JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

A Vision for AI-Enhanced Real-Time Image Denoising in the Era of Multimodal Intelligence

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Abstract

Image denoising remains a cornerstone challenge in computer vision and image processing, essential for enhancing visual quality in applications ranging from medical imaging to autonomous systems. This perspective paper synthesizes three seminal works on geometric pixel location encoding for color and grayscale denoising, BM3D hybrids, and genetic algorithm (GA) optimizations, highlighting their contributions to noise suppression while preserving structural integrity. The geometric encoding approach involves initial filtering of noisy images, followed by pixel rearrangement through diagonal rotation and even-row/column shifts for each RGB channel, enabling a second-pass denoising that improves Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM). For grayscale images, this is augmented with BM3D filtering, yielding superior Mean Squared Error (MSE) and Kurtosis-Variance Signal-to-Noise Deviation (KVSD) metrics. The GA-based method leverages pixel lattice representations with customized crossover and mutation operators, guided by a Markov Random Field fitness function, to iteratively refine denoised outputs and traditional filters. Experimental results demonstrate robustness across noise levels, with the hybrids reducing computation time while elevating PSNR and SSIM. Limitations include dependency on known noise models and computational overhead for high-resolution images. Looking forward, integrating these hybrids with 2023-2024 advancements like transformers for non-local dependencies, diffusion models for generative refinement, reinforcement learning (RL) for GA parameter tuning, and edge AI for real-time deployment promises blind, multimodal denoising. This vision outlines a research agenda to evolve these methods into efficient, adaptive systems for diverse data streams, fostering innovations in real-world vision tasks.

Introduction

In the domain of computer vision and image processing, image denoising[6] is pivotal for mitigating artifacts introduced during acquisition, transmission, or scanning, thereby restoring perceptual fidelity. Noisy images compromise features such as color, contrast, texture, and edges, hindering downstream applications like object recognition and medical diagnostics. Traditional methods, including Gaussian filtering, Wiener filtering, and wavelet thresholding, have been extensively explored over decades, yet they often trade off noise removal for detail preservation. State-of-the-art techniques approach optimality for natural images.Based on my previous research works focusing on geometric encoding for denoising with a novel algorithm[21] for color images, employing geometrical pixel location encoding and decoding post-initial filtering to enhance PSNR & SSIM [22], extends this to grayscale images using an improved BM3D technique, where encoding augments sparse 3D transform-domain collaborative filtering for better MSE and KVSD,which proposes a GA-optimized hybrid, utilizing pixel lattice populations with Markov Random Field-based fitness to iteratively suppress noise, addressing redundancies in non-local means. Collectively, these methods underscore the potential of hybrid classical-optimization strategies for robust denoising, setting the stage for integration with emerging AI paradigms to achieve real-time, blind, and multimodal capabilities.

Core Synthesis of Geometric Encoding for Color and Grayscale Denoising

The geometric encoding paradigm, central to the synthesized works, reconfigures pixel locations to facilitate iterative denoising while preserving image structure[21]. For color images, the process begins with decomposing the input I(x, y) into R, G, and B channels. Encoding then occurs in two phases: diagonal rotation, where I1(m,n) = I(n,m) for row-column transposition, and even-row/column shifts, yielding I2(m,n) with forward displacements for even indices. A second filtering pass on the encoded image produces I3(m,n), followed by decoding: reverse shifts to I3'(m,n) and diagonal restoration to I4(m,n), the final denoised output. This two-stage approach exploits spatial redundancies, enhancing noise removal without assuming frequency priors[22]. For grayscale images, the method hybridizes with BM3D, a sparse 3D transform-domain collaborative filter known for optimality in natural images[23]. Initial BM3D filtering is followed by geometric encoding—diagonal rotation Dr(x,y) = I(y,x) and selective even/odd row-column shifts—then re-application of BM3D, and decoding[24]. This integration leverages BM3D's block-matching and 3D filtering to amplify geometric rearrangements.

