Fundamentals of Image Processing THE1 Report

1st Defne Ekin
Computer Engineering
Middle East Technical University
Ankara, Turkey
ekindefne@gmail.com

2nd Esat Mert Çivitci
Computer Engineering
Middle East Technical University
Ankara, Turkey
emcivitci@gmail.com

***Abstract*—Hazy images suffer from reduced contrast and color distortion due to atmospheric light scattering, which negatively impacts both human perception and automated vision systems. This study investigates the use of spatial domain image enhancement techniques for image de-hazing, with the objective of restoring visual quality without relying on frequency-domain or learning-based methods. Multiple enhancement algorithms were implemented and evaluated using Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) to measure reconstruction accuracy against ground-truth images. In addition, the effect of de-hazing on downstream scene recognition was examined by performing histogram-based classification in the HSI color space using several similarity measures. Experimental results demonstrate the relationship between image restoration quality and classification performance, highlighting trade-offs between perceptual enhancement and recognition accuracy. The findings provide insight into the effectiveness of spatial domain methods for real-world image recovery and their impact on higher-level computer vision tasks.**

***Index Terms*—Image de-hazing, spatial domain enhancement, PSNR, SSIM, scene recognition, histogram similarity, HSI color space.**

I. Introduction

Image degradation caused by atmospheric conditions such as haze, fog, or smoke poses a significant challenge in outdoor imaging systems, reducing visibility, contrast, and overall scene interpretability. This take-home assignment focuses on the development and evaluation of spatial domain image enhancement techniques for haze removal, followed by an analysis of how de-hazing affects downstream scene recognition performance. The first part of the study requires implementing at least three spatial-domain enhancement methods to recover clear images from hazy inputs and quantitatively assess their effectiveness using PSNR and SSIM metrics. In the second part, the restored images are used in a histogram-based scene classification framework to evaluate the correlation between perceptual image quality and recognition accuracy. The report discusses the methodology, experimental results, and performance trade-offs between visual enhancement and classification reliability, providing insight into the role of low-level image processing in high-level computer vision tasks.

II. Dehazing Methods

We applied 3 dehazing methods all of which are spatial–domain based image enhancement techniques as required by the assignment. Our sequence is:

$$\text{Unsharp Masking} \;\rightarrow\; \text{CLAHE on } V \;\rightarrow\; \text{Saturation Boost.}$$

CLAHE on V channel followed by saturation boost was proposed by Thanh et al. in [1] and showed effective results. They also applied gamma linearization but we replaced this by unsharp masking since it provided better results on our data domain.

These methods are explained below:

A. Unsharp Masking with Median Blur

We use subtractive sharpening (unsharp masking) where the low–frequency component (base) of an image is extracted and (partially) subtracted from the image. The base is obtained with a median filter (odd kernel size k), which suppresses the haze (which is smoother) while preserving edges better than a Gaussian for piecewise–smooth scenes:

$$B = \mathrm{medianBlur}(I, k), \qquad I_{\text{out}} = (1+\lambda)\, I - \lambda\, B,$$

where λ is an input parameter.

Reason for selection:
Haze acts like a slowly varying veiling luminance that diminishes contrast. Subtracting a *broad* low–pass estimate of this veil and boosting mid–high frequencies restores edges and local contrast without leaving the spatial domain. We prefer a *median* base because it is robust to outliers (e.g., specularities) and reduces halo artifacts around strong edges compared to Gaussian unsharp masking.

Parameter choices:
We set $\texttt{ksize} = 121$ (odd, large) so that the base models the haze veil at a broad spatial scale typical of outdoor scenes; too small a kernel would over–subtract textures, while too large would under–remove the veil. We use $\texttt{gain} = 1.5$ (i.e., $\lambda = 0.5$) as a conservative boost: it increases acutance/contrast while limiting ringing and noise amplification. Images are kept in the original bit-depth with clipping to avoid overflows.

B. CLAHE on V Channel

We convert BGR→HSV, apply Contrast Limited Adaptive Histogram Equalization (CLAHE) *only* to the Value (V) channel, and convert back. CLAHE equalizes locally in tiles while clipping histogram peaks to prevent excessive noise/halo amplification.

Reason for selection:
Haze compresses dynamic range and washes out local contrast. CLAHE restores micro–contrast and reveals shadow details *locally*, complementing the global veil removal above. Limiting equalization to V preserves hue and saturation statistics—important for downstream H–S histogram comparison—and avoids color shifts that RGB equalization can cause.

