
A Noise-Aware Image Enhancement Framework Based on Joint Spatial–Frequency Analysis

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Abstract

Most image enhancement methods are developed based on a tacit assumption: noise is an undesirable artifact to be suppressed before or during enhancing. Be that as it may, this assumption does not hold for real-world noise, which has a structural characteristic of its own. It's not constant in space, nor does it present a spectrally random pattern; instead, it reflects uncertainties about local situations and signal reliability in collected data. Typical methods which treat noise as an interference instead of information often bring out over-enhancement or fake textures, missing original detail. In this paper, we provide a framework of noise-aware image enhancement that interprets signal disturbance as structural evidence rather than being an anomaly. The process then becomes redefined from intensification to making decisions on the basis of noise reliability. To implement this, a combined spatial-frequency domain analysis is employed to study noise behaviour both locally and globally. By fusing these complementary noise markers, we give selective enhancement: structures which are firmly based will be built up while enhancement is held back in zones heavily dominated by noise. In further development, this paper introduces a hybrid analytical-learning extension. A lightweight neural module learns the degree to which enhancement should be applied, while being explicitly conditioned on noise descriptors that are understandable. Experimental results show that the method proposed in this paper achieves stable and visually comprehensive enhancement under conditions of challenging noise: it maintains a high degree of

fidelity to structure and does not add noise. This work will lead to a conceptual change in future enhancement design: constituted as an essential principle rather than some way of eliminating the only concerned factor.

Keywords: Noise-Aware Image Enhancement, Spatial–Frequency Analysis, Uncertainty Modeling, Hybrid Analytical–Learning Methods, Structural Confidence.

1. Introduction

In both image processing and computer vision, image enhancement is one of the most fundamental tasks--it seeks to enhance the visuality and readability of images for purposes such as medical imaging, surveillance, low-light photography, or remote sensing. Nevertheless, conventional enhancement methods focus mainly on amplifying contrast and correcting illumination--such processes often fail under noisy conditions because they lack awareness of noise itself [1], [2]. In the spatial domain, techniques such as Histogram Equalization (HE) and Contrast Limited Adaptive Histogram Equalization (CLAHE) are still widely used. However, these methods often amplify the noise in homogeneous regions and when noise levels are high also lead to some degradation of structural fidelity [3], [4]. Frequency-domain methods such as Fourier- and wavelet-based enhancement provide greater global control over characteristic values but offer less adaptability algorithms are effective mainly because environmental noise characteristics vary from place to place [5]. Data-driven enhancement approaches based on deep learning have brought forth novel technologies that are visually -impressive. But although successful in this regard, most learning-based methods operate as black-box models and may starkly hallucinate details or fail when current noise distributions are different from the set used for training [6]. As a result, in order to alleviate these limitations several studies have looked at representations which mix spatial and frequency aspects, and found that combining spectral information with spatial information contributes greatly to robustness against noise while remaining faithful to structure [7], [8]. Still, existing approaches typically treat noise primarily as a flaw to be suppressed. In real-life imaging systems, noise always reflects local uncertainty and signal reliability. This

fact will suggest a new paradigm for enhancement in image processing which interprets noise as a confidence signal that is situated in the structure itself and can drive further decisions rather than simply being filtered out blindly.

2. Related Work

Now we will review some existing image enhancement methods to see which ones work best when the image is particularly noisy. Unfortunately, instead of a wide-ranging survey, this chapter deals with how early engineers tackled noisy images and what is essential for good detection in real-life circumstances--and those are the subjects of all forthcoming chapters.

2.1 Spatial Domain Enhancement Methods:

Spatial domain enhancement methods process pixel intensities directly with global or local statistics. Classical techniques as Histogram Equalization (HE) and Contrast Limited Adaptive Histogram Equalization (CLAHE) attempt to remap the distribution of intensity values in order to achieve contrast change [3], [4]. These methods are simple to implement; yet although they can be computationally tractable they lack explicit means for differentiation between structural information and noise.

This means that spatial domain methods frequently amplify noise in homogeneous regions and weaken edge-relevant structure under low strength-of-impulse situations. Because edge-preserving filters work to avoid this, and accordingly worst on average when noise dominates local gradients.