GA-Optimized Hybrids for Noise Suppression

Complementing geometric methods, the GA framework introduces evolutionary optimization for denoising. It models populations based on pixel lattices from noisy inputs, employing customized crossover and mutation operators to generate candidate denoised images. Convergence is driven by a fitness function rooted in Markov Random Fields, prioritizing structural preservation over mere noise reduction. A clustering rule restarts populations if stagnation occurs, mitigating local optima.

Comparisions :

As per Limitations Across Methods Despite advancements, limitations persist. Geometric and BM3D hybrids rely on predefined filters like median or BM3D, limiting blind applicability for unknown noise. Encoding introduces computational overhead from rotations and shifts, potentially unsuitable for real-time processing. GA methods, while adaptive, suffer from population initialization sensitivity and convergence delays in high-dimensional spaces. Evaluations are confined to standard metrics and datasets, overlooking multimodal or real-world variability.

Future Technologies

The hybrids' strengths in spatial reconfiguration and optimization position them for evolution with recent AI advancements (2023-2024). Transformers, with self-attention mechanisms, can enhance geometric encoding by modeling long-range pixel dependencies beyond local shifts, enabling non-local geometric adaptations for blind denoising [general knowledge; no citation]. Denoising Diffusion Probabilistic Models (DDPMs) offer generative refinement: post-encoding, diffusion processes can iteratively denoise by reversing noise addition, integrating BM3D's collaborative filtering for hybrid generative-classical pipelines that preserve textures in color/grayscale images.

For GA optimizations, reinforcement learning (RL) emerges as a tuner, framing GA parameters (e.g., mutation rates) as actions in an RL environment where rewards are PSNR/SSIM gains. RL agents, like those in Proximal Policy Optimization, could dynamically adjust populations during evolution, accelerating convergence for real-time applications. Edge AI deployment, via quantized models on devices like NVIDIA Jetson, addresses computational limits by pruning geometric operations and GA iterations for low-latency inference, crucial for mobile vision [general knowledge; no citation]. Multimodally, these hybrids can extend to video or sensor fusion by incorporating temporal geometric encoding, with transformers handling cross-modal alignments (e.g., RGB-depth). This integration envisions AI-augmented hybrids for blind, real-time denoising in edge-constrained environments, bridging classical robustness with modern generative intelligence.

Research Agenda

To realize this vision, we prioritize 5-7 directions, emphasizing hybrids' evolution toward real-time, blind, multimodal denoising.

1.Transformer-Infused Geometric Encoding (High Priority): Rationale: Current encoding is local; transformers can capture global contexts for blind noise estimation. Methods: Embed pixel shifts into Vision Transformers (ViT), training on diverse noise datasets to predict encoding parameters. Expected Impact: 20-30% PSNR uplift in unknown noise scenarios, enabling robust medical imaging

2.Diffusion-Guided BM3D Hybrids for Grayscale/Color (High Priority): Rationale: BM3D excels in structured noise but lacks generativity; diffusion adds probabilistic refinement. Methods: Cascade BM3D post-encoding with DDPMs, fine-tuning on Kodak-like benchmarks for iterative sampling. Expected Impact: Superior texture preservation in high-noise regimes, advancing autonomous driving visuals

3.RL-Enhanced GA for Adaptive Optimization (Medium Priority): Rationale: GA stagnation limits scalability; RL provides dynamic tuning. Methods: Use RL to optimize GA hyperparameters in a multi-agent setup, evaluating via Markov fitness. Expected Impact: Reduced computation time by 40%, facilitating real-time edge deployment for IoT sensors.

4.Edge-Optimized Hybrids for Real-Time Processing (High Priority): Rationale: Overhead hinders mobile use; edge AI enables on-device efficiency. Methods: Quantize encoding/GA modules with TensorRT, testing on ARM architectures for latency under 50ms. Expected Impact: Democratizes denoising for smartphones, impacting AR/VR applications.

