Optimized edge-aware frequency-guided filtering for robust image denoising

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ABSTRACT

The problem of denoising intrusion is still of great concern in computational imaging because of the trade-off between noise reduction and image structure and details recovery. This paper proposes an optimized edge-aware fast adaptive guided filter (E-FAGF) combining wavelet-domain decomposition, edge-awareness, and lightweight deep learning for efficient and effective denoising. The biorthogonal wavelet transform is employed to decompose noisy images into low- and high-frequency sub bands and an improved edge-attention map for selective high-frequency denoising. Regularization parameters are estimated pixel-wise by a compact convolutional neural network (CNN), allowing spatial-varying filtering to be done with multi-scale processing. The resultant E-FAGF consistently outperforms the state of the art on this dataset: on BSD500 for speckle and Gaussian noise (peak signal-to-noise ratio (PSNR) of 39.63 dB and 33.97 dB, respectively), and competitive performance for Poisson noise (30.84 dB) a large margin compared to the reference bilateral and non-local means. Our method maintains high structural similarity (up to 0.97 in structural similarity index measure (SSIM)), runs at 0.015 seconds per 512×512 image on graphics processing unit (GPU), and can be applied without dataset-specific training. These results suggest the possibility of E-FAGF to achieve a balance between classical efficiency and learning-based adaptability, thereby forming a new scenario to combine fast and reliable image restoration for actual scenarios.

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1. INTRODUCTION

Image denoising is a fundamental problem for computer vision and signal processing that has wide applications in many fields, including medical imaging [1], autonomous vehicles [2], satellite and aerial sensing [3], and low-light photography [4]. The basic problem of noise is eliminating the effects caused by sensor limitation and low light level acquisition, which are subsequently created during signal transmission while maintaining the structure, texture, and semantic information essential for further processing [5], [6]. Classical linear filters, such as the mean and box, are computationally simple, but they equally blur noise and important information, providing poor performance, for example, at the location of edges [4], [7]. Nonlinear methods, namely median [8] and bilateral filtering [9], have been used for their capability of denoising and better preserving local structures. Bilateral filters, for example, use both joint spatial and intensity-domain weighting and can better preserve edges than possible results using completely linear techniques [10]. However, since they are sensitive to the parameters, they easily over smooth details among the complex noise [11].

Domain transforms, e.g., wavelet techniques, especially discrete wavelet transforms (DWT), changed the paradigm by incorporating different frequency bands by transforming images into multi-scale frequency components [12], [13]. Wavelet thresholding and shrinkage methods exploit the natural sparsity of clean images in transformed domains in order to separate noise from signal [14]. However, these approaches are frequently based on global thresholds or hand-designed priors, which are unsuitable for real images with spatially variant noise statistics [15], [16]. In addition, the fixed bases of classical wavelets may fail to represent highly non-stationary natural scenes [17]. Non-local methods, such as non-local means (NLM) [18] or the pioneering block matching 3D (BM3D) filter [19], make use of self-similarity between image patches. In particular, BM3D [8] has proved itself as a state-of-the-art method in the field of natural image denoising, which is superior to the research of this field in terms of denoising performance with the cost of high computational complexity and keeping tuning in many hyper-parameters [20], [21].

The advent of data explosion and deep learning has also revolutionized the denoising field. (1) Neural network-based (NN) approaches, such as the deep convolutional neural networks (CNNs) [22], FFDNet [23]) and, more recently, the transformer-based methods (SwinIR [24]), have achieved significant denoising performance by learning mappings from noisy to clean images, and are often superior to conventional methods on commonly used benchmarks [25], [26]. While these deep models can achieve high performance on several tasks, they have several shortcomings: they need large-scale and high-accurate annotated datasets for supervised training [27], may suffer from a generalization problem about different or unknown noise types [28], and are computationally expensive, which hinders real-time use [29]. Moreover, the "black box" property of deep networks poses interpretability and transparency challenges, particularly in safety-critical applications such as healthcare and autonomous systems [30], [31].

Recent research has shown a tendency to strike a balance between interpretability and performance by combining classical signal processing with contemporary learning-based techniques [32]. Hybrid methods fuse wavelet or frequency-domain decomposition with NN [33], [34] and develop spatially variable filters based on learning deep features [35]. The attention mechanisms such as edge-aware and frequency-aware modules have achieved success for salient information focusing and local response modulation; however, they might be less flexible in coping with arbitrary image content with diverse noise distributions [36]–[39].