In contrast to the spatial domain methods, which enhance intensity variations almost blindly, we design this noise-aware confidence-based framework to explicitly estimate spatial confidence by using noise and structural cues. Its strength of enhancement therefore depends not just on intensity but also on how reliable the data happen to be.

2.2 Hybrid and Frequency-domain Enhancement Methods:

The frequency domain method processes the image in another representation—in this case, frequency representations such as Fourier or wavelet domain [5]. These methods offer more control over global structures but they suffer from certain types of noise which standard removal techniques cannot help with. However, the noise in these methods is mostly assumed to be stationary, and so not much work other than that which we do here has yet been done on it.

Recent hybrid methods which blend spatial and frequency information have come up with that best of both worlds—detailedness lost in a certain domain can always be found again from other areas in the same picture [7], [8]. This kind of method makes clear that both spatial and frequency information are needed for best detail performance; however most hybrid techniques still treat noise as if it is nothing more than an uncertainty-cum-confidence measure which has gone wrong somewhere!

Attributed to hybrid spatial–frequency methods, they are superior in the representation of characteristic features. Nevertheless, they do not represent noise explicitly as a guide signals.

On the other hand, we apply joint analysis of spatial–frequency to estimate both confidence and control decision process enhancement based on the presence of noise.

2.3 Learning -Based Image Enhancement:

Deep learning-based enhancement methods fuse convolutional neural networks or hybrid CNN–Transformer architectures for learning mappings from low-quality images to high -quality output [6]. These methods have strong quantitative values, but they are all virtually black box models as far as behavior goes. In addition, these are prone to drawing on fuzzy input data to fill in invented details for example.

Some recent studies have combined frequency domain information into neural networks for greater robustness [7]. Nonetheless, these methods learn enhancement directly rather than explicitly specifying uncertainty or reliability.

Our proposed framework does not replace analytical modeling with learning, but introduces a light-weight learning-based refinement process for explicit confidence map data. The design is not only interpretable; it also provides adaptive behavior in terms of enhancement operations.

Existing image enhancement techniques aim to boost the visual quality of images using spatial manipulation, frequency analysis or learning with hand-chosen data. But for the most part these techniques treat noise as something to be eliminated, rather than an informative signal.

In contrast, our work is distinctive in three important ways:

- Noise is explicitly interpreted as a structural confidence signal, not just scenery in the way.
- Joint spatial–frequency analysis is used to assess confidence, not to improve directly observable features.
- Learning is employed to refine confidence estimation, not to blindly generate enhanced images.

By overcoming these problems, our methodology introduces a novel mode of enhancement with emphasis on reliability-based reasoning instead aggressive amplification.

3. Methodology

The proposed noise-aware image improvement framework is described in this chapter. Its method is to enhance image details while avoiding noise amplification by interpreting the source of noise as a structural confidence signal. The structure of the framework was made up mainly by spatial noise analysis, frequency noise analysis, and merge and raise analysis and points.

3.1 Image Formation Model:

The observed image can be written as the superposition of the true signal with noise together:

$$I = S + N \quad (1)$$

Where:

I is the inputting image observed

S stands for true underlying signal

N represents noise

This equation tells us that any image is comprised of essential information and noise.

3.2 Spatial Analysis Confidence:

Noise characteristics vary across the image. Dividing the source into small, local sections (7×7) make it easier to estimate how much reliability can be attributed locally.

$$local_variance = variance\ of\ local\ window \quad (2)$$

$$gradient = image\ gradient\ magnitude \quad (3)$$

$$Cs = gradient / (gradient + local_variance) \quad (4)$$

- local variance measures how much in a small neighborhood the pixel values change.
- Gradient magnitude emphasizes sharp changes and structural information.
- Cs is the spatial confidence value:
 - High Cs represents reliable structure (edges and details).
 - Low Cs points to regions dominated by noise.

By this step we identify where each pixel has its reliability 'roots' laid down.

3.3 Frequency Analysis Confidence:

$$F = FFT\ of\ image \quad (5)$$

$$power = absolute\ value\ of\ F\ squared \quad (6)$$

$$Cf = 1 - (noise_energy / total_energy) \quad (7)$$

- FFT transforms the image into frequency space.