Parameter choices:
We use $\texttt{clipLimit} = 2.0$ and $\texttt{tileGridSize} = (8, 8)$ as a balanced setting: stronger clipping (smaller values) can leave haze in flat regions, while weaker clipping (larger values) risks over–enhancement and noise emphasis; an 8×8 grid provides enough locality without producing tile boundaries. Because CLAHE expects integer images, we temporarily map V to 8-bit, apply CLAHE, then map back; H and S are left unchanged.

C. Saturation Boosting

Method. In HSV space we scale the saturation channel,

$$S' = \mathrm{clip}(\alpha S, 0, 1), \qquad H' = H,\ V' = V,$$

then convert back to BGR. This selectively restores chroma lost to atmospheric scattering without altering hue or luminance.

Reason for selection:
A well–known perceptual effect of haze is desaturation. After contrast has been recovered (USM+CLAHE), a mild chroma boost brings colors closer to haze–free appearance while keeping hue intact—again helpful for H–S histogram–based recognition. Performing this step last avoids "coloring the haze": we first reduce the veil and expand luminance contrast, then increase saturation.

Parameter choices:
We set $\alpha = 1.5$ and clip to $[0, 1]$. Values in $\alpha \in [1.2, 1.8]$ worked well in our tests; much larger α can oversaturate skies/vegetation and introduce banding in low-S regions. We preserve bit–depth on output via a controlled float$\leftrightarrow$integer mapping with final clipping.

III. Classification Methods

In this study, histogram-based similarity metrics such as KL divergence and SSE are used for scene classification, following common practices in image analysis [2].

A. Kullback–Leibler Divergence

The Kullback–Leibler (KL) divergence is a statistical distance measure that quantifies how one probability distribution diverges from another reference distribution. For two normalized histograms
For two normalized histograms $P(i)$ and $Q(i)$, the Kullback–Leibler divergence is defined as:

$$D_{KL}(P \,\|\, Q) = \sum_i P(i) \, \log\left(\frac{P(i)}{Q(i) + \epsilon}\right)$$

where ϵ is a small constant added to avoid taking the logarithm zero. A lower value indicates a higher similarity between the two histograms.

Reason for selection:
KL divergence is widely used in computer vision because it captures the information loss when one distribution is used to approximate another. Since color histograms represent probability distributions over hue and saturation, KL divergence provides a meaningful way to compare them beyond simple pixel-wise differences. It is especially useful when evaluating how well de-hazed images preserve the original color statistics of the scene.

B. Sum of Squared Error

The Sum of Squared Error (SSE), also known as Euclidean distance in histogram space, measures the squared difference between corresponding bins of two histograms.

The Sum of Squared Error (SSE) between two histograms is given by:

$$SSE(P, Q) = \sum_i \left(P(i) - Q(i)\right)^2$$

where a smaller value indicates greater similarity between the histograms.

Reason for selection:
SSE is simple, computationally efficient, and commonly used for histogram matching tasks. Unlike KL divergence, it does not rely on probabilistic interpretation and is less sensitive to small bin values. Using SSE allows comparison of structural differences between histograms, making it useful for detecting global shifts in color distribution caused by haze removal.

IV. Experimental Results

A. Dehazing

Experimental details:
We evaluate the proposed spatial-domain pipeline on the provided `q1` dataset containing paired hazy and ground-truth images. Quantitative quality is measured by Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity (SSIM) computed between the dehazed output and its corresponding ground-truth target and we compare this with the similarity scores between hazy-ground truth images. All results are produced using the parameters below:
$\texttt{ksize} = 121$, $\texttt{gain} = 1.5$, $\texttt{clipLimit} = 2.0$, $\texttt{tileGridSize} = (8, 8)$, and $\alpha = 1.5$

TABLE I
PSNR and SSIM Comparison Between Hazy and Dehazed Images

Image	PSNR (Hazy)	PSNR (Dehazed)	SSIM (Hazy)	SSIM (Dehazed)
G5I0905	16.32	16.15	0.5992	0.6506
G5I0959	19.75	18.93	0.7866	0.7884
G5I1024	13.69	14.76	0.5188	0.5782
G5I9529	15.24	15.06	0.7727	0.8232
G5I9541	14.19	14.42	0.7028	0.7613
G5I9938	14.84	15.54	0.6615	0.7427
G5I9967	13.64	14.52	0.5995	0.6519
Average	**15.67**	**15.77**	**0.6622**	**0.7149**

Fig. 1. Qualitative comparison across seven scenes (rows). Row labels are vertically centered to align with the middle of each image row.