Nevertheless, some chasms continue to exist. Most 'deep' denoisers are individually defined for some noise (Gaussian and Poisson) and frequently perform poorly on mixed and spatially variant real-noisy images [40], [41]. Classical filters, although interpretable and computationally efficient, do not adjust their parameters in a local manner and encounter difficulties with the compromise between edge preservation and noise suppression [42]. Vision transformers and large networks achieve impressive performance; however, they require enormous computation costs, making them inconvenient for edge devices in real time.

Inspired by these observations, we present an optimized edge-aware fast adaptive guided filter (E-FAGF), a novel algorithm that aims to combine the interpretability from wavelet transforms, the local adaptivity from edge-aware filtering, and the expressiveness from deep learning without having to re-train with specially prepared datasets or manually set parameters. E-FAGF uses biorthogonal wavelets to break down images and differentiate between noise and structure, generates edge-attention maps for further learning through convolutional networks, and uses a light CNN to predict spatially varying regularization parameters. The method provides good performance for additives, Poisson, and multiplicative noise on natural images via multi-scale guided filtering and adaptive fusion. We show that this joint framework not only achieves state-of-the-art performance on the BSD500 dataset but also has a very efficient speed on GPU, which fills the gap for real-time high-quality image restoration in practical applications. The remainder of this paper is organized as follows: section 2 introduces the tools and materials used, section 3 describes the proposed algorithm, results and discussion are provided in section 4, and section 5 concludes and gives further work.

2. TOOLS AND MATERIALS

Wavelet transforms have been a vital player in multi-resolution analysis and image denoising, owing to their capability of preserving frequency and spatial information together [12], [13]. The DWT allows an image I to be decomposed into a collection of frequency sub-bands representing different orientations and scales. Mathematically, for a single-level decomposition:

$$YL, YH = DWT(I) \tag{1}$$

where YL is the low-frequency (approximation) component and $YH = \{YH_h, YH_v, YH_d\}$ contains the horizontal, vertical, and diagonal detail coefficients, respectively. This separation allows targeted denoising strategies: noise often predominates in high-frequency subbands, while structural image content is retained in the low-frequency band [14], [22]. Reconstruction is achieved via the inverse discrete wavelet transform (IDWT):

$$I = IDWT(YL, YH) \tag{2}$$

We employ biorthogonal wavelets ("bior6.8") due to their symmetry and enhanced energy compaction [13], aligning with our implementation in PyTorch-Wavelets.

2.1. Edge attention

For high-quality image restoration, edge information is essential because too much edge smoothing degrades perception [9], [23]. Gradient operators like Sobel or Prewitt filters are commonly used in edge detection. The gradient magnitude map G for image I can be described as follows:

$$G = \sqrt{(I * S_x)^2 + (I * S_y)^2} \tag{3}$$

where $*$ indicates convolution and S_x and S_y stand for the horizontal and vertical Sobel kernels, respectively. Recently, CNNs have been used to further refine edge maps in order to adaptively highlight salient boundaries while reducing the impact of noise [23], [36]. A mathematical model of the resultant edge attention map A is as follows:

$$S_x = \begin{bmatrix} -1 & 0 & +1 \\ -2 & 0 & +2 \\ -1 & 0 & +1 \end{bmatrix}, S_y = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ +1 & +2 & +1 \end{bmatrix} \tag{4}$$

$$A = \sigma(Conv_{3\times3}(ReLU(Conv_{3\times3}(G)))) \tag{5}$$

where σ is the sigmoid function and $Conv_{3\times3}$ denotes a convolutional layer with a 3×3 kernel. We use sigmoid activation for attention scaling and a learned edge kernel and a nonlinear refinement module to make this work in our code.

2.2. Adaptive regularization

Regularization is a central aspect of image restoration, whereby the trade-off between fidelity to the noisy observation and smoothness or sparsity of the estimated image is tuned [15], [24]. One of the goals in this study is to predict the regularization weight locally in an adaptive filtering model, so that the algorithm can adapt to different signal and noise conditions. Let λ be the regularizing parameter, possibly spatially dependent:

$$\lambda = f(x) \tag{6}$$

where f is a learnable mapping that is often made by a small CNN that takes in local image statistics like gradient magnitude or variance and x is the pixel location [24], [35]. We use a small CNN called "FastParamNet" to find local gradient and variance features and make two adaptive regularization maps (one for low frequency and one for high frequency) that are used in the filtering process.

