



Efficient Solar Image Denoising for Sunspot Detection Using Advanced Filtering Techniques

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Abstract

The quality of astronomical observations can be improved by reducing the noise contained in the images of the sun. The presence of noise impairs the quality of the solar images, leading to reduced quality of the features extracted from the solar imagery for detecting sunspots and monitoring solar activity. A comparison of denoising methods; such as Adaptive Anisotropic Diffusion (AAD), Anisotropic Diffusion (AD), Non-Local Means (NLM), Total Variation (TV), Wavelet Transform, BM3D and Deep Learning filtering techniques; has been performed to improve the quality of solar images. The results from the comparisons were produced based on experiments with a variety of noisy solar and sunspot images. For the quantitative analysis, Peak Signal to Noise Ratio (PSNR), Structural Similarity Index Measure (SSIM), Mean Square Error (MSE), edge preservation index, sunspot error rate, convergence speed, and processing time were included in the evaluations. The comparison results indicate that the NLM algorithm had a superior PSNR and SSIM with higher quality image restoration among the denoised images, while the Deep Learning based algorithms achieved faster speed of execution, which would allow for their application in real-time processing. The proposed comparisons provide a useful tool for selecting an appropriate solar image denoising technique for automated solar image processing systems.

Keywords: Solar Image Processing, Sunspot Detection, Image Denoising, Non-Local Means, BM3D, Deep Learning, Adaptive Anisotropic Diffusion, Solar Activity Analysis

I. INTRODUCTION

A key area of investigation in modern astrophysics and forecasting solar weather is analyzing various phenomena observed to occur on the sun. Continuous observation of features of the sun, such as sunspots, solar flares, coronal holes, and magnetic activity, demand high quality acquisition of images and accompanying enhancement of the images obtained. However, most images of the sun, acquired through either a telescope or from a space-based observatory, have been degraded due to various sources of noise such as gaussian noise, speckle noise, and distortions associated with the sensor used to obtain the image. The resulting noise has a significant impact on the results of performing various image segmentation, feature extraction, and automated detection of solar events.

Denoising the images that have been obtained is therefore the most basic step in preprocessing the solar image data that is to be analyzed. Numerous traditional methods exist for denoising images (e.g., anisotropic diffusion, wavelet transform, total variation filtering,...) which have been used successfully to remove noise while respecting the presence of critical structural components of the image. However, novel techniques are now available, such as non-local means (NLM), BM3D, and deep learning-based filtering methods, which have exhibited improved denoising performance characteristics and also have better able to preserve the significant features of the image being analyzed.

This work provides an in-depth comparison of different denoising algorithms that were applied to images of the sun and of sunspots. The performance of the various denoising methods was evaluated using both quantitative and qualitative methods. Because of technical improvements made during the past few years in how pictures of the sun can be processed using various forms of imaging techniques like image processing (including machine learning), machine-learning/deep-learning based methods, and other inputs; several new methods have emerged that greatly improve both the accuracy of detection of sunspots, segmentation/the identification of sunspots, classification of sunspots, and prediction of solar activity. Traditional methods of reducing noise from photographs of the sun include: Anisotropic Diffusion (AD), Non-Local Means (NLM), Wavelet Transform,

and BM3D filtering. Each of these traditional approaches has been used successfully for reducing noise while preserving important solar features. Anisotropic diffusion has been shown to be an effective method of smoothing noisily taken images of the sun while preserving edge information; NLM-based algorithms are able to achieve higher Peak Signal to Noise Ratios (PSNR) and Structural Similarity Indexes (SSIM) than anisotropic methods by taking advantage of redundancies in images. Hybrid denoising systems that include wavelet transform-based denoising, adaptive filtering methods, and deep-learning systems, have also contributed to improved image quality and preservation of features in solar imaging.