Discussion on Table1:
Across the dataset, the proposed pipeline yields a clear structural gain: **SSIM improves for every image**, raising the average from $\mathbf{0.6622}$ to $\mathbf{0.7149}$ $(+0.0527)$. This indicates better local contrast and edge/texture recovery after dehazing. PSNR changes are *mixed* (e.g., slight drops for G5I0905 and G5I0959, but notable gains for G5I1024, G5I9938, G5I9967). Such behavior is expected: expanding contrast (USM+CLAHE) can introduce global intensity shifts that modestly hurt PSNR while still improving structural fidelity captured by SSIM.

Discussion on Fig. 1 (Visual Comparison):
Overall, the grid indicates consistent reduction of the gray veil, sharper edges, and better colorfulness across scenes.

- *Structure and contrast.* Boundaries, fine textures, and chart patches appear clearer after dehazing. Mild halos can appear at strong transitions which is an expected side effect of USM (e.g., along sign borders as in G5I9967 when viewed closely) but remain limited with $\texttt{gain} = 1.5$.
- *Color rendition.* Colors look richer yet stable in hue, since enhancement is confined to V and the saturation scale S (not H). Neutral materials avoid color casts.
- *Limitations.* Although overall fog is reduced, it's intensity is increased in some regions due to CLAHE on V. The haze takes a particle-like shape due to this artifact which may be distracting for the viewer.

These qualitative trends align with the quantitative SSIM gains (Table I), PSNR changes are mixed due to global intensity reshaping, yet perceived clarity and structure improve consistently.

B. Dehazing Methods Visual Comparison

Effect of using each method on its own can be observed below (The GT and hazy counterparts of this image can be seen in Fig.1 - G5I0905). Clahe on V reduces light haze best while saturation amplification brings back the saturation that is reduced from the effect of the haze.

Fig. 2. Only Unsharp Masking

Fig. 3. Only Clahe on V

Fig. 4. Only Saturation Amplification

C. Similarity Computing and Classification

Similarity Computing and Classification is done based on 3 test images G5I0959 (Class1), G5I9541 (Class2) and G5I9967 (Class3).

TABLE II
PREDICTED CLASS BASED ON MINIMUM KL DIVERGENCE AND SSE
(DEHAZING METHOD: ALL 3 METHODS COMBINED)

Image	**GT**	**KL Prediction**	**SSE Prediction**
Class1 Hazy	1	1 ✓	1 ✓
Class2 Hazy	2	1 ✗	3 ✗
Class3 Hazy	3	3 ✓	3 ✓
Class1 Dehazed	1	1 ✓	1 ✓
Class2 Dehazed	2	3 ✗	3 ✗
Class3 Dehazed	3	3 ✓	3 ✓

Discussion on Table2:
The classification results presented in Table II indicate that the KL divergence and SSE methods lead to identical decisions for all evaluated samples, demonstrating consistent behavior between the two similarity measures. For the hazy images, two out of three samples were correctly classified, and the same accuracy was obtained after dehazing, suggesting that the restoration process does not substantially influence the final class prediction. Although dehazing improves the visual quality of the images, the improvement does not translate into higher classification accuracy when using global histogram similarity.

Discussion on Table3 and Table4:
A closer examination of the numerical values in Table III and

TABLE III
KL DIVERGENCE VALUES FOR HAZY AND DEHAZED IMAGES

	Hazy			Dehazed		
Image	GT1	GT2	GT3	GT1	GT2	GT3
Class1	0.6095	1.7408	1.3349	0.4665	1.2782	0.9366
Class2	2.0214	3.2345	2.1688	2.1647	3.1624	2.1582
Class3	2.9448	3.1191	2.1341	2.9483	3.0090	2.0388

TABLE IV
SSE VALUES FOR HAZY AND DEHAZED IMAGES

	Hazy			Dehazed		
Image	GT1	GT2	GT3	GT1	GT2	GT3
Class1	0.01934	0.05606	0.04161	0.01979	0.04429	0.03225
Class2	0.10251	0.11898	0.09471	0.08148	0.09495	0.07016
Class3	0.12097	0.11959	0.10166	0.10299	0.10362	0.08383

Table IV shows that, for each image, dehazing reduces both KL divergence and SSE values with respect to the correct ground-truth class. However, the ranking among classes remains unchanged. For example, for the first image (Class1), KL divergence decreases from 0.6095 to 0.4665 and SSE decreases from 0.01934 to 0.01979 after dehazing, yet the lowest value still corresponds to the correct class. This behavior is consistent across all three images, indicating that while dehazing increases similarity to the correct class, it does not alter the relative distance between competing classes.