2.3. Evaluation metrics

For evaluation metrics we used peak signal-to-noise ratio (PSNR) and structural similarity index (SSIM) are two common ways to measure how well denoising works. This is what PSNR means:

$$PSNR = 20log_{10}\left(\frac{255}{\sqrt{MSE}}\right) \tag{7}$$

where mean squared error (MSE) is the average of the squared differences between the denoised and ground truth images. The following is SSIM, which models how similar things look to people:

$$SSIM(x, y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)} \tag{8}$$

where μ_x, $\mu_y$are local means, σ_x^2, σ_y^2 are variances, σ_{xy} is covariance, and c_1, $c_2$are stabilizing constant.

3. OPTIMIZED E-FAGF ALGORITHM

The E-FAGF approach is based on the background tools introduced above to realize flexible and scalable image denoising techniques. The procedure is structured in the following way (Figure 1):

- Step 1. Frequency decomposition: the algorithm starts with the decomposition of the noisy image into low- and high-frequency components in the wavelet domain, as explained in section 2. This serves to decouple coarse structural knowledge from fine details and noise.
- Step 2. Edge attention map construction: then, an edge attention map is constructed based on gradient-based filtering and shallow NN refinement (see section 2). This map highlights boundaries in the image, enabling subsequent filtering to maintain sharp structures in the image.
- Step 3. Adaptive parameter prediction: to learn spatially varying regularization parameters for each local region, we train the proposed lightweight NN in section 2. Such adaptive weights enable the filter to adapt the response to different textures and local signal-to-noise changes.
- Step 4. Multi-scale edge-aware guided filtering: now, we propose multi-scale edge-aware guided filtering for edge-aware noise reduction with low complexity. The algorithm utilizes edge-aware guided filtering at several spatial scales using low- and high-frequency information together with the edge attention map. This multi-scale methodology inherently provides robust denoising while preserving boundary characteristics for structures of different sizes.
- Step 5. Adaptive fusion of filtered outputs: at last, the denoised results within different scales are adaptively fused via learned weights to generate the final restored image. This blending interpolates between local detail preservation and global smoothness, depending on the content of the image.