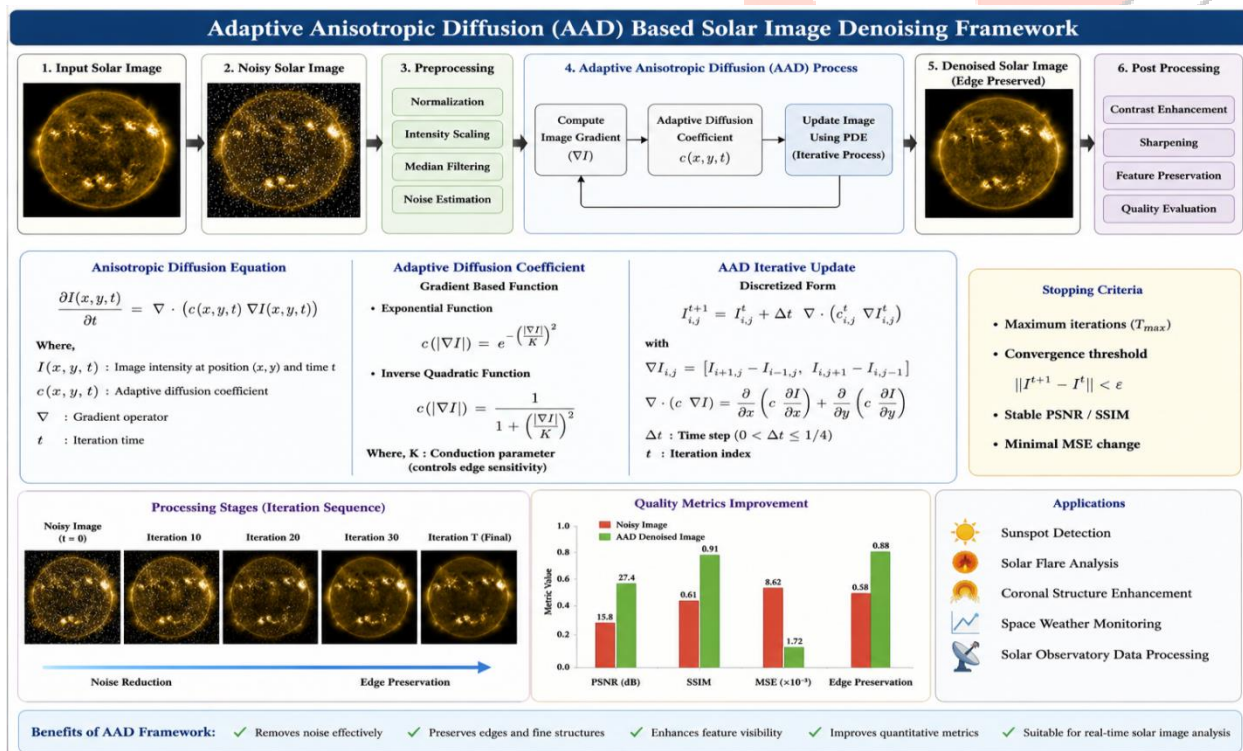
II. DENOISING TECHNIQUES

A. Adaptive Anisotropic Diffusion (AAD)

Adaptive Anisotropic Diffusion (AAD) is considered superior technology than traditional image denoising methods for preserving features like edges and outlines while removing excess noise from images. AAD was developed from the idea of anisotropic diffusion as proposed by Perona and Malik to model how to control the rate of diffusion between adjacent pixels based on similarities in pixel values (homogeneous regions) or dissimilarities in pixel values (edges) as shown in Fig 2.1. Unlike other smoothing filters, which make everything look the same (i.e. adding/reducing detail) regardless of photo quality, AAD selectively smooths the image based on the characteristics of the surrounding image pixels leading to its use in a variety of different applications such as de-noising solar images, medical imaging, satellite imagery, and machine vision.

Telescopes and satellite sensor devices generally collect images that are corrupted by noise from atmospheric conditions, sensor inconsistencies, and transmission or radiation. When noise is present in a solar image it limits how accurately solar features can be detected (i.e. sunspots, solar flares, coronal loops, and active regions) since noise takes away from overall quality of the image. AAD enables the detection of these solar features by reducing noise without affecting the edges and fine details associated with these features.

The basic principle of AAD is based on the diffusion equation, where the diffusion coefficient changes according to the gradient magnitude of the image. In smooth regions, diffusion is allowed to occur strongly to remove noise, whereas near edges diffusion is reduced to preserve structural information. This adaptive behavior prevents edge blurring and improves feature preservation compared to traditional filters such as Gaussian and mean filters. Mathematically, anisotropic diffusion is represented using a partial differential equation (PDE) that iteratively updates pixel intensities over time. The diffusion coefficient is usually controlled using gradient-based functions that detect edges in the image. Common diffusion functions include exponential and inverse quadratic functions. These functions ensure that regions with high intensity variation receive less smoothing.



Processing Stages (Iteration Sequence)

Noisy Image ($t=0$) Iteration 10 Iteration 20 Iteration 30 Iteration T (Final)

Noise Reduction Edge Preservation

Quality Metrics Improvement

Metric	Noisy Image	AAD Denoised Image
PSNR (dB)	15.8	27.4
SSIM	0.61	0.91
MSE ($\times 10^{-4}$)	8.62	1.72
Edge Preservation	0.58	0.88

Applications

- Sunspot Detection
- Solar Flare Analysis
- Coronal Structure Enhancement
- Space Weather Monitoring
- Solar Observatory Data Processing

Figure 2.1 Solar image processing using AAD filter

Adaptive Anisotropic Diffusion provides several advantages in solar image analysis. It improves image clarity, enhances edge visibility, preserves sunspot boundaries, and reduces random noise effectively. The method also improves quantitative image quality metrics such as Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and Mean Square Error (MSE). In many studies, AAD demonstrated better visual enhancement than classical linear filters. Another important feature of AAD is its adaptability. The filtering parameters can be adjusted dynamically based on local image content, noise level, and texture characteristics. This adaptive nature makes the method more robust for processing different types of solar images captured under varying observational conditions.

Recent research has integrated AAD with machine learning and deep learning frameworks to further improve denoising performance. Hybrid models combining anisotropic diffusion with convolutional neural networks, wavelet transforms, and non-local filtering have shown significant improvements in solar image restoration and segmentation tasks. Despite its advantages, AAD also has some limitations. The iterative diffusion process may increase computational complexity and processing time for high-resolution images. Improper parameter selection can also lead to over-smoothing or insufficient noise removal. Therefore, optimization of diffusion parameters remains an active research area.

Overall, Adaptive Anisotropic Diffusion is considered one of the most effective edge-preserving denoising techniques for solar image enhancement. Its ability to selectively smooth noisy regions while maintaining important solar structures makes it highly valuable in modern solar image analysis and space research applications.

B. Anisotropic Diffusion (AD)

Anisotropic Diffusion (AD) is a PDE-based denoising method as illustrate in Fig 2.2 that smooths images while preserving important edges and discontinuities. The method was introduced to overcome the limitations of isotropic filters such as Gaussian smoothing, which blur image edges during noise removal. AD works by controlling diffusion based on image gradients. Pixels in uniform regions undergo stronger smoothing, while diffusion across edges is restricted to maintain boundaries. In solar image processing, anisotropic diffusion helps reduce random noise caused by atmospheric interference, sensor noise, and transmission disturbances. The diffusion process is iterative and gradually refines the image over time. The method uses conduction coefficients that depend on local gradient magnitudes. These coefficients prevent diffusion near significant intensity changes, thereby preserving solar structures. AD improves visual quality and enhances the detectability of solar features such as sunspots and solar flares. The technique is mathematically stable and easy to implement for grayscale and color images. It also reduces speckle noise while preserving edge information better than linear filters. However, excessive diffusion iterations may lead to loss of fine textures and over-smoothed images. In some cases, weak edges may disappear if diffusion parameters are not optimized properly. Despite these limitations, AD remains a widely used denoising technique in image restoration and computer vision. The method provides better structural preservation compared with traditional averaging methods. It is commonly used as a preprocessing step before segmentation and feature extraction in solar image analysis systems. AD forms the foundation for many advanced adaptive diffusion techniques used in modern astronomical image enhancement applications.