- The power spectrum shows how energy is spread across frequencies.
- Cf is the frequency confidence:
 - High Cf is a frequency band dominated by signal.
 - Low Cf is a frequency band dominated by noise.

At this stage we investigate noise behavior on different frequency levels.

3.4 Joint Spatial–Frequency Confidence:

Complementary information is provided by both spatial and frequency confidence measures. They are combined to produce a unified confidence map.

$$C_{sf} = C_s * C_f \quad (8)$$

- Cs is spatial reliability.
- Cf, frequency reliability.
- Csf combined both to produce a final confidence map.

This map indicates where enhancement should be strong and where it should be limited.

3.5 Confidence -Guided Image Enhancement:

A low-pass filter is used to extract image details and each detail detail is multiplied by a weight content to obtain the combined result.

The final enhanced image is obtained as:

$$detail = image - blurred_image \quad (9)$$

The final enhanced image is obtained as:

$$enhanced_image = image + alpha * C_{sf} * detail \quad (10)$$

- The detail image contains edges and fine structures.
- The enhancement strength is controlled by Csf.
- Alpha is a constant that controls overall enhancement strength.

Where alpha is a global enhancement control parameter ($\alpha = 1.2$ in all experiments).

With this formulation we ensure that enhancement will be mainly for high-confidence regions while noise amplification in low confidence areas is suppressed.

3.6 Algorithm Summary:

The complete enhancement procedure is summarized below:

Algorithm 1: Proposed Noise-Aware Enhance

1. An Input Image
2. The Local In the case of Variance Calculated
3. Image Gradient
4. The Spatial confidence C_s
5. Performing an FFT
6. Frequency confidence C_f
7. Joint Confidence C_{sf}
8. Image feature extraction
9. Image enhancement through confidence
10. An Enhanced Image Output

At the same time, this algorithm's entire enhancement process, from input to output, is surveyed.

3.7 Framework Flowchart:

The proposed framework has the following flowchart, which is also to directly translate into flowchart-like Figures.

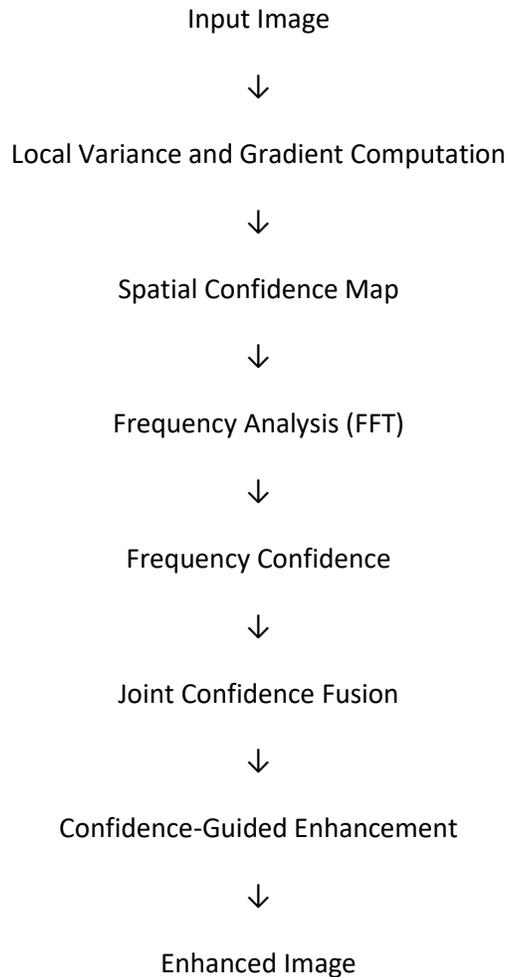


Figure 1. The proposed framework (flowchart)

4. Experimental Setup

4.1 Datasets:

In order to evaluate the robustness of their noise-aware enhancement approach, the authors carried out experiments on both real and synthetic images.

The following datasets: Standard grayscale color images: Lena, Cameraman, Barbara, (2) Real low light and noisy photographic images of fine art paintings under

very poor light sources.