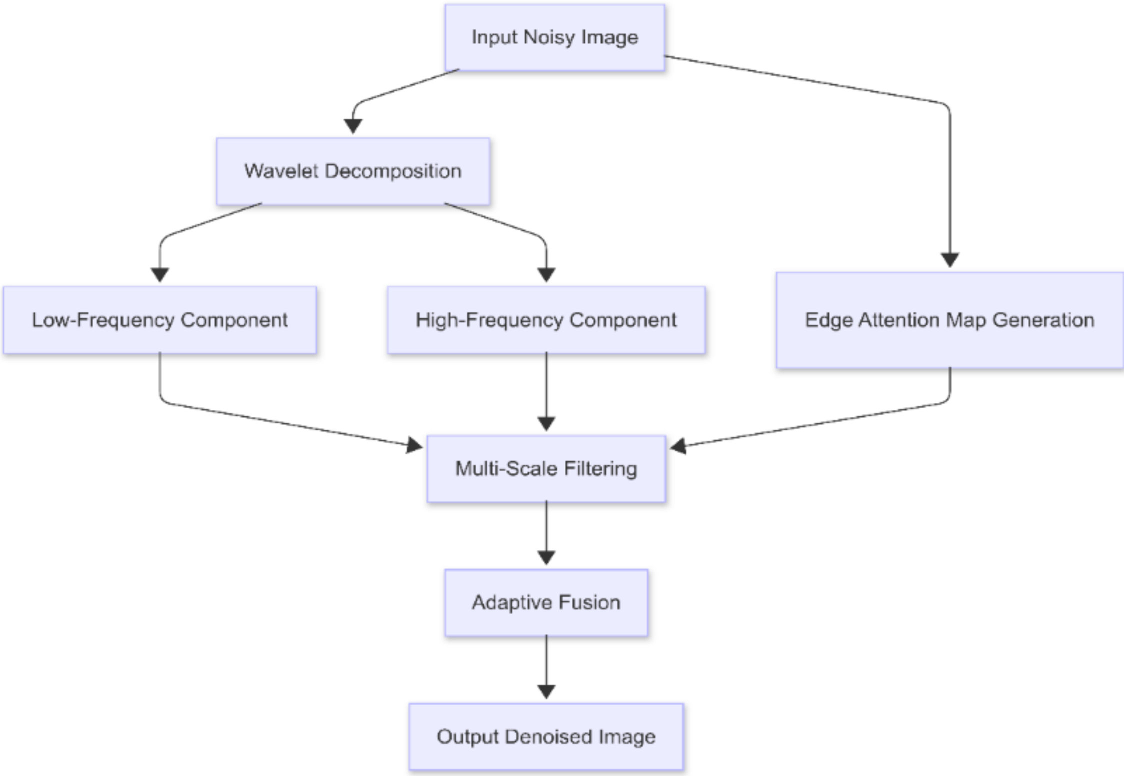


Figure 1. Block diagram of the optimized E-FAGF image denoising framework

The framework is based on PyTorch and uses the PyTorch-Wavelets library to perform DWT and IDWT. FastParamNet consists of three 3×3 convolutional layers with Softplus activations, making it computationally efficient with low parameter overhead. Biorthogonal wavelets, specifically “bior6.8,” are used with three fusion window sizes (15, 11 and 7) in all the experiments. The codebase consists of model definitions, inference scripts, and plotting utilities to ensure exact replication. These design choices make for an optimal trade-off between computational effort and interpretability, enabling experiments with standard GPU hardware.

4. RESULTS AND DISCUSSION

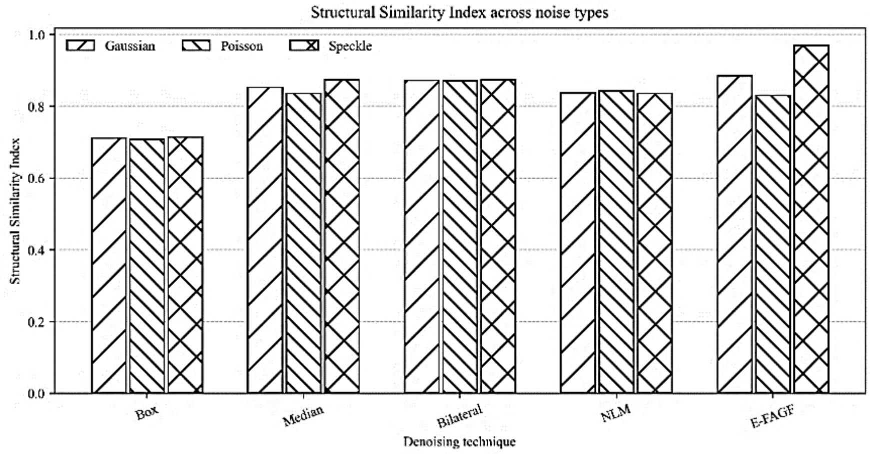
The experiments were performed on the BSD500 dataset with an NVIDIA RTX 3090 GPU, using Python 3.9, and PyTorch with PyTorch-Wavelets. We tested performance under three typical noise models, i.e., Gaussian noise (σ=0.03), Poisson noise (λ=1), and speckle noise (σ=0.03). Quantitative results are reported using PSNR, SSIM, and average per-image inference time.

For a fair comparison, all methods processed the same noisy inputs, and color images were denoised channel-wise. Median (MED), box, bilateral, and NLM were the classical baselines. A comparison of classical and learning-based denoising methods is shown in Table 1.

