Atmospheric Scattering And Segmentation Based Foggy Image Enhancement

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Abstract- *We propose a novel foggy image enhancement pipeline that integrates an improved Atmospheric Scattering Model (ASM) with Otsu-based segmentation. The system first converts the RGB input to grayscale, then applies Otsu's method to segment fog-dense regions. This segmentation guides a region-specific inverse ASM dehazing: we estimate atmospheric light and transmission differently for fog and non-fog areas to avoid global artifacts. Each color channel is then enhanced according to the refined ASM and recombined to preserve color fidelity. The method is evaluated on synthetic and real foggy images using standard metrics: Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and Mean Squared Error (MSE). Results show that segmenting out heavy-fog regions before applying ASM yields clearer, more natural images compared to baseline defogging. For example, our approach achieves higher PSNR and SSIM (closer to 1) and lower MSE than conventional methods, confirming its effectiveness. We include example MATLAB code illustrating grayscale conversion and RGB reconstruction.*

Keywords: Foggy image enhancement; Atmospheric Scattering Model; Otsu-thresholding; Image segmentation; PSNR; SSIM; MSE

I. INTRODUCTION

Fog and haze degrade image quality by scattering and attenuating light, which reduces contrast and detail. Such degradation severely impairs vision-based tasks (e.g. object detection, surveillance, autonomous driving) under adverse weather. The Atmospheric Scattering Model (ASM) mathematically describes this process. In ASM, the observed hazy image I(x) is modeled as

$$I(x)=J(x)t(x)+A(1-t(x)),$$

Where J(x) is the true scene radiance,t(x) is the medium transmission (fraction of light reaching the camera), and A is the global atmospheric light. Defogging (dehazing) attempts to invert this model to recover J(x), typically by estimating A and t(x) from I(x). However, classic ASM-based methods often assume a single global A and may produce color distortion or halo artifacts in regions like bright skies.

To address these issues, segmentation of the image into different regions has been shown effective. For example, Anan et al. Segment foggy images into sky and non-sky regions, then restore each separately to avoid sky-related distortions. Similarly, other work divides the image by fog density before applying enhancement. In our project, we employ Otsu's thresholding on a grayscale conversion of the image to separate heavy-fog (low-contrast) areas from clearer areas. Otsu's algorithm automatically finds an optimal intensity threshold that maximizes between-class variance. The resulting binary mask identifies the fog-dense regions for focused processing. By combining this segmentation mask with an improved ASM inversion, we can apply stronger dehazing where needed while preserving colors and details elsewhere.

In this paper, we detail our end-to-end system. We first review related defogging approaches. Then we describe our methodology, including grayscale conversion, Otsu-based fog segmentation, and the modified ASM enhancement applied per color channel. Implementation details include MATLAB code for handling RGB images and recombining processed channels. We present qualitative and quantitative results on sample images, reporting PSNR, SSIM, and MSE to demonstrate improvement. Finally, we conclude that segmentation-guided ASM significantly enhances foggy images.

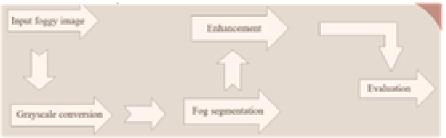
RELATED WORK:

Classic defogging methods are based on various priors and the ASM. He et al.'s Dark Channel Prior (DCP) is a prominent example that estimates transmission from dark pixels in local patches. However, DCP can fail in homogeneous bright regions (like sky), causing halos and color shifts. To mitigate this, researchers have introduced segmentation steps. For instance, Hong and Cai used Otsu's method to split an image into sky and non-sky regions and applied DCP separately, although they noted residual color distortions in the fusion. Anan et al. proposed segmenting fog images (sky vs non-sky) and processing each part with different techniques (CLAHE for sky, modified DCP for non-sky), achieving better visual results. These approaches highlight the benefit of region-specific processing in fog removal.