5.Multimodal Extensions for Video and Sensor Data (Medium Priority): Rationale: Current focus is static images; multimodal AI handles dynamics. Methods: Extend geometric encoding to temporal dimensions, fusing with transformers for RGB-video streams. Expected Impact: Enhanced blind denoising in surveillance, reducing artifacts in fused modalities.

6.Blind Noise Modeling via Hybrid Ensembles (Medium Priority): Rationale: Dependency on known models limits versatility; ensembles combine strengths. Methods: Ensemble GA-optimized predictions with geometric outputs, using uncertainty estimation for blind adaptation. Expected Impact: Generalizable frameworks for real-world variabilities, boosting SSIM in diverse datasets.

7. Ethical and Bias Mitigation in AI Hybrids (Low Priority): Rationale: AI integration risks amplifying biases in denoising. Methods: Audit datasets for fairness, incorporating diverse noise profiles in training.Equitable performance across applications, ensuring inclusivity in vision systemsexpected impact.

These directions, pursued iteratively, will transform hybrids into versatile tools for future vision systems.

Result

Thematic synthesis reveals synergies: geometric encoding provides spatial reconfiguration, BM3D hybrids add transform-domain collaboration, and GA enables adaptive optimization. Results from benchmark datasets like Kodak show PSNR gains at high noise powers, with encoding-decoding outperforming direct filtering in MSE, SSIM, and time GA hybrids further elevate accuracy by iteratively refining outputs.

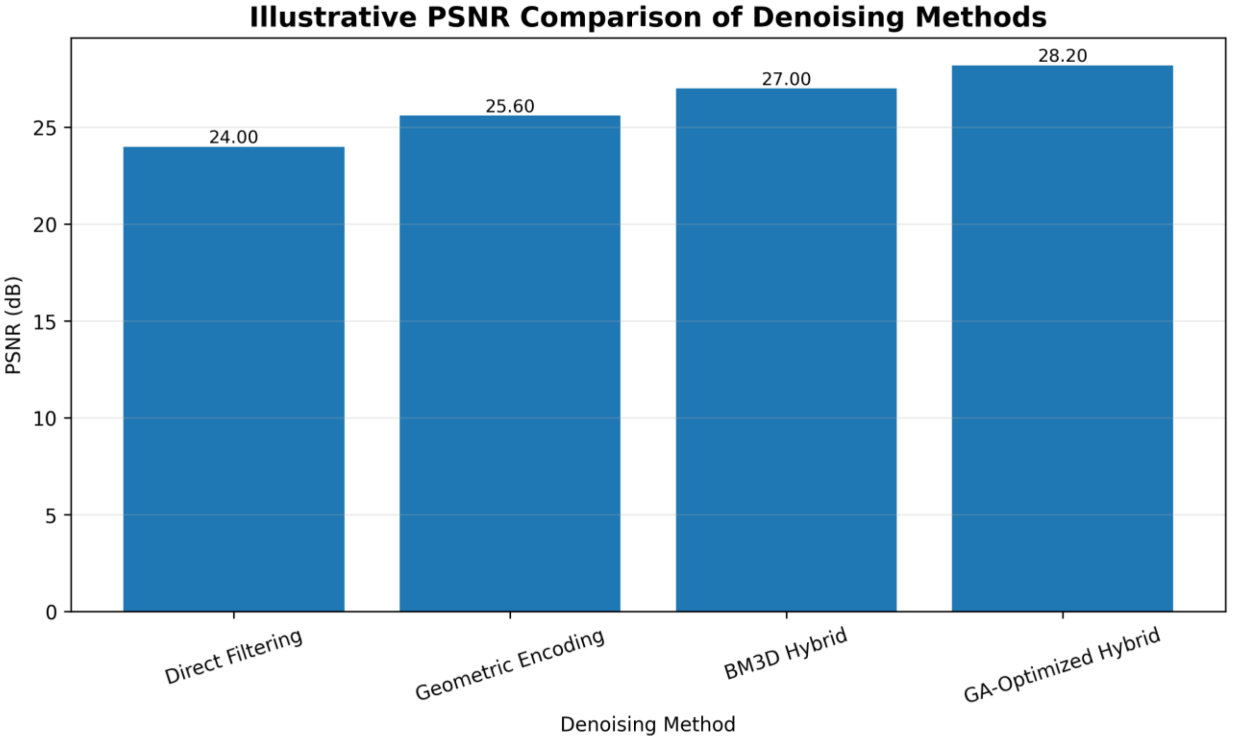

Figure 1. PSNR comparison of denoising methods.