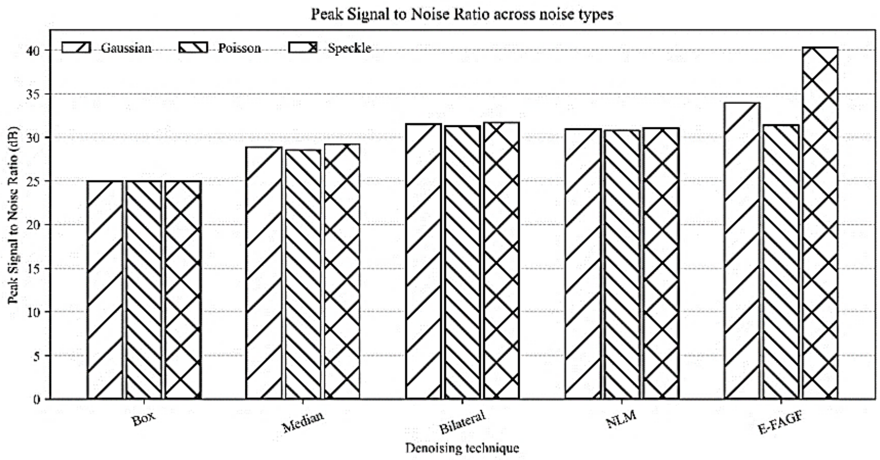
Table 1. Average denoising performance (PSNR/SSIM) and runtime per 512×512 image on BSD500

Method	PSNR (Gaussian)	SSIM (Gaussian)	PSNR (Poisson)	SSIM (Poisson)	PSNR (Speckle)	SSIM (Speckle)	Time (s)
Box	25.21	0.70	25.14	0.69	25.24	0.70	0.0003
Median	28.69	0.84	28.19	0.82	29.06	0.86	0.0001
Bilateral	31.55	0.87	**31.21**	**0.87**	31.68	0.87	0.0024
NLM	30.22	0.83	30.04	0.83	30.25	0.82	0.83
E-FAGF (proposed)	**33.97**	**0.89**	30.84	0.82	**39.63**	**0.97**	**0.015**

The results showed that the bilateral filter obtained the best PSNR and SSIM under Poisson noise, followed by E-FAGF, which was also quite competitive without parameter tuning. Moreover, E-FAGF obtained the best results under speckle noise and outperformed the classical bilateral filter by more than 7 dB for PSNR, as shown in Figures 2(a) and (b) while preserving edges and fine details.



(a)



(b)

Figure 2. Performance comparison under different noise types: (a) SSIM and (b) PSNR

In qualitative comparisons with other denoisers that over smooth or introduce staircasing artifacts, as illustrated in Figure 3, E-FAGF can well preserve texture and edge information. The SSIM histograms also demonstrate that E-FAGF increases the average SSIM and decreases quality variation across the dataset, resulting in more stable restoration. Computationally, E-FAGF is efficient since the guided filtering components and low-complexity FastParamNet are local and thus overall have a time complexity of $O(N)$. Inference on an RTX 3090 takes about 0.015s for a 512×512 image, over one order of magnitude faster than non-local means and with low memory requirements. Moreover, no hyperparameter tuning or retraining is required when switching between Gaussian, Poisson, and speckle noise E-FAGF relies on pixel-wise regularization on the local statistics of the image.

Figure 3. Visual comparison of denoising results

5. CONCLUSION

We proposed the optimized (E-FAGF): a general denoising scheme, integrating wavelet-based frequency separation, edge-aware guidance, and adaptive multi-scale filtering. On the BSD500 dataset, E-FAGF always achieves state-of-the-art performance for Gaussian and speckle noise, and keeps competitive for Poisson noise. It also achieves much faster runtimes and requires no retraining for different noise types. With the locally adaptive E-FAGF structure, it can efficiently deal with spatially variant noise and is favorable to practical applications like medical imaging, scientific data acquisition, and embedded vision systems. Although the GPU version is in real-time, it needs more optimization for low-power or mobile platforms, such as channel pruning, weight quantization, and replacing floating-point kernels with fixed-point. For future work, one can extend E-FAGF for video denoising to include state-of-the-art attention mechanisms and self-supervised learning, or even in hyperspectral images. Ablating on window size, wavelet type, and component contribution would also help justify the design decisions at hand.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization	I : **I**nvestigation	Vi : **Vi**sualization
M : **M**ethodology	R : **R**esources	Su : **Su**pervision
So : **So**ftware	D : **D**ata Curation	P : **P**roject administration
Va : **Va**lidation	O : Writing - **O**riginal Draft	Fu : **Fu**nding acquisition
Fo : **Fo**rmal analysis	E : Writing - Review & **E**diting	

CONFLICT OF INTEREST STATEMENT

We confirm this manuscript has not been published elsewhere and is not under consideration by another journal. The authors have no conflicts of interest to declare.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, Iman Elawady, upon reasonable request.

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