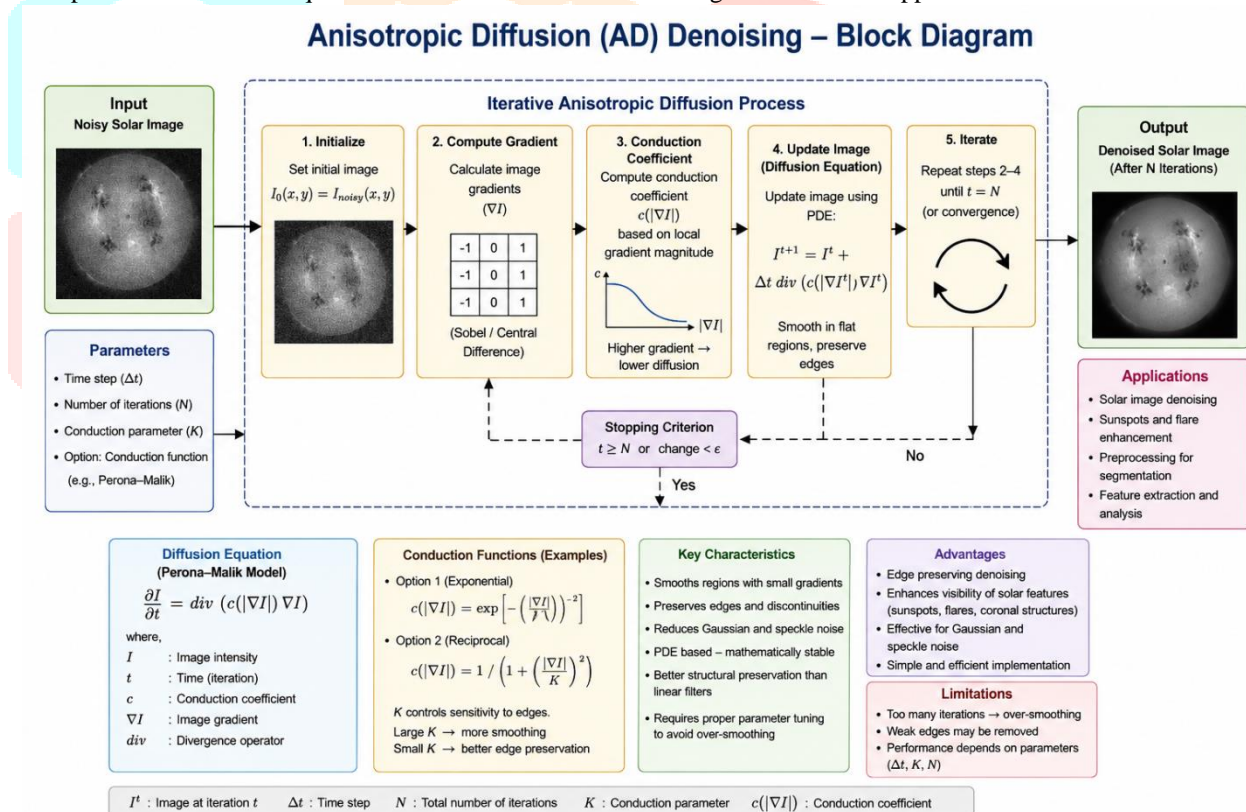


Figure 2.2 Anisotropic Diffusion Process for Solar Image Enhancement

C. Non-Local Means (NLM)

Non-Local Means (NLM) is a powerful denoising technique that removes noise by exploiting redundancy and self-similarity within an image. Unlike local filters that use neighboring pixels only, NLM compares image patches across the entire image to identify similar structures as shown in Fig 2.3. Pixels are restored by weighted averaging of similar patches, leading to excellent noise suppression while preserving textures and edges. In solar image denoising, NLM effectively enhances sunspots, coronal structures, and active solar regions without introducing significant blurring artifacts. The method computes similarity weights based on patch distance measures such as Euclidean distance. Regions with higher similarity contribute more strongly to the denoised output. NLM achieves superior performance in terms of PSNR and SSIM compared with many conventional filters. The algorithm preserves fine structural information and texture patterns effectively. It is particularly suitable for high-resolution solar images captured by telescopes and satellite systems. NLM also performs well under Gaussian and speckle noise conditions. However, the computational complexity of NLM is relatively high because of extensive patch comparisons across the image. To

improve efficiency, optimized and adaptive NLM variants have been proposed in recent studies. Hybrid frameworks combining NLM with wavelets and deep learning further enhance denoising performance. The method is widely used in medical imaging, remote sensing, and astronomical image reconstruction. In solar image analysis, NLM improves the visibility of solar structures and enables accurate feature extraction. Overall, Non-Local Means provides excellent denoising capability while maintaining important image details and edge information.