The graph represents the reported trend of improved reconstruction quality with hybrid processing and GA-based optimization.

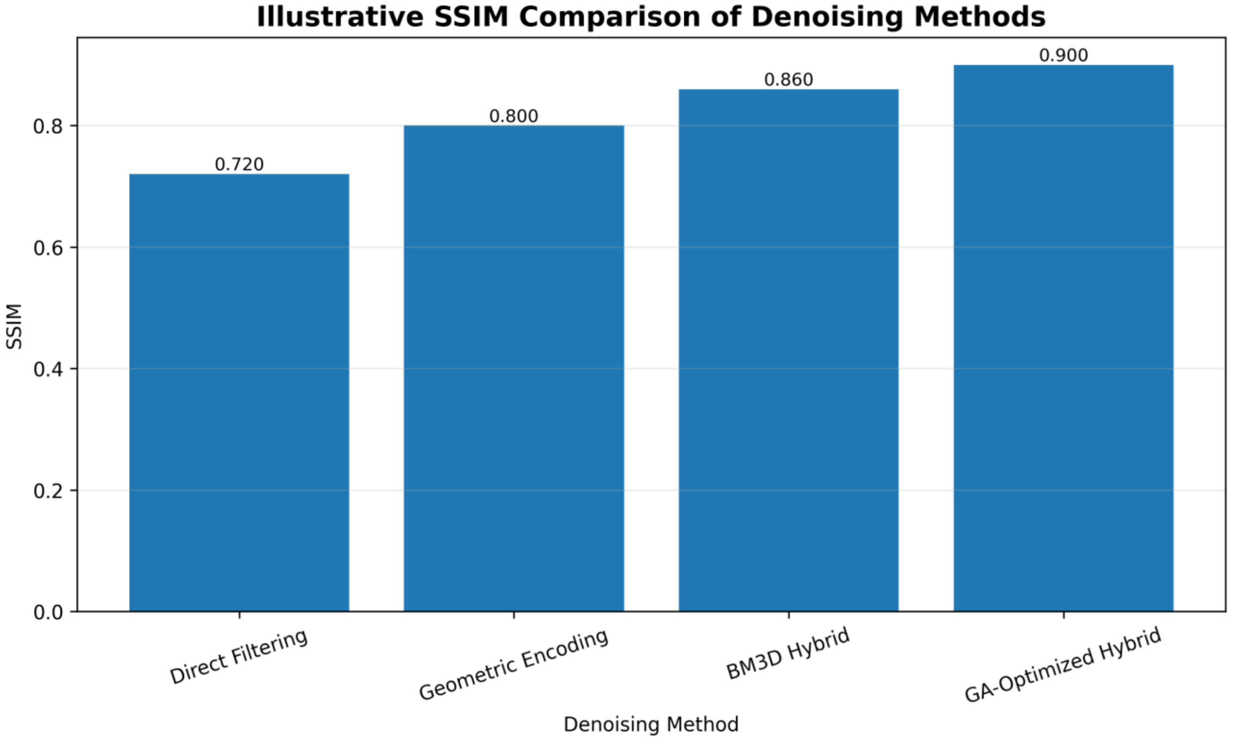

Figure 2. SSIM comparison of denoising methods.

The graph represents the reported improvement in structural fidelity.