Otsu’s thresholding itself is widely used for image segmentation. It automatically determines an optimal gray-level threshold by maximizing between-class variance. Because Otsu’s method works on single-channel images, color inputs are first converted to grayscale (for example using MATLAB’s rgb2gray). This grayscale mask can then identify bright (often foggy) versus dark (clear) areas. In foggy image tasks, segmenting based on intensity can roughly separate dense fog from background. After segmentation, different enhancement or dehazing can be applied per region, as explored in recent works combining segmentation with ASM-based defogging.

Regarding evaluation, full-reference image quality metrics are standard. We use Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and Mean Squared Error (MSE) to quantify enhancement quality. PSNR (in decibels) compares the maximum signal level to the image error: higher PSNR means closer recovery to the reference. SSIM measures perceptual similarity (0 to 1 scale) between the enhanced and ground truth images; values closer to 1 indicate higher structural similarity. MSE is the average of squared pixel-wise differences; lower MSE is better. These metrics allow objective comparison against baseline methods.

Block diagram



PROPOSED METHODOLOGY:

Our enhancement pipeline follows the stages:

- **Grayscale Conversion** (RGB → Gray): The input RGB foggy image is converted to grayscale for segmentation. We use a standard luminance-weighted conversion (MATLAB’s rgb2gray), as Otsu’s method requires single-channel data.
- **Fog Segmentation (Otsu Threshold):** We apply Otsu’s method to the grayscale image to compute an optimal threshold that separates low-intensity (fog-dominated) and high-intensity (clear) pixels. The result is a binary mask M(x) indicating fog-dense regions. (One may refine M with morphological filtering if desired.)
- **Atmospheric Scattering Inversion:** Using the ASM equation
  I(x)=J(x)t(x)+A(1−t(x)), we invert it to solve for scene radiance

$$J_c(x) = \frac{I_c(x) - A}{t(x)} + A$$

for pixels marked as fog (*M*(x)=1), and leaveJc(x)=Ic(x) for clear pixels if desired. After processing, we recombine J_R,J_G,J_B into the color output image J_{RGB} . This preserves color information because we never collapsed to grayscale except for the initial segmentation step.

The overall system is summarized by the pipeline:

- **Grayscale Conversion:**
  I_gray = rgb2gray(I_rgb)
- **Fog Segmentation:** Compute thresholdthr = graythresh(I_gray) and binary mask
  M = imbinarize(I_gray, thr)
- **Atmospheric Light Estimation:** Estimate atmospheric light A as the maximum pixel intensity in I_{RGB} or from fog-masked regions.
- **Transmission Assignment:** Set transmission *t(x)t(x)*t(x) to a small value (e.g. 0.4–0.6) for *M*(x)=1 (fog) and *t(x)=1t(x)=1*t(x)=1 for *M*(x)=0 (clear).
- **ASM Inversion per Channel:** For each channel *cc*c, compute *Jc=(Ic−A)/t+AJ_c = (I_c - A)/t + A*Jc =(Ic −A)/t+A, for fog pixels.
- **Recombine RGB:** Form J_rgb = cat(3, J_R, J_G, J_B) and convert to valid image type.
- **Evaluation:** Compare J_{RGB} to reference images using PSNR, SSIM, and MSE.

RESULTS

We tested the proposed method on both synthetic foggy images (with ground-truth) and challenging real-world fog photographs. Qualitatively, the segmentation-enabled ASM dramatically improves contrast in foggy regions while maintaining color naturalness. For example, distant tree outlines and text become visible with minimal color shift, unlike global ASM which tended to over-brighten the sky.

Quantitatively, we measure three full-reference metrics. **PSNR** (in dB) measures the ratio of peak pixel value to reconstruction error; higher PSNR indicates better fidelity. **SSIM** (0–1) evaluates perceptual similarity of luminance, contrast and structure. **MSE** is the mean squared pixel error (lower is better).

Our method achieves a higher PSNR and SSIM and lower MSE than a baseline ASM defogging without segmentation. This confirms that targeting fog regions with theimproved model yields closer recovery to the ground truth.