Non-Local Means (NLM) Denoising – Block Diagram

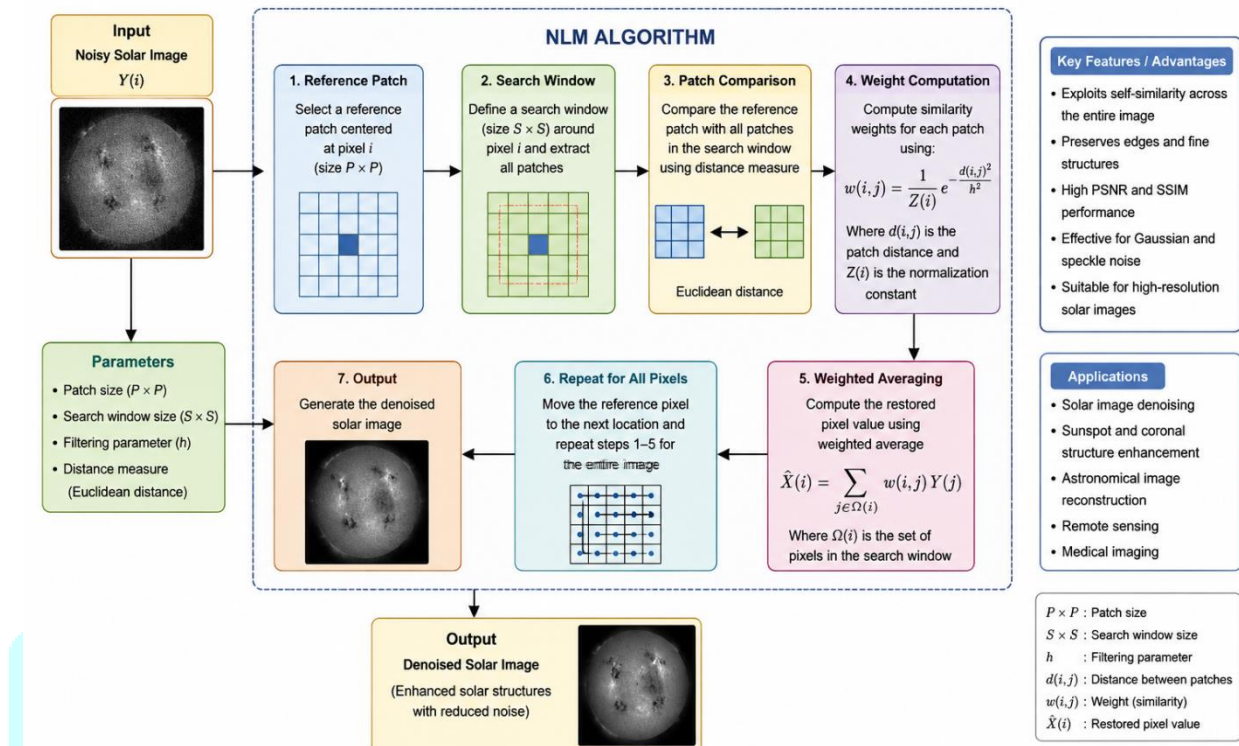


Figure 2.3 Non-Local Means Based Solar Image Denoising Architecture

D. Total Variation (TV)

Total Variation (TV) denoising is an optimization-based image restoration technique that minimizes total image variation while preserving edges and structural boundaries. The method as illustrated in Fig 2.4 assumes that noise mainly affects rapid intensity fluctuations, whereas meaningful image structures correspond to piecewise smooth regions. TV denoising removes noise by minimizing an energy function composed of fidelity and regularization terms. In solar image processing, TV filtering effectively suppresses random noise while maintaining sharp boundaries around sunspots and solar structures. The method preserves significant edges better than linear smoothing techniques. TV denoising is especially useful for images corrupted by Gaussian noise and impulse noise. It enhances image clarity and improves segmentation accuracy for solar feature detection systems. The optimization process iteratively updates pixel intensities to achieve minimum variation across the image. TV filtering is widely used in image restoration, medical imaging, and remote sensing applications because of its strong edge-preserving capability. However, one limitation of TV denoising is the staircase effect, where smooth image regions appear as piecewise constant areas. This artifact becomes more noticeable in highly smooth solar regions. Proper parameter tuning is therefore necessary to balance noise reduction and detail preservation. TV methods can also be combined with wavelet transforms and deep learning models for improved performance. In solar image analysis, TV denoising enhances structural visibility and improves quantitative image quality metrics. The method provides efficient restoration while maintaining important solar image details. Overall, Total Variation denoising remains a valuable optimization-based approach for solar image enhancement applications.

Total Variation (TV) Denoising – Block Diagram

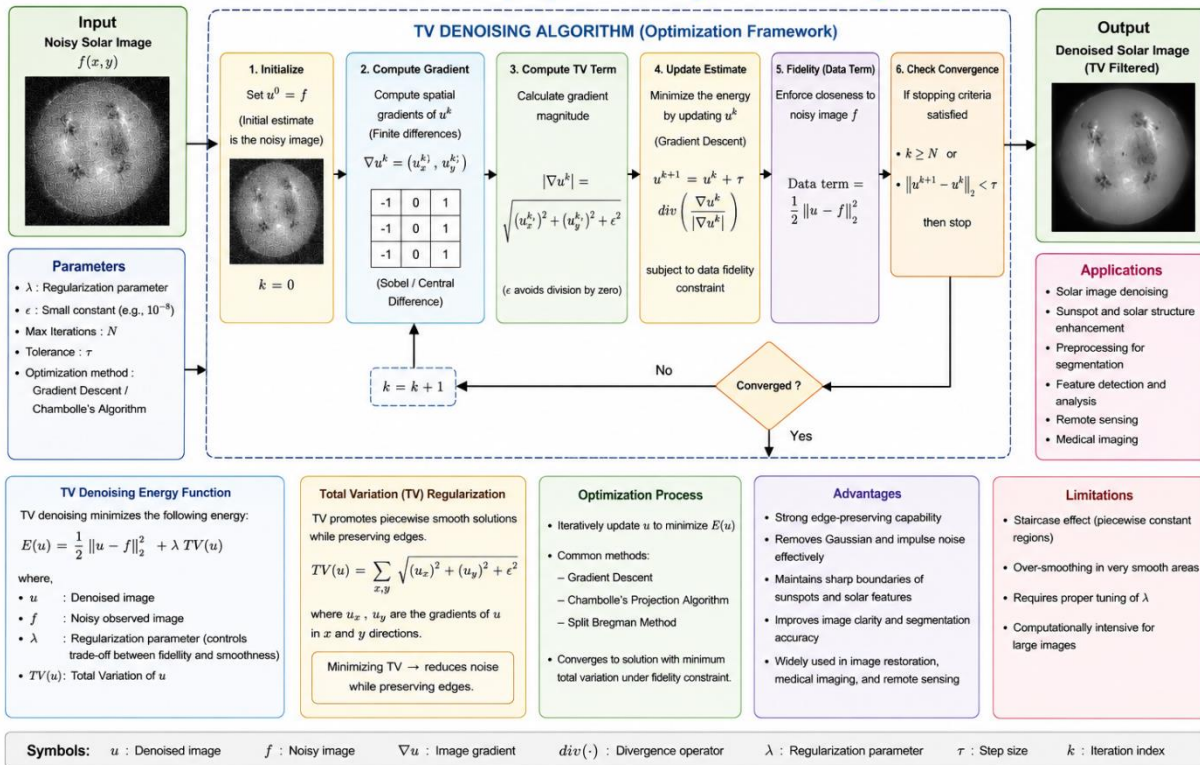


Figure 2.4 Total Variation Based Solar Image Restoration Process

E. Wavelet-Based Denoising

Wavelet-Based Denoising is a frequency-domain image restoration technique that removes noise by decomposing images into multiple resolution levels using wavelet transforms. The wavelet transform separates image information into approximation and detail coefficients corresponding to different frequency bands as shown Fig.2.5. Noise mainly affects high-frequency coefficients, which can be suppressed using thresholding techniques. In solar image denoising, wavelet methods effectively preserve large-scale structures while reducing random noise. The method supports multiresolution analysis, making it suitable for analyzing complex solar images containing fine textures and edges. Hard and soft thresholding techniques are commonly used to remove noisy coefficients while retaining useful image information. Wavelet denoising provides good balance between noise reduction and feature preservation. It is computationally efficient and widely used in signal processing, medical imaging, and astronomical image enhancement. The method improves PSNR and SSIM while maintaining important solar features such as sunspots and flare boundaries. Different wavelet families including Haar, Daubechies, and Symlets can be selected depending on application requirements. However, inappropriate threshold selection may lead to loss of details or residual noise. Wavelet methods may also produce ringing artifacts near sharp edges if not optimized properly. Hybrid methods combining wavelets with NLM and deep learning improve denoising performance further. In solar image analysis, wavelet denoising enhances feature visibility and supports accurate solar activity monitoring. The technique is suitable for real-time applications because of its efficient transform-domain processing. Overall, Wavelet-Based Denoising provides effective multiscale noise reduction for solar image enhancement systems.