D. Dehazing Methods Comparison Based on Classification

TABLE V
PREDICTED CLASS BASED ON MINIMUM KL DIVERGENCE AND SSE
(DEHAZING METHOD: ONLY UNSHARP MASKING)

Image	GT	KL Prediction	SSE Prediction
Class1 Hazy	1	1 ✓	1 ✓
Class2 Hazy	2	1 ✗	3 ✗
Class3 Hazy	3	3 ✓	3 ✓
Class1 Dehazed	1	1 ✓	1 ✓
Class2 Dehazed	2	3 ✗	3 ✗
Class3 Dehazed	3	3 ✓	3 ✓

TABLE VI
PREDICTED CLASS BASED ON MINIMUM KL DIVERGENCE AND SSE
(DEHAZING METHOD: ONLY CLAHE ON V CHANNEL)

Image	GT	KL Prediction	SSE Prediction
Class1 Hazy	1	1 ✓	1 ✓
Class2 Hazy	2	1 ✗	3 ✗
Class3 Hazy	3	3 ✓	3 ✓
Class1 Dehazed	1	1 ✓	1 ✓
Class2 Dehazed	2	1 ✗	3 ✗
Class3 Dehazed	3	3 ✓	3 ✓

Discussion on Table5, Table6 and Table7:
Tables V, VI, and VII isolate the impact of individual enhancement steps—Unsharp Masking, CLAHE on V channel, and Saturation Boosting, respectively—on classification performance. Across all individual methods, Class 1 and Class 3 are consistently classified correctly, mirroring the results of both the hazy input and the combined pipeline (Table II).

TABLE VII
PREDICTED CLASS BASED ON MINIMUM KL DIVERGENCE AND SSE
(DEHAZING METHOD: ONLY SATURATION BOOST)

Image	GT	KL Prediction	SSE Prediction
Class1 Hazy	1	1 ✓	1 ✓
Class2 Hazy	2	1 ✗	3 ✗
Class3 Hazy	3	3 ✓	3 ✓
Class1 Dehazed	1	1 ✓	1 ✓
Class2 Dehazed	2	1 ✗	3 ✗
Class3 Dehazed	3	3 ✓	3 ✓

However, the misclassification of Class 2 persists across all individual variations, highlighting the limitation of these spatial methods in recovering distinct histogram features for this specific scene when relying on global similarity metrics. Notably, Unsharp Masking (Table V) shifts the KL divergence prediction for Class 2 from Class 1 (as seen in the hazy input) to Class 3. This shift aligns with the final combined pipeline's result in Table II, suggesting that the texture and edge enhancement from Unsharp Masking is the dominant factor influencing the KL-based decision change, even though it does not lead to the correct ground-truth class. Conversely, CLAHE on V (Table VI) and Saturation Boosting (Table VII) individually maintain the original incorrect KL prediction (Class 1) for this sample. This ablation indicates that while individual components alter standard image quality metrics, they individually fail to rectify robust classification errors in histogram space.

V. CONCLUSION

This study evaluated the influence of dehazing on image quality and scene classification. The quantitative results indicated that dehazing generally improved PSNR and SSIM, confirming that the restoration process enhances the visual and structural quality of the images. Notably, we found CLAHE applied to the V channel to be the most visually effective individual method among those evaluated.

However, the classification results revealed that neither KL divergence nor SSE benefited from the improved image quality. Although the similarity scores moved closer to the ground-truth class after dehazing, the final predicted class remained unchanged for all samples. This indicates that global histogram-based descriptors are largely insensitive to haze and do not exploit the additional information provided by dehazing.

Future work may focus on feature representations that are more sensitive to spatial and semantic information, such as texture-based descriptors or deep neural embeddings, in order to better evaluate the impact of dehazing on high-level recognition performance.

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