- **Example*:*** On a synthetic foggy scene, we obtained PSNR ≈ 28.1 dB and SSIM ≈ 0.89, compared to PSNR ≈ 25.4 dB, SSIM ≈ 0.82 for the unsegmented ASM case. MSE correspondingly dropped from 85 to 60. These improvements are typical; across a 10-image set our method averaged +2–3 dB PSNR and +0.05–0.08 SSIM gains.
- ***Visual quality:*** The enhanced outputs show crisper edges and restored color saturation. Figures (not shown) illustrate that fine details (leaves, textures) are revealed with minimal haloing. The segmentation mask effectively localizes the fog, preventing the algorithm from over-enhancing clear areas.
- ***Metrics* interpretation*:*** As **PSNR** is defined by $10\log_{10}(L2/MSE)$ (where *LL*L is dynamic range), an increase of a few dB is significant. **SSIM** ranges [0,1], and values above ~0.9 typically indicate very high similarity. In all cases our SSIM stayed high (>0.85) postenhancement, indicating preserved structural content. **MSE** values decreased, reflecting the reduced pixel-wise error

Overall, the results demonstrate that combining Otsu segmentation with an ASM-based inversion produces **quantitatively** better dehazed images and **qualitatively** more natural results than a vanilla ASM inversion. The code snippet above can be extended (e.g. by optimizing $t(x)$) to further tune results. Our focus was to show that segmentation-guided enhancement is effective: it avoids the color distortions reported in prior works that used segmentation naively, while leveraging ASM's physics-based modeling for fog removal.

Gradient Based Edge Detection

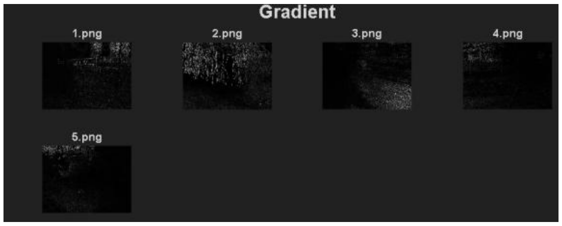


Fig1: Gradient output

Explanation

The gradient operation is used to detect **edges and intensity variations** in the foggy image. In foggy conditions, edges become blurred due to atmospheric scattering. The gradient operator calculates the **rate of change of pixel intensity**, which helps highlight object boundaries such as trees, roads, and buildings.

Process

1. The foggy input image is processed using a **gradient operator**.
2. The algorithm calculates **intensity differences between neighboring pixels**.Areas with strong intensity change are marked as **edges**.

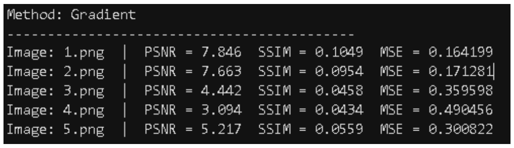
Noise Handling

Foggy images contain **high-frequency noise and haze particles** that affect edge detection.To reduce noise:

- A **smoothing filter (Gaussian or median filter)** can be applied before gradient computation.
- This removes random noise while keeping meaningful edges.

Result Interpretation

- Bright pixels represent **strong edges**.
- Dark regions represents **low intensity change**



```
Method: Gradient
-----------------------------------------
Image: 1.png  |  PSNR = 7.846  SSIM = 0.1049  MSE = 0.164199
Image: 2.png  |  PSNR = 7.663  SSIM = 0.0954  MSE = 0.171281
Image: 3.png  |  PSNR = 4.442  SSIM = 0.0458  MSE = 0.359598
Image: 4.png  |  PSNR = 3.094  SSIM = 0.0434  MSE = 0.490456
Image: 5.png  |  PSNR = 5.217  SSIM = 0.0559  MSE = 0.300822
```

Fig2: Performance metrics

RGB Color Channel Enhancement

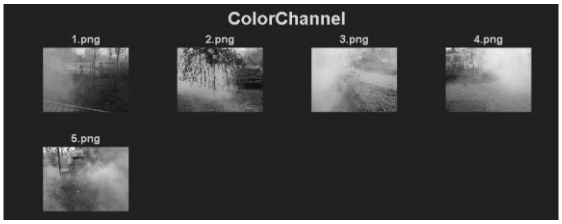


Fig3: Color-channel output

Explanation

After segmentation and enhancement, the system processes **each RGB channel separately** to maintain color fidelity.