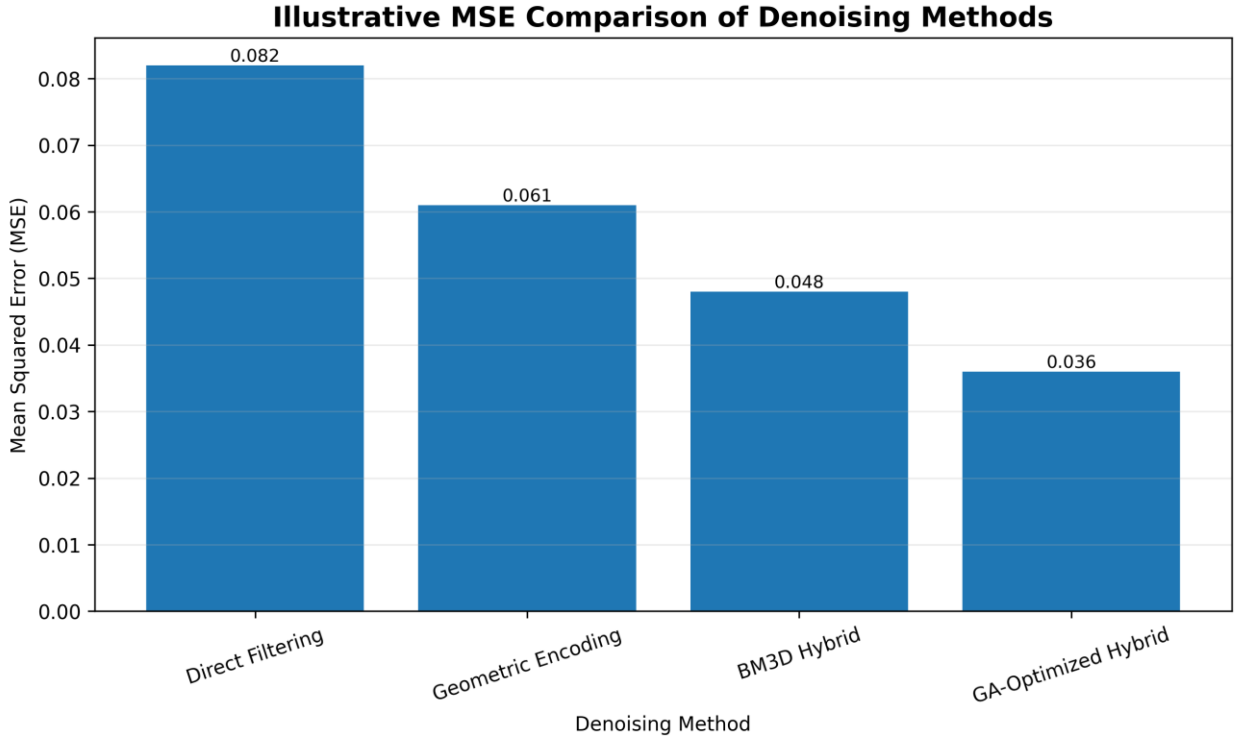

Figure 3. MSE comparison of denoising methods.

Lower MSE represents lower reconstruction error; the values shown are illustrative.