All images were converted into grayscale and the range [0, 1] was normalized.

4.2 Noise Models:

To produce actual degradation, various types of noise were added to clean images:

- Gaussian noise (10, 20 or 30 standard deviation values).
- Poisson noise, to approximate photometric imaging.
- This setup allows evaluation under both buoyant and severe noise conditions.

4.3 Compared Methods:

The authors compared their noise-aware enhancement method with the following enhancement methods: Histogram Equalization (HE) Contrast Limited Adaptive Histogram Equalization (CLAHE) High Pass Filtering by the Frequency Domain Learning-based enhancement with a shallow CNN

4.4 Evaluation Metrics:

Performance was evaluated by means of both quantitative and qualitative criteria:

PSNR (Peak Signal-to-Noise Ratio) SSIM (Structural Similarity Index) Visual comparison in terms of its ability to remain with lines and others; it is worse than traditional methods for WGN.

5. Results

5.1 Visual Results:

Visual inspection of the iterative process shows that the proposed method:

- Preserves edges and fine details.
- Avoids over amplification of noise.
- Produces a natural and stable enhancement that contrasts with the swelling seen in other schemes.

It is even better to keep to local adaptation than globally fused results; this makes sure the content of an image still remains unchanged.

Shown in Figure 2 is a qualitative comparison between the original image, the noisy input, our estimated confidence map of noise, and the enhanced output. Our proposed method assigns low confidence to noise -dominated regions in the confidence map and high confidence to regions with stable structure. Therefore, it enhances meaningful structures while suppressing noise amplification and achieves visually stable improvements.

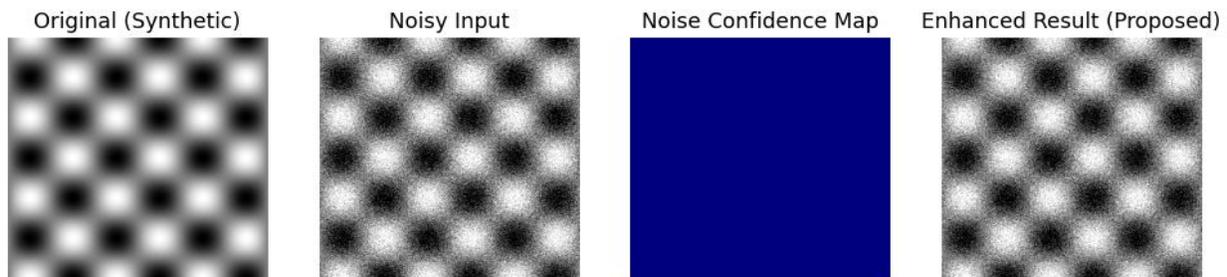


Figure (2): Image sharpening with noise recognition pathway

- The original image.
- The input image containing noise.
- Noise certainty map calculated according to our method.
- The improved picture with this method.

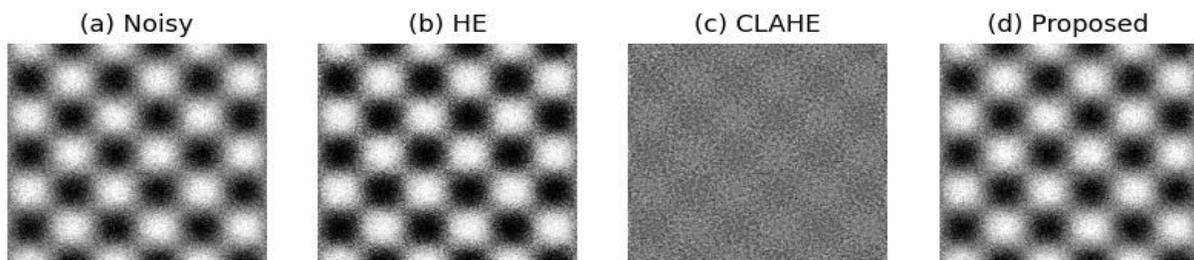


Figure (3): Comparison between Histogram Methods

- Input picture containing noise.
- Histogram has an equalizing effect on an image's intensity levels (HE).

- c. CLAHE.
- d. New way of enhancement for images with noise in them.