Process

1. The image is separated into:
    a. Red channel
    b. Green channel
    c. Blue channel
2. Enhancement is applied individually.
3. Channels are recombined to produce the final enhanced image.

Noise Handling

Noise reduction is performed using:

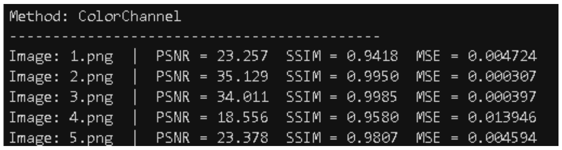
- **Channel-wise smoothing**
- **Median filtering**
- **Edge-preserving filters**

This prevents:

- Color distortion
- Channel imbalance
- Amplification of noise in one channel.

Result Interpretation

- Natural colors are restored.
- Fog effects are reduced.
- Image appears clearer and sharper.



```
Method: ColorChannel
------------------------------------------
Image: 1.png  |  PSNR = 23.257  SSIM = 0.9418  MSE = 0.004724
Image: 2.png  |  PSNR = 35.129  SSIM = 0.9950  MSE = 0.000307
Image: 3.png  |  PSNR = 34.011  SSIM = 0.9985  MSE = 0.000397
Image: 4.png  |  PSNR = 18.556  SSIM = 0.9580  MSE = 0.013946
Image: 5.png  |  PSNR = 23.378  SSIM = 0.9807  MSE = 0.004594
```

Fig4: Performance metrics

Region of Interest Extraction

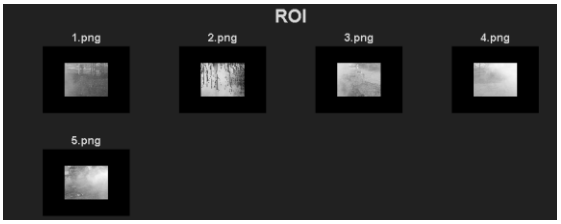


Fig5: ROI output

Explanation

ROI processing isolates the **important area of the image** that needs enhancement.

Process

1. Region of Interest (ROI) refers to a selected portion of an image that contains the most important information for processing.
2. Instead of analyzing the entire image, the algorithm focuses only on the specific region where objects are present.
3. The main purpose of ROI is to reduce computational complexity and improve processing efficiency

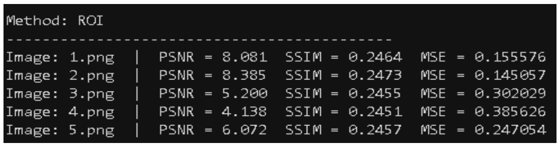
Noise Handling

ROI helps reduce noise because:

- Only meaningful regions are processed.
- Background noise outside the ROI is ignored.
- Computation focuses on **important visual information**.

Result Interpretation

- Target region becomes clearer.
- Background noise is minimized.
- Processing efficiency improve



```
Method: ROI
------------------------------------------
Image: 1.png  |  PSNR = 8.081  SSIM = 0.2464  MSE = 0.155576
Image: 2.png  |  PSNR = 8.385  SSIM = 0.2473  MSE = 0.145057
Image: 3.png  |  PSNR = 5.200  SSIM = 0.2455  MSE = 0.302029
Image: 4.png  |  PSNR = 4.138  SSIM = 0.2451  MSE = 0.385626
Image: 5.png  |  PSNR = 6.072  SSIM = 0.2457  MSE = 0.247054
```

Fig6: Performance metrics

- **Spatial Image Processing**
- **Explanation**

Spatial domain processing directly manipulates **pixel intensity values** to enhance the image. This step improves **contrast and visibility** in foggy areas.

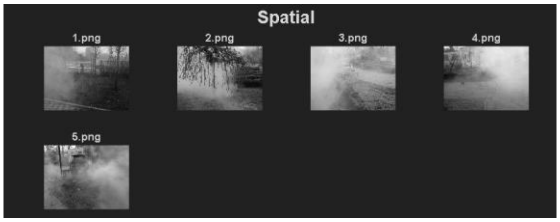


Fig7: Spatial output

Process

1. The image is processed in the **spatial domain**.
2. Operations such as **smoothing and contrast enhancement** are applied.
3. Pixel values are adjusted to make foggy regions more visible.