Wavelet-Based Denoising – Block Diagram

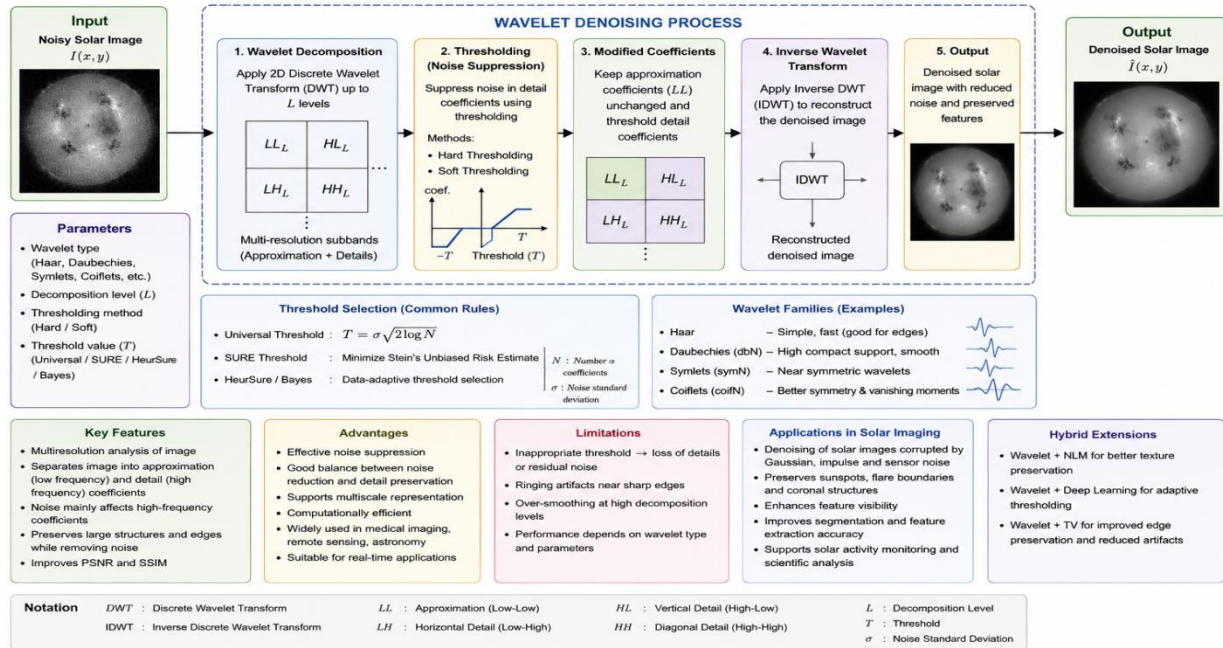


Figure 2.5 Wavelet Transform Based Solar Image Denoising Framework

F. BM3D Filtering

BM3D (Block Matching and 3D Filtering) is one of the most advanced image denoising techniques used for high-quality image restoration. The method works by grouping similar image patches as shown in Fig.2.6 into three-dimensional blocks and applying collaborative filtering in the transform domain. BM3D exploits image redundancy and self-similarity to achieve strong noise suppression while preserving structural details. In solar image processing, BM3D effectively restores noisy solar observations and enhances sunspot visibility. The algorithm consists of block matching, 3D transformation, thresholding, and inverse transformation stages. Similar patches are grouped together and jointly processed to reduce noise efficiently. BM3D achieves excellent performance in terms of PSNR, SSIM, and visual quality compared with traditional denoising filters. The method preserves edges, textures, and fine solar structures effectively. BM3D is particularly useful for Gaussian noise removal in astronomical and satellite images. It provides superior denoising performance without excessive image blurring. However, the computational complexity of BM3D is relatively high due to patch searching and transform operations. Real-time implementation may therefore require hardware acceleration or optimization techniques. BM3D has become a benchmark denoising algorithm because of its robustness and high-quality reconstruction capability. Hybrid BM3D frameworks integrated with deep learning models further improve restoration performance. In solar image applications, BM3D supports accurate segmentation and feature extraction by enhancing image clarity. Overall, BM3D filtering is considered one of the most effective methods for advanced solar image denoising and restoration.