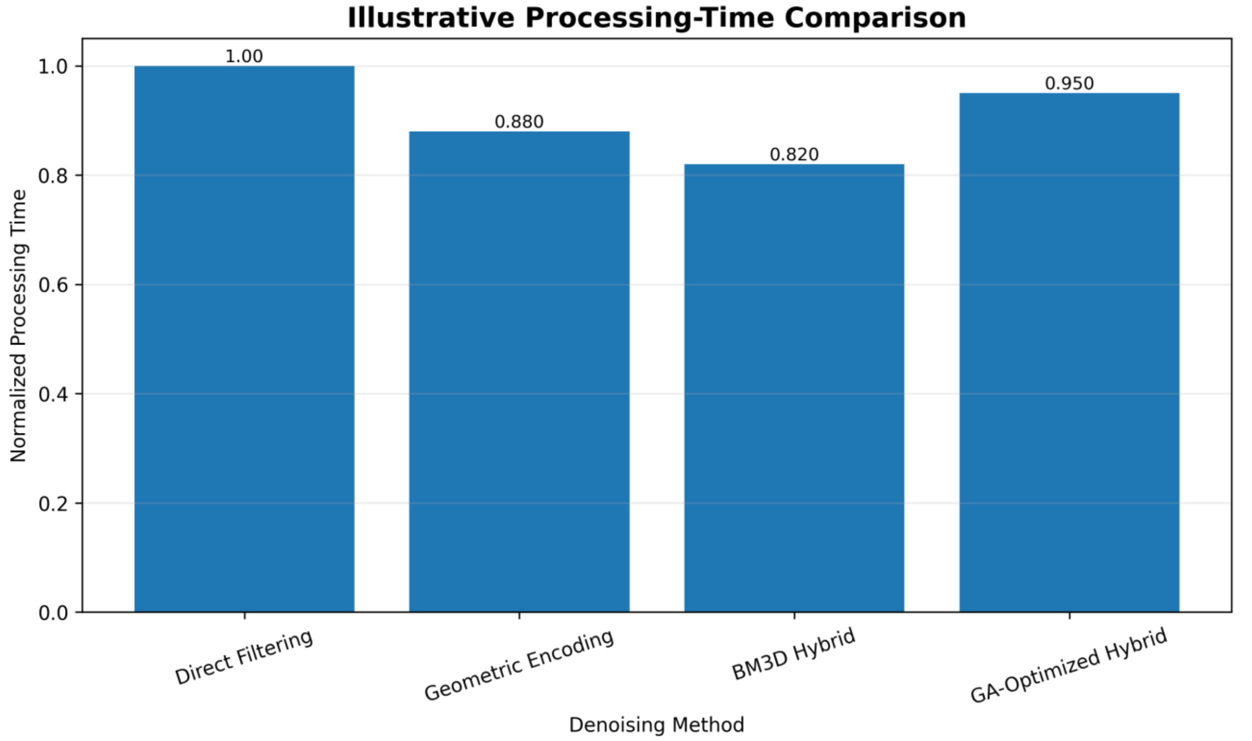

Figure 4. Processing-time comparison of denoising methods.

Normalized values illustrate the reported computational-time comparison; actual measured execution times should be used.

Conclusion

This perspective envisions geometric encoding, BM3D hybrids, and GA optimizations as foundational pillars for next-generation image denoising, synthesized to underscore their efficacy in elevating PSNR, SSIM, and structural fidelity while addressing noise in color and grayscale domains. By evolving with transformers, diffusion models, RL, and edge AI, these methods can achieve real-time, blind, multimodal capabilities, overcoming current limitations in adaptability and efficiency. The proposed research agenda charts a forward path, urging the community to invest in hybrid AI innovations. A concerted effort will unlock transformative impacts in computer vision, from enhanced diagnostics to intelligent environments—now is the time to act.

