Since FPA is simple, flexible and exponentially better to solve the optimization issues. Thus, an optimal patch size is automatically selected to remove the high-density impulse noise.

The rest of the article is structured as follows: Section II provides the previous researches related to impulse noise removal techniques based on image patches. Section III explains the proposed noise removal technique using an automatic selection of an optimal patch size in brief. Section IV compares the performance of the proposed technique with the existing technique and Section V concludes the research work.

II. RELATED WORK

An image denoising algorithm [7] was proposed with a patch-based Principal Component Analysis (PCA). In this scheme, three patch-based denoising algorithms were proposed which are differed by learning the dictionary such as local PCA, hierarchical PCA and global PCA. These three algorithms were performed hard thresholding on the coefficients of the patches in image-specific orthogonal dictionaries. However, this method requires the user for selecting the three parameters such as a size of patches, threshold level and searching zone width or the number of recursions.

A Two-Direction Non-Local (TDNL) variational model [8] was proposed for image denoising. This model has three components in which one component was a scaled version of the original observed image and the other two components were obtained by using the similarities. A nonlocal-means-like estimation of the patch was acquired with the consideration to all similar patches by using the similarity between columns when the weights were not the pairwise similarities but a set of clusterwise coefficients. Likewise, nonlocal-autoregression-like estimations for center pixels of the similar patches were obtained by using the similarity between rows. However, the drawback of this model was its high computational complexity.

A novel fast patch-based denoising [9] was proposed by using approximated Patch Geodesic Paths (PatchGP). In this method, the image patches and patch differences were treated as nodes and edge weights, respectively to compute the geodesic paths. After that, the path lengths were used as weights of the smoothing or denoising kernel. This model was approximated by Minimum Hop Paths (MHP) that normally corresponds to Euclidean line paths connecting two patch nodes. Moreover, the denoising kernel was constructed by discretizing the MHP search directions and using only patches along the search directions. Then, a weight propagation scheme was applied along each MHP for computing the path distance. Finally, wavelet image decomposition was applied for handling the noise at multiple scales and this proposed model was applied at each scale. However, in this method, search directions and patch sizes were fixed.

A Patch-based Exponentially Weighted Aggregation (PEWA) [10] was proposed for image denoising. In this method, an image patch was estimated from weakly denoised image patches in the input image. A boosted estimator was obtained by combining weak denoised versions of the input noisy images. Also, a spatial Bayesian prior and a Gibbs energy distribution were used for selecting good candidate patches. Moreover, a dedicated MCMC sampling process was proposed for computing the PEWA estimator efficiently. However, computational complexity was high.

Image denoising scheme [11] was proposed based on Gaussian membership function. In this scheme, the corrupted image was converted into the fuzzy values by using the fuzzification method. After that, all patches with overlaps were extracted and each patch was to be permuted. Then, the fuzzy Gaussian membership function was applied and fuzzy defuzzification method was applied for converting fuzzy values to the crisp values. However, the PSNR value of this scheme was less.

A patch-based denoising method [12] was proposed by using a low-rank technique and a targeted database for denoising the Optical Coherence Tomography (OCT) image. In this method, an internal and external denoising were combined during the selection of the similar patches for the noisy patch by using the other images relevant to the noisy image in which the targeted database was obtained by these two kinds of images. Moreover, a low-rank technique was applied for denoising the group matrix consisting of the noisy patch and the corresponding similar patches. Finally, a new noisy image was constructed by using a Gabor transform that includes some missing information to layers in the denoised image. However, the mean running time of this method was high.

Improved sparse matrix denoising technique [13] was proposed by using affinity matrix for noise removal. In this method, affinity matrix was used for finding the similarity between the pixels in an image and traversing the image. The similarity between the pixels was computed and each similarity was traversed. This process was continued until all the noisy pixels were eliminated from the image. Once noisy pixels were removed, denoised image was obtained. However, Mean Square Error (MSE) was high.

III. METHODOLOGY

In this section, the proposed OPS-e4-ALOHA for image denoising model using optimization algorithm is explained in brief. In this proposed technique, the quality of a restored image is improved by selecting an optimal patch size automatically for each image individually. Initially, the group of similar patches and its corresponding patch size for each image are searched by using FPA with maximum iterations. Using the number of iterations, an optimal patch size is obtained for the corresponding group of similar patches. As a result, the spectrum of a patch is sparse enough to reconstruct the noise-free images. This technique consists of the following two phases:

- The initial phase involves searching for the similar patches and selecting an optimal image patch size based on FPA.
- The second phase performs e4-ALOHA i.e., denoising algorithm by making use of the obtained optimal patch size and optimal patch group.