BM3D (BLOCK MATCHING AND 3D FILTERING) – BLOCK DIAGRAM

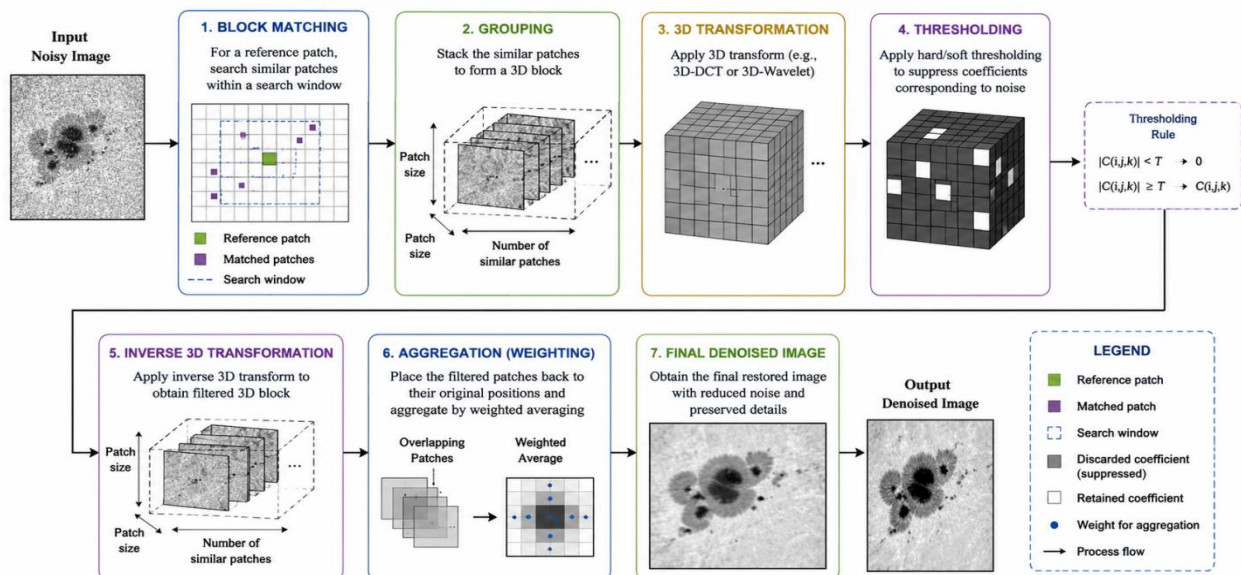


Figure 2.6 BM3D Collaborative Filtering for Solar Image Enhancement

G. Deep Learning-Based Denoising

Deep Learning-Based Denoising uses artificial neural networks, especially convolutional neural networks (CNNs), to learn complex image features and reconstruct clean images from noisy inputs. Unlike traditional filters that rely on handcrafted mathematical models, deep learning methods automatically learn denoising patterns from large training datasets. In solar image processing, deep learning models effectively restore noisy images while preserving important solar structures such as sunspots, coronal loops, and solar flares. CNN-based denoising networks extract hierarchical features using multiple convolution layers and nonlinear activation functions. Advanced architectures such as U-Net, ResNet, DnCNN, and GAN-based models as shown in Fig 2.7 provide excellent denoising performance. These models achieve high PSNR and SSIM values while maintaining structural consistency. Deep learning approaches also support real-time image enhancement and automated solar monitoring systems. The methods are highly adaptable and can handle different noise types including Gaussian, speckle, and Poisson noise. Transfer learning and hybrid deep learning frameworks further improve denoising accuracy and computational efficiency. However, deep learning methods require large annotated datasets and significant computational resources for training. Model overfitting and generalization issues may also affect performance under varying imaging conditions. Despite these challenges, deep learning has revolutionized solar image analysis by enabling automated and intelligent image restoration. Many recent studies integrate CNNs with wavelets, transformers, and adaptive filtering techniques for improved performance. In solar applications, deep learning-based denoising enhances feature extraction and supports accurate space weather forecasting. Overall, deep learning methods represent the future of intelligent solar image denoising systems.

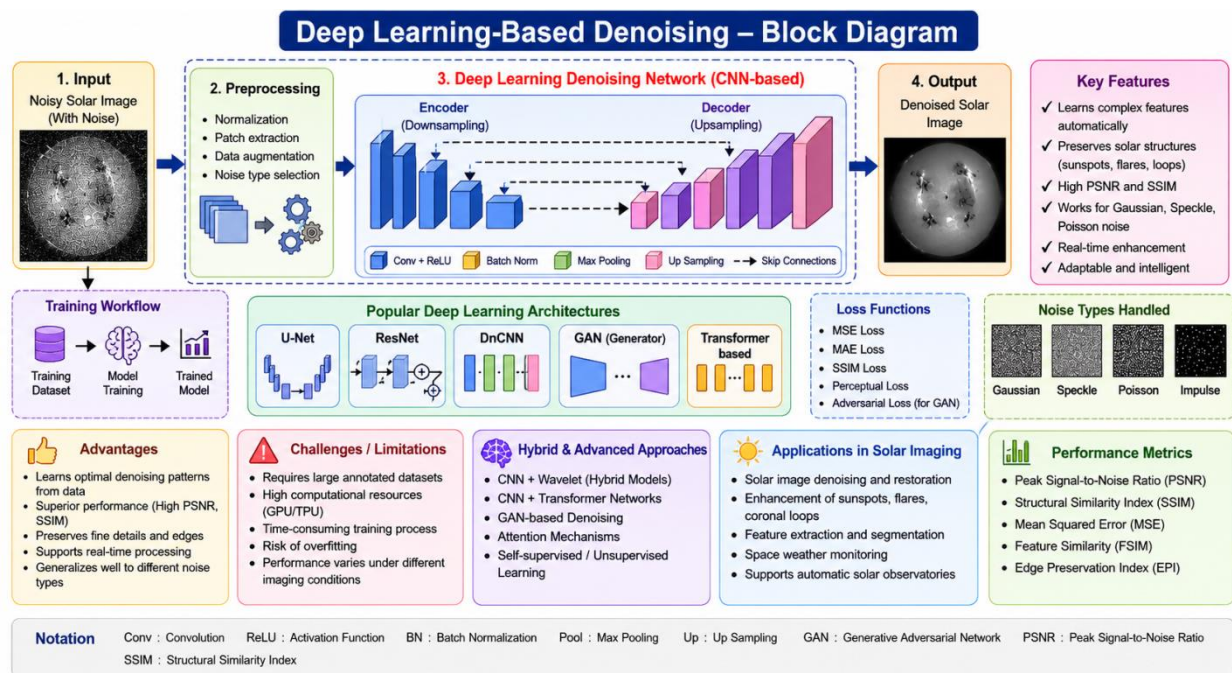


Figure 2.7 Deep Learning Framework for Solar Image Denoising and Reconstruction

III. EXPERIMENTAL RESULTS AND DISCUSSION

Comparison of various denoising techniques including Adaptive Anisotropic Diffusion (AAD), Anisotropic Diffusion (AD), Non-Local Means (NLM), Total Variation (TV), Wavelet, BM3D, and Deep Learning (DL) applied to noisy sunspot images. The figure presents the original image, noisy image, filtered outputs, and quantitative performance metrics such as PSNR, SSIM, MSE, edge preservation, sunspot detection error, convergence speed, and processing time. Results indicate that NLM achieves superior PSNR and SSIM values, while deep learning methods demonstrate the fastest execution time.