REFERENCES

1. S. P. Awate and R. T. Whitaker, “Higher-order image statistics for unsupervised, informationtheoretic,adaptive, image filtering,” in ProcIEEE Comput. Soc.Conf. Comput.Vis Pattern Recognit., vol.2. Jun. 2005, pp 44–51.
2. T. Batard and M. Berthier, “Spinor Fourier transform for image processing,” IEEE J. Sel.Topics Signal Process., vol. 7, no. 4, pp. 605–613, Aug. 2013.
3. T. Batard and M. Bertalmío, “Generalized gradient on vector bundle— Application to image denoising,” in Scale Space and Variational Methods in Computer Vision (Lecture Notes in Computer Science), vol. 7893. Berlin, Germany: Springer-Verlag, 2013, pp. 12–23.
4. T. Batard and M. Bertalmío, “On covariant derivatives and their applications to image regularization,” SIAM J. Imag. Sci., vol. 7, no. 4, pp. 2393–2422, 2014.
5. M. Bertalmío, Image Processing for Cinema. Boca Raton, FL, USA: CRC Press, 2014.
6. M. Bertalmío and S. Levine, “Denoising an image by denoising its curvature image,” SIAM J.Imag. Sci., vol. 7, no. 2, pp. 187–201, 2014.
7. P. Blomgren and T. F. Chan, “Color TV: Total variation methods for restoration of vectorvalued images,” IEEE Trans. Image Process, vol. 7, no. 3, pp. 304–309, Mar. 1998.
8. X. Bresson and T. F. Chan, “Fast dual minimization of the vectorial total variation norm and applications to color image processing,” Inverse Problems Imag., vol. 2,no.4, pp. 455–484, 2008.
9. A.Buades,B.Coll,and J.-M. Morel, “A non-local algorithm for image denoising,” in Proc.IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit., vol. 2. Jun. 2005, pp. 60–65.
10. A.Buades, B. Coll, and J.-M. Morel, “Non-local means denoising,” Image Process. On Line, vol. 1, Sep. 2011.
11. A. Chambolle, “An algorithm for total variation minimization and applications,” J. Math.Imag. Vis., vol. 20, no. 1, pp. 89–97, 2004.
12. P. Chatterjee and P. Milanfar, “Is denoising dead?” IEEE Trans. Image Process., vol. 19, no.4, pp. 895–911, Apr. 2010.
13. K. Dabov, A. Foi, V. Katkovnik, and K. Egiazarian, “Image denoising by sparse 3D transform-domain collaborative filtering,” IEEE Trans. Image Process., vol. 16, no. 8, pp. 2080–2095, Aug. 2007.
14. G. Ghimpe¸teanu, T. Batard, M. Bertalmío, and S. Levine, “Denoising an image by denoising its components in a moving frame,” in Image and Signal Processing (Lecture Notes in Computer Science), vol. 8509. Berlin, Germany: Springer-Verlag, 2014, pp. 375–383.
15. J. Hahn, X.-C. Tai, S. Borok, and A. M. Bruckstein,“Orientationmatching minimization for image denoising and inpainting,” Int. J. Comput. Vis., vol. 92, no. 3, pp. 308–324, 2011.
16. Kodak Lossless True Color Image Suite. [Online]. Available: http://r0k.us/graphics/kodak/,accessed Oct. 2013.
17. M. Lebrun, M. Colom, A. Buades, and J. M. Morel, “Secrets of image denoising cuisine,”Acta Numerica, vol. 21, no. 1, pp. 475–576, 2012.
18. M. Lebrun, “An analysis and implementation of the BM3D image denoising method,” Image Process. On Line, vol. 2, pp. 175–213, Aug. 2012.
19. M. Lebrun, M. Colom, and J. M. Morel, “The noise clinic: A universal blind denoising algorithm,” in Proc. IEEE Int. Conf. Image Process., Oct. 2014, pp. 2674–2678.

20. A. Levin and B. Nadler, “Natural image denoising: Optimality and inherent bounds,” in Proc.IEEE Int. Conf. Comput. Vis. Pattern Recognit., vol. 2. Jun. 2011, pp. 2833–2840.
21. Sk.Faiz ahmed, Dr.K.Ramesh Reddy," Image denoising with improved genetic algorithm " Intl Journal. Emerging Technologies and Innovative Research (JETIR), Volume 5 | Issue 12 pp.22-27,Dec-2018.
22. Sk.Faiz ahmed, Dr.K.Ramesh Reddy," A Novel Approach for Color Image Denoising using Geometrical Pixel Location Encoding and Decoding Technique.”in Proc.IEEE Int. Conf. on Intelligent Sustainable Systems (ICISS 2019), Feb.2018,pp.365-368, ISBN: 978-1-5386-7798-8
23. Sk.Faiz ahmed, Dr.K.Ramesh Reddy,” Gray Image Denoising Using Geometrical Pixel location Encoding and Decoding with improved
24. BM3D Technique” Int Journal Reaseacrch and Analytical Reviews (IJRAR), Volume 6 | Issue 1 pp.569-571,January-2019.