For a given noisy image patch $M \in \mathbb{R}^{M \times N}$, consider the initial patch size p. For each pixel x_j where j is the location of the pixel, the corresponding similar neighborhood sequence $\Omega^p(x_j)$ is searched by using FPA. In FPA, two processes are performed such as global pollination and local pollination. In the global pollination process, flower pollens are carried out by pollinators like insects and the pollens can move over a long distance since insects may regularly fly and travel in a much longer distance. This guarantees the pollination and reproduction of the most fitness value which is represented as g^*. In this algorithm, the flower constancy may be considered as the reproduction probability is proportional to the similarity of the two flowers involved in the pollination process. Also, both local and global pollination are controlled by a switch probability $\delta \in [0,1]$. Based on these constraints, the following update process is performed:

$$s_k^{t+1} = s_k^t + L(s_k^t - g^*) \qquad (3.1)$$

Equation (3.1), s_k^t refers the pollen k or solution vector s_k at iteration t and g^* refers the current best solution obtained among all solutions at the current iteration. The parameter L refers to the strength of the pollination or step size. As insects may travel over a long distance with different distance steps, a Levy flight is used to mimic this characteristic efficiently. Therefore, $L > 0$ is obtained from a Levy distribution.

$$L \sim \frac{\lambda\Gamma(\lambda)\sin\left(\frac{\pi\lambda}{2}\right)}{\pi}\frac{1}{a^{1+\lambda}}, (a \gg a_0 > 0,\ \lambda = 1.5) \qquad (3.2)$$

Equation (3.2), $\Gamma(\lambda)$ refers the gamma function of levy exponent λ and this distribution is valid for large steps $a > 0$. Similarly, the flower constancy for local pollination is represented as the following update function:

$$s_k^{t+1} = s_k^t + \epsilon(s_l^t - s_k^t) \qquad (3.3)$$

Equation (3.3), s_l^t and s_k^t are pollens from the different flowers of the same plant species. Basically, this mimics the flower constancy in a limited neighborhood. If both s_l^t and s_k^t are selected from the same species, then a local random walk is achieved with $\epsilon \in [0,1]$ i.e., a uniform distribution. Practically, adjacent flowers in the not-so-far-away neighborhood are more likely to be pollinated by local flower pollens that those far away. For this case, a switching probability is used to switch between common global pollination to intensive local pollination. This process is continued until the maximum number of iterations and a current best solution i.e., similar patch group is found. This similar patch group under the patch size p is selected as the most optimal patch group $x[n]$ and the patch size is chosen as the most optimal patch size.

Finally, the selected image patch group $x[n]$ in the discrete domain has sparse spectral components in different transform domains like log-exponential, wavelet, generalized Hough and gradient domains. Due to this, a corresponding annihilating filter exists in the image domain. Moreover, the denoising process is carried out in the above-mentioned transform domains efficiently.

A. Algorithm

Input: Noisy image patch $\mathrm{M} \in \mathbb{R}^{\mathrm{M \times N}}$ with patch size

Output: Optimal patch group $x[n]$ with optimal patch size

1. Define objective function i.e., maximize PSNR.
2. Initialize a population of f flowers with random solutions.
3. Compute objective function $O(f), f = (f_1, f_2, \dots, f_f)$.
4. Find the best solution g^* in the initial population.
5. Define a switch probability $\delta \in [0,1]$.
6. $while(t < max\_generation)$
7. $for\ i = 1{:}f$
8. $if(rand < \delta)$
9. Obtain a step vector L that obeys a Levy distribution.
10. Do global pollination based on (3.1).
11. $else$
12. Obtain ϵ from a uniform distribution in $[0,1]$.
13. Select k and l randomly among all the solutions.