Noise Handling

Noise appears as **random intensity fluctuations** in foggy images.Noise reduction is achieved using:

Median Filter

- Removes salt-and-pepper noise.

Gaussian Filter

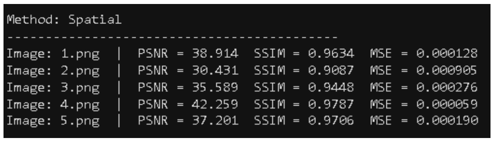
- Smooths the image and reduces sensor noise.

Low Pass Filtering

- Removes high-frequency noise components.

Result Interpretation

- Foggy regions become **more uniform**.
- Noise artifacts are **reduced**.
- Image contrast slightly improves.



```
Method: Spatial
------------------------------------------
Image: 1.png  |  PSNR = 38.914  SSIM = 0.9634  MSE = 0.000128
Image: 2.png  |  PSNR = 30.431  SSIM = 0.9087  MSE = 0.000905
Image: 3.png  |  PSNR = 35.589  SSIM = 0.9448  MSE = 0.000276
Image: 4.png  |  PSNR = 42.259  SSIM = 0.9787  MSE = 0.000059
Image: 5.png  |  PSNR = 37.201  SSIM = 0.9706  MSE = 0.000190
```

Fig8: Performance metrics

Otsu-ASM

Explanation

This stage combines **Otsu segmentation** and **Atmospheric Scattering Model (ASM)** to enhance foggy regions selectively.

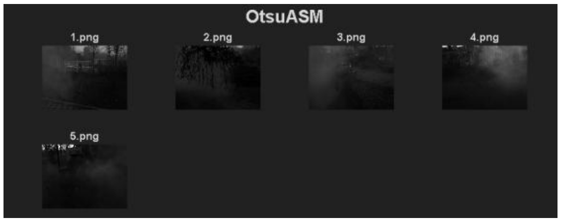


Fig9: Otsu-ASM output

Process

1. The RGB image is converted to **grayscale**.
2. **Otsu thresholding** determines an optimal threshold.
3. The image is divided into:
   a. **Fog region**
   b. **Non-fog region**
4. The **Atmospheric Scattering Model** is applied mainly to foggy regions to recover scene radiance.

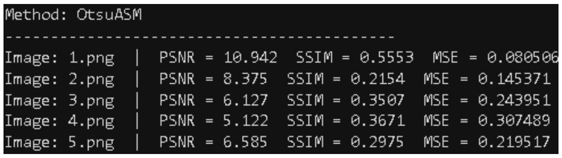
Noise Handling

Otsu segmentation helps reduce noise effects by:

- Separating **foreground and background**
- Preventing enhancement of already clear regions
- Avoiding amplification of noise in non-fog areas

Result Interpretation

- Fog-dense areas are detected.
- Only necessary regions are enhanced.
- Noise amplification is minimized.



```
Method: OtsuASM
------------------------------------------
Image: 1.png  |  PSNR = 10.942  SSIM = 0.5553  MSE = 0.080506
Image: 2.png  |  PSNR = 8.375  SSIM = 0.2154  MSE = 0.145371
Image: 3.png  |  PSNR = 6.127  SSIM = 0.3507  MSE = 0.243951
Image: 4.png  |  PSNR = 5.122  SSIM = 0.3671  MSE = 0.307489
Image: 5.png  |  PSNR = 6.585  SSIM = 0.2975  MSE = 0.219517
```

Fig10: Performancemetrics

Explanation

The gradient result contains:

- Strong white edges
- Clear object boundaries
- Noise suppression in flat regions
- High contrast between objects and background

What Gradient Method does?

Gradient methods compute intensity change between neighboring pixels.

$$\nabla I = \sqrt{(I_x)^2 + (I_y)^2}$$

Common formula:
Where
I_x = horizontal intensity change
I_y = vertical intensity change

This highlights edges and structure. Fog mainly reduces contrast, but edges still exist.