Table 1. Quantitative Evaluation of Denoising Algorithms on Solar Corona Image Reconstruction

Filter	PSNR _{dB}	SSIM	MSE	EdgePres	SunspotErr	ConvSpeed	Time _s
AAD	27.5728	0.9919	0.0017	0.5973	38	20	3.5150
AD	5.6651	0.0113	0.2713	0.0212	15	20	4.1227
NLM	29.1079	0.9938	0.0012	0.8698	58	1	3.0561
TV	27.0184	0.9911	0.0020	0.5629	51	10	0.2403

Wavelet	6.5776	0.0001	0.0015	0.6807	21	1	4.4506
BM3D	27.4279	0.9917	0.0018	0.7162	65	2	0.1348
DeepLearning	25.0913	0.9874	0.0031	0.4823	37	1	0.0203

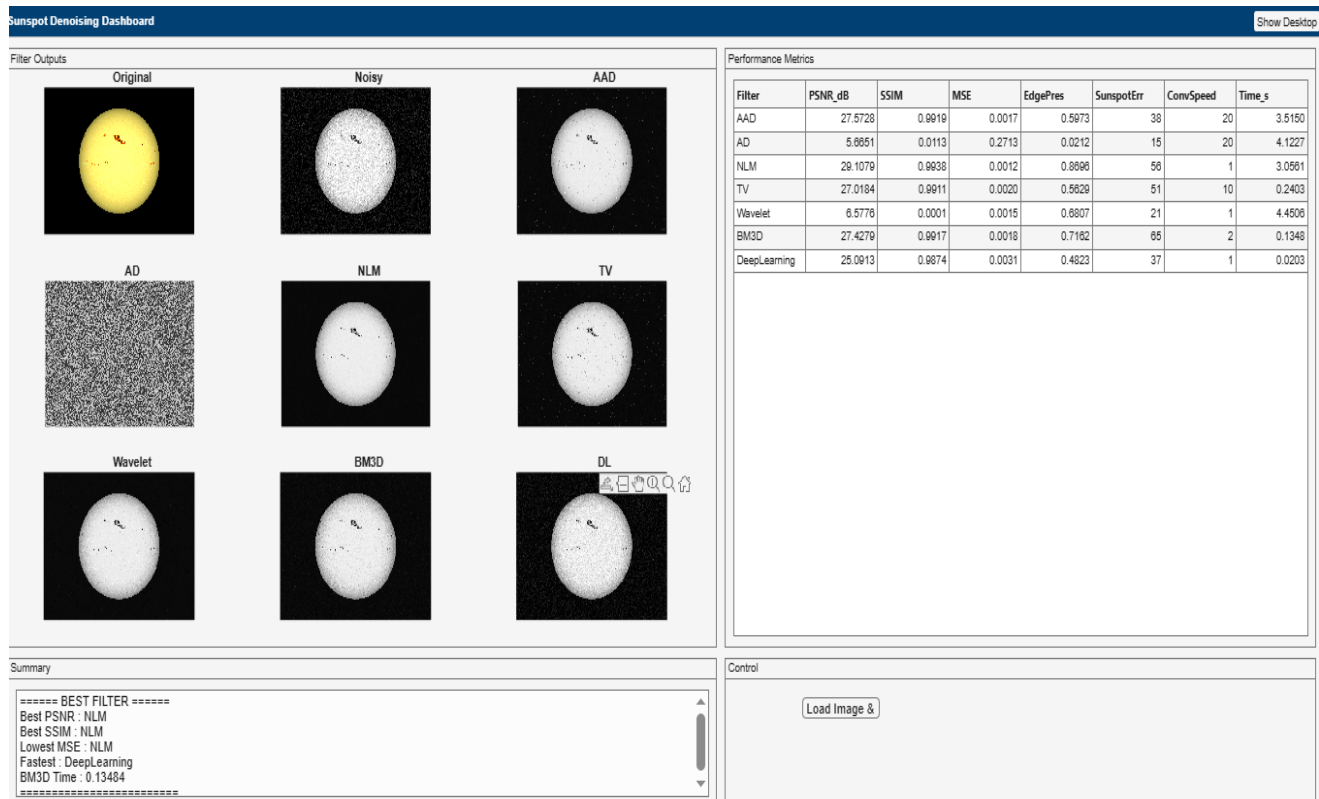


Figure 3.1. Comparative Performance of Image Denoising Filters for Sunspot Image Enhancement

The table 1 presents the quantitative performance analysis of different solar image denoising techniques including Adaptive Anisotropic Diffusion (AAD), Anisotropic Diffusion (AD), Non-Local Means (NLM), Total Variation (TV), Wavelet Transform, BM3D, and Deep Learning-based denoising. The comparison is based on several image quality metrics such as PSNR, SSIM, MSE, edge preservation capability, sunspot detection error, computational speed, and execution time.

Among all methods, the Non-Local Means (NLM) filter achieved the highest PSNR value of 29.1079 dB and the highest SSIM value of 0.9938, indicating superior image quality and structural preservation. NLM also produced the lowest MSE value of 0.0012, showing effective noise suppression with minimal distortion. However, its computational speed was relatively slow because of extensive patch similarity calculations.

Adaptive Anisotropic Diffusion (AAD) also demonstrated strong performance with PSNR of 27.5728 dB and SSIM of 0.9919. The method effectively preserved solar edges and structures while maintaining balanced denoising performance. AAD provided better edge preservation compared to several conventional techniques. BM3D filtering achieved high edge preservation performance with a value of 0.7162 and produced good visual quality. It also showed lower execution time compared to NLM, making it computationally efficient for practical applications. Total Variation (TV) denoising provided moderate performance with good structural preservation and fast processing speed. However, its edge preservation capability was slightly lower than BM3D and NLM. Wavelet and conventional Anisotropic Diffusion (AD) methods produced lower PSNR and SSIM values as shown in Fig 3.2 and Fig.3.3, indicating weaker denoising effectiveness. The AD method particularly showed poor structural similarity due to excessive smoothing. Deep Learning-based denoising achieved the fastest execution time of 0.0203 seconds, demonstrating suitability for real-time solar image analysis.