14. Do local pollination using (3.3).
15. $endif$
16. Evaluate new solutions.
17. $if\,(new\ solutions\ are\ better)$
18. Update them in the population.
19. $endif$
20. $endfor$
21. Find the current best solution g^*.
22. Find the optimal patch group and optimal patch size corresponding to that optimal patch group.
23. $endwhile$

IV. Results and Discussion

In this section, the performance analysis of the proposed technique OPS-e4-ALOHA is presented. The experimental analysis is carried out in MATLAB 2018a and the evaluation is compared with the existing technique e4-ALOHA in terms of Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index Metric (SSIM) and reconstruction (computation) time for different images such as Lena, Barbara, balloon and cameraman at noise density level is 25%.

A. Peak Signal-to-Noise Ratio (PSNR)

PSNR defines the fraction of the maximum possible signal power to the corrupting noise power. Generally, it is computed by using MSE as:

$$PSNR = 10\log_{10}\frac{255^2}{MSE} \qquad (4.1)$$

$$Where, MSE = \frac{1}{m\,n}\sum_{i=1}^{m-1}\sum_{j=1}^{n-1}\left(M_{ij} - I_{ij}\right)^2 \qquad (4.2)$$

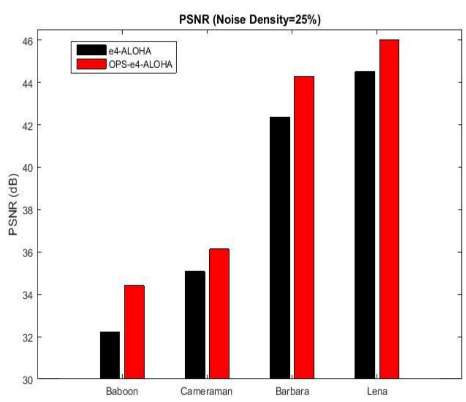

Figure.1 Comparison of PSNR

Figure 1 shows the comparison of different approaches by considering the images such as baboon, cameraman, Barbara and Lena in terms of PSNR (dB) at noise density level is 25%. For example, when Lena image is considered, the PSNR value of proposed OPS-e4-ALOHA is 3.37% higher than e4-ALOHA. From the analysis, it is observed that the OPS-e4-ALOHA has better PSNR than the e4-ALOHA.

B. Reconstruction Time

Reconstruction or computation time is the time taken for reconstructing the noise-free images from noisy images.

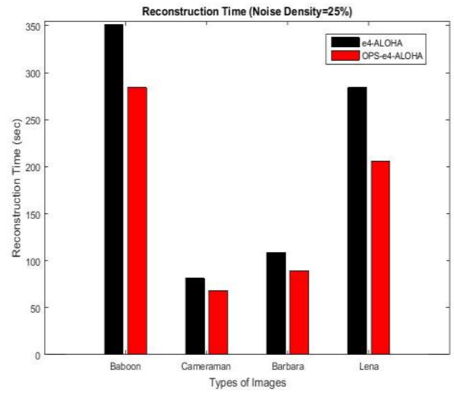

Figure.2 Comparison of Reconstruction Time

Figure 2 demonstrates the comparison of reconstruction time (seconds) for different approaches by considering various images like baboon, cameraman, Barbara and Lena at noise density level is 25%. For example, when Barbara image is considered, the reconstruction time of the proposed OPS-e4-ALOHA is 17.76% less than e4-ALOHA. Through the analysis, it is that noticed that OPS-e4-ALOHA has reduced reconstruction (computation) time than the e4-ALOHA.

C. Structural Similarity Index Metric (SSIM)

SSIM defines the similarity value between the original and denoised images. It is computed as:

$$SSIM(x,y) = \frac{(2\mu_M\mu_I + c_1)(2\sigma_{MI} + c_2)}{(\mu_M^2 + \mu_I^2 + c_1)(\sigma_M^2 + \sigma_I^2 + c_2)} \qquad (4.3)$$

Here, μ_M, μ_I are averages and σ_M^2, σ_I^2 are variances of an original image (M) and the noiseless image (I) respectively. Also, c_1, c_2 are constants and σ_{MI} is the covariance of $M\ and\ I$.