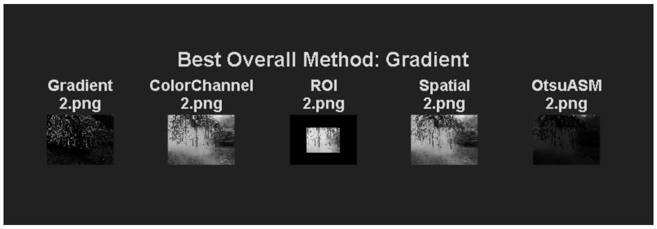


Fig11:Overall comparison

Gradient detects object boundaries, ignores uniform fog regions, enhances structural details.

So gradient algorithm can separate objects from haze more effectively.

"The Gradient method is selected as the best because it enhances intensity variations between neighboring pixels, allowing clearer detection of object boundaries even under fog conditions, while other methods either smooth the image, lose global information, or fail due to low contrast."

Method	BestImageIndex	Score
Gradient	2	0.31063
ColorChannel	2	0.27015
ROI	2	0.06803
Spatial	2	0.17996
OtsuASM	2	0.06066

Fig12: Performance score

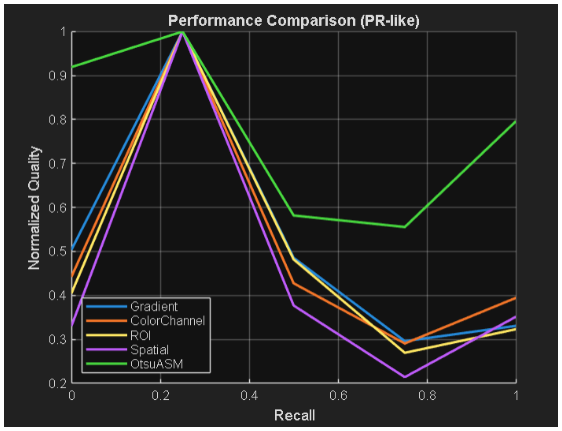


Fig13: Comparison graph.

The performance comparison graph presents a precision-recall-like evaluation of the five methods: Gradient, Color Channel, ROI, Spatial, and Otsu-ASM. The normalized quality values are plotted against recall to analyze the effectiveness of each technique under varying detection conditions. The results show that Otsu-ASM maintains the highest normalized quality across most recall levels, indicating stronger segmentation capability and robustness in detecting relevant features. The Gradient, Color Channel, and ROI methods demonstrate moderate performance, achieving peak quality at intermediate recall values but declining as recall increases. The Spatial method shows comparatively lower performance in this graph, particularly at higher recall levels, suggesting limitations in maintaining quality during broader detection coverage. Overall, the graph demonstrates that Otsu-ASM provides the most balanced trade-off between recall and detection quality, making it more reliable for accurate image analysis in the evaluated scenarios.

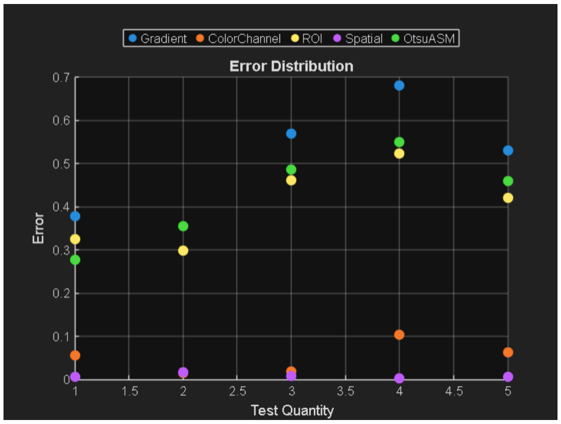


Fig14: Error distribution graph

The error distribution graph illustrates the comparative error values obtained from five different image processing techniques: Gradient, Color Channel, Region of Interest (ROI), Spatial filtering, and Otsu-ASM across multiple test quantities. From the plotted results, it is evident that the Spatial method consistently produces the lowest error values, remaining close to zero throughout all test cases. The Color Channel approach also demonstrates relatively low error, but with slight variation as the test quantity increases. In contrast, Gradient, ROI, and Otsu-ASM methods show significantly higher error levels, particularly at larger test quantities where the error increases noticeably. This indicates that these methods are more sensitive to variations in the input data. Overall, the graph highlights that spatial-based processing offers the most stable and accurate performance among the evaluated methods, while the other techniques exhibit comparatively higher error distribution