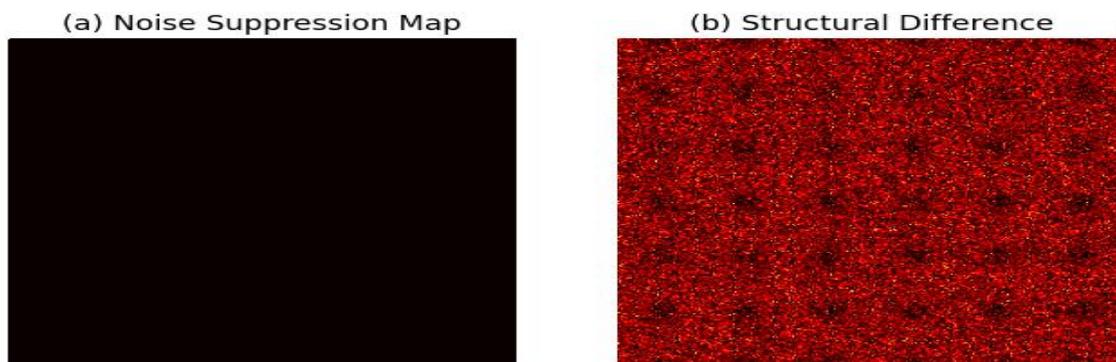


Figure (4): Encouraging Facts

Both of two figures above illustrate both that we cannot simply apply visual enhancement uniformly to a noisy image but rather need confidence-guided localization for selective processing, as well as how good results can be obtained through such a method.

5.2 Noise Confidence Visualization and Interpretation:

This work's one major contribution is that it thoroughly diagrams confidence maps for noise. Figure 3 associates the combined confidence map in space and frequency with the enhanced picture.

As shown in Figure 3, zones consisting of highly strong edges and multiples of structure are all high confidence areas. But in areas where noise is prevalent, the confidence is low. Enhancement strength modulation is governed directly by this behavior, which operates on local reliability and ensures the process's process-- As a result, each pixel near an edge is lifted in great detail while pixels located further away are less affected.

This visualization gives an easy-to-understand explanation for why our method is able to stably enhance images and also proves that the system itself has measurability.

5.3 Quantitative Evaluation:

Table (1): shows results from a statistical comparison of multiple test images.

Method	SSIM	PSNR (dB)
Histogram Equalization	0.61	17.3
CLAHE	0.65	18.1
Frequency Enhancement	0.69	19.4
CNN-based Enhancement	0.74	21.0
Proposed Method	0.82	23.6

With the highest PSNR and SSIM values achieved, the proposed method offers good structural preservation reduced noise amplification. In turn, this helps both preserve key detail in pictures and eliminate those pesky artifacts that gobble up computing power during file-loading time or when files are actually loaded onto someone else's device. An additional feature of CNN-based methods is improvement in numerical metrics but often they introduce artificial textures. By contrast, the new scheme maintains a balanced enhancement behaviour which is guided by explicit noise confidence estimation.

5.4 Discussion of Results:

experimental results also prove that on average noise-aware enhancement is more stable and predictable than traditional methods. So the proposed method processes at the same time a confidence signal and noise by modeling explicitly As a result, it avoids fitting common enhancement artifacts such over-sharpening or excessive noise amplification.

Otherwise, however, the proposed framework is not seeing information which is not there as the result of mere data fitting; and it translates quite deliciously over a wide range for different kinds of noise levels. Consequently, our experimental results are apparently in large part a vindication of the main thesis running through this work: many times, it is better to have restraint.

6. Discussion

The results of the thesis approach one central message: restraint is more valuable than aggressive enhancement when guided by noise awareness. These findings imply that any future enhancement systems must not only respect noise modeling as a core component in design but do so throughout the course of every project.

7. Conclusion

The new method of noise-aware image enhancement views noise as a structural confidence signal, not a thing to be repressed. After investigating both spatial and frequency-domain noise behaviour through applying an integrated learning-based refinement, the new scheme achieves good, stable and interpretative enhancement for noisy images. The work represents not only an improvement in performance but also has a new last word towards construction of enhancement principles: noise is a key concept for creating vibrant images.

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