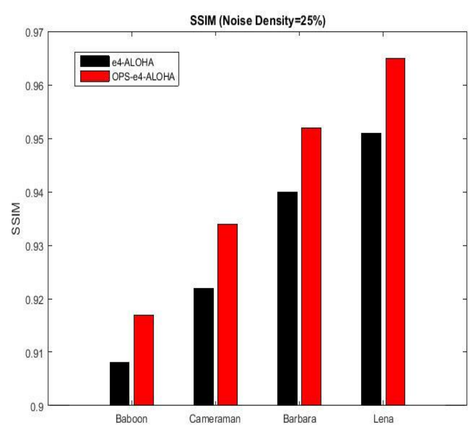

Figure.3 Comparison of SSIM

Figure 3 demonstrates the comparison of SSIM for different approaches by considering various images like baboon, cameraman, Barbara and Lena at noise density level is 25%. For example, when the cameraman image is considered, the SSIM value of proposed OPS-e4-ALOHA is 1.3% higher than e4-ALOHA. Through the analysis, it is that concluded that OPS-e4-ALOHA has improved SSIM than the e4-ALOHA.

V. CONCLUSION AND FUTURE SCOPE

In this article, an optimal patch size based sporadic decomposition of Hankel structured matrix in gradient transform domain for impulse noise removal from images that comprises an adaptive patch size and patch groups for modeling the Hankel matrix. In this technique, the similar patches in the given image are clustered to find the most optimal patch group and select the most optimal patch size to model the underlying image. To achieve this, FPA is applied that performs based on two processes namely local and global pollination. Based on this optimization, the best optimal patch size with optimal patch group is chosen. The optimal patch is selected automatically so that, the spectrum of a patch is sparse enough and it may be annihilated by a smaller size annihilating filter. Moreover, the image patches are sparse in the gradient transform domain to reconstruct the noiseless image. Finally, the experimental results are proved that the proposed OPS-e4-ALOHA has better performance than the existing image denoising technique. As a part of future work, a parallel computing framework would be developed to speed-up the denoising process using different images simultaneously.

REFERENCES

[1] P. Kamboj, V. Rani, "A brief study on various noise model and filtering techniques", Journal of Global Research in Computer Science, Vol.4, Issue.4, pp.166-171, 2013.

[2] A. Suganthi, M. Senthilmurugan, "Comparative study of various impulse noise reduction techniques", International Journal of Engineering Research and Applications, Vol.3, Issue.5, pp.1302-1306, 2013.

[3] K. Pritamdas, Kh. M. Singh, L. L. Singh, "A summary on various impulse noise removal techniques", International Journal of Science and Research, Vol.6, Issue.3, pp.941-954, 2017.

[4] K. H. Jin, J. C. Ye, "Sparse and low-rank decomposition of a hankel structured matrix for impulse noise removal", IEEE Transactions on Image Processing, Vol.27, Issue.3, pp.1448-1461, 2018.

[5] L. B. Victoria, S. Sathappan, "A sporadic decomposition of hankel structured matrix in logarithmic and wavelet domain for impulse noise removal", International Journal of Engineering & Technology, 2018.

[6] L. B. Victoria, S. Sathappan, "A sporadic decomposition of hankel structured matrix in generalized Hough and gradient transform domain for impulse noise removal", In International Conference on Research Trends in Computing Technologies (ICRTCT18), 2018.

[7] C. A. Deledalle, J. Salmon, A. S. Dalalyan, "Image denoising with patch based PCA: local versus global", In BMVC, Vol.81, pp.425-455, 2011.

[8] X. Zhang, X. Feng, W. Wang, "Two-direction nonlocal model for image denoising", IEEE Transactions on Image Processing, Vol.22, Issue.1, pp.408-412, 2013.

[9] X. Chen, S. Bing Kang, J. Yang, J. Yu, "Fast patch-based denoising using approximated patch geodesic paths", In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp.1211-1218, 2013.

[10] C. Kervrann, "PEWA: Patch-based exponentially weighted aggregation for image denoising", In Advances in Neural Information Processing Systems, pp.2150-2158, 2014.

[11] K. Kundu, "Image Denoising using Patch based Processing with Fuzzy Gaussian Membership Function", International Journal of Computer Applications, Vol.118, Issue.12, pp.35-40, 2015.

[12] X. Liu, Z. Yang, J. Wang, J. Liu, K. Zhang, W. Hu, "Patch-based denoising method using low-rank technique and targeted database for optical coherence tomography image", Journal of Medical Imaging, Vol.4, Issue.1, pp.014002(1-12), 2017.

[13] M. Kaur, B. Jindal, "Improved sparse matrix denoising technqiues using affinity matrix for geographical images", International Journal of Scientific Research in Computer Science and Engineering, Vol.5, Issue.5, pp.51-57, 2017.

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