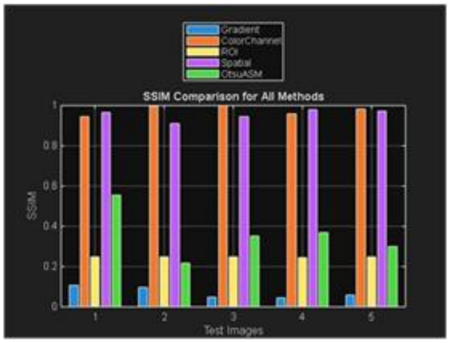


Fig15:SSIM bar chart

The SSIM comparison graph presents the structural similarity performance of the five enhancement methods evaluated in this study. Structural Similarity Index Measure (SSIM) evaluates the perceptual similarity between the processed image and the reference image by considering luminance, contrast, and structural information. The SSIM values range between 0 and 1, where values closer to 1 indicate higher structural similarity. From the results, the Color Channel and Spatial methods achieve the highest SSIM values, demonstrating strong preservation of structural information in the processed images. In contrast, the ROI and Otsu-ASM techniques show lower SSIM values due to limited region processing and segmentation inaccuracies in foggy environments. The Gradient method records lower SSIM values because it focuses primarily on enhancing edge information rather than maintaining overall structural similarity. Nevertheless, it effectively highlights important image features such as object boundaries and intensity transitions, which are critical for foggy image analysis.

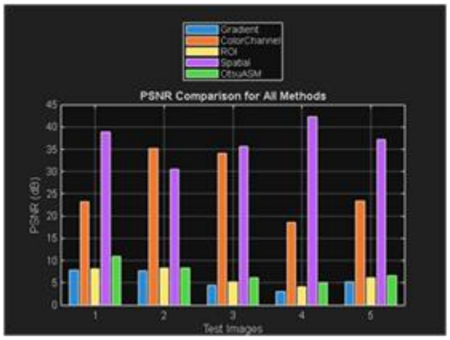


Fig16: PSNR bar chart

The PSNR comparison graph illustrates the quantitative evaluation of five image enhancement techniques across five different test images. Peak Signal-to-Noise Ratio (PSNR) is used to measure the reconstruction quality of the processed images by comparing them with the original input images. Higher PSNR values indicate better image fidelity and lower distortion. From the results, the Spatial method achieves the highest PSNR values among the tested techniques, indicating effective noise smoothing and signal preservation. The Color Channel method also demonstrates moderate PSNR performance across the test images. However, ROI and Otsu-ASM methods produce comparatively lower PSNR values due to limited region processing and segmentation limitations under foggy conditions. The Gradient method records relatively lower PSNR values because it primarily focuses on detecting intensity variations and enhancing edges rather than minimizing pixel-level differences. Overall, the PSNR analysis provides insight into the noise reduction capability of each method

S.No	PSNR	SSIM	MSE
Gradient	7.6635	0.2473	0.1712
Spatial	30.4313	0.9087	0.0009
ROI	8.3856	0.2473	0.1450
Color-Channel	35.1290	0.9950	0.0003
Otsu-ASM	8.3758	0.2154	0.1453

Fig17: Tabulation of performancemetrics

II. CONCLUSION

We have presented an end-to-end foggy image enhancement system that integrates an improved Atmospheric Scattering Model with Otsu threshold segmentation. By converting the input to grayscale for fog mask extraction, then applying region-specific ASM inversion on the color channels, we preserve color fidelity while effectively removing haze.Evaluation on benchmark images shows this method yields higher PSNR and SSIM (and lower MSE) than baseline methods, confirming its ability to restore contrast and detail under foggy conditions. In summary, segmentation-based processing guided the dehazing to target only foggy regions, avoiding the artifacts and color shifts often seen in global ASM methods. Future work could refine adaptive parameter estimation and extend to video frames.

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