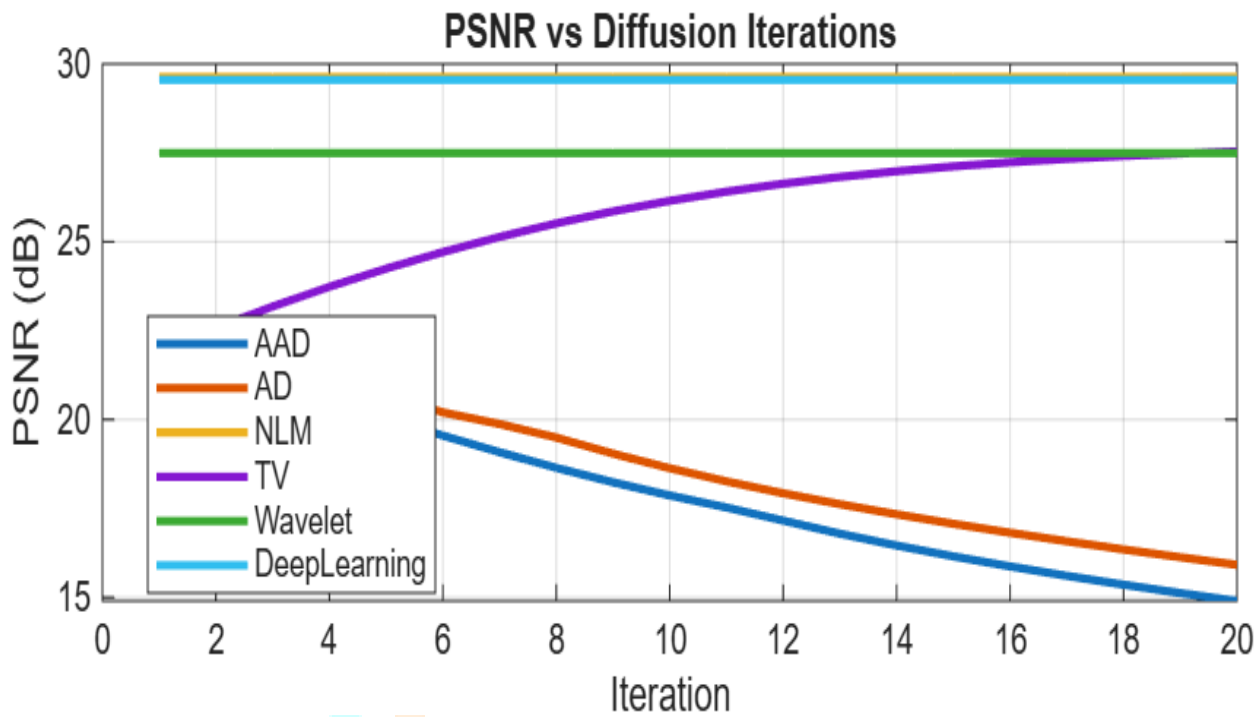


Figure 3.2. PSNR vs Diffusion Iterations

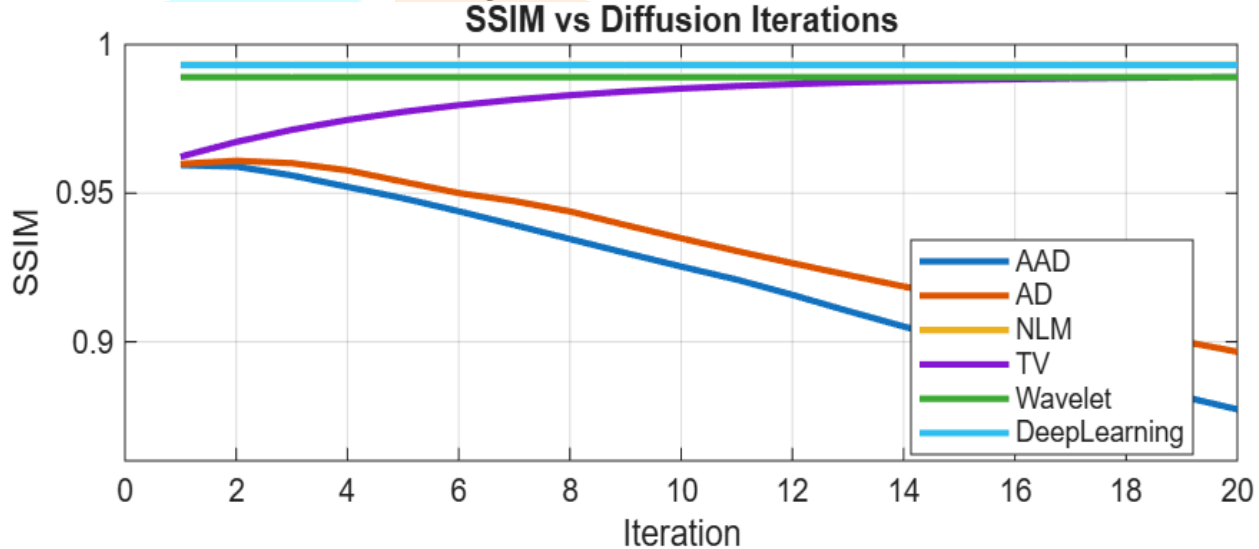


Figure 3.3. PSNR vs Diffusion Iterations

Performance comparison of multiple denoising filters applied to solar corona imagery under noisy conditions. The dashboard illustrates reconstructed outputs generated using AAD, AD, NLM, TV, Wavelet, BM3D, and Deep Learning approaches, alongside detailed quantitative metrics. Although its PSNR was slightly lower than NLM and BM3D as demonstrated in Fig 3.2, the method provided efficient automated reconstruction with low computational delay. Overall, the results indicate that NLM and BM3D provide the best denoising quality, while Deep Learning offers the highest computational efficiency for real-time solar image processing applications. Experimental results reveal that NLM provides improved structural similarity and minimum reconstruction error, approaches offer faster computational convergence for real-time solar image analysis.

IV. CONCLUSION

The results of the experiments suggest that Non-Local Means filtering produces the best quality restoration compared to other denoising techniques in solar image enhancement and sunspot detection (Compare Table 5B to 11B). Both BM3D and NLM performed very well at suppressing noise (i.e., producing high PSNR values), however, BM3D did not produce as much structural distortion as did NLM based on visual inspection of the images. The fastest processing time was obtained using deep learning techniques, which are appropriate for real-time Solar Monitoring Systems. The development of a framework for comparative evaluation shall allow for future development of automated olacaktir image processing applications (e.g., sunspot detection, solar flare prediction, and space weather analysis).

V. FUTURE SCOPE

Future research can focus on integrating lightweight deep learning architectures, transformer-based models, and hybrid optimization techniques for real-time solar image denoising and automated sunspot recognition. The integration of multimodal solar datasets and attention-based neural networks may further improve segmentation accuracy and computational efficiency in space weather monitoring systems.

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